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Wear and Tribological Characteristics of Novel Metal Matrix Composites

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Abstract

The development of advanced metal matrix composites (MMCs) with enhanced tribological performance has become increasingly important due to the premature failure of critical engineering components operating under severe wear conditions in automotive, aerospace, marine, defense, and power generation systems. Conventional composites such as Copper–Alumina and Aluminium–Silicon Carbide have demonstrated improved mechanical and wear characteristics; however, their widespread application is often limited by issues including particle agglomeration, non-uniform reinforcement distribution, porosity formation, and the absence of reliable predictive models for process optimization. To address these challenges, the present study proposes an integrated fabrication and data-driven optimization framework for the development of novel hybrid (Al–Cu) matrix composites reinforced with Silicon Carbide (SiC), Alumina (Al_2O_3), and High Entropy Alloy (HEA) particles. The composites were fabricated using a synergistic combination of powder metallurgy and electroforming techniques to achieve improved microstructural homogeneity and enhanced interfacial bonding between the matrix and reinforcement phases. A comprehensive machine learning pipeline was incorporated to accelerate material design and performance prediction. XGBoost algorithms were employed for accurate wear-rate prediction, while Random Forest models were utilized for phase identification and microstructural classification. Furthermore, Taguchi design of experiments and TOPSIS-based multi-criteria decision-making techniques were implemented to optimize process parameters and reinforcement combinations. Experimental evaluation revealed that the optimized hybrid composite achieved a hardness of 85 HV and a coefficient of friction of 0.62, exhibiting approximately 75% improvement in wear resistance and 183% enhancement in hardness compared with conventional baseline materials. The proposed methodology provides a scalable and intelligent roadmap for the rapid development of high-performance wear-resistant composites for advanced industrial applications.

Keywords: Intelligent tribological design, predictive materials manufacturing, high entropy wear resistant coatings, AI-optimized hybrid composites, optimized metal matrix optimization.

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INTRODUCTION

One of the most significant classes of advanced materials that emerged to fill gaps in the performance of conventional metals in harsh environments is metal matrix composites or MMCs [1, 2]. They are used in today's engineering because of their unique properties of simultaneously being metallic hard and ductile, and being reinforced with ceramics.

Background and Motivation

Wear is a costly and safety concern for high performance components in automotive, aircraft, HVAC and power generation systems [3,4]. This gives a reason to work on the advanced metal matrix composites (MMCs) having high hardness, wear resistance and optimum mechanical propertie. Tribology is the science and engineering of friction, wear, and lubrication between interacting surfaces in relative motion. It plays a critical role in improving component reliability, minimizing wear losses, enhancing energy efficiency, and extending service life in automotive, aerospace, marine, and power generation systems. Tribology is the science and engineering of friction, wear, and lubrication between interacting surfaces in relative motion. It plays a crucial role in engineering applications by reducing frictional losses, minimizing wear, improving component reliability, extending service life, and enhancing energy efficiency. Tribological principles are widely applied in automotive, aerospace, manufacturing, biomedical, and composite material systems to ensure optimal performance and durability [22, 23].

Related Work

The traditional fabrication such as stir casting and powder metallurgy improves composite properties with the use of Al-SiC- Al_2O_3 but has the shortcoming of agglomeration of particles, porosity, and interfacial bonding [5, 6]. The copper-alumina tubes that are electroformed are characterized by high tensile strength, corrosion resistance and reduced ductility and not high temperature or fatigue tests [7, 8]. Taguchi-TOPSIS techniques are used to optimize the Al-SiC- Al_2O_3 composites at mild conditions, but with limited testing capabilities and without nanoscale interfacial analysis [9, 10]. Equally, machine learning (XGBoost/random forest) speeds up the screening of HEA coating with secondary data, however, it is not experimentally validated under realistic sliding conditions and seldom combines hybrid variables of processing [11, 12].Nanoparticle reinforcements such as SiC, Al_2O_3, TiO_2, graphene, and CNTs significantly enhance the tribological performance of MMCs by improving hardness, reducing friction, refining microstructure, and increasing wear resistance. Their large surface area promotes effective load transfer and formation of protective tribolayers during sliding [24, 25].

