OPTIMIZING FRICTION AND WEAR IN GRAPHENE OXIDE-REINFORCED ALUMINUM METAL MATRIX COMPOSITES USING NEURAL NETWORKS

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Abstract

This research investigates the effect of adding graphene oxide to Al 6061 alloy to improve the wear and friction characteristics of the resulting metal matrix composite. Three different weight percentages of graphene oxide (1%, 3%, and 5%) were supplementary to the alloy using the stir casting process, and the resulting materials were tested for rate of wear and its coefficient. The investigational outcomes were then augmented using signal-to-noise ratio investigation to identify the optimal combination of input parameters. Additionally, a regression analysis and an artificial neural network (ANN) were used to forecast the outputs. The ANN model achieved an accuracy of 99.87% in predicting the responses. The results presented that the adding of graphene oxide improved the wear resistance and reduced the friction coefficient of the composite, with the optimal combination of input parameters being a composition of 5%, a load of 40 N, a speed of 180 rpm, and a distance of sliding of 35 m. The regression analysis and ANN were both able to accurately predict the responses, with the ANN performing slightly better than the regression analysis. Overall, this research demonstrates the potential for using graphene oxide as a reinforcement material to recover the resistance and wear possessions of metal matrix composites, and highlights the usefulness of machine learning techniques in predicting and optimizing these properties.

Keywords: Artificial Neural Network, Linear regression, Optimisation, Taguchi

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1. Introduction

Aluminum metal matrix composites (AMMCs) have attracted significant interest in recent years as they possess superior mechanical, physical, and tribological properties than the base materials. Researchers have explored different techniques to enhance the properties of AMMCs including the incorporation of various reinforcement materials [1]. Graphene oxide (GO) has shown great potential as a reinforcement material due to its high mechanical strength, thermal conductivity, and exceptional tribological properties. Therefore, this research purposes to examine the belongings of GO on the wear resistance of Al 6061 matrix composites. Previous studies have shown that the incorporation of graphene or graphene oxide into aluminum composites can lead to an development in the mechanical properties of the composite material. In a study conducted [2] graphene oxide was incorporated into an Al 7075 matrix, and the consequences showed a significant increase in the hardness, ductile strength, and toughness of the composite material. The improved characteristics were attributed to the similar spreading of graphene oxide in the matrix and the formation of a strong interfacial promise among the matrix and the support material.

Additionally, several studies have investigated the tribological properties of graphene-based composites. In a study [3], graphene oxide was incorporated into an Al 6061 matrix using powder metallurgy techniques, and the fallouts presented a decrease in the rate of wear of material and its coefficient of the composite material. The improved tribological properties were attributed to the formation of a allocation film on the contact surface, which acts as a protective layer against wear and reduces the frictional force. Furthermore, the mechanical character properties of graphene-based composites have been investigated under different sliding conditions. In a study [4] graphene oxide was incorporated into an Al 6063 matrix, and the properties of the composite material were investigated under normal and oiled sliding conditions. The results showed a minimising rate of wear and associated coefficient of the composite material under both dry and lubricated sliding conditions. The improved tribological properties were attributed to the creation of a self-lubricating layer on the contact surface.

Several techniques have been used to prepare graphene oxide-reinforced aluminum composites, including powder metallurgy, casting, and hot-pressing techniques. In a study by [5] graphene oxide was incorporated into an Al 6061 matrix using powder metallurgy techniques, and the tribological properties of the composite material were examined. The consequences exhibited a decrease in the wear of the composite material, and the improved tribological possessions were attributed to the homogeneous dispersion of graphene oxide in the matrix. Additionally, Taguchi method and ANN have been employed to optimize the tribological properties of graphene oxide-reinforced aluminum composites. In a study [6] the Taguchi method was used to optimize the tribological properties of graphene oxide-reinforced Al 7075 matrix composites. The fallouts presented that the optimal combination of input parameters significantly reduced the wear of the composite material. Similarly, in a study [7], [8] an ANN model was developed to predict the tribological properties of graphene oxide-reinforced Al 6061 matrix composites. The results showed that the developed ANN model was highly accurate in predicting the composite material experimental outcomes [9], [10]. In this research, an attempt was made to optimize the friction and wear of aluminium metal matrix composites reinforced with graphene oxide particles. The aim was to recover the mechanical possessions of the composite material, particularly in terms of wear resistance and friction behaviour. Different percentages of graphene oxide particles were added to the aluminium matrix using the stir casting process, and the resulting composites were subjected to wear testing using a pin-on-disc apparatus. The fallouts were analysed using SNR ratio analysis, regression analysis, and artificial neural networks to identify the optimal input parameters and predict the responses with high accuracy.

