CHAPTER 5

MECHNANICAL PROPERTIES OF NFRP HYBRID COMPOSITE: MODELING AND OPTIMIZATION

5.1 INTRODUCTION

In previous chapters, the experimental results are considered in analyzing the mechanical and water absorption properties. Though, this work produces accurate results, it is not suitable for the case of mass production due to the following reasons as stated below.

- Limitations in the prototype model (consuming high demand).
- Cost expensive.
- Wastage of materials.
- Time consumption.
- High testing cost.

In order to overcome such limitations in experimental methods, optimization method using Neuro fuzzy and Genetic Algorithm (GA) is proposed in this chapter. In this proposed methodology, the parameters (Fiber content, matrix proportion, fiber length) of materials are chosen as input variables which provides the numerical data for the regression model.

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 research contribution, a new attempt is made to predict and optimize the tensile property of short bamboo and sisal fiber hybrid polyester composite using Neuro-fuzzy modeling and GA method. The better tensile, flexural and Impact property with optimum fabrication parameters are obtained by using the single objective optimization method of GA. The tensile property of the natural fiber hybrid polyester composite can be predicted and optimized using Neuro-Fuzzy modeling as a potential modeling technique within the ranges of fabrication parameters.

5.2 SOFT COMPUTING APPROACHES

The optimization of output functionalities with respect to input patterns are achieved using the following algorithms as stated below.

- Neural Networks;
- Fuzzy Logic principles;
- Genetic Algorithm;

In this research work, Neural Networks are combined with fuzzy principles and GA methodology for obtaining best in the optimization process.

5.3 EXPERIMENTAL DETAILS

5.3.1 Materials and Processing

The alkali treated hybrid composite specimens are prepared by keeping the weight ratio of bamboo and sisal 50:50 In this work, nine composite specimens are fabricated based on the fabrication parameter combinations. The physical appearance of the fabricated composite specimen of this work is shown as Figure 5.1.

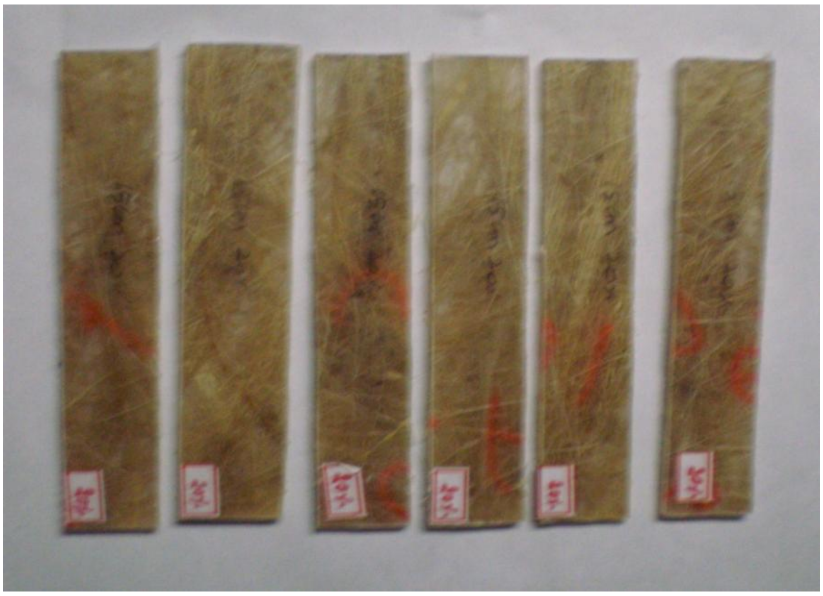


Figure 5.1 Fabricated composites

Table 5.1 Effects of fiber length and weight percentage of mechanical properties of treated 50:50 fiber weight % of sisal/bamboo hybrid unsaturated polyester composites

Fiber length (cm)	Fiber weight (%)	Tensile strength (MPa)	Flexural strength (MPa)	Impact strength (kJ/m^2)
5	10	13.3	31.2	11.2
	15	19.8	48.4	15.3
	20	30.1	61.2	22.3
10	10	25.4	46.4	13.3
	15	32.3	53.2	21.6
	20	38.2	68.6	26.8
15	10	26.7	48.5	18.6
	15	34.6	61.7	25.8
	20	38.4	78.2	30.3

Table 5.1 shows, the experimental data of mechanical properties of treated 50:50 fiber weight percentage sisal/bamboo hybrid unsaturated polyester

composite in which maximum tensile strength is observed as 38.4 MPa, maximum flexural strength as 78.2 MPa and the maximum Impact strength as 30.3 kJ/m^2.

5.3.2 Development of Regression Model

At present, 3^2 factorial design is used to develop a mathematical model for the mechanical strength. Two fabrication parameters such as fiber length, fiber content are used as input variables; each parameter is on three levels, arranged in a factorial experiment, then this constitutes a 3^2 factorial design.

To develop the proposed regression model for tensile, flexural and Impact strength, Statistical Package for the Social Science (SPSS) software Version 20.0, is used and it is license free software version. The proposed model used in this software is in the form of:

$$T \text{ and } F \text{ and } I = k * L^{x} * C^{y} \tag{5.1}$$

where as,

L: Length of fiber

C: Fiber content

k, x, y and z are constant parameters.

The Regression Model for tensile strength is developed as:

$$\text{Tensile Strength (T) (MPa)} = 10982.833 \text{x } L^{0.132} \text{ x } C^{0.009.} \tag{5.2}$$

The Regression Model for flexural strength is developed as:

$$\text{Flexural Strength (F) (MPa)} = 10765.675 \text{ x } L^{0.653} \text{ x } C^{0.0541} \tag{5.3}$$

The Regression Model for Impact strength is developed as:

$$\text{Impact Strength (I) (kJ/m}^2) = 11984.7864 \times L^{0.3846} \times C^{0.024} \qquad (5.4)$$

These mathematical formulations of the tensile, flexural and impact strength are used as objective functions in this research work. The squared residual values (R^2) for regression equations of the tensile, flexural, impact strength and water absorption behaviour are 0.9125, 0.9031, and 0.8971.

5.4 ANFIS ARCHITECTURE (Neuro – Fuzzy Hybrids)

This is well developed and constructed architecture which uses two different classification and optimization technique. In this research work, Neural Networks with fuzzy principles are used for producing the common architecture. In this way, the non-linearilities of each layer is developed for producing maximum response based on the extracted nodes. This relationship is well analyzed for producing high number of valid output responses. On the other hand, the precision of outputs is quite often limited and does not admit zero error, but the only minimization of least squares errors. Besides, the training time required for an NN can be substantially larger. Also, the training data has to be chosen carefully to cover the entire range over which the different variables are expected to change.

The following are the advantages of this ANFIS architecture based on the functionalities of each internal layer.

- Works with any type of membership function.
- Produces flexible output response based on the mathematical relationship between each layer
- Constructs fuzzy rules as per user requirement.
- Functions on linear functionality.
- Supports both active and passive node.

The proposed ANFIS systematic architecture is constructed with the aid or integration of Neural Networks and Fuzzy logic principles. Haykin (1994) and Kartalapoulos (1996) developed this type of static and dynamic architecture based on the nodes behaviour with each internal layers. Takagi & Hayashi (1988) used this type of developed architecture for optimizing the designed methodology with respect to variable input parameters.

