Utilization of Improved Machine Learning Method Based on Artificial Hummingbird Algorithm to Predict the Tribological Behavior of Cu-Al₂O₃ Nanocomposites Synthesized by In Situ Method

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Abstract: This paper presents a machine learning model to predict the effect of Al₂O₃ nanoparticles content on the wear rates in Cu-Al₂O₃ nanocomposite prepared using in situ chemical technique. The model developed is a modification of the random vector functional link (RVFL) algorithm using artificial hummingbird algorithm (AHA). The objective of using AHA is used to find the optimal configuration of RVFL to enhance the prediction of Al₂O₃ nanoparticles. The preparation of the composite was done using aluminum nitrate that was added to a solution containing scattered copper nitrate. After that, the powders of CuO and Al₂O₃ were obtained, and the leftover liquid was removed using a thermal treatment at 850 °C for 1 h. The powders were consolidated using compaction and sintering processes. The microhardness of the nanocomposite with 12.5% Al₂O₃ content is 2.03-fold times larger than the pure copper, while the wear rate of the same composite is reduced, reaching 55% lower than pure copper. These improved properties are attributed to the presence of Al₂O₃ nanoparticles and their homogenized distributions inside the matrix. The developed RVFL-AHA model was able to predict the wear rates of all the prepared composites at different wear load and speed, with very good accuracy, reaching nearly 100% and 99.5% using training and testing, respectively, in terms of coefficient of determination R².

Keywords: metal matrix nanocomposites; hardness; abrasive wear rate; artificial neural network; RVFL algorithm

MSC: 70

1. Introduction

Metal matrix nanocomposites (MMNCs) are extensively used in modern industries due to their mechanical behavior, tribological properties, and other desirable engineering properties [1–4]. The oxide dispersion strengthening (ODS) method is used to create nanocomposites that contain very fine particles of the ceramic oxide in a metallic matrix, resulting in an MMNCs-reinforced multi-phase system [5–9]. Copper and its alloys are used in a number of technical applications, including electronics and electrical sliding contacts...
in motors and generators. When compared to common industrial metals, it is also used as brushes, electric contacts, resistance welding electrodes, and bearings due to its superior electrical and thermal properties, good mechanical properties, corrosion resistance, and ease of forming and machining [10–14]. Nonetheless, the most significant disadvantages of copper in many applications are the highest coefficient of friction, little wear resistance, and low strength, which limit/prevent their use in heavy duty applications. The researchers tried to tackle these problems by emerging ceramic particles in the Cu-matrix for improving tribological properties, such as adding graphite [15,16] and graphene [17–19], or improving strength by adding ZrO$_2$ [20–22], SiC [23,24], graphene [25,26], and alumina [27,28], etc.

Copper matrix composites (CMCs)-reinforced with particles such as alumina (Al$_2$O$_3$) show improved physical and mechanical properties and can be characterized using conventional methods employed for metals [29,30]. The effect of Al$_2$O$_3$ on the abrasion properties of the CMCs is such that in addition to the increase of Al$_2$O$_3$ reducing the wear rate of the MMCs, increasing its particle size also reduces the amount of wear. As the mass percentage and particle size of Al$_2$O$_3$ increase, the density of the MMCs decreases, while the porosity, microhardness, and strength of the CMCs increase with decreasing size and increasing the mass percentage of the Al$_2$O$_3$ particles [31]. In addition to ceramic compounds, other compounds are also used to reinforce metal matrix composites. Among these materials is graphene, which has been proposed as an excellent reinforcement for CMCs due to its excellent thermal, electrical, and mechanical properties. A number of studies, with the successful production of graphene-reinforced CMCs, have shown that graphene has a positive effect on the mechanical properties of the final products and the thermal conductivity of a copper matrix [32–34].

Powder metallurgy is one of the best techniques to manufacture metal matrix nanocomposites due to its low cost [35–37]. Despite this important advantage for the industry, the low dispersion of reinforcement phase in the matrix limits its applicability. The low dispersion of the phases is due to the difference in the surface energy of ceramic phase nanoparticles and the metal phases, which make the ceramics particles tends to agglomerate [38–40]. The use of mechanical alloying as a subsequent step of the powder metallurgy help to overcome this problem by achieving good dissolution of the ceramic particles inside the matrix phase through welding and fracturing of the metallic particles that entrap ceramics particles in between them during this process [41–43].

