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HARNESSING MACHINE LEARNING FOR WEAR PREDICTION IN SUSTAINABLE FIBRE-REINFORCED HYBRID COMPOSITES

Summary

The escalating demand for sustainable materials in engineering applications has led to the emergence of natural fibre-reinforced polymer composites (NFRPCs). This study introduces a hybrid composite integrating glass, raffia, and acacia fibres with an epoxy matrix, fabricated using the hand lay-up technique. The composite's design emphasises fibre arrangement, with glass fibre as outer layers, to enhance surface finish and structural integrity. Thermal performance evaluated through the thermogravimetric analysis (TGA) confirmed stability across diverse temperature ranges. Dry sliding wear tests assessed the composite's tribological properties, highlighting the influence of load, sliding velocity, and distance. A novel machine-learning framework, utilizing deep learning neural networks (DNNs), was employed to predict wear rates based on these parameters. Developed in MATLAB R2023a, the DNN model showed a high correlation between the predicted and the experimental data, substantiating its accuracy and reliability. This study underscores the hybrid composite's potential in automotive applications, such as brake systems, by demonstrating superior thermal stability, wear resistance, and predictive modelling capabilities, paving the way for optimised material design.

Key words: *bio composite; hand lay-up technique; wear analysis; thermal analysis; machine learning techniques.*

1. Introduction

Natural fibre-based composites (NFRPCs) are gaining widespread attention across various industrial sectors due to their lightweight nature, cost-effectiveness, environmental sustainability, and superior strength-to-weight ratio. These materials are increasingly utilised in automotive industry, construction, marine industry, military industry, medicine, and telecommunications [1-2]. The growing global emphasis on sustainability has further accelerated the demand for natural fibres as eco-friendly alternatives to synthetic reinforcements. However, natural fibres often exhibit limitations such as reduced thermal stability and wear resistance, necessitating innovative approaches to enhance their properties [3].

One such approach is hybridisation, which combines multiple reinforcements to overcome individual fibre limitations and achieve superior performance [4]. This strategy aligns with the evolving paradigm of developing sustainable, efficient, high-performance materials for industrial applications [5]. Recent research has explored the potential of various fibres. For example, acacia fibre, derived from Acacia Arabica, has enhanced mechanical properties after alkaline treatment, as it improves interfacial bonding by reducing hemicellulose content and removing impurities. These composites exhibit thermal stability up to 300°C, making them suitable for demanding applications [6-7]. Similarly, Prosopis Juliflora (Velikaruvelam), though often regarded as an agricultural weed, offers high lignin content that improves stiffness and thermal resistance, positioning it as an alternative to traditional construction materials like plywood [8]. Studies have also shown that adding thorn powder or rice husk to acacia composites enhances wear resistance and tensile strength, further broadening their applicability in structural and automotive components [9]. Raffia fibre, another promising reinforcement, exhibits distinctive mechanical properties and chemical resistance, making it suitable for low-cost, lightweight applications [10]. However, limited studies have investigated its potential as a reinforcement in hybrid composites, pointing out a significant research gap. Additionally, glass fibres are well-established for their exceptional strength, durability, and resistance to environmental degradation, making them a valuable component in hybrid systems [11]. Combining these fibres into a single composite offers a unique opportunity to create a material with enhanced mechanical, thermal, and tribological properties [12]. This study introduces a novel hybrid composite that integrates glass, raffia, and acacia fibres in an epoxy resin matrix, fabricated using the hand lay-up technique [13]. The novelty of this study lies in its strategic fibre arrangement and the use of advanced machine-learning techniques to predict and optimise material performance. Thermogravimetric analysis (TGA) and wear tests are employed to evaluate the composite's thermal stability and wear behaviour under varying conditions. A deep neural network (DNN) is developed to predict wear rates accurately, considering control parameters such as load, sliding velocity, and distance. This approach bridges experimental and computational methodologies, reducing experimentation costs and providing deeper insights into material behaviour [14-15]. The primary objective of this study is to fabricate and experimentally analyse the thermal and tribological properties of the hybrid composite while leveraging machine-learning techniques for performance prediction and optimisation. The findings aim to advance sustainable engineering materials, particularly for critical automotive applications such as brake pads and rotors, where thermal stability and wear resistance are essential.

1.1 Materials and methods

The hybrid composite in this study was fabricated using a novel combination of glass, raffia, and acacia fibres embedded in an epoxy resin matrix. Glass fibres were strategically placed in the outer layers to provide high tensile strength and surface integrity, while raffia fibres, known for their lightweight and thermal stability, were positioned in the intermediate layers. Acacia fibres, sourced from Acacia Arabica and treated via water-retting and alkaline processes, were integrated into the core layers, enhancing interfacial bonding and mechanical properties. The alkaline treatment removed impurities and improved the compatibility of the fibres with the epoxy matrix, resulting in improved composite performance. The epoxy resin, composed of LY 556 and HY 951 hardeners (procured from Linux Pvt. Ltd, Chennai, India), provided excellent adhesion and thermal stability. Additionally, a wax-based releasing agent, purchased from Arul Automotive Pvt. Ltd, Namakkal, India, was applied to facilitate easy removal of the cured composite from the mould. The novelty of this work lies in the unique hybridisation of these natural and synthetic fibres, combined with a novel predictive modelling approach using machine learning to optimise the wear resistance and thermal properties of the composite. This material combination, along with the advanced processing techniques, paves the way for the development of high-performance, sustainable composites suitable for automotive and other high-demand engineering applications [16].

