Original Article

Prediction of specific wear rate for LM25/ZrO₂ composites using Levenberg–Marquardt backpropagation algorithm

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A B S T R A C T

In this study, the wear estimation capability of RSM and artificial neural network (ANN) modelling techniques are examined and compared in this study. Though both RSM and ANN model performed well, ANN-based approach is found to be better in fitting to measure output response in comparison with the RSM model. The comparison of the productive capacity of RSM and LMBP (Levenberg–Marquardt backpropagation) neural network architecture for modelling the output, as well as output, predicted for the wear samples in terms of various statistical parameters such as coefficient of determination (R²), etc., has been done. The coefficient of determination (R²) is higher for which the evaluated value shows that the ANN models have a higher modelling ability than the RSM model. The comparison between the experimental value and predicted value obtained by the ANN and RSM models reveals the coefficient of model determination (R²) for the ANN and RSM model is close to unity. The results obtained from the comparison of specific wear rate values using ANN and RSM were proved to be close to the reading recorded experimentally with a 99% confidence level.

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1. Introduction

The use of artificial neural networks (ANNs) represents a new methodology in many different applications of composite materials including the prediction of tribological properties

[1]. An artificial neural network was recently introduced into the field of material science as a tool for systematic parameter studies in the design of composite materials based on its parallel processing property [2,3]. The process of artificial neural work developing involves many critical steps (1) data presentation, (2) data normalization, (3) training, (4) testing. Many kinds of literatures pointed out that the ANN approach is a successful analytical tool that can be used to predict the wear behaviour of new material and composites and concluded that

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the ANN is good analytical tool to predict the wear properties [4–9]. It was reported that ANN network showed excellent performance in producing wear volume loss, specific wear rate and friction coefficient as a function of sliding speed and load for different composition fibre and particulate reinforced composites [10].

Veeresh Kumar et al. analysed the dry sliding wear performance of Al7075/SiC metal matrix composites by varying the weight percentage i.e. 2–6 wt% of SiC fabricated by using through liquid metallurgy process. The result reveals that the increase in the percentage of SiC increases the wear resistance properties. An ANN model was developed to predict the tribological properties of the Al7075-SiC composites. The predicted values from the tribological properties using a well trained ANN were found in good agreement with measured values [10].

Genel et al. modelled a multiple-layer feed-forward artificial neural network (ANN) for the prediction of tribological behaviour on the short alumina fibre reinforced zinc-aluminium composites. The composite materials were prepared by various volume percentage fibre contents such as 10, 15, 20 and 30 vol.% using pressure die casting method. The wear test was conducted using pin-on-disc experiments under the constant sliding speed of 1 m/s with different loads. The result reveals that the wear behaviour and frictional coefficient of the composites are majorly affected by fibre volume fraction. They identified that the specific wear rate was decreased with an increase in fibre volume fraction and increased with an increase in load. The ANN modelled data and experimental data were compared and 3D plots and empirical expressions for specific wear rate and frictional coefficient, related to loading and fibre volume fractions were established [11].

Moreover, different researchers have presented various prediction techniques to predict the wear behaviour of the composites. Overall of this, the chapter gives a brief review of the composite material and its classification, various types of MMCs and its reinforcements, optimization and prediction techniques related to wear behaviour were also discussed. Many researchers have developed RSM using design expert software [12,13]. Some of researchers are attempted ANN model using MATLAB [1,14,15]. There are very few researchers have attempted to study and develop the ANN model for the prediction of tribological properties of Aluminium MMC. Very few works have been predicted through the BACK PROPAGATION algorithm. The objective of the present work is to discuss detailed experimental values of the LM25/ZrO2 composite at various conditions and also predict the LM25/ZrO2 composite tribological behaviour using the artificial neural network from the experimental values of various loads, sliding distance and particle reinforcements.

2. Materials and methods

2.1. Materials

The base matrix material for the present studies selected was LM25 alloy and it was reinforcement with ZrO2 particle size of 1–10 μm. The fabrication of composites has been done through a liquid metallurgy route via a stir casting technique. The preheated ZrO2 powder at 575 °C in a separate muffle furnace was introduced into the vertex of the molten alloy. The mechanical stirring of the molten alloy for duration of 15 min was achieved by using ceramic coated steel impeller. A speed of 950 rpm was maintained. A pouring temperature of 850 °C was maintained and the molten composite was poured into the preheated cast iron moulds. The extent of incorporation of ZrO2 in the matrix alloy was varied from 0, 3, 6, 9, 12 wt% in the LM25 alloy. The cylinders of 22 mm × 210 mm cast composites of LM25/ZrO2 were obtained as shown in Fig. 1. Similar studies have been observed by many other researchers [16,17].

