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Effect of Control Parameters on Erosion Wear Performance of Glass-Epoxy Composites Filled with Waste Marble Powder

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Abstract: Marble waste is the principal solid waste generated during the processing of marbles in stone processing industries. Managing solid waste create a challenge for society. In the present study, composites are fabricated with different proportions (0, 5, 10, and 15 wt. %) of waste marble powder (WMP) along with epoxy and glass fiber by a simple polymer casting method. Erosion wear characterization of the composites have been conducted by following ASTM G76 standard. The experiment was statistically designed as per Taguchi's L_{16} model. The incorporation of WMP had shown an improvement in erosion resistance of composites. A theoretical model has been developed to predict the erosion wear rate of the composites. Subsequent to this, a neural network model is also developed to predict the erosion wear properties of glass-epoxy-marble (GEM) composites based on their experimental results obtained from the erosion test. The input data were trained in such a manner that the neural network model can precisely predict erosion wear properties of these composites. Moreover, the experimental results are compared with the predicted data to validate the neural network model. It is inferred, from the validation that the developed model can be utilized to predict the erosion wear rate of composites up to an accuracy of 95%.

Keywords: glass fiber; waste marble particle; erosion resistance; neural network model

1. Introduction

Over few decades, polymer matrix composites (PMC) are slowly replacing conventional materials due to their low cost, higher fatigue resistance, lightweight, good chemical resistance, and superior wear resistance properties[1]. Particulate-filled PMCs beg a significant contribution in the engineering field due to their low cost. In past years, conventional fillers such as alumina powder, nickel, TiO_2, silicon oxides, etc. have been widely used to fabricate polymer composites[2]. However, the ever increase in cost, technical aspects, soaring material properties open up an avenue of replacing conventional fillers with cheap and abundantly accessible fillers such as industrial wastes by partially compromising with the quality. Marble waste is such an industrial waste that bears the quality to be used as a filler material in PMCs. A marble is created from the limestone during the ecological process. Marble is also considered an ornamental stone and chemically contains dolomite and calcite. In past years, the use of marble stone is highly increased in the construction sector. During the cutting and polishing of marbles up to 30% of scarp and powder is produced in the marble processing industries. Disposal of million tons of WMP causes serious environmental impact worldwide. Hence, alternative use of these wastes in some useful material is highly needed. However, WMP is used in landfills, used as a substitute for natural aggregates for manufacturing bricks, production of cement, construction, sculpture, and other allied industries.

Corinaldesiet al. [3]reported the utilization of marble dust as a natural additive for making concrete with and without the addition of a superplasticizer. The concretes are made with a sand to cement ratio of 3:1. About 10% substitution of sand showed optimum compressive strength with respect to other samples at the same workability level. Singh et al.[4] partially replaced cement with marble dust in concrete and studied their different physicochemical properties. The drying shrinkage of concrete is reduced and mechanical properties are improved up to 15% replacement of marble dust with sand. Singh et al.[5]studied the use of granite and marble dust in the manufacturing of concrete. The flexural strength of concretes are found to be enhanced up to 15% of marble and 25% of granite replacement. Vardhan et al. [6] have prepared six different types of concretes by using 10-60% of WMP. The optimum value of strength and durability was obtained with 40% marble powder replacement of sand in concrete. Torres et al.[7] developed roof tiles by the incorporation of granite waste. The incorporation of around 10% granite dust reduced the plastic deformation and water absorption properties and enhanced the bending strength of the tiles. Binici and Aksogan [8] studied that the concretes made up of granite, sand, marble powders and basalt powder showed superior performance than normal concretes. The compressive strength, abrasion resistance, and freeze-thaw characteristics of the developed concretes are found to be improved. Bilgin et al.[9] studied the physico-mechanical properties of marble dust-added bricks. Up to 10% addition of marble waste enhanced the physico-chemical, and mechanical properties of newly developed bricks. Rodrigues et al.[10]found the mechanical characteristics of concretes made from marble sludge along with plasticizers. The mechanical properties such as tensile, compressive strength, elastic modulus, and abrasion resistance of concrete improved up to 10% marble replaced with cement. Ulubeyli and Artir et al.[11] observed that splitting tensile, compressive, flexural strength, elasticity, surface hardness, of conventional concrete was developed by the use of WMP, whereas these properties found to be declined in case of self-compacting or polymer concrete. During sawing and polishing of marble slabs, marble dust is produced and these wastes can threaten the groundwater recharge due to their grain size distribution and high chemical oxygen demand[12]. Cinar and Kar [13] observed an improvement in hardness, tensile and impact strength, thermal conductivity, and non-inflammatory properties of the composite prepared by extrusion method using polyethylene terephthalate waste bottle and marble waste. Borsellino et al. [14] have reported an improvement in rheological, static flexural, impact, water absorption, and strain resistance properties of both polyester and epoxy composites up to 60% addition of marble dust. Benjeddou et al.[15] studied the performance of mortar containing waste marble powder. Similar compressive strengths of the concretes were obtained by replacing cement with 5% of marble powder in control mix concrete.