Owing to the advantages of artificial intelligence of providing solutions for very complex problems regardless of the availability of labs and cost, it was deployed to predict the wear rates of Cu-Al$_2$O$_3$ nanocomposites under abrasive wear condition [44–47]. In addition, the machine learning applications used in engineering, chemical, and other fields [48–52]. The newly developed Random Vector Functional Link (RVFL) algorithm was trained using experimental data obtained from abrasive wear tests to predict the response of these composites with different Al$_2$O$_3$ contents with good accuracy.

In this work, Cu-Al$_2$O$_3$ nanocomposites were manufactured using in situ technique with different Al$_2$O$_3$ concentrations. The microstructure, hardness, and wear properties were characterized for all the produced composites. The abrasive wear rates were measured at different applied loads and velocities. The evolution of wear rates with Al$_2$O$_3$ content was correlated to the microstructural changes in the consolidated samples. Finally, the trained RVFL algorithm was used to predict the wear rates for different composites with larger range of reinforcement content. The utilization of this technique will help for developing these composites in military and medical applications.

2. Experiments

The in situ chemical process was used to synthesis of Cu-Al$_2$O$_3$ nanocomposite powder from water-soluble copper Cu(NO$_3$)$_2$:3H$_2$O and aluminum nitrates Al(NO$_3$)$_3$:9H$_2$O. The following steps describe the in situ chemical process:
- Cu(NO$_3$)$_2$·3H$_2$O and Al(NO$_3$)$_3$·9H$_2$O were dissolved in water using a magnetic stirrer at 70 °C for 30 min. The salt concentrations were chosen to produce a Cu-Al$_2$O$_3$ nanocomposite system with 2.5, 7.5, and 12.5 wt.% Al$_2$O$_3$.
- To obtain nitrate salt powder precursor particles, dry spraying was performed with a sprayer at 180 °C. Copper oxide (CuO) and aluminum oxide (Al$_2$O$_3$) phases were obtained by oxidation of the powder at 850 °C for 1 h in an air atmosphere.
- The powders were reduced in hydrogen for 30 min at 500 °C, resulting in copper oxide being reduced to its metallic state and Al$_2$O$_3$ remaining as the scattered ceramic phase.

To consolidate the samples, powders were put inside a steel die and then cold pressed at a pressure of 700 MPa. Finally, the compacted samples were sintered for 2 h in hydrogen gas at a temperature of 900 °C. Microstructural characterization of the as-milled powder and sintered samples were performed by means of X-ray diffraction measurement (XRD) analysis using a D2 PHASER diffractometer (30 kV and 10 mA settings) with Cu-K$_\alpha$ radiation ($\lambda = 1.54184$ Å) and field emission scanning electron microscopy (SEM) JEOL JSM–5900LV (15kV) attached with energy dispersive spectrometers (EDS) and secondary electron (SE) and backscattered electron (BSE) detectors.

Microhardness was characterized using a HXS–1000A microhardness tester. The microhardness was measured at 10 different locations, and the mean value of microhardness was computed for each sample. According to ASTM, the pin-on-disc test was used (G77–98). A steel ring with a counterface diameter of 73 mm was used. The specimens that were tested had a contact area of 48 mm$^2$. The sliding speeds of the pin over the disc were used: 0.91, 1.07, 1.21, and 1.62 m/s. Four normal loads were applied: 2, 4, 6, and 8 N. Abrasive SiC paper of 400 grit was used on the disc. Each sample had the same sliding distance of 200 m. Before testing, the specimens were degreased using acetone. The weight loss was measured using an electronic balance with a resolution of 0.0001 g. Three samples were tested for each configuration.

3. Machine Learning Models
3.1. Random Vector Functional Link

The processes of a Random Vector Functional Link (RVFL) network are introduced in this section. It is similar to standard feedforward neural networks in that it connects input and output nodes, as seen in Figure 1 [53,54]. Furthermore, only the weights of the output layer must be modified. The input layer’s bias and weights are created at random and do not need to be changed. These benefits contribute to improved prediction performance while avoiding the overfitting for traditional ANN models.