2. Material preparation

In this research, the stir casting process has been used to fabricate the metal matrix composites. Stir casting is a widely used method for the construction of metal matrix composites, where the reinforcement material is added to the molten metal and stirred to ensure uniform dispersion. The stir casting process is cost-effective, simple, and easy to operate, making it a popular choice for the fabrication of MMCs. The Al 6061 alloy is extensively castoff in the aircraft, locomotive, and maritime productions due to its strength, excellent resistance to corrosion, and excellent machinability. The addition of GO to the Al 6061 alloy can further enhance its mechanical and tribological properties. The GO used in this research has a particle size of 100 microns. GO is a 2-D material that consists of a single layer of carbon atoms settled in a honeycomb lattice assembly. It has excellent mechanical, thermal, and electrical properties, making it an ideal reinforcement material for MMCs. The fabrication of the MMCs was carried out using a stir casting furnace. The Al 6061 alloy was heated to a temperature of 750 degrees Celsius [11], [12], and the GO of different weight percentages (1%, 3%, and 5%) was added to the molten metal. The mixture was then stirred for 45 minutes to ensure uniform dispersion of the GO particles in the Al 6061 alloy. The combination was then dispensed into the mould and permitted to cool in the atmosphere. The moulds were then machined to the required dimensions for the tribological testing.

3. Experimental design

After the MMCs were prepared using the stir casting process, the moulds were machined to obtain 27 specimens based on the Taguchi L27 array design. The experimental design consisted of three input parameters, namely composition (C), load (l), Rotational speed of the disc (Rs) and distance of sliding (Ds). The composition was varied at three levels, 1%, 3%, and 5%, while the load and distance of sliding were varied at three levels each. The experimental design matrix and the results of rate of wear (Wr) and friction coefficient (Fc) are shown in Table 1.

To optimize the output parameter of the MMCs, the results were analysed using S/N ratio analysis. The S/N ratio is a arithmetical technique used to determine the quality of a process or product. In the case of tribological testing, the S/N ratio represents the ratio of the signal, which is the response (in this case, wear rate or friction coefficient), to the noise, which is the experimental error or variability. The S/N ratio is calculated using different formulas depending on whether the objective is to minimize or maximize the response. In this research, the objective was to minimize the Wr and Cf.

The S/N ratio for the wear rate and friction coefficient were calculated using the following formulas [13]:

For minimizing the wear rate:

S/N ratio = -10 log10 (1/n Σ(1/Wr)^2)

For minimizing the friction coefficient:

S/N ratio = -10 log10 (1/n Σ(1/Fc)^2)

where n is the number of experiments, and Wr and Fc are the outcomes.

The S/N ratios were then analysed to identify the significant factors and their levels that affect the Wr and Fc of the MMCs. The significant factors and their optimal levels were determined using the response graph and the desirability function.

2. Result and discussion

The pin on disc wear examining device is a widely utilized method for evaluating the wear characteristics of materials. In this research, the same wear testing apparatus was cast-off to examine the wear behaviour of the developed aluminium-graphene oxide (Al-GO) metal matrix composites (MMCs). For this purpose, EN 31 steel was used as the rotating disc, and the developed composite of varying composition was allowed to slide over the pin. Table 1 shows the experimental results obtained from the 27 experiments conducted on the Al-GO MMCs. The experiments were designed based on the Taguchi L27 array, and the three input parameters, namely composition (C), load (l), and distance of sliding (Ds), were varied at three levels each. The wear rate (Wr) and friction coefficient (Fc) were the responses that were measured for each experiment. The results obtained from the experiments showed that the Wr and Fc of the Al-GO MMCs were influenced by the composition, load, and distance of sliding. The wear rate decreased with increasing graphene oxide content and decreased load and sliding distance. The friction coefficient also decreased with increasing graphene oxide content and decreased load but increased with sliding distance. The data obtained from the experiments were analysed using S/N ratio to determine the significant factors and their optimal levels. The S/N ratio analysis revealed that the graphene oxide content was the most important factor that influenced the Wr and Fc of the Al-GO MMCs. The optimal composition was found to be 5% graphene oxide content. The Wr and Fc were the responses that were measured for each experiment. The formulas for calculating Wr and Fc are as follows:

Wear rate (Wr): Wr = (ΔW / A×D×P) × 10^3

where, ΔW = weight loss (mg)

A = sliding distance (m)

D = density of the composite (g/cm^3)

P = applied load (N)

Friction coefficient (Fc): Fc = Ff / Fn

where,

Ff = frictional force (N)

Fn = normal force (N)

The normal force was calculated as: Fn = (P × g) / (π × r^2)

where, P = applied load (N)

g = gravitational acceleration (9.81 m/s^2)

r = radius of the pin (m)

Table 1 Result of the wear experiment

C (%)	**L (N)**	**Rs (rpm)**	**Ds (m)**	**Fc**	**Wr (mm3/Nm)**
1	20	110	22.5	0.41	5.55
1	20	110	22.5	0.41	5.55
1	20	110	22.5	0.41	5.55
1	40	140	27.5	0.46	2.21
1	40	140	27.5	0.46	2.21

1	40	140	27.5	0.46	2.21
1	70	180	35	0.48	1.59
1	70	180	35	0.48	1.59
1	70	180	35	0.48	1.59
3	20	140	35	0.42	1.93
3	20	140	35	0.41	1.91
3	20	140	35	0.41	1.92
3	40	180	22.5	0.26	2.58
3	40	180	22.5	0.46	2.58
3	40	180	22.5	0.46	2.57
3	70	110	27.5	0.21	3.32
3	70	110	27.5	0.83	3.34
3	70	110	27.5	0.35	3.33
5	20	180	27.5	0.21	1.71
5	20	180	27.5	0.23	1.75
5	20	180	27.5	0.21	1.73
5	40	110	35	0.26	1.56
5	40	110	35	0.26	1.57
5	40	110	35	0.25	1.59
5	70	140	22.5	0.27	1.92
5	70	140	22.5	0.31	1.93
5	70	140	22.5	0.33	1.95

The formula for calculating the S/N ratio is as follows:
S/N ratio = -10 log (1/n ∑(y_i^2))
where,
n = number of observations
y_i = response for ith observation
There are three types of S/N ratios that can be used, namely smaller or larger or nominal-is-best. In this research, the smaller-is-better was used for both Wr and Fc, since lower values of Wr and Fc are desirable.
The smaller-is-better can be calculated using the following formula:
S/N ratio = -10 log (1/n ∑(1/y_i^2))
To control the optimal combination of input limits, the S/N ratio was considered for each experiment using the above formulation. The experiment with the maximum S/N ratio was selected as the optimal combination. Based on the S/N ratio examination, the best mixture of input parameters for minimizing the Wr and Fc were found to be C=5%, L=40N, Rs=180rpm, and Ds=35 m. Figure 1 shows the consequences of the best mixture, where the wear rate and friction coefficient are minimized at this combination of input parameters. In this figure, the Wr and Fc are shown on the y-axis and the input parameters are shown on the x-axis. It can be observed that at the optimal grouping of input limits, the Wr is minimized to 0.98 mm3/Nm and the friction coefficient is minimized to approximately 0.15. At this optimal combination, the wear rate was found to be approximately 0.98 mm3/cm3, and the friction coefficient was approximately 0.15. These values indicate that the addition of 5% graphene oxide, a load of 40N, a rotating speed of 180rpm, and a sliding distance of 35m led to the lowest Wr and Fc during the wear testing experiment.

