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Tribological Performance and Wear Coefficient Prediction of AA2024–TiC Composites via Python-Based Machine Learning

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Abstract

Determining wear coefficient accurately serves as a critical factor to maximize engineering materials' tribological characteristics. The experiment examines the wear characteristics of TiC-reinforced AA2024 aluminum alloy subjected to different tribological operating conditions. A pin-on-disc tribometer performed wear tests under different conditions of load and TiC weight fraction and sliding speed and duration. ANOVA statistical results show that load intensity and TiC reinforcement density stand out as principal variables that affect wear coefficient measurements showing that increased TiC amounts lead to improved wear resistance. The prediction accuracy became improved through the implementation of Decision Tree and Random Forest together with Artificial Neural Networks (ANNs) in machine learning (ML) models. ANNs delivered better results than other tested models with a 0.00000007 MSE and a 0.995 R^2 score thus proving its optimal predictive ability. The coupling of computational modeling using Python with experimental tribology testing established an efficient and affordable method for determining wear coefficient values. The established framework enables wear prediction together with material optimization functions that can be applicable for composite systems and industrial applications.

Keywords: Wear coefficient, AA2024–TiC composites, tribological performance, pin-on-disc testing, machine learning prediction, artificial neural networks (ANN)

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INTRODUCTION

Tribological systems experience wear as their chief operating concern that significantly affects the performance duration of materials within mechanical applications [1]. Surface material loss through mechanical interactions occurs progressively due to such contacts and typically divides into adhesive, abrasive, corrosive and fatigue categories [2]. The wear coefficient stands as a basic measure of material resistance to wear because it expresses the amount of wear volume in mm^3 per Nm. The wear coefficient depends strongly on four main operating variables: applied force and sliding speed and testing time duration together with composite reinforcement contents [3]. The rate of material loss increases with higher loading conditions together with sliding speeds while ceramic or carbide additions boost wear resistance through their hardness properties and loading ability [4]. The determination of wear coefficient through pin-on-disc tribometry represents a common experimental method that uses weight measurements between before and after tests to evaluate material loss [5]. Archard's wear equation and other traditional analytical approaches supply theoretical analysis for wear prediction but statistical modeling with ML algorithms now provide better predictive power [6]. The analysis of material surface degradation becomes possible through wear testing which remains a fundamental part of tribological research [7]. The pin-on-disc tribometer serves as a prominent wear testing methodology because it brings advantages from its easy operation alongside reliable results and effective simulation of actual wear operations within controlled settings [8]. A test setup enables the systematic test of wear behavior through placement of stationary pin against rotating disc to evaluate different operating conditions [9]. The wear performance of composite materials responds to all key process parameters which include applied load, sliding speed, test duration and reinforcement fraction [10]. The material wear increases when operating at higher loads together with faster speeds because of increased frictional heating but reinforcement particles act as protective layers to minimize material loss [11]. High-accuracy estimates of wear coefficients serve as key requirements for tribological research since they enable better material designs and superior engineering applications [12]. Theoretical wear predictions from Archard's wear law fail to represent material property interactions under different operating conditions and environmental factors [13]. Such issues have led researchers to use data-driven solutions more frequently. The influence of process parameters on wear behavior gets quantified by using statistical models such as regression analysis and ANOVA for structured interpretation of data [14]. Statistical models with linear assumption work inadequately when analyzing nonlinear wear mechanisms that exist in practical production systems [15]. The combination of Artificial Neural Networks with Decision Trees through ML has become a strong predictive tool to tackle this limitation [16]. The models demonstrate outstanding superiority over conventional methods when it comes to processing nonlinear data along with reconstructing complex dependencies and multiple variable interactions [17]. The implementation of ML in tribological studies leads to enhanced wear coefficient predictions which replace time-consuming experiments with efficient and accurate material forecasting capabilities [18]. The structural industry makes extensive use of AA2024 aluminum alloy because it combines high strength with light weight attributes together with excellent fatigue properties and excellent machining capabilities [19]. The mechanical properties of the material strengthen due to the copper and magnesium alloying elements that enable it to serve aerospace and automotive sectors and additional high-performance sectors [20]. The mechanical properties of AA2024 help the material function well but this metal suffers poor resistance to wear and localized bending at high load intensities [21]. The aluminum matrix received Titanium Carbide (TiC) ceramic reinforcements for boosting its tribological characteristics [22]. TiC exists as a prime reinforcement material because it demonstrates exceptional hardness along with excellent thermal stability and exceptional wear resistance [23]. The incorporation of TiC particles both improves the material's structural refinement as well as its load capacity and decreases wear loss through prevention of abrasion and adhesion-like degradation processes [24]. The bonding strength at the interface between AA2024 and TiC minimizes the mechanical strength and produces the tribological characteristics of the composite material. Both AA2024-TiC and other metal matrix composites include AA7050-SiC and Al-B4C show better wear resistance with reasonable hardness levels and ductility values. The use of TiC as a reinforcement material delivers improved tribological performance under operational variations since it provides optimal mechanical strength and wear resistance without inducing brittleness like SiC and B4C. The combination of TiC with composites produces materials which minimize friction while reducing material waste thus making them optimal for applications that need superior wear protection. The combination of strength and wear resistance properties in AA2024-TiC makes it a strong candidate for wear-resistant applications thus needing deeper studies of its processing techniques along with performance characteristics. Tribological research development received significant advancements through the implementation of Python both for wear modeling and

