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Multi-Objective Optimization of Properties of Sponge Gourd-Bagasse Hybrid Reinforced Polymer Composite Using Fuzzy Logic, PSO, Modified Desirability Function and NSGA II

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Abstract

Development of mathematical models for prediction of properties of materials is often complex and cumbersome. This led to the advent of simpler, and often more accurate, computational models based on artificial intelligence for predicting materials properties. The aim of this study is to predict the mechanical properties of a newly developed hybrid composite material made with sponge gourd, bagasse and epoxy resin for golf club application using fuzzy logic (FL) and carry out a multi-objective optimization of the properties with modified desirability function (DF) and NSGA II algorithm. The inputs were %Wt of bagasse, %Wt of Sponge gourd and Fiber size (μm) while the response variables were tensile strength, hardness, flexural strength, modulus, elongation and impact strength. The FL model was separately coupled, as fitness function, with the modified DF algorithm and the NSGA II algorithm respectively. The DF was optimized with particle swarm optimization (PSO) algorithm. The results showed that the FL model predicted the mechanical properties accurately and the minimum correlation coefficient (R) between the experimental responses and FL predictions was 0.9529. The modified algorithms took care of certain peculiarities in the desirability properties such as elongation whose desirability is constant over a range. The optimized properties were found to be worse if the optimization algorithms were not modified.

Keywords: Fuzzy logic; Genetic Algorithm; Particle Swarm Optimization; Desirability Function; Composite; Multi objective optimization

1.0 Introduction

Artificial intelligence (AI) is currently gaining traction in all fields of human endeavour. Modern applications of AI can be broadly categorized into three namely: clustering, prediction and classification. One of the most extensive uses of AI in science and engineering is in prediction. Prediction applications range from materials properties prediction, prediction

of chemical process outputs, prediction of industrial processes outputs etc. Often prediction models whether mathematical or computational are sought because experiments are expensive to conduct [1, 2, 3].

Development of excellent prediction and optimization models for materials science and engineering applications is critical for advances in modern engineering. Hence, extensive researches are currently geared towards this direction with AI leading the charge [4, 5, 6, 7]. There are several AI tools used in science and engineering which include but not limited to Artificial Neural Networks (ANN), Adaptive Neuro-Fuzzy Inference System (ANFIS), Fuzzy Logic (FL), Genetic Algorithm (GA), Particle Swarm Optimization (PSO) etc [8, 9, 10, 11, 12, 13]. In this present application, Fuzzy Logic, Non Dominated Sorting Genetic Algorithm (NSGA II) and Particle Swarm Optimization were used for prediction and multi objective optimization of properties of a newly developed hybrid composite for golf club application.

The literature is replete with several applications of AI to prediction and optimization of materials properties [3, 14, 15, 16, 17, 18, 19]. Nwobi-Okoye et al. [8] used ANN, ANFIS and NSGA II for multi objective optimization of properties of Aluminum Alloy A356/Cow Horn Particulate Composite subjected to age hardening. They successfully optimized hardness and cost as function of composition, temperature and age hardening time. Their findings showed that ANFIS was less effective than ANN as a fitness function for the NSGA II optimization algorithm. Nwobi-Okoye et al [9] used NSGA II algorithm combined with ANN as its fitness function to carry out multi objective optimization of dry compressive strength of groundnut shell ash particles and ant hill bonded foundry sand. The optimization objectives were maximization of compressive strength and minimization of cost of mould production. The Pareto front obtained from the NSGA II algorithm showed the optimum strength and cost achievable with corresponding process input variables. Chowdhury et al. [20] used fuzzy logic for the prediction and optimization of erosion rate of carbon fiber-reinforced ebonite. They used experimental data to develop a fuzzy logic model for predicting the erosion rate in response to variations in impact velocity, impingement angle, erodent size, and stand-off distance. The results showed that the fuzzy logic model predicted the experimental results with an accuracy of 94.45%. Sinha et al. [1] used fuzzy logic for the prediction of the mechanical properties of hybrid abaca-reinforced polymer composite. The input variables for the prediction model were weight per cent of abaca fibre, particle size of red mud and weight per cent of red mud while the output parameters were tensile strength and flexural strength. The results showed that the validated model had a prediction accuracy of 87%. Umeonyiagu and Nwobi-Okoye [10] used ANN and NSGA II for multi objective optimization of bamboo reinforced concrete beams. The objectives of their optimization were minimization of cost and maximization of tensile and flexural strengths of the concrete beams. The input parameters were percentage bamboo composition and age hardening days. Their findings showed that optimization results would serve as an excellent guide in designing strong and cost effective concrete beams reinforced with bamboo. Nwobi-Okoye and Uzochukwu [11] carried out multi objective optimization of Al 631/Egg shell metal matrix composite material produced through stir casting process using NSGA II algorithm which used ANN as its fitness function. the optimization objectives were minimization of

