International Journal of Mechanical and Thermal Engineering

E-ISSN: 2707-8051
P-ISSN: 2707-8043
IJMTE 202; 6(2): 30-38
www.mechanicaljournals.com/ijmte
Received: 18-05-2025
Accepted: 20-06-2025

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Based-predicting of tribological properties in brass and bronze under variable loads

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DOI: https://www.doi.org/10.22271/27078043.2025.v6.i2a.93

Abstract
This study investigated the tribological behavior of copper-based alloys, specifically Admiralty Brass, under varying loads during a continuous 30-minute sliding test. Results showed a direct correlation between applied load and contact temperature, which reaching about 42 °C under a 1500 g load and staying below 32 °C at 250 g. This temperature rise is due to increased surface pressure and frictional heat. Although Admiralty Brass has good mechanical properties, it exhibited higher sensitivity to temperature compared to other alloys like copper-brass. An Adaptive Neuro-Fuzzy Inference System (ANFIS) model was developed to predict the coefficient of friction based on parameters such as load, sliding time, and specimen type. The model showed high accuracy with a 0.67% error. For Bronze alloy, the prediction error was 4.60%, while for Admiralty Brass, it a 2.52%. The friction force prediction error was as low as 0.02%, confirming the model's reliability for performance forecasting and material selection.

Keywords: ANFIS, tribological, admiralty bronze, bronze alloy

1. Introduction

Tribology is the science that studies friction and the engineering technology of interacting surfaces in relative motion. It deals with the mechanics of mo ving surfaces, which generally involve the dissipation of mass (wear) and energy (friction). Friction and wear are not inherent material properties but result from operational conditions and usage factors. The term "tribology" is derived from the Greek word *tripos*, meaning friction, and *logy*, meaning science. Thus, its literal translation is "the science of friction." It is a scientific discipline that examines the mutual effects between surfaces in contact under relative motion, also encompassing the study of solid-body interactions. The fundamental subjects of tribology research are friction systems-physical systems consisting of contacting surfaces, frictional films, and the stresses generated. Different materials exhibit distinct wear behaviors due to variations in their physical, chemical, and mechanical properties [1]. Although there is no direct correlation between wear and mechanical properties such as tensile strength, hardness, bending resistance, and elongation strength, tribology remains a highly interdisciplinary field that integrates physics, chemistry, mathematics, biology, and engineering. The application of computational simulation is indispensable for solving mathematical problems and fundamental hydrodynamics. With the advancement of engineering technology, industrial product structures and specialized equipment have become increasingly complex, and operating conditions have grown more demanding. Simultaneously, the requirements for reliability and operational stability continue to rise. [2] It also addressed a group studying the properties of engineering materials, including: The research analyzes compressive properties using straight and curved fibers in brushes that include various fractions of bronze alongside graphite has been conducted. The results indicated that brushes filled with curved fibers exhibited compressive strength similar to that of brushes filled with straight fibers, while the friction coefficients and wear rates of the brushes were reduced [3]. A research study analyzed the tribological behavior between steel-copper materials and steel-steel materials when adding graphene as a lubricating compound. The steel/steel sliding pair exhibited outstanding tribological properties even at high load conditions, while scientists gained better insight into graphene's lubricant mechanism [4]. Furthermore, the relationship between the friction coefficient of the "60/40" copper alloy and three types of steel, as well as the factors influencing the wear mechanism under dry sliding conditions and normal loads, was examined. The results confirmed that the material types significantly affect both wear and friction [5]. Regarding the effect of changing the Counter face material between the sliding surfaces, studies have shown that differences in the counter face material significantly affect both wear and friction [6]. The researchers studied the wear characteristics of wire rod rolling mill bearings with Monoblock material through testing three different lubricating oil compositions containing either 2.5% or 5% flakes or no flakes included. The research used bronze as the bearing material in combination with steel for the rotating shaft under solid particle-containing oil conditions. Among all parameters the environmental variable demonstrated the strongest effect by increasing solid particles to generate more volume loss together with higher friction coefficient values [7].

2. Experimental part

2.1 Pin-on-Disc Tribometer

The American Society for Testing and Materials (ASTM) classifies the experimental procedure of the Pin-on-Disc (PoD) device under standard ASTM G99 for estimating the wear rate between two materials in sliding contact. In this device, the pin serves as the stationary test specimen, while the disc rotates at a constant speed.

In this study, a PoD tribometer, model ED-201 Friction Monitor and Wear Tester**,** of Indian origin, was used. The device is illustrated in Figure 1 and is situated in the Mechanical Engineering Laboratories of the College of Engineering at the University of Tikrit. The rotating disc is made of stainless steel (C440) with a hardness value of approximately 62 HRC, and a surface roughness (Ra) of 2.394 µm**,** where *Ra* represents the average surface roughness.

