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PROPHECY OF WEAR RATE AND MICROHARDNESS OF COMMERCIAL MATERIALS BY EXPERIMENTATION AND ARTIFICIAL NEURAL NETWORKS

PRATAPA REDDY YAKKALURI[1], LAKSHMI NARAYANA KAVULURU[1], KEDAR MALLIK MANTRALA[2], MADHAV T. P. BODDAPATI[3,*]

[1]Department of Mechanical Engineering, Koneru Lakshmaiah Education Foundation, Green Fields, Vaddeswaram, Guntur District, 522 302, Andhra Pradesh, India
[2]Department of Mechanical Engineering, Vasireddy Venkatadri Institute of Technology, Nambur, Guntur District, 522508, Andhra Pradesh, India
[3]Department of ECE, Koneru Lakshmaiah Education Foundation, Green Fields, Vaddeswaram, Guntur District, 522 302, Andhra Pradesh, India
[*]Corresponding Author: btpmadhav@kluniversity.in

Abstract

When two metallic surfaces rub or slide against each other, wear is caused due to friction that plays a decisive role in a machine component's life span and efficiency. The wear rate depends on parameters such as material composition, surface contact, applied load, surface roughness, velocity, surrounding environment, etc. In the present experimental work, an attempt has been made to predict the wear rate, friction force, and Coefficient of friction of commercially available materials like Brass, Copper, Mild Steel, and Stainless-Steel using a Pin on Disc (PoD) tribometer under user-defined test parameters. The test results show that the Copper specimen has a wear rate of 566.93 µm, which is higher than the other materials due to its high ductility and malleable property. In contrast, Mild Steel has the lowest wear rate, indicating it has much wear resistance with its high hardness property due to carbon percentage. The pin temperature attained by all sample specimens is nearly identical, with a negligible difference. For Stainless Steel, the friction coefficient is higher, while for Brass, it is lower. Vickers microhardness test is carried out on all specimens to find the hardness value. The hardness of the Stainless-steel specimen is higher (583 Hv) than that of the other samples, which indicates that the Stainless-steel is much more rigid than other materials. The higher the Hv value, the more complicated the resistance that the material offers to the load that is being applied. The mean square error (MSE) predicted the attrition rate of artificial neural networks and found the performance as $2.86e^{+5}$. The obtained gradient value is $6.31e^{+}5$. The control parameter, Mu, is taken as 0.00100 for the present training and observed that six validation checks had been performed during training. The results showed that the best performance through ANN was achieved at 238 epochs/cycles.

Keywords: Artificial neural network, Coefficient of friction, Friction force, Micro-hardness, Pin on disc, Wear rate.

1. Introduction

When two metal surfaces slide against each other, they undergo wear due to friction generated between them depending on sliding conditions. Because of wear, the machine or engine components alter their size and shape by prolonged usage, affecting the machine's efficiency and life span. The amount of wear in the material depends on contact surface area, applied load, surrounding atmospheric temperature, material properties, etc. The wear can be reduced by lubricants and surface coatings on components with other wear-resistive materials.

Pin on Disc Tribometer is widely used to estimate the wear rate of various materials. A specimen pin is stationary in the pin holder, and a disc rotates with a user-defined speed. The pin makes perpendicular contact to the disc with applied load at a defined track diameter. The materials of both pin and disc are chosen according to user-defined test conditions. The tribometer uses various combinations and compositions of metals as specimens for pin and disc to evaluate wear rate, friction force, and friction coefficient. When low carbon steel, Al, Copper, and Brass materials slide against Hardened Steel (EN31) which has 58 HRc, due to load, speed, and time and under certain user-defined conditions, the wear rate exhibits direct proportionality to the time of the run, speed, and load. Still, low carbon steel shows a lesser wear rate than other materials, and the friction coefficient also varies due to the enhancement of sliding velocity. Austenite steel of grades like SS-202 and SS-304 plays a key role and attracting industries with specific features like good tribological properties [1-3].

The wear is controlled by the usage of proper lubrication and the application of coatings [4]. In machines, journal bearings are used, which are made of conventional non-ferrous materials like gun-metal and Brass, which exhibits more wear rate and needs lubrication which increases the maintenance cost. Still, introducing new materials that show minor wear and generate less heat always occupies a key position with unique features and characteristics. Cast nylon is one of them [5]. Before using the material to fabricate, the material composition, material properties, the load applied, speed, and surrounding media always consider estimating the material's wear rate. The researchers and industrial experts first predict sliding parts' wear rate using simulation software like Finite Element Analysis. The stress-strain values generated in simulation help the researchers vary and select the best material composition [6].

Farrahi et al. [7] prepared two sets of atmospheric conditions to predict the wear of AISI 316 type steel with SAE 52100 steel in both ambient and cryogenic temperatures. The wear rate between sliding parts in Cryogenic temperatures exhibits better results than ambient temperatures when AISI 316 Steel pin slides against SAE 52100 using a pin on disc apparatus.

Yang and McKellar [8] collected seven types of sample blanks made of different compositions like Ni/Cu/Ni, which slides over Steel, Nickel over Steel, Ni/Cu over Zinc, Cupro-Nickel, Yellow Bronze/Copper over Zinc, Yellow Bronze over Steel and Al over Bronze. The samples are tested according to ASTM standards using Pin on Disc apparatus to predict the wear rate and observed that the first four compositions exhibit high wear resistance (low wear rate) than others; due to the presence of Nickel in alloy composition, it reduces the corrosion and wear rate where the austenitic phase is stabilized down in austenitic steel by addition of Nickel.