To find the potentiality of industrial waste as a secondary filler in polymer matrix composite (PMC), the performance of composites should be tested under different wear mode. Generally, PMCs used in industrial sector comes under two types of wear, such as abrasion and erosion wear. Erosion is defined as the loss of material caused by the striking of the solid particles along the exposed surface. This subsequently originates degradation and roughening of the surface, thinning of parts, and reduces the overall life of the component. This type of wear mechanism is mostly found in turbine blades, pump impellers, aircraft fans, coal and fertilizer handling pipes, structural components exposed in the desert, etc.[16]. Therefore, erosion resistance of the PMC can be taken as one of the important properties while designing composites for industrial applications. Erosion wear seems to be one of the complex phenomena as it depends on several factors such as striking velocity, impact angle, size of solid erodent particle, and hardness of the composite surface. Previously many researchers have reported the erosion characteristics of polymer composites filled with solid wastes such as red mud, kiln bypass dust, cement industry waste, copper and blast furnace sludge, etc. The performance of PMCs can be improved by the addition of hard ceramic fillers to the composites and can be useful for industrial applications.

From the work reported till date, it can be observed that though marble dust has extensively used as construction material, its use as a filler in polymer composites still remains a less explored area. In this context, the present work emphasizes on development of a new class of composites and to study the erosion characterization of those composites. The effects of various factors on erosion wear of composites were analyzed. The test was designed based on Taguchi's L_{16}model and response tables were presented to set the optimum level of control parameters responsible for reducing the wear loss of composites. To estimate erosion wear rate of composites regression models are developed. Furthermore, to avoid replications of experiments and subsequently to reduce cost and time, another model was developed based on neural network approach under these experimental conditions.

2. Experimental details

In the present investigation, a mixture (10:1) of epoxy (L 12) and hardener (K 6) are used as matrix material. Epoxy possesses a density of 1.10gm/cc, and modulus of 3.42Gpa. The matrix materials are collected from M/s. Tirupati Suppliers, Kolkata, India. In this work, glass fiber is selected as the primary reinforcement. Glass fiber possesses a density of 2.59gm/cc and modulus of 72.5GPa.The glass fiber having an approximate diameter of 8µm is procured from Saint Govian Ltd. Waste marble powder (WMP) is used as a secondary reinforcement in this study. WMP holds a density of 2.68 gm/cc. The WMP chemically consists of CaO, Al_2O_3, Fe_2O_3, K_2O, SO_3, and MgO, etc. The WMP is collected from local construction sites. The WMPs are heated in the furnace, moisture is removed and then sieved to a size of about 100 to 150µm for characterization. The flow chart of the present study is shown in figure 1.

2.1 Composite fabrication

Matrix and fillers are mixed thoroughly using a mechanical stirrer as per the composition. The glass fiber mats are placed in the mold. The solution is poured on the glass fiber mat and again over another layer of glass fiber, resin is applied. To obtain a thickness of 4.5mm eight layers of glass fibers are used. The inside portion of the mold is sprayed with a mold-release silicon spray. Two numbers of Teflon sheets are placed at the bottom and top part of the casting for easy removal of the composite. The composites are fabricated using a simple liquid casting approach. The materials after pouring in the mold were kept for 72h for solidification. After solidification, the mold was broken and the samples are cut for erosion characterization. Hand lay-up method is previously adopted by various researcher for producing laminated polymer composites using natural fibers [17-18] . The details of the composition of the samples are presented in Table 1.