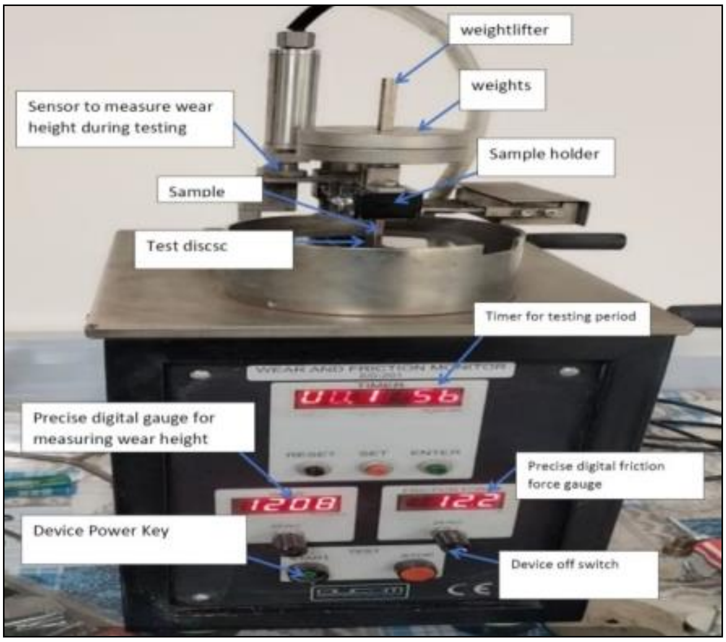

Fig 1: Pin-on-Disc Device Used for Wear and Friction Testing.

2.2 Material

Copper Alloys Used in the Study Bronze is an alloy primarily composed of copper and tin, and may also contain other elements such as aluminum, phosphorus, or manganese. The bronze alloy used in this study, with its composition detailed in Table 1, was selected for its mechanical and chemical properties (specimen 1. Admiralty brass, also known as admiralty bronze, is a specialized type of copper-zinc alloy with a small addition of tin. This alloy was specifically developed for marine applications, hence its name “Admiralty” referring to the British Royal Navy, which widely adopted it in the 19th century. The Mechanical Properties of Bronze Alloys and Admiralty Brass are shown in Tables 1 and 2. The Composition Analysis of Bronze Alloys (Specimen 1) is shown in Table 3. The content of the admiralty brass alloy used in this study is shown in Table 4 (specimen 2).

Table 1: Mechanical Properties of Bronze Alloys

Property	Typical Value
Tensile Strength	250 - 850 MPa
Yield Strength	150 - 450 MPa
Young's Modulus	100 - 120 GPa
Elongation	5 - 30%
Brinell Hardness	60 - 200 HB
Density	8.79624 [g/cm^3]
Melting Point Range	850 - 1050 °C
Thermal Conductivity	30 - 60 W/m·K
Specific Heat Capacity	350 - 400 J/kg·K
Coefficient of Thermal Expansion	17 - 20 × 10^{-6}/ °C

Table 2: Mechanical Properties of Admiralty Brass

Property	Typical Value
Tensile Strength	310 - 480 MPa
Yield Strength	105 - 250 MPa
Elongation	25 - 45%
Brinell Hardness (HB)	80 - 120 HB
Modulus of Elasticity	~110 GPa
Density	8.4405 g/cm³
Melting Point Range	865 – 890 °C
Thermal Conductivity	~109 W/m·K
Specific Heat Capacity	~377 J/kg·K
Coefficient of Thermal Expansion	~19 x 10^{-6} / °C

Table 3: Composition Analysis of Bronze Alloys (Specimen. 1)

No	Element	%	Min	Max
1	Cu	90.71	88.62	91.00
2	Sn	8.29	9.00	11.00
3	Fe	0.34	0.00	0.01
4	Zn	0.15	0.00	0.20
5	Cr	0.07	N/A	N/A
6	Mn	0.02	N/A	N/A
7	Te	0.01	N/A	N/A
8	Bi	0.01	N/A	N/A
9	Ni	0.01	N/A	N/A
10	Se	0.00	N/A	N/A
11	Pb	-0.18	0.00	0.05

Table 4: Analysis of Admiralty Alloy (Specimen. 2)

No	Element	%	Min	Max
1	Cu	91.05	92.00	96.70
2	Sn	7.97	N/A	N/A
3	Fe	0.34	0.00	0.80
4	Zn	0.12	0.00	1.50
5	Cr	0.06	N/A	N/A
6	Mn	0.02	0.05	1.30
7	Te	0.02	N/A	N/A
8	Bi	0.01	N/A	N/A
9	Ni	0.01	0.00	0.60
10	Se	0.00	N/A	N/A
11	Pb	-0.20	0.00	0.05

2.3 Specimen Hardness
Due to the significance of material hardness in tribological testing, the hardness of the four copper alloy specimens was measured in the laboratories of the Department of Mechanical Engineering, College of Engineering, University of Tikrit. To ensure the reliability of the test results, the measurements were repeated at the Technical Institute in Al-Dour using the same testing device, a Vickers Digital Automatic Micro Hardness Tester **.**The Company Name Mitutoyo MVK-H Series and type of company Mitutoyo**,** as shown in figure 2.

