A STUDY ON EROSION PERFORMANCE ANALYSIS OF GLASS-EPOXY COMPOSITES FILLED WITH MARBLE WASTE USING ARTIFICIAL NEURAL NETWORK

Subhrajit RAY[1], Arun Kumar ROUT[2]*, Ashok Kumar SAHOO[3]

This present study describes the solid particle erosion behavior of epoxy glass fibre composites filled with different weight percentages of marble powder fabricated by simple hand lay-up technique. To obtain minimum erosion loss by avoiding repeated experimentation an artificial neural network method is proposed. Erosion test shows that among all the influential parameters, the filler content is the most effective factor followed by the impact velocity, impingement angle, and the erodent size. The erosion wear rate decreases with increase in the filler content in the composites. Predicative model values based on artificial neural network show a good agreement with experimental values.

Keywords: epoxy, marble powder, erosion, artificial neural network

1. Introduction

After a few decades of active research, composites based on polymers and glass fibres are now beginning to make a significant contribution to industrial and engineering practice. Polymer matrix composites (PMCs) have many advantages over monolithic materials such as higher stiffness-to-density ratios, better fatigue resistance, and better wear resistance. Nowaday's epoxy matrix composites has much more significance because of its unique characteristics like low weight, low density, low cost, high shear strength, good corrosion resistance, excellent abrasion resistance, minimal attack by fuels, excellent mechanical and thermal properties (low thermal conductivity) etc. Polymer matrix composite material reinforced with fibre consists of various constituents on macro-scale, and also different chemical combination which has a tremendous potential to replace the conventional material [1]. Polymer matrix modification is one of the challenges by adding different filler content with different weight proportion to meet the demand.

With the addition of particulates, the execution of polymer composites improves their properties and hence been subjected to modern and auxiliary

[1] KIIT DEEMED TO BE UNIVERSITY, India, E-mail: subhrajitmech@gmail.com
[2] *VSSUT, India, corresponding author: E-mail: arun.rout.6314@gmail.com
[3] KIIT DEEMED TO BE UNIVERSITY, India

industrial applications. But in this context, the use of such ceramic-rich industrial waste in polymer matrices has been hardly explored.

To fulfill such needs, the importance of industrial usage of polymer composite materials filled with industrial waste instead of high cost ceramic filler has tremendously increased.

Therefore, this inorganic industrial waste should be reused or recycled. In this manner, it is a fundamental to look for new choices to reuse or recycle these inorganic by-products.

Marble is an ornamental stone created from limestone kept under pressure and heat in the earth's covering due to ecological processes. Chemically, marble is a crystalline stone containing mostly dolomite and calcite. In last decades, marble industry has grown up showing its industrial applications. At the time of marble processing, 20-30 % of marble goes to scrap due to its small size and irregular shape. Every year during extraction of marble, million tons of marble dust are produced. Significant environmental pollution occurs due to production of marble powder from the marble industries. Marble waste causes vomiting, nasal infection, skin diseases, asthma etc. to the human body. To overcome these problems an alternative solution should be found to use these industrial wastes as environmentally acceptable and to reduce the cost of disposal, make it economically viable and avoid soil and water pollution. However, apart from these disadvantages, marble dust plays the role of useful substance as a filler material in several applications like land filling, making of bricks, cement manufacturing, sculpture industries, construction and other allied field of civil engineering applications. An enormous quantity of solid waste is generated as a by-product of mineral resources to meet the most potential consumer demand in civil engineering construction industry [2]. Development of new composites considering the strength, cost, and eco-friendliness are being major criteria for the researcher [3]. Fly ash is the principal industrial waste produced by burning the coal in power plants; it causes huge industrial pollution and also its storage cost is very high [4]. Previous researchers demonstrated the use of marble waste as partial substitute of natural aggregates in production of concrete structure [5].The effect of different ceramic filler on the mechanical properties of the composite samples have been tested earlier [6].An attempt has been made in this present work to effectively utilize the marble particulate as filler for making epoxy modified glass fibre reinforced hybrid composites.