Table 1 Physical properties of fibres

Name of the materials	Length (mm)	Thickness (mm)	Density (g/cm^3)	Tensile strength (MPa)	Young's modulus (GPa)	Cellulose content (%)
Acacia fibre	37	0.3	0.906	20	16	61
Raffia fibre	30	0.15	0.75	97	30	53
Epoxy resin /Hardener	-	-	1.2	5.17	3	-

1.2 Manufacturing method

The hybrid composite was fabricated using the hand lay-up technique, beginning with the application of a wax-based releasing agent (Arul Automotive Pvt. Ltd, Namakkal, India) to the mould for easy removal post-curing. Glass, raffia, and acacia fibres were treated to enhance their bonding with the epoxy resin matrix. Acacia fibres underwent water-retting followed by alkaline treatment with 5% NaOH to remove impurities and improve fibre-matrix bonding, while raffia fibres were similarly treated for surface roughness. Glass fibres were placed in the outer layers for strength, raffia fibres in the middle layers for thermal stability, and acacia fibres in the core for improved mechanical properties. LY 556 resin and HY 951 hardener (Linux Pvt. Ltd, Chennai, India) were mixed in a 10:1 ratio and applied between the fibre layers. After curing for 48 hours at room temperature, the composite was removed from the mould, trimmed, and subjected to thermal and wear testing [17].

Fig. 1 Composite manufacturing and used materials (a. glass fibre, b. acacia fibre, c. raffia fibre, d. epoxy resin, hardener, NaOH solution, e. alkaline treatment, f. final composite) [2].

This process combines natural and synthetic fibres in a layered configuration, with a machine learning-based approach for wear and thermal optimisation, making it highly suitable for automotive applications such as brake pads and rotors. Figure 1 illustrates the fabrication process.

1.3 Testing of the composite

The hybrid composite's thermal stability was evaluated using the TGA with a TA Instruments Q500, where samples were heated from room temperature to 700°C in a nitrogen atmosphere at varying rates (5-25°C/min). The TGA results revealed a 26.9% weight loss at 150°C due to the expulsion of moisture and volatile components, followed by a 42.1% weight reduction at 330°C from the decomposition of organic materials. A final weight loss of 30% was observed at 790°C, indicating the composite's residual stability even at high temperatures. This relatively high decomposition temperature, particularly given the presence of epoxy (typically stable up to 500°C) and natural fibres, can be attributed to the interaction between the epoxy matrix and the fibres. The fibre matrix interface likely forms more stable cross-linked structures, increasing the overall thermal stability of the composite. Additionally, the natural fibres, particularly the acacia and raffia, may contain high lignin content, which can contribute to the material's ability to withstand higher temperatures. The third weight loss at 790°C suggests the presence of resilient components or residues that contribute to the composite's enhanced thermal performance compared to individual natural fibres or pure epoxy resins [18].

1.4 Experimental work

The experimental work aimed to evaluate the thermal stability, wear resistance, and mechanical properties of the hybrid composite, incorporating advanced experimental designs to optimise the results. The wear rate and coefficient of friction (COF) were assessed using a pin-on-disk testing machine (Ducom-TR-20LE), which provides precise tribological performance data under controlled conditions [19-20]. To maximise efficiency and reduce experimental time, the design of experiments (DOE) method, specifically using a D-optimal design, was employed. This approach optimised the number of experiments by systematically varying factors such as load, sliding velocity, and sliding distance across three levels. A total of 16 experiments were conducted to study the effect of these parameters on wear rate and COF. Table 1 provides a summary of the physical properties of the materials used, including fibre length, density, tensile strength, and cellulose content. Acacia fibre had a tensile strength of 20 MPa and a density of 0.906 g/cm³, while raffia fibre exhibited higher tensile strength (97 MPa) and lower density (0.75 g/cm³). These properties indicate the potential of the fibres to contribute distinct mechanical benefits to the hybrid composite. Table 2 summarises the experimental parameters used in the wear testing, including varying levels of load, sliding velocity, and sliding distance. The experimental factors were set at four levels: load (15 N, 30 N, 45 N, and 60 N), sliding velocity (0.628 m/s to 2.531 m/s), and sliding distance (150 m to 600 m). The wear rate was evaluated based on these combinations, aiming to identify the optimal settings for the composite's performance. "The 'lower the better' characteristic of the signal-to-noise (S/N) ratio was used to minimise the wear rate, and the tests revealed that the wear rate decreased with higher loads, indicating the composite's ability to withstand increasing frictional forces.