Fig 2: Digital Automatic Micro Vickers Hardness Tester.

Each specimen was securely mounted on the device platform, the load was set to 500 N, and the diamond indenter was applied. The load was held for 15 seconds, after which it was slowly removed from the table (5).

Table 5: Hardness of Copper Alloy Specimens Used in the Tests

Specimen No	Harness (Hv) [pa]E+08
1	1.13
2	3.10
3	1.62
4	1.2252

3. Experimental Program
Sixteen specimens with dimensions of (30 × 6 × 6) mm were prepared using mechanical machining processes (cutting and milling) at the Salahaddin Factory in Al-Dour District, as the pieces obtained from the Beiji refinery had various shapes. The operating parameters used in the practical experiments are presented in Table 6. These parameters were determined based on previous experiments [2, 3]. Additionally, the requirements of the ANFIS method were taken into consideration to ensure a wide range of normal loads for each test.

Table 6: Operating Parameters Used in the Practical Experiments

Specimen Type	Sliding Time (t) [min]	Vertical Load [g]
1, 2	10, 20, 30	250, 500, 1000, 1500

3.1 Design of ANFIS Model
A fuzzy system is a system in which the input, output, and state variables are defined over fuzzy sets, serving as a generalization of deterministic systems. From a holistic perspective, fuzzy systems capture the ambiguous characteristics of human brain reasoning, offering advantages in representing high-level knowledge. They can emulate comprehensive human inference to handle ambiguous information-processing problems that are difficult to solve using traditional mathematical methods, thus expanding computer applications in the humanities, social sciences, and complex systems.

Fuzzy Adaptive Neuro-Fuzzy Inference Systems (ANFIS) are artificial intelligence modeling techniques with structures resembling human brain cells. ANFIS combines the best features of Fuzzy Logic (FL) systems and Artificial Neural Networks (ANN), making it a specialized member of the ANN family. In this study, an ANFIS model was developed to predict the tribological behavior of four types of copper alloys based on experimental data obtained from practical tests. The ANFIS network consists of five layers, as illustrated in Figure 3**.** The fuzzy inference system forms the core of the ANFIS network. The first layer receives inputs and transforms them into fuzzy values using membership functions [12].

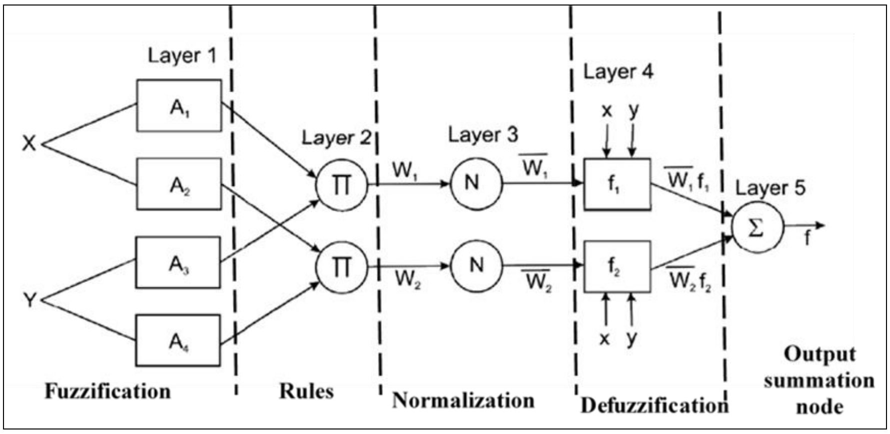

Fig 3: Components of the ANFIS Network

4. Experimental Working

4.1 Coefficient of Friction

Bronze Alloy (Specimen 1)

Figure 4 illustrates the relationship between sliding time (minutes) and the coefficient of friction (μ) under four different applied loads. Based on the experimental results, it was observed that at a load of 250 g, the coefficient of friction was relatively high (0.22-0.245) and showed a slight upward trend over time. This indicates that increased mechanical contact or the development of a wear layer may contribute to the increased resistance in the alloy. Under a load of 500 g, the coefficient of friction initially decreased from 0.125 to 0.10, suggesting stability or a reduction in real contact area due to load redistribution. At 1000 g, a slight variation was observed within the range of 0.095-0.105, indicating a quasi-stable frictional behavior. The lowest coefficient of friction (0.08-0.09) was recorded under the 1500 g load and remained relatively low with a slight tendency to decrease over time. From these findings, we conclude the following:

1. The coefficient of friction decreases as the applied load increases, which is a well-known behavior in tribology due to:
   - Increased pressure between the surfaces reducing the real contact area.
   - Changes in the surface layer that lead to reduced resistance.
2. Friction is more stable at higher loads (1000-1500 g), making these conditions suitable for applications requiring mechanical stability.
3. Lower loads (e.g., 250 g) exhibited a gradual increase in the coefficient of friction, which may indicate:
   - Progressive wear over time.
   - Accumulation of frictional by-products that affect the surface [12].