Solid particle erosion demonstrates itself in progressive loss of material due to external bombardment of the small solid particles. This causes thinning of components, surface roughening, surface degradation in microscopic view, and decline in efficient life of the structure. Such applications are found in pipe line carrying sand slurries in chemical industries, aircraft rotor blades, pump impellers, turbines and engineering structure exposed to dusty and desert environment. [7]

Hence erosion resistance has been considered as an important material property for different failure modes in engineering application, particularly while selecting polymer composite as alternating material. It is due to the complexity and nonlinear correlation between the input control factors as erodent size, particle content, velocity of bombardment, impingement angle, etc. to the output ones, i.e., erosion rate. Though previously some research report is available on erosion loss of glass-fibre-reinforced composites, there is no work existing on study of erosion wear behavior of marble powder-filled glass-fibre-reinforced-epoxy composites. Against these reports, the objective of the present work is to study the effect of marble-filled-epoxy-glass fibre composites on the erosion wear and to set up neural calculation as a successful tool for anticipating the wear response of such composites. Experimental tests have been conducted according to the design of experiment to deal with build up the ideal parameter settings for lowest erosion rate.

2. Experimental details

2.1. Materials and methods

In this present experimental study, marble particulates are used with epoxy matrix. The epoxy resin as a matrix material and 2% HY 951 as a hardener mixed thoroughly prior to manufacture the composite specimen. The unmodified epoxy resin (LY 556) and hardener (HY 951) are supplied by Ciba Geigy Ltd., India. Epoxy resin has a modulus of 3.42 GPa and density of 1.10 g/cm^3. Bidirectional glass fibre mats possess a modulus of 72.5 GPa and having density of 2.59 g/cm^3 is supplied by Saint Gobian Ltd., India. Marble waste is used as filler material. The density of marble powder is 2.68 g/cm^3[8]. The marble powder was brought from the nearby marble industry. The marble powders are kept in an oven for drying with a temperature of 100°C to remove water particle and sieved to a size of 90-120µm.

The chemical composition of the used marble powder as filler material based on weight percentage is presented in Table 1[11]. Alkali treatment has been adopted to improve the mechanical and tribological properties of the composites as stated by Jawaid et. al. [9]. This chemical treatment removes the surface impurities and O-H groups so as to improve the interfacial adhesion and hydrophobic characteristics of the fibre [10] as presented in Equation(1).

$$OH + NaOH = O^{-}Na^{+} + H_2\,O + impurities \qquad (1)$$

Table 1

Chemical composition of waste marble powder [11]

Ceramic Oxides	Marble powder (%)
MgO	0.4
CaO	51.7
SiO_2	0.18
Al_2O_3	0.67
Fe_2O_3	0.44
K_2O	0.21
SO_3	0.08
LOI	46.04

LOI-Lost on Ignition

2.2 Fabrication of Composite

Four different composites were prepared with the glass fibres by varying the treated marble powder content (0, 5, 10, and 15 wt. %) as CM0, CM1, CM2, and CM3, respectively, as shown in Table 2. All the composites are fabricated by hand-lay-up technique. The laminated composite samples are prepared by light compression molding. Before placing the cast in mould, a gel coat with 2% (w/w) is smoothly applied in the mould box. Leaving the gel coat to be cured, each layer of glass fibre material was preimpregnated with a resin matrix and a laminated structure was obtained. Then the mould was subjected to a hot press (5 tons) for 1 h at a temperature of 110°C. The cast was kept in ambient air for another 24 h. for curing. Developed composites with required dimensions were cut with the help of diamond point cutter for erosion test.

Table 2

Designation of the hybrid composites composition

Designation of composites	**Composition**
CM0	Epoxy (60 wt %) +glass fibre (40 wt %) +filler (0 wt %)
CM1	Epoxy (55 wt %) +glass fibre (40 wt %) +marble powder (5 wt %)
CM2	Epoxy (50 wt %) +glass fibre (40 wt %) + marble powder (10 wt %)
CM3	Epoxy (45 wt %) +glass fibre (40 wt %) + marble powder (15 wt %)

2.3 Erosion Test

Erosion experiments were conducted in an air jet erosion test rig at room temperature as per ASTM G76 standard as shown in Fig. 1. It consists of five basic units such as a filter-regulator unit, erodent hopper, air-erodent mixing chamber, testing chamber, and an erodent collector unit. Initially, air from the compressor flows through the filter-regulator unit and at the same time, the erodent (alumina powder) is put into the hopper. After moving through the mixing chamber, the air-erodent mixture passes through a converging nozzle so as to get the required velocity. Then the high-velocity erodent particles strike against the specimen placed in a specimen holder. Specimens can be placed in angular positions (0°, 15°, 30°, 45°, 60°, 75°, and 90°) before the nozzle by means of a specimen holder. After the impact, the erodent is collected in the collection chamber and weighed to calculate the erosion rate of the samples. In the present work, four different sizes of erodent were used such as 50 µm, 100µm, 200 µm, and 300 µm. After the test was conducted, the composite samples were cleaned with acetone, dried, and weighed up to ±0.1 mg accuracy. The weight loss was measured for later estimation of the erosion wear rate. The whole procedure was repeated at least three times for reaching a steady-state erosion rate.