2.2. Modelling with artificial neural network

In recent years, there has been an explosion of interest in neural networks to solve various problems in material science, welding, biomedical and engineering. The ANN can also be effectively applied as a powerful technique for a wide range of problems in areas such as medicine, finance, geology, engineering, etc. Artificial neural networks are a very powerful tool used to solve a variety of problems in science and Engineering, which cannot be carried out by conventional modelling methods. ANN is also a very sophisticated advanced modelling and prediction-making technique, capable of modelling extremely complex functions and data relationships.

The ANN has the capability to study by example is one of the many features of neural networks, which enables the user to model data and develop perfect rules for governing the fundamental relationship between various experimental data and attributes. Since the artificial neural network has a good and significant performance model with the independence of various data sets, they are suitable for various applications of real-world problems. ANN is a logic programming technique which works like a human brain with features such as learning, deciding, remembering, and making an inference, without receiving any aid. The smallest units that form the basis of the operation of ANN are called artificial neural cells. Each artificial neural cell consists of mainly five elements such as inputs, summation functions, weights, activation functions and outputs as shown in Fig. 2.

There are three main layers that are followed in artificial neural network such as input, hidden and output layers. In this work, prediction networks are created with two-layer feed-
forward Levenberg–Marquardt backpropagation (LMBP) neural networks.

The two-layer feed-forward backpropagation algorithm is applied as follows:

Step 1: To initialize all weights function and bias (normally a small number of random values) for normalizing the training data.
Step 2: To compute all the output of neurons in the hidden layer and in the output layer (net) using the following equations

\[ n_i = \sum w_{ij} x_j + \theta_i, \]  
\[ w_{ij}(n + 1) = w_{ij}(n) + \alpha \delta_i(n)x_j(n) \]

where \( w_{ij} \) is the weight for node \( j \) to \( i \) and it is calculated as follows

where \( x_j \) – transformation function, \( \theta_i \) – bias, \( \delta_i(n) \) – weighted summation of error, and \( \alpha \) is the stepsize for network.

Step 3: Compute the error and weight update. The weights functions are tuned using the modified delta rule.
Step 4: To update all weights function, bias and repeat Steps 2 and 3 for all training data.
Step 5: Repeat Steps 2–4 until the error converges to an acceptable level.

2.3. Artificial neural network (ANN) structure

The prediction was carried out using artificial neural network modelling (ANN) with a two-layer feed-forward Levenberg–Marquardt backpropagation (LMBP) learning algorithm. The architecture of ANN consisting of three layers is shown in Fig. 3, which consists of a three-input layer (load, wt% of ZrO2, Sliding distance), one output layer (specific wear rate) and two hidden layers. In this investigation, an ANN was modelled using MATLAB software.

2.4. Development of Levenberg–Marquardt backpropagation

Levenberg–Marquardt utilizes to supervise the learning way called backpropagation for ANN training the network with an appropriate iterative algorithm for solving unconstrained non-linear optimization problems. They are used for training the ANN network. A Levenberg–Marquardt backpropagation is an adaptive network, where each node in the network has the same node function. This algorithm is a function, which uses the Jacobian matrix for calculations that assumes the performance as a mean or sum of squared error.

The general structure of the Levenberg–Marquardt network with input, hidden and an output layer as shown in Fig. 4, in which, \( X_1, X_2 \) & \( X_3 \) are used as input layers and \( y \) is chosen as an output layer.

In Levenberg–Marquardt techniques, the Hessian matrix can be approximated as

\[ H = J^T J \]  
\[ g = J^T e \]

where \( J \) is the Jacobian matrix and \( e \) is the vector of network error.

The Levenberg–Marquardt performance function for feedforward network is calculated from the mean square error (MSE), From Eq. (5), the average squared error is calculated between the network output value ‘\( a \)’ and the target output value ‘\( t \)’.

\[ F = \text{mse} = \frac{1}{N} \sum_{i=1}^{N} (e_i)^2 = \frac{1}{N} \sum_{i=1}^{N} (t_i - a_i)^2 \]

2.5. Development of ANN models for wear behaviour in composite materials

ANN models have been developed for composite material to predict a correlation between the input process parameter and output response. The total experimental (specific wear rate) data are collected for ANN training purposes at 70% of the approximate random value, while the remaining 30% is reserved for testing and validation. A detailed description of the networks created for predicting the wear properties of LM25/ZrO2 composite is presented in this work. The Levenberg–Marquardt backpropagation (LMBP) with different topologies (the number of hidden neurons with the connection types, learning algorithms for composites and various transfer functions of input process parameters and hidden layers) are tested for the estimation and prediction of the wear properties of LM25/ZrO2 composites. Each algorithm is trained with different activation and error activation function. It is very important to choose the most optimal parameters such as a number of hidden neurons, type of network structures and complexity of the task. This method generally has to be done by trial and error methods. The number of hidden neurons is increased in the neurons up to a particular point and usually, they obtained results are in a good learning performance.

