Journal of Manufacturing Engineering, 2009, Vol.4, Issue.2, pp 111-118

MECHANICAL PROPERTIES OF SHORT ROSELLE AND SISAL FIBER HYBRID POLYESTER COMPOSITE: MODELING AND OPTIMIZATION COATING WITH TAGUCHI APPROACH

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ABSTRACT

The modeling and optimization techniques are becoming more popular in engineering design activities because of the availability and affordability of high-speed computers. In this present contribution, a new attempt was made to predict and optimize the mechanical properties of short roselle and sisal fiber hybrid polyester composite using Neuro-fuzzy modeling and Genetic algorithm method. The better mechanical properties with optimum fabrication parameters were obtained by using single objective optimization method of Genetic Algorithm (GA). The mechanical properties of the natural fiber hybrid polyester composite can be predicted and optimized using Neuro-Fuzzy modeling as a potential modeling technique and Genetic algorithm within the ranges of fabrication parameters.

Keywords: *Natural fibers, Polymer-matrix composites, Mechanical Properties, Nuero - Fuzzy, Genetic Algorithm*

1. Introduction

Generally the natural fibers are easily available, low price, recyclable, high specific strength and enough modulus material. In recent years, the natural fiber reinforced polymer composites have more attention and interest for development of environmental friendly material and partly replacing currently used glass or carbon fibers in fiber reinforced composites [1]. The natural fiber hybrid composites of sisal/silk unsaturated polyester based hybrid composites with different fiber lengths were fabricated using hand lay-up method. Variation of mechanical properties such as tensile, flexural, and compressive strengths of these composites with different fiber lengths were studied. The effect of alkali treatment on the tensile, flexural, and compressive properties of the sisal/silk hybrid composites were studied [2]. Mechanical properties such as tensile, flexural, impact, and dynamic mechanical thermal analysis of novolac type phenolic composites reinforced with jute/cotton hybrid woven fabrics were investigated as a function of fiber orientation and roving/fabric characteristics. It was concluded that this combination of natural fibers is suitable to product composites for lightweight structural applications [3]. The static and dynamic mechanical properties of kenaf fibers and wood flour hybrid polypropylene composite were studied [4]. The tensile strength of plain weave hybrid ramie–cotton fabrics polyester matrix composites was determined as a function of the volume fraction and orientation of the ramie fibers [6]. The dynamic properties such as the storage modulus, damping behaviour and static mechanical properties such as tensile, flexural and impact of randomly oriented intimately mixed short banana/sisal hybrid fiber reinforced polyester composites as a function of total fiber volume fraction and the relative volume fraction of the two fibers were investigated [7]. The effects of concentration and modification of fiber surface in sisal/oil palm hybrid fiber reinforced rubber composites have been studied [8]. A neural network was used for the prediction of yarn properties especially tenacity and breaking elongation and a genetic algorithm was used to optimize the input parameters [9]. The prediction performance of linear regression, ANN and compared for the prediction of cotton yarn tensile properties [10, 11].

1.1 Design of experiments

The 3^k factorial design is the most widely used factorial design having three levels for each of 'k' factors. The three levels of factors are referred to as low (-1), intermediate (0) and high (+1). If there are three factors under study and each factor is at three levels arranged in a factorial experiment, then this constitutes a 3^3 factorial design. Each main effect has two degrees of freedom; each two-factor interaction has four degrees of freedom. If they are *n* replicates,

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then there are (n x 3^3 – 1) degrees of freedom and ^{3} (n-1) degrees of freedom for error [12].

1.2 Neuro-fuzzy and genetic algorithm

Neuro-fuzzy modeling refers to the way of applying various learning techniques developed in the neural network literature to fuzzy modeling. The neuro-fuzzy systems have potential to capture the benefits of both the fascinating fields into a single frame-work. This system eliminates the basic problem in fuzzy system design (i.e. obtaining a set of fuzzy if-then rules) by effectively using the learning capability of an ANN for automatic fuzzy if-then rules generation. As a result, these systems can utilize linguistic information form of the human expert as well as measured data during modeling. Such applications have been developed for signal processing, automatic control, process control, data-base management etc.

