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Machine Learning and Predictions on Effect of Fiber Size, Hybridization on the Mechanical Properties of Coir/Luffa Reinforced Hybrid Composite

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Abstract- This study is to further investigate at what percentage of coir/luffa fibers will generate hybrid composite with the best mechanical behavior while maintaining 30% fiber weight with 70% epoxy resin polymer. The composites were produced by varying the fiber weight fractions and the fiber size. Each composite comprises 30% fiber and 70% epoxy resin. At corresponding fiber sizes of 200 µm, 400 µm, and 600 µm, hybridization of the fibers was carried out in the following weight ratios: 0:30, 10:20, 15:15, 20:10, and 30:0 wt/wt of Coir/Luffa. When the tensile strength, flexural strength, and impact strength of the composites were examined, it was found through controlled experiments that these properties increased as the fiber size increased. Additionally, it was found that sample R [15%wt Coir and 15%wt Luffa] provided the optimum mechanical qualities across a range of fiber sizes because the fibers were distributed evenly throughout the matrix. Machine learning tools such as artificial neural networks [ANN] and fuzzy logic designers were utilized to model and foretell the experimental outcomes of the hybrid composites. The model's output variables were tensile strength, flexural strength, and impact strength; the input variables were the weights of coir and luffa and the fiber size. Based on their coefficient of determination [R^2], the two analyzed models' performances and appropriateness were compared. Tensile strength, flexural strength, and impact strength all have fuzzy logic coefficients of determination [R^2] of 0.9752, 0.9773, and 0.9730, respectively. Similar to this, the ANN coefficients of determination [R^2] for tensile strength, flexural strength, and impact strength are 0.9608, 0.904, and 0.9378, respectively. Based on this statistical analysis, the fuzzy logic designer produced a much more accurate prediction than the ANN in terms of the coefficient of determination [R^2] and mean square error [MSE] values.

Indexed Terms- Fuzzy logic designers, Artificial Neural Network, Mean square error, Hybrid Composite, Coefficient of determination, contour plot

I. INTRODUCTION

Composite materials are man-made materials that are produced with the intention of replacing conventional materials, primarily metals. As a result, they are becoming a viable alternative to stainless steel and other materials for harsh environments due to their many benefits, including higher specific strength, stiffness, hardness, biodegradability, corrosion resistance, and wear resistance [1, 2].

Natural fibers are rapidly been used as reinforcing agent in composite due to the difficulties in accessing synthetic fibers such as glass, basalt or ceramic fibers in various part of the world, easy processing from plants or animals [1], environmental friendly unlike some synthetic fibers such as carbon and aramid fiber which emits carbon dioxide causing air pollution, ability to be recycled, light weight, low cost and biodegradable [3-10].

Sisal, jute, bagasse, luffa, rice husk, pineapple leaf, cotton, banana, kenaf, flax, and coir are a few examples of natural fibers that have efficiently replaced synthetic fibers in a variety of applications including constructions, sport, and automotive industries. However, the water retention qualities of natural fibers, which diminish compatibility between the hydrophilic fiber and hydrophobic polymer, are mostly to blame for the decline in their use [11–15]. Alkaline treatment is one of the most successful chemical surface treatments performed to fibers to fix these issues by eliminating the hydroxyl group [-OH] present in natural fibers [16-20].

Sreeramulu and Ramesh [21]; Lu, Askeland, and Drzal [22]; Krishnudu, Sreeramulu, and Reddy [23]; Mohana Krishnudu, Sreeramulu, and Reddy [24] and Chibueze I G, Atuanya C U, Nwobi Okoye C C and Obele C M [1], all researched on the effect of alkaline chemical treatments on the mechanical properties of hybrid composites and they all discovered that alkaline treatment reduces the amount of hydroxyl group present in the fibers, which automatically led to improvement in the bonding, reduces shrinkage due to reduction in the moisture content present in the fiber, thus improving the mechanical and thermal properties of natural fiber reinforced composites.

Hybridization, which involves the combination of two or more fibers, such as synthetic and natural fibers [5], two different natural fibers or synthetic combinations, and a filler powder impregnated into a natural fiber in a composite material, has recently been an effective development in the field of composites. Researchers like Vijaya Ramnath, Junaid Kokan, and Niranjan Raja [25] demonstrated that hybrid abaca-jute-GFRP composites are superior than GFRP, Jute fiber reinforced polymer, and Abaca fiber reinforced polymer in terms of tensile strength, hardness, and yield strength. In their 2013 study on sisal-jute-GFRP hybrid polyester composites, Ramesh, Palanikumar, and Reddy [26] found that sisal-jute-GFRP composites outperformed sisal-GFRP and jute-GFRP composites under flexural loading conditions [26]. Moreover, the mechanical and thermal properties of jute and banana fiber reinforced epoxy hybrid composites were studied by Boopalan, Niranjana, and Umapathy [27], they discovered that the addition of banana fiber [up to 50% weight fraction] increased the tensile and flexural strength of hybrid composites and decreased their hydrophilicity [27].

Conventionally, polymer composites are often produced in the laboratory by the trial and error method, thereby making the experimental analysis of the composite costly and time-consuming [28, 29]. In order to save time and cost, the need to consider a suitable low-cost way of predicting the composite's mechanical properties is dearly required [29]. One way this could be achieved is by developing a mathematical model based on regression analysis, which conventionally has been the incipient tool used by engineers to model the mechanical properties of engineering materials [30, 31]. Due to rapid advances in technology and computation, artificial intelligence and machine learning computation tools are rapidly replacing mathematical-based models because they are simple to create, more reliable, and produce better outcomes than mathematical models [32 , 33]. With mathematical and computational models, a designer can easily find the best combination of constituent materials to balance output and cost.

A few of the computational-based models for robust designs include fuzzy logic designers, artificial neural networks, genetic algorithms, Taguchi robust designers, and simulation annealing. These models are used to produce high-quality products at a very low cost and within the shortest amount of time [29].
An artificial neural network [ANN], usually called ‘neural network’, is a computational model that is exhilarated by the structure and/or functional aspects of biological neural networks [30-34]. Artificial neural networks [ANNs] have been a useful modeling tool and are versatile computational methods used in modeling engineering materials mechanical properties. Researchers such as Nwobi-okoye and Umeonyiagu [31] utilized ANN to predict the strength of a concrete made with locally sourced concrete making materials. Atuanya C U, Nwobi-Okoye C C and Onukwuli O D. [35] utilized ANN to successfully model and predict the tensile strength, impact strength, and hardness of a date fiber–polythene composite with a correlation factor of 96%. Using ANN, Keerthi Gowda, Easara Prasad and Velmurugan [36] predicted the tensile strength, flexural strength and impact strength of a coir/sisal reinforced polyester composite with a correlation factor of 0.999. Satash Pujari, Rama Krishma, and Balaram Padel [28] used ANN and regression models to model and predict the water absorption behavior of

jute and banana fiber reinforced epoxy composites, the ANN coefficient of multiple determinations [R^2] for jute fiber was 0.97 and 0.99 for banana fiber reinforced composites, while the regression model coefficient of multiple determinations [R^2] was 0.846 for jute fiber and 0.928 for banana fiber reinforced composites.

Fuzzy logic was introduced in 1965 by Zadec and is often used by engineers to model the mechanical properties of materials and the various uncertainties associated with them [28]. The development of fuzzy logic helps engineers and scientists to consider and understand how to manage vagueness and uncertainty when considering precision in designs and measurement [37]. Recent research investigation showed that Chibueze I G, Atuanya C U, Nwobi Okoye C C and Obele C M [1] successfully predicted the flexural strength, impact strength and hardness of bagasse/luffa reinforced epoxy polymer with fuzzy logic designer, producing a correlation factor [R] of 99.6%, 99.4% and 94.6% respectively [1]. Anukwonke M C, Chibueze I G, and Nnuka N N [38] also used fuzzy logic to successfully predict the average grain size with 99.9% accuracy, as well as ultimate tensile strength, yield strength,% elongation, hardness, and impact strength with 99.8%, 99.7%, 99.5%, and 99.7% accuracy for AL-5%Mg doped with nickel.