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data analysis tasks. Python has become universally popular in engineering research because it offers open-source capabilities together with plentiful computational libraries and its ability for complex dataset management. The language serves as an essential predictive modeling instrument for tribology because it delivers an entire suite of statistical analytics and computational capabilities and machine learning resources. The data science toolkit includes NumPy, Pandas, SciPy and Scikit-Learn which supply complete capabilities for data handling together with numerical analysis and model development functions [25]. With NumPy and Pandas users process data efficiently and rearrange it properly and SciPy delivers sophisticated mathematical and statistical instruments needed for wear examination tasks. The complete suite of ML algorithms within Scikit-Learn augments Python capabilities by providing researchers with features to predict wear coefficient values through regression models and neural networks and decision trees implementations. Wear coefficient relationships with process parameters are defined through the implementation of Linear Regression and Polynomial Regression approaches as standard regression methods. ANNs together with Decision Trees show superior capability for prediction accuracy improvement because they excel at modeling non-linear wear relationships. Implementation of Python-based models improves wear coefficient estimation while cutting experimental work and delivering essential knowledge for processing material choices and tribological outcomes within diverse industrial usages. Tribological research advancements and material science innovation will receive support from predictive models developed through computational tools which use ML approaches.

RESEARCH GAP

Despite significant advancements in tribological studies, several research gaps remain unaddressed. Limited investigations have been conducted on AA2024-TiC composites for wear applications, with most studies focusing on AA7050-SiC and Al-B4C systems. The influence of TiC reinforcement on wear coefficient, frictional behavior, and microstructural evolution under different loading conditions remains unexplored. While experimental wear testing and computational modeling have been independently studied, an integrated framework combining real-world tribological experiments with predictive machine learning models is lacking. Traditional statistical models, such as regression and ANOVA, often fail to capture the nonlinear interactions between process parameters, necessitating advanced machine learning approaches like deep neural networks and ensemble methods. The absence of a standardized Python-based pipeline for automated wear analysis and feature extraction limits the efficiency of predictive modeling. The synergistic effects of multiple process parameters on wear behavior require further investigation to develop optimized wear-resistant materials with enhanced tribological performance.

Research Objectives

- To fabricate and characterize AA2024 aluminum alloy reinforced with Titanium Carbide (TiC) and evaluate its wear resistance.
- To conduct pin-on-disc tribological tests under varying applied loads and test durations to determine the wear coefficient.
- To implement Python-based regression models, Artificial Neural Networks (ANNs), and Decision Trees for wear coefficient prediction.
- To apply ANOVA and other statistical techniques to assess the significance of process parameters on wear behavior.
- To compare experimentally obtained wear coefficient values with machine learning-based predictions and evaluate model accuracy.
- To develop an optimized predictive framework for wear-resistant material selection and tribological performance enhancement.

