Artificial neural network approach for the prediction of wear for Al6061 with reinforcements

Rahmath Ulla Baig1, Syed Javed2, Azharuddin Kazi3 and Mohammed Quyam3

1 Department of Industrial Engineering, College of Engineering, King Khalid University, Abha, Saudi Arabia
2 Department of Mechanical Engineering, College of Engineering, King Khalid University, Abha, Saudi Arabia
3 Department of Mechanical Engineering, PES University, South Campus, Bangalore, India

E-mail: syedjavedme@gmail.com

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Abstract

In the prospect of finding a lightweight and wear-resistant materials, researchers have considered aluminium-based metal matrix composites (MMC), as aluminium has a wide variety of applications but possesses low wear resistance properties. To enhance the wear resistance of aluminium alloys, ceramic particles are reinforced. In this endeavour, commercially available aluminium alloy is reinforced with 2, 4 and 6 wt% of silicon carbide (SiC) and Vanadium pentoxide (V2O5) powder to improve its wear resistance. The intensity of reinforcement in the matrix was uniform, and the Scanning Electron Microscope image showed the grain refinement and grain boundary of the MMC’s. Wear tests were performed for L16 array set, uncertainty analysis of wear measurement is evaluated, and data were used to develop Artificial Neural Network (ANN) model. The efficient ANN model with a regression coefficient of 0.999 was used to make predictions for remaining sets. Experimental and predicted wear results were analysed; it is observed that higher wt% reinforcement of V2O5 increased wear resistance of aluminium compared to SiC. The methodology adapted using ANN for prediction of wear using meagre experimentation, will lay a path for tribologists to predict the wear of novel metal matrix composites in their endeavour of finding wear-resistant materials.

1. Introduction

With the objective of finding lightweight & wear-resistant materials in automotive, aerospace and chemical industries: Aluminium based Metal Matrix Composites (MMC) are considered pivotal. These MMC’s have excellent mechanical properties with meagre wear resistance. In the quest to enhance wear characteristics, researchers have reinforced with hard particles of TiO2, TiB2, ZrB2 and nano-composite of Al2O3 [1–4]. The most sought aluminium alloy for general applications is Al6061, which requires superior wear behaviour. Researchers have investigated wear behaviour of Al6061 with a reinforcement of Ni-P coated Si3N4, Al2O3, fibre & Sic, rock dust, Sic, Al4C3, B4C and TiB2 [5–15]; The experimentation resulted in an increase of wear characteristics.

The studies of in situ aluminium cast composites with particulate composites are characterised by homogenous distribution and enhanced wear properties [2, 3, 16–19]. The fascinating dominance of nanomaterials with superior mechanical and physical properties is noticed [20–23]: exhibiting enhanced wear resistance.

Experimental investigations on wear behaviour of MMC’s are carried out by almost all the researchers, but theoretical predictions are meagre. Theoretical predictions by modifying Archard’s wear model were reported by Yang [24]. A meticulous prediction of wear characteristics using Artificial Neural Network (ANN) was studied [24–27] and found to be effective, as the great ability of ANN is to predict the output for an unknown input presented to it. ANN is a nonlinear technique based on the configuration of the human brain. In ANN
predictions, the meagre experimental data is used to train the neural network; the trained network exhibits the capability of finding predictions for a new set of inputs.

Vanadium Pentoxide ($V_2O_5$) is a lubricious oxide and is used at elevated temperature as a solid lubricant; also the addition of Silicon carbide (SiC) has the benefit of enhancing the hardness and reduced wear [28]. In the current investigation, wear behaviour of Al6061 reinforced with fly ash (2 wt%) & different percentages of $V_2O_5$ and SiC in enhancing wear resistance is effectuated. Fly ash is added for both specimens to improve the wettability of the casting, and it is found to reduce wear [29]. Design of experiments was carried out using Taguchi technique. The meagre data obtained during experimentation were used to develop the model. The ANN modelling was carried out in detail with the variation of the number of neurons in the hidden layer, stopping criteria, the data presented to the model and also with various transfer function and algorithms. The developed model predicted wear for the remaining sets.

2. Materials and methods

2.1. Materials
Aluminium 6061 is used as base material and two different set of specimens were prepared: type 1 - Al6061 + $V_2O_5$ (2, 4 & 6 wt%) and type 2 - Al6061 + SiC (2, 4 & 6 wt%). Fly ash (2 wt%) is added for both specimens.