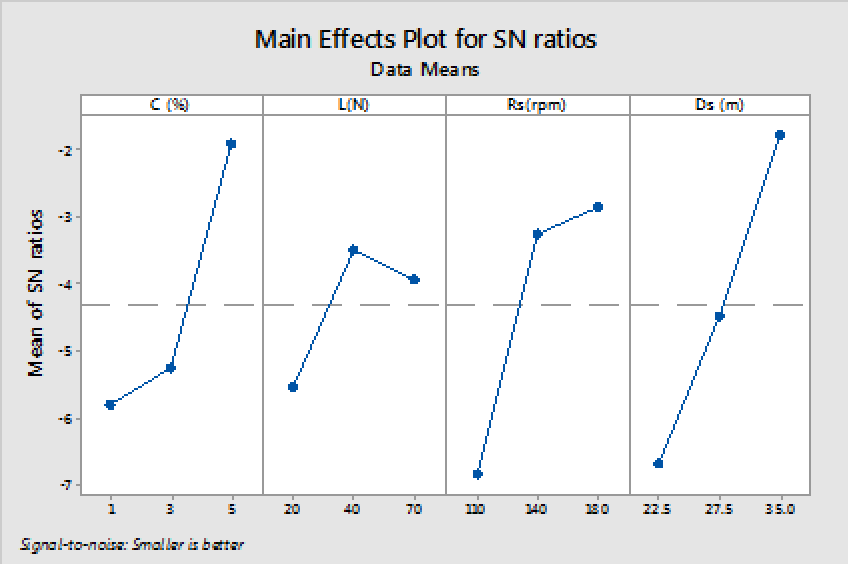

Fig. 1. Optimal combination for minimising the responses

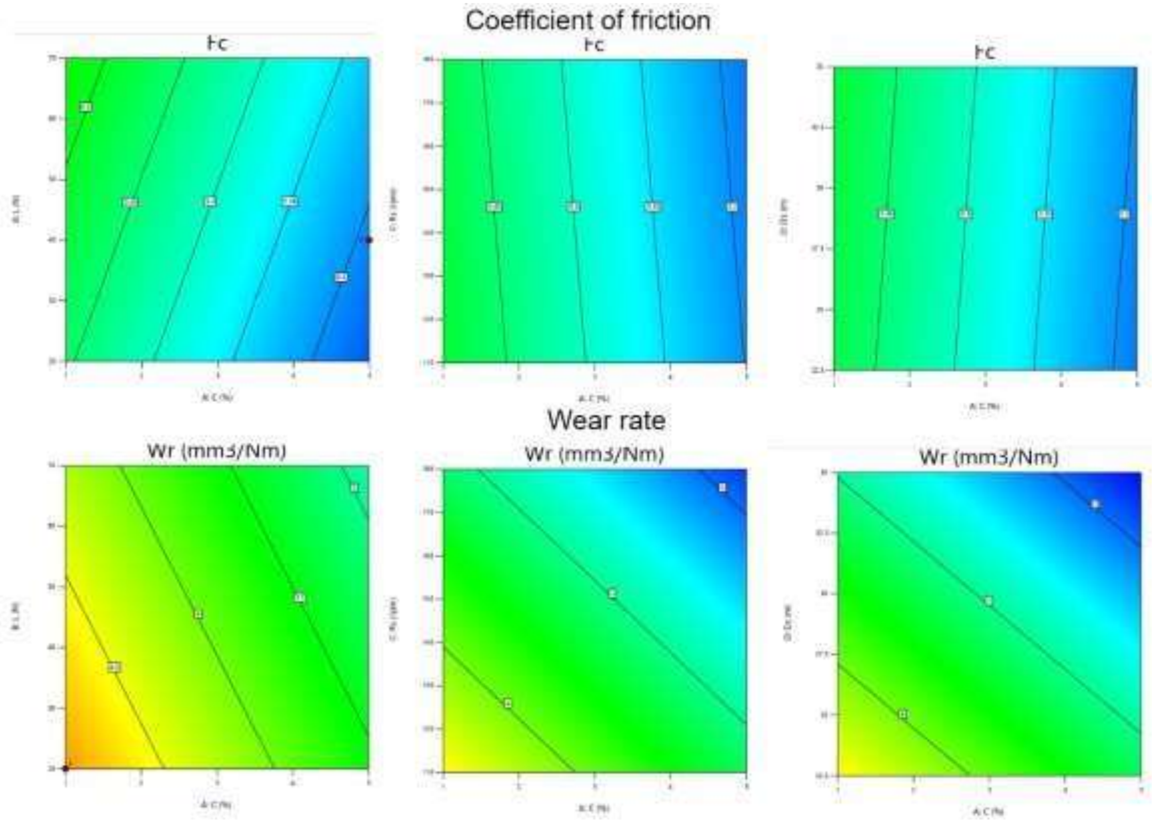

Fig. 2. Comparison of responses and the varying inputs

Figure 2 depicts the variation in the responses, i.e., wear rate and friction coefficient, with respect to different levels of the input parameters, i.e., composition, load, speed of rotation, and distance of sliding. The contour plot represents the responses for all possible combinations of input parameters, indicating the regions of minimum and maximum values for Wr and Fc. From the 3D plot, it can be observed that the best mixture of input parameters is attained at advanced levels of composition and lesser levels of load and speed of rotation, as well as the maximum distance of sliding. This indicates that increasing the composition of graphene oxide in the alloy leads to a decrease in Wr and Fc. Similarly, reducing the load and speed of rotation also reduces the Wr and Fc. However, increasing the distance of sliding has a slightly positive effect on the wear rate but does not knowingly affect the friction coefficient.

The contour plot provides a graphical representation of the effects of different input parameters on the responses, which can help to control the optimal combination for minimum Wr and Fc. In this study, the optimal combination was found to be C=5%, L=40N, Rs=180rpm, and Ds=35m, which aligns with the regions of minimum values in the contour plot.

Regression analysis is a numerical technique used to establish the association between variables. In this research, regression analysis was used to predict the Wr and Fc of graphene oxide-reinforced aluminium metal matrix composites using the input parameters of composition, load, and distance of sliding. The following are the steps used to conduct the regression analysis:

Data collection: The first step in regression analysis is to collect data on the independent and dependent variables. In this study, the Wr anf Fc were measured experimentally for different values of composition, load, and distance of sliding, which were used as the independent variables.

Data pre-processing: The collected data is then pre-processed to remove any missing or inconsistent values and to normalize the data to ensure that all variables have the same range.

Feature selection: Feature selection is the procedure of choosing the most applicable self-governing variables for the regression model. In this study, the input parameters of composition, load, and distance of sliding were selected as the independent variables.