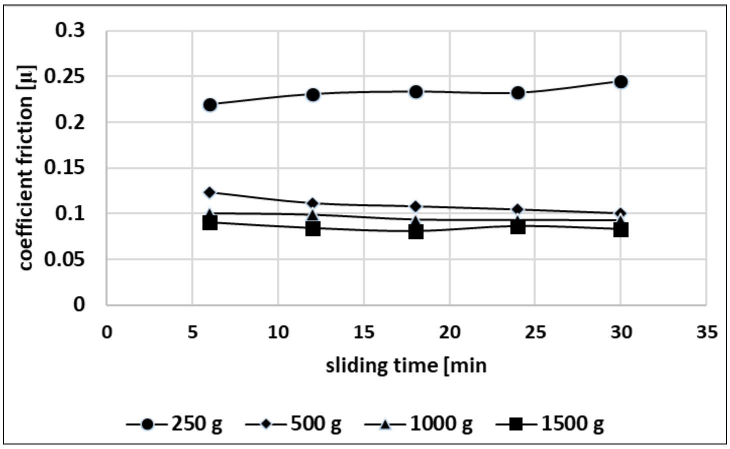

Fig 4: Illustrates the variation of the coefficient of friction for Specimen 1 vs the sliding time of 30 minutes.

Admiralty Brass Alloy (Specimen 2)

Figure 5 presents the relationship between the coefficient of friction and sliding time for the admiralty brass alloy under four different applied loads. The results showed that at a 250 g load, the highest coefficient of friction was recorded (0.27-0.28). It then stabilizes somewhat, followed by a decrease around the 15-minute mark, and finally reaches a steady state. This suggests that at low loads, contact between surfaces is more localized, leading to higher friction values. At a load of 500 g, the coefficient of friction was also relatively high (0.17-0.18), likely due to the absence of a well-developed wear layer. It gradually increases until around 15-20 minutes, then begins to stabilize. This behavior indicates the initial formation of a stable tribo-film (wear layer) that helps reduce sudden changes in friction. At 1000 g, lower friction values were observed (0.10-0.115) with a slight increase over time, eventually stabilizing with a slight upward trend by minute 25. This can be explained by the increased plastic deformation of the surfaces under higher loads, which helps stabilize the surface layer and reduce fluctuations in the coefficient of friction. At the highest load of 1500 g, the lowest coefficient of friction was recorded (0.07-0.09), with very minimal variation over time. This suggests that higher loads promote the flattening or merging of microscopic asperities, which reduces surface interlocking and consequently lowers friction, from this we conclude:

- Increasing the applied load leads to a decrease in the coefficient of friction.
- This is due to increased actual contact area and surface deformation, which reduce resistance to motion.
- The coefficient of friction tends to stabilize after 15-20 minutes of sliding, likely due to the formation of a wear layer or adaptation of the contacting surfaces.
- Heavier loads enhance the stability of performance and reduce fluctuations in friction [8].

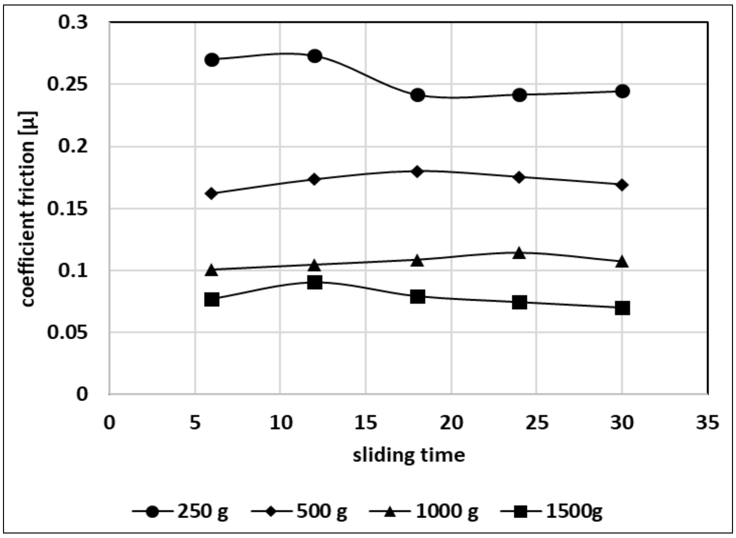

Fig 5: Illustrates the variation of the coefficient of friction for Specimen 2 vs the sliding time of 30 minutes.

4.2 Design of ANFIS Model for Friction Coefficient Predictions

The ANFIS (Adaptive Neuro-Fuzzy Inference System) model was developed and constructed after inputting the controlled parameters-namely, the applied normal load and sliding time-along with the experimentally obtained data for the friction coefficient, friction force, and temperature variation at the contact surfaces of the test specimens and the test rig disc (an uncontrolled parameter). These data were collected from experimental tests conducted on four types of copper alloys (Specimens 1 and 2). Figure 6 illustrates the appropriate ANFIS predictive model structure for estimating the friction coefficient [9].