2.2. Specimen preparation
Commercially available aluminium with 95.90 wt% is used as a matrix and was heated in a crucible for one hour for oxidising the surface using a muffle furnace, and powdered fly ash is added to it. For preparing type 1 specimens, $V_2O_5$ powder was directly added to the molten aluminium because of relative solubility of $V_2O_5$. Aluminium and SiC were preheated at a temperature of 450 and 1100 °C respectively in a different crucible and mixed to form type 2 specimen. In both types, reinforcement was stirred from 250–300 rpm with the help of a mechanical stirrer. Finally, the molten liquid was poured into the metal mould and castings were obtained. The castings obtained were not of required dimensions. Hence, the specimens were turned on a lathe to ASTM dimensions accurately for the wear test.

2.3. Characterisation of specimens
Scanning Electron Microscope (SEM) with Energy Dispersive x-ray Spectroscopy (EDS) was used for the characterisation of the extent of SiC and $V_2O_5$ particles distribution in the mechanically prepared samples. As seen in the SEM micrographs, figures 1(a)–(c) of Al-SiC composites the SiC particles were more agglomerated in the matrix than the Al particles which are due to their smaller size. The SEM images also illustrate the effect of grain boundary formation within the matrix; however, some deformations were seen because of the larger dendrites which were broken down. As SiC powder consists of particles with irregular shapes but close to spherical which were observed at a working distance of 10.3 mm. Compared to the SiC particles, the $V_2O_5$ particles were more uniformly distributed in the aluminium matrix at a working distance of 9.9 mm as seen in the figures 1(d)–(f). Also, there were no cracks as observed in the Al-SiC images. The irregular shapes of the $V_2O_5$ were seen with the small-sized fly ash particulate of size less than 10 μm, and the grains appeared were more refined which account for proper miscibility of the reinforcement.

The SEM analysis for the commercial aluminium alloy confirms some alloying element like Fe, Si and SiO₂, which are dispersed into the aluminium shown as a small granular structure in the metal. Compared to the MMC’s SEM image, this image is more settled with less agglomerated particles as seen in figures 2(a)–(c). The EDS test confirms the composition of the metal used for the preparation of the MMC castings with the highest peak for aluminium (95.90 wt%) and traces of Iron (Fe), silicon (Si) and Silicon-dioxide (SiO₂) in the metal as tabulated in table 1.

The x-ray diffraction measurements were carried out with the help of an advance Rigaku model using x-ray radiation at an accelerating voltage of 40 kV and a current of 20 mA. The samples were scanned with a scan rate of 2° min⁻¹. XRD graphs, thereby, confirm the presence of reinforcement in the matrix. The XRD patterns obtained for Al-SiC with high peaks at 38.5° or 44.8° showed the corresponding intensity to be 800 counts per second (cps) for 2% SiC reinforced aluminium. For 4% Al-SiC the peaks as at 38.5° or 44.8° and corresponding intensity to be 2500 cps and 6% Al-SiC the peaks were at 38.5° or 44.37° which showed the corresponding intensity to be around 2500 cps (figures 3(a)–(c)). Similarly, the x-ray diffraction pattern graphs for the Al-$V_2O_5$ for 2, 4 and 6 wt% of $V_2O_5$ are shown in figures 3(d)–(f). There is a slight phase shift of 0.1° on increasing the mass percentage of the $V_2O_5$ powder in the matrix.
2.4. Experimentation

Set of experimentation that describes the variation of information under conditions that are meant to reflect variation, i.e., the design of experiment using Taguchi approach was carried out. Wear test was performed on a pin-on-disc wear testing machine.