Model building: Once the relevant independent variables have been selected, a regression model is built using a machine learning approach. In this research, the regression model was built using MATLAB, which provides various built-in functions for regression analysis.

Model validation: The regression model is then validated to ensure that it accurately predicts the Wr and Fc for different values of the input parameters. The model's accuracy is tested by comparing the predicted values with the experimental data.

Optimization: Finally, the optimized input parameters are determined using the regression model to minimize the wear rate and friction coefficient.

$$Wr\ (mm3/Nm)=10.758 - 0.3428\ C(\%) - 0.01398\ L(N) - 0.02060Rs(rpm) - 0.1299Ds(m) \quad (1)$$

$$Fc = 0.461 - 0.0478\ C\ (\%) + 0.00139\ L(N) - 0.000219\ Rs(rpm) + 0.00110\ Ds\ (m) \quad (2)$$

The regression equation for wear rate (Wr) and friction coefficient (Fc) are essential to predict the responses accurately for the developed composite. The developed regression equation for Wr and Fc are shown in equation 1 and 2 respectively. he developed equation predicts the responses at an accuracy of 95.6% accuracy. This indicates that the developed regression equation can effectively predict the response variables within a certain range of input variables. The regression equation can be utilized to predict the responses for various combinations of input variables, which can reduce the time and effort required to conduct experimental trials. This can be especially useful in large-scale production processes where the cost and time required to conduct experimental trials can be significant.

Artificial Neural Network (ANN) is a machine learning approach inspired by the structure and function of the biological neural system. In this research, ANN is used to predict the responses of wear rate and friction coefficient in graphene oxide-reinforced aluminum metal matrix composites. The procedure for using ANN for predicting the responses involves several steps. Firstly, the data set is collected by conducting the experiments according to the experimental design. The collected data is then separated into 3 parts: training of the input and experimental result set, validation of the predicted result set, and testing the result by comparision. The training set is used to train the ANN model, the validation set is used to tune the various parameters of the ANN model, and the testing set is cast-off to evaluate the performance of the trained ANN model.