Generally optimization is the act of obtaining the best solution under given circumstances [13, 14]. It can be defined as the process finding the condition (parameter values) that gives the maximum and minimum value of a function [15]. Genetic algorithm is a global population search and optimisation technique based on the principle of natural genetics and natural selection. It operates on the principle of the survival of the fittest, where weak individuals die before reproducing, while stronger ones survive and bear many off-springs and breed children, which often inherit the qualities that are in most cases superior to their parents. It is naturally used for solving maximization problems [15]. However, there is no discussion on the application of these techniques for natural fiber hybrid polymer composite. The major objective of this work is to study the potentiality of neuro-fuzzy systems and genetic algorithm method in short natural fiber hybrid polymer composites.

2. Experimental Details

2.1 Materials and processing

The untreated roselle and sisal fibers with dry condition were taken as reinforcement fillers. The matrix material used was based on commercially available polyester resin, Trade name satyan polymer supplied by GV Traders. Methyl ethyl ketone and Cobalt were used as accelerator and catalyst respectively. The roselle and sisal fibers contents were set at 10, 20 and 30 wt%. The fiber length is 5, 10 and 15 cm respectively. In present work, 9 fabrication processes were done based on the fabrication parameter combinations. The physical appearance of the fabricated composite specimen for this work is shown as Figure 1. The tensile strength of the composites was measured with a computerized FIE universal testing machine in accordance with the ASTM D638 procedure.

Fig. 1 A view of fabricated composite

2.2 Development of Regression Model

In present work, 3^3 factorial design is used to develop a mathematical model for the tensile strength. Three fabrication parameters such as fiber length, fiber content and matrix proportion are used as input variables; each parameter is at three levels, arranged in a factorial experiment, then this constitutes a 3^3 factorial design. To develop the model for tensile strength, the software known as SPSS is used and the model will be in the form of:

$$T \text{ and } F = k \times L^{x} \times C^{y} \times M^{z}$$

where k, x, y and z are constant parameters.

The Regression Model for tensile strength and flexural strength was developed as: Tensile Strength (T) (MPa) = 10125.402193 x $L^{0.218574013}$ x $C^{-0.054115110}$ x $M^{-1.306879431.}$ The squired residual values (R^2) for the Regression model for tensile strength are found to be 0.92821. This mathematical formulation of the tensile strength is used as objective function.

2.3 ANFIS Architecture

Adaptive Neuro-fuzzy inference system (ANFIS) is Sugeno fuzzy models put in the framework of adaptive systems to facilitate learning and adaptation. Such a framework makes fuzzy system more systematic and less relying on expert knowledge. For simplicity, it is assumed that the fuzzy inference system under consideration has two inputs x and y and one output. For first order Sugeno fuzzy model, a common rule set with two fuzzy 'If then rule' is as follows:

Rule 1: IF x is A_1 and y is B_1,

THEN $f_1 = p_1 x + q_1 y + r_1$

Rule 2: IF x is A_2 and y is B_2, THEN $f_2 = p_2 x + q_2 y + r_2$

Where p_1, q_1, r_1 p_2, q_2, r_2 are the linear parameters and A_1, B_1, A_2 and B_2 are non - linear parameters. The corresponding equivalent ANFIS architecture is shown in Fig. 2. The entire system consists of five layers namely fuzzy layer, Product layer, Normalized layer, Defuzzy layer, and Total output layer

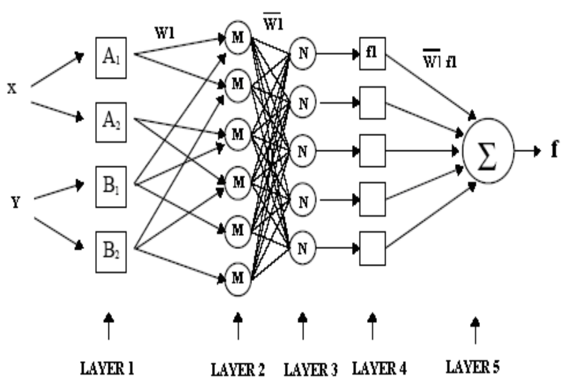


Fig. 2 ANFIS Architecture

It may be seen that the circle indicates a fixed node whereas a square indicates an adaptive node (the parameters are changed during adaptation or training). In fuzzy layer, x and y are the input nodes and A_1, B_1 and A_2, B_2 are the linguistic labels in the fuzzy theory (such as low or high) for dividing the membership function. The membership relationship between the output and input functions of this layer can be expressed as follows.