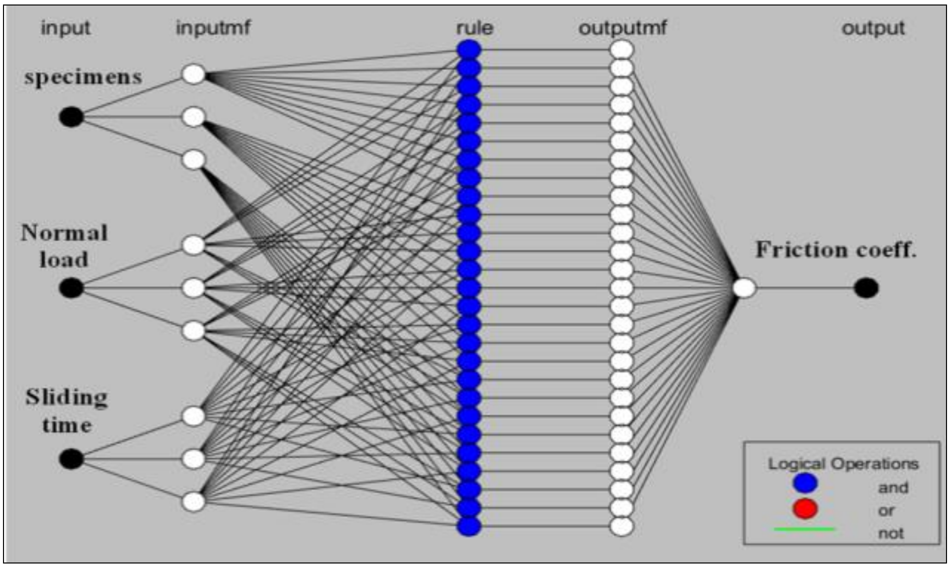

Fig 6: Generation of an ANFIS Predictive Model for Friction Coefficient

The input layer of the ANFIS network represents the experimental data for the type of test specimen, sliding time, and applied normal load (controlled parameters), while the output layer represents the experimentally measured friction coefficient (an uncontrolled parameter). The convergence of training error is directly related to the number of training iterations within the proposed ANFIS model. In this model, the minimum number of adaptive iterations was 50, achieving a prediction error rate of 0.67% for all copper alloy specimens, as demonstrated in Figures 7 and 8.

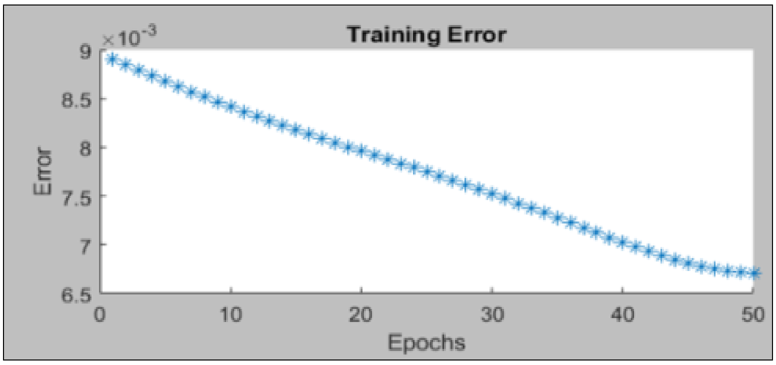

Fig 7: represents the number of iterations performed during the training process of the ANFIS neural network.

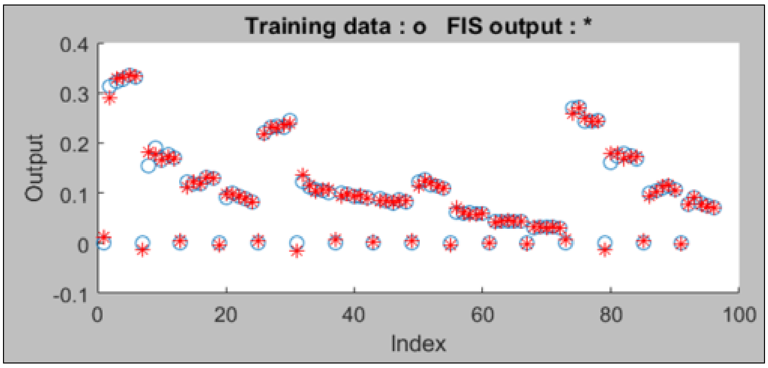

Fig 8: Illustrates the error and validation results of the ANFIS neural network in predicting the coefficient of friction for all test specimens.

Figure 9 displays the rule base governing the input data (type of test specimen, sliding time, and applied normal load) and the output data (coefficient of friction). These rules can be utilized to perform various predictions to determine the coefficient of friction values for all test specimens.