hardness and maximization of toughness. The optimization results expanded effectively the applicability of Al 631/Egg shell metal matrix composite materials in areas where ductility is of utmost importance. Nwobi-Okoye et al. [12] used NSGA II algorithm coupled with ANN based prediction model as objective function for multi objective optimization of particle boards produced from recycled high density polyethylene and newboldia laevies fibres. The properties optimized were modulus of rupture, modulus of elasticity, internal bonding, thickness swelling and water absorption. The results showed that the optimized composite materials could be used extensively for the production of high quality particle boards for domestic and industrial use. Tarasov et al. [21] applied fuzzy logic based prediction model for modelling of yield strength of as-cast A356 alloy. They developed two fuzzy logic models to model the relationship between yield strength against chemical composition and the rate of solidification of cast A356 alloy. Their findings showed that the models had very good prediction accuracy with prediction errors of 3.53% and 3.19% respectively. Aamir et al. [22] used Taguchi Method and Fuzzy Logic to model and optimize the Process Parameters in Multi-Hole Simultaneous Drilling. The results showed that the Taguchi optimization, optimal drilling parameters occur at a low cutting speed and feed rate using a poly-drill head. The results of the fuzzy logic model which was used to predict the surface roughness and hole size were found to be in good agreement with the experimental values.

Having looked at the literature above, this study is unique because it used a specially modified desirability function, optimized with PSO coupled with a fuzzy logic model as its fitness function, as well as a modified NSGA II algorithm coupled with a fuzzy logic prediction model as its fitness function for multi objective optimization of a newly developed hybrid polymer composite material made with sponge gourd, bagasse and epoxy resin.

2.0 Methodology

2.1 Composite Material Production

2.1.1 Materials

The baggase fiber used in the work as shown in Figure 1 was obtained from the local market in Awka, Nigeria while the sponge gourd as shown in Figure 2 was sourced locally from the bush. The epoxy resin and the hardener used were bought from the local market.

Figure 1: Untreated baggase fiber

Figure 2: Untreated Sponge gourds Fiber

2.1.2 Preparation of the baggase and sponge gourd fiber.

The baggase and sponge gourd fibers are prepared separately and independently. The baggase was soaked in water for 24hrs so as to remove any dirt or debris in the fiber and sun dried for 2 days, thereafter the dried bagasse was soaked in 10% concentration NaOH solution for 24hrs (Figure 3) in order to remove lignin, wax and other impurities from the fiber, hence increasing the fiber roughness and adhesiveness. The alkaline treated fiber was therefore continually rinsed with water until a pH value of 7 is obtained so as to obtain a neutral solution (fiber). The rinsed fiber is sun dried again for 2 days before subjecting to methanol treatment where the fiber is soaked in a dilute methanol solution (60:40) for 3hrs which help in further increasing the fiber roughness and bonding properties of the fiber as shown in Figure 4. The methanol treated fiber was therefore sun dried for 2 days thereafter

making the fiber ready for pulverization. These procedures were also repeated for preparation of sponge gourd fiber.

Figure 3: Treatment of the fiber using dilute NaOH solution

Figure 4: Treatment of the fiber using dilute methanol solution

2.1.3 Particle size analysis

The surface areas of the fibers (baggage and sponge gourd) were increased by pulverization technique, which convert the long grain fibers to a powdered form as shown in Figure 5.

(a). Pulverized baggase fiber

(b). Pulverized sponge gourd fiber

Figure 5: Pulverized fibers

The particle size analysis of the pulverized fibers was carried out in accordance with ASTM-60. 200g of the fiber particles were placed into a set of sieves arranged in descending order of fineness and electrically shaken for 15 minutes which is the recommended time to achieve complete classification as shown in Figure 6. The weight retained on 150 μ m, 300 μ m and 600 μ m were used in this research.

Figure 6: Electronic sieving Machine

2.1.4 Composite Sample Production.

The wt% of the fibers (bagasse and sponge gourd), polymer were measured accordingly via an air tight electronic weighing balance (Figure 7) using the data analysis obtained from the design of experiment using Taguchi.

Heating of the paraffin wax to its melting point (50⁰c) was done with the help of a Bunsen burner; thereafter the liquid wax was immediately sprinkled on the metal mould before casting. This is done for easy removal of the samples from the metal mould. After waxing the mould, the composite materials (wt% of bagasse, %wt of sponge gourd, polymer and hardener) are mixed in a crucible plate and stirred continuously using a stirrer until a uniform mixture is obtained.

The mixture was therefore poured into a 300mm × 300mm waxed metal mould and allowed to set; the design formation from Table 5 was used in the production of the composite.

Figure 7: Electronic weighing Machine

2.1.5 Design of Experiment

The design of the experiment was done via Taguchi robust design which involves reducing the variation in a process through robust design of experiments. Classical experimental design methods are too complex and are not easy to use. A large number of experiments have to be carried out when the number of process parameters increase. To solve this problem, the Taguchi method uses a special design of orthogonal arrays to study the entire parameter space with only a small number of experiments. Three superplastic forming parameters are considered as controlling factors. They are %wt of fiber 1 (bagasse), % wt of fiber 2(sponge

gourd) and fiber particle size (Chibueze, 2021). Each parameter has three levels – namely low, medium and high, denoted by 1, 2 and 3 respectively (Chibueze, 2021).

Orthogonal arrays are special standard experimental design that requires only a small number of experimental trials to find the main factors effects on output. Before selecting an orthogonal array, the following step must be followed (Chibueze, 2021).

