# Statistical Analysis and Predictive Learning of Mechanical Parameters for TiO<sub>2</sub> Filled GFRP Composite

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#### II. EXPERIMENTAL DISCUSSION

#### Abstract—The new, polymer composites consisting of e-glass fiber reinforcement with titanium oxide filler in the double bonded unsaturated polyester resin matrix were made. The glass fiber and titanium oxide reinforcement composites were made in three different fiber lengths (3cm, 5cm, and 7cm), filler content (2 wt%, 4 wt%, and 6 wt%) and fiber content (20 wt%, 40 wt%, and 60 wt%). 27 different compositions were fabricated and a sequence of experiments were carried out to determine tensile strength and impact strength. The vital influencing factors fiber length, fiber content and filler content were chosen as 3 factors in 3 levels of Taguchi's L<sub>9</sub> orthogonal array. The influences of parameters were determined for tensile strength and impact strength by Analysis of variance (ANOVA) and S/N ratio. Using Artificial Neural Network (ANN) an expert system was devised to predict the properties of hybrid reinforcement GFRP composites. The predict models were experimentally proved with the maximum coincidence.

*Keywords*—Analysis of variance (ANOVA), Artificial neural network (ANN), Polymer composites, Taguchi's orthogonal array.

#### I. INTRODUCTION

CLASS Fiber Reinforced Polymer Composite (GFRP) is composed of fiber embedded in a matrix material. Particulate Composites are composed of particles distributed or embedded in a matrix body. The particles may be flakes or in the powder form. Mechanical properties of composites are improved by adding particles with the composite [1], [2]. The fiber-matrix interface polymer composites are used in automobile, marine and industrial applications. The addition of the nano particles increases the bonding strength of the composites and improves the strength [3]-[6]. Taguchi method is used for optimization of various parameters [7]-[9]. Expert system is the efficient tool to predict various process parameters [10]-[12]. In this work, the development and characterization of a new set of hybrid polymer composites consisting of glass fiber reinforcement, unsaturated polyester resin and TiO<sub>2</sub> particulate fillers was performed. Composites are characterized and the predictive learning model was developed within the parameters.

# A. Materials

The important consideration is mandatory for a proper selection of material include fiber material, fiber volume, fiber reinforcement form, matrix material, processing cost and safety factors for polymer composites. E-glass is a low alkali glass with a typical nominal composition of SiO<sub>2</sub>-54wt%, Al<sub>2</sub>O<sub>3</sub>-14wt%, CaO+MgO-22wt%, B<sub>2</sub>O<sub>3</sub>-10wt% and Na<sub>2</sub>O+K<sub>2</sub>O less then 2wt%. E-glass fibers are commercially used because of its low cost, high productive rates, good chemical resistance and high density. Particulate fillers are widely used to meliorate the properties of matrix materials such as to improve wear and abrasion resistance, reduce friction, improve the surface hardness, and machinability. Eglass fiber was used as reinforcement and titanium oxide TiO<sub>2</sub> was the filler content. The Unsaturated Polyester resin was used as composite matrix. Butanone, also known as methyl ethyl ketone / MEK, [CH<sub>3</sub>C (O) CH<sub>2</sub>CH<sub>3</sub>] organic compound was used as accelerant and cobalt (ii) naphthenate was used catalyst.

#### **B.** Specimen Preparation

The mould was cleaned and dried before applying a wax polish. After this a layer of Unsaturated Polyester resin and eglass fiber was laid up evenly on the mould twice with adopting hand layup technique. Unsaturated Polyester resin was mixed with 1.5 wt. % of butane and 1.5 wt. % of cobalt (ii) naphthenate. Titanium Oxide particulate was added to this mixture and churned well. The mould was kept closed and pressed uniformly about 24 hours to cure. Specimens were cut to the standard size after the composites were completely dried.

Composites with three variables and three levels of 27 different compositions were prepared with the same manner and different compositions of the hybrid composites are shown in Table I and various units for different properties used in this work is given in Table II.