5.4.1 Fuzzy BP Architecture

In this research work, feed forward methodology is used in conjuction with back propagation technique. This constructed architecture have three internal layers with different static and dynamic nodes. This developed architecture works in the following modes as stated below.

1. Learning or Training, and
2. Inference.

Let $\tilde{I}_p = (\tilde{I}_{p1}, \tilde{I}_{p2}, ..., \tilde{I}_{pl})$ p = 1, 2, ..., N be the $_p$th pattern among N input patterns that fuzzy BP needs to be trained, with $\tilde{I}_o = (1, 0, 0)$ as the bias. Here, Ĩpi indicates the ith input component of the input pattern p and is an LR-type triangular fuzzy number, i.e. $\tilde{I}_{pi} = (I_{pmi,} I_{p\propto i}, I_{p\beta i})$. Let $\widetilde{O}_{pi}$ be the output value of the ith input neuron, O'_{pj} and O''_{pk} are the jth and kth crisp defuzzification outputs of the hidden and output layer neurons respectively. $\widetilde{W}ji$ and $\widetilde{W}kj$ are the LR-type fuzzy connection weights between the ith input neuron and the jth hidden neuron, and the jth hidden neuron and kth output neuron respectively.

In this research work**,** Adaptive Neuro-Fuzzy Inference System (ANFIS) algorithm (Yang Wang & Ouyang, 2014) is used to predict the optimal value with minimized error rates.

In this work, the fuzzy models can be categorized into Sugeno and Mamdani which works based on the functionalities of nodes response in each constructed layer in the developed architecture. The developed architecture uses IF-THEN rule for obtaining best output pattern based on the nodes behaviour in each layer of the developed architecture. In this architecture, 'x' and 'y' are set as input variables which are connected with extracted nodes behaviour .

Rule 1: IF x is A_1 and y is B_1, THEN $f_1 = p_1 x + q_1 y + r_1$ (5.6)

Rule 2: IF x is A_2 and y is B_2, THEN $f_2 = p_2 x + q_2 y + r_2$ (5.7)

where as,

$p_1, q_1, r_1 \;\; p_2, q_2, r_2$: Linear parameters

A_1, B_1, A_2 and B_2 : Non - linear parameters.

The corresponding equivalent generic ANFIS architecture is shown in Figure 5.2. The entire system consists of five layers, namely fuzzy layer, Product layer, Normalized layer, Defuzzy layer, and Total output layer.

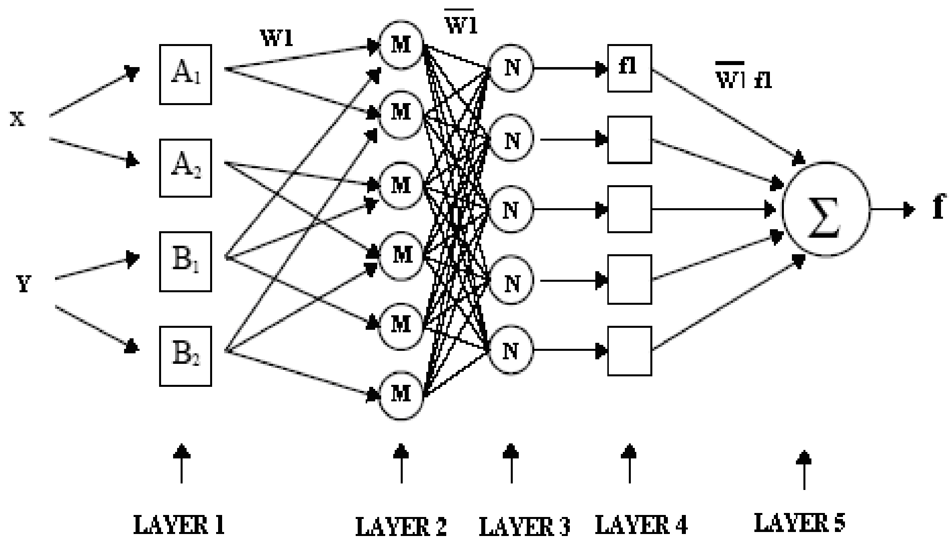


Figure 5.2 Generic ANFIS architecture

In this architecture, nodes are spread and categorized as either fixed or variable nodes based on its functionalities with previous response of each layer in the developed or constructed architecture. The fixed nodes in this developed architecture is noted as circle mode and the variable nodes in this developed architecture is noted as square mode. The membership function correlates the functionalities between each layer in this developed architecture as stated in Equation 5.8 as stated below.

$$\begin{aligned} O_{1,i} &= \mu_{A_i}(x) \quad i = 1,2 \\ O_{1,i} &= \mu_{B_{i-2}}(x) \quad i = 3,4 \end{aligned} \tag{5.8}$$

In this research work, bell shaped membership function is utilized for achieving best functional response as well as the output is based on the input feature sets from respective nodes. The functionalities between used membership functional in this research work are stated in the following equation 5.9.

$$\mu_{A_i}(x) = \frac{1}{1 + [\frac{(x - c_i)^2}{a_i^{\,2}}]^{b_i}} \tag{5.9}$$

where as,

$\mu_{A_i}(x)$ and $: \mu_{B_i}(x)$: Appropriate parameterized membership functions; $\{a_i, b_i, c_i\}$: Premise parameters;

$O_{1,i}, O_{1,i}$: 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 all incoming signals. This is defined as follows.

$$O_{2,i} = w_i = \mu_{A_i}(x) \times \mu_{B_i}(x) \qquad i = 1, 2 \tag{5.10}$$

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 using the equation 5.11 as,

$$O_{3,i} = \overline{w}_i = \frac{w_i}{w_1 + w_2} \qquad i = 1, 2 \tag{5.11}$$

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 as follows.

$$O_{4,i} = \overline{w}_i f_i = \overline{w}_i (p_i x + q_i y + r_i) \tag{5.12}$$

where as,

$\{p_i, q_i, r_i\}$: Consequent parameters;

$O_{4,i}$ 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.

$$O_{5,1} = overall\ output = \sum_i \overline{w}_i f_i \tag{5.13}$$

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

The input-output relationship is modeled using the ANFIS in which knowledge base of the fuzzy system is designed automatically using a neural network.

Figure 5.3 shows the Training and Testing of ANFIS classification approach, which clearly illustrates the training and testing parameters for ANFIS architecture.