Step 1: Consider the factors with three various levels. The factors and levels are as shown in Table 1.

Table 1: Factors and there levels

FACTOR	LEVEL
Wt% of baggase (A)	3
Wt% of sponge gourd (B)	3
Fiber size (C)	3

Step 2: Determine the degree of freedom (D.O.F).

DOF refers to the number of ways a system can independently vary when a constraint is imposed. The degree of freedom (D.O.F) is shown in Table 2.

Table 2: Degree of freedom (D.O.F)

FACTORS	LEVEL (S)	D.O.F=S-1
A	3	2
B	3	2
C	3	2
A×B		2×2 =4
A×C		2×2 = 4
B×C		2×2 = 4
		D.O.F = 18

Step 3: The total number of experimental runs

$$T_{\text{experiment}} = 1 + \text{D.O.F} = 1 + 18 = 19$$

STEP 4: We select the suitable orthogonal array which must be greater than or equal to 19

Thus referring to the standard orthogonal array table, the nearest orthogonal array is L₂₇.

Step 5: Visualize the required linear graph (RLG) as shown in Figure 8

Figure 8: Required linear graph for L_{27}

STEP 6: Compare the Required linear graph and standard linear graph for L_{27} as shown in Figure 9.

Figure 9: Required linear graph and standard linear graph for L_{27}

Step 7: allocate the factors to the column of the orthogonal array as shown in Table 3.

Table 3: Factors with node assigned

Factors	Column/node assigned
A	1
B	2
C	5
A×B	3,4
B×C	8, 11
A×C	6,7

STEP 8: We chose the experimental layout referring to the default orthogonal array design layer as shown in Table 4.

Table 4: Default orthogonal array

FACTOR	Level1	Level 2	level 3
Wt% of baggase (A)	5wt%	10wt%	20wt%

Wt% of sponge gourd (B)	5wt%	10wt%	20wt%
Fiber size (C)	150μm	300μm	600μm

The number of experimental runs with their parameters is as shown in Table 5. As shown in Table 5, the number of experiments conducted based on the prescriptions of Taguchi experimental design was 27.

Table 5: Number of experimental runs with their parameters and data

FACTORS				RESPONSE					
s/n	%wt bagasse	%wt S.G	Fiber size (μm)	Tensile strength	Hardness	Flexural strength	Flexural modulus	Elongation	Impact strength
1	5	5	600						
2	10	5	600						
3	20	5	600						
4	5	10	600						
5	10	10	600						
6	20	10	600						
7	5	20	600						
8	10	20	600						
9	20	20	600						
10	5	5	300						
11	10	5	300						
12	20	5	300						
13	5	10	300						
14	10	10	300						
15	20	10	300						
16	5	20	300						
17	10	20	300						
18	20	20	300						
19	5	5	150						
20	10	5	150						
21	20	5	150						
22	5	10	150						
23	10	10	150						
24	20	10	150						
25	5	20	150						
26	10	20	150						
27	20	20	150						

2.1.6 Composite Testing Procedure

The properties that were tested are density, tensile strength, hardness, modulus, flexural strength, elongation and impact strength.

2.1.6.1 Density

The density of the composite was obtained from mathematical expressions and calculations after pouring the composite into a small graduated cylinder with known volume.

Let volume of the cylinder = V

Mass of cylinder = M1

Mass of cylinder + composite = M2

Therefore ,

$$\text{Mass of composite } M3 = M2 - M1.$$

Thus;

Density of composite = mass/ volume

$$\text{Density} = \frac{M3}{V} \quad (1)$$

2.1.6.2 Flexural Test

Prior to the test, all the samples were conditioned at a temperature of 25⁰c and relative humidity of 65% according to ASTM D618-08(Rotton, 1999). Test samples were made according to the recommended standard for flexural testing. Flexural test was performed on a M500-25CT testometric testing machine at Civil Engineering, Material Laboratory of University of Nigeria, Nsukka (Figure 10).

Figure 10: M500-25CT testometric testing machine

A three point bending configuration was used with specimen nominal dimension of 200mm × 20mm × 5mm. the load was applied continuously throughout the test at a uniform rate of 50mm/min.

The flexural strength was determined in accordance with ASTM D790- 10 standard test method. The flexural strength was calculated for each specimen in accordance with the following equations.

$$R_b = \frac{3P_{\max}L}{2bd^2} \quad (2)$$

Where

b= width of specimen measured in dry condition (mm)

d= thickness of span in mm

$P_{\max}$ =maximum load (N).

2.1.6.3 Tensile Strength

The tensile strength measurement experiment was performed on a testometric testing machine at University of Lagos, Nigeria.