Varying the composition of brass material made by the sand-casting process is examined for the influence of parameters on wear rate and the reduction of pin length in microns(μm) [9]. Various materials like Cu, SS410, and Al are analysed and compared as a group of specimens with different times, loads, and speeds to predict the wear rate of the selected material using a pin-on-disc apparatus [10].

Nowadays, most advanced manufacturing processes like Additive Manufacturing (AM), Weld Arc Additive Manufacturing (WAAM) process, and Cold Spray Methods (CSM) attract researchers and industrialists with their exclusive features like less wastage of material, complex and customized product development with enhanced properties. Generally, the AM process is done by deposition powder material in layer form through CAD model design.

The products fabricated by AM process are primarily preferred in medical fields as bio-implants, and suitable materials for these processes are titanium and its alloys, Co-Cr-W alloy, Co-Cr-Mo alloy Inconel Series, and Magnesium alloy, etc., where these materials exhibit less corrosion rate and less wear rate with improved characteristics like high strength. Conventionally fabricated components need some post-heat treatment process to achieve desired mechanical, tribological, and microstructural properties. Post-heat treatment of metals improves the specific features and affects the material properties due to changes in the rearrangement of molecules and the structure refinement [11-14].

Lightweight and high-strength composites are always preferred over conventional materials in various fields like automotive, aircraft, medical, and space satellites because of the high weight ratio resistance. Metal matrix composites (MMCs) are manufactured by adding other materials to achieve desired properties, such as enhanced tribological and mechanical properties. Aluminum (Al-6061/ 7075) exhibits lower density, is preferred for manufacturing machine parts, and is made as MMCs by adding MoS_2 and SiC_p. In some cases, aluminum composites are substituted with other materials, such as duralumin. Hybrid metal matrix composites are manufactured by adding at least two reinforcement materials to the parent metal. Different compositions, reinforcements, and phases are manufactured using the conventional hand lay-up process to improve wear resistance compared to MMCs [15-17].

Artificial Neural Networks (ANN) is a technique composed of nodes suitable to estimate various parameters based on the signal processing capacity of neurons inspired by biological neurons in the human brain. A neuron has no storage capacity; only it transmits signals. Neural network data is transmitted as weight and bias. In ANN, propagation work acts as a training tool in two ways, back-forward feed propagation and back-back feed propagation, also referred to as recurring.

Feedforward is always preferred when input data propagates through the hidden layers between input and output layers and estimates the percent error. Using these propagation methods, the wear rate and coefficient of friction of different materials like Al6061-Si_3N_4 and other composite materials like Poly-tetra-fluor-ethylene (PTFE) based bearing materials added with varying percentages of the weight of additives are analysed [18-21].

This prediction of the wear rate is always made on the tribometer, either wet or dry. Under conditions of wet slippage, lubrication plays a key role, which reduces the material's wear rate by facilitating the development of friction between the sliding parts. If external lubrication is not permitted in some machines and sliding elements, self-lubricating materials are preferred as copper-pewter hybrid composites [22].

Optimization techniques like ANOVA are used to fix with ANN-based on Monte-Carlo to predict the wear rate and other sliding parts' tribological properties. The results are compared with different techniques, such as Grey-Relational Analysis (GRA), to find the best approach. They are also used to forecast errors, efficiency, complexity, variety of inputs, etc. [23]. A hyperbolic sigmoid transfer function (TANSIG) is used to compute the layer's output from the given net entry. The result values are between -1 and 1. The log-sigmoid transfer function (LOGSIG) is another log transfer function used to predict the material wear rate [24].

Using ANN, plastics' wear rate is expected when coated with metal surfaces and sliding against other parts, reinforced with glass fibres like C120 and Rp3 [25]. This ANN contains a famous backpropagation technique called Levenberg-Marquardt backpropagation, and it exhibits better results when attached to optimization techniques like Response Surface Methodology (RSM) [26].

Polymer composites are reviewed about the influence of fatigue life, wear performance, material response under various loading conditions, and mechanical properties. The design of composites and polymer material properties are also reviewed using the ANN technique [27]. Metal Matrix Composites (MMCs) are primarily used, and versatile composites are mainly preferred in many structural applications due to their advanced and promising features. Al /Al_2O_3 MMCs are developed using the conventional powder metallurgy method, and the wear rate and effect of the volume fraction of Al_2O_3 particulates in MMCs using the ANN process hardness are evaluated under various conditions [28].

Ultrahigh molecular weight polyethene (UHMWPE)composite materials added and fed with input parameters based on additives like Carbon Nanotube (CNT), Carbon Fibre (CF), Graphene Oxide (GO), wall austenite are analysed using ANN to predict the influence of applied load, sliding speed, type, and weight percentages of reinforcements on wear rate [29].

In the present work, the specimen pins made of materials like Copper, Brass, Mild Steel, and Stainless Steel were tested to investigate the wear rate under defined experimental conditions using PoD apparatus and later the experimental results were evaluated with ANN.

2. Experimentation

2.1. Pin on disc

American Society of Testing for Materials (ASTM - G99) describes the experimental procedure on the PoD apparatus to estimate the wear rate between two materials while they slide against each other. In this apparatus, a pin is a specimen kept stationary, and the disc rotates with the desired speed. One end of the pin is made spherical or flat to contact the disc's upper surface made of different materials with higher hardness. The test parameters may vary according to user application like pin size, pin shape, pin material, contact surface area of the pin, applied load, speed of the disc, and the test run's duration.