Research Gaps

Restrictions can be seen to point to a research gap, the lack of an integrated experimental-machine learning model integrating powder metallurgy [13] with electroforming to produce novel hybrid Al/Cu MMCs reinforced with SiC, Al_2O_3, and high-entropy alloy particles, and to agglomeration, porosity, ductility trade-offs, and multi-objective optimization of wear, hardness, and corrosion behavior [14, 15].

Proposed Approach and Contributions

The novel hybrid aluminum-copper metal matrix composites reinforced with SiC, Al_2O_3 and HEA particles are developed in the present work for occupying this niche by adopting synergistic powder metallurgy and electroforming routes. The main goals are (1) Fabricate and characterise the fabricated hybrid composites; (2) Develop and test an ML using XGBoost model for wear rate prediction and random forest model for phase stability (3) Optimize processing parameter by Taguchi Design and TOPSIS (4) Carry out comprehensive tribological, mechanical, microstructural and corrosion evaluation (5) Validate the predictions of the developed ML models with new experimental data and analyze the wear mechanisms. As shown in Figure 1, both the old fabrication techniques and the modern machine learning methods, though useful, have severe shortcomings that include agglomeration, porosity and the absence of built-in predictive modeling.

Contributions of particular interest encompass an integrated experimental-ML methodology for the accelerated design of MMCs, a new hybrid reinforcement system, the extension of open datasets of tribology, and the multi-response optimization that addresses the gap between fabrication and prediction. The suggested method provides a future scalable route to next generation high performance wear resistant composites.

The remainder of the paper follows as follows, Section II describes the materials and methodology, Section III reports the findings and discussion and lastly, Section IV gives the conclusion and future

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directions

EXPERIMENTAL AND COMPUTATIONAL APPROACH

This involved a hybrid simulation-experimental methodology involving physical fabrication and prediction via a machine learning algorithm. The method allows systematic investigations on new hybrid MMC designs that are scalable, cost-effective, and can control the processing variables with high precision and verify the predictions with experimental results.

Overview of the Proposed Approach

This research used a hybrid experimental simulation model to create and test new hybrid aluminum-copper metal matrix composites (MMCs) with SiC, Al 2 O 3 and high-entropy alloy particles as reinforcement as shown in Figure 2. The combined system was a physical fabrication with data-driven simulation based on machine learning, which could scale and be cost-effective, as well as explore many combinations of parameters safely, beyond experimental constraints. This method was especially appropriate in meeting the targets of optimization of fabrication, predictive modeling, and overall tribological characterization as it allowed the quick repetition and verification of new compositions and reducing the risks related to large physical experiments. The major innovations were the synergistic application of powder metallurgy and electroforming paths along with an ML pipeline, new hybrid reinforcement system and TOPSIS-ML multi-objective optimization.