For the tensile test, the composite samples were 160mm×20mm× 4mm in dimension in accordance with ASTM 638-10 standard test method for tensile properties of polymer. The tests were performed at a constant strain rate of 0.5mm/min. the maximum tensile strength was calculated in accordance with the equation:

$$R_T = \frac{P_{\max}}{Bd} \quad (3)$$

Where

B = width of reduced cross section of the specimen measured in dry conditioning (mm)

D = thickness of the specimen measured in dry condition

$P_{\max}$ = maximum tensile load (N)

R_t = maximum tensile stress (MPa)

2.1.6.4 Impact Strength Test

The impact testing of the composite samples were conducted using Avery dension test machine at the department of Metallurgical and Materials Engineering, University of Nigeria, Nsukka, Nigeria (Chibueze, 2021). Charpy impact tests was conducted on the samples with 100mm ×20mm ×5mm dimension in accordance with ASTM D256-10 standard test method for determining the chary pendulum impact resistance of plastics (Chibueze, 2021). Before the test, samples were mounted on the machine, the pendulum was released to calibrate the machine. The test samples were then gripped horizontally in a vice and the force required to break the bar was released from the freely swinging pendulum. the value of the angle through which the pendulum swung before the test sample was broken correspond with the value of the energy absorbed in breaking the sample and this was read from the calibrated scale on the machine (Chibueze, 2021).

2.1.6.5 Hardness test.

The hardness testing of the samples was done using leeb hardness tester at the department of Metallurgical and Materials Engineering, University of Nigeria, Nsukka, Nigeria.

Leeb hardness testing was conducted on the samples with 20mm×20mm×20mm according to ASTM A956 standard, prior to the test, the samples were mounted on the anvil as shown in Figure 11, and then the impact device accelerates an impact body using spring force. The velocity of the impact body is broken down into three phases.

1. Approach phase, during which the impact body is accelerated towards the test surface by means of the spring force.
2. Impact phase, during which the impact body and the specimen are in direct contact. The specimen is thereby elastically and plastically deformed and the impact body is brought to a complete standstill. The elastic spring-back of impact body and specimen causes the impact body to rebound.
3. Rebound phase, during which the impact body is again accelerated out of the impact phase with the remaining energy.

Thus, the ratio of rebound velocity V_r to impact velocity V_i , multiplied by a factor of 1000 gives the leeb hardness.

Ie

$$HL = \frac{\text{Rebound velocity}}{\text{Impact velocity}} \times 1000 \quad (4)$$

Thereafter leeb hardness results in HL are converted to traditional hardness scale HR (hardness according to Rockwell) from classified hardness chart.

Figure 11: Leeb hardness tester

2.1.6.6: Specific strength

Specific strength is also known as strength to weight ratio. And it is measured as

$$\text{Specific strength (Nm/Kg)} = \frac{\text{tensile strength}}{\text{density of the material}} \quad (5)$$

2.1.6.7: Specific Stiffness

Specific stiffness is also referred to as Modulus to weight ratio, and its represented as:

$$\text{Specific Modulus (Nm/Kg)} = \frac{\text{modulus}}{\text{density of the material}} \quad (6)$$

2.2 Fuzzy Logic Modelling

The experimental data acquired from testing the produced composite material was modeled with fuzzy logic. The input-output data obtained from the experiment described in section 2.1.6 underwent both fuzzification and defuzzification as shown in Figure 12 in order to obtain the fuzzy logic model for prediction of the properties of the composite material.

Figure 12: Component of fuzzy system

Figure 13 shows the fuzzy inference system for predicting the mechanical properties of the hybrid composite studied. As shown in Figure 11, %wt of bagasse, %wt of sponge gourd and fiber size are inputs to the fuzzy inference system, while the tensile strength, flexural strength, elongation, impact strength, hardness and modulus derived from defuzzification are the output. The membership function for %wt bagasse, %wt sponge gourd and fiber size are shown in Figures 14 – 16 respectively. The membership function for %wt bagasse and %wt sponge gourd as shown in Figure 14 and 15 consists of five (5) linguistic variables namely: Very low (VL), low (LW), Medium (M), High (H), Very High (VH). The membership function for fiber size shown in Figure 16 consist of 8 variables, namely; FS1, FS2, FS3, FS4, FS5, FS6, FS7, FS8.

Figure 13: Fuzzy interference system of hybrid composite.

Figure 14: Membership function for % wt Bagasse

Figure 15: Membership function for % wt sponge gourd

Figure 16: Membership function for the fiber size

Six fuzzy logic models were used in the prediction modeling. Model I has 24 linguistic variables for the output (hardness) as shown in Figure 17a, model 2 have 49 linguistics for the output flexural strength (Figure 17b), model 3 contain 26 linguistic variables for flexural modulus (Figure 17c), model 4 have 16 variables for elongation (Figure 17d) and model 5 have 26 variables for impact strength (Figure 17e).

The fuzzy logic model generates 27 different rules. The 27 rules were used by the Mamdani fuzzy inference system to predict the mechanical properties (tensile strength, hardness, flexural strength, elongation, impact strength and modulus) after defuzzification using the centroid method. Eighty percent (80%) of the experimental data were used to develop the fuzzy logic model while twenty percent (20%) were used for testing and validation. The results of the fuzzy modeling process are presented in section 3.2.

Figure 17a: Membership function for hardness

Figure 17b: Membership function for flexural strength

Figure 17c: Membership function for Modulus

Figure 17d: Membership function for Elongation

Figure 17e: Membership functions for impact strength.