The ASTM-G99 does not specify any test parameters, but these are chosen by users accordingly. For experimentation, the PoD apparatus is used under different conditions or methods like dry, wet, or lubrication, pin heating, and chamber heating with additional accessories. The PoD is the most recurrently used equipment due to its simplicity. The ASTM test method provides information to calculate both mass loss and geometrical loss of material due to wear.

In the present work, the PoD apparatus (Make: DUCOM Instruments Pvt Ltd, Bangalore, Model No: LE-240-PH 400-CH400) was employed with a rotary disc made of Stainless Steel (EN31) with a hardness value of 58-62 HRc, with a surface roughness value of 1.6 R_a, where R_a is the average surface roughness value. Here, four types of conventional materials: Stainless Steel, Brass, Copper, and Mild Steel, are collected and machined to size, shaped toa standard size, and cylindrical shape, as shown in Fig. 1. The specifications of the selected pins are mentioned in Table 1.

Copper.

Brass.

(c) Stainless steel.

(d) Mild steel.

Fig. 1. Images of tested specimens.

Table 1. Specifications of pin specimens.

Pin Material	Pin Diameter (mm)	Pin Length (mm)	Pin Weight (g)
Mild Steel	8	44	17.958
Copper	8	44	20.036
Brass	8	44	17.982
Stainless Steel	8	44	16.153

The present wear test is carried out under the dry sliding condition at ambient (room) temperature of 27±1 °C with parameters like load applied, disc speed, track diameter, and time to run the test, etc., like as mentioned in Table 2.

Table 2. Orthogonal array of test parameters for wear test.

Standard Taguchi Orthogonal Array					Experimental Orthogonal Array			
Exp No	**A**	**B**	**C**	**D**	**Load (N)**	**Disc Speed (rpm)**	**TD (mm)**	**Time (min)**
L1	1	1	1	1	20	200	30	54
L2	1	2	2	2	20	300	40	27
L3	1	3	3	3	20	400	50	16
L4	2	1	2	3	30	200	40	40
L5	2	2	3	1	30	300	50	22
L6	2	3	1	2	30	400	30	27
L7	3	1	3	2	40	200	50	32
L8	3	2	1	3	40	300	30	36
L9	3	3	2	1	40	400	40	20

2.2. Calculation of time to conduct wear test on Pin on Disc Apparatus (for L3 experiment of the above table)

Assumed that the pin travels or runs approximately 1 km. The track diameter is fixed at 50 mm, and rpm is taken as 400 rpm, then the distance = 1 km (say) and circumference of disc = $2\pi r$ or πD_w, where D_w is wear track diameter.

When the track diameter is 50 mm, then the circumference is given by $=2\pi(50)$ mm = 157.05 mm. When the distance of 1 km is converted to mm, then = 1000 × 100 × 10 = 10^6 mm, then, the number of revolutions made by the pin = 10^6 / 157.05 = 6367.389 rev.

By considering the speed of the disc as 400 rpm, then time duration to run the test is given by 6367.389/400 = 15.918 min = 16 min (approx.). It means that when the experimentation runs by 16 min, the pin travels 1 km in a circular path at 50 mm track diameter with 400 rpm speed.

2.3. Working principle of PoD

Pin on Disc (PoD) apparatus is always preferred to determine wear rate and Coefficient of friction under the influence of applied load according to user-defined test parameters mentioned in Table 2.The pin is the specimen that needs to be tested against a rotating disc (here, 400 rpm).Various pin sizes can be used to experiment on this apparatus which are 3,6-, 8-, 10-, and 12-mm diameter, respectively, to find the wear rate in microns, friction force in newtons, and Coefficient of friction and pin temperature in °C.

Similarly, metals, polymers, composites, and plastics are fabricated by conventional manufacturing methods like forming, casting, and other advanced manufacturing techniques like stir casting and Additive Manufacturing (AM). The wear rate of a particular material depends on test conditions like the speed of the disc, applied load, track diameter and time of the run, selected material composition, material properties, type of material, etc. The general working principle of apparatus by CATIA design and actual PoD apparatus used for experimentation are shown in Figs. 2(a) and 2(b).

(a) Schematic working principle of PoD. **(b) Pin on Disc Apparatus.**

Fig. 2. Pin on Disc apparatus.

3. Methodology

3.1. Procedure to prepare apparatus

The general procedure to initialize the PoD apparatus attached to Control Unit for experimentation is mentioned in the below-mentioned steps.

Step 1: Setup of Apparatus or equipment
Step 2: Setup of Electronic Controller (EC)
Step 3: Setup of Software (WINDUCOM - 2010 Version)

In Step 1, the desired pin is first selected and cleaned with solvent (preferably with Acetone liquid) and fixed in a suitable pin holder. The assembly of the pin holder is set at the end of the lever arm of the apparatus. Ensure that the pin is in contact with the disc surface but not pressed against the disc. Load the pan, which is at the back of the apparatus, with a suitable weight. Make sure that the lever is in light contact with the force sensor. Specimen pin made of Stainless steel with diameter 8 mm size and pin holder is shown in Figs. 3 and 4.

Fig. 3. Stainless steel specimen.

Fig. 4. Pin holder (For 8 mm pin).