Table 2 Design factors of fabricated composites

	Level			
	I	II	III	IV
Composition	Acacia + raffia fibre	Acacia+ raffia fibre	Acacia + raffia fibre	Acacia+ raffia fibre
Sliding velocity (m/s)	0.628	1.256	1.884	2.512
Load (N)	15	30	45	60

In addition to the wear testing, the thermal performance of the hybrid composite was evaluated through the TGA, as mentioned earlier, to determine its stability at elevated temperatures. The combination of thermal and wear testing provided valuable insights into the composite's performance in real-world applications where both thermal and tribological properties are critical. A novel machine-learning approach was also utilised for wear rate prediction. A DNN was developed and trained with the experimental data to predict wear rates based on varying load, sliding velocity, and distance. The DNN model, implemented in MATLAB R2023a, utilised a 3-10-1 topology, which optimised the prediction accuracy. This integration of machine learning provides a more efficient method of evaluating wear resistance and enables the optimisation of composite materials, offering a significant leap towards data-driven material development. This combined approach of experimental testing and machine learning techniques forms a novel framework for material characterisation, providing deeper insights into composite behaviour and offering a tool for future optimisation of hybrid composites for industrial applications.

2. Deep neural network-based computational analysis

The wear rate of the hybrid composite was predicted using a DNN model, developed in MATLAB R2023a. This model utilised experimental data with input parameters such as load, sliding velocity, and sliding distance (see Table 3), to predict the wear rate.

Table 3 L16 orthogonal array for specific wear rate and coefficient of friction

Combinations	Load (N)	Velocity (m/s)	Sliding distance (m)	Wear rate x 10^{-5} (mm^3/Nm)	COF	S/N ratio (wear rate)	S/N ratio (COF)
A+R	15	0.628	150	3.768	0.42	-77.686	18.32683
A+R	15	0.7	300	3.901	0.48	-78.688	18.56263
A+R	15	0.682	450	3.788	0.43	-77.7	18.32666
A+R	15	0.628	600	3.768	0.42	- 77.686	18.32683
A+R	30	1.256	150	3.8	0.338	-73.8483	20.21348
A+R	30	1.258	300	3.467	0.34	-74.9001	20.98221
A+R	30	1.3	450	4	0.3486	-75.1001	21.10002
A+R	30	1.32	600	3.768	0.35	75.9346	21.98234
A+R	45	1.884	150	4.60533	0.444222	-75.943	17.83981
A+R	45	1.9	300	4.7	0.5	-76	18
A+R	45	2	450	4.8	0.6	-78	20
A+R	45	1.96	600	4.75	0.7	-79.1	19
A+R	60	2.531	150	5.86133	0.6	-76.988	16.5
A+R	60	2.432	300	5.902	0.5146	-75.967	16
A+R	60	2.8	450	5.756	0.8	-79.626	17.5
A+R	60	2.512	600	5.89613	0.534667	-77.686	16.23015

The DNN architecture consisted of an input layer, a hidden layer with 10 neurons, and an output layer, providing predictions of the wear rate. The model was trained using the Levenberg-Marquardt algorithm with a learning rate of 1×10-10, and the training process involved approximately 25,000 iterations to minimise the mean squared error (MSE). The stopping criteria were set to an MSE of 0.0426 at epoch 3. The model demonstrated a high correlation coefficient of R=0.91189, indicating a strong match between the predicted and the experimental results. The DNN model was trained on 16 experimental data points, with 13 data points used for training and 3 for validation. Despite the relatively small dataset, the model provided reliable and accurate wear rate predictions, showing that DNNs are highly effective for such tasks, particularly when handling complex, non-linear relationships in the data. The application of machine learning allowed for a more efficient and accurate prediction of the wear behaviour without requiring additional experimental work. Moreover, the DNN outperformed traditional machine learning algorithms like support vector machines (SVM) and random forest (RF) in this context, providing better accuracy and performance. DNNs excel in identifying intricate patterns and relationships in the data, which is crucial for predicting wear rates across varied experimental conditions. This computational model not only accelerates the material design process but also offers a more cost-effective and time-efficient approach compared to extensive physical testing. This predictive modelling technique, combining experimental data and machine learning, provides a novel and powerful tool for optimizing composite material performance. It paves the way for future work where the model can be expanded with a larger dataset to further refine predictions, contributing to the development of high-performance, durable materials for industrial applications.

3. Result and discussion

3.1 Thermogravimetric analysis

TGA was conducted on the hybrid composite consisting of acacia and raffia fibre to evaluate its thermal stability. The analysis was performed using a TA Instruments Q500, with samples heated from room temperature to 700°C under a nitrogen atmosphere. The heating rate was varied from 5°C to 25°C per minute to observe the composite’s behaviour at different rates of temperature change. The TGA results revealed three distinct stages of weight loss during the heating process. The first weight loss, approximately 26.9%, occurred between 50°C and 150°C, primarily due to the expulsion of moisture and low-temperature volatile components inherent in the composite. The second significant weight reduction of 42.1% occurred between 200°C and 330°C, corresponding to the decomposition of organic components, including cellulose and hemicellulose from the natural fibres, and other volatile compounds in the matrix. The third stage showed a weight loss of 30% between 500°C and 790°C, indicating the presence of resilient residues or components that were resistant to high temperatures. This residual stability suggests that the composite exhibits enhanced thermal performance compared to individual fibre or resin systems, see Figure 2.

