

## SOLID PARTICLE EROSION RESPONSE SIMULATION OF ALUMINA REINFORCED ZA-27 METAL MATRIX COMPOSITES

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### ABSTRACT

Inspired by the biological nervous system, an artificial neural network (ANN) approach is a fascinating computational tool, which can be used to simulate a wide variety of complex engineering problems such as tribo-performance of metal matrix composites (MMCs). In the present investigation, ANN approach is used to predict the solid particle erosion wear behaviour of alumina ( $\text{Al}_2\text{O}_3$ ) reinforced of ZA-27 MMCs. Composites of different compositions with  $\text{Al}_2\text{O}_3$  particle (0, 3, 6 and 9 wt %) reinforced in ZA-27 matrix are prepared by stir casting method. Solid particle erosion wear trials are conducted following a well planned experimental schedule based on design-of-experiments (DOE). Significant control factors influencing the wear rate are identified. An ANN approach taking into account training and test procedure is implemented to predict the dependence of wear behaviour on various control factors. The effects of the impact velocity and alumina content on the erosion rate are studied and predicted using this ANN model.

**Keywords:** ZA-27/ $\text{Al}_2\text{O}_3$  MMC, Solid Particle Erosion, Taguchi Method, ANN Simulation.

### 1. INTRODUCTION

In recent years, metal matrix composites (MMCs) have found ever increasing applications as structural materials in various engineering systems. The discontinuously reinforced Al-alloy-MMCs with short fibers or particles of ceramics such as alumina, titanium boride and silicon carbide result in composites of high specific strength and stiffness, suitable for advanced engineering applications, such as in the aerospace and automotive industries [1]. ZA-27 is the high strength performer of the zinc alloys originally developed as a high strength gravity casting alloy and was suitable for thin wall die casting [2]. It is also the lightest alloy and offers excellent bearing and wear resistance properties. Its friction and wear characteristics can compare to the standard bearing material of industrial SAE660 lead-tin bronze [2]. Due to good tribo-mechanical properties, low weight, excellent foundry cast-ability and fluidity, good machining properties, high as-cast strength and hardness, corrosion resistance, low initial cost, energy-saving melting, environmental friendly technology and equivalent or even superior bearing and wear properties, the ZA alloys (mostly ZA-12 and ZA-27) are capable of replacing aluminum cast alloys and bearing bronzes [3]. Besides its use as thin wall castings and in components such as electrical, automotive, industrial and farm equipment, it is increasingly popular in the markets for bearings, wear-resisting parts, valves, pulleys and sheaves [4]. However, major limitations of the alloy system are its interior elevated temperature mechanical and wear

properties, dimensional instability at temperature above  $100^0$  C [5,6]. Hard and thermally stable ceramic reinforcement in ZA alloys contributes to a higher hardness, superior elastic modulus and lower coefficient of thermal expansion of the matrix alloy at ambient temperature [7]. In the case of particulate reinforcement, Cornie et al. and Karni et al. indicated that the presence of SiC particles in ZA alloys leads to a substantial improvement in elastic modulus and hardness [6]. This work investigates and then simulates the erosion wear response of these metal matrix composites filled with  $\text{Al}_2\text{O}_3$  particles using artificial neural networks (ANN) which is inspired by the biological neural system.

### 2. EXPERIMENTAL DETAILS

#### 2.1 Material Preparation

In the present study, ZA-27 alloy had a chemical composition of 25 to 28 wt% Al, 2 to 2.5 wt% Cu, 0.01 to 0.02 wt% Mg and a balance of zinc, in accordance with ASTM B 669-82 ingot specification and was used as the matrix alloy. Alumina ( $\text{Al}_2\text{O}_3$ ) was used as the reinforcement material with particle size of 90-120  $\mu\text{m}$ . A stir casting technique is used to prepare the composite specimens by varying the weight percentage of  $\text{Al}_2\text{O}_3$  from 0 to 9 percent in steps of 3%. After solidification, the specimens are cut in the size of 30mm $\times$ 30mm $\times$ 5mm for erosion test. The surfaces of the samples are polished with sand paper prior to testing.