In Step 2, the Electronic Controller (EC) unit, wear and frictional force values should be zero. Set the time to run the experiment in seconds / min / hours. Press the start (green) button to initiate the machine and confirm the apparatus's speed then rotate the speed knob in a clockwise/anticlockwise direction to get the desired speed (here, 400rpm). In step 3, double-click the icon of WINDUCOM 2010 to open the software, which shows the software interface as shown in Fig. 5.

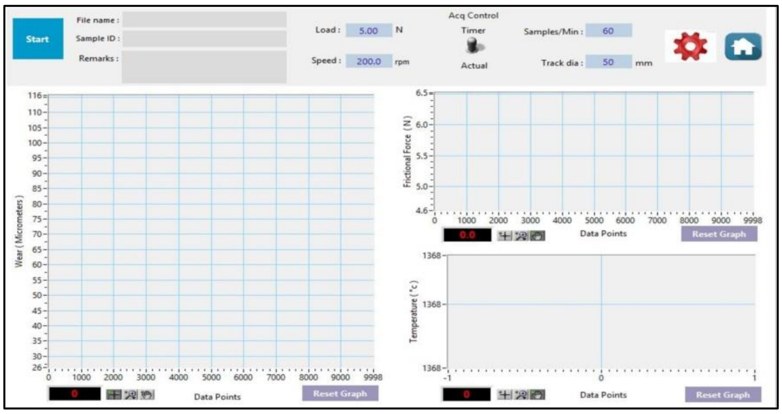

Fig. 5. Interface of WINDUCOM Software (V 2010).

In the software interface shown in Fig. 5, enter the selected test conditions like load in newton (N), speed in rpm, and specimen details like Filename, Sample ID, etc., for quick reference of file. Click on the start button in the EC unit and press the start button in the software. The apparatus initiates disc rotation. The software starts acquiring the experimentation data, which can be confirmed by observing a blinking signal (rectangle shape) below the stop button in the software interface. After completing the experiment, the equipment or apparatus automatically stops, and the time display blinks, indicating the experimentation was conducted according to the time input. Click on the stop button in the software, and power off the machine and controller unit.

3.2. Vickers microhardness test

According to the ASTM (E-384), hardness is defined as the resistance offered by the material against the applied load or resistance provided by the material against plastic deformation due to externally applied load. In the present work, the Vickers Microhardness apparatus (Make: METCO, Chennai, India. Model: ECONOMIST, VH-1 MDX) shown in Fig. 6 is used, which is feasible to apply an inbuilt load from 10g to 1kg. A diamond indenter shown in Fig. 7 is fed against the specimen's surface by an average applied load defined by the user, and the diamond indentation on the sample surface is shown in Fig. 8. In the Vickers Hardness tester, the diamond indenter angle is usually 1360, and the dwell time varies from 10 to 20 seconds. The values of D1 and D2 (two diagonals of diamond indenter) are measured, and the HV value is determined using the relation mentioned in Eq. (1).

According to ASTM standards, in the present work, an average load of 200 g was applied (dwell time of 10 sec) on tested samples. The mathematical formula to calculate the hardness value of the material on the Vickers scale is given by Eq. (1).

$$Hv = 1.854F/(D_{avg})^2 \quad (1)$$

Fig. 6. Microhardness apparatus.

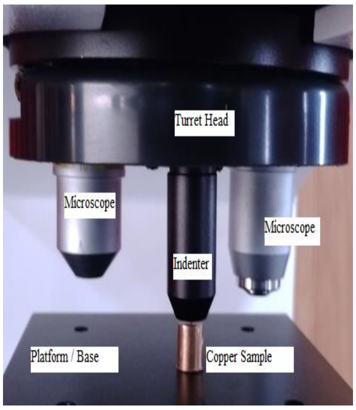

Fig. 7. Hardness test (Copper Sample).

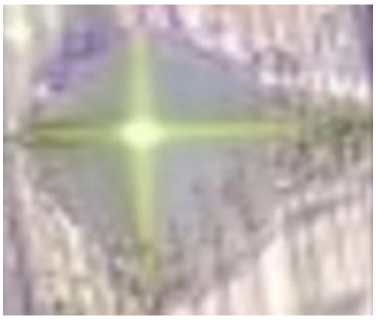

Fig. 8. Diamond indentation on copper sample.

3.3. Artificial neural network

An artificial Neural Network (ANN) is a network-based computing system that collects several points or nodes, termed neurons, or artificial neurons, based on their presence in a human brain to transmit signals through neurons. This signal is to recognize the object, which is termed image recognition. This ANN is mainly organized by a network containing an input layer, a hidden layer, and an output layer. The general network of neurons in ANN is shown in Fig. 9. The weights of the input signal are indicated as w_1, w_2, $w_3 \ldots . w_n$. The neural network information got stored in weights (W) and bias(b). The input function (f) calculates the aggregated net input signal to the neuron $u=f\,(x, w)$, where x and w are the input and weight vectors.

The input signal values are multiplied with the weights before entering the nodes, represented by the Eq. 2 (for the network shown in Fig. 9).

Output Signal=

$$(Aw_1+Aw_2+Aw_3+Aw_4+Aw_5+Aw_6) + (Bw_1+Bw_2+Bw_3+Bw_4+Bw_5+Bw_6) + (Cw_1+Cw_2+Cw_3+Cw_4+Cw_5+Cw_6) + \text{Bias} \quad (2)$$

The output of the node is the weighted sum. The higher the weight, the greater the effect on the signal, which affects the output signal. The simple way to mention these weights and input signals in a matrix form is given by Eq. (3).