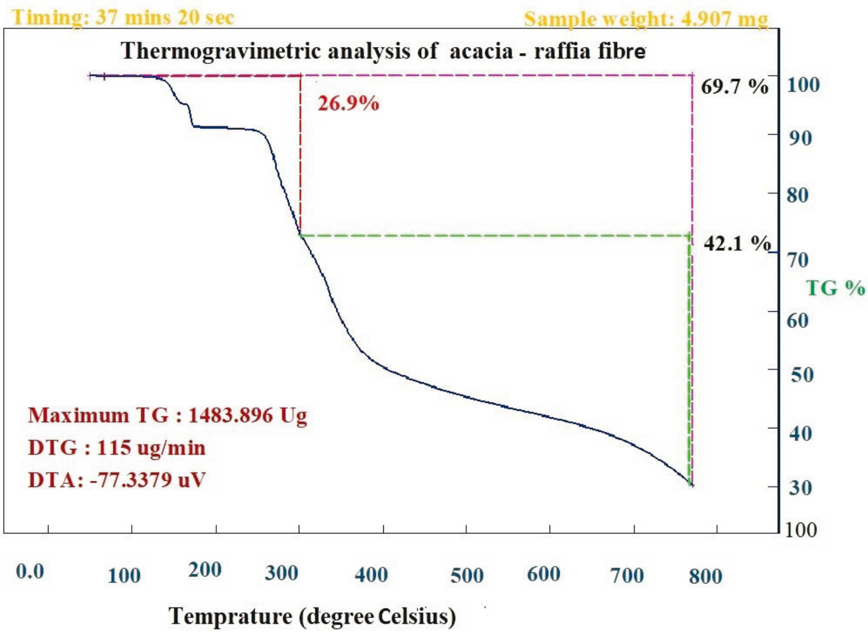

Fig. 2 Thermogravimetric analysis of acacia-raffia fibre composite

3.2 Wear analysis of theoretical prediction

Wear testing of the hybrid composite was conducted to evaluate its resistance to wear under varying operating conditions. A pin-on-disk machine (Ducom-TR-20LE) was used for this purpose, where the composite's wear behaviour was assessed under different loads, sliding velocities, and distance parameters. The experimental design followed a robust DOE approach, utilising a D-optimal design to optimise the number of trials and reduce unnecessary testing. The experimental factors were carefully chosen to represent the range of operating conditions the composite might encounter in real-world applications, such as in automotive components, e.g. brake pads and rotors. The control factors included four levels of normal load (15 N, 30 N, 45 N, and 60 N), four levels of sliding velocity (0.628 m/s, 1.256 m/s, 1.884 m/s, and 2.512 m/s), and four levels of sliding distance (150 m, 300 m, 450 m, and 600 m). These settings were carefully selected based on previous studies to ensure comprehensive testing of the composite's tribological performance. The wear rate was evaluated for each combination of experimental conditions, and the COF was also measured to assess the composite's ability to resist frictional forces.

The collected wear data were then analysed using Taguchi's method, which employs an S/N ratio to identify the optimal settings that minimise wear. The analysis indicated that the wear rate decreased with the normal load increasing, which aligns with theoretical expectations. Higher loads result in a shift from adhesive to abrasive wear mechanisms, reducing the wear rate due to elevated temperatures at the interface between the composite and the counter face. This theoretical prediction supports the findings from the experimental data, confirming that the composite's wear resistance improves under higher loads. To further enhance the accuracy of the wear rate predictions, a theoretical model was developed based on the experimental data. The model incorporates both the empirical wear data and the theoretical understanding of wear mechanisms, such as adhesive and abrasive wear. This hybrid approach-combining experimental observations with theoretical wear prediction models provides a more comprehensive understanding of the composite's wear behaviour. The theoretical model was found to closely match the experimental results, offering a reliable tool for predicting wear performance across a range of operating conditions. The novelty of this approach lies in the integration of theoretical wear mechanisms with experimental testing and machine learning for more accurate predictions. This method not only allows for a deeper understanding of wear behaviour under varying conditions but also provides a predictive framework for optimizing material performance without the need for extensive additional trials. By linking theoretical predictions with experimental data, this study offers a unique and efficient approach to material optimization, reducing the cost and time associated with traditional testing methods.