In this study, hybrid composite was made using 30% coir and luffa fibers with 70 % epoxy. The unusual qualities of coir and luffa fibers, such as their mechanical properties, biodegradability, and availability, in addition to the social considerations, led to their selection. Cellulosic fiber known as "coir" is extracted from coconut seeds and has 42% cellulose content, 0.5% hemicellulose content, and a very high lignin concentration [21]. In saline water, coir has a great corrosion resistance.

In Central and South America, the Luffa cylindrica, often known as loofah or luffa, or locally as a sponge gourd, is commonly found. Because of their vascular character, which typically creates tri-dimensional layers when dried, they give the composite a higher degree of toughness [20]. They belong to the same cucumber family. High cellulose, tensile strength, and hardness are all present in luffa fiber [28]. In polymer composites, luffa fiber can be employed in a variety of forms, including chopped, powder, woven, and continuous [1].

The purpose of this study is to further investigate at what percentage of coir/luffa fibers will generate hybrid composite with the best mechanical behavior while maintaining 30% fiber weight with 70% epoxy resin polymer and utilizing machine learning tools such as artificial neural networks [ANNs] and fuzzy logic designers to model the multiple inputs and multiple outputs performance of coir and luffa reinforced epoxy polymer composites and subsequently predicting the hybrid composite's tensile strength, flexural strength, impact strength, and hardness.

II. METHODOLOGIES

2.1: Materials and Equipment’s

The materials and equipments used in this research are coir and luffa fibers, epoxy resin, hardener. Universal tensile testing machine, hardness tester, impact testing machine, pulverizing machine, scanning electron microscope [SEM], and metal mould

2.2: Preparation of the fibers

Separate preparations were made for the coir and luffa fibers. The coir was cleaned of any filth or debris by being submerged in water for 24 hours, followed by two days of sun drying. After that, the dried coir was immersed in a 10%concentrated solution of sodium hydroxide for 12 hours. This helped to remove lignin, wax, and hydroxyl groups from the material, which decreased the fiber's tendency to be hydrophobic and increased its roughness and adhesiveness [1]. After that, water was used to rinse the alkaline-treated fiber repeatedly until a pH of 7 was achieved. After being cleaned, the fiber was once more sun dried for two days before being oven dried at 100^0C and then pulverized in a crushing machine. Following that, an electrically powered sieve with mesh sizes of 200µm, 400µm, and 600µm was used to filter the pulverized coir fiber into its various sizes, before it was then placed in a plastic container for further processing.

These procedures were also repeated for the preparation of luffa fiber.

2.3: Preparation of Composites and Test Specimens

The composites were produced by the hand lay-up technique by varying the weight fractions and size of the fiber powders. Fifteen different composites were produced with three different fiber sizes each [200µ m, 400 µm, and 600µm]. Each composite was made up of 30% fiber and 70% epoxy resin. Hybridization of the fibers was done in this proportion: P: C/L [0% / 30%]; Q: C/L [10% / 20%]; R: C/L [15% / 15%]; S: C/L [20% / 10%]; T: C/L [30% / 0%] fiber weight. Where P, Q, R, S, T are the composite tag names whereas C/L is the ratio of coir fiber to luffa fiber respectively.

2.4: Casting of the Composites

A 300 mm by 300 mm steel mold was used. To make it simple to remove the cast from the mould, polyvinyl alcohol [PVA] was first used to polish the mold. First, the epoxy resin was combined in a 2:1 ratio with the hardener in a porcelain bowl and then the fibers. To spread the fibers throughout the matrix, the mixture was manually agitated before being poured into the mould. Before being taken out of the mold, the casts of each were given a 24-hour air cure. After being removed from the mold, the cast was post-cured in the air for an additional 48 hours. For mechanical testing, specimens with the appropriate ASTM dimensions were cut using a diamond cutter and labeled with the appropriate designation of the composites.

Taguchi robust design was used to design the experiment, with the template from the design shown in table1 [1].

Table 1: Samples of the composite from Taguchi design [1]

Composites	Tensile Strength[MPa]	Flexural Strength[MPa]	Impact Strength [MPa]
P_{200}			
P_{400}			
P_{600}			
Q_{200}			
Q_{400}			
Q_{600}			
R_{200}			
R_{400}			
R_{600}			
S_{200}			
S_{400}			
S_{600}			
T_{200}			
T_{400}			
T_{600}			

P_{200} =EPOXY [70wt %] + C [0wt %] + S [30wt %] at fiber length 200µm
P_{400} =EPOXY [70wt %] + C [0wt %] + S [30wt %] at fiber length of 400µm
P_{600}=EPOXY [70wt %] + C [0wt %] + S [30wt %] at fiber length of 600µm
Q_{200}= EPOXY [70wt %] + C [10wt %] + S[20wt %] at fiber length of 200µm
Q_{400}= EPOXY [70wt %] + C [10wt %] + S [20wt %] at fiber length of 400µm
Q_{600}= EPOXY [70wt %] + C [10wt %] + S [20wt %] at fiber length of 600µm
R_{200}= EPOXY [70wt %] + C [15wt %] + S[15wt %] at fiber length of 200µm
R_{400} = EPOXY [70wt %] + C [15wt %] + S [15wt %] at fiber length of 400µm
R_{600}= EPOXY [70wt %] + C [15wt %] + S[15wt %] at fiber length of 600µm
S_{200}= EPOXY [70wt %] + C [20wt %] + S[10wt %] at fiber length of 200µm
S_{400}= EPOXY [70wt %] + C [20wt %] + S [10wt %] at fiber length of 400µm
S_{600}= EPOXY [70wt %] + C [20wt %] + S [10wt %] at fiber length of 600µm
T_{200}= EPOXY [70wt %] + C [30wt %] + S [0wt %] at fiber length of 200µm
T_{400}= EPOXY [70wt %] + C [30wt %] + S[0wt %] at fiber length of 400µm
T_{600}= EPOXY [70wt %] + C [30wt %] + S[0wt %] at fiber length of 600µm

2.5: Sample testing

The tests performed on the composite samples were tensile strength, flexural strength and impact strength.

2.5a: Tensile testing
A Hounsfield Monsanto Universal Tensometer Machine was used to evaluate the material's tensile strength at the Mechanical Engineering Laboratory of the Nnamdi Azikwe University, Awka. According to the ASTM 638-10 standard test technique for tensile properties of polymers, the composite samples were 160 mm by 20 mm by 4 mm in size.

2.5b: Flexural testing
The flexural of the samples, also known as bending strength, was assessed using the three-point bend method. A customized UTM machine was used to conduct the test in accordance with ASTM D790-03. Each composite specimen was rectangular in shape and had dimensions of 200 mm by 20 mm by 5 mm. The trials employed a cross head speed of 0.5 mm/min. Then, using a simple bending moment diagram, the flexural of a simply supported beam under a central point load was calculated.

2.5c: Impact testing
The impact test was conducted using a Veekay instrument to ascertain how resilient the composites were. The specimen supported on a cantilever beam was broken by a blow delivered at a specific distance from the edge of the specimen clamp during the Charpy impact test, which was carried out in accordance with ASTME23 standard to describe the impact behavior of hybrid composites. In the typical sample size of 100 mm by 20 mm by 5 mm, a V-notch was produced with a root depth of 2 mm and an angle of 45^0.

III. RESULTS AND DISCUSSION

3.1: Results
The following results were obtained from the mechanical testing of the samples as shown in Table 2.