$W = [w_1\ w_2\ w_3]$ and $X = [\ x_1;\ x_2;\ x_3]$ (3)

This ANN technique is employed for many applications, including cancer detection, pattern recognition, vehicle control, data analysis, face identification, and many more.

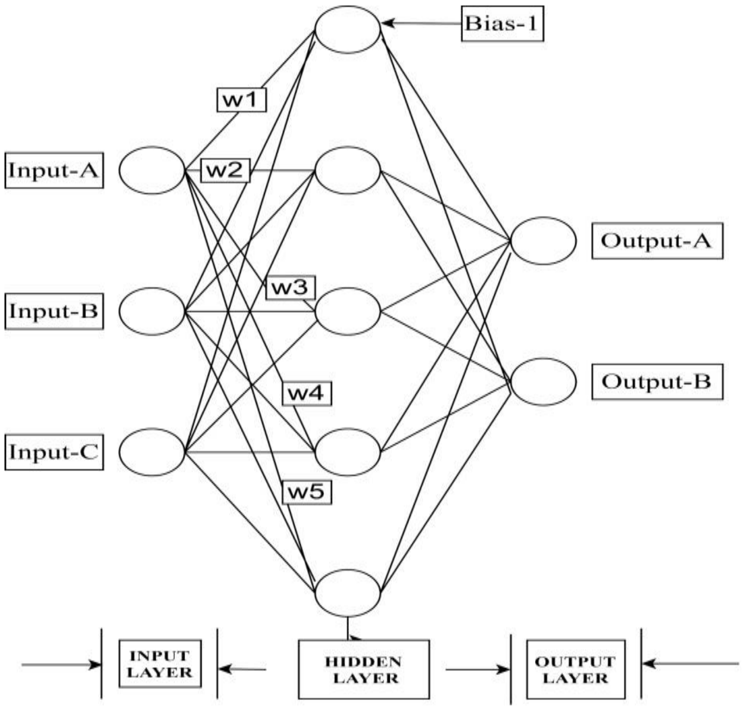

Fig. 9. General structure of ANN.

In the present work, to perform the ANN technique in MATLAB, the experimental results obtained from the wear test are considered input and output data for training, testing, and validation of neural networks. This analysis uses four input data parameters (load, time of run, disc speed, and track diameter) and three outcomes (wear rate, frictional force, and pin temperature) to train, test, and validate the network. 70% of input and output data is evaluated for training, 15% is used to validate results, and 15% is considered for testing the data. The ANN training process is based on the neural network training tool (nntraintool). The hidden layer consists of 4 layers that describe the output layer, which has four node points. Data division is made random (dividend) mode where training, testing, and validation tests are collected randomly. The training process is done using the Levenberg-Marquardt technique. The performance test was done by using Mean Squared Error (MSE) technique which estimates the minor error. Equation (4) gives the Mean Squared Error (MSE).

$\mathrm{MSE} = \Sigma_i |y_i - F(X_i)|^2$ (4)

where F is summation Σ_i

4. Results and Discussions

After experimentation on PoD, the obtained results in graphs and numerical values are plotted between different parameters: time vs. Wear rate, time vs. Frictional force, time Vs. Coefficient of friction and time vs. Pin temperature etc., are shown in Figs. 10 to 13.The description of the colours of materials in the graphs is Copper (Black colour), Brass (Blue colour), Stainless Steel (Red colour), and Mild Steel (Green colour).

4.1. Wear

The maximum values attained after experimentation on all samples during the wear test on a pin on disc apparatus are mentioned in Table 3.

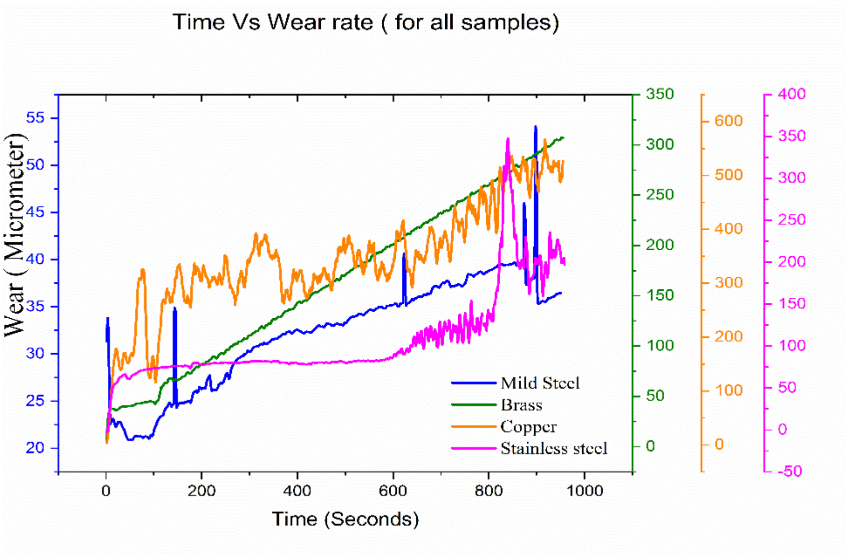

Fig. 10. Comparison graph of time vs. wear rate.