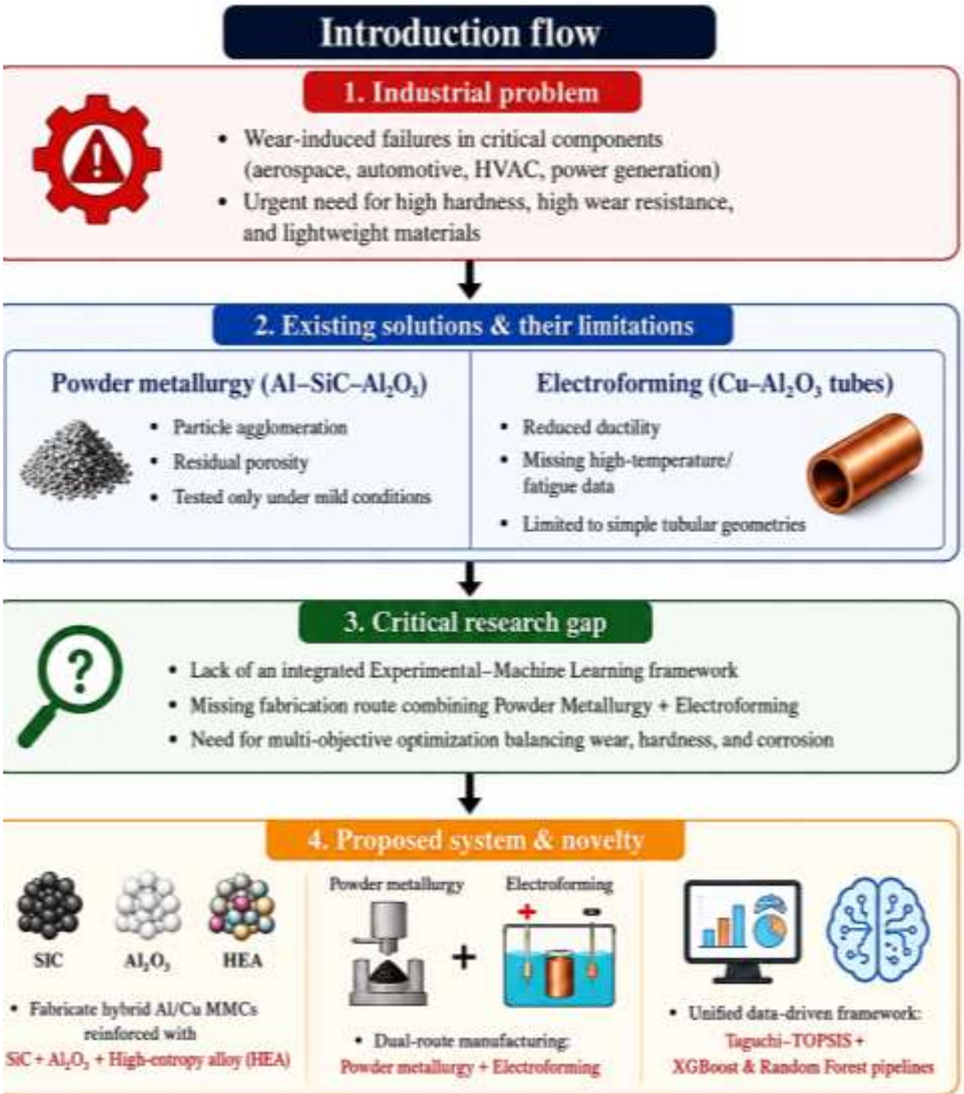

Figure 1. Research context, challenges in existing approaches, and identified gaps motivating the