2.3 Multi objective Optimization with Desirability Function and NSGA II Algorithm

2.3.1 Desirability Function Development

Desirability function is a popular multi objective optimization tool. The function is such that if the objective is to maximize, the following relationship obtains:

$$di = \begin{cases} 0 & \hat{y} \leq Li \\ \left(\frac{\hat{y} - Li}{Ti - Li}\right)^s & Li < \hat{y} < Ti \\ 1 & \hat{y} \geq Ti \end{cases} \quad (9)$$

Similarly, if the objective is to minimize, the following relationship obtains:

$$di = \begin{cases} 1 & \hat{y} \leq Ti \\ \left(\frac{Ui - \hat{y}}{Ui - Ti}\right)^s & Ti < \hat{y} < Ui \\ 0 & \hat{y} \geq Ui \end{cases} \quad (10)$$

If it is desired that the response be a target value with an upper and lower limit, the desirability is given as:

$$di = \left(\frac{\hat{y} - Li}{Ti - Li}\right)^s \quad Li \leq \hat{y} \leq Ti \quad (11)$$

$$di = \left(\frac{Ui - \hat{y}}{Ui - Ti}\right)^s \quad Ti \leq \hat{y} \leq Ui \quad (12)$$

$$di = 0 \quad \text{if } \hat{y} < Li \quad (13)$$

$$di = 0 \quad \text{if } \hat{y} > Ui \quad (14)$$

We introduce a new criterion such that if the desirability is constant over a certain interval then the following equation obtains:

$$di = \begin{cases} 0 & \hat{y} \leq Li \\ 1 & Li < \hat{y} < Ui \\ 0 & \hat{y} \geq Ui \end{cases} \quad (15)$$

$$di = \begin{cases} \left(\frac{\hat{y} - Li}{T1i - Li}\right)^s & \hat{y} \leq Li \\ 1 & T1i < \hat{y} < T2i \\ \left(\frac{Ui - \hat{y}}{Ui - T2i}\right)^s & \hat{y} \geq Ui \end{cases} \quad (16)$$

Where d_i = desirability value

L_i is the lower limit of the response

U_i is the lower limit of the response

T_i is the target value

$\hat{y}$ is the lower limit of the response

The variable s is a constant that defines the shape of the desirability function. For $s = 1$, the desirability function is linear, similarly if $s < 1$, the desirability function is convex while for $s > 1$ the desirability function is concave.

The composite desirability (DC) is given by:

$$DC = (d_1 \times d_2 \times d_2 \times \dots \times d_n)^{\frac{1}{n}} = \left(\prod_{i=1}^n d_i \right)^{\frac{1}{n}} \quad (17)$$

Where n is the number of variables.

If weights are assigned to d_i , and the weights w_i is such that:

$$w_1 + w_2 + w_3 \dots w_n = 1 \quad (18)$$

Where $0 < w_i < 1$

w_i could be determined from principal component analysis, rank order centroid method, analytic hierarchical process (AHP), entropy etc.

$$DC = (d_1^{w_1} \times d_2^{w_2} \times d_3^{w_3} \times \dots \times d_n^{w_n})^{\frac{1}{n}} \quad (19)$$

The weights w_i were obtained through analytical hierarchical process (AHP).

The AHP matrix obtained from the attributes is as shown in Table 6.

Table 6: AHP matrix

Criteria	Tensile Strengt h	Specific Strengt h	Flexural Strengt h	Elongatio n	Hardnes s	Impact Strengt h	Modulu s	Specific Stiffnes s
Tensile Strength	1	1	2	3	4	5	6	6
Specific	1	1	2	3	4	5	6	6

Strength								
Flexural Strength	1/2	1/2	1	2	3	4	5	5
Elongation	1/3	1/3	1/2	1	2	3	4	4
Hardness	1/4	1/4	1/3	1/2	1	2	3	3
Impact Strength	1/5	1/5	1/4	1/3	1/2	1	2	2
Modulus	1/6	1/6	1/5	1/4	1/3	1/2	1	1
Specific Stiffness	1/6	1/6	1/5	1/4	1/3	1/2	1	1

The priority vector obtained from the normalized eigenvector of the matrix in Table 6 is shown in Table 7.

Table 7: Priority vector matrix

Criteria	Tensile Strength	Specific Strength	Flexural Strength	Elongation	Hardness	Impact Strength	Modulus	Specific Stiffness	Priority
Tensile Strength	1	1	2	3	4	5	6	6	0.260276
Specific Strength	1	1	2	3	4	5	6	6	0.260276
Flexural Strength	1/2	1/2	1	2	3	4	5	5	0.171214
Elongation	1/3	1/3	1/2	1	2	3	4	4	0.114833
Hardness	1/4	1/4	1/3	1/2	1	2	3	3	0.076688
Impact Strength	1/5	1/5	1/4	1/3	1/2	1	2	2	0.050608
Modulus	1/6	1/6	1/5	1/4	1/3	1/2	1	1	0.033053
Specific Stiffness	1/6	1/6	1/5	1/4	1/3	1/2	1	1	0.033053

From the priority vector, the following weights 0.26135, 0.26135, 0.166618, 0.108597, 0.071001, 0.046807 and 0.032083 were assigned to tensile strength, specific strength, flexural strength, elongation, hardness, impact strength and specific stiffness respectively. The parameter settings for the optimization program were done according to Table 8.