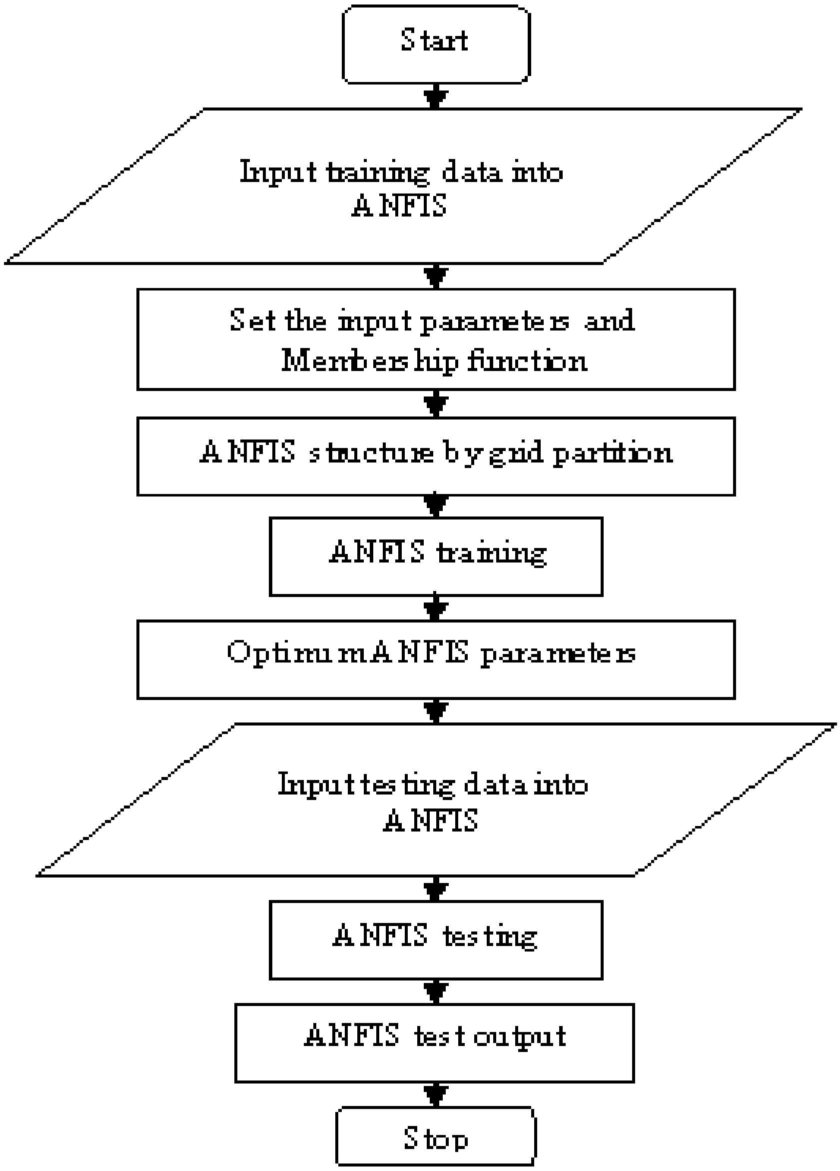


Figure 5.3 Training and testing of ANFIS classification approach

5.5 GA OPERATORS

GA is the algorithmetic approach for programming optimization technique which works based on genes mutation and crossover with other genes. The population list works well on genes with respect to mutation and crossover approaches between two different chromosomes as stated in Garg et al. (2012). GA is an iterative procedure, and consists of a constant-size population of individuals.

The fitness between two different chromosomes are based on genes mutation property with other genes in either ascending or descending order. Gill and Singh (2010) developed GA procedure based on the mutation and crossover properties.

GA is radically different from most of the traditional optimization methods. GA work with a string coding of variables instead of the variables. The advantages of working with a coding of variable are that coding discreteness the search space, even though the function may be continuous. On the other hand, since GA requires only function values at discrete points, a discrete or discontinuous function can be handled with no extra cost.

Even though GAs, are different than most traditional search algorithms, there are some similarities. In traditional search methods, where a search direction is used to find a new point, at least two points are either implicitly or explicitly used to define the search direction. In the crossover operator, (which is mainly responsible for GA search) two points are used to create new points. Thus, cross over operator is similar to a directional search method with an exception that the search direction is not fixed for all points in the population and that no effort is made to find the optimal point in any particular direction (Jarrah et al. (2002)). Since two points used in crossover operator are chosen at random, many search directions are possible. Among them, some may lead to global basin and some may not. The reproduction operator has an indirect effect of filtering the good search direction and helps to guide the search. The purpose of mutation operator is to create a point in the vicinity of the current point.

Benefits of GA

The concept of genetic algorithms is

1. Easy to understand,
2. Modular, separate from application,
3. Supports multi-objective optimization,
4. Good for noisy environment
5. We always get an answer and the answer gets better with time,
6. Inherently parallel and easily distributed,
7. There are many ways to speed up and improve a GA's basic application as knowledge about the problem domain is general,
8. Easy to exploit for previous or alternate solutions,
9. Flexible in forming the building blocks for hybrid applications, and
10. Has substantial history and range of use.

A simple genetic algorithm largely uses three basic operators which are

- Reproduction
- Cross over
- Mutation

These genetic operators can be explained in the following sections.

5.5.1 Reproduction

Reproduction generates a mating pool by selecting good fitness strings from the population. Although there are numerous reproduction operators reported in the literature, the essential idea in all of them is the same:

Strings with finesses above-average are picked from the current population and strings with finesses below-average are removed from the population. This procedure may involve maintaining multiple copies of good strings in order to keep the population size fixed. The reproduction operator acts as a filtering mechanism for the selection of good strings in a population.

5.5.2 Cross Over

After the reproduction phase is over, the population is enriched with better individuals. Reproduction makes clones of good strings, but does not create new ones. Cross over operator is applied to the mating pool with a hope that it would create a better string. The aim of the crossover operator is to search the parameter space. In addition, the search is to be made in a way that the information stored in the present string is maximally preserved because these parent strings are instances of good strings selected during reproduction.

A crossover is a recombination operator, which proceeds in three steps. First, the reproduction operator selects at random a pair of two individual strings for mating, then a cross-site is selected at random along the string length and the position values are swapped between two strings following the cross site. For instance, let the two selected strings in a mating pair be A = 11111 and B = 00000. If the random selection of a cross-site is two, then the new strings following cross over would be A* = 11000 and B* = 00111. This is a single-site crossover. Though these operators look very simple, their combined action is responsible for much of GA's power. From a computer implementation point of view, they involve only random number of generations, string coping, and partial string swapping. There exist many types of crossover operations in genetic algorithm which are discussed in the following sections.

Single – Site Cross Over

In a single-site crossover, a cross-site is selected randomly along the length of the mated strings and bits next to the cross-sites are exchanged as shown in Figure 5.4.