Table 2: Mechanical properties of the Samples

Samples	COIR [wt %]	LUFFA [wt%]	FIBER SIZE[µm]	Tensile Strength [MPa]	Flexural Strength [MPa]	Impact Strength [MPa]
P_{200}	0	30	200	8.5	20.5	18
P_{400}	0	30	400	7	21	17.4
P_{600}	0	30	600	5.2	32	27
Q_{200}	10	20	200	5.5	21	18.5
Q_{400}	10	20	400	9	21.5	18.8
Q_{600}	10	20	600	13	38	26
R_{200}	15	15	200	7.5	30	20
R_{400}	15	15	400	13	38	25
R_{600}	15	15	600	20	50.5	32.5
S_{200}	20	10	200	4	21.5	23
S_{400}	20	10	400	7	28	20
S_{600}	20	10	600	14.5	32	25
T_{200}	30	0	200	7	46	21
T_{400}	30	0	400	10	30	22
T_{600}	30	0	600	12.5	35	28

3.2: Discussion of the result

3.2a: Tensile strength

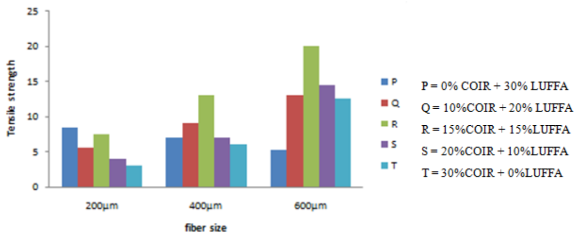

Figure 1: Effect of fiber size and hybridization on tensile strength of the composites

Figure 1 depicts how hybridization and fiber size affect the tensile strength of epoxy composites reinforced with coir and luffa. The tensile strength for composites at 200µm fiber size demonstrates that the tensile strength starts to decline when the volume of luffa drops while the volume of coir fiber simultaneously increases. This is due to the coir fiber absorption of volume from the luffa, thereby decreasing the amount of luffa in the composites. As a result, a low tensile strength was attained since there was not enough luffa fiber to prevent the matrix from experiencing stress failure.

But as the fiber size grows from 200µm to 600µm, the tensile strength increases because the composites become more refined. The composite R [15% Coir with 15% luffa] had the maximum tensile strength at each fiber size, which was a result of the hybrid fiber compositions', high dispersion and equal volume proportion. It might also be because there was less fiber aggregation during fiber loading as a result of the fiber and matrix's greater surface connection. Atuanya C U, Nwobi-Okoye C C and Onukwuli O D [35] and Abdul et al. [9] also reported maximum tensile strength at equal fiber volume fraction and distribution for various hybrid composites. Nevertheless, the tensile strength of the composites spontaneously decreased as the coir fiber weight was raised to 20% and 30%, respectively. It's possible that inadequate fiber dispersion and increased fiber aggregation during loading are to be blamed for the decline in tensile strength, because as more coir fibers are added, more fiber ends are created, and the more fiber ends present, the more likely the composite will be prone to fracture, reducing the tensile strength. This is in accordance to previous research conducted by Abdul et al [9], Arumuga Prabu V, Thirumalai Kumaran S and Uthayakumar [10].

3.2b: Flexural strength

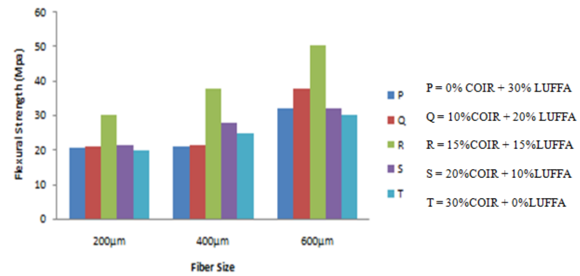

Figure 2:Effect of fiber size and hybridization on flexural strength of the composites

The influence of fiber size and weight on the flexural strength of hybrid composites reinforced with coir and luffa is depicted in Figure 2. It was found that the flexural strength of the various hybrid composites improves along with the fiber size. This was explained by the fact that composite materials with bigger fiber sizes are better able to repel cracks or fracture and withstand stress than those with smaller fiber sizes. The difficulty of aligning smaller fiber diameters is another aspect that may have an impact on the flexural strength of composites. This difficulty might make it easier and faster for cracks to spread throughout the composites, reducing their flexibility. This is in accordance with Atuanya C U, Nwobi-Okoye C C and Onukwuli O D.[35], who quoted that if the fiber size is tiny or small, the composite may experience energy dissipation since little energy will be needed to pull the fiber out of the matrix, which will speed up the crack's progression and make the material brittle.

Additionally, Figure 2 shows that for different fiber sizes, the flexural strength improves as the amount of coir increases. The equal distribution of coir and luffa fibers throughout the matrix allowed composite R [15 percent coir and 15 percent luffa] to achieve the highest level of flexural strength. The flexural strength started to decline as the weight of the coir fiber increases. This could be as a result of fiber clustering as additional coir is added, which may cause poor bonding between the fibers and the matrix and limited workability of the composite, which in turn causes a decrease in flexural strength.

3.2c: Impact strength

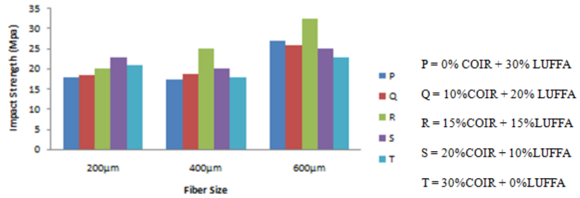

Figure 3: Effect of fiber size and hybridization on impact strength of the composites

Figure 3 depicts how the amount of fiber size affects the impact strength of epoxy-reinforced coir/luffa composites. The impact strength was seen to rise as the fiber size increased in Figure. 3. This might be as a result of effective fiber-matrix surface interaction, which would increase the fiber's ability to absorb stress. The impact strength improves at 200µm, 400µm, and 600 µm, reaching its peak at composite R [15 percent coir and 15 percent luffa], before decreasing when more coir fiber is added. The disruption of the fiber's dispersion in the matrix, which occurs when the fibers contact to form bundles, may be the reason why the impact strength decreases when more coir is added, which is in-line with findings made by Atuanya C U, Nwobi-Okoye C C and Onukwuli O D [35].

Because of the weak surface bonding between the fibers and matrix at 200 µm fiber size, impact strength was found to be at its lowest at 200 µm fiber size. This weak surface bonding supports cracks on the composite because the composite exhibits less energy, which cannot stop or hinder pending crack propagation.

IV. CONTOUR PLOTS

Contour plots are used to examine the relation between the response variable and two control variables by viewing discrete contours of the predicted response variables.