$$O_{1,i} = \mu_{A_i}(x) \quad i = 1, 2$$

$$O_{1,i} = \mu_{B_{i-2}}(x) \quad i = 3, 4$$

Here the membership for the A_1 can be any appropriate parameterised membership function such as generalized bell shaped function as follows. As the value of these parameters change, the bell shaped function varies accordingly, thus exhibiting various forms of membership function for fuzzy set.

$$\mu_{A_i}(x) = \frac{1}{1 + [\frac{(x - c_i)^2}{a_i^2}]^{b_i}}$$

Where $\mu_{A_i}(x)$ and $\mu_{B_i}(x)$ are appropriate parameterized membership functions, $\{a_i, b_i, c_i\}$ are premise parameters and $O_{1,i}$, $O_{1,i}$ are denoting the output functions. In product layer, nodes are labeled as M. Each node output represents the firing strength of a rule. In general, fuzzy AND operators can be used as the node function in this layer. The output W_1 and W_2 are the weight function of the next layer. The output of this layer is the product of the all incoming signals. This is defined as follows.

$$O_{2,i} = w_i = \mu_{A_i}(x) \times \mu_{B_i}(x) \qquad i = 1, 2$$

Where $O_{2,i}$ denotes the output of the layer 2. In normalized layer the nodes are labeled as N. Its function is to normalize the weight function in the following process.

$$O_{3,i} = \overline{w}_i = \frac{w_i}{w_1 + w_2} \qquad i = 1, 2$$

Where $O_{3,i}$ denotes the output of layer 3. In defuzzy layer the nodes are adaptive. The defuzzy relationship between the input and output of this layer can be defined follows.

$$O_{4,i} = \overline{w}_i f_i = \overline{w}_i (p_i x + q_i y + r_i)$$

Where $\{p_i, q_i, r_i\}$ are consequent parameters and $O_{4,i}$ denotes the output of layer 4.

In total output layer, the output is the summation of the input signals of the layer 4. This can be written as follows.

$$O_{5,1} = overall\ output = \sum_i \overline{w}_i f_i$$

Where $O_{5,1}$ denotes the output of the system.

In this experimental study, nine set of experimental readings were taken for training the Neuro-fuzzy model. The input-output relationship is modeled using the ANFIS in which knowledge base of the fuzzy system is designed automatically using Neural network so that the output i.e. mechanical properties can be predicted for any set of input parameters. The morphology for the mechanical properties prediction model is shown in Figure 3.

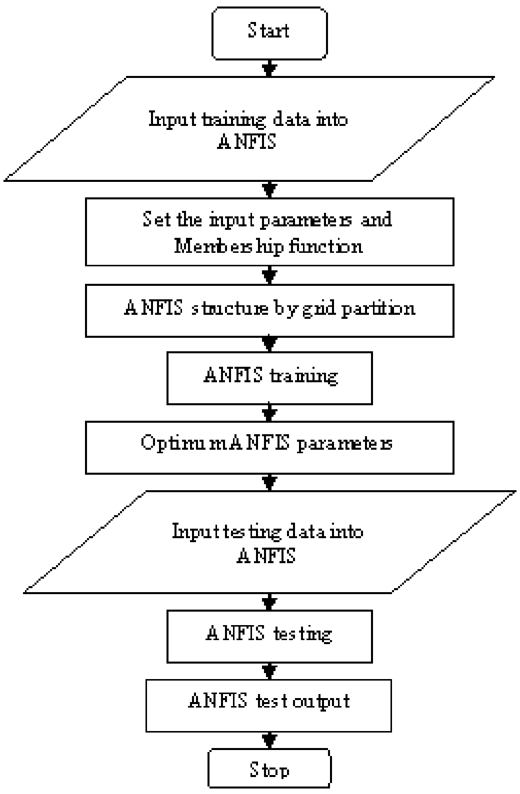


Fig. 3 Morphology of ANFIS model

2.4 Genetic algorithm operators

Reproduction is a process in which the pairs of individuals or strings are chosen from the population to form a mating pool in such a way that those with high fitness value will be chosen more frequently. It is also names as selection operator. Crossover operator is applied to the mating pool with a hope that it would create a better string .There are five types of the crossover operators available in genetic algorithm i.e. single point crossover, two-point crossover, multi-point crossover, uniform crossover and two-dimensional crossover. The single point crossover operator is carried out by randomly choosing a crossing site along the string after that all bits on the right side of the crossing site are exchanged [15].