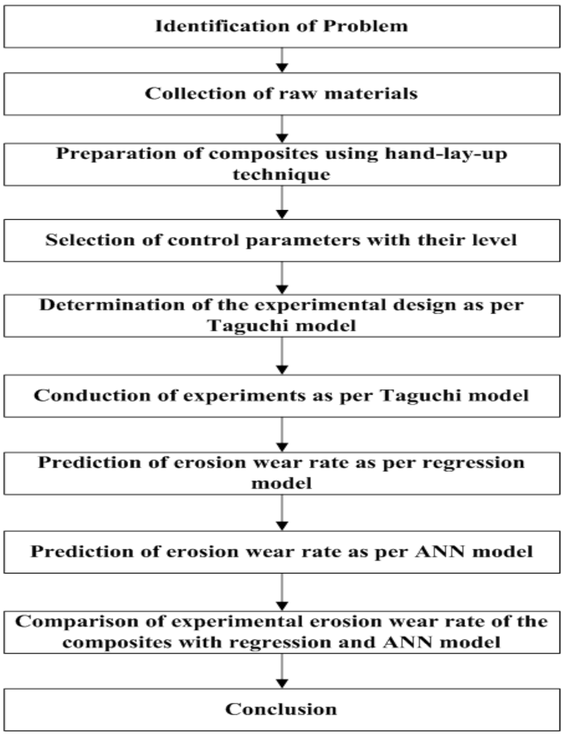

Fig.1: Flow chart of the present study

Table 1. Nomenclature of composites.

Symbol of composites	Composition		
	Epoxy (Wt %)	Glass fiber (Wt %)	WMP (Wt %)
GEM0	60	40	0
GEM1	55	40	5
GEM2	50	40	10
GEM3	45	40	15

2.2 Erosion Characterization

In the present investigation, an air erosion test rig was used to measure the erosion loss of the composites as per ASTM G-76 standard. The test rig of model TR-470 was supplied by Ducom Industries Ltd., Bangalore. Dry alumina powder is presently selected as erodent and fed from the hopper to the mixing chamber under gravity. Compressed air is supplied to the mixing chamber and accelerates the erodent. Alumina particle with the size of 100µm, 200µm, 300µm and 400µm for the erosion process. Then, the air-alumina mixture is projected to the specimen through a converging nozzle with the required velocity. The specimen holder can be placed at angles of 0° to 90° with 15º step. The composite specimens of size 25×25×4 mm^3 are selected for the test. The schematic view of test set up is shown in figure **2**.

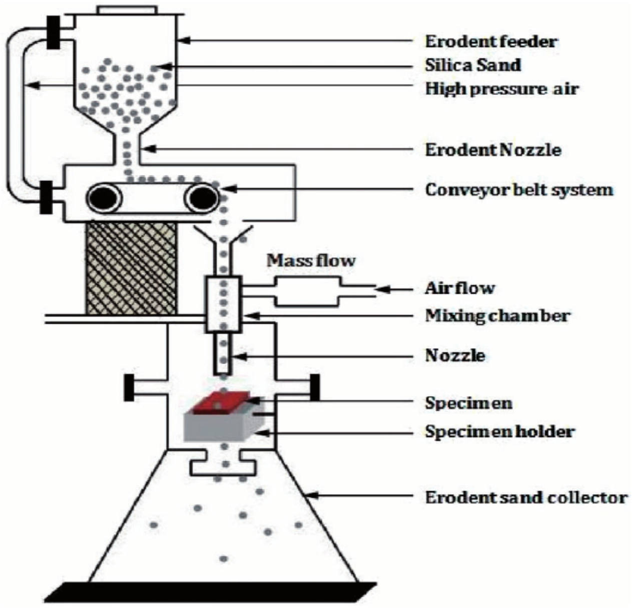

Fig.2: Erosion test setup

2.3 Taguchi Design

The design of the experiment is an efficient time and cost-saving technique to optimize the output result without compromising with its quality and performance[19]. Before selecting the optimization model, the control parameters should be selected with their level. Previous literature study indicates some input factors such as velocity of impact, WMP content, angle of impact, and size of erodent[20]. Taguchi design is also successfully applied to predict the material removal rate and surface roughness of various objects[21-24]. It is difficult to carry out all the test runs as a full factorial design for 4^4=256 numbers of experiments. The erosion wear test keeping four input parameters each at four levels are mentioned are presented in Table 2. Since the number of experiments are high, it may be reduced without compromising with output response. Therefore, Taguchi's L16 model is considered in the present work by reducing the cost and time of the test. For each set of combinations of parameters, an erosion test is conducted on three same composites and the average of three erosion wear rates are considered as the output data. The detailed arrangement of the experimental design of input parameters and erosion wear rates obtained from the experiments are presented in Table 3. The results are later on transformed to S/N ratios. The ratio of change in output parameter (signal) to changes in input parameters caused due to some interference of noise is termed as signal-to-noise ratio. In most of engineering problems, it is difficult to avoid the background noise in the input parameters. In this study, the erosion wear performance (output) depends on input factors. Hence, S/N ratio plays a vital role to show the significance of each input factor, when worked in interrelating applications. Since erosion loss has to be minimized, S/N ratio coming under "Lower is better" category is selected. The logarithmic transfer function is taken as,