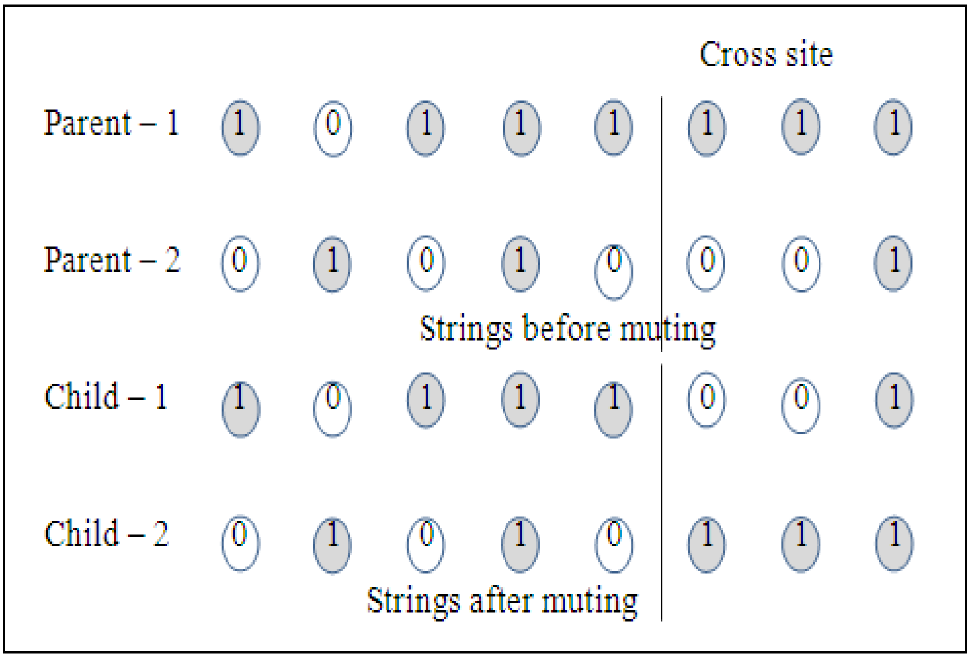


Figure 5.4 Single - site cross over

Two-point Cross Over

In a two-point crossover operator, two random sites are chosen and the contents bracketed by these sites are exchanged between two mated parents. If the cross – site 1 is three and cross-site 2 is six, the strings between three and six are exchanged as shown in Figure 5.5.

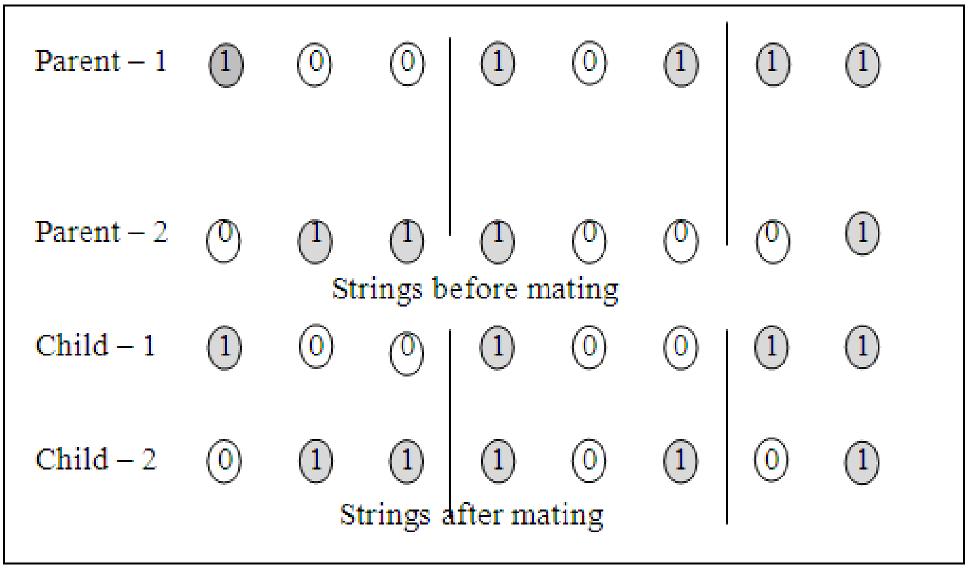


Figure 5.5 Two-point cross over

Multi-point Cross Over

In a multi-point crossover, again, there are two cases. One is even number of cross – sites and the second one is the odd number of cross-sites. In case of even numbered cross-suits, the string are treated as a ring with no beginning or end. The cross-sites are selected around the circle uniformly at random. Now the information between alternate pairs of sites is interchanged as shown in Fig.5.6.

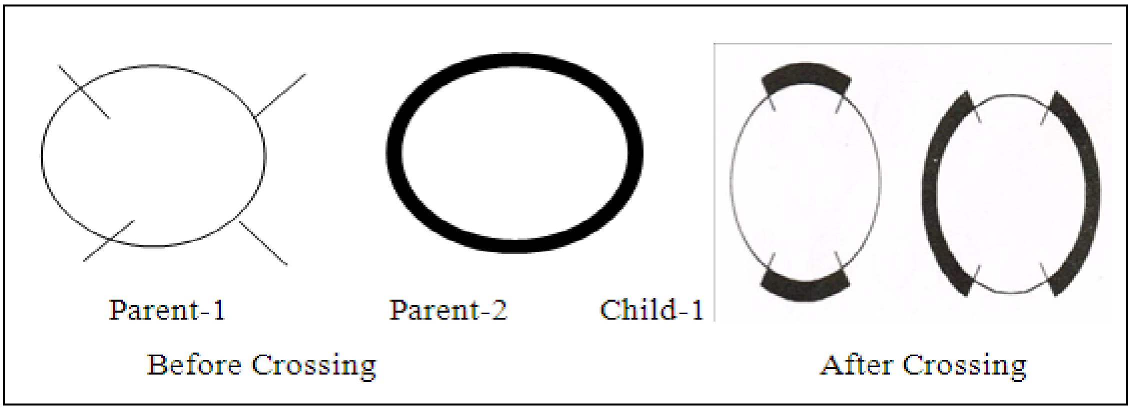


Figure 5.6 Multi-point crossover with even number of cross - sites

5.5.3 Mutation

After crossover, the strings are subjected to mutation. Mutation of a bit involves flipping it, changing 0 to 1 and vice versa with a small mutation probability P_m. The bit-wise mutation is performed bit-by-bit by flipping a coin with a probability of P_m. Flipping a coin with a probability of P_m is simulated as follows.

A number between 0 to 1 is chosen at random. If the random number is smaller than P_m then the outcome of coin flipping is true, otherwise the outcome is false. If at any bit, the outcome is false. If at any bit, the outcome is true, then the bit is altered, otherwise the bit is kept unchanged. The bits of the strings are independently muted, that is, the mutation of a bit does not affect the probability of mutation of other bits.

Mutation Rate P_m

It is defined as the rate at which the genes are muted between each chromosomes which works on the types of mutation points within chromosomes. This rate will be high when there are high number of genes muted with each other and this rate will be low when there are low number of genes muted with each other.

Typically, the simple genetic algorithm uses the population size of 30 to 200 with the mutation rates varying from 0.001 to 0.5. Figure 5.7shows the flow chart of GA, which clearly illustrates the entire operations of GA.