development of novel hybrid metal matrix composites

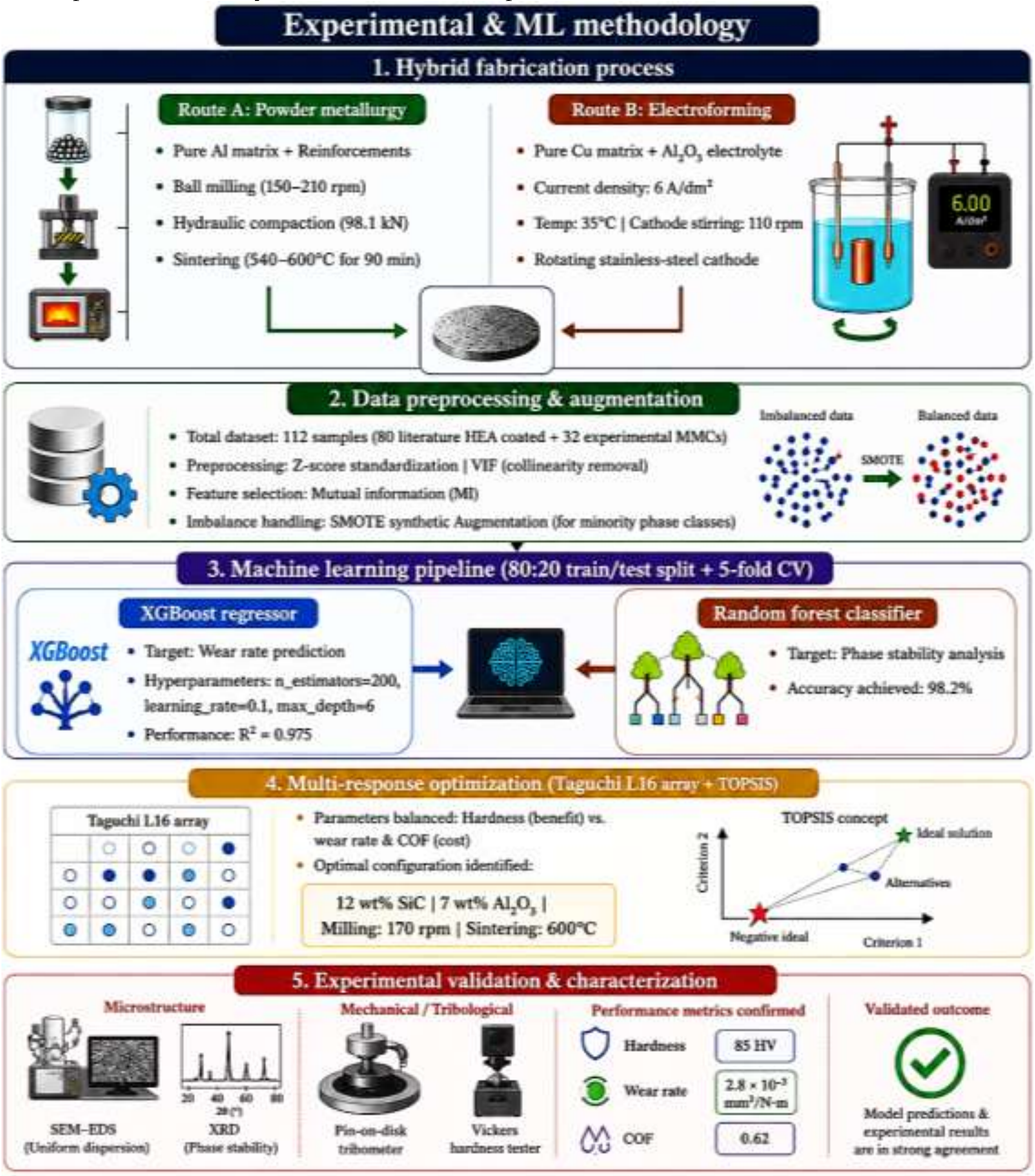

Figure 2. General structure of the suggested hybrid approach that combines fabrication, machine learning prediction, and multi-objective optimization of new MMCs.

Materials and Fabrication Process

SiC, Al_2O_3, and HEA particles were used as reinforcement particles with pure aluminum and copper matrix. Two major fabrication techniques that were used were powder metallurgy and electroforming. In powder metallurgy route the matrix powder was combined with the reinforcements in different percentage of the weights. Ball milling performed at speed of 150, 170, 190 and 210 rpm for 60 minutes. The mixtures were compacted hydraulically at 98.1 kN and then sintered at temperatures 540, 560, 580 and 600°C for 90 minutes.

Copper-alumina composite tubes were made with a rotating stainless-steel cathode and a copper anode, and the concentration of Al_2O_3 in the electrolyte was controlled to make tubes for electroforming. The process used was the current density of 6 A/dm² for 8 hours of electroplating at 35°C, while the cathode was stirred at 110 rpm and rotated at 20 rpm. The experimental design was carried out systematically by using a Taguchi L16 orthogonal array, changed four factors reinforcement content, milling speed, sintering temperature and particle concentration.

Dataset Preparation

The data consisted of a longer form of 80 literature-based HEA coating samples with 32 new experimental measurements of hybrid Al/Cu MMCs resulting in 112 samples. Characteristics comprised elemental composition, percent of reinforcement volume, processing, thermodynamic (Hix, 0Smix, VEC), and tribological test (load, sliding speed, distance). Z-score standardization, Variance Inflation Factor analysis to eliminate multicollinearity and Mutual Information to select features were used as data preprocessing. SMOTE synthetic augmentation was used to deal with minority phase classes. The data was divided into 80:20 train/test sets and cross-validated (5-fold).