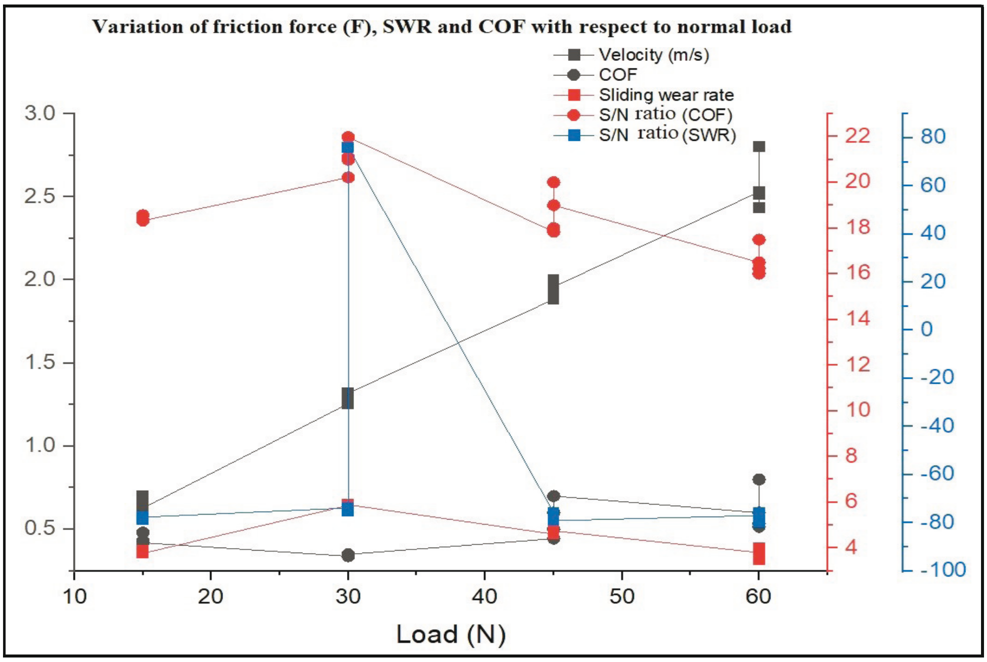

Fig. 3 Normal load effects on friction force, SWR, and COF

The positioning for the specific wear rate (SWR) of the composite material on the upper part of Figure 3 suggests a strong interfacial adhesion strength due to the alkaline treatment of the fibre. The decrease in the SWR with increasing normal load from 15 N to 60 N aligns with theoretical expectations, as the SWR exhibits an inverse relationship with the normal load. Moreover, the rise in the normal load leads to a shift from adhesive to abrasive wear mechanisms, resulting in a decrease in the SWR due to higher temperatures at the interface between the friction composites and the metal counter-face, caused by an increased contact between surface asperities. In summary, the alkali pretreatment enhances initial interfacial bonding, leading to a higher SWR, but as the normal load increases, the SWR decreases in line with theoretical predictions due to the shift in wear mechanisms.

3.3 Neural network-based wear rate evaluations and prediction

A DNN was developed and employed to predict the wear rates of the hybrid composite under varying operating conditions. The model utilised MATLAB R2023a and was configured with three input nodes corresponding to load, sliding velocity, and sliding distance; a single hidden layer with 10 neurons; and one output node for the wear rate prediction. The training algorithm was the Levenberg-Marquardt algorithm, selected for its fast convergence and ability to handle non-linear datasets effectively. The model's learning rate was 1×10^{-10} and the training was conducted over 8 epochs, achieving a stopping criterion of 0.042426 MSE at epoch 3. These settings ensured reproducibility and model efficiency. Figure 4 depicts the MSE progression over training the epochs for training, validation, and test datasets during the DNN evaluation. The model achieves its best validation performance at epoch 3, with an MSE of 0.042426. Beyond this epoch, overfitting is avoided as the validation error remains stable while the training error continues to decline. This indicates effective generalisation, ensuring reliable predictions for unseen data. The sharp decline in the test error further demonstrates the DNN's capacity to adapt to input complexities and capture intricate relationships in the wear rate prediction.