For example

00010 | 10001 ⇨ 00010 | 0111
0
10100 | 0111 10100 | 10001
0

After crossover process the strings are subjected to mutation. It changes 0 to 1 and vice versa with a small mutation probability, which is also needed to maintain diversity in the population. It is explained with following example in which all four strings have‘1’ in the leftmost bit position. The required optimum solution is ‘0’in all four strings. But all strings have ‘1’ in that position. Only mutation operator can create probability from ‘1’ to ‘0’ [15].

1001000110
1110010101
1010101010
1000100001

Fitness function is a measure of how well a parameter set performs and plays very important roll in Genetic algorithm. Generally the fitness function f(x) is derived from the objective function. For maximization problems the fitness function can be considered to be same as that of objective function [15].

ie, $F(x)=f(x)$

Genetic algorithms are ideally suited for unconstrained optimization problems. The present problem is also an unconstrained one. Flow-chart of genetic algorithm is given in Figure 4.

The parameters or variables have to be used for Neuro-fuzzy and Genetic algorithm is fiber length, fiber content and matrix proportion in order to model and optimize the tensile strength of the composite specimen.

Fiber length $5 \le L \le 15$
Fiber content $10 \le C \le 30$
Matrix proportion $70 \le P \le 90$

3. Result and Discussions

3.1 Results of Neuro-fuzzy system and Regression method

The average absolute error between the predicted and observed value are taken as the performance measures. The prediction was based on the input data sets discussed above. Using nine training data sets and six testing data sets and hybrid method consisting of back propagation for the parameters associated with the input membership function and the least square estimation for the parameters associated with the output membership functions, prediction was made for tensile strength of the short roselle and sisal fiber hybrid polyester composite. Predicted and observed values of tensile strengths along with the average absolute percentage error from Neuro-fuzzy model and Regression model are given in tables 1 and 2. The average absolute error for Regression model and Neuro-fuzzy model are 3.42%and 0.10% respectively. Training performance of Neuro-fuzzy model is shown as Figure 5a.

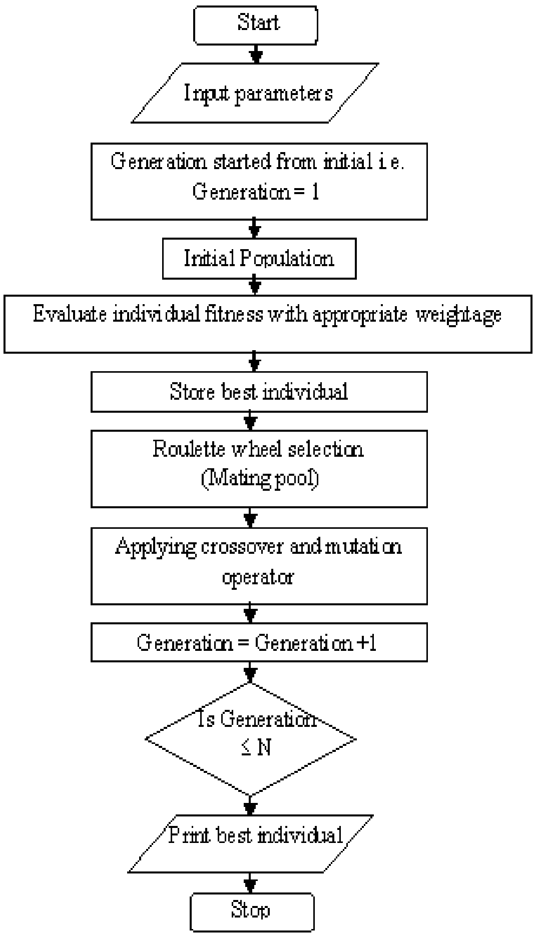


Fig.4 Flow chart of genetic algorithm

From average absolute error, it can be said that results obtained from Neuro-fuzzy model were highly encouraging and precise. Surface graphs between the inputs and the predicted output are shown in Figs. 6a, 6b and 6c. ANFIS structure for Neuro-fuzzy with three input parameters and four rules is shown in Fig. 7. The membership function of each input was tuned using the hybrid method consisting of back propagation for the parameters associated with the input membership function and the least square estimation for the parameters associated with the output membership functions (Figs. 8a, 8b and 8c). The results obtained with ANFIS model were compared with the experimental results in the ANFIS test output as shown in Fig. 9.