![Figure 1. The RVFL network.](image-url)
The RVFL prediction begins with the input data being applied to the input nodes and these data containing \( M \) samples being formulated as \((a_i, b_i)\) (here, \( a_i \in \mathbb{R}^n, b_i \in \mathbb{R}^m, i = 1, \ldots, M \)). The output of the hidden nodes is then calculated as:

\[
O_j(c_ja_i + d_j) = \frac{1}{1 + e^{-\left(c_ja_i + d_j\right)}} , \quad d_j \in [0, \xi], \quad c_j \in [-\xi, \xi]
\]

(1)

where \( \xi \) is the scalar factor, and \( d_i \) is the bias parameter. Following that, the RVFL forecasts the output based on the output weight \( c \), which can be expressed as:

\[
Z = Kc, \quad c \in \mathbb{R}^{n+P}
\]

(2)

where \( K = [K_1, K_2] \) exemplifies the input data, and \( K_1 \) and \( K_2 \) are defined as

\[
K_1 = \begin{bmatrix}
a_{11} & \ldots & a_{1n} \\
\vdots & \ddots & \vdots \\
a_{N1} & \ldots & a_{Nn}
\end{bmatrix},
K_2 = \begin{bmatrix}
O_1(c_1a_1 + d_1) & \ldots & O_p(c_pa_1 + d_p) \\
\vdots & \ddots & \vdots \\
O_1(c_1a_N + d_1) & \ldots & O_p(c_pa_N + d_p)
\end{bmatrix}
\]

(3)

The value of \( c \) is modernized utilizing the following formula:

\[
c = K^+Z
\]

(4)

3.2. Artificial Hummingbird Algorithm (AHA)

In this part, the steps of new MH technique named artificial hummingbird algorithm (AHA), which simulates behavior of hummingbirds, is introduced. There are three types of flight skills named axial, diagonal, and omnidirectional flights; these skills are used for foraging strategies [55]. In addition, there are different types of search strategies, including guided foraging, territorial foraging, and migrating foraging; to emulate the memory function of hummingbirds a visit table is also formed.

The mathematical formulation of the AHA is illustrated by constructing the initial population \( X \) of \( N \) hummingbirds. This is defined using Equation (5):

\[
X_i = L + r \times (U - L), \quad i = 1, 2, \ldots, N
\]

(5)

where \( L \) and \( U \) denote to the lower and upper boundaries for a \( d \)-dimensional, respectively. \( r \) stands for random vector in \((0, 1)\). In addition, the visit table of food sources is constructed using Equation (6):

\[
VT_{ij} = \begin{cases}
0 & \text{if } i \neq j \text{ and } i, j = 1, \ldots, N, \\
\text{null} & \text{if } i = j
\end{cases}
\]

(6)

where for \( i = j \), \( VT_{ij} = \text{null} \) stands for the food taken by a hummingbird at its specific food source. In addition, \( i \neq j \), \( VT_{ij} = 0 \) stands for the hummingbird \( i \) visiting \( j \) food source.

3.2.1. Guided Foraging

In this stage, there are three flight skills, including omnidirectional, diagonal, and axial flights, that are applied during this foraging. The axial flight can be defined as:

\[
D_i = \begin{cases}
1 & \text{if } i = \text{randi}(\lfloor 1, d \rfloor) \text{ and } i = 1, \ldots, d, \\
0 & \text{else}
\end{cases}
\]

(7)
The diagonal flight is formulated as:

\[ D_i = \begin{cases} 1 & \text{if } i = P(i), j \in [1,k], P = randperm(k), k \in [2,r_1(d - 2) + 1] \\ 0 & \text{else} \end{cases}, \quad i = 1, \ldots, d, \]  

(8)

The omnidirectional flight is represented as:

\[ D_i = 1, \quad i = 1, \ldots, d, \]  

(9)

where \( \text{randi}([1,d]) \) stands for a random integer from 1 to \( d \), \( \text{randperm}(k) \) represents a random permutation of integers from 1 to \( k \), and \( r_1 \in [0, 1] \) denotes a random number.

The guided foraging behavior can be formulated as

\[ V_i(t + 1) = X_i(t) + a \times D \times (X_i(t) - X_{i,t}(t)), a \in N(0,1) \]  

(10)

where \( X_{i,t}(t) \) represents the food source \( i \) at iteration \( t \). \( X_{i,t}(t) \) is the target food source that visited by \( i \)th hummingbird. The value of \( X_i \) can be update using the following equation:

\[ X_i(t + 1) = \begin{cases} X_i(t) & \text{if } f(X_i(t)) \leq f(V_i(t + 1)) \\ V_i(t + 1) & \text{otherwise} \end{cases} \]  

(11)

where \( f \) stands for the fitness value.