TABLE I							
VARIOUS COMPOS	TTION OF FIBER REINFORCED P	OLYMER COMPOSITES					
Fiber length (cm)	Particulate content (wt %)	Fiber content (wt %)					
3 (A)	2 (U)	20 (X)					
5 (B)	4(V)	40 (Y)					
7 (C) 6(W) 60 (Z)							
7 (C) = 6(W) = 60 (Z)							

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TABLE II	
UNITS FOR PROPERTIES USED	
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Symbol	Quantity
ANOVA	Analysis of Varaince
DF	Degree of Freedom
Seq SS	Sequential sum of squares
Adj SS	Adjusted sum of square
Adj MS	Adjusted mean square
Р	Percentage of contribution
S	Standard deviation of the error in the model
$S^2$	Mean sum of square
R-Sq	Co-efficient of determination
R-Sq(adj)	Accounts for the number of predictors in the model

#### C. Mechanical Characterization

Tensile test was performed on a Shimadzu AG-IS 50 KN Autograph Universal testing machine according to the guidelines of ASTM D638. The impact strength of the composites was measured on international equipments impact testing machine with ASTM D256.

#### D. Taguchi Method

Taguchi method uses a special design of orthogonal arrays to study the entire parameter space with a small number of experiments. The experimental results are then transfigured into a signal-to-noise (S/N) ratio. Taguchi recommends the use of the S/N ratio to measure the characteristics deviating from the desired values. The S/N ratio for each level of process parameters is computed based on the S/N analysis.

The total number of factor chosen for the experiment was three. The three factors are fiber length (cm), fiber content (wt %), particulate content (wt %) and the number of levels was chosen as three. A  $L_9$  orthogonal matrix array was selected for the experiment. The  $L_9$  orthogonal array is given in Table III.

TABLE III
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L <sub>9</sub> Orthogonal Array for Three Variables and Three Levels					
Fiber length (cm)	Particulate Content (wt %)	Fiber content (wt %)			
1	1	1			
1	2	2			
1	3	3			
2	2	1			
2	3	2			
2	1	3			
3	3	1			
3	1	2			
3	2	3			

The purpose of the analysis of variance (ANOVA) is to examine the design parameters that significantly affect the characteristic of the process. Fisher test is employed to identify the design parameters having a significant effect on the quality characteristic. This is accomplished by separating the total variability of the S/N ratios, which can be measured by the sum of the squared deviations from the total mean S/N ratio, into contributions by every design parameters. The three parameter fiber length (cm), fiber content (wt %) and particulate content (wt %) were examined in this study.

# E. Artificial Neural Network

Artificial neural network entails three phases viz. Neural network analysis, training and testing neural networks, which are simplified models of biological neuron system, is a massively parallel distributed processing system made up of highly interconnected neural computing elements that have the ability to learn and acquire knowledge and make it available for use. As the study involves a neural network model which works on past data; a back propagation neural network has been chosen. This was used to predict output parameter for given input set.

The neural network is trained so that the application of set of input produces the desired output. Training is accomplished by sequentially applying the input vectors and adjusting the network weights according to the predetermined algorithm. Training is being done until the network weights gradually converge to values such that each input vector produces the desired output vectors. Once the training completed the weights been set for the optimum value and new value feed into the network, then the output of the network is predicted. The predicted value is compared with an experimental value if the error value is less than desired value then the network deemed to have learnt the mapping.

# III. RESULTS AND DISCUSSION

## A. Tensile Strength

The Tensile strength is marked to be a parameter which primly depends upon three factors. They are concentration of the fiber, fiber length, and the bonding between fiber and the matrix. It may be seen from the experiments that the tensile strength of the composite increases with increase in the fiber content and particulate loading. The chemical reaction at the interface between the filler material and the matrix is strong enough to transfer the tensile strength property [2].

The foremost inference from the tensile strength experiment is that the advantage of using the composite in fiber form is the proper distribution of load which unquestionably plays a key role in the fiberbond strength.

#### B. Impact Strength

From the impact test it has been inferred that the impact strength increases with increase in fiber content. The good bonding strength of the composite has increased its resistance to load applied. The Impact strength ranges from 38J to 53J.

#### C. Taguchi method

The tensile strength based on all the three deciding parameters fiber length, fiber content and particulate content were tested using Taguchi method. Table IV lists tensile strength obtained and the S/N ratio for the various combinations of the hybrid composite. Then the mean S/N ratio of response for the tensile strength is given in Table V.