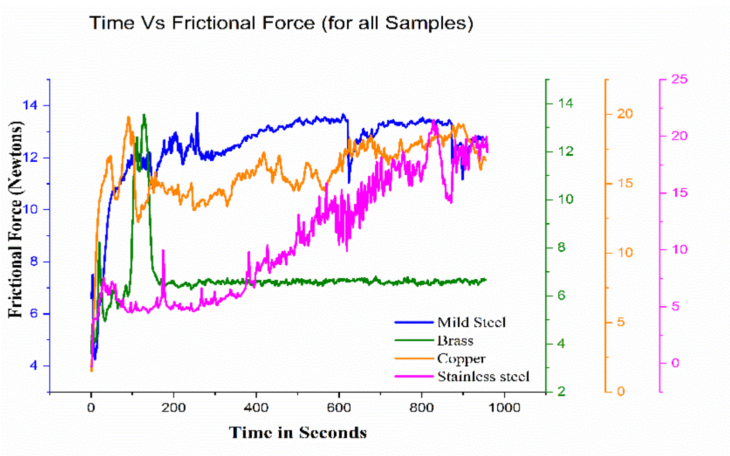

Fig. 11. Comparison graph of time vs. frictional force.

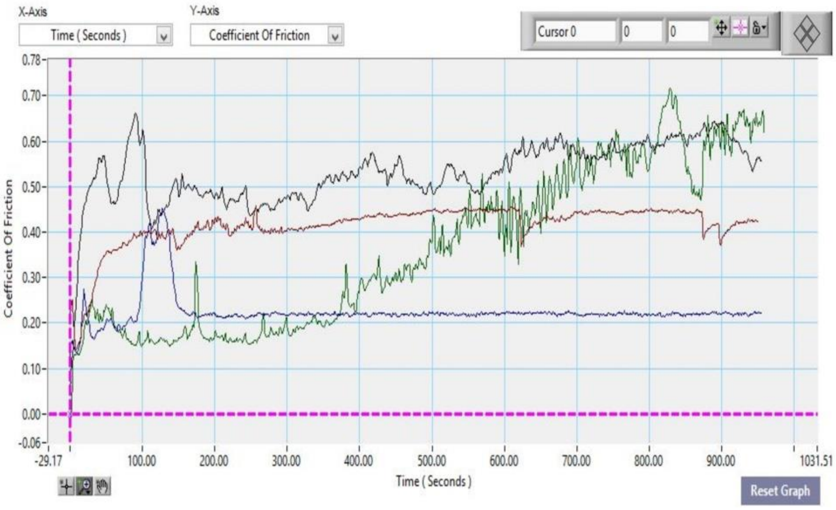

Fig. 12. Comparison graph of time vs. CoF.

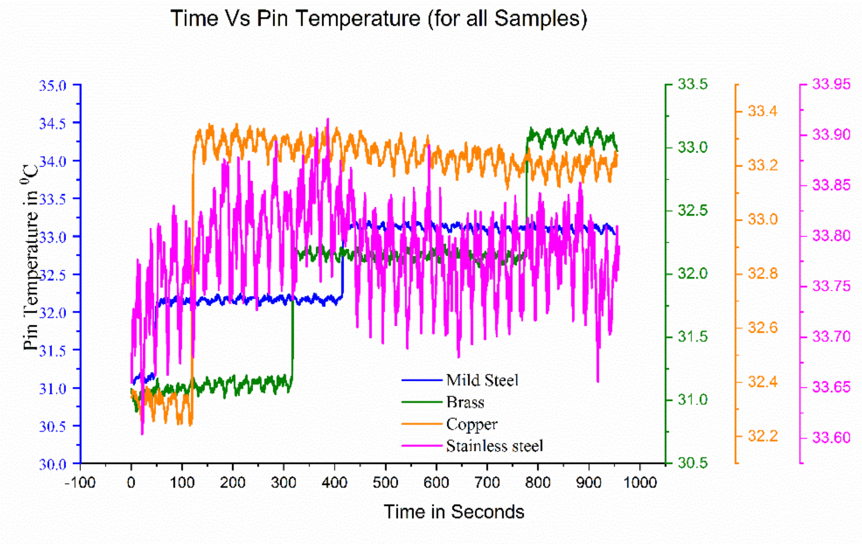

Fig. 13. Comparison graph of time vs. pin temp.

Table 3. Maximum values attained after experimentation on samples.

Sl. No	Sample Material	Wear Rate (µm)	Pin Temp. (°C)	Friction Force (N)	CoF (No Units)
1.	Brass	307.56	33.99	6.72	0.450
2.	Copper	566.93	33.254	18.50	0.661
3.	Mild Steel	36.47	33.167	12.83	0.457
4.	Stainless Steel	229.98	33.821	19.97	0.716

4.2. Artificial neural network

By considering the data of wear test parameters (applied load in newton (N), sliding speed in rpm, track diameter in mm, and test of runs in seconds) as input variables, the Artificial Neural Networks (ANN) technique was implemented to estimate the error through ANN using MATLAB (nntool) code. The various test conducted in ANN is performance, training, error, and testing. Diverse graphs were plotted after the ANN test, shown in Figs. 14 to 18.

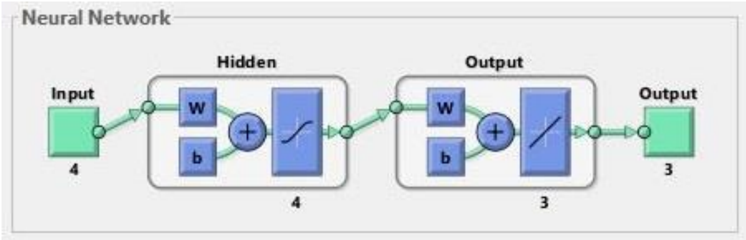

Fig. 14. Pattern recognition shown by ANN.