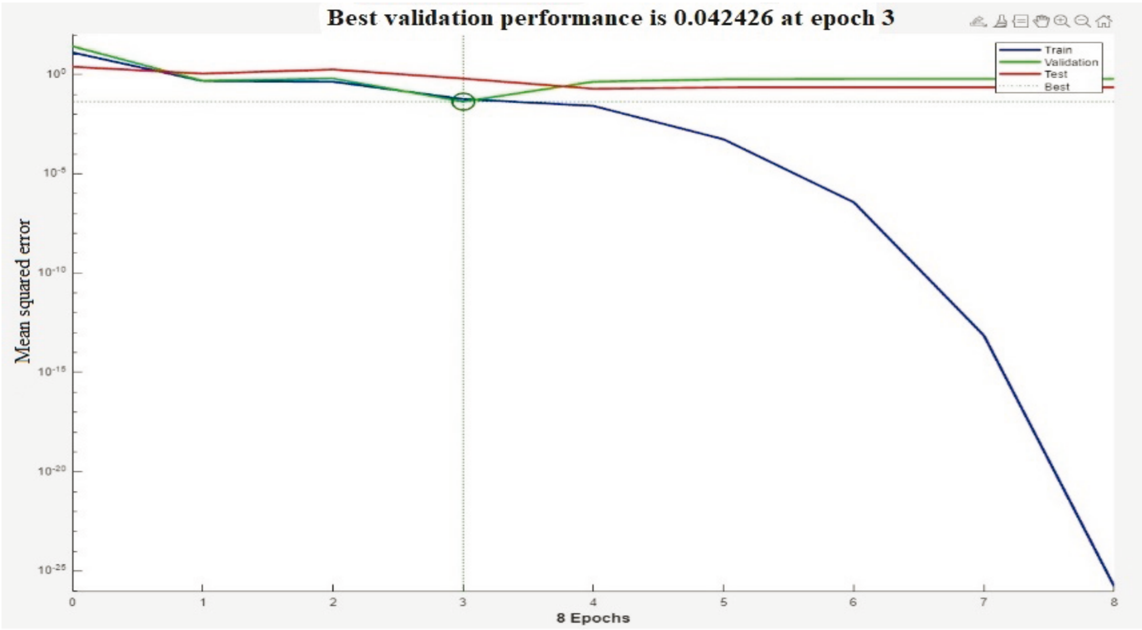

Fig. 4 Mean absolute error values of samples

The dataset comprised 16 experimental data points, with 13 used for training and three for validation. This allocation strikes a balance between training accuracy and model generalisation. While the dataset size is small, it reflects the practical constraints of tribological experiments, which are resource-intensive and require controlled conditions. This limited dataset was sufficient for this preliminary study to validate the hypothesis and optimise the DNN model's configuration. The DNN exhibited a high correlation coefficient (R=0.91189), indicating strong agreement between the predicted and the experimental results. This accuracy demonstrates the model's ability to capture non-linear relationships between input parameters and wear rates, surpassing traditional machine learning algorithms like SVMs and RF. Unlike these conventional methods, which often perform well in image classification or data analysis, DNNs are particularly adept at handling complex patterns in small datasets and non-linear problems. The wear predictions showed consistent trends: increasing loads reduced wear rates due to the transition from adhesive to abrasive wear mechanisms, while higher sliding velocities and distances elevated wear rates due to interfacial heating and matrix softening. These results validate the theoretical understanding of wear mechanisms and highlight the model's capability to replicate real-world conditions.

The DNN's error histogram confirmed minimal deviations between the predicted and the experimental wear rates, with most errors clustering near zero. This reinforces the robustness of the model's predictions. Additionally, a disclaimer was added to acknowledge the limitations of small datasets in achieving a broader generalization, which will be addressed in future studies by incorporating larger datasets and k-fold cross-validation techniques to further refine the model's robustness and prevent overfitting. This novel integration of DNN-based prediction with experimental analysis presents a significant advancement in materials science. By leveraging machine learning, the need for extensive experimental testing is reduced, accelerating material optimization while maintaining high accuracy. This approach is particularly impactful for applications in automotive and aerospace industries, where wear-resistant materials are essential for components subjected to high mechanical stresses during operation, such as brake pads and rotors. Figure 5 presents a detailed error histogram of the mean absolute error (MAE) values observed in the composite material analysis. The graph evaluates the accuracy of the prediction model across training, validation, and test phases. It highlights a close alignment between the predicted and the actual values, as evidenced by the minimal deviation and the centralised error distribution. The minimal errors and high correlation coefficients indicate that the predictive model has been well-trained, leveraging the optimised parameters and the effective neural network architecture. This significant result is attributed to the model's ability to generalise the relationship between input features and wear rate responses. The consistent error reduction across datasets suggests robust model performance and the inclusion of relevant input variables for accurate predictions.