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Fiber length (cm)	Particulate content (wt%)	Fiber content (wt%)	Ultimate strength (KN)	Tensile strength (Gpa)	S/N ratio
3	2	20	3.5	0.0583	10.8814
3	4	40	4.8	0.0800	13.6248
3	6	60	3.4	0.0967	15.2686
5	2	40	5.8	0.0567	10.6296
5	4	60	5.2	0.0867	14.3201
5	6	20	4.5	0.0750	13.0643
7	2	60	4.4	0.0733	12.8691
7	4	20	5.6	0.0933	14.9638
7	6	40	5.4	0.0900	14.6479

TABLE IV

TABLE V							
MEAN S/N RESPONSE FOR	TENSILE ST	FRENGTH U	SING LARG	ER THE B	ETTER		
Parameter	Level1	Level 2	Level 3	Delta	Rank		
Fiber length (cm)	13.258	12.674	14.160	1.486	2		
Fiber content (wt%)	11.460	13.884	14.327	2.867	1		
Particulate content (wt%)	12.970	12.967	14.153	1.186	3		

The main effects plot for S/N ratios is shown in Fig. 1. It further confirms the inference that particulate content significantly increases the tensile strength. The percentage contribution of these parameters was determined by analysis of variance (ANOVA) table.



Fig. 1 Main effect plot for S/N ratio for tensile strength

TABLE VI							
	AN	JVAFOR	I ENSILE ST	FRENGTH			
Source	DF	Seq	Adj	Adj	F	Р	
		SS	SS	MS			
Fiber length (cm)	2	0.8861	0.8867	0.4433	4.29	0.189	
Particulate Content (%wt)	2	4.2067	4.2067	2.1033	20.35	0.047	
Fiber content (%wt)	2	0.7200	0.7200	0.3600	3.40	0.223	
Error	2	0.2067	0.2067	0.1033			
Total	8	6.0200					
$S = 0.321455 R^2 = 96.57\% R-Sq(adj) = 86.27\%$							

The measured value of tensile strength as the function of the parameters was determined and the corresponding S/N ratio was found. Table VI shows the analysis of variance (ANOVA) of tensile strength. The significant influences of the variables

were determined and the tensile strength was more significant with the fiber content.

When the tensile load was applied to the composites, the pull load was distributed to the randomly oriented fibers and particulate in the matrix. The increased fiber content transmits with different orientation in the strong matrix to withstand the load applied.

TABLE VII								
S/N RATIO RESPONSE FOR IMPACT STRENGTH USING TAGUCHI METHOD								
	Fiber length (cm)	Particulate content (wt%)	Fiber content (wt%)	Impact strength (J)	S/N ratio			
	3	2	20	52	34.3201			
	3	4	40	51	34.1514			
	3	6	60	38	34.9638			
	5	2	40	56	31.5957			
	5	4	60	48	33.6248			
	5	6	20	46	33.2552			
	7	2	60	45	33.0643			
	7	4	20	52	34.3201			
	7	6	40	50	33.9794			

TABLE VIII Mean S/N Response for Impact Strength Using Larger the Better							
Parameter	Level1	Level 2	Level 3	Delta	Rank		
Fiber length (cm)	34.478	32.825	33.788	1.653	1		
Fiber content (wt%)	33.057	34.032	34.066	1.009	2		
Particulate content (wt%)	33.965	33.242	34.066	0.824	3		



Fig. 2 Main effect plot for S/N ratio for impact strength

TABLE IX ANOVA FOR IMPACT STRENGTH						
Source	DF	Seq SS	Adj SS	Adj MS	F	Р
Fiber length (cm)	2	122	122	61	11.44	0.080
Particulate Content (%wt)	2	60.667	60.667	30.333	5.69	0.150
Fiber content (%wt)	2	24.667	24.667	12.333	2.31	0.302
Error	2	10.667	10.667	5.333		
Total	8	218.001				
$G = 2.20040 \text{ D}$ $G_{\pm} = 05.110/\text{ D}$ $G_{\pm}(-1) = 00.420/$						

S = 2.30940 R-Sq = 95.11% R-Sq(adj) = 80.43%

Table VII shows the measured values of impact strength and the S/N ratio. In order to determine the influences of the parameters, the mean S/N ratio was determined and the major influencing factor is determined by the rank given to the mean S/N ratio. The mean S/N response for impact strength is given

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in Table VIII. The fiber length is the prominent factor to determine the impact strength. When fiber length increases the impact strength was increased. The sudden applied load and velocity are integrated to form the variation in the cumulative energy as a function of time. When load applied to the composite, it will be absorbed and distributed through the fiber reinforcement. The increased fiber length consist good strain energy absorption capacity to with stand the applied load. Table IX shows ANOVA table for impact strength and Fig. 2 shows the main effect plot for S/N ratio of impact strength.