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

Where n is the number of test runs and y is the mean.

Table 2. Fixed parameter setting

Sl. No.	Parameter	Value
1.	Size of specimen	25×25×4 mm^3
2.	Erodent	Alumina powder
3.	Erodent feed rate	10±1 g/min
4.	Diameter of nozzle	3 mm
5.	Height of nozzle	80 mm
6.	Nozzle tip distance	100 mm

Table 3. Arrangement of input parameters along with their levels

Control factors	**Velocity of impact (A)**	**Filler content (B)**	**Impingement angle (C)**	**Erodent size (D)**
Levels	**m/s**	**Wt.%**	**Degree**	**μm**
I	40	0	45	100
II	50	5	60	200
III	60	10	75	300
IV	70	15	90	400

Table 4. Experimental erosion wear rate (EWR) of glass-epoxy-marble (GEM) composites as per statistical design

Sl. No. of test run	**Impact Velocity (A)** (m/s)	**WMP Content (B)** (Wt.%)	**Impingement Angle (C)** (degree)	**Erodent Size (D)** (μm)	**Erosion Wear Rate (EWR)** (mg/kg)	***S/N* ratio** (dB)
1.	40	0	45	100	562.37	-55.0004
2.	40	5	60	200	477.49	-53.5793
3.	40	10	75	300	456.75	-53.1936
4.	40	15	90	400	482.59	-53.6716
5.	50	0	60	300	602.73	-55.6025
6.	50	5	45	400	604.51	-55.6281
7.	50	10	90	100	562.83	-55.0075
8.	50	15	75	200	568.28	-55.0912
9.	60	0	75	400	719.41	-57.1395
10.	60	5	90	300	692.55	-56.8090
11.	60	10	45	200	624.37	-55.9088
12.	60	15	60	100	578.61	-55.2477
13.	70	0	90	200	753.03	-57.5362
14.	70	5	75	100	760.71	-57.6244
15.	70	10	60	400	628.65	-55.9682
16.	70	15	45	300	656.46	-56.3442

2.4 Neural network model

A Neural network is a versatile and powerful tool to be used to estimate the output of decision-making problems. Neural networks are generally employed in different sectors such as electronics, manufacturing, auto-industries, aerospace, health, finance, insurance, etc. Moreover, the neural network is applied to problems that are ambiguous or may not be clearly defined. This method is found to be capable to deal with such arbitrarily arranged complex problems. The system consists of three sections like input, hidden, and output layers. Input layers consist of input parameters responsible for quantifying the output response. Input layers are interconnected by neurons and the neurons can predict the output data [25]. In the present investigation, impact velocity, WMP content, impingement angle, and size of erodent are considered as input neurons. The input neurons are normalized to lie within the value of 0-1. The output layer, i.e. erosion wear rate is considered as one neuron. In between input and output layers hidden layers are staying. Hidden layers are selected by fluctuating the effect input data on the output response and selected based on the hit and trial method. In the present study, twelve numbers of hidden layers are selected after fluctuating the data. The whole process is divided into three stages like training, testing, and validation. From the experimental data set around 80% of data are selected for training. In the training phase, the model understands the interconnection mechanism and train itself to predict the output response within or beyond the design domain. In the testing phase, another 10% of data are used to predict the output result. In the validation phase, the results are validated by comparing the predicted data with experimental values[26]. In general, for a multi-layered neural network problem, Levenberg-Marquardt the backpropagation algorithm is used. The neurons in input and hidden layers use a sigmoidal activation function, whereas the neurons in the output layer use a linear function based on the experimental values. The multi-layered model created using a backpropagation algorithm can be systematically approached as follows:

At first, the response results are normalized to a range of -1 to 1 using equation (2).

$$X_N = 2\frac{X - X_{min}}{X_{max} - X_{min}} - 1 \qquad (2)$$

Where X_N is the normalized, X is the measured, X_{max} and X_{min} are the maximum and minimum valuation of factors, respectively.