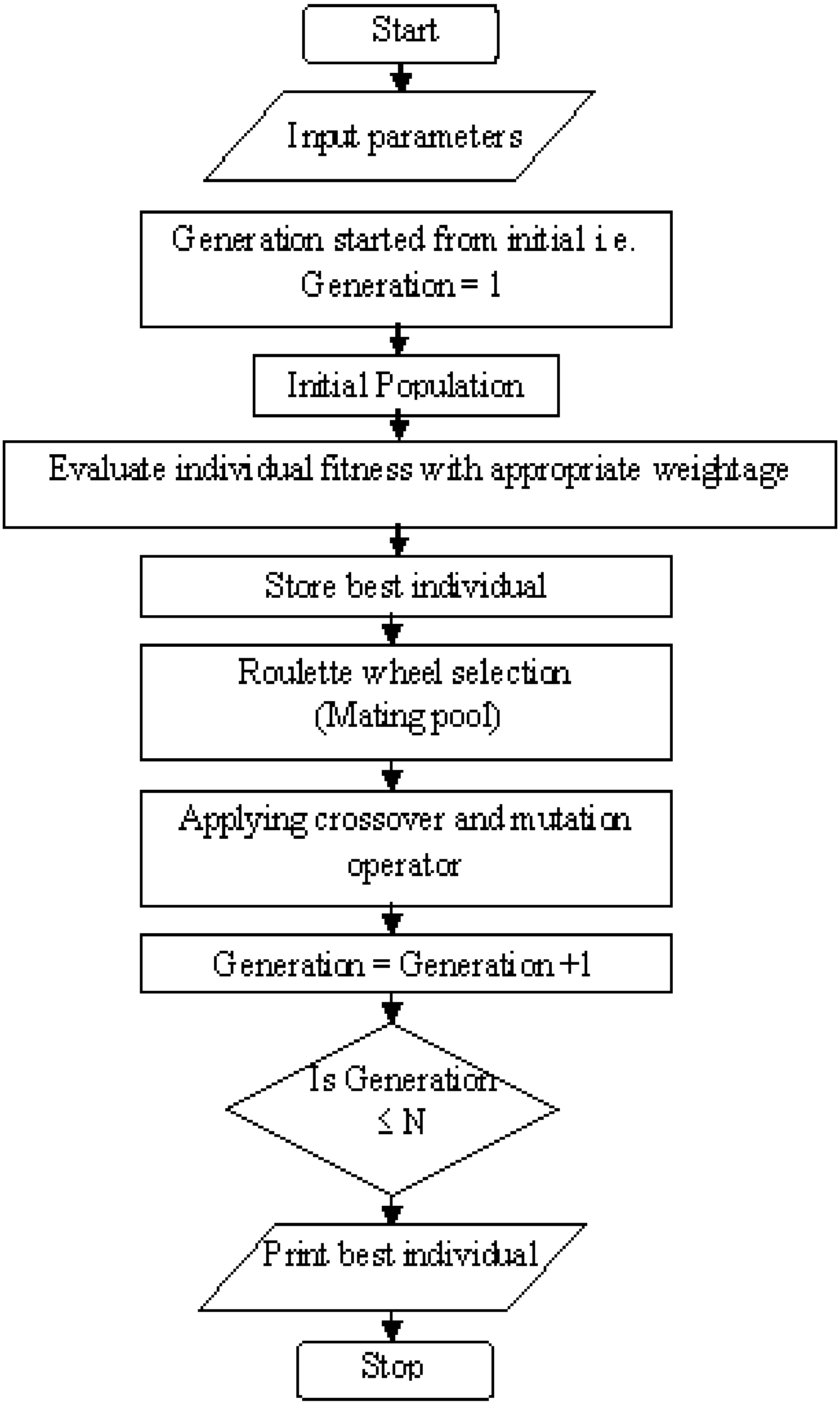


Figure 5.7 Flowchart of GA

5.5.4 Convergence of Genetic Algorithm

The situation of good strings with a population set and random information exchange among good strings are simple and straight forward. No mathematical proof is available for convergence may be such that when a fixed percentage of columns and rows in population matrix becomes the same, it can be assumed that convergence is attained. The fixed percentage may be 80% or 85%.

The convergence criteria can be explained from the schema point of view in the lines of Goldberg (1988). A schema is a similar template describing a subset of strings with similarities at certain positions. In other words, a schema represents a subset of all possible strings that have the same bits at certain string positions. As an example, consider a string with five bits. A schema **000 represents the strings 00000, 01000, 10000 and 11000. Similarly a schema 1*00* represents the strings 10000, 10001, 11000 and 11001. Each string represented by a schema is called an instance of the schema. The symbol * signifies that a 0 or 1 could occur at the string position. Thus, the schema***** represents all possible strings of five bits. The fixed positions of a schema are the string positions that have 0 or 1 (In **000, the third, fourth and fifth positions).

5.6 RESULT AND DISCUSSIONS

5.6.1 For Neuro-Fuzzy System and Regression Method

The regression model is developed using experimentally measured data for predicting tensile strength of hybrid composite. To validate the above model, six different composites are fabricated with varying Fiber Length (FL) and Fiber Content (FC). The average absolute error between the predicted and observed value are taken as the performance measures. The prediction is based on the input data sets discussed above.

In this research work, training pattern with 9 total counts and testing pattern with 6 total counts are used for obtaining high classification rate. The least square estimation methodology is used for reducing the error rate between differenent training and testing patterns. The developed Neuro –fuzzy and RM models are depicted in the following tables.

From average absolute error, it can be said that results obtained from Neuro-fuzzy model is highly encouraging and precise. The membership function of each input is 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. The results obtained with ANFIS model are compared with the experimental results in the ANFIS test output.

Table 5.2 shows the experimental and predicted values of tensile strength from RM.

Table 5.2 Comparison of experimental and predicted values of tensile strength of regression model (RM)

Test samples	**Fiber Length** (cm)	**Fiber Content** (wt%)	**Experimental values** (MPa)	**Predicted values** (MPa)	**Error** (%)
Test1	5	11	13.3	15.2	-14.28
Test2	7	20	22.5	24.2	-7.55
Test3	12	9	21.6	23.5	-8.79
Test4	9	11	31.9	34.2	-7.2
Test5	11	12	26.7	28.1	-5.24
Test6	15	19	37.1	39.2	-5.66
Average absolute error					8.12

Figure 5.8 shows the graphical illustrations of Experimental and predicted values of tensile strength from Regression Model (RM).

Figure 5.8 Graphical illustrations of experimental and predicted values of tensile strength of regression model (RM)

When these data are compared with the data given by Regression model, the result showed less errors and both values were close to each other. Since average absolute error is less, regression model can be used for predicting tensile properties.

A Neuro Fuzzy model is also developed using experimentally measured data for predicting tensile properties of hybrid composite. To validate the above model, six different composites are fabricated with varying FL and FC. Table 5.3 shows the experimental and predicted values of tensile strength from Neuro-fuzzy model.

Table 5.3 Comparison of experimental and predicted values of tensile strength from Neuro-fuzzy model

Test samples	**Fiber Length** (cm)	**Fiber Content** (wt%)	**Experimental values** (MPa)	**Predicted values** (MPa)	**Error** (%)
Test1	5	11	13.3	14.8	-11.27
Test2	7	20	22.5	24.7	-9.77
Test3	12	9	21.6	23.2	-7.4
Test4	9	11	31.9	34.6	-8.46
Test5	11	12	26.7	23.8	10.86
Test6	15	19	37.1	38.8	-4.58
Average absolute error					5.1

Figure 5.9 shows the graphical illustrations of Experimental and predicted values of tensile strength from the Neuro fuzzy model.

Figure 5.9 Graphical illustrations of experimental and predicted values of tensile strength from Neuro fuzzy

When these data are compared with the data given by Neuro Fuzzy model, the result showed less errors and both values were close to each other.

Since average absolute error is less, Neuro Fuzzy model can be used for predicting tensile properties as depicted very closely.

The regression model is also developed using experimentally measured data for predicting flexural strength of hybrid composite. To validate the above model, six different composites are fabricated with varying FL and FC. Table 5.4 shows the observed and predicted values of flexural strength from Regression Model (RM).