## D. Artificial Neural Network

TABLE X Elements Involved in the Feed Forward Neural Network					
Network	Supervised network				
No. of hidden layers	1				
No. of neurons in the input layer	3				
No. of neurons in the hidden layer	3				
No. of neurons in the output layer	1				
Activation function used (for hidden layer)	Bi-polar sigmoid				
Activation function used (for output layer)	Bi-polar sigmoid				
Error goal	$1.0 \times 10^{-3}$				
No of epochs	100				

The feed forward neural network was used for the predictive learning of the hybrid composites. Table X shows various elements involved in the feed forward neural network. The 7 sets of data were used for the testing purpose. The test data also should be in normalized from. After the successful training, the test data will be given as input to the system. The network gives the predicted output parameters. The test data

involved in the testing phase is given in Table XI and training phase of tensile strength and impact strength is given is given in the Tables XII and XIII.

	TABLE XI						
	TRAINING PHASE						
Fiber	Particulate	Fiber	Impact	Tensile			
Length	Content	content	strength	strength			
(cm)	(wt.%)	(wt.%)	(J)	(GPa)			
3	2	20	52	0.0583			
3	2	40	44	0.0817			
3	2	60	45	0.0617			
3	4	20	58	0.0633			
3	4	60	51	0.0933			
3	6	40	52	0.0667			
3	6	60	56	0.0900			
5	2	20	45	0.0733			
5	2	40	46	0.0567			
5	2	60	50	0.0900			
5	4	20	54	0.0733			
5	4	40	44	0.0867			
5	6	20	46	0.0933			
5	6	60	53	0.0933			
7	2	20	48	0.1033			
7	2	40	49	0.0833			
7	4	40	46	0.0933			
7	4	60	56	0.0633			
7	6	40	50	0.0967			
7	6	60	45	0.0667			

TABLE XII STING PHASE OF TENSILE STRENGT

Runs	Fiber length (cm)	Particulate content (wt.%)	Fiber content (wt.%)	Tensile strength (actual) (GPa)	Tensile strength (predicted) (GPa)	Error
21	3	4	40	0.0892857	0.09847	-0.0091843
22	3	6	20	0.0803571	0.08662	-0.0062629
23	5	4	60	0.0857143	0.093251	-0.0075367
24	5	6	40	0.0821429	0.080367	0.0017759
25	7	2	60	0.0928571	0.088608	0.0042491
26	7	4	20	0.0984615	0.096003	0.0024585
27	7	6	20	0.0785714	0.080832	-0.0022606

TABLE XIII								
TESTING PHASE OF IMPACT STRENGTH								
Runs	Fiber length (cm)	Particulate content (wt.%)	Fiber content (wt.%)	Impact strength (actual)	Impact strength (predicted)	Error		
21	3	4	40	0.774194	0.78528	-0.011086		
22	3	6	20	0.677419	0.626	0.051419		
23	5	4	60	0.83871	0.8742	-0.03549		
24	5	6	40	0.645161	0.70865	-0.063489		
25	7	2	60	0.709677	0.58863	0.121047		
26	7	4	20	0.903226	0.87155	0.031676		
27	7	6	20	0.83871	0.74185	0.09686		



Fig. 3 Performance curve for the tensile strength of the composites



Fig. 4 Performance curve for the impact strength of the composites

The performance curve from the neural network is shown in Figs. 3 and 4. It ensures that the experiments carried out are within the goal and the results are within the tensile and impact strength ranges.

#### IV. CONCLUSION

The hybrid reinforced polymer composites were prepared adopting hand layup technique with 27 different compositions with fiber reinforcement with titanium oxide particulate in the polyester resin matrix. The three factors fiber content, particulate loading, fiber lengths differentiate the samples. Two important essential features of the fiber tensile and impact strength were experimentally tested. It is concurred that the fiber content is the most important among all the factors deciding the strength of the composites. Optimization of the fiber composites was done by Taguchi method from which the design parameter which influences the strength of the fiber was found out. Artificial Neural Network was used to form an expert system for prediction of tensile and impact strengths. Final experiments ensured with the maximum coincide from the values of expert system.

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