Table 8: Parameter settings

Parameter	Lower Limit	Upper Limit	Weight
Inputs			
%Wt of baggase	5	20	
%Wt of Sponge gourd	5	20	
Fiber size (μm)	150	600	
Responses			

Tensile Strength	50	250	0.260276
Specific Strength	40	300	0.260276
Flexural Strength	150	400	0.171214
Elongation	10	20	0.114833
Hardness	15	40	0.076688
Impact Strength	15	40	0.050608
Modulus	30	100	0.033053
Specific Stiffness	73	400	0.033053

2.3.2 The Codes for the New Model

The following pseudo codes shows the algorithm of the new desirability function criteria used to write the program to improve the desirability function implementation used for the multi-objective optimization program developed for this research.

// First Pseudo code

```

if y>=Li && y<=Ui
    d(i)=1
else
    d(i)=0
end

```

// Second Pseudo code

```

if y>=T1 && y<=T2
    d(i)=1
elseif y>T2
    d(i)=(Ui-y) / (Ui-T2)
elseif y>Ui
    d(i)=0
elseif y<T2
    d(i)=(y-Li) / (T1-Li)
else

```

```
    d(i)= 0  
end
```

// Third Pseudo code used in NSGA-II

```
if y>=T1 && y<=T2  
    output =constant  
elseif y>T2  
    output=Ui-y  
  
else  
    output=y  
  
end
```


2.3.3 Fuzzy Inference Coupled PSO Optimized Desirability Function

Figure 18: Fuzzy inference coupled PSO optimized desirability function program flowchart

Figure 18 shows the Fuzzy inference system coupled PSO optimized desirability function program flowchart. As shown in the flowchart, the PSO generates an input X, a 1 by 3 matrix containing the inputs namely: %Wt of baggase, %Wt of Sponge gourd and Fiber size (μm). The PSO module contacts the desirability function (DF) module and sends X to the DF

module. The DF module contacts the fuzzy inference system (FIS) module to obtain the outputs which corresponds to the inputs. The outputs are tensile strength, hardness, flexural strength, modulus, elongation and impact strength. The DF module makes use of the output of the FIS module to determine the desirability (D) of the output. The iteration continues until the optimum desirability (D) is reached.

We introduced the modifications to the desirability function model because of the elongation property of the golf club material whose desirability follows the graph in Figure 19.

Figure 19: Desirability function graph for model 1

2.3.4 Fuzzy Inference Coupled NSGA II Model

Figure 20 shows the Fuzzy inference system coupled NSGA II program flowchart. As shown in the flowchart, the NSGA II module generates an input X consisting of the initial population of the input variables namely: %Wt of baggase, %Wt of Sponge gourd and Fiber size (μm). The NSGA II module contacts the multi objective fitness function (FF) module and sends X to the FF module. The FF module contacts the fuzzy inference system (FIS) module to obtain the outputs which corresponds to the inputs. The outputs are as stated previously. The FF module makes use of the output of the FIS module to determine the fitness of the input. The iteration continues until the optimum Pareto front is reached.

Figure 20: Fuzzy inference coupled NSGA II program flowchart

For the NSGA II algorithm, the elongation is modeled according to Figure 21. But in the NSGA II algorithm desirability is not used instead the values of the elongation are used to simulate desirability. The higher the values below the acceptable range the better. Values in

the acceptable range are equally good. The lower the values above the acceptable range the better.

Figure 21: Desirability function graph for model 2

3.0 Results and Discussion

3.1 Experimental Results

Table 9 shows the results of the experiment conducted to obtain the mechanical properties of the composite as was designed in section 2.3. There were 27 experimental runs. The maximum value of the tensile strength was 80 MPa while the minimum value was 26.5 MPa. The maximum value of the hardness was 52 while the minimum value was 10. The maximum value of the flexural strength was 240 MPa while the minimum value was 55 MPa. The maximum value of the modulus was 50 GPa while the minimum value was 9 GPa. The maximum value of the elongation was 33 while the minimum value was 11. The maximum value of the impact strength was 27.44 MPa while the minimum value was 19 MPa.

Table 9: Experimental results

S/N	%Wt of baggase	%Wt of Sponge gourd	Fiber size (μm)	Tensile strength (MPa)	Hardness (Rockwell)	Flexural strength (MPa)	Modulus (GPa)	Elongation	Impact Strength (MPa)
1	5	5	600	32	17.9	90	10	12	19
2	10	5	600	35	18.2	103	13.5	16	20.58
3	20	5	600	42	18.4	110	15	18	22
4	5	10	600	33	18.6	90	22	20	22.54
5	10	10	600	33	20	85	25	22	21.56
6	20	10	600	31	17.9	80	12	26	22