2.4.1. Design of experiments

The experiments were designed to analyse the influence of parameters on Specific Wear rate (SWR) of Al6061 + SiC and Al6061 + V2O5 based on Taguchi Design of Experiments (DOE) wherein the experimental results are converted into Signal-to-Noise ratio (S/N ratio), which is an alogarithmic transformation of quality loss function [30]. The parameters for this study were considered based on the literature, Speed (A), Load (B) and Wt % of reinforcement (C), which were depicted in table 2. Here, three factors with four levels were selected for
the Taguchi design of experiments. L16 orthogonal array was opted based on the number of factors and their levels, wherein 16 experiments were conducted while conventional full factorial experiment design would require $4^3 = 64$ experiments. Smaller the better characteristic was chosen to evaluate $S/N$ ratio. Smaller the

Figure 2. SEM image for the Al base alloy at a zoom of: (a) 25 k, (b) 10 k, (c) 5 k.
Table 1. Constituents and their compositions of the Aluminium sample used as a matrix.

| Composition | Weight % | Atomic % |
|-------------|----------|----------|
| SiO₂        | 2.64     | 2.33     |
| Al₂O₃       | 95.90    | 95.82    |
| Fe          | 0.90     | 0.41     |
| Si          | 0.56     | 0.44     |

Figure 3. XRD pattern of Al-SiC showing its presence at 38.5°, 44.8°, 65° and 78° for (a) 2 wt%, (b) 4 wt%, (c) 6 wt% and XRD pattern of Al-V₂O₅ for (d) 2 wt%, (e) 4 wt%, (f) 6 wt%.

Table 2. Design of experiment parameters, control factors, and their levels.

| Design of experiments | Levels |
|----------------------|--------|
| Parameter            | I      | II     | III    | IV     |
| Speed (RPM)           | (A) 500| 600    | 700    | 800    |
| Load (N)              | (B) 9.81| 19.62  | 29.43  | 39.24  |
| Reinforcement (wt%)   | (C) 0  | 2      | 4      | 6      |
better characteristic is considered for minimum wear rate, which is expected to be as low as possible. Analysis of variance was performed to identify the statistical significance parameter.

2.4.2. Analysis of Taguchi’s design of experiment

S/N ratio for specific wear rate (SWR) was determined using Minitab. Table 3 shows the L16 orthogonal array with the response as SWR in column 6 and 8 for Al6061 + SiC and Al6061 + V2O5 respectively. S/N ratio response shown in table 3 is calculated for each level of control factors to determine the most influential control factor.

| Trail no | Speed (RPM) | Load (N) | wt% of reinforcement | Specific wear rate (mm³/N-m) | S/N ratio | Specific wear rate (mm³/N-m) | S/N ratio |
|----------|-------------|----------|-----------------------|------------------------------|-----------|------------------------------|-----------|
| 1        | 500         | 10       | 0                     | 8.3783E-05                  | 81.54     | 8.3783E-05                  | 81.537    |
| 2        | 500         | 20       | 2                     | 7.7374E-05                  | 82.23     | 9.8432E-05                  | 80.137    |
| 3        | 500         | 30       | 4                     | 2.7564E-04                  | 71.19     | 1.0729E-04                  | 79.389    |
| 4        | 500         | 40       | 6                     | 8.5736E-03                  | 41.56     | 5.2217E-05                  | 85.644    |
| 5        | 600         | 10       | 2                     | 1.1706E-04                  | 78.63     | 4.6803E-05                  | 86.595    |
| 6        | 600         | 20       | 0                     | 1.4095E-03                  | 57.04     | 1.4059E-03                  | 57.041    |
| 7        | 600         | 30       | 6                     | 1.3169E-04                  | 77.61     | 2.0856E-03                  | 53.615    |
| 8        | 600         | 40       | 4                     | 6.6185E-04                  | 63.58     | 2.3988E-03                  | 52.400    |
| 9        | 700         | 10       | 4                     | 1.3995E-04                  | 77.08     | 6.6541E-04                  | 63.538    |
| 10       | 700         | 20       | 6                     | 2.0417E-04                  | 73.80     | 2.6949E-03                  | 51.389    |
| 11       | 700         | 30       | 0                     | 9.6606E-03                  | 40.30     | 9.6606E-03                  | 40.300    |
| 12       | 700         | 40       | 2                     | 2.1731E-02                  | 33.24     | 1.7852E-03                  | 54.966    |
| 13       | 800         | 10       | 6                     | 1.3943E-04                  | 77.11     | 1.5208E-04                  | 76.359    |
| 14       | 800         | 20       | 4                     | 7.5223E-04                  | 62.47     | 1.9560E-04                  | 74.133    |
| 15       | 800         | 30       | 2                     | 4.8873E-04                  | 66.22     | 2.7058E-03                  | 51.354    |
| 16       | 800         | 40       | 0                     | 1.9183E-02                  | 34.34     | 1.9183E-02                  | 34.342    |