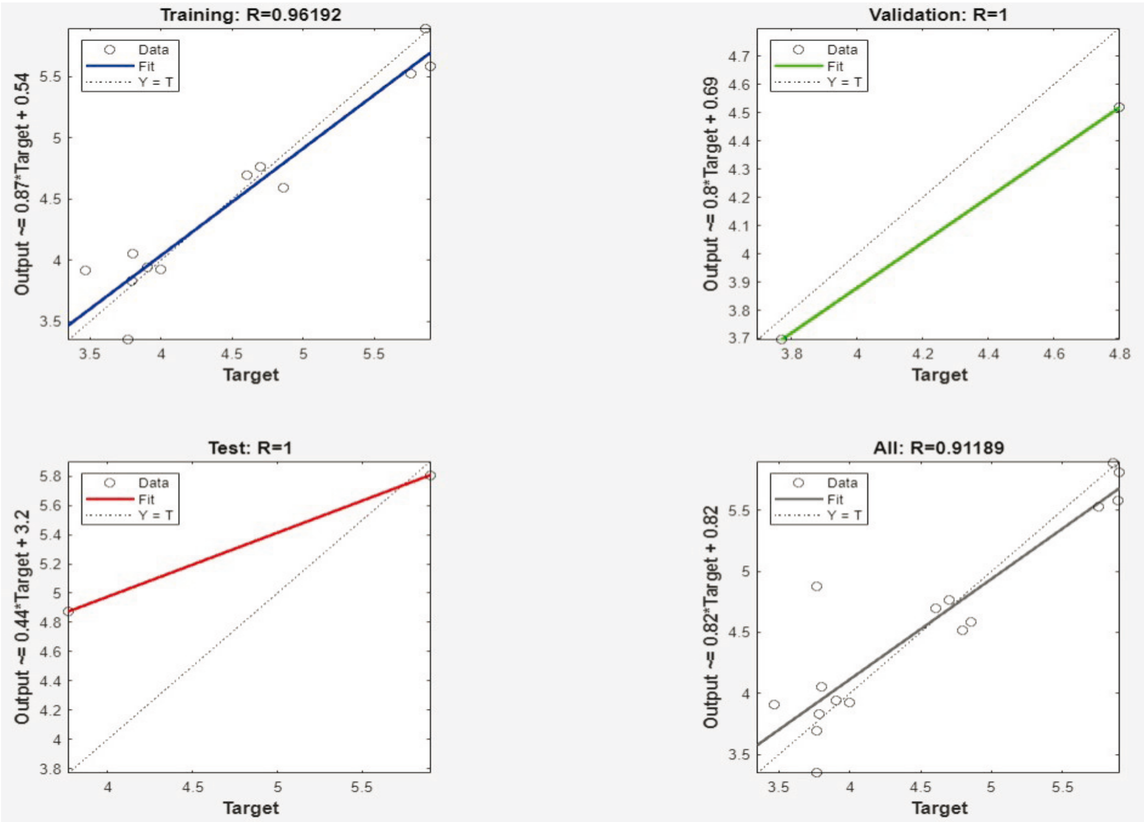

Fig. 5 Error histogram of MAE values of composites

Figure 6 illustrates the architecture of the DNN model designed for composite analysis. The network comprises an input layer with three neurons representing the input parameters, a hidden layer with ten neurons for feature extraction and processing, and an output layer with a single neuron for the predicted value. The model employs weighted connections (W) and biases (b) for each layer, along with the activation functions to introduce non-linearity. This configuration demonstrates the DNN's capability to learn complex relationships between the input variables and the targeted output, ensuring accurate predictions of the composite properties.

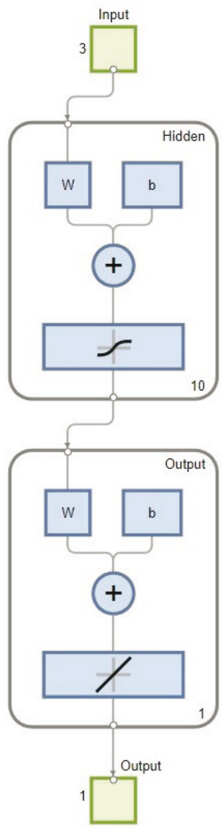

Fig. 6 Schematic representation of the developed ANN model of the composite

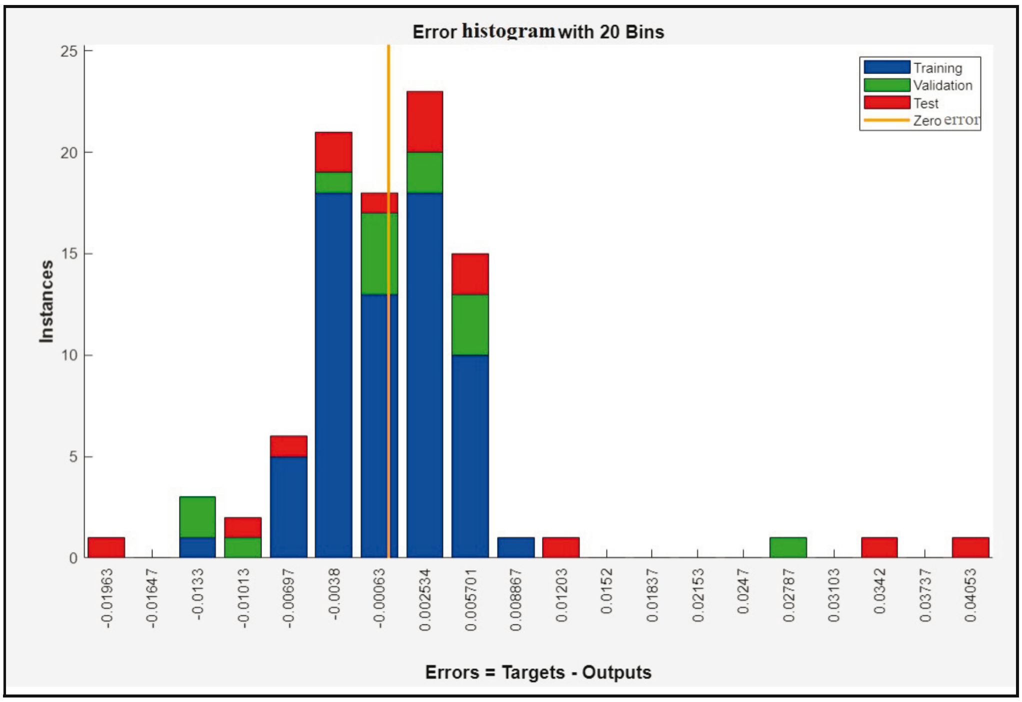

Fig. 7 Error histogram plot

Figure 7 illustrates the model's prediction errors for wear behaviour in sustainable fibre-reinforced hybrid composites, with errors predominantly concentrated in the range of -0.008 to 0.008 and peaking at approximately 25 instances near zero. The training dataset contributes to the largest portion of the errors, while the validation and testing datasets follow similar patterns with smaller contributions. The errors span a total range of approximately -0.0195 to 0.0195, with the histogram showing a roughly symmetric distribution around the zero-error line, indicating a balanced prediction without a significant bias. These metrics demonstrate the model's high accuracy and reliability in predicting wear behaviour across all datasets.