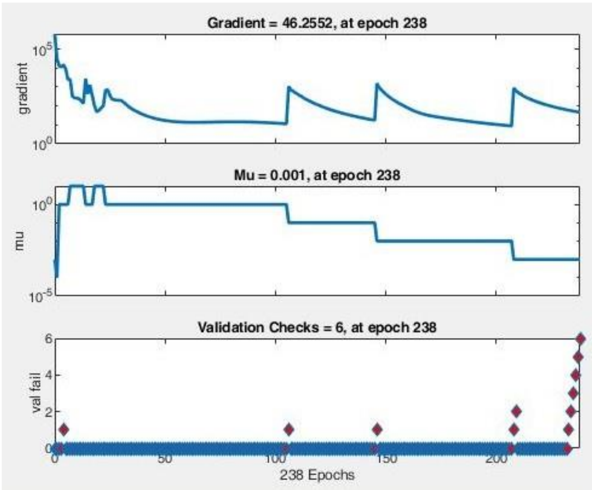

Fig. 15. ANN training process.

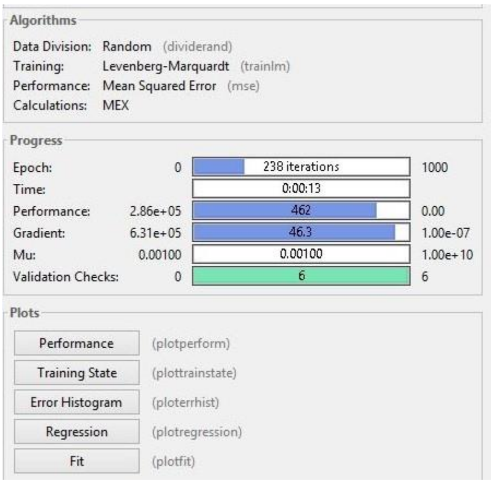

Fig. 16. Performance test using ANN.

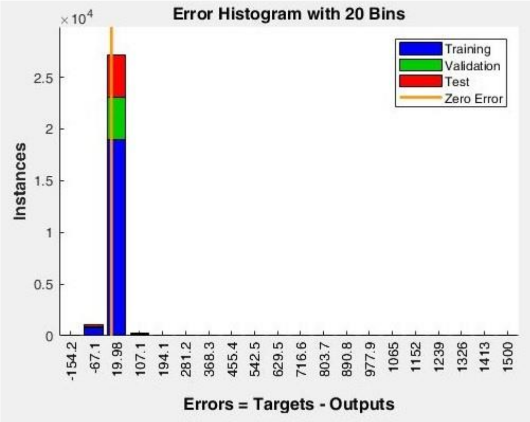

Fig.17. Error histogram of ANN.

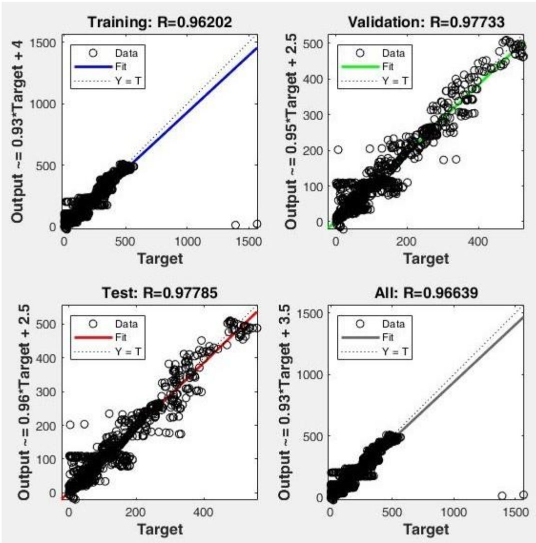

Fig. 18. Regression graphs of ANN.

4.3. Vickers micro hardness test

According to ASTM standards, the available load applied varies from 100 g to 200 g according to the test conditions to conduct a microhardness test on materials. In the present trial, a pack of 200 g is used on all specimens with a diamond pointer for 10 s dwell time. D_1 and D_2 values are taken to find Vickers Hardness's value, and the obtained results are tabulated in Table 4.

Table4. Vickers hardness values (*Hv*) of samples.

Sl. No	Sample Material	Hv Value at 200g
1.	Copper	172
2.	Brass	241
3.	Stainless Steel	583
4.	Mild Steel	364

The above hardness value of brass material is expressed as 241 Hv 0.2 / 10, indicating that the Hardness value of brass material on the Vickers scale is 241 at 200 g load applied for 10 s of dwell time. The comparison graph is drawn for the Hv value of all specimens, which is shown in Fig. 19.

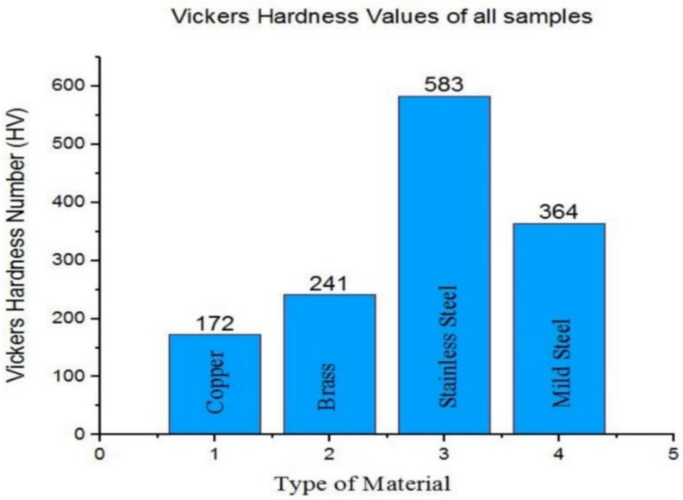

Fig. 19. Comparison graph of Vickers hardness value of samples.