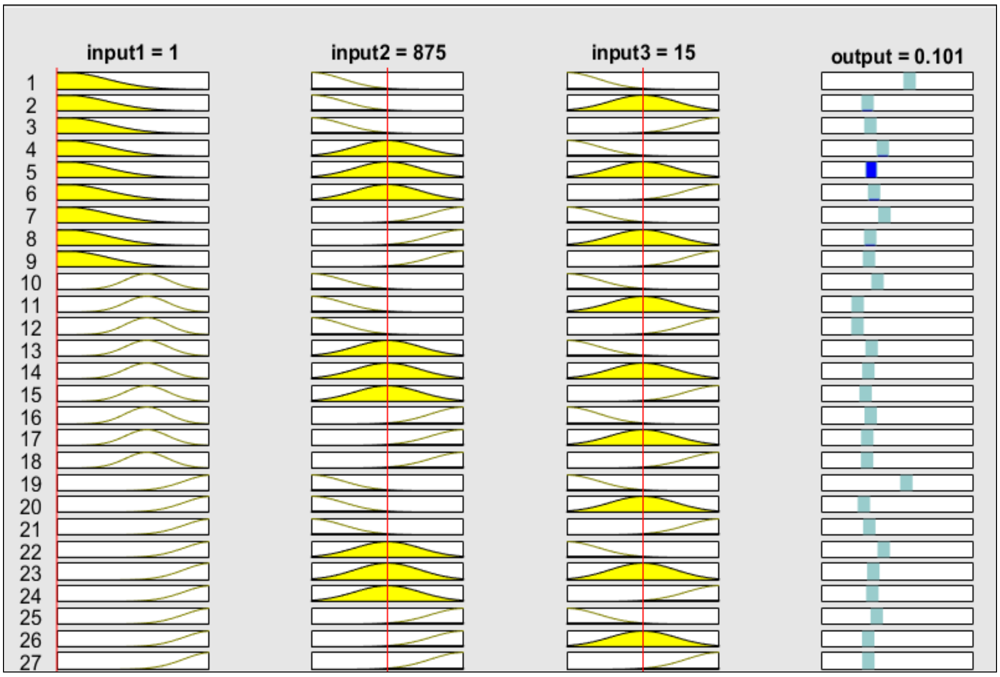

Fig 9: presents the rule base governing the relationship between the input and output data.

To compare the experimental values with the predicted values obtained from the ANFIS model for the variation of the coefficient of friction for specimens (1and *2*), the analysis was carried out randomly according to the applied load, as follows:

Specimen 1 (Bronze alloy)
Figure 10 illustrates the variation in the coefficient of friction for Specimen 2 with changing sliding time under a normal load of 500 grams, based on both experimental and predicted results. The average error was 4.60%**.**

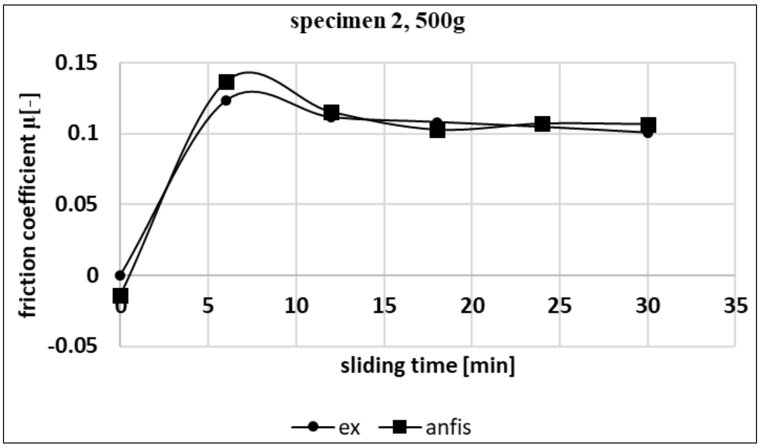

Fig 10: shows the variation of the coefficient of friction with sliding time for Specimen 2 at a normal load of 500 grams, comparing the experimental and predicted results using ANFIS.

Specimen 2 (Admiralty alloy)
Figure 11 represents the variation of the coefficient of friction for Specimen 4 with sliding time under a normal load of 1500 grams, comparing experimental and predicted results, where the average error was 2.52%.

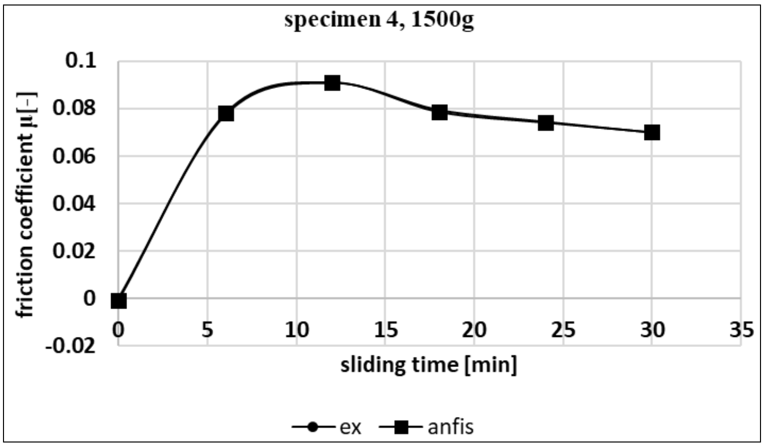

Fig 11: Illustrates the variation of the coefficient of friction with sliding time for Specimen 2 under a normal load of 1500 grams, showing both experimental and predicted results using ANFIS.