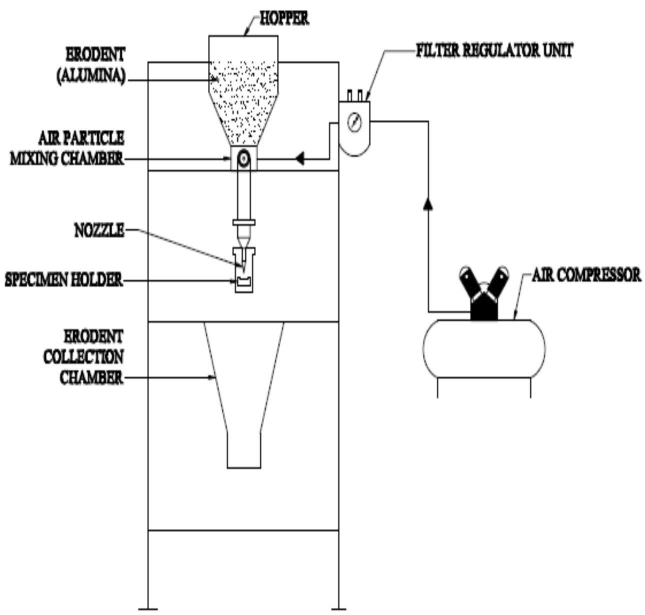

Fig.1. Schematic diagram of erosion test rig

2.4 Experimental Design

The design of the experimental methodology is a simple, time saving, cost effective approach to quality as well as performance parameters [12]. In this work, the effect of four factors such as filler content, impact velocity, particle striking angle, and erodent size, with each at four levels, on the erosion rate is studied (Table 3). Taguchi experimental design is an efficient analysis tool for optimizing performance, quality and cost [13].In order to identify the significant factors, 4^4 = 256 experiments are required to carry out a study in a conventional experimental method, where by using Taguchi method, only 16 experimental runs are required. This becomes advantageous with respect to minimizing the cost and time of experiment. The outputs of the experiment (erosion rate) are converted to "signal to noise" (S/N) ratios for a better analysis of the problem.

Since the goal of the review is to limit the erosion rate, the S/N ratio is considered under "Lower is better" (LB) qualities and the logarithmic transformation of misfortune capacity appears underneath as:

$$\frac{S}{N} = -10log_{10}\left[\frac{1}{n}\left(\sum y^2\right)\right] \quad (2)$$

Where n is the number of investigation and y is the investigated data.
The experiments were conducted as per the design shown in Table 4, where row presents test condition and column stands for test parameters. According to design of experiment: Erodent striking(impact) velocity, marble powder(filler) content, angle of impingement, erodent size, erosion rate assigned to second, third, fourth and fifth columns respectively.

Table 3

Control factors with their levels used in experiment

Control factors	**Levels**				
	I	II	III	IV	Units
Impact velocity (A)	33	47	57	68	m/s
Filler content(B)	0	5	10	15	Wt.%
Impingement angle(C)	45	60	75	90	degree
Erodent size(D)	50	100	200	30	µm

Table 4

Design of experiment according to L_{16} orthogonal array with S/N ratio

Test run	Impact velocity(A)	Filler content(B)	Impingement angle(C)	Erodent size (D)	Erosion rate (E_r)	*S/N* ratio
	(m/s)	(Wt.%)	(degree)	(μm)	(mg/kg)	(dB)
1.	33	0	45	50	188.58	-45.5099
2.	33	5	60	100	179.63	-45.0876
3.	33	10	75	200	205.56	-46.2588
4.	33	15	90	300	185.65	-45.3739
5.	47	0	60	200	206.28	-46.2891
6.	47	5	45	300	185.45	-45.3645
7.	47	10	90	50	182.43	-45.2219
8.	47	15	75	100	214.76	-46.6391
9.	57	0	75	300	203.28	-46.1619
10.	57	5	90	200	210.58	-46.4683
11.	57	10	45	100	175.43	-44.8821
12.	57	15	60	50	163.12	-44.2501
13.	68	0	90	100	230.25	-47.244
14.	68	5	75	50	211.51	-46.5066
15.	68	10	60	300	202.48	-46.1276
16.	68	15	45	200	172.25	-44.7232