7	5	20	600	33.6	41	98	18	33	19.6
8	10	20	600	30	37	65	40	22	21.56
9	20	20	600	27	49	55	45	21	19
10	5	5	300	38	31	105	22.7	17	19.6
11	10	5	300	45	28	115	24	16	20
12	20	5	300	54	26	120	25	13	21.56
13	5	10	300	39	25.5	95	14	13	21.56
14	10	10	300	60	30	156	25	12	27.44
15	20	10	300	41	33	110	22	12	21
16	5	20	300	38	40	100	20	11	19.6
17	10	20	300	27	38	80	13	13	26.46
18	20	20	300	26.5	36	78	17	18	20.58
19	5	5	150	49	48.5	135	26.5	12	20.58
20	10	5	150	75	51	215	9	14	20.58
21	20	5	150	63	51.5	170	47	12	20
22	5	10	150	45	52	119	16	23	20.58
23	10	10	150	80	20	240	50	12	20.58
24	20	10	150	75	18	210	40	12	20.2
25	5	20	150	68	18	202	41.5	12	20.58
26	10	20	150	62	13	171	47.4	12	23.52
27	20	20	150	45.5	10	140	20.4	20	21.56

The values of the properties were within the range in the specifications of properties required for golf club materials as shown in Table 10.

Table 10: The properties of golf club materials

Properties	Value
1. Tensile strength (MPa)	50 – 250
2. Flexural strength (MPa)	150 – 400
3. Hardness(Rockwell)	15 – 40
4. Elongation (%)	10 – 20
5. Specific strength (Nm/kg)	15 – 40
6. Specific stiffness (Nm/kg)	20 – 50
7. Impact strength (MPa)	15 – 40
8. Modulus (GPa)	30 - 100

3.2 Fuzzy Logic Modelling Results

Table 11 shows the experimental values and the fuzzy logic predicted values of the mechanical properties of the hybrid polymer composite material.

Table 11: Experimental results and fuzzy logic predictions

Tensile strength	Predicted tensile strength	Hardness	Predicted hardness	Flexural strength	Predicted flexural strength	Modulus	Predicted Modulus	Elongation	Predicted Elongation	Impact Strength	Predicted impact strength
95	94	17.9	18	90	90	10	10	12	12	19	19
103.6	102	18.2	18	103	102	13.5	14	16	16	20.58	20.6
120	118	18.4	18	110	110	15	14	18	18	22	22
100	98	18.6	18	90	90	22	22	20	20	22.54	22.6
100	98	20	20	85	86	25	24	22	22	21.56	21.6
95	94	17.9	18	80	78	12	12	26	26	22	22
102	102	41	40	98	98	18	18	33	32	19.6	19.6
70	70	37	36	65	70	40	40	22	22	21.56	21.6
60	58	49	49	55	54	45	44	21	20	19	19
107	106	31	30	105	106	22.7	22	17	16	19.6	19.6
130	130	28	28	115	114	24	24	16	16	20	20
150	150	26	26	120	118	25	24	13	12	21.56	21.6
110	110	25.5	26	95	94	14	14	13	12	21.56	21.6
170	170	30	30	156	154	25	32	12	12	27.44	27.4
115	114	33	32	110	110	22	22	12	12	21	21
110	110	40	40	100	98	20	20	11	10	19.6	19.6
83	82	38	38	80	78	13	12	13	12	26.46	26.4
81	82	36	36	78	78	17	16	18	18	20.58	20.6
138	148	48.5	48	135	136	26.5	27	12	12	20.58	20.6
216.6	216	51	50	215	216	49	50	14	14	20.58	20.6
180	182	51.5	52	170	170	47	46	12	12	20	20
121	122	52	52	119	118	16	16	23	22	20.58	20.6
248	246	20	20	240	238	50	50	12	12	20.58	20.6
220	220	18	18	210	212	40	40	12	12	20.2	20.2
206	204	18	18	202	199	41.5	42	12	12	20.58	20.6
181	182	13	12	171	170	47.4	48	12	12	23.52	23.4
144	142	10	9.9	140	138	20.4	20	20	20	21.56	21.6

Table 12 shows the correlation coefficients between the experimental values and fuzzy logic predicted values shown in Table 11. As shown in Table 12, flexural strength has the highest R value of 0.9912 while impact strength had the lowest R value of 0.9529.

Table 12: Statistics of fuzzy logic predictions of responses

Fuzzy Logic Predictions Vs Experimental Data	R
Tensile Strength	0.9912
Hardness	0.9657
Flexural Strength	0.9922
Modulus	0.9857
Elongation	0.9637
Impact Strength	0.9529

3.3 Optimization Results

After running the modified NSGA II algorithm, the process decision variables corresponding to each of the Pareto optimal solutions is shown in Table 13. A closer look at Table 13 it should be observed that only 5 of the parameters on the Pareto front have desirability values above zero. It means that the other process variables on the front have one or more mechanical properties that fail to meet the requirements for golf club application as shown in Table 10.