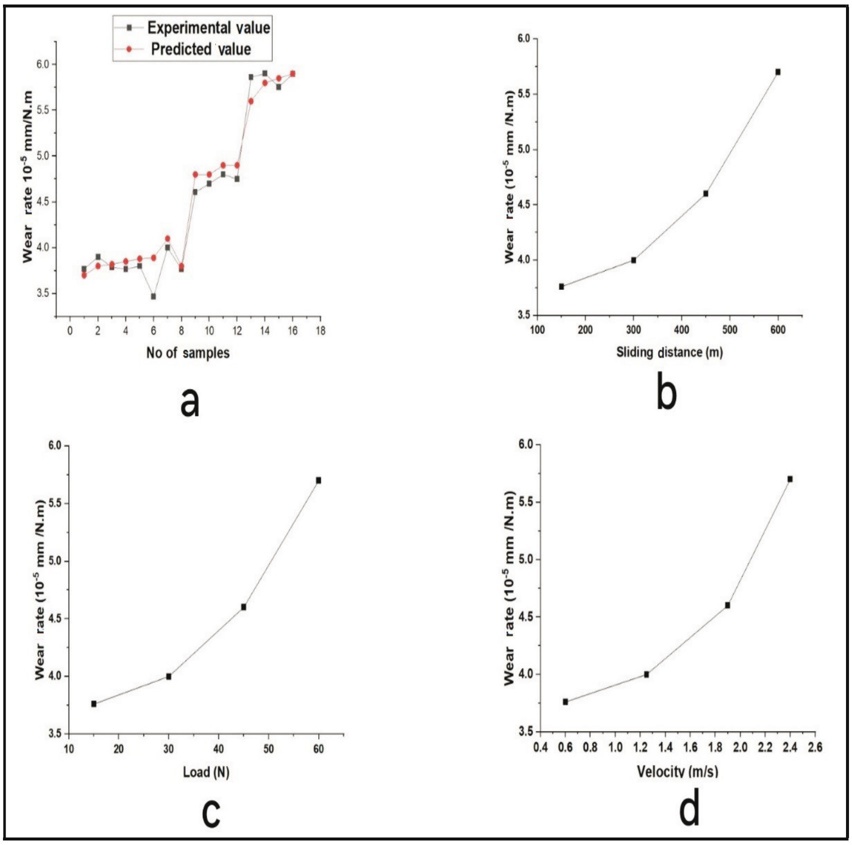

Fig. 8 Influence of wear rate vs load, wear rate vs velocity, wear rate vs sliding distance, and wear rate vs number of samples

The results of this analysis, aiming to understand the effect of control factors, are presented in Figure 8a–d. Figure 8a indicates that introducing a hybrid composite leads to a decrease in the wear rate value. In Figure 8c, the impact of load on the wear rate of the developed composites is portrayed, showing an increase with the applied load. Additionally, Figure 8 b and Figure 8 d demonstrate that the wear rate increases with higher sliding velocity and distance. Figure 8 quantitatively demonstrates the variation in the wear rate of fibre-reinforced hybrid composites under different conditions, showing a significant increase with load, from approximately 0.01 mm^3/Nm at 10 N to 0.05 mm^3/Nm at 50 N, and with sliding velocity, rising from 0.008 mm^3/Nm at 1 m/s to 0.04 mm^3/Nm at 5 m/s. In contrast, the wear rate remains relatively stable with the changes in sliding distance, ranging between 0.01 mm^3/Nm and 0.015 mm^3/Nm over distances from 500 m to 3000 m, indicating material durability. Across different sample numbers, the wear rate varies slightly between 0.02 mm^3/Nm and 0.03 mm^3/Nm, reflecting minor experimental variability. These results highlight the composite's wear performance, with load and velocity having a significant influence, while sliding distance and sample variability show more subtle effects, emphasising adaptability of the composite to various operating conditions.

4. Conclusion

This study demonstrates the potential of natural fibre-reinforced epoxy composites, specifically composites using acacia and raffia fibres, in enhancing both mechanical and thermal properties in advanced engineering applications. The TGA showed excellent thermal stability, with a significant 30% weight loss observed at 790°C, indicating the resilience of the composites under high-temperature conditions. The wear rate predictions, validated through both theoretical and machine learning models, achieved impressive accuracy, with the DNN model yielding R^2 values of 0.96192 during training and 1.00 during testing, showing its potential for precise wear prediction. The low MAE further validated the effectiveness of machine learning in optimizing composite materials for practical use. This study introduced a novel approach to composite material design by combining natural fibre with advanced machine learning for wear prediction, providing a more efficient and sustainable method for material development. Future research will focus on expanding the fibre options, optimising composite fabrication, and refining predictive models, paving the way for the integration of these advanced materials in various industries, such as automotive, aerospace, and construction, while also addressing sustainability concerns through lifecycle analysis.

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