2.5 Artificial Neural Network (ANN)

Parida and Chackraverty [14] derived artificial neural network, motivated according to biological nervous system, which is an excellent tool for predicting complex processes like erosion rate. The material erosion loss is taken as non linear problem with respect to its controlling parameters such as type of material (composition), (erodent striking) impingement angle and impact velocity, erodent size etc. Suitable combinations of these factors are to be initially planned in order to obtain a minimum erosion rate, before conducting experiments. In this way, a strong philosophy like ANN is required to concentrate these interrelated impacts. It is a framework made out of many cross-connected straight forward preparing units known as neurons. The system comprises three sections associated in the arrangement: input layer, output layer and hidden layer. The neuron is the basic unit of an ANN model. These neurons are connected to each other with a weight factor which determines the strength of interconnections as adopted by Amirjan et al. [15]. Therefore, the contribution of these interconnections passes to the next neuron. In the present work, A, B, C and D correspondingly impact velocity, filler content, impingement angle, and erodent size have been considered as input parameters, in order. Each factor is portrayed by one neuron in the sequence layer of the ANN configuration. The system can be prepared to play out a specific capacity by changing the estimations of weight elements between neurons by getting data from sources of input. Test results are utilized to prepare the ANNwith a specific end goal to comprehend the input–output connections as stated by Zhang et al.[16]. The database is then separated into three classifications, for example, approval, preparing, and testing category. The number of neurons in each layer is adjusted in the validation category whereas the weights of the neurons are adjusted in the training category and in the testing part, the results of training data being validated by Kranthi and Satapathy[17]. The input informations are standardized in order to lie in a similar range gathering of 0 to 1. The output layer represents the erosion rate having only one neuron.

Usually, the multilayered neural network is widely used by most of the investigators. The Levenberg– Marquardt back propagation algorithm can be used as a learning algorithm for a multilayered neural network due to its good performance with experimental values. A sigmoidal activation function is used for all neurons in the input layers and hidden layers, and a linear function is used for the output layer. The multilayered neural network was solved using back propagation algorithm which is explained precisely as follows:

Initially the output data are standardized in range (-1 to 1) using equation (3).

$$X_N = 2\frac{X-X_{min}}{X_{max}-X_{min}} - 1 \tag{3}$$

Where X_N is the standardized estimation of specific parameters, X is the deliberate estimation of the parameter, and X_{min} and X_{max} are the base and greatest estimations of the parameter, respectively.

Different network parameters such as learning rate, the number of epochs, the number of hidden layers, and the number of neurons in the concealed layer were set and after that the input information of the preparation were given. Here, only one hidden layer is used. The number of units in the hidden layer was varied from 3 to 20 and optimized at 12, whereas the learning rate value was kept as 0.1.

The output signals of neurons were calculated using equation 4.

$$Net_j = \sum_{i=1}^{m} W_{ij} X_i + b_j \tag{4}$$

Where Net_j is the yield of the neuron j, W_{ij} is the association of weight from neuron i to j, X_i is the info signal of neuron i, and bj is the partiality of neuron j. A log-sigmoid transfer function was used to translate Net_j for every neuron in the hidden layer.

The sum of squared errors (SSE) was calculated after the convergence by using the equation.

$$SSE = \sum_{i=1}^{n} (T_i - Y_i)^2 \tag{5}$$

Where T_i is the real value and Y_i is the predicted value.

The performance of the network was determined on the basis of standard deviation (*y*) using Eq. (6) and average absolute error (*Er*) using Eq. (8)

$$y = \sqrt{\frac{1}{N}[(X_1 - \mu)^2 + (X_2 - \mu)^2 + (X_3 - \mu)^2 + \cdots + (X_N - \mu)^2]} \tag{6}$$

$$\mu = (X_1 + X_2 + X_3 + \cdots + X_N) \tag{7}$$

Where $X_1, X_2, X_3 ...... X_N$ are different values obtained in the test run of ANN

$$E_r = actual - \mu \tag{8}$$

In this study, filler content, impact angle, impact velocity and erodent size were considered as input parameters and erosion rate was the output parameters related to the neural network model. A multilayered feed forward network of the info neurons and yield neurons was considered as Levenberg–Marquardt back propagation algorithm.