For comparison between the experimental and predicted values obtained from the ANFIS model for the variation of friction force for specimens (1 and 2) randomly and according to the applied load, the following is presented:

Specimen 1 (Bronze Alloy)
Figure 8 shows the variation of friction force for Specimen 1 with changing sliding time at a normal load of 500 grams, presenting both experimental and predicted results, with an error rate of 3.25%.
b) Specimen 2 (Admiralty Brass Alloy):
Figure (9) depicts the variation of friction force for Specimen 2 with changing sliding time at a normal load of 1500 grams for both experimental and predicted results, where the error rate was 0.02%.

4.3 ANFIS Model Design for Predicting Loss Material between Contact Surfaces
An ANFIS (Adaptive Neuro-Fuzzy Inference System) model was developed and generated by incorporating controlled variables, namely specimen type, normal load, and sliding distance, along with the uncontrolled variable-material loss between the contact surfaces. These data were obtained from experimental tests conducted on copper alloy specimens (1and 2). Figure 12 illustrates the appropriate ANFIS model for predicting material loss. Due to the variation in input and output data, normalization of both input and output parameters was performed to achieve an acceptable prediction error rate [10, 11].

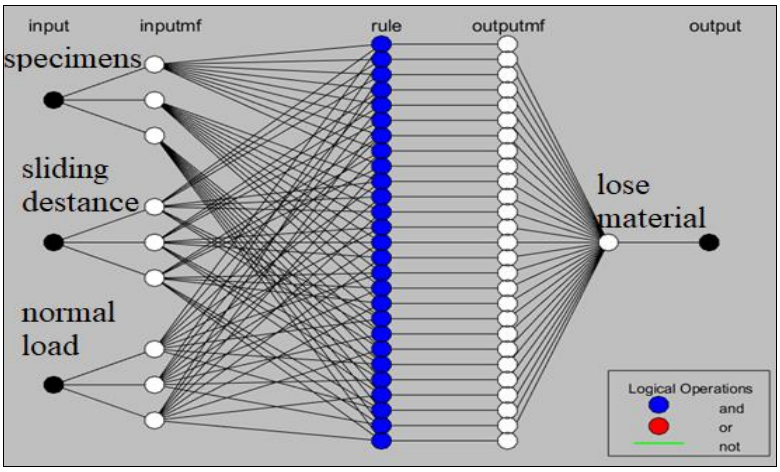

Fig 12: Generation of the ANFIS Predictive Model for Contacts Material Loss.

The input layer represents the experimental data for the specimen type, sliding distance, and normal load applied to the test specimen s (controlled variables), while the output layer represents the experimental data for the contact material loss of the test specimen (uncontrolled variable). The convergence of the training error is related to the number of iterations used in the proposed ANFIS model. In this model, the minimum number of adaptive iterations was 50, achieving a prediction error rate of 0.0109% for all copper alloy specimen s. This is illustrated in Figure 13, while Figure 14 presents the training results of the ANFIS model across all iterations.

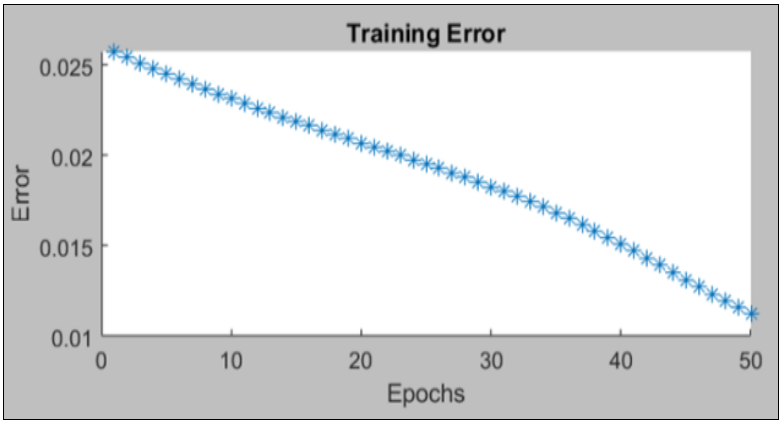

Fig 13: Illustrates the number of iterations performed during the training process of the ANFIS neural network and the calculated error rate across all iterations for predicting the material loss of the test specimen.