4.1: Tensile strength

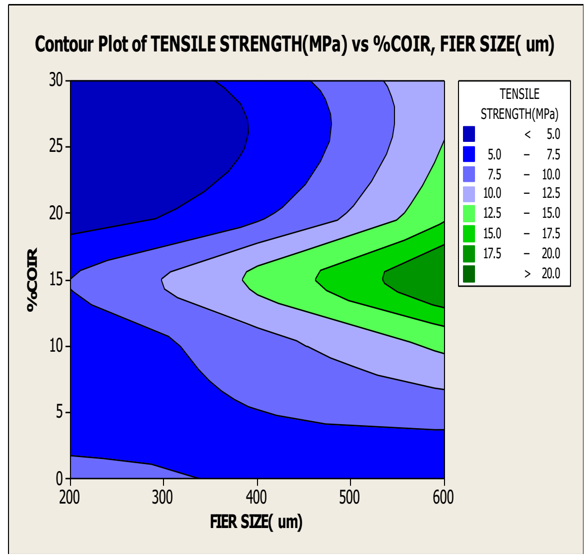

Figure 4: Contour plot of tensile strength VS %wt of coir and fiber size

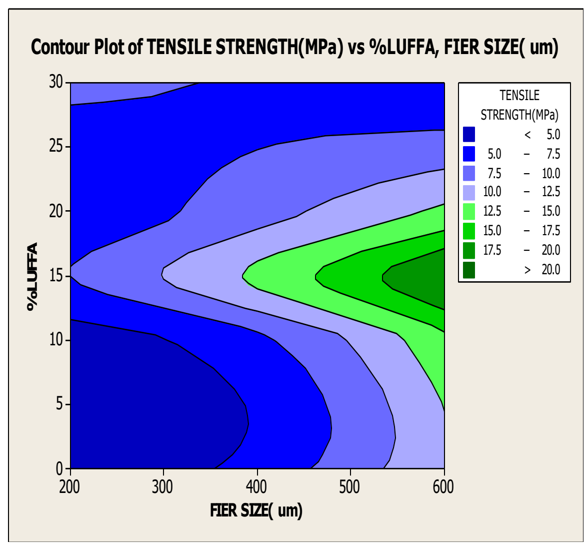

Figure 5: Contour plot of tensile strength VS %wt of luffa and fiber size

The contour plots in Figure. 4 and 5 illustrate how the process variables and tensile strength values relate to one another. According to Figure 4, maximum tensile strength value was obtained between the regions of 12.5%wt-17.5%wt of coir fiber and at 550µm-600µm fiber size, and a minimum tensile value was obtained between the regions of 18.5%wt-30%wt of coir fiber and at 200µm-350µm fiber size. According to Figure.5, maximum tensile strength was attained between 12.5%wt and 17.5%wt of luffa and at

550µm to 600µm fiber size, whereas minimum tensile strength was attained between 0%wt and 12%wt of luffa and at 200µm to 380µm fiber size. This only suggests that the tensile strength of the composites improves along with the fiber size.

4.2: Flexural strength

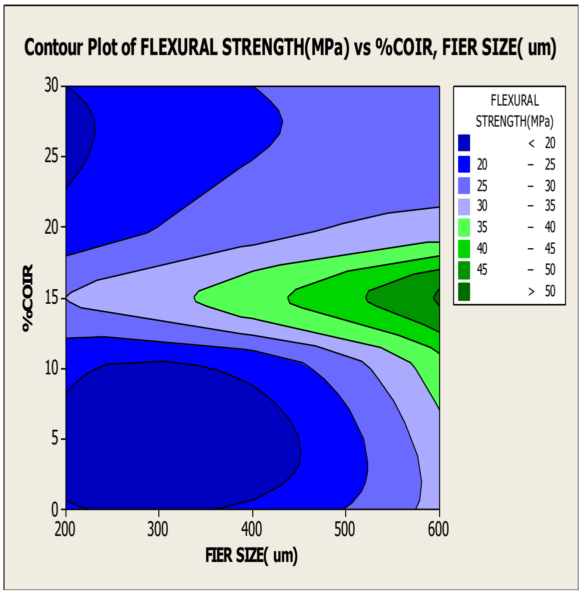

Figure 6: Contour plot of flexural strength VS %wt of coir and fiber size

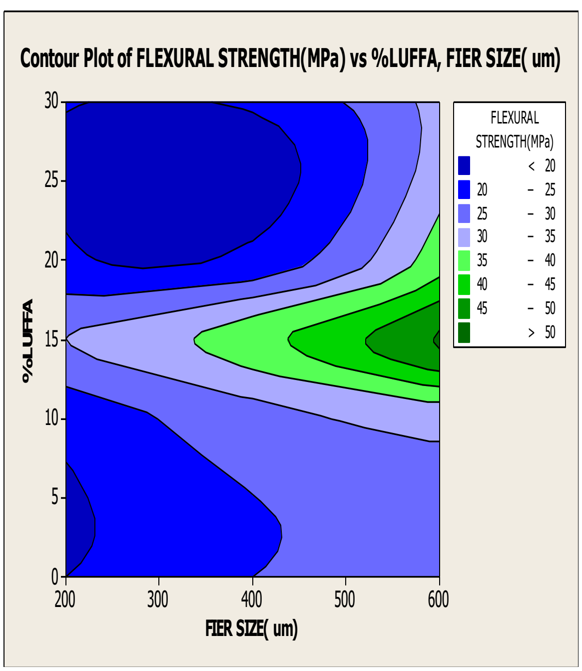

Figure 7: Contour plot of tensile strength VS %wt of luffa and fiber size

The contour plots in Figure. 6 and 7 illustrate the correlation between the process parameters and the values of flexural strength. According to Figure.6, high values of flexural strength were achieved at 15% wt of coir, and at 600 µm fiber size, whereas low values of flexural strength were attained between 0% wt and 10% wt of coir and 22% wt to 30% wt of coir, and at 200 µm fiber size. According to Figure 7, maximum flexural strength was found at 15%wt luffa at 600 µm, whereas minimum flexural strength was found between 20%wt and 30%wt luffa at 200-400 µm.

4.3: Impact strength

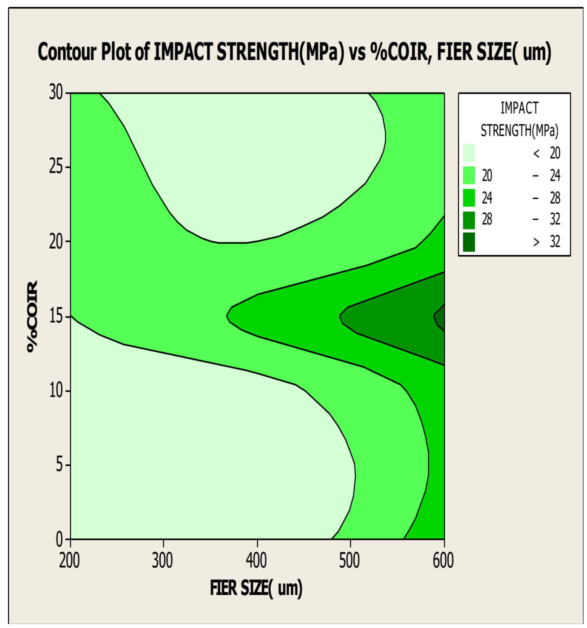

Figure 8: Contour plot of impact strength VS %wt of coir and fiber size

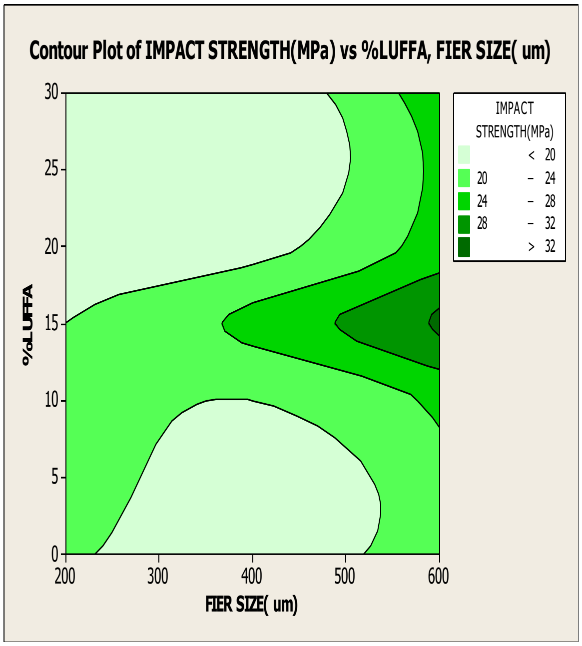

Figure 9: Contour plot of flexural strength VS %wt of luffa and fiber size

The contour plots in Figure. 8 and 9 illustrate how the process parameters and impact strength values relate to one another. At 15%wt of coir and luffa, respectively, and at 600µm fiber size, high impact strength values are obtained [Figure 8 and 9]. Similar to this, 0%wt-15%wt coir and at 200µm-480µm fiber size as well as 20%wt-30%wt coir at 250µm-500µm fiber size both showed poor impact strength, as can be shown in Figure. 8.