Around 80% of the test informations were used to prepare the neural system. Assorted ANN structures with a moving number of neurons in the covered layer attain steady cycles, learning rate, error resistance, vitality parameter, noise component, and grade parameter [18]. The quantity of neurons in the shrouded layer was fluctuated and optimized at 12 as appeared in Fig. 2.

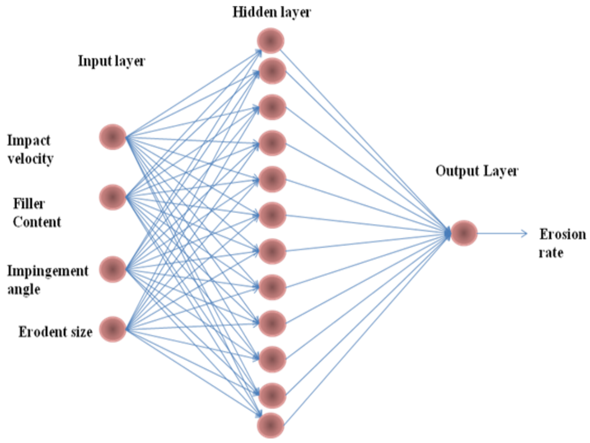

Fig.2. Three-layer network diagram of ANN

In view of the least error criterion, one structure presented in Table 4 has been chosen for preparing the input–output information. The number of cycles chosen amid preparing was sufficiently substantial for ANN models to be systematically trained. NEURALNET software for neural calculation utilizing the back-proliferation calculation was utilized as the forecast instrument for erosion loss of specimens inside and outside the test area.

Table 5

Input factors taken for ANN prediction

Input Parameters for Training	Values
Learning rate (ß)	0.01
Error tolerance	0.01
Noise factor (NF)	0.001
Momentum parameter(α)	0.01
Slope parameter (£)	0.6
Amount of epochs	20,00,000
Amount of hidden layer neuron (H)	12
Amount of input layer neuron (I)	4
Amount of output layer neuron (O)	1

3. Results and discussion

3.1 Wear Analysis Using Experimental Design

The erosion rate found for each of the 16 test trials together with the equivalent S/N ratio are shown in Table 4. The average value for the S/N ratio of the wear rate is calculated as -45.7568 dB. The analysis is carried out with the help of the MINITAB 16 software. The S/N ratio investigation is given in Table 6, which indicates that among all control parameters, the impact velocity, filler content, erodent size subsequently affects the material loss. One may see that the angle of impingement has the minimum effect on the erosion wear rate of marble-filled-glass-epoxy composites. The effect of each control parameters is shown in Fig. 3. The testing of the results shown in Table 6: it was concluded that the combinations of the factors A_3 (impact velocity:57 m/s), B_4(filler content:15 wt. %), C_1(impingement angle: 45°), and D_1 (erodent size: 50 μm) gives a minimum erosion rate.

Table 6

Signal-to-noise ratio for erosion rate

Level	A	B	C	D
1	-45.56	-46.30	-45.12	-45.37
2	-45.88	-45.86	-45.44	-45.96
3	-45.44	-45.62	-46.39	-45.93
4	-46.15	-45.25	-46.08	-45.76
Delta	0.71	1.05	1.27	0.59
Rank	3	2	1	4