The few hidden neurons are limited for the ability of the ANN neural network to model the various input process parameters. It may also be allowed too much freedom for the weights function to adjust the result in learning and the noise present in the database used for training [19,20]. The artificial
neural network models are developed to predict a relationship between tribological properties and Wear input process parameters for LM25/ZrO$_2$ composites. The inputs for the networks include load, sliding distances and weight percentages of ZrO$_2$. The output of the network includes a specific wear rate.

3. Result and discussion

3.1. Wear prediction of LM25/ZrO$_2$ composites using ANN

In this work, 100 experimental sets are carried out by varying the wear input process parameters such as load (10, 20, and 30 N), sliding distance (1000, 1200 and 1400 m) and percentages of ZrO$_2$ (0, 3, 6, 9 and 12%) in LM25/ZrO$_2$ composites for predicting the specific wear rate in LM25/ZrO$_2$ composites. Out of 100 experiments results, the 66 data sets are allotted for training, 17 for validation and 17 for testing. This artificial neural network training function updates the weight and bias values according to the Levenberg-Marquardt algorithm. The wear prediction performance is confirmed through mean square error. A two-layer feed-forward network with sigmoid hidden neurons and linear output neurons (newfit), can fit multi-dimensional mapping problems arbitrarily well, given consistent data and enough neurons in its hidden layer. The training with hidden layers is given in Fig. 5.

3.2. Prediction of specific wear rate for LM25/ZrO$_2$ composites

The training, validation, and testing have been continued until the result reaches the minimum mean square error. From Table 1, it is identified that the multi-layer network structure
(3–5–1–1) gives the minimum mean square error when compared to the other number of trials. Hence, this structure is finally used for ANN prediction systems.

The selected network structure is 3–5–1–1, which shows that the relationship of tribological properties i.e. specific wear rate. The results predicted through the proposed ANN model are compared with the experimental value. In Fig. 6, it is evident that even with a very small number of epochs (97) the network attains an accuracy of 0.00019855.

3.3. Mean Squared Error (MSE) of performance plot using ANN

From Fig. 5, it is identified that the data good fit well because of good training and therefore, it is concluded that the network system with better training gives the output with minimum error and it can also be used to predict the unknown value for the future. The regression coefficient value gives the correlation between output and target value. When R-value reaches
It means a very close relationship exists between the output and target. If R-value is 0, the random relationship exists and if R-value is greater than 0.9, the quality of the result is better as stated in literatures [10,21,22].

3.4. Regression plots of training, testing, validation using ANN

Fig. 7 shows the training, validation, testing and combined set of all having the R-value is 0.999, which indicates that the selected network structure (3–5–1–1) has no error.

3.5. Functional fit diagram of the training

From Fig. 8, the training target, training outputs, validation targets and all targets and all outputs fit well with the functional graph and also it shows the ‘no error’.

Fig. 6 – Mean Squared Error (MSE) of performance plot using ANN for LM25/ZrO₂ composites.

Fig. 7 – Regression plots of training, testing, validation, and combination with all sets of specific wear rate using ANN for LM25/ZrO₂ composites.
3.6. **Comparison of ANN and RSM results for LM25/ZrO₂ composites**

From the previous literature, RSM and ANN have become the most efficient method for the prediction of process parameters for manufacturing machining processes. These models were used to reveal the influence of input variables on the output responses and also identify the interaction between the variables. These two models can solve linear and non-linear multivariable regression problems and therefore it is very important to identify how much close this model can produce when compared to the actual value.

Hence in this work, RSM and ANN models are constructed from the experimental data and they are correlated reasonably well while having an $R^2$ value of 0.8468 and 0.9999 respectively. This result clearly indicates that RSM prediction has a greater deviation than ANN prediction. The result comparison of predicted wear loss values from ANN and RSM was proved to be close to the reading recorded experimentally with a 99% confidence level.

3.7. **Confirmation test for LM25/ZrO₂ COMPOSITES**

The confirmation test was conducted to validate the developed RSM and ANN model by preparing for four specimens with different weight percentages of ZrO₂. The prepared four specimens are subjected to dry sliding wear tests by varying various input process parameters such as load, sliding distances and percentages of ZrO₂ and their corresponding specific wear rate values are tabulated in Table 2. The experimental values were again tested using the already developed ANN model as shown in Fig. 9 for the specific wear rate. From Fig. 8, the regression $R$ values and mean square error are found to be 0.9994 & 1.13080e–3 respectively. Based on the experimental and predicted results using RSM and ANN models and their corresponding percentages of error were calculated and presented in Table 2. From Table 2, it is identified that the percentage of error for ANN model is lower than RSM model.