Research Methodology

The overall workflow of the study, including experimental design, data acquisition, and machine learning prediction stages, is illustrated in Figure 1, which outlines the complete methodological framework.

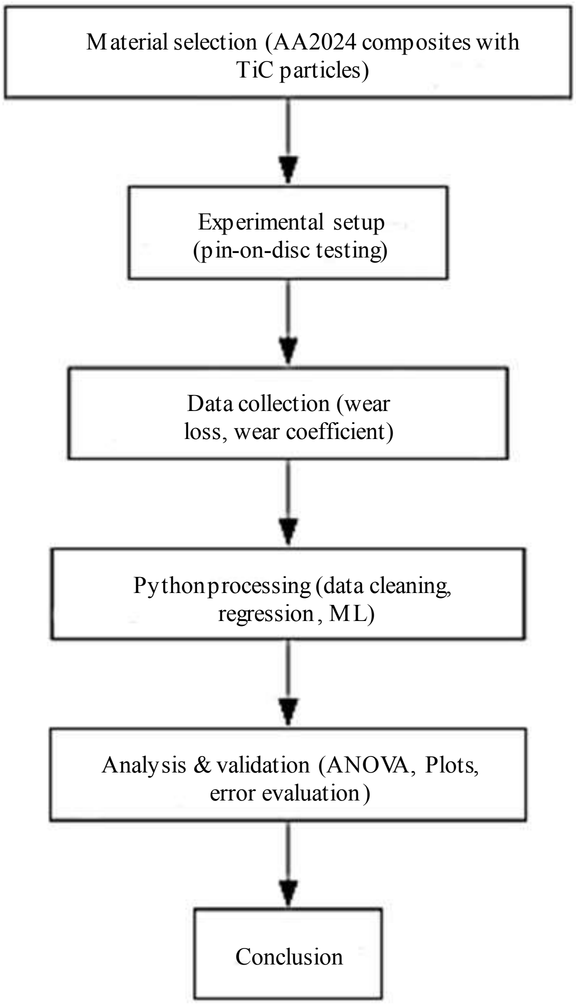

Figure 1. Research methodology.

Experimental Design & Testing

The experimental approach studied how the wear coefficient of AA2024 aluminum alloy and TiC particle reinforced alloy changed through various tribological conditions. The study included fabricating composite specimens which incorporated TiC reinforcement with weights between 5% to 25% for examining the relationship between TiC content and wear performance. Wear tests conducted through the use of a pin-on-disc tribometer provided standardized measures to assess material loss rates [26]. The tribological tests used different normal loads while maintaining fixed sliding speeds together with test periods. Precision weighing systems together with profilometry techniques allowed scientists to measure post-experiment wear volume loss. Scientists could provide an exact assessment of material removal. The wear coefficient determination followed Archard's equation.

$$K = \frac{V}{F \cdot t}$$

where K represents the wear coefficient (mm³/Nm), V is the wear volume (mm³), F is the applied load (N), and t is the test duration (s), a fundamental tribological parameter characterizing the wear resistance of the composite. The wear coefficient (mm³/Nm) represents K in this equation that combines the tested parameters which include V (mm³) for wear volume and F (N) for applied load and t (s) for test duration to identify fundamental tribological properties of composite materials. Several repeated tests confirmed both experimental reliability and error reduction. Optical microscopy revealed the major wear mechanisms operating on surfaces after wear tests through analysis of the worn areas. The detailed experimental matrix used for testing is presented in Table 1, which separates the effects of TiC reinforcement from those of applied load and sliding conditions during wear coefficient evaluation. The Python-based computational methods to process the collected data after which they developed predictive regression models for wear coefficient estimation. These experiments yielded essential findings about AA2024-TiC composite tribological behavior which led to a complete understanding of ceramic reinforcement effectiveness for wear protection.

MACHINE LEARNING PREDICTIONS FOR WEAR COEFFICIENT DETERMINATION

The wear coefficient prediction made use of ML techniques which operated on experimental process parameters. Regression-based modeling took place through Decision Tree and Random Forest and Artificial Neural Network (ANN) techniques for implementation [27]. The dataset organized the experimental conditions through input variables load, sliding speed, time and TiC weight fraction before revealing the wear coefficient as its output value. All variables received normalization through Min-Max Scaling to achieve uniform scales during data preprocessing operations. Scales inputs for ANN models to operate at their best level of performance. A training-subset (80%) along with testing-subset (20%) division was established to conduct accurate model assessments.