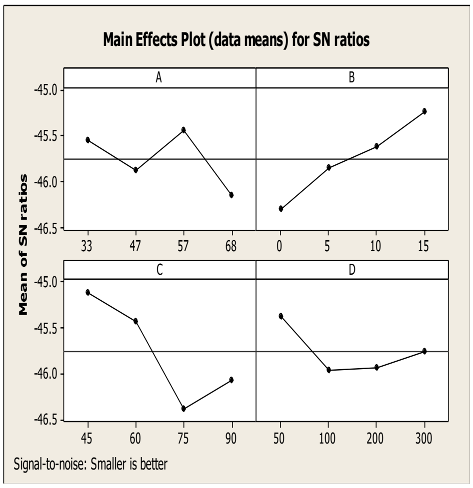

Fig.3. Main effect plot for S/N ratio

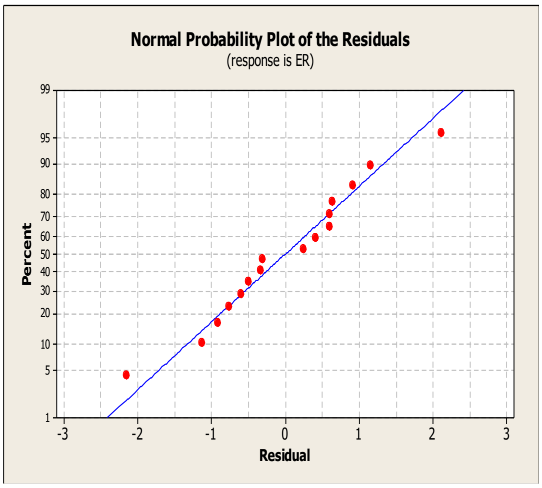

Fig.4.Normal probability plot for residuals

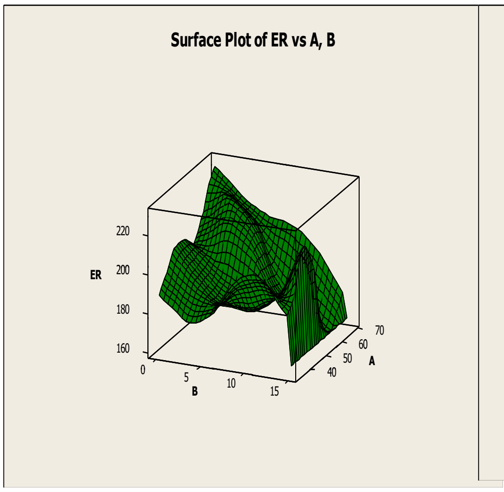

Fig.5. Surface plot for erosion rate vs. impact velocity and filler content

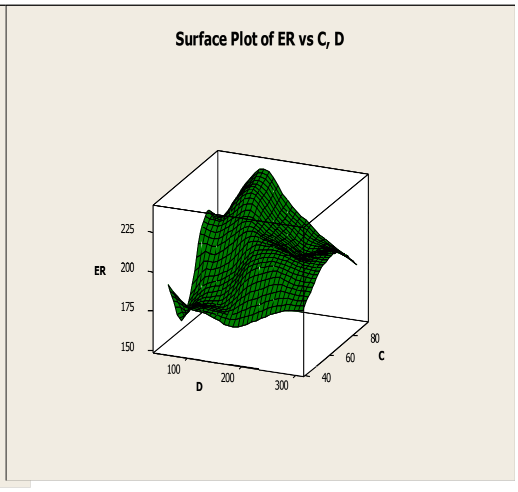

Fig.6. Surface plot for erosion rate vs. impingement angle and erodent size

3.2 Wear Analysis and Prediction Using Neural Computation

Table 7 demonstrates a correlation between the test values and the ANN anticipated outcomes for erosion rate of marble-filled-glass-epoxy composites. The fourth column of Table 7 presents the percentage errors between the two obtained values. The error in ANN model was found to be in range of 1-5% showing the authenticity of neural calculation.

From the experimental data it is critically viewed that, the erosion wear rate improves almost exponentially when raising the impact velocity and at the same time, it is reduced with increase in the filler content. This behavior of the composite can be attributed to the presence of hard particulates in the surface, which has reduced the mass loss of the specimen. Generally, when erodent strikes the composite surface at a certain angle, it produces two velocity components. The normal component of velocity gives depth of penetration whereas the tangential component increases the erosion distance. The product of abrading distance and depth of penetration account for the volume of erosion loss from the composite body. Therefore, rise in velocity of impact of the erodent is directly affecting the material loss from the surface of composites. However, the inclusion of marble particle into the composite offers resistance to the velocity of impact and resulting reduction in material loss with addition of fillers to theses composites. Similar results were found by Rout and Satapathy [19].