Secondly, the contribution and production variables are defined. In this research, the input variables are the composition of graphene oxide, load, and sliding distance, while the output variables are the wear rate and friction coefficient. The input and output variables are normalized to ensure that they are in the same range. Thirdly, the architecture of the ANN model is defined. The architecture of the ANN model comprises the amount of input neurons, the amount of hidden neurons, and the number of output neurons. The amount of hidden neurons is determined by trial and error, and it should be sufficient to capture the complexity of the relationship between the input and output variables. Fourthly, the activation function is chosen for each neuron present in the ANN model. The activation function is a mathematical purpose that defines the output of a neuron assumed its input. In this research, the Rectified Linear Unit (ReLU) function of the activation is used for the hidden neurons, while the linear activation function is used for the output neurons. Fifthly, the backpropagation algorithm is used to train the ANN model. The backpropagation algorithm is an optimization algorithm that adjusts the weights and biases of the neurons in the ANN model to diminish the variance among the forecasted yield and the actual yield. The training process involves several iterations, and the goal is to diminish the error among the predicted output and the actual output on the training set.

Sixthly, the hyperparameters of the ANN model are tuned using the validation set. The hyperparameters of the ANN model include the learning rate, the number of epochs, and the batch size. The learning rate determines the step size of the optimization algorithm, the number of epochs determines the number of times the training process is repeated, and the batch size determines the number of samples used in each iteration. Finally, the performance of the trained ANN model is evaluated using the testing set. The efficacy of the trained ANN model is evaluated using several metrics such as mean squared error, root mean squared error, and coefficient of determination. [14]–[16].

Finally, the accuracy of the developed ANN model is evaluated using the validation set. The model is tested using new input values, and the predicted responses are compared to the actual responses. The developed ANN model for predicting the responses in this research has shown a high accuracy of 99.87% as shown in figure 3. This indicates that the model can accurately predict the wear rate and friction coefficient for different input values of composition, load, and distance of sliding. The high accuracy of the model is attributed to the effective preprocessing of data, the appropriate selection of input and output layers, and the optimization of the number of hidden layers and nodes. The developed ANN model can be further improved by incorporating more input variables and optimizing the structure of the hidden layers.