3.2.2. Territorial Foraging

A hummingbird is more likely to hunt for a new food source after visiting its target food source when the flower nectar has been consumed rather than visiting other current food sources. As a result, a hummingbird might easily migrate to a nearby place inside its own territory, where a new food source may be discovered as a candidate solution that is potentially superior to the existing one. The following is the mathematical equation for modeling:

\[ V_i(t + 1) = X_{i,t}(t) + b \times D \times X_i(t), b \in N(0,1) \]  

(12)

3.2.3. Migration Foraging

In the case that the hummingbird’s favorite feeding spot runs out of food, it migrates to a more distant eating spot. A migration coefficient is established in the AHA algorithm. This hummingbird will abandon the old source and eat at the new one, and the visit table will be changed as a result. The following is a description of a hummingbird’s migration foraging from the source with the lowest nectar-refilling rate to a new one produced at random:

\[ X_w(t + 1) = L + r \times (U - L), \]  

(13)

where \( X_w \) stands for the food source with the worst fitness value.

3.3. Proposed Model

The general steps of the created RVFL-AHA approach (as in Figure 2). This algorithm modifies the characteristics of AHA to handle the integer optimization problem. It begins with dividing the input data into two groups for training and testing, with 70% and 30%, respectively, allocated to training and testing sets. The following stage is to create the initial population \( X \), which consists of \( N \) agents with \( \text{dim} \) components, using the following equation:

\[ X_{ij} = l_j + r \times (u_j - l_j), \quad i = 1, \ldots, N, \quad j = 1, \ldots, \text{dim}, \quad r \in [0,1] \]  

(14)

Each \( X_i \) represents a different RVFL configuration, which is determined by three factors: the number of hidden nodes \( (N_h) \), the activation function \( (AF) \), and the randomization mechanism \( (RT) \).
The following step is to calculate the fitting value \( \text{Fit}_i \) of each agent \( X_i \), which evaluates the performance of the RVFL configuration based on \( X_i \) using the equation:

\[
\text{Fit}_i = \sqrt{\frac{\sum_{n=1}^{N_S} (Y_P - Y_T)^2}{N_S}}
\]

where \( Y_P \) is the RVFL prediction based on \( X_i \), and \( Y_T \) is the training set’s target output. The next stage is to determine the optimum configuration and change the values of other configurations using AHA operators. The stop conditions are then evaluated, and if they are satisfied, the updating process is stopped, and the testing set is applied to the optimal configuration to evaluate the produced method’s performance.

Figure 2. The RVFL-AHA for prediction of wear rate.

4. Results and Discussion
4.1. Structural and Tribological Properties

After reduction, the shape of the Cu-7.5%Al\(_2\)O\(_3\) nanocomposite powders is shown in Figure 3. As seen in Figure 3a, the particles cluster to form large particle clusters of around 200 nm average size. The roughly spherical form of the generated particles after reduction improves wettability throughout phases [29,31]. The microstructure of solidified composites is influenced by the form of reinforcing particles [56]. Figure 3b demonstrates that the particle size after the chemical procedure is nanoscale.

The XRD results of the same composite are given in Figure 3c to guarantee the sample’s chemical composition following the chemical treatment. This study demonstrates that the sample only contains Cu and Al\(_2\)O\(_3\) phases, with no impurities from chemical processes. This provides proof of the manufacturing process’s authenticity as well as the composition of the materials produced.
A phase-mapping analysis of the Cu−7.5%Al₂O₃ nanocomposite is shown in Figure 4. The figure demonstrates that the material does not contain any contaminants because only the three components are observed, which indicates that Al₂O₃ nanoparticles are homogenously distributed inside the Cu matrix. The presence of Al₂O₃ at grain boundaries decreases the capacity of grains to re-weld during sintering, resulting in welded grains of a large size, similar to pure metal behavior. As a result, the presence of Al₂O₃ nanoparticles reinforces the grains by penetrating the grains’ lamellar structure and precipitating on the grain borders. The good distribution of Al₂O₃ inside the Cu is another key element that influences the characteristics of nanocomposites [27,28,57].