3.3 Wear Analysis and Prediction Using Mathematical Model

The test results are utilized to determine a mathematical model for erosion rate (E_r) utilizing a linear deterioration observation by considering four input factors as A,B,C,D representing velocity of impact, marble content, impact angle, size of the erodent. The examination predicts a reasonable guess for the genuine utilitarian connection between the response and the input factors. The function showing the erosion wear rate and the autonomous input factors can be communicated below:

$$E_r = f\,(A, B, C, D) \tag{9}$$

Where $\mathbf{E_r}$ stands for the required response and f indicates the response function.

The connection between self-regulating parameters and erosion loss can be established by a linear degeneration equation using MINITAB 16 software as

$$E_r = K_0 + K_1A + K_2B + K_3C + K_4\,D \tag{10}$$

Here K_0 shows the independent relapse condition, and K_1, K_2, K_3, and K_4 are linear terms, individually. The estimation of these coefficients is assessed with regression strategy. At the point when the information are examined for erosion rate, the accompanying reaction direct capacity is acquired for marble filled glass-epoxy composites in un-coded units:

$$E_r = 149 + 0.297\,A - 1.50\,B + 0.575\,C + 0.0185\,D \tag{11}$$

$$R^2 = 91\%,\ R^2\ (adjusted) = 88\%$$

The regression models (Eqs. 11) presented high correlation coefficient (R^2 = 0.91 explaining 91 % of the variability in the erosion wear rate for marble-based composites. Higher R^2 data shows the integrity of fit of the model to the real information and high measurable criticalness of the model. Be that as it may, higher R^2 may not be sufficiently essential to speak to a superior model.

Hence the R^2 (adjusted) measurable investigation has been incorporated into the present model. One may see that the estimation gotten from the difference amongst R^2 and the adjusted R^2 is modest and shows better relationships between the trial and anticipated estimations of disintegration erosion rate for composites. In Table 7, the last column represents the percentage error between the experimental and mathematical model. The error in the mathematical model lies in the range of 1 to 10% which is larger than the percentage error (1 to 5%) in the ANN model. This indicates that the ANN model is effective in predicting the erosion rate of the developed composites.

Table 7

Comparison of experimental results with ANN and mathematical model

Test run	**Erosion wear rate: E_r (experimental)**	**Erosion wear rate: E_r (ANN)**	**Error**	**Erosion wear rate: E_r (mathematical model)**	**Error**
	(mg/kg)	(mg/kg)	%	(mg/kg)	%
1.	188.58	187.36	2.30	185.601	1.58
2.	179.63	180.41	1.40	187.651	4.47
3.	205.56	204.75	1.67	190.626	7.27
4.	185.65	187.23	2.93	193.601	4.28
5.	206.28	205.81	0.97	201.159	2.48
6.	185.45	184.57	1.63	186.884	0.77
7.	182.43	181.54	1.62	200.634	9.98
8.	214.76	215.36	1.29	185.434	13.66
9.	203.28	201.43	3.76	214.604	5.57
10.	210.58	211.14	1.18	213.879	1.57
11.	175.43	174.21	2.14	178.654	1.84
12.	163.12	162.31	1.32	178.854	9.65
13.	230.25	229.37	2.03	222.796	3.24
14.	211.51	212.45	1.99	205.746	2.73
15.	202.48	201.39	2.21	194.246	4.07
16.	172.25	171.59	1.14	176.271	2.33

4. Conclusions

The present experimental and analytical work illustrates not only the use of the neural network in a complex process like erosion wear, but also predicts effectively the erosion wear rate within and beyond the tested domain. Two prescient models, one in light of the mathematical model and one as an ANN prediction, are proposed.

One may observe that the ANN model has shown minimum error (within 5%), whereas mathematical model shows higher error (more than 5%) with respect to the experimental values of erosion rate. Hence, the present analysis shows the significant capability of a well-trained neural network for prediction of erosion wear in such a multi component hybrid composite. The Taguchi design of experiment suggests that parameters like filler content, erodent size, impact velocity, and impingement angle have considerable effect on erosion wear rate. The combinations of the factors: impact velocity -57 m/s, filler content -15 wt. %, impingement angle-45° and erodent size -50 μm gives a minimum erosion rate. From the experimental result it is clear that filler content has appreciable effect than other control factors.

R E F E R E C E S

[1] *F. E. Heuze,* "High-temperature mechanical, physical and thermal properties of granitic rocks-a review", *International Journal of Rock Mechanics and Mining Sciences & Geomechanics Abstracts*, **Vol. 20**, No. 1, Pergamon, 1983.