Table 1: Observed and predicted values of tensile strength from regression model (RM).

1	**F C** (wt%)	**M P** (wt%)	**O TS** (Mpa)	**P TS** (Mpa)	**Error** (%)
5	11	89	33.3	35.8	-7.51
7	20	80	42.5	42.9	-0.94
12	9	91	41.6	42.6	-2.4
9	30	69	51.9	53.8	-3.66
11	22	78	46.7	48.7	-4.28
15	29	71	57.1	58.1	-1.75
Average absolute error					3.42

FL-Fiber Length, FC-Fiber Content, MP-Matrix Proportion, OTS-Oberved Tensile Strength, PTS-Predicted Tensile Strength

Table 2: Observed and predicted values of tensile strength from Neuro-fuzzy model.

F L (cm)	**F C** (wt%)	**M P** (wt%)	**O TS** (Mpa)	**P TS** (Mpa)	**Error** (%)
5	11	89	33.3	32.9	1.2
7	20	80	42.5	43.1	-1.41
12	9	91	41.6	41.1	1.2
9	30	69	51.9	52.4	-0.96
11	22	78	46.7	45.9	1.71
15	29	71	57.1	57.8	-1.22
Average absolute error					0.1

FL-Fiber Length, FC-Fiber Content, MP-Matrix Proportion, OTS-Oberved Tensile Strength, PTS-Predicted Tensile Strength