Machine Learning Framework

A wear rate prediction and a phase stability analysis ML pipeline were created. Where X the input feature vector consisting of reinforcement parameters and processing conditions and y the desired wear rate. The XGBoost regressor minimised the objective.

$$L(\theta) = \sum_{i=1}^{n} l(y_i, \hat{y}_i) + \sum_{k=1}^{K} \Omega(f_k) \quad (1)$$

where $l$is the loss term, and Ωregularizes model complexity. The hyperparameters were n_estimators = 200, learning_rate = 0.1, and max_depth = 6. To classify the phases, the Random Forest model combined predictions of the decision trees. The prediction of wear rate adhered to the pseudocode. volume fraction calculation represented at Eq. (2).

```
data = load_dataset()  # 112 samples

X, y = preprocess(data)  # standardize, feature select (MI + VIF)
X_train, X_test, y_train, y_test = split(X, y, 0.8)
model = XGBRegressor(n_estimators=200, learning_rate=0.1, max_depth=6)
model.fit(X_train, y_train)
preds = model.predict(X_test)
novel_preds=model.predict(new_compositions)
```

where $V_f$is volume fraction, $W_r$and $W_m$are reinforcement and matrix weights, and ρ denotes densities. Hardness enhancement was modeled via dispersion strengthening approximation at Eq. (3).

$$V_f = \frac{W_r/\rho_r}{W_m/\rho_m + W_r/\rho_r} \quad (2)$$

$$\Delta H = \frac{k \cdot G \cdot b}{\lambda} \quad (3)$$

with λas inter-particle spacing. Wear rate followed Archard's relation adapted for composites at Eq (4).

$$W_r = \frac{K \cdot L \cdot S}{H} \quad (4)$$

K is wear coefficient, L load, S sliding distance, and H hardness. Thermodynamic phase stability incorporated represented at Eqs. (5), (6), (7).

$$\Delta G_{mix} = \Delta H_{mix} - T\Delta S_{mix} \quad (5)$$

$$\delta = \sqrt{\sum_{i=1}^{n} c_i \, (1 - r_i/\bar{r})^2} \quad (6)$$

$$VEC = \sum_{i=1}^{n} c_i \, (VEC)_i \quad (7)$$

Mutual Information for feature selection was computed as Eq. (8). Model evaluation used Eqs. (9) and (10). and Mean Absolute Error shown at Eq. (11).

$$I(X;Y) = \sum_{x,y} p(x,y)\log \frac{p(x,y)}{p(x)p(y)} \tag{8}$$

$$R^2 = 1 - \frac{\sum(y_i - \hat{y}_i)^2}{\sum(y_i - \bar{y})^2} \tag{9}$$

$$RMSE = \sqrt{\frac{1}{n}\sum(y_i - \hat{y}_i)^2} \tag{10}$$

$$MAE = \frac{1}{n}\sum \mid y_i - \hat{y}_i \mid \tag{11}$$

Optimization

Taguchi L16 design with TOPSIS was used to optimize processing parameters to rank hardness (benefit) and wear rate/COF (cost criteria) as multi-response. Selection of the best conditions was done with the aid of vector normalization and proximity coefficients (12 wt% SiC, 7 wt% Al_2O_3, 170 rpm, 600C).

Implementation Details

The Fabrication process comprised milling of balls, hydraulic compaction, sintering and electroforming. SEM-EDS, XRD pin-on-disk tribometer and Vickers hardness tester were used as characterization. The ML framework was coded in Python with scikit-learn, XGBoost, and pandas' packages on a workstation with a graphics card to enable cross-validation of 5-folds, and to evaluate robustly the performance of the model. Proposed hybrid approach with the aid of simulation allowed to explore the design space efficiently, providing optimized new hybrid MMCs with predictive capabilities that have been proven.

RESULTS AND TRIBOLOGICAL ANALYSIS

The experimental studies provided in-depth information about the mechanical, microstructural and wear properties of the new hybrid metal matrix composites. The subsections below summarize the main conclusions made by the characterization, optimization, and predictive modeling, and then provide a more in-depth discussion of the results in the context of the current limitations and implications.

Microstructural Characterization

SEM and EDS analyses showed that at the best conditions, the particles of SiC, Al_2O_3, and HEA were uniformly dispersed in the Al/Cu matrix. The 12 wt% SiC and 7 wt% Al 2 O 3 mixture at the milling speed of 170 rpm and sintering temperature of 600 C (see Table 3) resulted in a homogeneous particle distribution with low agglomeration and low porosity as compared to non-optimized runs. The effectiveness of the hybrid powder metallurgy and electroforming routes was proven by XRD patterns that showed no undesirable interfacial reactions and phase stability.