Table 3. L16 Orthogonal array with S/N ratio.

| Al6061 + SiC | Control factors |
|--------------|-----------------|
| level        | A    | B    | C    |
| 1            | 69.13 | 78.59 | 53.30 |
| 2            | 69.22 | 68.89 | 65.08 |
| 3            | 56.11 | 63.83 | 68.58 |
| 4            | 60.04 | 43.18 | 67.32 |
| δ            | 13.11 | 35.41 | 15.28 |
| Rank         | 3     | 1    | 2    |

Table 4. Control factors for Al6061 + SiC.

| Al6061 + V2O5 | Control factors |
|--------------|-----------------|
| level        | A    | B    | C    |
| 1            | 81.68 | 73.97 | 53.30 |
| 2            | 62.41 | 68.71 | 68.26 |
| 3            | 52.55 | 56.16 | 64.33 |
| 4            | 59.05 | 56.84 | 69.79 |
| δ            | 29.13 | 17.81 | 16.48 |
| Rank         | 1     | 2    | 3    |

Table 5. Control factors for Al6061 + V2O5.

better characteristic is considered for minimum wear rate, which is expected to be as low as possible. Analysis of variance was performed to identify the statistical significance parameter.

2.4.2. Analysis of Taguchi’s design of experiment

S/N ratio for specific wear rate (SWR) was determined using Minitab. Table 3 shows the L16 orthogonal array with the response as SWR in column 6 and 8 for Al6061 + SiC and Al6061 + V2O5 respectively. S/N ratio response shown in table 3 is calculated for each level of control factors to determine the most influential control factor.

Delta (δ) value shown in tables 4 and 5 is calculated by taking the difference between maximum and minimum S/N ratio for an individual factor. Sample calculations for tables 3–5 were presented in appendix. The higher Delta value denotes the significant influence of a corresponding control factor. It is profound from table 4 that the significant influence is demonstrated by factor B ‘load’ followed by C ‘wt% of reinforcement’ and factor
A ‘speed’ for Al6061 + SiC. It is also observed from table 5 that the significant influence is demonstrated by factor A ‘speed’ followed by factor B ‘load’ and C ‘wt% of reinforcement’ for Al6061 + V2O5.

Analysis of the S/N ratio by Taguchi technique uses a conceptual approach by plotting the special effects and making visual implications of other influential control factors. The optimal levels of each control factor can be identified by considering the influence of each control factor on SWR graphically as shown in the figures 4 and 5 for Al6061 + SiC and Al6061 + V2O5 respectively.

Figure 4 reveals the variation in S/N ratio for a change in the control factors from one level to the other level. Figure 4 insinuates the optimum arrangement of control factors to minimise the SWR in association with A2B1C3 levels of control factors for Al6061 + SiC. From figure 5 the optimum arrangement of control factors to minimise the SWR in association with A1B1C4 levels of control factors is shown for Al6061 + V2O5.

2.4.3. ANOVA and effects of control factors on specific wear rate

Analysis of variance (ANOVA) is performed on data as mentioned by Panwar and Chauhan [31] to find the statistical importance of control factors on SWR. Tables 6 and 7 depicts the ANOVA results for SWR for Al 6061 + SiC and Al 6061 + V2O5 respectively.

The percentage contribution of the control factors on the performance output is presented in table 6, and it is evident that load (B) (P = 53.12%) has a significant effect on SWR while speed (A) (P = 16.8%) and wt% of reinforcement (C) (P = 16.49%) have less significance on SWR for Al6061 + SiC. Similarly, for Al6061 + V2O5, wt% of reinforcement (C) (P = 34.07%) has a significant effect on SWR while the speed (A) (P = 18.69%) and load (B) (P = 20.41%) have less significance on SWR.
2.5. Percentage uncertainty analysis of SWR

In the current research work, wear test is conducted on pin-on-wear test apparatus. Specimen weights were measured to pre-and post-wear tests. Evaluation of weights and density involves uncertainties as weighing instrument hold fix errors. The errors in measured parameters propagate to the evaluation of SWR. Hence, uncertainty in the measurement of SWR has to be done to ascertain the validity of experimental results. The uncertainty in SWR measurement is evaluated as per the procedure presented by Javed et al 2017 [32]. The highest uncertainty in SWR measurement is found to be 4.81%. A typical sample calculation is mention below:

- Specimen and testing conditions:
  - Reinforcement: 2 wt% SiC
  - Load (L): 39.24 N
  - Speed (N): 700 RPM
  - Time (T): 10 min
  - Radius (R): 0.035 m
  - Density (δ): 2.68 * 10^{-3} ± 0.1 * 10^{-3} gm mm^{-3}

- Difference between pre-and post-weight (W): 0.023 ± 0.0007 gm

\[
\text{Sliding distance} (S) = \frac{2\pi NTR}{60} = 1539.38 \text{ m}
\]  

- Uncertainty in pre-and post-test volume difference of specimen (ΔV):

\[
\text{Volume difference} (V) = \frac{W}{\delta} = \frac{0.023}{2.68 \times 10^{-3}} = 8.582 \text{ mm}^3
\]

\[
\Delta V = \sqrt{\left(\frac{\partial V}{\partial W} \Delta W\right)^2 + \left(\frac{\partial V}{\partial \delta} \Delta \delta\right)^2} = 0.41325 \text{ mm}^3
\]

- Percentage uncertainty in SWR (% ΔSWR):

\[
\text{SWR} = \frac{V}{S \times L} = 1.4207 \times 10^{-4} \text{ mm}^3 \text{ Nm}^{-1}
\]

\[
\text{Uncertainty in SWR} (\Delta \text{SWR}) = \frac{1}{S \times L} \times \Delta V = 6.8413 \times 10^{-6}
\]
cases were employed as inputs and targets respectively to develop the ANN model. The model is trained with 22 reinforcement. Henceforth, the experimental data consists of 32 sets. The inputs and outcomes of 32 experimentation, 16 sets of wear test were conducted, data is split with respect to wt% percentage of two.

3.1. ANN results

2.6. Artificial neural network model
Artificial Neural Network (ANN) aids in developing prediction models; a simple network comprises of a set of input nodes (in input layer), output nodes (in the output layer), weights connecting the layers and bias. The functioning of ANN is similar to the human brain; receives an input signal at input nodes, weights the signal before passing onto the output nodes. The summation of signals received at the output node is subjected to an activation function; the resulting signal is the prediction for a given set of inputs. The predictions of the network are compared with the targets (experiment outcomes); the error is feedback, and the weights & bias are modified, the process is repeated till error falls within the acceptable range. Such a network is known as a feedforward-backpropagation neural network. Obtaining the predictions by modifying the weights and bias is known as training the network; various training algorithms can be employed to generate weights and bias. Depending on the requirement, hidden layers are included to develop an efficient prediction model. Literature proves that in general one hidden layer is sufficient to generate accurate predictions [33].

2.6.1. Development of ANN model
The proficiency of the network model depends on data sets employed, training algorithm, transfer function and network configuration. In the current research work, uncertainty in SWR measurement is found to be 4.81%, the experiment data with such a low uncertainty is valid to be used to train the network. Standard training algorithms employed to obtain prediction model are Levenberge Marquardt (trainlm), Gradient descent with adaptive learning rate (traingda), Gradient descent with momentum and adaptive learning rate backpropagation (traingdx), Resilient backpropagation (trainrp), Conjugate gradient backpropagation with Fletcher–Reeves updates (traincfg), Scaled conjugate gradient backpropagation with Fletcher–Reeves (traincfg) and Broyden, Fletcher, Goldfarb, & Shanno (BFGS) quasi-Newton backpropagation (trainbfg). The three transfer functions tested are Hyperbolic tangent sigmoid (tansig), Logarithmic sigmoid (logsig) and Linear (purelin). As there is no standard rule to define optimum network configuration, the number of neurons in the hidden layer are varied from 1–15 to design the best network configuration for the single hidden layer.