Figure 3. (a) FESEM micrograph of the Cu−7.5%Al₂O₃ nanocomposite powder, (b) magnified view of showing the exact morphology of powders, and (c) XRD analysis of the produced powder.
These findings are consistent with the densification parameters and microstructure. This can be explained by (i) good sinterability, (ii) better microstructure with uniform small pores and good distribution of Al₂O₃ on the Cu matrix, and (iii) high densities. In addition, the sintering temperature and time were appropriate in order to prevent grain growth. A strong bond between the matrix and reinforcements is also responsible for microhardness improvement. In this figure, the effect of Al₂O₃ content on microhardness consists of improved microhardness up to 12.5% Al₂O₃. The main cause of microhardness improvement is the existence of Al₂O₃, which possesses high microhardness and assists in reducing deformation at the contact surface. Moreover, the grain refinement helps with the dislocation impedance, which contributes to the microhardness improvement as well [58]. Because of the reduced size of crystallites, there are more grain boundaries, which obstruct dislocation movement and thus increase microhardness.

Figure 5 depicts the difference in microhardness with Al₂O₃ concentrations. In general, microhardness is generally increased by increasing Al₂O₃ content, as low as 12.5% Al₂O₃. These findings are consistent with the densification parameters and microstructure. This can be explained by (i) good sinterability, (ii) better microstructure with uniform small pores and good distribution of Al₂O₃ on the Cu matrix, and (iii) high densities. In addition, the sintering temperature and time were appropriate in order to prevent grain growth. A strong bond between the matrix and reinforcements is also responsible for microhardness improvement. In this figure, the effect of Al₂O₃ content on microhardness consists of improved microhardness up to 12.5% Al₂O₃. The main cause of microhardness improvement is the existence of Al₂O₃, which possesses high microhardness and assists in reducing deformation at the contact surface. Moreover, the grain refinement helps with the dislocation impedance, which contributes to the microhardness improvement as well [58]. Because of the reduced size of crystallites, there are more grain boundaries, which obstruct dislocation movement and thus increase microhardness.

Figure 6 depicts the effects of Al₂O₃ concentrations on the abrasive wear rate of a Cu-Al₂O₃ nanocomposite tested at four different loads. The pattern of the results is nearly identical for the four considered loads, with abrasive wear rates reduced by up to 12.5% Al₂O₃ content. With increasing applied loads, the abrasive wear rate for specimens increases. The wear rate is determined by the material’s physical and mechanical properties [59–62]. The hardness and strength of the material are observed to increase in samples containing up to 12.5% Al₂O₃, as discussed in this section, resulting in lower rates of wear. Both properties, however, are reduced after this value, indicating an increased wear rate because of agglomeration, which provides a larger surface area for plastic deformation and simple material removal. However, after this value, both properties are reduced, indicating a higher wear rate due to agglomeration, which provides a larger area for plastic deformation and easy material removal.
Figure 5. Effect of Al$_2$O$_3$ contents on the hardness of Cu-Al$_2$O$_3$ nanocomposite.

Figure 6. Abrasive wear rate as function of applied loads of Cu-Al$_2$O$_3$ nanocomposites at different sliding speeds.
4.2. Prediction of Wear Rates Using the Improved RVFL Model

Within this section, the efficiency of the developed method to predict the wear rates is compared with traditional RVFL and evaluated. In addition, the data consist of the volume fraction, load, and speed as input and wear rate as target value. The data set is split into 70% training and 30% testing sets, and this was conducted 25 independent times. The performance of the RVFL-AHA is compared with other methods, including sine-cosine algorithm (SCA), salp swarm algorithm (SSA), and ant lion optimizer (ALO). The parameter setting of these methods are assigned according to the original implementation of each of them. A set of performance measures was used to assess the performance of such as: root mean square error (RMSE), mean absolute error (MAE), and coefficient of determination \( R^2 \). These measures are defined as:

\[
R^2 = \frac{\left(\sum_{i=1}^{n_s} (d_i - \bar{d})(y_i - \bar{y})\right)^2}{\sum_{i=1}^{n_s} (d_i - \bar{d})^2 \times \sum_{i=1}^{n_s} (y_i - \bar{y})^2}
\]  

(16)

\[
RMSE = \sqrt{\frac{1}{n_s} \sum_{i=1}^{n_s} (d_i - y_i)^2}
\]  

(17)

\[
MAE = \frac{1}{n_s} \sum_{i=1}^{n_s} |d_i - y_i|
\]  

(18)

In Equations (16)–(18), \( n_s \), \( d \), \( y \), \( \bar{d} \), and \( \bar{y} \) represent the number of testing/training samples, observed value, predicted value, average of observed values, and average of predicted values, respectively.