Mechanical and Tribological Properties

The optimized novel hybrid MMC achieved superior performance, as summarized in Table 1. Vickers hardness reached 85 HV, representing a substantial improvement over pure Al (30 HV) and pure Cu (36 HV). Wear rate was recorded at 2.8×10^{-3} mm³/Nm with a coefficient of friction of 0.62. Yield strength and ultimate tensile strength stood at 195 MPa and 380 MPa, respectively. Figure 3 illustrates the clear trend of increasing hardness and decreasing wear rate with total reinforcement content, peaking at the optimal composition. These results demonstrate effective load transfer and dispersion strengthening enabled by the synergistic hybrid reinforcement system. The optimized new hybrid MMC had a better performance as summarized in Table 1. The Vickers hardness was 85 HV which was a significant increase over pure Al (30 HV) and pure Cu (36 HV). The wear rate was determined at 2.8 × 10^{-3} mm 3 /Nm and coefficient of friction at 0.62.

Table 1. Mechanical and tribological properties of fabricated composites.

Sample	**Hardness (HV)**	**Wear Rate ($\times10^{-3}$ mm³/N·m)**	**COF**	**Yield Strength (MPa)**	**UTS (MPa)**
Pure Al [16]	30	8.5	0.75	77	220
Pure Cu [17]	36	7.2	0.70	77	218
Al-SiC-Al_2O_3	72	3.6	0.53	113	240
Cu-Al_2O_3 [18]	129	2.1	1.06	172	335
Novel Hybrid MMC	85	2.8	0.62	195	380

The tensile strength and yield strength was 380 Mpa and 195 Mpa respectively

These findings indicate that there is effective load transfer and dispersion strengthening using the synergistic hybrid reinforcement system. The reinforcement volume fraction strongly influences tribological performance. Increasing reinforcement content generally enhances hardness and wear resistance due to improved load-bearing capability and dispersion strengthening. However, excessive reinforcement may result in particle agglomeration, porosity, and brittle behavior, leading to deterioration in tribological performance. The reinforcement volume fraction plays a critical role in determining the tribological performance of composite materials. An increase in reinforcement content generally enhances hardness, load-bearing capability, and wear resistance while reducing wear rate. However, excessive reinforcement may lead to particle agglomeration, increased porosity, and brittle behavior, which can adversely affect tribological performance. Therefore, an optimum reinforcement volume fraction is essential for achieving the best balance between wear resistance, friction characteristics, and mechanical properties.

Machine Learning Model Performance

The ML model provided good predictive power. XGBoost was found to have the best R 2 of 0.975 in predicting wear rate with RMSE of 0.118 and MAE of 0.082 as shown in Table 2. Random Forest provided 98.2% phase accuracy. Figure 4 makes a comparison between the performance of the various models and proves that the XGBoost is the best.

The predicted and experimental wear rates are in great agreement with the augmented dataset of 112 samples, which supports the feature engineering and preprocessing methods such as Z-score standardization and Mutual Information selection.