## 2.2 Erosion wear test

Erosion wear tests are carried out in an Air Jet Erosion test rig as per ASTM G 76. The setup is mainly consists of an air compressor, an air-particle mixing chamber and accelerating chamber. This setup is capable of creating reproducible erosive situation for assessing erosion wear resistance of the prepared composite samples. In the present study, dry silica sand of particle sizes 450µm was used as erodent. Before subjected to the test rig, the samples are cleaned and weighted. Then the samples are eroded in the test rig with different angle of impingement (varies from 45<sup>0</sup> to 90<sup>0</sup>) for 20 min each. After that the sample are again weighted to determine the weight loss. The process is repeated till the erosion rate attains a constant value called *steady state erosion rate*. The erosion rate is defined as the weight loss of the specimen due to erosion divided by the weight of the erodent causing the loss.

## 2.3 Experimental Design

Design-of-experiment is a powerful analysis tool for modeling and analyzing the influence of control factors on performance output. The erosion wear tests on the composites are carried out under different operating conditions considering five parameters, viz., impact velocity, standoff distance, erodent temperature, impingement angle and filler content each at four levels as listed in Table 1 in accordance with Taguchi's L<sub>16</sub> (4<sup>5</sup>) orthogonal array. The impacts of these five parameters are studied using this L<sub>16</sub> array and the tests are conducted as per this experimental design. The experimental observations are further transformed into signal-to-noise (S/N) ratios. The S/N ratio for minimum wear rate can be expressed as "smaller is better" characteristic, calculated as logarithmic transformation of loss function as shown below [8].

$$\frac{S}{N} = -10 \log \frac{1}{n} \sum y^2 \quad (1)$$

Here, 'n' is the number of observations and 'y' is the observed data.

In conventional full factorial experimental design, it would require 4<sup>5</sup> = 1024 runs to study five factors each levels whereas, Taguchi's factorial experiment approach reduces it to only 16 runs offering a great advantage in terms of experimental time, cost and to estimate erosion rate (Er).

Table 1: Control factors and their selected levels

Control Factor	Level				Units
	1	2	3	4	
A: Impact Velocity	35	45	55	65	m/sec
B: Stand-off-Dist.	55	65	75	85	mm
C: Erodent Temp.	35	70	105	140	°C
D: Impingement Angle	45	60	75	90	deg
E: Filler Content	0	3	6	9	wt %

## 3. RESULTS AND DISCUSSION

### 3.1 Wear Analysis Using Experimental Design

The specific wear rates obtained for all the 16 test runs along with the corresponding S/N ratio are presented in Table 2. From this table, the overall mean for the S/N ratio of the wear rate is found to be -43.6992dB. This is done using the software MINITAB 14 specifically used for design of experiment applications. The S/N ratio response analysis shows that among all the factors, impact velocity is the most significant factor followed by filler content while others has less significance on wear rate of the particulate filled composites under this investigation. The effects of individual control factor are assessed by calculating the response and the results of response analysis lead to the conclusion that factor combination of A<sub>1</sub>, B<sub>3</sub>, C<sub>2</sub>, D<sub>4</sub> and E<sub>4</sub> gives the minimum wear rate.

### 3.2 Wear Rate Prediction Using ANN

Wear process is considered as a non-linear problem with respect to its variables: either materials or operating conditions. To obtain minimum wear rate, appropriate combinations of operating parameters have to be planned. In this work, a statistical method, responding to the constraints, is implemented to correlate the operating parameters. This methodology is based on ANN, which is a technique that involves database training to predict input-output evolutions. In the present analysis, the impact velocity, standoff distance, erodent temperature, impingement angle and filler content are taken as the five input parameters. Each of these parameters is characterized by one neuron and consequently the input layer in the ANN structure has five neurons. Different ANN structures with varying number of neurons in the hidden layer are tested at constant cycles, learning rate, error tolerance, momentum parameter, noise factor and slope parameter.

Table 2: Experimental design ( $L_{16}$  orthogonal array) with output and S/N ratio

A	B	C	D	E	Erosion rate	S/N ratio
35	55	35	45	0	145.667	-43.2672
35	65	70	60	3	101.287	-40.1111
35	75	105	75	6	80.924	-38.1615
35	85	140	90	9	72.500	-37.2068
45	55	70	75	9	125.001	-41.9383
45	65	35	90	6	143.693	-43.1487
45	75	140	45	3	182.572	-45.2287
45	85	105	60	0	194.888	-45.7957
55	55	105	90	3	199.287	-45.9896
55	65	140	75	0	221.333	-46.9009
55	75	35	60	9	112.500	-41.0231
55	85	70	45	6	145.615	-43.2641
65	55	140	60	6	249.998	-47.9587
65	65	105	45	9	160.834	-44.1276
65	75	70	90	0	243.333	-47.7240
65	85	35	75	3	232.858	-47.3418

Based on least error criterion, one structure is selected for training of the input-output data. A software package NEURALNET for neural computing using back propagation algorithm is used as the prediction tool for erosion rate of the composite samples under various test conditions. The three-layer neural network having an input layer (I) with four input nodes, a hidden layer (H) with eight neurons and an output layer (O) with one output node used in this work is shown in figure 2.