V. SOFT COMPUTATIONAL BASED MODELING

5.1: Fuzzy logic modeling

In order to solve difficulties involving decision-making, fuzzy logic, a dynamic and highly adaptable soft computing-based modeling technique, was created from the fuzzy set theory put forth by Zadeh [37]. Specifically, the term "fuzzy" describes something that is unclear or imprecise.

Figure 10 illustrates the fundamentals of fuzzy logic, which include the rule base [IF-then sentences], the fuzzifier, and the defuzzifier. Using a membership function, such as triangular, Gaussian, or trapezoidal membership function, the fuzzifier transforms the input variables into fuzzy numbers. Following the entry of these ambiguous quantities, a collection of rule-based systems analyses the ambiguous data through a decision-making unit, the decision unit produces fuzzy output data, which is then fed through a defuzzifier, which transforms the output data into crisp data.

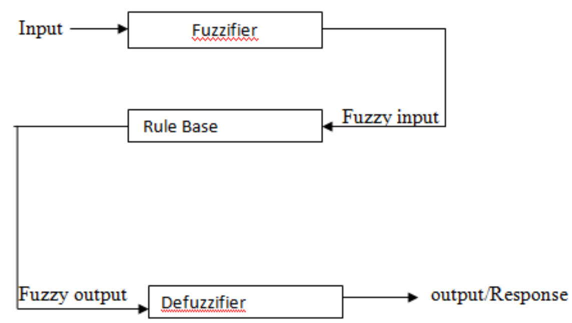

Figure 10: Components of fuzzy logic system

In fuzzy logic, the membership grade ranges from 0 to 1, and the machining variables/parameters are frequently represented by language phrases like Low, Medium, High, etc.

In this study, fuzzy logic was used to create a multi-response predictive model for the effects of fiber size and hybridization on the mechanical characteristics of coir/luffa fiber reinforced hybrid composites. The three steps of fuzzy logic modeling are the fuzzification of the variables, creation of the rule base system, and defuzzification-based response prediction. With the use of a membership function, variables were fuzzified. Due to the ease and effectiveness of the triangular-based membership function in fuzzifying the input data, it was chosen [29]. Therefore, Coir [0 - 30%wt], Luffa [0 - 30%wt], and fiber size [300-600µm] are fuzzified into three fuzzy sets.

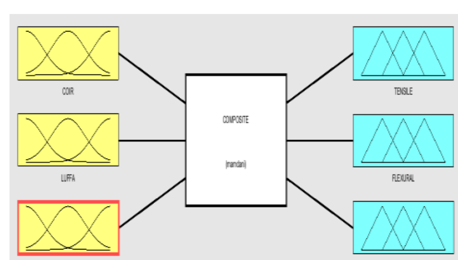

Figure 11: Fuzzy inference system for predicting the mechanical properties of the hybrid composite studied.

The fuzzy inference technique used to predict the mechanical characteristics of the hybrid composite under investigation is shown in Figure 11.

As seen in Figure 11, the fuzzy inference system uses the tensile strength, flexural strength, and impact strength as outputs and the %wt of Coir, %wt of Luffa, and fiber size as an input. Figures 12 to 14 present the membership functions for%wt Coir, %wt Luffa, and fiber size, respectively. According to Figures 12 to14, the membership functions for Coir and Luffa each have seven linguistic variables: C1, C2, C3, C4, C5, C6 and C7, and S1, S2, S3, S4, S6, and S7, respectively. The membership function for fiber size is shown in Figure 13 consists eleven [11] variables: namely; F1, F2, F3, F4, F5,F6,F7,F8,F9,F10 and F11.

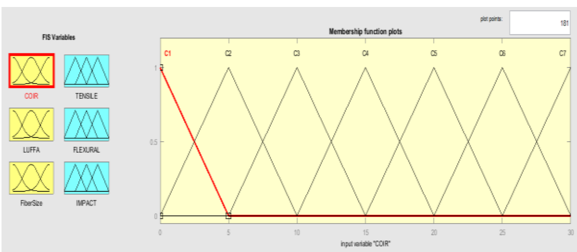

Figure 12: Membership function for %wt of coir fiber

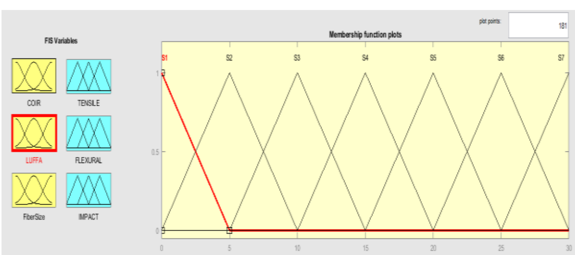

Figure 13: Membership function for %wt of luffa fiber

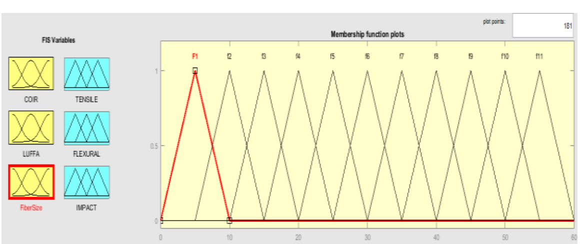

Figure 14: Membership function for fiber size

The prediction modeling employed three fuzzy logic models. Model 1 has 10 language variables for the output [tensile strength], Model 2 has 14 linguistic variables for the output [flexural strength], and Model 3 has 15 linguistic variables for impact strength, as shown in Figures 15 to Figure 17.

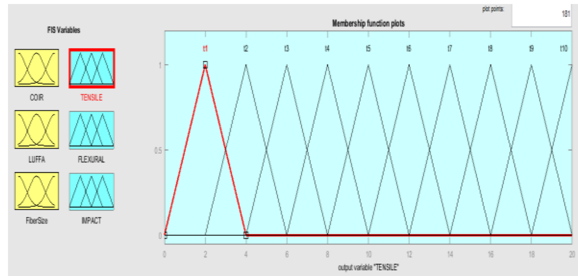

Figure 15: Membership function for tensile strength of the composite

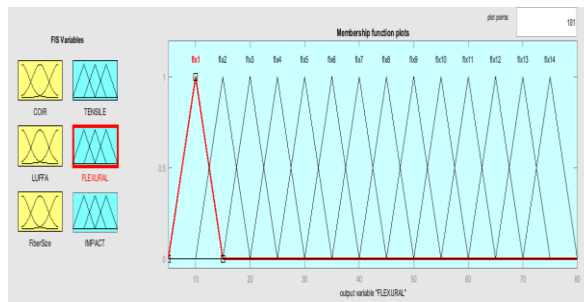

Figure 16: Membership function for flexural strength of the composite

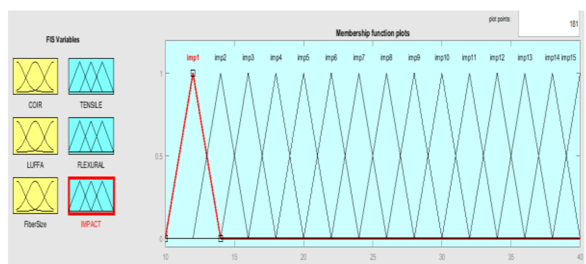

Figure 17: Membership function for impact strength of the composite

Fifteen [15] distinct rules are generated using the fuzzy logic model. After defuzzification using the centroid approach, the Mamdani fuzzy inference system employed the 15 rules to predict the mechanical properties [tensile strength, flexural strength, and impact strength]. Table 3 displays the outcomes of the fuzzy forecasts.