Table 5.4 Comparison of experimental and predicted values of flexural strength of regression model (RM)

Test samples	**Fiber Length** (cm)	**Fiber Content** (wt%)	**Experimental values** (MPa)	**Predicted values** (MPa)	**Error** (%)
Test1	5	11	32.5	36.1	-11.07
Test2	7	20	63.2	68.4	-8.22
Test3	12	9	33.2	38.2	-15.06
Test4	9	11	40.6	46.5	-14.5
Test5	11	12	46.2	52.2	-12.9
Test6	15	19	77.8	79.4	-4.19
Average absolute error					10.99

Figure 5.10 shows the graphical illustrations of Experimental and predicted values of flexural strength from Regression Model (RM).

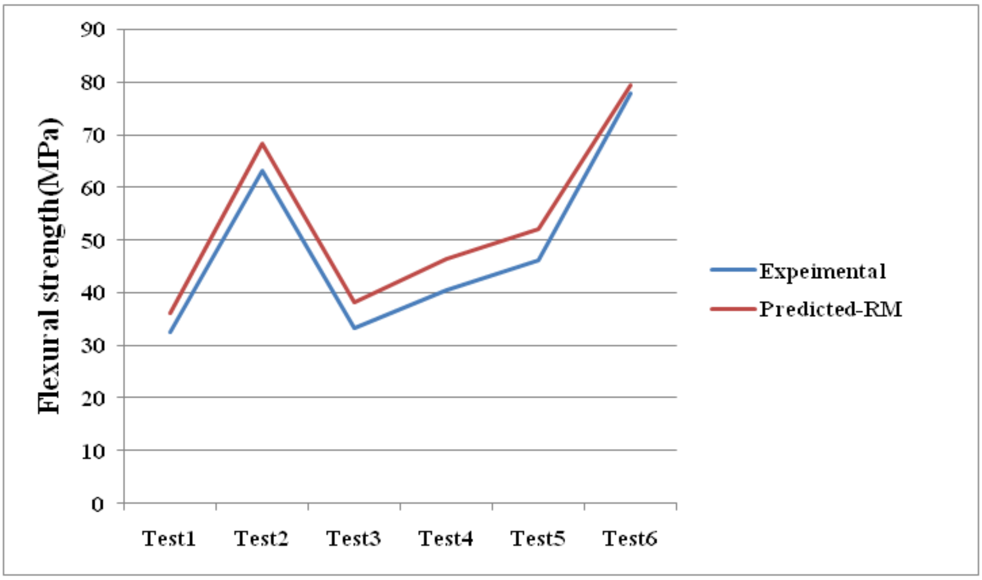


Figure 5.10 Graphical illustrations of experimental and predicted values of flexural strength of regression model (RM)

When these data are compared with the data given by the regression model, the result showed less errors and both values were close to each other. Since average absolute error is less, regression model can be used for predicting flexural properties.

A Neuro fuzzy model is developed using experimentally measured data for predicting flexural of hybrid composite. To validate the above model, six different composites are fabricated with varying FL and FC. Table 5.5 shows the observed and predicted values of flexural strength from Neuro-fuzzy model.

Table 5.5 Comparison of experimental and predicted values of flexural strength from Neuro fuzzy model

Test samples	Fiber Length (cm)	Fiber Content (wt%)	Experimental values (MPa)	Predicted values (MPa)	Error (%)
Test1	5	11	32.5	29.1	10.46
Test2	7	20	63.2	66.2	-4.7
Test3	12	9	33.2	36.1	-8.73

Table 5.5 Continued

Test4	9	11	40.6	45.4	-11.8
Test5	11	12	46.2	50.6	-9.52
Test6	15	19	77.8	78.8	-3.41
Average absolute error					4.61

Figure 5.11 shows the graphical illustrations of Experimental and predicted values of flexural strength from Neuro Fuzzy model.

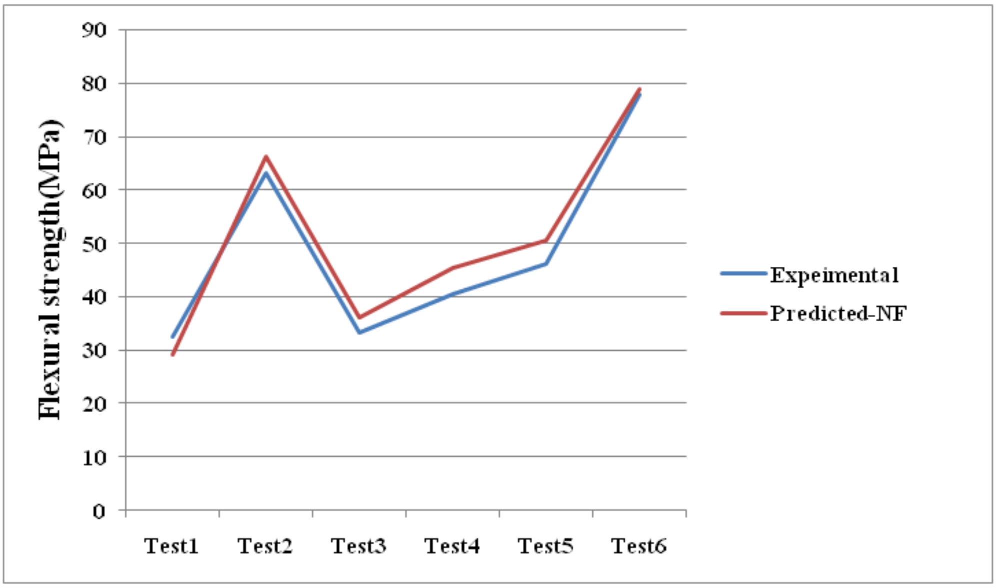


Figure 5.11 Graphical illustrations of experimental and predicted values of flexural strength from Neuro fuzzy

When these data are compared with the data given by the Neuro fuzzy model, the result showed less errors and both values were close to each other. Since average absolute error is only 4.61%, the Neuro fuzzy model can be used better for predicting flexural properties.

The regression model is developed using experimentally measured data for predicting the impact of hybrid composite. To validate the above model, six different composites are fabricated with varying FL and FC. Table 5.6 shows the observed and predicted values of Impact strength from Regression Model (RM).

Table 5.6 Comparison of experimental and predicted values of impact strength from regression model (RM)

Test samples	**Fiber Length** (cm)	**Fiber Content** (wt%)	**Experimental values** (MPa)	**Predicted values** (MPa)	**Error** (%)
Test1	5	11	12.5	14.2	-13.6
Test2	7	20	23.2	26.6	-14.6
Test3	12	9	15.6	17.4	-11.5
Test4	9	11	13.5	15.2	-12.5
Test5	11	12	20.2	22.6	-11.8
Test6	15	19	29.5	28.5	3.38
Average absolute error					10.1

Figure 5.12 shows the graphical illustrations of Experimental and predicted values of impact strength from Regression model.