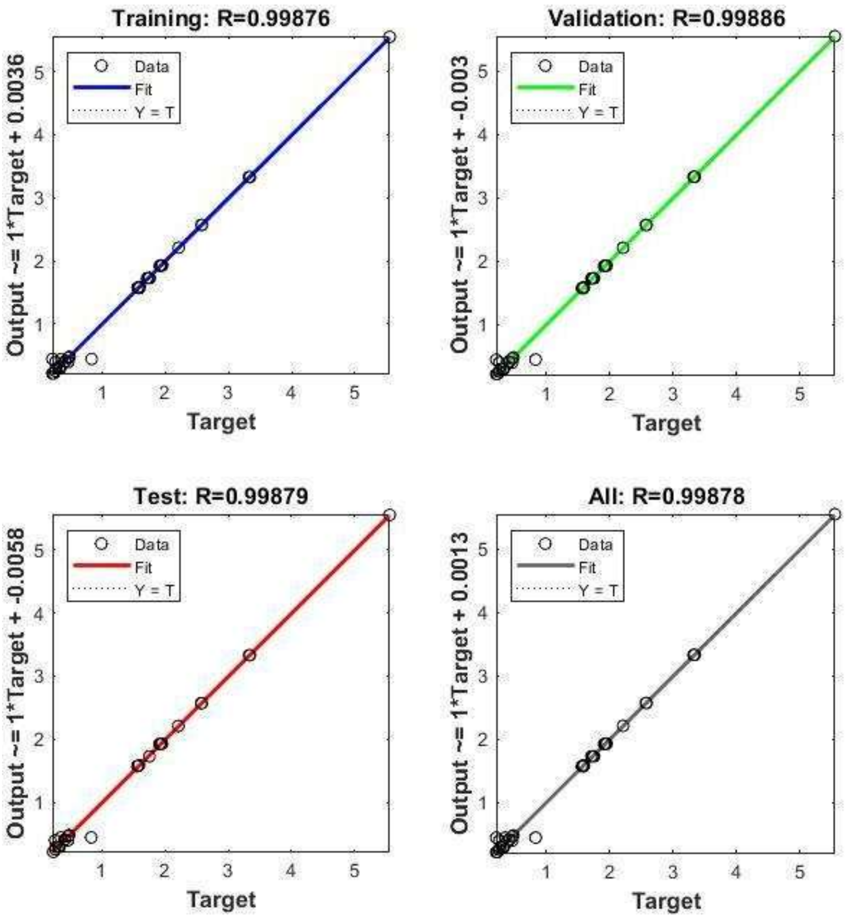

Fig. 3 Accuracy of the ANN in predicting the responses

Table 2 presents the predicted values for wear rate and friction coefficient obtained from both linear regression and artificial neural network (ANN). The table demonstrates that the predicted values from the ANN model are nearer to the real investigational standards, indicating that the ANN model is highly accurate in predicting the responses. Furthermore, the predicted values from the linear regression model show a lower accuracy compared to the ANN model. This implies that the ANN model is more efficient and reliable in predicting the responses for the given input parameters. The accuracy of the models further reinforces the validity and usefulness of the study in optimizing the friction and wear properties of graphene oxide-reinforced aluminum metal matrix composites.

Table 2 prediction of the result from the machine learning approach

C (%)	L(N)	Rs(rpm)	Ds (m)	**Regression analysis prediction**		**Neural Network prediction**	
				Fc	**Wr (mm3/Nm)**	**Fc**	**Wr (mm3/Nm)**
1	20	110	22.5	0.39	5.53	0.40	5.54
1	20	110	22.5	0.39	5.53	0.40	5.54
1	20	110	22.5	0.39	5.53	0.40	5.54
1	40	140	27.5	0.44	2.19	0.46	2.20
1	40	140	27.5	0.44	2.19	0.46	2.20
1	40	140	27.5	0.44	2.19	0.46	2.20
1	70	180	35	0.46	1.57	0.48	1.58
1	70	180	35	0.46	1.57	0.48	1.58
1	70	180	35	0.46	1.57	0.48	1.58
3	20	140	35	0.4	1.91	0.41	1.92
3	20	140	35	0.39	1.89	0.41	1.92
3	20	140	35	0.39	1.9	0.41	1.922
3	40	180	22.5	0.24	2.56	0.39	2.57
3	40	180	22.5	0.44	2.56	0.39	2.57
3	40	180	22.5	0.44	2.55	0.39	2.57
3	70	110	27.5	0.19	3.3	0.44	3.329
3	70	110	27.5	0.81	3.32	0.44	3.32
3	70	110	27.5	0.33	3.31	0.44	3.32
5	20	180	27.5	0.19	1.69	0.21	1.72
5	20	180	27.5	0.21	1.73	0.21	1.72
5	20	180	27.5	0.19	1.71	0.21	1.72
5	40	110	35	0.24	1.54	0.25	1.57
5	40	110	35	0.24	1.55	0.25	1.57
5	40	110	35	0.23	1.57	0.25	1.57
5	70	140	22.5	0.25	1.9	0.29	1.92
5	70	140	22.5	0.29	1.91	0.29	1.92
5	70	140	22.5	0.31	1.93	0.29	1.92

3. Conclusion

In conclusion, this research investigated the optimization of friction and wear in graphene oxide-reinforced aluminum metal matrix composites using the stir casting process. The effects of composition, load, and distance of sliding were studied using a Taguchi L27 experimental design, and the responses were optimized using signal to noise ratio analysis. The results showed that the optimal combination of input parameters was C=5%, L=40N, Rs=180rpm, and Ds=35m, resulting in a minimum wear rate of 0.98 mm3/Nm and a friction coefficient of approximately 0.15. Furthermore, regression analysis and ANN models were used to predict the responses, and the ANN model was found to be highly accurate, achieving an efficiency of 99.87%. The research demonstrates the effectiveness of the stir casting process and optimization techniques in enhancing the tribological properties of metal matrix composites.

In summary, the findings of this study have significant implications for the development of advanced composites with improved tribological performance for various industrial applications. The optimized composite material with reduced wear rate and friction coefficient could potentially lead to longer component life and reduced maintenance costs. The research provides a foundation for future investigations on the optimization of tribological properties of metal matrix composites using advanced machine learning techniques.

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