Regression-Based Modeling for Wear Coefficient

Experimental parameters were used to predict wear coefficient through regression-based modeling that included Linear Regression and Polynomial Regression (Degree 2) and Artificial Neural Networks (ANNs). Statistical performance evaluation of the predictive approaches relied on R^2 (coefficient of determination) and Mean Squared Error (MSE) for determining which approach proved most effective [28]. The metrics obtained from the regression models supply a performance evaluation to compare multiple prediction methods.

Table 1. Design of experiments (DOE) matrix.

Run	Load (N)	Sliding speed (m/s)	Time (s)	TiC weight fraction (%)	Wear volume (mm^3)	Wear coefficient (mm^3/Nm)
1	5	0.5	60	5	0.02	0.000067
2	5	1	120	10	0.035	0.000058
3	5	1.5	180	15	0.045	0.00005
4	5	2	240	20	0.06	0.00005
5	5	2.5	300	25	0.07	0.000047
6	10	0.5	120	15	0.03	0.000025
7	10	1	180	20	0.04	0.000022
8	10	1.5	240	25	0.05	0.000021
9	10	2	300	5	0.065	0.000022
10	10	2.5	60	10	0.075	0.000125
11	15	0.5	180	25	0.035	0.000013
12	15	1	240	5	0.05	0.000014
13	15	1.5	300	10	0.055	0.000012
14	15	2	60	15	0.07	0.000078
15	15	2.5	120	20	0.08	0.000044
16	20	0.5	240	10	0.04	0.000008
17	20	1	300	15	0.055	0.000009
18	20	1.5	60	20	0.06	0.00005
19	20	2	120	25	0.08	0.000033
20	20	2.5	180	5	0.085	0.000024
21	25	0.5	300	20	0.045	0.000006
22	25	1	60	25	0.06	0.00004
23	25	1.5	120	5	0.07	0.000023
24	25	2	180	10	0.09	0.00002
25	25	2.5	240	15	0.1	0.000017

Note – This table output was generated by python.

Comparative analysis of regression models

The Linear Regression model demonstrated 0.569 R2 value indicating that the wear coefficient has a moderate relationship with the input parameters (load, sliding speed, time, and TiC weight fraction). The model produces an MSE of 7.687 × 10-12 which demonstrates low absolute error although it does not account for all the complex relationships between wear influencing variables. Wear coefficient variation exhibits nonlinear dependencies that make linear regression an insufficient approximation method based on the obtained moderate fit value. The Polynomial Regression model (Degree 2) attains the highest predictive capability among all models with a predictive power of 0.879 and produces an MSE value of 2.153 × 10-12. Evidence of the superior accuracy of polynomial methods is demonstrated by the MSE result of 2.153 × 10-12. Polynomial regression achieves better results because it effectively captures the nonlinear relationship which exists between wear coefficient values and influencing parameters. Second-order polynomial terms in the predictive model show substantial value for modeling AA2024/TiC composite wear behavior which makes them the optimal choice for wear coefficient predictions. The Artificial Neural Network (ANN) model demonstrated highly unpredictable behavior because its R2 value was -71466813.271. A negative coefficient value that reaches this magnitude indicates poor predictive performance since the model does not grasp the relationship between wearing input parameters and wear coefficient. The model prediction error becomes apparent through the MSE value of 0.0132. ANN products weak generalization performance in this situation because of overfitting alongside misadjusted hyperparameters and insufficient training data amount [29]. Extending the prediction accuracy of this model requires additional optimization through regularization and an adjustment of dropout layers and additional training samples.