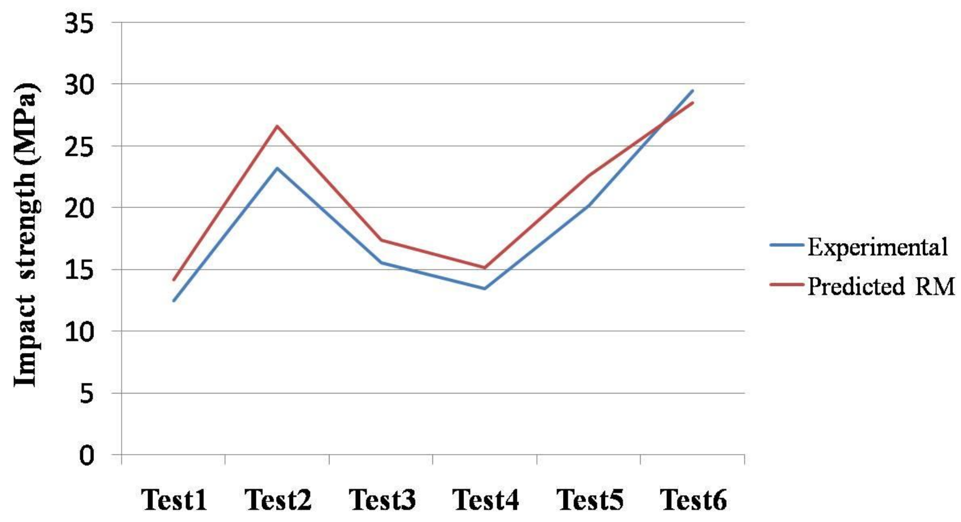


Figure 5.12 Graphical illustrations of experimental and predicted values of impact strength from RM

When these data are compared with the data given by Regression model, the result showed less errors and both values were close to each other. For average absolute error is less, Regression model can be used for predicting impact properties.

A Neuro Fuzzy model is developed using experimentally measured data for predicting the impact of hybrid composite. To validate the above model, six different composites are fabricated with varying FL and FC. Table 5.7 shows the observed and predicted values of Impact strength from Neuro-fuzzy model.

Table 5.7 Comparison of experimental and predicted values of impact strength from Neuro-fuzzy model

Test samples	**Fiber Length** (cm)	**Fiber Content** (wt%)	**Experimental values** (MPa)	**Predicted values** (MPa)	**Error** (%)
Test1	5	11	12.5	13.8	-10.4
Test2	7	20	23.2	21.6	6.8
Test3	12	9	15.6	17.5	-12.2
Test4	9	11	13.5	15.8	-17
Test5	11	12	20.2	23.5	-16.3
Test6	15	19	29.5	27.2	7.8
Average absolute error					6.8

Figure 5.13 shows the graphical illustrations of Experimental and predicted values of impact strength from Neuro Fuzzy model.

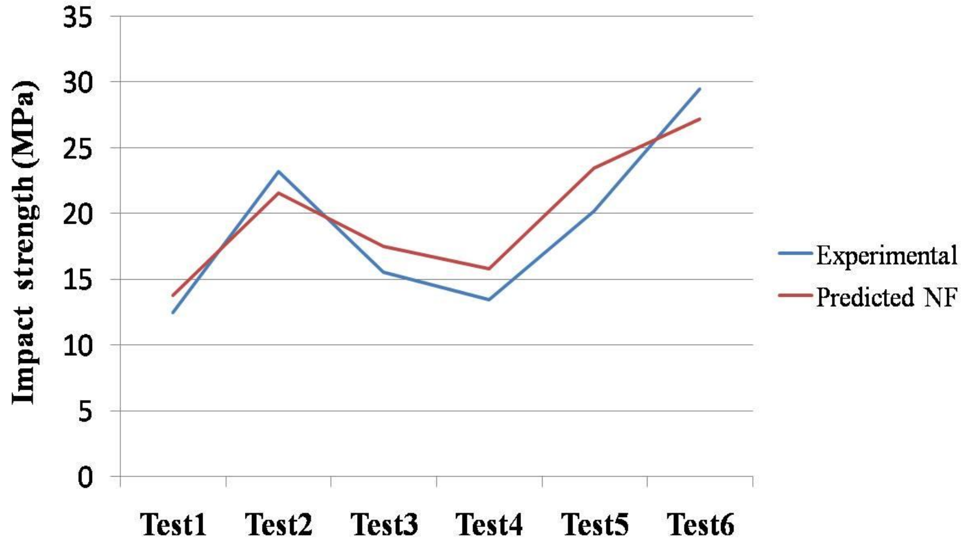


Figure 5.13 Graphical illustrations of experimental and predicted values of impact strength from Neuro fuzzy model

When these data are compared with the data given by Neuro Fuzzy model, the result showed less errors and both values were close to each other. Hence, Neuro Fuzzy model can be used for predicting impact properties.

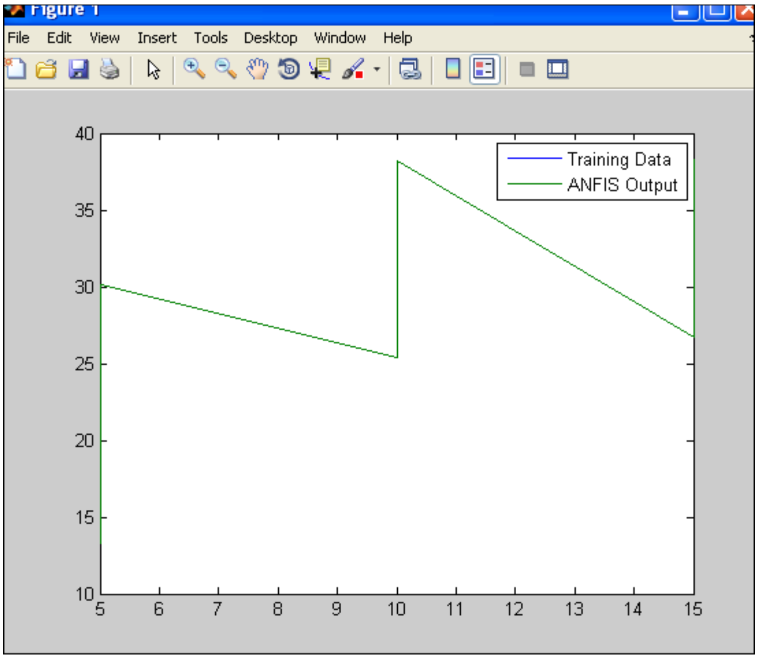
Table 5.8 shows the Average Absolute Error for regression and Neuro fuzzy models to predict mechanical properties. It is very clear from Table 5.8, that the absolute error for tensile, flexural and impact strength in regression model is moderate than the absolute error for tensile, flexural and impact strength in the Neuro fuzzy model. The experiments are carried out over six different samples with respect to fiber length and fiber content as depicted in Table 5.8.