The graphs in Figures 18 to figure 20, shows the trend lines for the mechanical properties and as shown in the graphs, the fuzzy logic designer prediction of tensile strength [Figure 18] shows a coefficient of determination [R^2] of 0.9752, similarly for flexural strength [Figure 19], the prediction coefficient of determination [R^2] is 0.9773, Impact strength prediction via fuzzy logic shows a coefficient of determination [R^2] of 0.9730 [Figure 20]

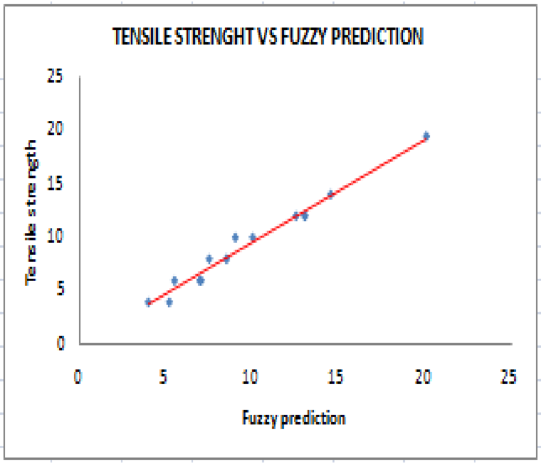

Figure 18: Actual tensile strength Versus Fuzzy prediction

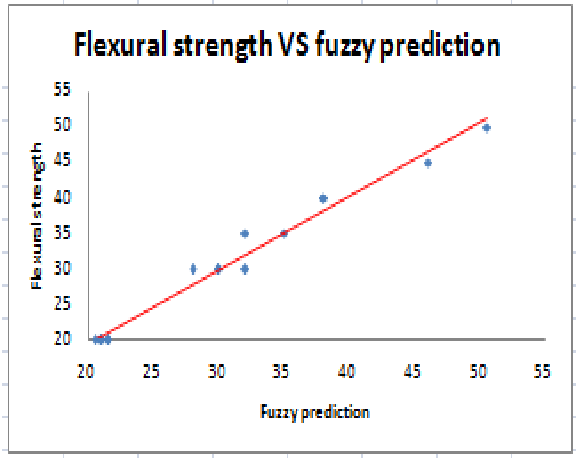

Figure 19: Actual flexural strength Versus Fuzzy prediction

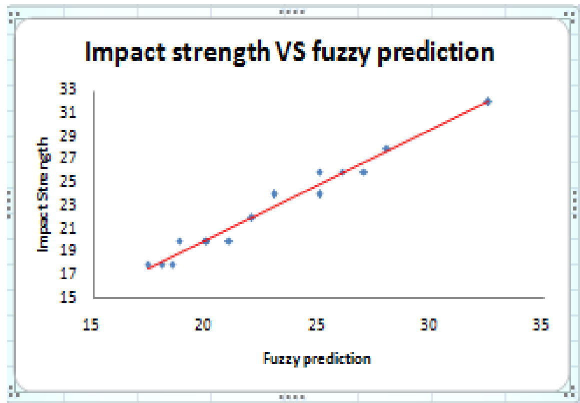

Figure 20: Actual impact strength Versus Fuzzy prediction

Table 3: Fuzzy predictions of the experimental results

Samples	COIR [wt %]	LUFFA [wt%]	FIBER SIZE[μm]	Tensile Strength [MPa]	Fuzzy tensile strength	Flexural Strength [MPa]	fuzzy flexural strength	Impact Strength [MPa]	fuzzy Impact strength
P_{200}	0	30	200	8.5	8	20.5	20	18	18
P400	0	30	400	7	6	21	20	17.4	18
P600	0	30	600	5.2	4	32	30	27	26
Q200	10	20	200	5.5	6	21	20	18.5	18
Q400	10	20	400	9	10	21.5	20	18.8	20
Q600	10	20	600	13	12	38	40	26	26
R200	15	15	200	7.5	8	30	30	20	20
R400	15	15	400	13	12	38	40	25	24
R600	15	15	600	20	19.4	50.5	50	32.5	32
S200	20	10	200	4	4	21.5	20	23	24
S400	20	10	400	7	6	28	30	20	20
S600	20	10	600	14.5	14	32	35	25	26

T200	30	0	200	7	6	46	45	21	20
T400	30	0	400	10	10	30	30	22	22
T600	30	0	600	12.5	12	35	35	28	28

5.2: ARTIFICIAL NEURAL NETWORK [ANN]

Artificial neural networks are soft computational models inspired by the brain's neural network that are widely regarded as the computing technology of the future [39]. ANN is a self-learning process; therefore, they don't necessarily require the conventional programming skills of a programmer. The brain retains information as patterns, which can often be difficult to understand [29].

Artificial intelligence is a new field in computing that was created as a result of the process of storing data as patterns, exploiting those patterns, and then using those patterns to solve multiple challenging issues. As indicated earlier, this area includes the creation of parallel networks known as neural networks and the subsequent training of such networks to address particular issues rather than necessarily using traditional computing.

A multiple layer feed forward approach with three layers—the input layer, hidden layer, and output layer—was used for this work, as illustrated in Figure. 21. [39, 40]. The neurons in the hidden layer receive signals from all the neurons that came before them and then provide a feed forward path to the output layer using the hyperbolic tangent sigmoid transfer function before producing an output value or data using the pure-linear transfer function [40, 41].

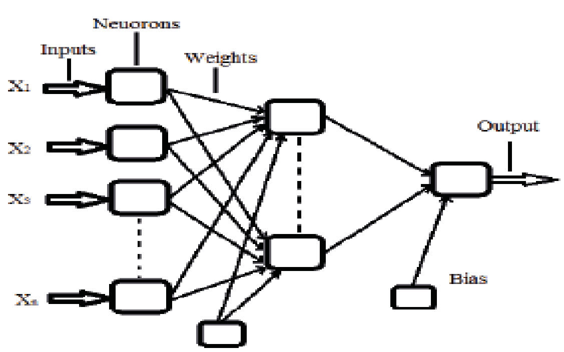

Figure 21: The ANN architecture used as the prediction model

The coir fiber, luffa fiber, and fiber size were represented by three input neurons in the ANN model that was created using MATLAB software [The Mathworks, Inc., R2017c]; the flexural strength and impact strength of the hybrid composites were represented by one hidden layer of neurons and one output neuro; and the tensile strength of the composite was represented by two hidden layers of neurons and one output neuro.

As can be seen from Figure 21, the hidden layer's required number of neurons is determined by the sum of the input weight and its bias.

The experimental data sets were split into three groups for the model's design, with 50% of the data sets being used to train the network, 25% being used for validation, and 25% being used for the model testing.

The number of inputs determines the number of neurons in the input layer, while the number of outputs controlled the number of neurons in the output layer. The neural network is often trained continuously to find the hidden layer until the output mean square error [MSE] or root mean square error [RMSE] is as low as it can be [40].

To accurately predict the mechanical properties of the hybrid composites, the number of hidden layers was varied from 1 to 5 layers, and the number of neurons in the hidden layers was also varied from 0 to 100 neurons using an algorithm editor code in Matlab, and then optimized to get the best neuron network with the lowest MSE. This is done to avoid having either an overly-fit network, which would result in a complex network, or an under-fit network, which would result in a network that is too basic. The results of the created ANN model for predicting the values of tensile, flexural, and impact strength are displayed in Table 4, while the results of the ANN structure for each of the mechanical properties are displayed in Figures. 22 – 24.