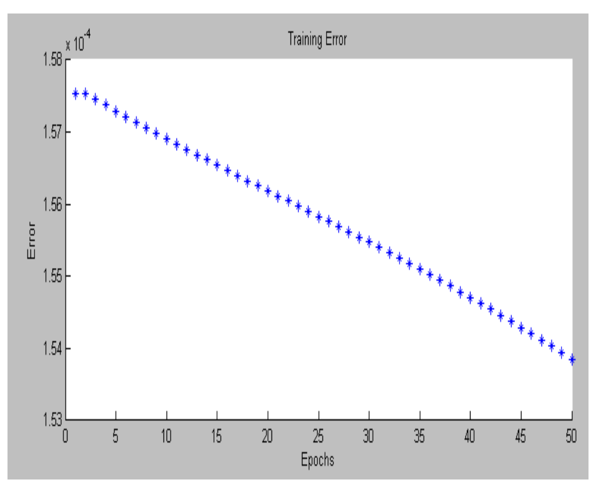


Fig. 5a Performance graph of the neuro-fuzzy model

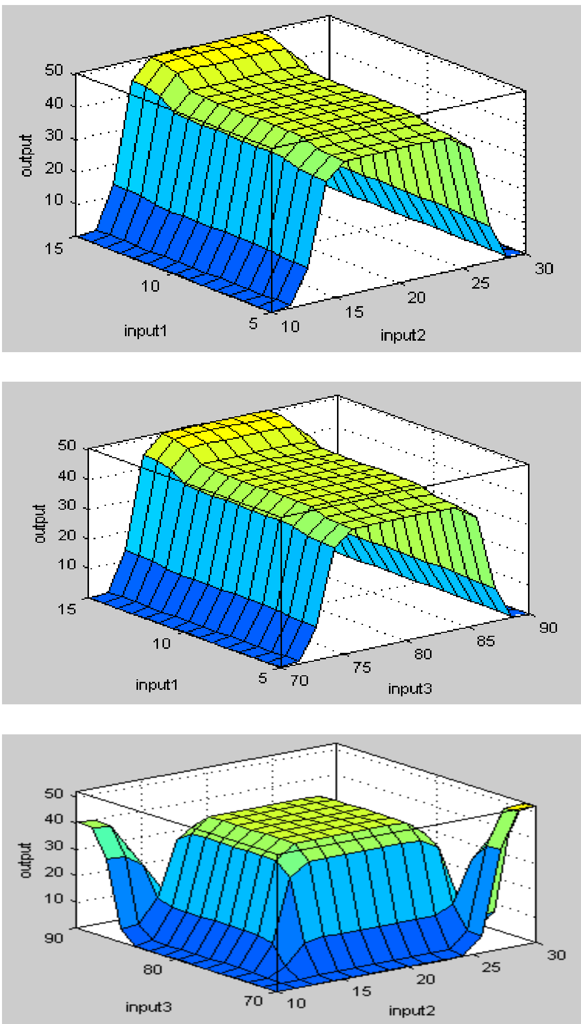


Fig. 6 Surface graph showing relationship of (a) input 1 and input 2 with predicted output, (b) input 1 and input 3 with predicted output, (c) input 3 and input 2 with predicted output, input 1 is fiber length, input 2 is fiber content, input 3 is matrix proportion and output is predicted tensile strength by Neuro-fuzzy model.

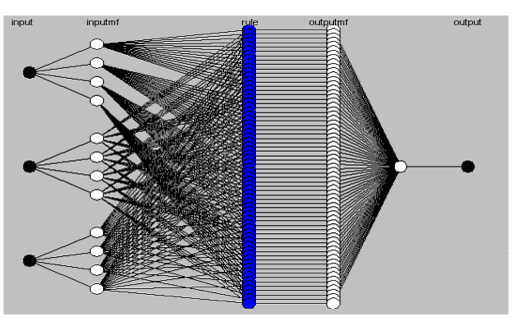
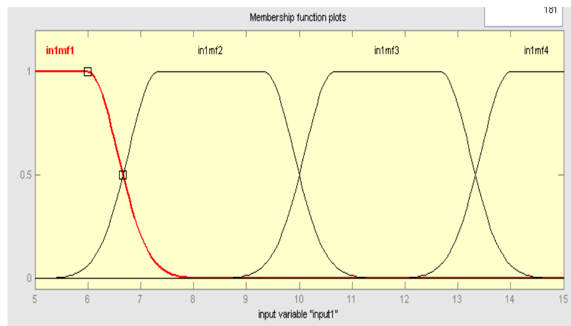
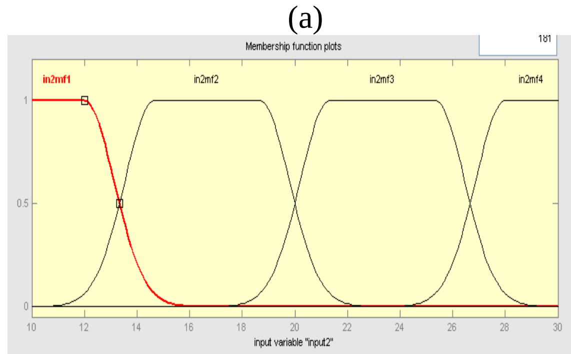


Fig. 7 ANFIS structure for neuro-fuzzy with three input parameters and four rules



(a)



(b)