4.4. Discussion on wear rate and hardness

The material properties, chemical composition, density, hardness, and friction coefficient play a significant role in the material's wear resistance.

In time vs. wear graph (Fig. 10), and the copper shows a high wear rate compared to other specimen materials. Brass (copper-66% & Zinc-34%) shows less wear rate than copper due to 34% zinc content, which offers excellent resistance to wear and material corrosion.

The Mild Steel has more Coefficient of Friction (CoF of MS is 0.6 max.) and shows a significantly lower wear rate than Stainless Steel. For sliding, friction between copper and steel is 0.36, which encourages the wear rate. Brass and Stainless-Steel's sliding conflict lies from 0.42 to 0.44 and shows the nearer wear rate, but less than copper due to high friction value.

The smaller value of hardness on the Vickers scale (Hv) indicates the material exhibits lesser hardness against an applied load. Or the enormous value of Hv suggests the material is challenging.

4.5. Discussion on ANN

To conduct the ANN test, 9484 sample data were considered for analysis using the nntool technique in MATLAB (Ver-2018b). Of the total samples, 70% (6638 samples) are taken for training, 15% (1423 samples) are considered for validation, and the remaining 15% (1423 samples) are observed for Testing the network.

In the training performance graph (Fig. 16), the performance that occurred at 2.86×10^{-5} indicates how much the error gets minimized during the training in terms of epochs or cycles. The best performance in 238 epochs demonstrates that the data set gets updated 238 times to reduce the error.

Gradient (Fig. 15) indicates the slope of the curve or line about the occurrence of variation in the error rate. The gradient of 46.2552 occurs at 238epoch/cycle. The role of the validation test is to analyse the given test's input value parameters, which provide the most negligible error value.

From Fig. 15, the validation curve or line lies at zero levels from the start to the approximate endpoint, indicating that the error is constant.

In the Error Histogram graph, one vertical bar indicates one Bin. From Fig. 17, the complete error history occurs with 20 bins ranging from -154.2 to 1500. Theoretically, the width of each vertical bar or Bin is given by Eq. (5).

$$\text{(Max. value - Min. value) / No. of Bins} \tag{5}$$

Each vertical bar in the graph indicates the number of samples considered in the data set. The maximum number of models considered for validation is19.98, and the thin vertical line (orange colour) indicates zero value. The red rectangle in the vertical bar indicates Training data, green indicates validation data, and blue indicates Test data.

The regression graph (Fig. 18) in ANN is plotted between Target and Output. The line which joins two corners diagonally indicates an actual fit line. The points above the true line show the data related to the existing positive data set, and the data points below the primary line indicate the false positive data set. The issues nearer to the actual line suggests that the data tested and validated have much accuracy.

5. Conclusions

After experimentation with selected test conditions, the following conclusions are drawn:

- Copper shows a wear rate of 566.93 µm, higher than other materials due to its ductility, malleability, and accessible machinable property. Mild steel exhibits a minor wear rate of 36.47 µm compared to other materials due to its internal resistance and presence of carbon (up to 0.29% in mild steel) which improves the hardness of steel.
- The pin temperature attained by all samples during the test is approximately the same. The friction coefficient is higher for stainless steel and lower for Brass specimens. The frictional force is higher for stainless steel and lower for Brass material. The Stainless-steel sample exhibits a higher hardness value of 583 Hv due to the presence of chromium content.
- To perform an ANN test, a total count of 9484 data values were considered for analysis, of which 70% of samples are taken for training, 15% for validation, and 15% for testing. The error percentage has turned negligible after 238 iterations through six validation checks. The performance is observed as $2.86e10^{+5}$.
- The correlation between experimental results and ANN results was studied. In general, the correlation value ranges from -1 to 1 and zero. If the correlation value between two data sets is zero, it indicates a 'No' relation. If it exhibits

values between -1 to 1, it suggests that the two data sets are either positively or negatively correlated.

- This investigation has identified and concluded that wear properties could be predicted for common materials using ANN with sufficient test data results.

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Conflict of Interest

All the authors declare that they have NO conflict of interest.

Nomenclatures

A, *B*, *C*,	Input data values to Artificial Neural Network
D_{avg},	Average mean length of two diagonals (D_1 and D_2), mm
D_w	Diameter of wear track, mm
F	Applied force, N
R	Spherical radius of the pin, mm
V	Volume loss of material, mm^3
W	width of wear track occurred on disc, mm
W_1, W_2, W_3	Weight of signal

Abbreviations

ANN	Artificial Neural Network
ANOVA	Analysis of Variance
ASTM	American Society for Testing and Materials
CF	Carbon Fiber
CNT	Carbon NanoTube
CoF	Coefficient of Friction
EN31	High Carbon Alloy Steel
FF	Feed Forward
MSE	Mean Squared Error
nntraintool	Neural Network training tool
PoD	Pin on Disc
RoC	Receiver Operating Characteristic
scg	Scaled Conjugate Gradient
UHMWPE	UltraHigh Molecular Weight Polyethylene

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