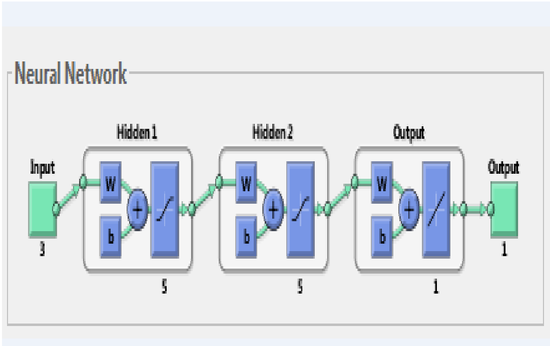

Figure 22: ANN structure for tensile strength

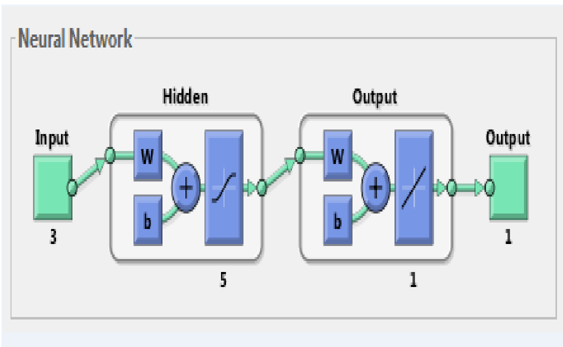

Figure 23: ANN structure for impact strength

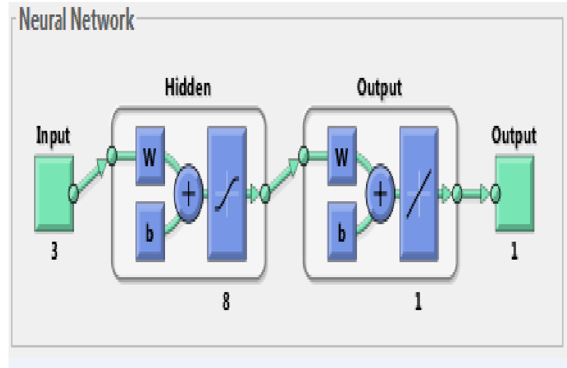

Figure 24: ANN structure for flexural strength

Comparing the experimentally obtained real values of the mechanical properties to those predicted by ANN, as shown in figure 25 – 27, reveals that the model is compatible. Accordingly, focusing on the outcomes of the ANN prediction model, it was found that the tensile strength, flexural strength, and impact strength correlation coefficients [R] for training, validation, and all data sets, respectively, were 0.96418, 0.99776, and 0.98022, 1, 0.63745, and 0.95081, and 0.98595, 0.90347, and 0.96938. According to the correlation coefficient [R] values, there was always full agreement between experimental and anticipated values as well as with the created model.

Similarly, the coefficient of determination [R^2] value suggests that the model can explain only 96.08% of the variation in the actual and predicted values for tensile strength, 93.97% of the variation in the actual and predicted values for flexural strength, and 90.4% of the variation in the actual and predicted values for impact strength.