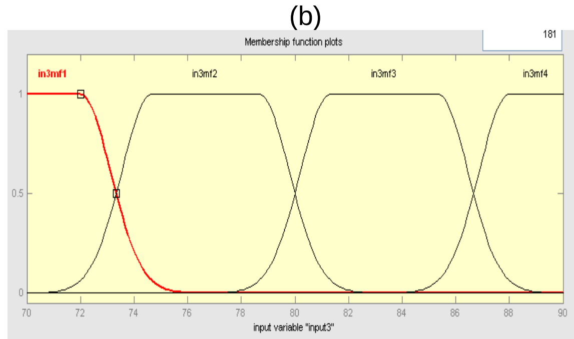


Fig. 8 Membership function plots for (a) input 1 (b) input 2 (c) input 3

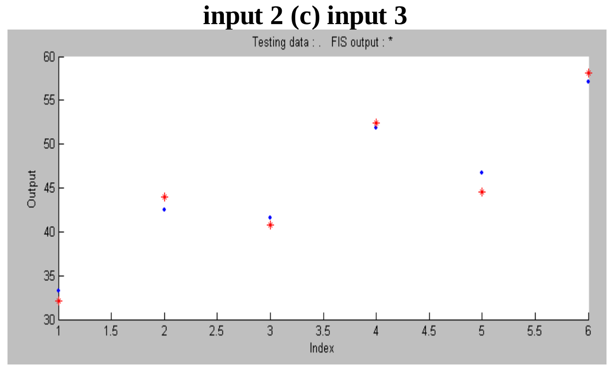


Fig. 9 ANFIS Test output for tensile strength

3.2 Results of Genetic Algorithm

The linear ranking methods proposed by Baker were used for reproduction. In cross-over, the two strings are picked from the mating pool and portion of the strings are exchanged between these strings with cross-over probability of 0.8. A single point cross over is employed. A bit-wise mutation is used with a probability of 0.001 for every bit. The maximum tensile strength is obtained at 22th generation. The effects of genetic algorithm on tensile strength are shown as Table 3. The maximum value of tensile strength with optimized fabrication parameters are presented as Table 4. The required program for this study is implemented on a PC by using C Language.

The following parameters were used in Genetic Algorithm

Number of generation **:** 35
Number of population **:** 18
String length **:** 10
Single point crossover **:** 0.8
Mutation probability **:** 0.001

Table 3: The effects of genetic algorithm on tensile strength

No. of generation	**Max. objective T S** (MPa)	**Parameters (L, C, M)**		
0	54.18	11.81	23.74	72.54
1	56.02	13.91	27.81	72.19
2	51.86	13.91	22.79	77.21
3	56.23	13.91	28.04	71.96
4	56.23	13.91	28.04	71.96
5	56.27	13.91	28.08	71.92
6	56.02	13.91	27.81	72.19
7	53.64	11.40	27.81	72.19
8	57.40	14.84	28.44	71.56
9	54.82	10.93	29.69	70.31
10	58.61	14.84	29.69	70.31
11	58.61	14.84	29.69	70.31
12	58.91	14.84	30.00	70.00
13	58.91	14.84	30.00	70.00
14	58.91	14.84	30.00	70.00
15	58.64	14.53	30.00	70.00
16	58.74	15.00	29.69	70.31
17	58.91	14.84	30.00	70.00
18	58.91	14.84	30.00	70.00
19	58.61	14.84	29.69	70.31
20	58.78	14.69	30.00	70.00
21	59.05	15.00	30.00	70.00
22	59.05	15.00	30.00	70.00
23	59.05	15.00	30.00	70.00
24	59.05	15.00	30.00	70.00
25	59.05	15.00	30.00	70.00
26	59.05	15.00	30.00	70.00
27	59.05	15.00	30.00	70.00
28	59.05	15.00	30.00	70.00
29	59.05	15.00	30.00	70.00
30	59.05	15.00	30.00	70.00
31	59.05	15.00	30.00	70.00
32	59.05	15.00	30.00	70.00
33	58.78	14.69	30.00	70.00
34	58.78	14.69	30.00	70.00
35	59.05	15.00	30.00	70.00

L-Fiber length in cm, C-Fiber content in wt%, M-Matrix proportion in wt%

Table 4: Maximum value of the objective function (Tensile strength) and optimized fabrication parameters values

Maximized value of objective function (Tensile strength) (MPa)	**Optimized fabrication parameters**		
	Fiber length (L) (cm)	**Fiber content (C)** (wt%.)	**Matrix proportion (M)** (wt%)
59.05	15.00	30.00	70.00

4. Conclusion

In the present study, a new attempt has been made to model and maximize the mechanical properties like tensile strength in short roselle and sisal fiber hybrid polyester composite by using Neuro-fuzzy and Genetic algorithm. A Regression model has been developed for the tensile strength with fabrication parameters. The lower average absolute error obtained by the Neuro-fuzzy model suggests its good potentiality for prediction of mechanical properties of short roselle and sisal fiber hybrid polyester composites. Eventhough Neuro-fuzzy model were highly encouraging and precise than Regression model, as an initial attempt, regression model was used with Genetic algorithm. The predicted tensile strength using Genetic algorithm is higher than the observed value within range of used fabrication parameters. So it shows its good potential to maximize the mechanical properties of short roselle and sisal fiber hybrid polyester composites. The Neuro-fuzzy and Genetic algorithm method presented in this paper shows a good potentiality to model and maximize the mechanical properties of natural fiber hybrid polymer composites.

Nomenclature

Symbol	Meaning	Unit
T	Tensile strength	MPa
F	Flexural strength	MPa
L	Fiber length	cm
C	Fiber content	wt%
M	Matrix proportion	wt%

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