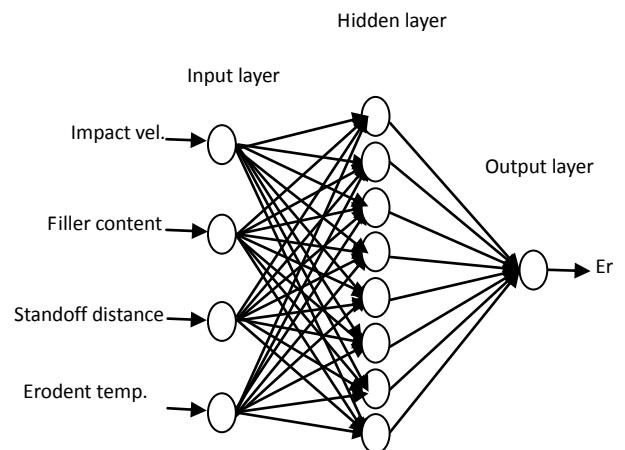


Fig 2. The three-layer neural network

The simulated erosion rates indicating the effect of varying sliding velocity is presented in Fig. 3. It is interesting to note that the erosion rate increases with the increase in impact velocity.

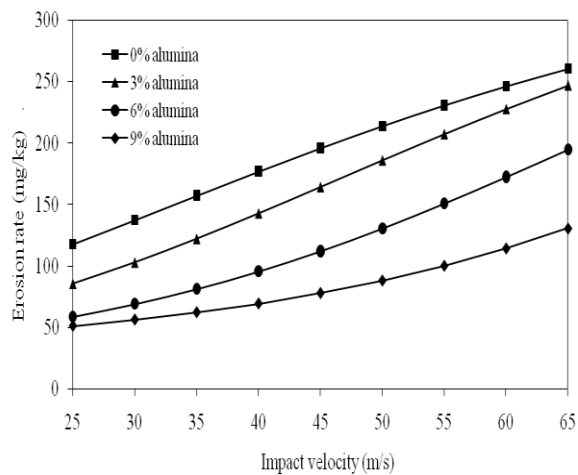


Fig 3. Effect of Al<sub>2</sub>O<sub>3</sub> content on erosion rate at different impact velocities

In Fig. 4 the simulated erosion rates indicating the effect of varying filler content are presented. It is interesting to note that the erosion rate decrease with the increase in filler content.

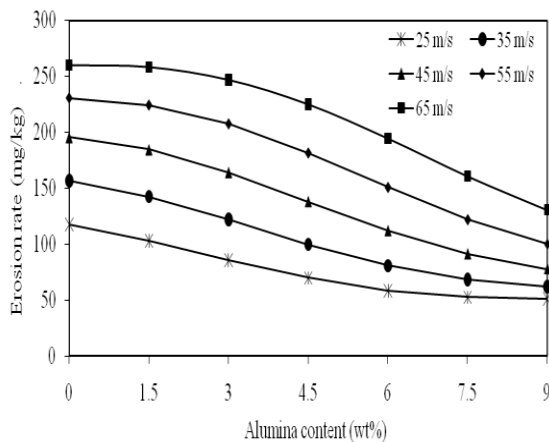


Fig 4. Effect of impact velocities on erosion rate at different Al<sub>2</sub>O<sub>3</sub> content

#### 4. CONCLUSIONS

Erosion wear characteristics of ZA-27 metal matrix composites can be experimented following a design-of-experiment approach. This study also reveals that Al<sub>2</sub>O<sub>3</sub> possesses good filler characteristics as it improves the erosion wear resistance of the composite. ANN technique is successfully applied in this investigation and it is seen that the use of the neural network model to simulate experiments with parametric design strategy is quite effective for prediction of wear response of such composite materials within and beyond the experimental domain.

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#### 6. NOMENCLATURE

Symbol	Meaning
S/N	Signal to noise ratio
n	Number of observations
y	The observed data

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