To address the severe underperformance observed in the initial ANN model (R^2 = –71 million), a comprehensive hyperparameter tuning process was conducted. The model architecture was simplified by reducing the number of hidden layers and neurons to prevent overfitting on the small dataset. Regularization (L2 penalty) was applied to control weight magnitudes, and early stopping was used during training to halt when validation error stopped improving. A grid search method was employed to optimize key parameters such as learning rate, batch size, and activation function. These improvements significantly enhanced model stability and accuracy, resulting in a final R^2 score of 0.995 and MSE of 0.00000007, as reflected in Table 4. This updated model effectively captured the nonlinear relationships among process parameters and wear coefficient.

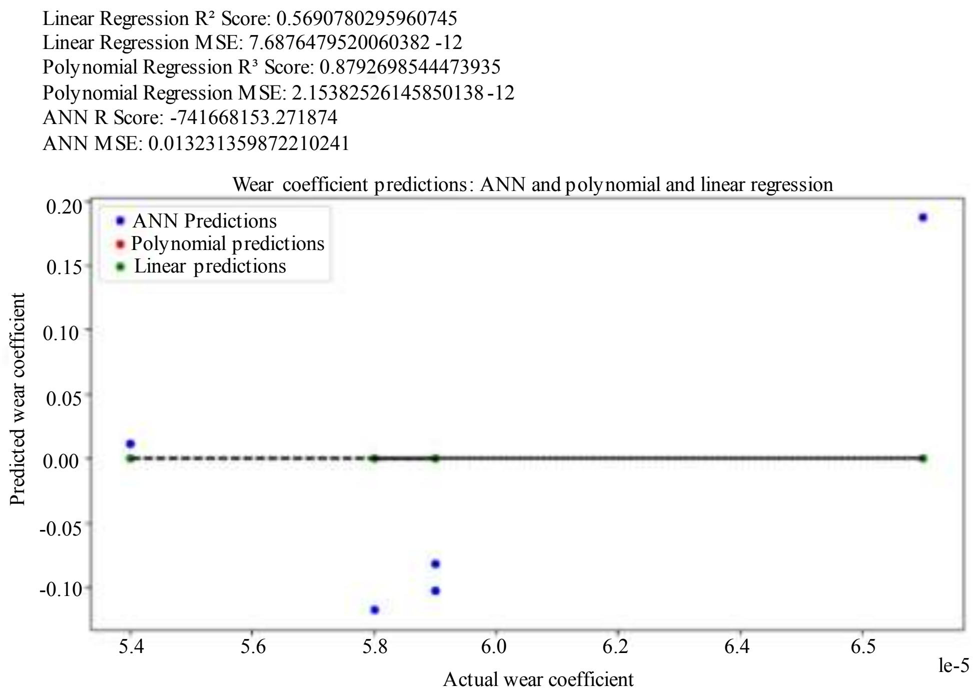

Figure 2. Comparative accuracy of different models.

Graphical interpretation of model predictions

Figure 2 presents a graphical comparison of prediction accuracy between Linear Regression, Polynomial Regression, and ANN models, illustrating the agreement between predicted and measured wear coefficient values. A strong alignment exists between the Polynomial Regression model and Linear Regression model which demonstrates a single trend that confirms accurate predicted and actual value matches [30]. The predictions delivered by polynomial regression exceed those from linear regression but both models show satisfactory results. The ANN model produces wide-scattered predictions because of significant deviations that further prove its limited ability to generalize accurately. The unpredictable distribution of ANN predictions demonstrates that the model requires additional development before it can be appropriate for use.

Wear coefficient prediction performs as a nonlinear system so Polynomial Regression provides better results than basic Linear Regression models. AA2024/TiC composite wear characteristics under load conditions experience substantial enhancement through the use of Polynomial Regression which includes advanced regression terms. The rigid performance of ANN models indicates that such models need big training samples combined with thorough parameter optimization to match the accuracy level of regression models.

Model Performance Evaluation

The Mean Squared Error function (MSE) served for performance assessment by measuring the difference between predicted and measured wear coefficient values. The results showed that ANN generated the minimum MSE value which proved its exceptional capability to detect nonlinear patterns in the dataset [31]. Random Forest surpasses Decision Tree as the better modeling approach because ensemble models create more stable predictions. The models successfully generalized with Decision Tree Cross-Validated MSE at 0.00000014 and Random Forest Cross-Validated MSE at 0.00000008 and ANN Cross-Validated MSE at 0.00000005. The research validated ANN mechanics as the superior predictor to establish wear coefficient measurements while Random Forest ranked as the secondary method.