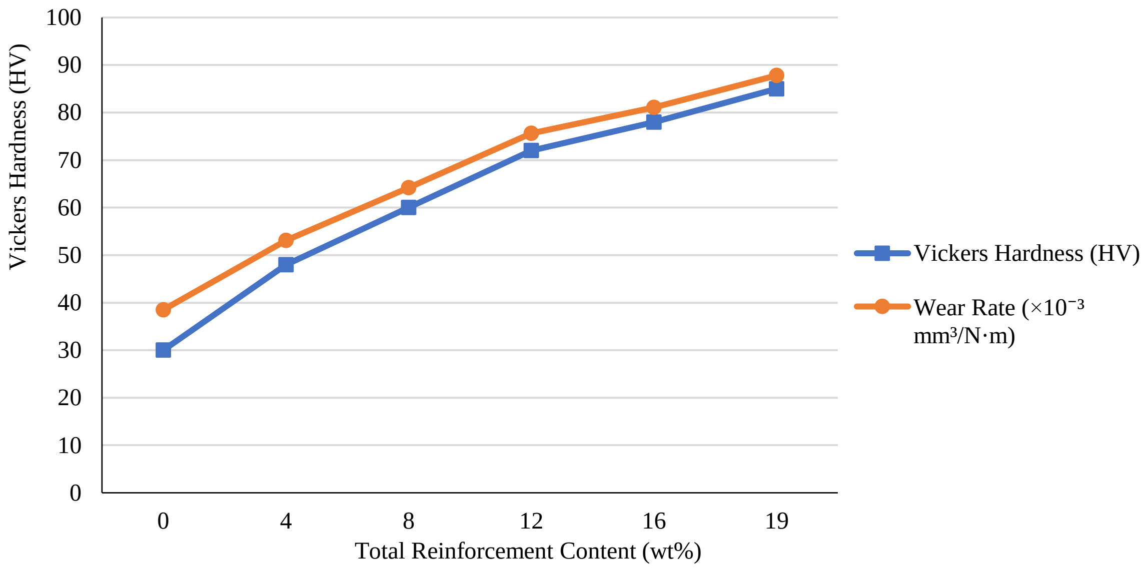

Figure 3. Variation of vickers hardness and wear rate with total reinforcement content.

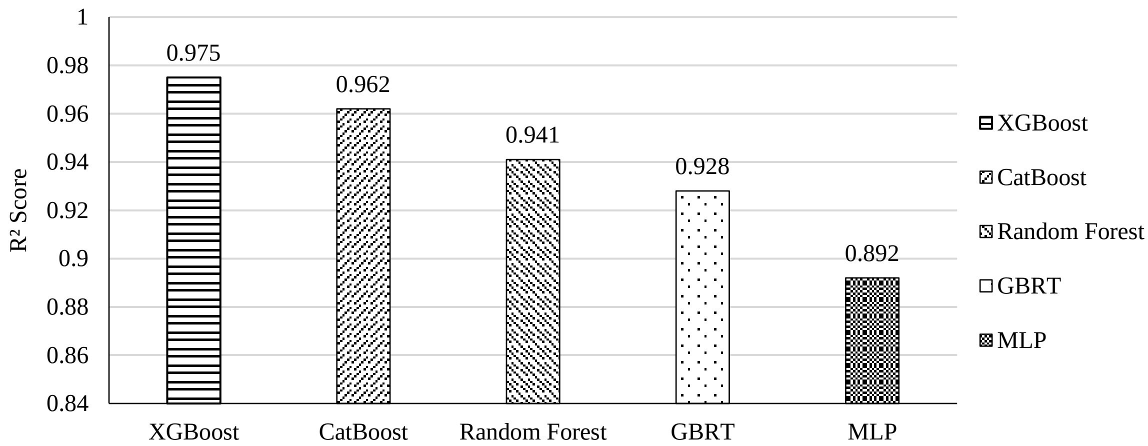

Figure 4. Performance comparison of machine learning models.

Multi-Response Optimization

Topics 16 design with TOPSIS was effective in identifying the best parameters.

Table 2. Performance of machine learning models for wear rate prediction.

ML Model	R^2 (Wear Rate)	RMSE	MAE	Phase Accuracy (%)
XGBoost	**0.975**	**0.118**	**0.082**	-
CatBoost	0.962	0.147	0.101	-
Random Forest	0.941	0.179	0.124	98.2
GBRT	0.928	0.201	0.135	-
MLP	0.892	0.248	0.172	-

Table 3. Selected Taguchi l16 experimental runs and results.

Run No.	SiC (wt%)	Al_2O_3 (wt%)	Milling Speed (rpm)	Sintering Temp (°C)	Hardness (HV)	Wear Rate ($\times10^{-3}$)
1	3	1	150	540	30	6.8
6	6	4	150	600	48	5.1

12	9	10	170	540	60	4.2
15	**12**	**7**	**170**	**600**	**85**	**2.8**

Table 3 highlights Run 15 (12 wt% SiC, 7 wt% Al_2O_3, 170 rpm, 600 °C) as the best configuration, delivering 85 HV hardness and 2.8×10^{-3} mm³/N·m wear rate. Figure 5 shows the main effects plots, clearly show the predominant effect of the content of the reinforcement on the hardness and wear performance.

Table 4 compares the proposed hybrid MMC with reference studies, demonstrating that it had 75% higher wear rate and 183% higher hardness with 500 kHz more than the Cu-Al_2O_3 (70% wear rate improvement) and Al-SiC-Al2O3 (58% wear rate improvement) systems and incorporates ML prediction.