Initially, input parameters like number of epochs, learning rate, number of hidden layer and number of neurons in the hidden layers are fixed. A series of data are selected for training. By hit and trial method the hidden layers are varied and optimized at 12, and the learning rate is fixed at one. The signals for response results were evaluated using equation (3).

$$Net_j = \sum_{i=1}^{m} W_{ij} X_i + b_j \qquad (3)$$

Where Net_j indicates the output of the response j, W_{ij} represents connotation of responses i to j, X_i shows the feedback signal of input I, and partiality of data j is given as b_j. To transform Net_j for each data in the hidden layer a log-sigmoid function was utilized.

By merging all the transfer function, the sum of squared errors (SSE) was evaluated using equation (4).

$$SSE = \sum_{i=1}^{n} (T_i - Y_i)^2 \qquad (4)$$

Where T_i stands for experimental value and Y_i uses the anticipated value.

The value of standard deviation was calculated based on the network performance equation (5) and mean error was determined equation (7).

$$y = \sqrt{\frac{1}{N}\left[(X_1-\mu)^2 + (X_2-\mu)^2 + \cdots + (X_N-\mu)^2\right]} \qquad (5)$$

$$\mu = (X_1 + X_2 + X_3 + \cdots + X_N) \qquad (6)$$

Where $X_1, X_2, X_3 ...... X_N$ are the data found from test run phase of ANN model.

$$E_r = actual - \mu \qquad (7)$$

Different ANN models with steady cycles were tested. A major number of data selected for training to ensure the rigorous training of the model to minimize the error. Depending on the least error criteria, the model is constructed. Presently, error tolerance, learning rate, momentum parameter, noise factor, number of epochs, and slope parameters are selected as 0.01,0.01,0.01,0.001, 10 lakh, and 0.6 respectively. In the present study, impact angle, impingement velocity, WMP content, size of erodent are considered as input parameters and erosion wear rate as output response. The neural network model is developed as a multi-layered feed forward network using Levenberg–Marquardt backpropagation algorithm. Neuralnet software is used to devlop the model. The ANN structure is shown in Figure 3.

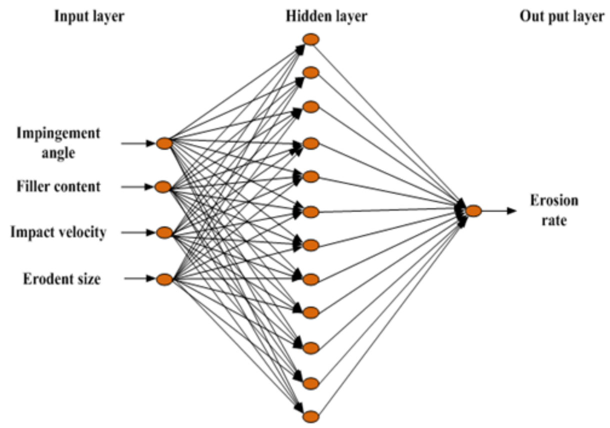

Fig.3: Three-layer network diagram of ANN

3. Result and Discussion

3.1 Erosion wear test result

The erosion wear rates (EWR) and S/N ratios for all the 16 experiments are shown in Table 4. From the experimental result, the mean of the S/N ratios is found as -55.5845 dB. The analysis of results is conducted using Minitab 17 package. The main effect curves obtained for S/N ratios and data means are plotted in figures 4 and 5. These graphs indicate the corresponding significance of the control factor on the output response of the experiment, i.e. erosion wear rate. The response table for S/N ratios and data means are presented in Tables 5 and 6 respectively. From Table 5 and 6, it is evident that the EWR is strongly influenced by the impact velocity and filler (WMP) content. In the addition to these two factors impingement angle and erodent size had a marginal effect on the EWR as compared with the other two factors. From the experimental data, the least EWR is obtained for a factor combination of A_1 (40 m/s), B_3 (10wt.%),C_2 (60°),D_3 (300µm).