Parallel grooves and scratches were obtained in the sliding direction. This was due to abrasion, which occurred primarily due to ploughing and wedge formation. The Deep grooves, delamination, and pits were also observed in Fig. 10.
Table 2 – Comparison of output for LM25/ZrO₂ Composites using RSM and ANNs.

<table>
<thead>
<tr>
<th>Ex. No.</th>
<th>Load (N)</th>
<th>Sliding distance (m)</th>
<th>% of ZrO₂%</th>
<th>Comparison</th>
<th>Specific wear rate (x10⁻⁴ mm²/N m)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>RSM</td>
<td>ANNs</td>
</tr>
<tr>
<td>1</td>
<td>20</td>
<td>1200</td>
<td>3</td>
<td>Actual</td>
<td>5.3231</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>Predicted</td>
<td>5.1316</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>Error</td>
<td>3.73%</td>
</tr>
<tr>
<td>2</td>
<td>20</td>
<td>1000</td>
<td>5</td>
<td>Actual</td>
<td>4.2535</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>Predicted</td>
<td>4.6811</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>Error</td>
<td>10.05%</td>
</tr>
<tr>
<td>3</td>
<td>20</td>
<td>1200</td>
<td>10</td>
<td>Actual</td>
<td>3.8221</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>Predicted</td>
<td>3.9651</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>Error</td>
<td>3.74%</td>
</tr>
<tr>
<td>4</td>
<td>20</td>
<td>1400</td>
<td>14</td>
<td>Actual</td>
<td>3.3132</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>Predicted</td>
<td>3.6321</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>Error</td>
<td>9.62%</td>
</tr>
</tbody>
</table>

Fig. 10 – SEM micrographs of worn surface of LM25/ZrO₂ composites.

4. Conclusion

ANN prediction of the specific wear rate for LM25/ZrO₂ composites is carried out and compared with the results obtained from the RSM techniques. The ANN model was developed based on the data obtained from the experimental results and it was trained and tested. The wear estimation capabilities of RSM and ANN modelling techniques were examined and compared in this study.

Based on the comparison and study the following conclusions are drawn:

1. In this work, the backpropagation model network was developed and the accuracy of the trained network was accessed by comparing the predicted value against the experimental value and it is identified that backpropagation algorithm network 3–5–1–1 produced closure results with experimental value for LM25/ZrO₂ types of composites.
2. The training, validation, testing and combined set of all having the R-value as 0.999, which indicates that the selected network structure (3–5–1–1) has no error.
3. The selected network structure is 3–5–1–1, which shows that the relationship of tribological properties i.e. specific wear rate. The results predicted through the proposed ANN model are compared with the experimental value. It is evident that even with a very small number of epochs (97) the network attains an accuracy of 0.00019855.
4. A comparison of the predictive capacity of the RSM and artificial neural network architecture to model the output as well as output predicted for the test samples in terms of various statistical parameters such as coefficient of determination R² has been calculated.
5. RSM and ANN models are constructed from the experimental data and they are correlated reasonably well while having an R² value of 0.8468 and 0.9999 respectively. This result clearly indicates that RSM prediction has a greater deviation than ANN prediction. The result comparison of predicted wear loss values from ANN and RSM was proved to be close to the reading recorded experimentally with a 99% confidence level.
6. The R-value for artificial neural network (ANN) in which the evaluated value shows that the ANN model has higher modelling ability than the RSM model for the prediction of specific wear rate for LM25/ZrO₂ composites.
7. The comparison of the experimental values and predicted values obtained by ANN and RSM model reveal that the coefficient of determination for ANN and RSM is closer to unity.
8. The regression R values and mean square error are found to be 0.9994 & 1.13080e–3 respectively. Based on the experimental and predicted results using RSM and ANN models and their corresponding percentages of error were calculated. It is identified that the percentage of error for the ANN model is lower than the RSM model.
9. The results of the coefficient of determination (R²) value for the ANN model-based prediction are more accurate than the RSM based model and hence it is clearly identified that ANN has a superior modelling capability.
10. ANN model generation requires a large number of iterative calculations whereas with the RSM model it is only a single step calculation based on nonlinearity of problem and number of parameters. Therefore, ANN may require a high computational cost when compared with the response surface model.
Conflicts of interest

The authors declare no conflicts of interest.

REFERENCES