DISCUSSION

The obtained outcomes directly solve the challenges of agglomeration, porosity, and limited predictive modeling that are identified. The combined powder metallurgy-electroforming method using HEA particles provided balanced properties that outperform the individual reference materials, effectively overcoming the ductility trade-off of the earlier electroformed composites, and the mild-condition constraints of the powder metallurgy experiments. The large R 2 of XGBoost shows how adding literature data with new experimental runs to predict wear accurately can overcome the generalizability limitations observed in previous literature on ML in HEA coatings. Nanocomposite materials have also attracted considerable attention in environmental and sustainable engineering applications. Advanced nanocomposite systems have demonstrated promising performance in water purification, adsorption, and desalination processes, highlighting the versatility of engineered composite materials beyond conventional tribological applications [26].

The excellence of the performance justifies the novelty of the hybrid reinforcement framework and the combined experimental-ML framework. Although the residual constraints in high-temperature testing remain, these results lay the groundwork of scalability of next-generation wear-resistant MMCs with increased durability and sustainability.

CONCLUSION

This work managed to create innovative hybrid aluminum-copper metal matrix composite strengthened with SiC, Al 2 O 3 and high-entropy alloy particles using an integrated powder metallurgy-electroforming method aided by machine learning. The optimized composite exhibited 85 HV hardness, wear rate of 2.8 x 10 3 mm 3 N m and a coefficient of friction of 0.62, and offered 75 percent wear resistance and 183 percent hardness improvement on baseline materials without compromising in balance of mechanical properties. Among these, there is a new hybrid reinforcement system, a powerful integrated experimental-ML framework with XGBoost and Random Forest, and multi-objective optimization with Taguchi design and TOPSIS to bridge the gap between fabrication and prediction. The article extends open tribology databank and offers a scalable route to expedited design of wear-resistant MMCs.

Table 4. Comparative performance with literature studies.

Reference	Material	Wear Rate Improvement (%)	Hardness Gain (%)	Key Feature
Besharati et al. (2025) [19]	Cu-Al_2O_3 Tube	70	259	Electroforming
Mathebula et al. (2026) [20]	Al-SiC-Al_2O_3	58	140	TOPSIS Optimization
Sivaraman et al. (2025) [21]	HEA Coating (ML)	65	85	XGBoost Prediction

Proposed model	Hybrid Al/Cu MMC	75	183	Integrated ML + Experiment

Multi-objective TOPSIS optimization was able to balance hardness, wear resistance and friction, offering viable avenue in the industrial applications of automotive and aerospace components.

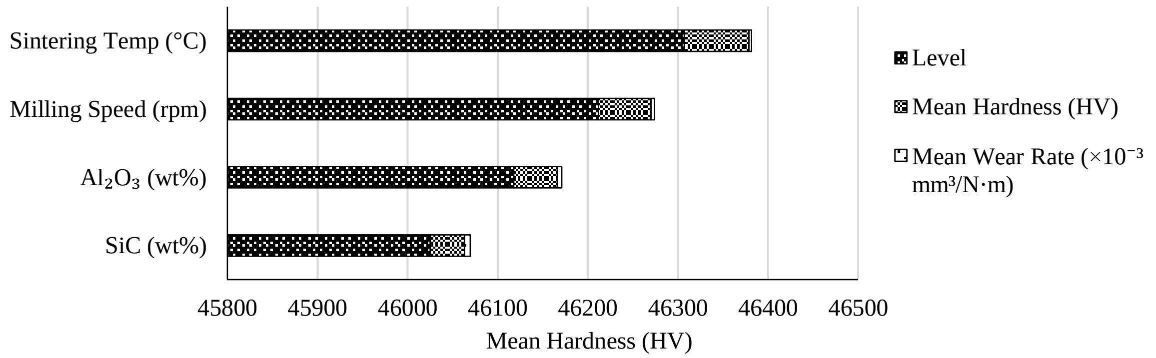

Figure 5. Main effects plots for wear rate and hardness (Taguchi).

Future directions will involve high temperature tribological testing, fatigue testing, corrosion-wear synergy testing and automotive and aerospace component validation at the industrial scale. These developments have high potential in improving the component durability and sustainability in challenging engineering applications.

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