The network under consideration comprises of four input nodes which receive reinforcement percentages of V2O5 & SiC, load and speed of SWR test. The signal at the output nodes gives the SWR predictions of the model. The network configuration of the current model is shown in figure 6. The reinforcement percentages of V2O5 & SiC, load, speed of SWR test and SWR are considered as input data to develop the ANN model. The data is normalised between −1 and +1 before feeding to develop the model. Also, the data is randomly discretised into three segments, i.e. training set (70%), a validation set (15%) and testing set (15%) [34]. The following standard benchmark statistical indicator employed to evaluate the performance of the model.

\[
\text{Regression Coefficient (R)} = \sqrt{1 - \frac{\sum_{i=1}^{n}(T_i - O_i)^2}{\sum_{i=1}^{n} O_i^2}}
\]

\[
\text{Mean Squared Error (MSE)} = \frac{1}{n} \sum_{i=1}^{n} (T_i - O_i)^2
\]

\[
\text{Mean Absolute Percentage Error (MAPE)} = \frac{100}{n} \sum_{i=1}^{n} \left| \frac{T_i - O_i}{T_i} \right| \%
\]

Where,

- \(n\) number of trial cases
- \(O_i\) output for ith trial case
- \(T_i\) target for ith trial case

3. Results and discussion

3.1. ANN results
The development of the ANN model is carried out on a MATLAB platform. Adopting the Taguchi design of experimentation, 16 sets of wear test were conducted, data is split with respect to wt% percentage of two reinforcement. Henceforth, the experimental data consists of 32 sets. The inputs and outcomes of 32 experiment sets were employed as inputs and targets respectively to develop the ANN model. The model is trained with 22 cases (i.e. 70% of data) whereas, five cases (i.e. 15% of data) each were deployed for validation and testing the model.

\[
\% \Delta \text{SWR} = \frac{\Delta \text{SWR}}{\text{SWR}} \times 100 = 4.81\% \tag{6}
\]
The benchmark indicators of models for each combination of training algorithm and activation function is portrayed in Table 8. The figures 7–9 depict that model with trainlm is the best training algorithm for the current research work. The network structure of 4–8–2 with logsig-tansig activation functions between input-hidden and hidden-output layers yields overall regression of 0.9993, overall MSE of 2.02E-12 and overall MAPE of 0.8394%, falls under acceptable range (Regression $\approx 1$, MSE $\approx 0$ and MAPE $\leq 5\%$) [33]. Regression analysis and comparison plot of 15% testing cases were depicted in figures 10–11.

3.2. Effect of load on specific wear rate
SWR prediction of 96 cases for which experimentation was not conducted is made with the developed ANN model. As seen from the figure 12, as load increases with increase in speed pure aluminium wear rate increases. The effect of $\text{V}_2\text{O}_5$ is evident, which reduces the wear rate compared to pure aluminium. From figure 13, the effect of the addition of SiC is witnessed at lower load & speed; but as load and speed increase the wear rate of SiC-based MMC is same as that of aluminium. The objective of increasing wear resistance of aluminium is effectuated with $\text{V}_2\text{O}_5$.

3.3. Effect of speed on specific wear rate
Effect of speed on wt% reinforcement of $\text{V}_2\text{O}_5$ and SiC were studied from figures 14–15. As the speed increases wear increases with the increase in load, the effect of lower wt% addition of $\text{V}_2\text{O}_5$ is evident at lower speeds, but at a higher speed, only 6 wt% of $\text{V}_2\text{O}_5$ has prominent influence in reducing wear. In case of addition of SiC, at lower speed SiC is competent, but at higher speed, there is no effect of addition SiC to aluminium. Hence from the study of the effect of speed on wt% reinforcement of $\text{V}_2\text{O}_5$ and SiC, $\text{V}_2\text{O}_5$ is an apt contender to reduce wear. Compared to SiC particles, $\text{V}_2\text{O}_5$ particles are uniformly distributed in MMC.

3.4. Confirmation test
The combination of control factors and their associated levels indicate their significance in minimising the SWR by analytical method. For confirmation, the test was conducted by considering the combination of the control factors and their associated levels to validate the statistical analysis. Table 9 shows the performance or output of
the predicted specific wear rate for both ANN predictions and experimental method. It was found that when the actual runs are performed on the above control factor settings, an error was found between the ANN predictions and the experimental values.

**Figure 7.** Comparison plot of regressions for various training algorithms.

**Table 8.** Benchmark indices in de-normalised form for wear rate predictions with different training algorithms and transfer function combinations.
3.5. Comparative study
The results obtained with the developed ANN model were compared with similar studies in the literature. Singla et al. [35] conducted wear test of Al6061 reinforced SiC, Al2O3 and Red Mud at a load of 20 N. Singla et al. observed
that the wear rate increases initially and then gradually decreases with the increase of sliding distance. At 20 N load the wear test speed is varied from 500 to 800 RPM, i.e. sliding distance is increased from 1099.55 to 1759.29 m; from figures 12(b) and 13(b), it is noted that wear rate initially increases and then decreases as sliding distance increases. Also, Singla et al noted that wear rate decreases with increase in reinforcement weight percentage. From figures 12 and 13, it is observed that higher wt % of reinforcement has the lowest wear rate. This is to conclude that the predictions were analogous to the similar experimental work mentioned in literature.