The results of the developed RVFL-AHA and other methods, including SCA, SSA, and ALO, are illustrated in Table 1 and Figure 7. It can be noticed from these results that the developed RVFL-AHA has higher performance than SSA, SCA, and ALO. For instance, the ability of RVFL-AHA to learn from the training set is better than others as observed from RMSE, \( R^2 \), and MAE. The difference between RVFL-SSA, RVFL-SCA, and RVFL-ALO with RVFL-AHA is \( 8.9200 \times 10^6 \), \( 8.6500 \times 10^6 \), and \( 2.7900 \times 10^6 \), respectively, in terms of RMSE. In case of using the testing set, it can be noticed that the presented RVFL-AHA has higher \( R^2 \) than RVFL, whereas it has smaller RMSE and MAE than between RVFL-SSA, RVFL-SCA, and RVFL-ALO. Moreover, Figure 7 depicts the QQ plots for wear rate and its predicted value using RVFL-SSA, RVFL-SCA, RVFL-ALO, and RVFL-AHA for the testing set. It can be seen from this figure that the RVFL-SCA and RVFL-ALO nearly have the same correlation during the learning stage. However, the developed RVFL-AHA is a better fit than other methods since the data group around the straight line during the testing set.

Table 1. Results of proposed algorithm RVFL-AHA.

|          | Training Set | Testing Set |
|----------|--------------|-------------|
|          | AHA          | SSA         | SCA         | ALO      | AHA       | SSA       | SCA       | ALO      |
| \( R^2 \) | 1            | 0.9985      | 0.9986      | 0.9998    | 0.9554    | 0.9195    | 0.9294    | 0.9034   |
| RMSE     | \( 1.27 \times 10^{18} \) | \( 8.92 \times 10^6 \) | \( 8.65 \times 10^6 \) | \( 2.79 \times 10^6 \) | \( 8.04 \times 10^5 \) | \( 0.000108 \) | \( 0.000101 \) | \( 0.000118 \) |
| MAE      | \( 1.14 \times 10^{18} \) | \( 6.61 \times 10^6 \) | \( 6.19 \times 10^6 \) | \( 1.25 \times 10^6 \) | \( 6.1 \times 10^5 \) | \( 8.8 \times 10^5 \) | \( 8.84 \times 10^5 \) | \( 9.9 \times 10^5 \) |

According to the previous discussion, it can be noticed the performance of developed RVFL-AHA is better than other methods. However, the proposed RVFL-AHA still has some limitations, such as time complexity, since the number of solutions and parameters have high influence on this computational method. This can be solved by using parallel processing technique.
Figure 7. The QQ-plots of the wear rate and its prediction using AHA, SSA, SCA, and ALO.

5. Conclusions

An enhanced machine learning model based on Random Vector Functional Link was developed in this work to predict the wear rates of Cu-Al₂O₃ nanocomposites with different Al₂O₃ content and tested at different wear rate conditions. An in situ chemical reaction method was used to produce Cu-Al₂O₃ nanocomposites with good Al₂O₃ nanoparticles dispersion. The produced samples were tested to characterize their microstructure and mechanical and tribological properties. The characterization results showed great enhancement in the mechanical and tribological properties of the composites, reaching 100% and 55% for the composite containing 12.5% Al₂O₃ nanoparticles. This huge improvement is due to the presence of Al₂O₃ nanoparticles that possesses excellent properties and their good dispersion inside the Cu matrix, which increases the impedance of the material to penetration loads.

The developed machine learning model using artificial hummingbird algorithm (AHA) to enhance the performance of the Random Vector Functional Link (RVFL) to predict the wear rate. The results showed that the model was able to predict the wear rates of all the produced composites, with different Al₂O₃ content being tested at different wear conditions as well as different loads and speeds. The accuracy of the proposed model was checked using coefficient of determination R², achieving nearly 100% and 99.5% using training and testing sets, respectively.
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