From the above analysis, impact velocity is found as the most influential factor responsible for erosion loss of the GEM composites. Similar reports have been found by some previous researchers[27]. Generally, the striking of erodent takes place at a certain angle to the composite surface. The velocity of impact can be resolved into two components, i.e. normal component and tangential component. The normal velocity component causes the depth of penetration and determines the contact time. The product of the tangential velocity component and time of contact creates abrading distance on the surface of the material. Again, the product of penetration area and abrading distance gives volume loss of composite. Consequently, by increasing the impact velocity, the erosion loss of material also increases exponentially. However, the EWR is reduced with an increase in filler content of the composite. This phenomenon may be attributed due to the presence of hard sloid fillers in the composites and these fillers restricted the erosion loss of composites [28-30].

From the above analysis, it may be noted that the erosion behavior of different filler reinforced polymer composites highly depend on some input control parameters such as impact velocity, stand-off distance, impingement angle, size of erodent, the temperature of erodent, etc. Again, material properties like volume/weight fraction of fiber/filler, distribution of particle reinforcement, the orientation of fiber, type of matrix material, the density of composites, etc. Though in general, the addition of filler in the composites increases the erosion resistance, in some cases the erosion resistance is found to be reduced[31]. Hence, proper selection of matrix, fiber, and filler is very vital before used in the industrial sector.

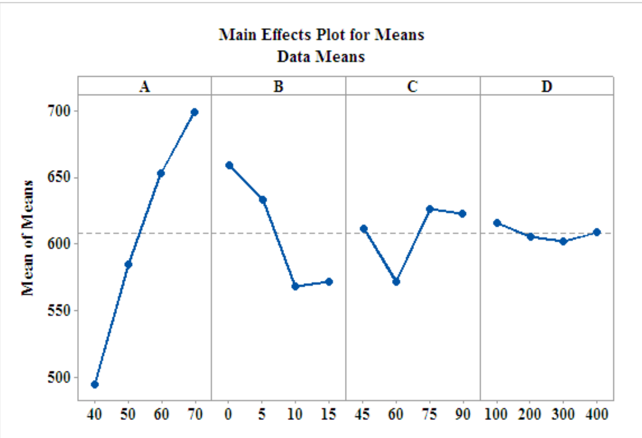

Fig.4: Variation of S/N ratio based on control factors

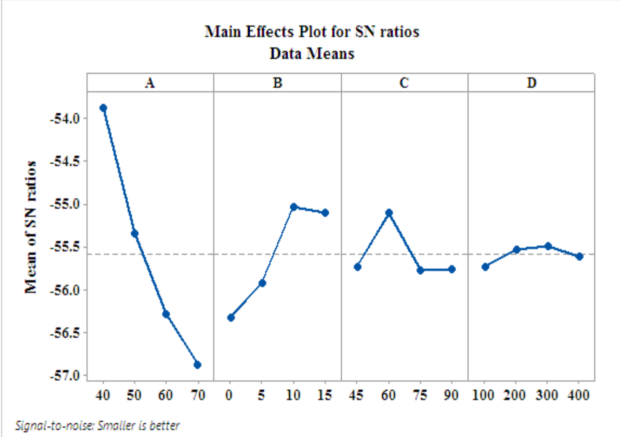

Fig.5: Variation of S/N ratio based on data means

Table 5. Response table of mean S/N ratios for EWR of GEM composite

Level	A	B	C	D
1	-53.86	-56.32	-55.72	-55.72
2	-55.33	-55.91	-55.10	-55.53
3	-56.28	-55.02	-55.76	-55.49
4	-56.87	-55.09	-55.76	-55.60
Delta	3.01	1.30	0.66	0.23
Rank	1	2	3	4

Table 6. Response table of data means for EWR of GEM composite

Level	A	B	C	D
1	494.8	659.4	611.9	616.1
2	584.6	633.8	571.9	605.8
3	653.7	568.1	626.3	602.1
4	699.7	571.5	622.8	608.8
Delta	204.9	91.2	54.4	14.0
Rank	1	2	3	4

3.2 Prediction of EWR using regression model

The erosion wear loss (EWR) of composites can be predicted using a non-linear regression equation. Presently, the EWR depends on several control parameters like velocity of impact (A), WMP content (B), angle of impingement (C), and size of erodent (D). Hence, EWR can be written as a function of these input parameters. Mathematically, it can be expressed as:

$$EWR = f(A, B, C, D) \quad (8)$$

The mathematical relationship between the EWR and the control factors is done after analyzing the experimental results with the help of MINITAB 16 software.