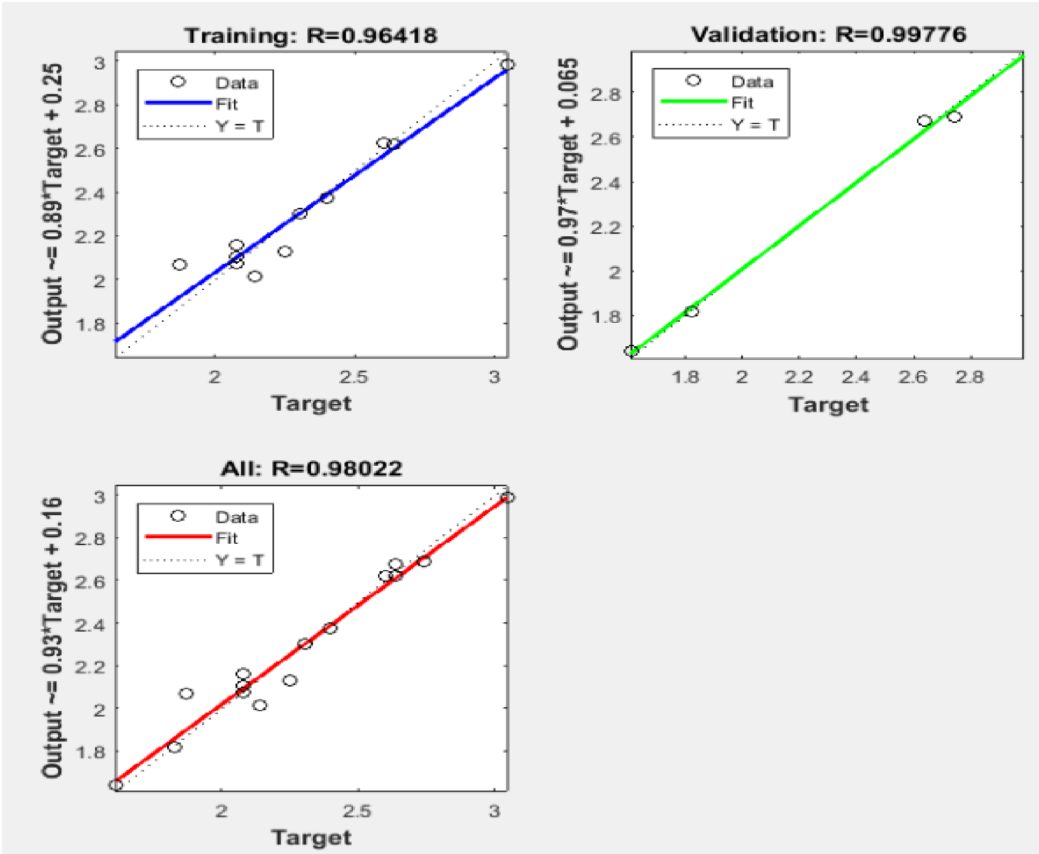

Figure 25: Actual tensile strength versus target value

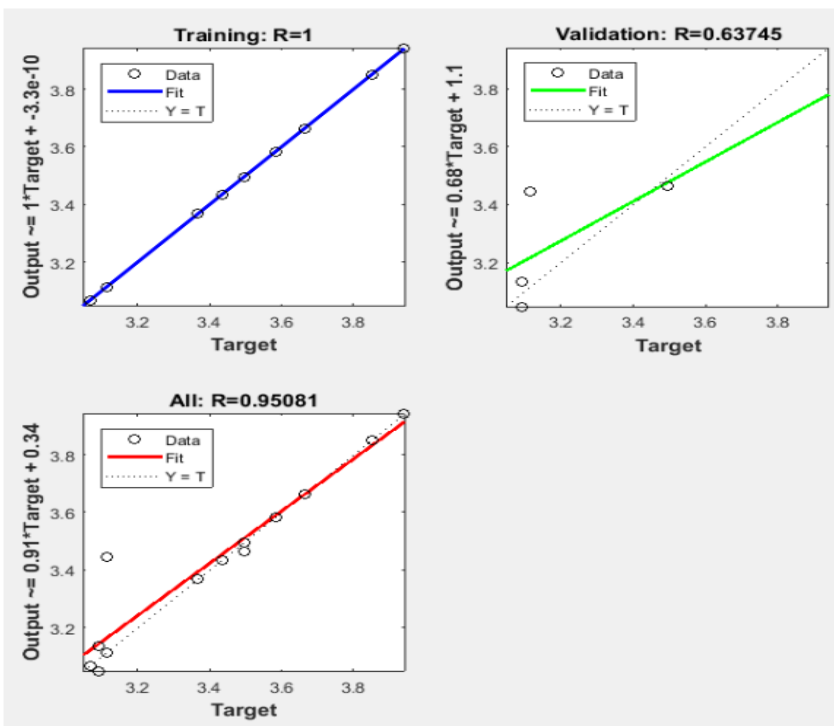

Figure 26: Actual flexural strength versus target value

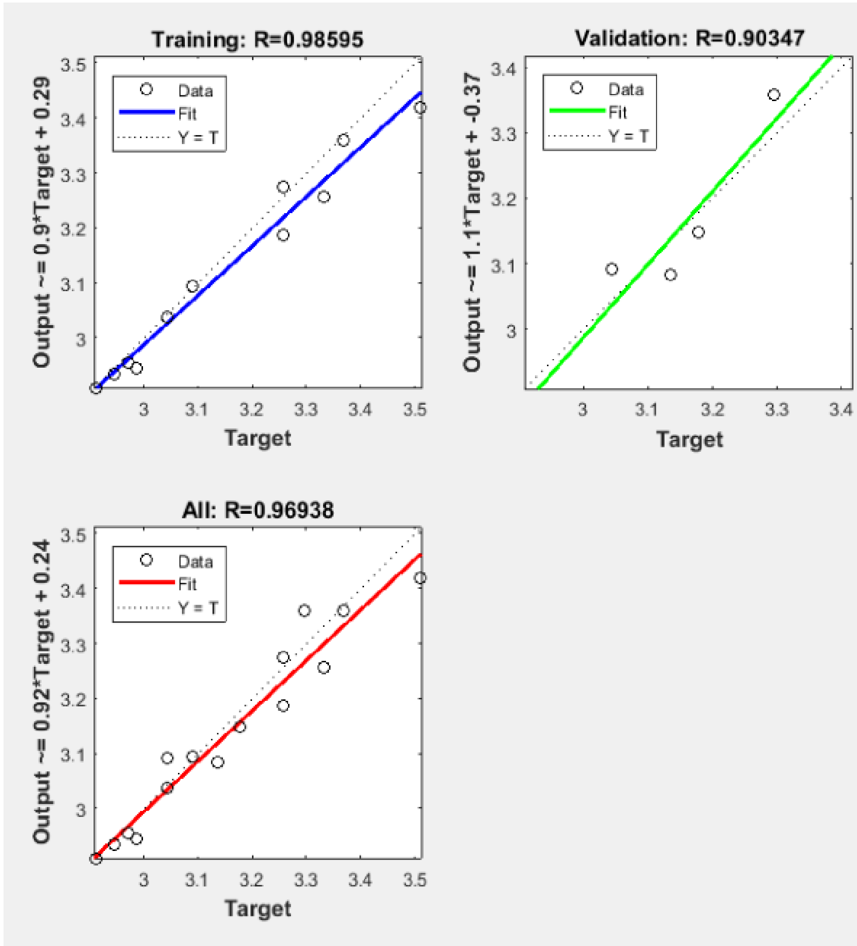

Figure 27: Actual impact strength versus target value

Table 4: ANN predicted values

Samples	COIR [wt%]	Luffa [wt%]	Fiber Size[um]	Tensile Strength [MPa]	ANN Tensile Strength [MPa]	Flexural Strength [MPa]	ANN Flexural Strength [MPa]	Impact Strength [MPa]	ANN impact Strength [MPa]
P5	0	30	200	8.5	7.399885	20.5	20.5	18	17.78177
P25	0	30	400	7	7.191965	21	21.5	17.4	17.31965
P50	0	30	600	5.2	5.14373	32	20.0804	27	24.91834
Q5	10	20	200	5.5	6.905724	21	21.9919	18.5	18.19603
Q25	10	20	400	9	8.974355	21.5	21.9919	18.8	17.97957
Q50	10	20	600	13	12.74446	38	38	26	27.7404
R5	15	15	200	7.5	6.496394	30	30	20	20.9908
R25	15	15	400	13	13.5075	38	38	25	23.1982
R50	15	15	600	20	18.81505	50.5	50.5	32.5	29.50702
S5	20	10	200	4	4.16785	21.5	22	23	22.2848
S25	20	10	400	7	7.676113	28	28	20	19.85502

S50	20	10	600	14.5	13.743	32	32	25	25.44986
T5	30	0	200	7	6.949716	46	46	21	21.05095
T25	30	0	400	10	9.735358	30	30	22	20.8053
T50	30	0	600	12.5	12.78436	35	35	28	27.74911

VI. MICRO STRUCTURAL ANALYSIS OF THE FRACTURED SURFACE

The scanning electron microscope [SEM]JEOLJSM-6480LV was used to identify the fracture samples after a flexural strength test. Figures 28 - 29 show the SEM fracture surface for samples R_{200}[15.5%wt Coir, 15%wt of Luffa at 200um fiber size [Figure 28], S_{600}[20%wt of Coir, 10%wt of Luffa at 600um fiber size [Figure 29].

The flexural cracked surface of the sample depicted in Figure 28 SEM micrograph reveals that the specimen failed mostly due to brittle failure, with the coir/luffa fibers debonding from the matrix and, in some spots, being pushed out of the matrix. Figure 29 demonstrates that the specimen's failure was mostly caused by coir fiber fracture and luffa fibers being pulled out of the matrix. Luffa fiber has a higher tensile strength than other fibers, hence more tensile forces are needed to break it and remove it from the matrix. Comparing luffa fiber and matrix to coir fiber and matrix, luffa fiber and matrix exhibit significantly greater interfacial adhesion. The combined effect of fracture of most of the luffa fiber and pulling out of coir fiber leads to a higher tensile strength of the hybrid composite.

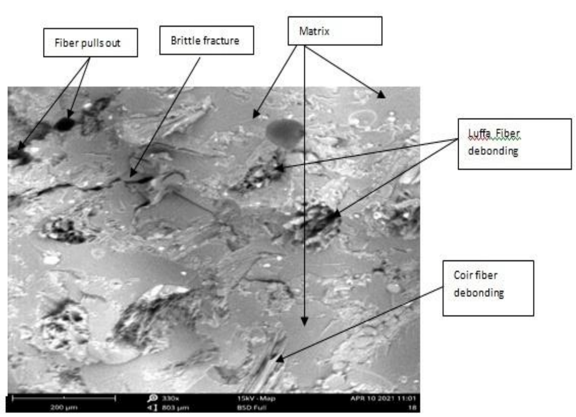

Figure 28: SEM fracture surface for sample containing 15%wt Coir, 15%wt of Luffa at 200um fiber size

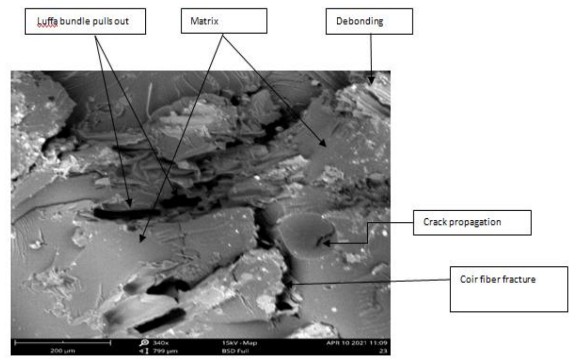

Figure 29: SEM fracture surface for sample containing 20%wt of Coir, 10%wt of Luffa at 600um fiber size

CONCLUSION

The effect of fiber size and hybridization on the mechanical properties of coir/luffa reinforced epoxy hybrid composites with prediction of their experimental results using fuzzy logic and ANN were evaluated. The following conclusions were drawn from the investigation:

- Highest and lowest values of tensile strength was 20MPa [15%wt coir and 15%wt luffa at 600µm] and 7MPa [0%wt coir and 30%luffa at 200µm], 50.5MPa [15%wt coir and 15%wt luffa at 600µm] and 20.5MPa [0%wt coir and 30%luffa at 200µm] for flexural strength, 32.5MPa[15%wt coir and 15%wt luffa at 600µm] and 17.4MPa[0%wt coir and 30%wt luffa at 400µm] respectively.
- 15%wt coir and 15%wt luffa at 600µm fiber size produced the best mechanical properties because of the uniform and equal distribution of fiber weight in the matrix.
- Fiber size is the most critical variable or factor that influences the mechanical properties of coir/luffa reinforced hybrid composite.
- Fuzzy model developed can comfortably predict the tensile strength of the hybrid composite with an accuracy of 97.5% for tensile strength, 97.8% accuracy for flexural strength and 97.3% accuracy for impact strength of the composites.

- The two models prediction results signify that there is a perfect understanding between the experimental and predicted values.
- ANN model predictions gave an accuracy of 96.8% for tensile strength, 90.4% for flexural strength and 94% for the impact strength of the hybrid composite.
- Fuzzy logic gave a more accurate predictions with minimum errors than the ANN

DECLARATION OF INTEREST

The authors report no conflicts of interest. The authors alone are responsible for the content and writing of this article.

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