Table 5.8 Average absolute error of regression and neural fuzzy models

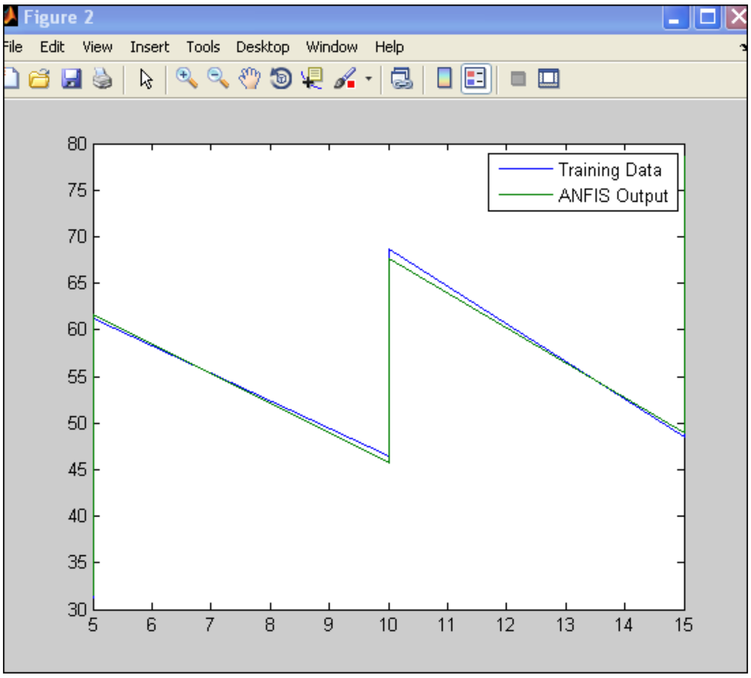
Test samples	F L (cm)	F C (wt%)	Regression Model			Neuro Fuzzy Model		
			Tensile error (%)	Flexural error (%)	Impact error (%)	Tensile error (%)	Flexural error (%)	Impact error (%)
Test1	5	11	-14.28	-11.07	-13.6	-11.27	10.46	-10.4
Test2	7	20	-7.55	-8.22	-14.6	-9.77	-4.7	6.8
Test3	12	9	-8.79	-15.06	-11.5	-7.4	-8.73	-12.2

Table 5.8 Continued

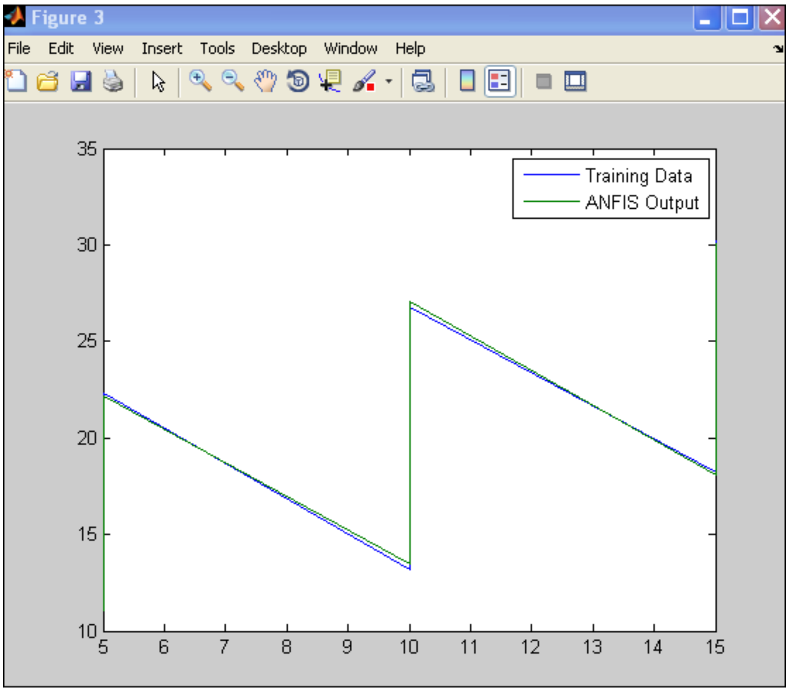
Test4	9	11	-7.2	-14.5	-12.5	-8.46	-11.8	-17
Test5	11	12	-5.24	-12.9	-11.8	10.86	-9.52	-16.3
Test6	15	19	-5.66	-4.19	3.38	-4.58	-3.41	7.8
Average absolute error			8.12	10.99	10.1	5.10	4.61	6.8



(a)



(b)



(c)

Figure 5.14 Output graph plots for (a) Tensile (b) Flexural and (c) Impact

Figure 5.14 shows the output graph plots for Tensile, Flexural and Impact in Neuro fuzzy models with respect to various fiber lengths and contents.

Figure 5.14 (a) shows the simulation result of the tensile strength which represents the fiber length as its X-axis and its corresponding tensile strength as its Y-axis. It is very clear from Figure 5.14 (a) that the absolute error of the tensile strength is moderate in case of tensile properties, where there is small band gap between training and testing values.

Figure 5.14 (b) is the simulation result of the flexural strength from MATLAB software which represents the fiber length as its X-axis and its corresponding flexural strength as its Y-axis. It is very clear from Figure 5.14 (b) that ANFIS output is almost parallel to test data. Hence the ANFIS model can predict flexural strength with good accuracy.

Similar to tensile and flexural strength, ANFIS model is also developed separately for predicting impact strength of sisal/bamboo hybrid composite. Figure 5.14 (c) shows the prediction capability of ANFIS model in respect of impact strength. Since the ANFIS output is very close with the test data, the model can very well be used for predicting impact strength of NFRP hybrid composites very closely.

5.6.2 Results of GA

The linear ranking methods (Baker 1987) are used in this research work for reproduction. In crossover, the two strings are picked from the mating pool and the portion of the strings is exchanged between these strings with crossover probability of 0.7. 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 28^{th} generation.

In this research work, the following parameters are used in GA for obtaining the optimized results.

- Number of generations: 38
- Number of population: 19
- String length: 10
- Single point crossover: 0.7
- Mutation probability: 0.001

Table 5.9 shows the maximum value of the objective function (Tensile, flexural and Impact strength) and optimized fabrication parameters Values.

Table 5.9 Maximum value of the objective function (Tensile, flexural and impact strength) and optimized fabrication parameter values

Maximized value of objective function (Tensile strength) (MPa)	Maximized value of objective function (Flexural strength) (MPa)	Maximized value of objective function (Impact strength) (kJ/m^2)	Optimized fabrication parameters	
			Fiber length (L) (cm)	Fiber content (C) (wt%.)
39.4	78.8	30.8	15.00	20.00

The MATLAB code of this proposed research work is included in the Appendix of this thesis with sample screen shots.

5.7 SUMMARY

In this chapter, a mathematical model for the mechanical properties of Bamboo/sisal fiber hybrid polyester composite using Regression model and Neuro-fuzzy is created. A Regression model has been developed for predicting mechanical strength with fabrication parameters. The lower average absolute error obtained by the Neuro-fuzzy model suggests its good potentiality for the prediction of mechanical properties of bamboo/sisal fiber hybrid polyester composites. The predicted mechanical strength using GA is higher than the observed value within range of used fabrication parameters. So it shows its best potential to maximize the mechanical properties. ANFIS classification approach along with GA algorithm achieves high optimization value for mechanical properties.

The proposed methodology with an optimization technique (GA) used the optimization parameters as 15 cm fiber length, 20 weight% fiber content and 80 weight% matrix proportion for obtaining the 39.4 MPa tensile strength improvement, 78.8 MPa flexural strength improvement and 30.8 MPa Impact strength improvement. By obtaining these optimized results in this chapter, the material cost and also wastage of materials will be reduced.