Table 13: Process decision variables corresponding to each of the Pareto optimal solutions

S/N	%Bg	%SG	FS	TS	H	FS	Mod	El	IS	Sstr	Sstif	Des
1	5.00	5.00	150.00	53.63	39.37	160.50	26.58	15.98	20.61	33.52	16.61	0.00
2	13.80	10.00	168.03	81.01	19.98	237.98	50.01	11.97	20.63	50.63	31.26	0.83
3	12.59	10.00	168.03	81.00	19.98	237.99	49.99	11.99	20.61	50.63	31.25	0.83
4	10.00	15.98	202.93	27.40	37.94	78.00	11.87	11.95	26.36	17.13	7.42	0.00
5	13.67	10.00	168.04	81.02	19.99	237.99	50.00	11.98	20.63	50.64	31.25	0.83
6	10.00	10.17	281.57	58.09	30.51	150.19	30.72	11.99	27.33	36.31	19.20	0.00
7	9.75	16.58	504.17	32.34	38.16	85.99	25.75	25.50	20.61	20.21	16.09	0.00
8	15.75	17.41	512.55	27.19	48.00	54.00	44.01	19.98	18.97	16.99	27.51	0.00
9	12.96	16.31	502.64	28.90	41.70	58.00	42.00	21.00	20.28	18.06	26.25	0.00
10	10.00	15.87	156.49	63.00	12.01	170.00	48.01	11.99	23.40	39.38	30.00	0.00
11	15.43	16.70	503.82	27.37	47.85	54.00	44.12	19.95	18.96	17.10	27.57	0.00
12	14.83	16.17	506.36	27.85	45.14	55.67	43.08	20.36	19.51	17.40	26.93	0.00
13	10.00	12.84	247.91	42.33	34.39	112.41	21.14	11.99	26.83	26.46	13.21	0.00
14	5.13	10.48	153.63	51.99	37.04	143.46	24.68	21.51	20.82	32.50	15.42	0.00
15	9.94	11.99	172.37	71.88	17.17	205.80	47.53	12.66	21.91	44.93	29.71	0.79
16	14.85	15.86	270.90	27.07	36.07	78.00	15.78	17.67	20.91	16.92	9.86	0.00
17	15.43	16.71	503.81	27.37	47.85	54.00	44.12	19.95	18.96	17.10	27.57	0.00
18	9.91	9.94	177.24	75.51	22.66	224.61	45.77	13.03	20.61	47.20	28.61	0.82

Table 14 show the optimal solution obtained after running the modified desirability function program whose flowchart is depicted in Figure 18. The optimum desirability is 0.8418 for three runs of the optimization algorithm. The unique thing about the desirability function model is the modification introduced in Equation 15 to model the elongation property.

Designers usually model such properties by adopting the larger the better or the nominal the best model assumption. If the larger the better model (Equation 9) was adopted for elongation, the result shown in Table 15 was obtained. Similarly, if the nominal the best model (Equations 11-14) was adopted the results shown in Table 16 was obtained. It is clear that the optimum properties obtained from the modified model was better than what was obtained by not modifying the models because the desirability values in Table 14 are clearly higher than those in Tables 15 and 16.

Table 14: Optimum solutions obtained using the modified desirability function

Run	Bg%	SG%	Fs	TS	H	FI	Mod	El	Is	Sstr	Sstif	Desirability
1	10	6.62	150.00	78.16	39.33	227.97	49.99	12.94	20.61	48.85	24.58	0.841761
2	10	6.62	150.00	78.16	39.33	227.97	49.99	12.94	20.61	48.85	24.58	0.841761
3	10	6.62	150.00	78.16	39.33	227.97	49.99	12.94	20.61	48.85	24.58	0.841761

A comparison of the optimum mechanical properties in Table 14 and the mechanical properties of golf club materials shown in Table 10 shows that the mechanical properties of the optimized composite material conforms excellently well to the specifications of materials for golf club applications.

Table 15: Optimum solutions obtained using the larger the better assumption

Run	Bg%	SG%	Fs	TS	H	FI	Mod	El	Is	Sstr	Sstif	Desirability
1	10	5.52	150.00	78.01	40.00	227.29	49.99	12.99	20.61	48.76	25.00	0.8186237
2	10	5.52	150.00	78.01	40.00	227.29	49.99	12.99	20.61	48.76	25.00	0.8186237
3	10	5.52	150.00	78.01	40.00	227.29	49.99	12.99	20.61	48.76	25.00	0.8186237

Table 16: Optimum solutions obtained using the nominal the best assumption

Run	Bg%	SG%	Fs	TS	H	FI	Mod	El	Is	Sstr	Sstif	Desirability
1	10	5.523	150.00	78.01	39.99	227.30	49.99	12.99	20.61	48.76	25.00	0.83175985
2	10	5.523	150.00	78.01	39.99	227.30	49.99	12.99	20.61	48.76	25.00	0.83175985
3	10	5.523	150.00	78.01	39.99	227.30	49.99	12.99	20.61	48.76	25.00	0.83175985

4.0 Conclusion

The utility of smart systems based on artificial intelligence in prediction and multi objective optimization of hybrid polymer composite material developed from sponge gourd and bagasse and epoxy resin has been shown in this study. The study has equally shown that fuzzy logic is an excellent tool in modeling non linear relationships which often occurs between input (s) and output (s) variables in materials development and processing. The modified desirability function and NSGA II algorithm represents important contributions to multi criteria decision analysis and its applications to engineering.

The complex system developed by linking desirability function to PSO coupled to a fuzzy logic model has extended the frontier of artificial intelligence applications in building smart systems that would create high quality optimized engineering products. The same applies to the modified NSGA II algorithm coupled with fuzzy logic model as its fitness function.

Declaration of interests

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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