[2] *F. Saboya Jr, G. C. Xavier, and J. Alexandre.*, "The use of the powder marble by-product to enhance the properties of brick ceramic", *Construction and Building Materials*, **Vol. 21**, No. 10,2007, pp.1950-1960.

[3] *Hanifi Binici, T. T Shah, O Aksogan, H Kaplan* , "Durability of concrete made with granite and marble as recycle aggregates", *Journal of materials processing technology*, **Vol. 208**, No.1-3, 2008, pp.299-308.

[4] *Tayfun Uygunoğlu et al.*, "The effect of fly ash content and types of aggregates on the properties of pre-fabricated concrete interlocking blocks (PCIBs)", *Construction and Building Materials*, **Vol. 30**,2012, pp.180-187.

[5] *H. Hebhoub, H. Aoun, M. Belachia, H. Houari, and E. Ghorbel*, "Use of waste marble aggregates in concrete", *Construction and Building Materials*, **Vol. 25**, No.3, 2011, pp. 1167-1171.

[6] *Ramesh K. Nayak, Alina Das, and B.C. Ray*, "Effect of epoxy modifiers ($Al_2O_3/Si_2/TiO_2$) on mechanical performance of epoxy/glass fibre hybrid composites", *Procedia Materials Science*, **Vol. 6**,2014, pp.1359-1364.

[7] *U.S. Tewari, A.P. Harsha, A.M. Hager*, "Solid particle erosion of unidirectional carbon fibre reinforced polyetheretherketone composites", *Wear,* **Vol. 252**, No.11-12, 2002, pp. 992-1000.

[8] *F. Gameiro, J. de Brito, D. Correia da Silva*, "Durability performance of structural concrete containing fine aggregates from waste generated by marble quarrying industry", *Engineering Structures*, **Vol.59**, 2014, pp.654-662.

[9] *M. Jawaid, H. P. S. Abdul Khalil, A. Abu Bakar, and P. Noorunnisa Khanam*, "Chemical resistance, void content and tensile properties of oil palm/jute fibre-reinforced polymer hybrid composites", *Mater.Design*, **Vol.32**, No.2, 2011, pp.1014-1019.

[10] *K. Sabeel Ahmed and S. Vijayarangan*," Tensile, flexural and inter laminar shear properties of woven jute and jute-glass fabric reinforced polyester composites", *Journal of*

materials processing technology, **Vol. 207**, No.1-3, 2008, pp.330-335.

[11] *Ali Ergün*, "Effects of the usage of diatomite and waste marble powder as partial replacement of cement on the mechanical properties of concrete", *Construction and Building Materials*, **Vol.25**, No.2, 2011, pp.806-812.

[12] *D. C. Montgomery*, “Design and Analysis of Experiments”, 4th ed., New York: Wiley. 1997.

[13] *G. Taguchi*, “Introduction to quality engineering”, Tokyo: Asian Productivity Organization, 1990.

[14] *P. K. Parida, and S. Chakraverty*, “Artificial neural network based numerical solution of ordinary differential equations”, *M.Sc. Thesis, NIT, Rourkela*. 2012.

[15] *Z. Zhang, N. M. Barkoula, J. Karger-Kocsis, and K. Friedrich*, “Prediction of erosive wear properties of polymers using artificial neural networks”, *Wear*, **Vol. 255**, No. 1-6, 2003, pp. 708-713.

[16] *G. Kranthi, and A. Satapathy*, “Evaluation and prediction of wear performance of pine wood dust-filled epoxy composites using neural network”, *Comput. Mater. Sci.*, **Vol. 49**, No.3, 2010, pp.609-614.

[17] *S. Rajasekaran, and G. A. Vijayalakshmi Pai*, “*Neural Networks, Fuzzy Logic and Genetic Algorithms- Synthesis and Applications*”, Prentice Hall of India. 2003.

[18] *A. K. Rout and A. Satapathy*, “Study on mechanical and erosion wear performance of granite filled glass-epoxy hybrid composites”, *Proc. IMechE Part L, J. Mater. Design Appl.*, **Vol. 229**, No.1, 2015, pp.38-50.

[19] *A. K. Rout and A. Satapathy*, “Study on mechanical and tribo-performance of rice husk-filled glass epoxy hybrid composites”, *Mater. Des.* , **Vol. 41**,October 2012,pp.131-141.