The relationship between EWR and input parameters can be turned into a non-linear regression equation as:

$$EWR = X_0 + X_1 A + X_2 B + X_3 C + X_4 D \qquad (9)$$

X_i (i= 0, 1, 2, 3, 4) are the model constants.

After analyzing the experimental data with the help of software, the EWR for WMP filled (glass-epoxy-marble or GEM) composites can be written as stated below.

$$EWR_{GEM} = 248.8 + 6.839A - 6.59B + 0.579C - 0.0257D \qquad (10)$$

From equation (10), due to a high correlation coefficient (r^2) of 0.90 obtained for erosion loss of GEM composites, the acceptability of model constants is established. However, the error of EWR (experimental vs. predicted) from this regression model lies around 10%. The percentage of error obtained from the predictive model can be reduced. Therefore, another statistical method based on ANN is suggested for further prediction of erosion wear loss of composites [32]).

3.3 Prediction of EWR using ANN model

Different error percentage obtained from predicted EWR (both regression and ANN model) are compared with experimental data and presented in figure 6. From the figure it is observed that the error percentage obtained from ANN model remains less as compared with regression model. Furthermore, the maximum error percentage obtained from regression model lies as 9.14%, whereas the maximum error percentage found from ANN model is coming around 4.73%. This shows the adequacy of the ANN model over regression model.

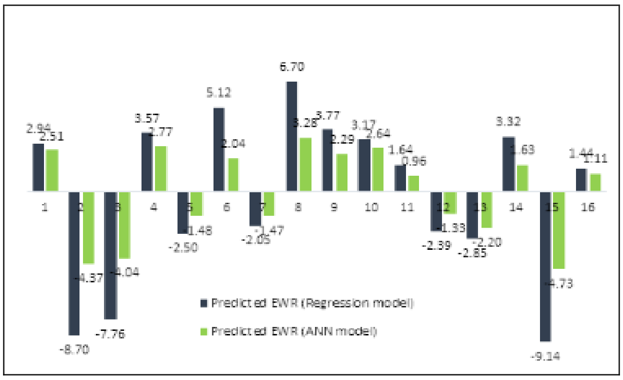

Fig.6: Error percentage obtained from predicted EWR (both regression and ANN)

If the position of residuals lies closer to the mean line in a normal probability plot, then the model stands suitable for the prediction of that particular problem. As shown in figure 7, it is indicated that the residual distribution is very closer to the straight line. Therefore, the ANN model developed for the erosion loss of composites found to be acceptable for the prediction of output result.

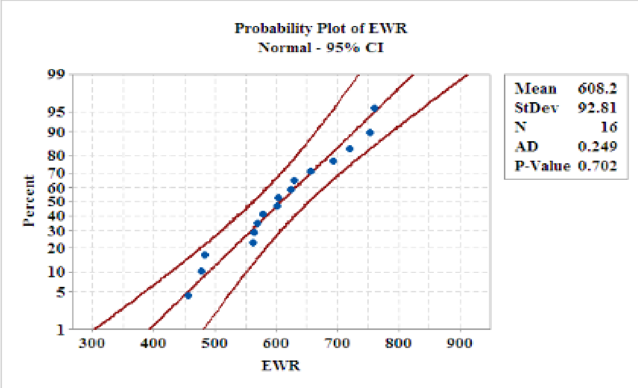

Fig.7: Normal probability plot

4. Conclusion

- A new class of glass-epoxy composite filled with waste marble powder (WMP) has been successfully fabricated following simple polymer casting method.
- The experimental data revealed that by the addition of 15wt% of WMP, the GEM composites showed maximum erosion resistance behaviour.
- Erosion wear rate (EWR) of the developed composites were analysed based on L_{16} Taguchi orthogonal array design.
- The statistical analysis concluded that impact velocity, filler content were found to be influential factors for the erosion loss of composites followed by impingement angle and erodent size.
- Taguchi design has the ability to determine the optimum parameter setting to meet the cause of erosion loss of composites applied in industrial sector.
- A regression model is developed and suggested to estimate the EWR of the composites within and beyond the test domain.
- This study shows the promising feature of WMP which is an industrial waste for possible utilization in useful polymer composites.
- Prediction of EWR using neural network model is accomplished and compared with the experimental values. It is demonstrated that the developed model well reflects the effect of various factors on the EWR.

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The author declares that he has no conflict of interest.

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