Figure 11. Comparison of experiment and predicted SWR for 15% test cases.

Figure 12. Effect of load on wt% reinforcement of V2O5 at: (a) 10 N, (b) 20 N, (c) 30 N, (d) 40 N.
4. Conclusions

Aluminium was reinforced with V$_2$O$_5$ & SiC and wear test was performed by using pin-on-disc wear testing equipment. Experiments were performed using the Taguchi design of experiment. Uncertainty of experimentation was performed, and it is found to be 4.81%. ANN model was developed by training with data obtained from the experimentation and trained ANN model was used to predict wear for which

Figure 13. Effect of load on wt% reinforcement of SiC at: (a) 10 N, (b) 20 N, (c) 30 N, (d) 40 N.

Figure 14. Effect of speed on wt% reinforcement of V$_2$O$_5$ at: (a) 500 RPM, (b) 600 RPM, (c) 700 RPM, (d) 800 RPM.
experimentation was not carried out. ANN model was tried with various transfer function and training algorithm. ANN predictions were accurate with an overall regression of 0.9993. The addition of V2O5 has increased the wear resistance of aluminium MMC.

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Data statement

The raw data required to reproduce these findings are available to download from [https://data.mendeley.com/datasets/nym46s5vv7/draft?a=40d27453-1342-495a-9948-e5e51fade0d9].

Conflict of interest

The authors have no conflict of interest to declare.

Appendix

A.1. Sample calculation for S/N ratio in table 3

For Trail no-1: Specific Wear Rate for Al6061 + SiC: 8.3783E-05

| Table 9. Results of the confirmation test. |
|-------------------------------------------|
| Optimal control factors obtained from S/N plots | The expected response obtained from ANN prediction for SWR | Experimental response for SWR | % Absolute Error |
| A2B1C3 for (Al6061 + SiC) | 6.0705E-5 | 5.8946E-05 | 2.98 |
| A1B1C4 for (Al6061 + V2O5) | 7.2561E-5 | 7.5403E-05 | 3.76 |

Figure 15. Effect of speed on wt% reinforcement of SiC at: (a) 500 RPM, (b) 600 RPM, (c) 700 RPM, (d) 800 RPM.
S/N ratio is calculated based on ‘Smaller is better’

\[
\frac{S}{N} = -10 \times \log \left( \frac{\Sigma(Y^2)}{n} \right)
\]

\[
\frac{S}{N} = -10 \times \log \left( \frac{\Sigma(0.000083783)^2}{1} \right) = 81.54
\]

A.2. Sample calculation for control factors for Al6061 + SiC in table 4

For Factor B (Load) and Level 3 (30 N):

Control Factor = Mean of \( S/N \) ratio values of Factor B (Load) for level 3 (30 N) from table 3

\[
\text{Control Factor} = \frac{(71.19 + 77.61 + 40.30 + 66.22)}{4} = 63.83
\]

A.3. Delta (\( \delta \)) calculation for control factors for Al6061 + SiC in table 4

For control factor A:

Delta (\( \delta \)) = difference between maximum and minimum for an individual factor

\[
\text{Delta}(\delta) = 69.22 - 56.11 = 13.11
\]

A.4. Sample calculation for control factors for Al6061 + \( V_2O_5 \) in table 5

For Factor C (wt% of reinforcement) and Level-4 (40 N):

Control Factor = Mean of \( S/N \) ratio values of factor C for level 4 table 3

\[
\text{Control Factor} = \frac{(85.644 + 53.615 + 63.538 + 76.359)}{4} = 69.789
\]

A.5. Delta (\( \delta \)) calculation for control factors for Al6061 + \( V_2O_5 \) in table 5

For control factor B:

Delta (\( \delta \)) = difference between maximum and minimum for an individual factor

\[
\text{Delta}(\delta) = 73.97 - 56.16 = 17.81
\]

ORCID iDs

Syed Javed © https://orcid.org/0000-0001-6035-3447

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