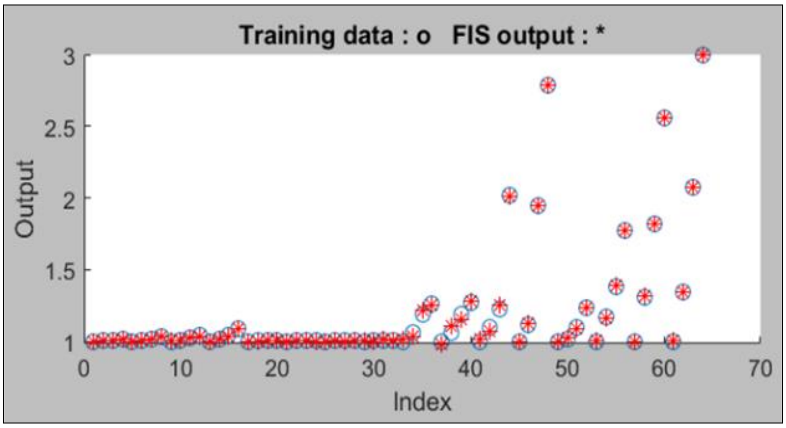

Fig 14: illustrates the error magnitude and validation results of the ANFIS neural network for predicting material loss in all test specimens**.**

Figure 18 presents the rule base governing the input data (type of test specimen, sliding distance, and applied normal load) and the output data (material loss of the test specimen), which can be utilized to perform various predictions and determine the material loss values for all tested specimens. To compare the experimental values with the predicted values obtained from the ANFIS model for changes in contact surface temperature of the specimens (1 and 2), random comparisons were conducted under the applied load as follows:

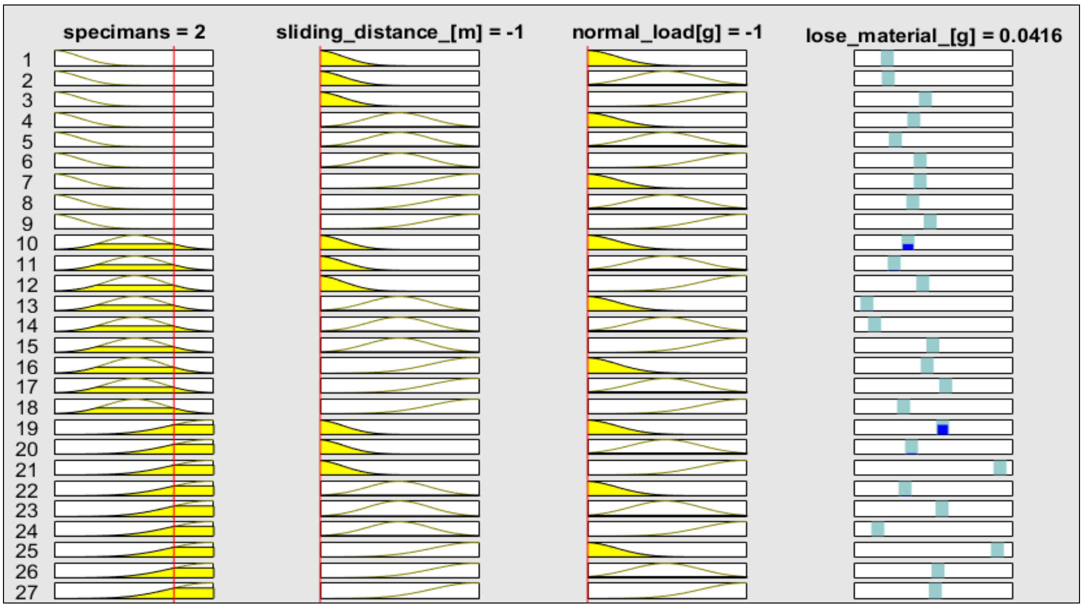

Fig 18: Illustrates the governing rules between the input and output data for the material loss of the test specimen.

Conclusions

1. The tribological analysis of Admiralty Brass (Specimen 2) revealed a direct relationship between applied load, sliding time, and contact temperature. Higher loads resulted in increased frictional heat and elevated contact temperatures.
2. Admiralty Brass showed greater thermal sensitivity compared to other tested alloys, which could limit its suitability for high-load or prolonged operational environments.
3. Despite its favorable mechanical properties, Admiralty Brass is more prone to thermal accumulation under continuous friction, which may affect long-term performance.
4. The ANFIS model developed for predicting the coefficient of friction and friction force demonstrated high accuracy, with prediction errors as low as 0.67%, confirming the effectiveness of neuro-fuzzy systems in tribological forecasting.
5. The comparative analysis between experimental and predicted results showed excellent consistency, validating the use of ANFIS in simulating tribological behavior of different copper-based alloys.

Recommendations

1. Admiralty Brass should be used in applications with moderate loads or intermittent operating conditions to minimize thermal buildup and avoid performance degradation.
2. Future material selection for mechanical systems should consider both tribological and thermal characteristics, especially in dynamic friction environments.
3. The use of AI-based modeling tools like ANFIS is highly recommended for early prediction of frictional behavior, reducing the need for extensive physical testing.
4. Further research is encouraged to expand the ANFIS model by incorporating additional parameters such as humidity, lubrication conditions, and surface roughness for broader application accuracy.
5. Industries dealing with wear-critical components should integrate predictive modeling approaches into their design processes to enhance material efficiency and operational safety.

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