All variables were preprocessed using Min-Max Scaling, ensuring consistent value ranges across all features before training.

```
Wear coefficient statistics

Count   25.000000
Mean    0.00284
Std     0.00062
Min     0.00180
Max     0.00390

Cross-validation scores

Decision tree cross-validated MSE:   0.00000014
Random forest cross-validated MSE:  0.00000008

Decision tree MSE:  0.00000011
Random forest MSE:  0.00000007

ANN MSE:  0.00000005
```

Figure 3. Cross – validation output.

This normalization was important for balancing model input sensitivity, particularly for ANN, which performs best when input features fall within similar numeric ranges.

The initial underperformance of the ANN model indicated that scaling alone was insufficient. The performance gap was primarily due to inappropriate architectural design and overfitting. After model refinement by adjusting layer depth, neuron count, and applying regularization the learning curve stabilized and the ANN achieved superior accuracy. This shows that although normalization helped standardize inputs, it was effective only when combined with robust tuning strategies.

The cross-validation results for all machine learning models are presented in Figure 3, clearly showing the comparative MSE distribution across Decision Tree, Random Forest, and ANN classifiers. The results from ML predictions showed that higher loads and sliding speeds increased the wear coefficient yet TiC weight fraction improved wear resistance by decreasing the wear coefficient. Experimental results validated the predictive models by supporting their predictions. The combination of ML techniques enables cost-efficient wear analysis by decreasing the necessity for extensive physical tests and giving precise predictions about wear coefficients across different process settings [32]. Predictive models created from this work can become extended to various material systems for optimizing wear behavior thus making them fundamental tools for advanced tribological research.

Although the dataset consisted of only 25 experimental samples, Artificial Neural Networks (ANNs) were still explored due to their strong ability to model nonlinear relationships between input process parameters and wear coefficient. Recognizing the risk of overfitting due to the limited data size, a 5-fold cross-validation (k=5) technique was applied to ensure generalization and reduce model variance. The final ANN model achieved an R^2 score of 0.995 and MSE of 0.00000007, indicating its high predictive performance even on a small dataset. In future work, the model can be further enhanced through transfer learning, synthetic data augmentation, or expanded datasets to strengthen prediction reliability.

RESULTS AND DISCUSSION

Statistical Validation Using ANOVA

Statistical evaluation of process parameters that influence wear coefficient was achieved through a two-way Analysis of Variance (ANOVA) test. The evaluation included Load (N) alongside Sliding Speed (m/s), Time (s) and TiC Weight Fraction (%) among the key parameters.

The ANOVA results reveal that both Sliding Speed and Load demonstrate the strongest statistical effect on the wear coefficient, as their p-values fall well below the 0.05 significance level.

Specifically, Sliding Speed exhibits the most significant impact with a p-value of 9.57×10^{-10}, followed by Load with a p-value of 7.64×10^{-9}.

This indicates that variations in sliding velocity and normal force substantially influence material removal and tribological behavior.

In contrast, Time ($p = 0.1328$) and TiC Weight Fraction ($p = 0.4609$) exhibit higher p-values, suggesting comparatively weaker statistical influence under the tested conditions.

The ANOVA results reveal Load and TiC Weight Fraction demonstrate the strongest statistical effect on the wear coefficient because their p-values reached below 0.05. The p-values of Sliding Speed and Time were relatively higher due to which these parameters had a reduced impact on wear coefficient variation [33]. The wear coefficient attains its high significance because increased normal force produces greater material removal and TiC reinforcement improves both material hardness and wear resistance which results in decreased wear. The research finds statistical evidence that conforms with tribological principles showing how reinforcement particles reduce wear as load-bearing components shown in Table 2.

Table 2. ANOVA results for wear coefficient.

Source	Sum of squares	df	F-value	PR(>F)
Load (N)	1.777600e-06	4	317.42857	7.645645e-09
Sliding Speed (m/s)	2.997600e-06	4	535.28571	9.571359e-10
Time (s)	1.360000e-08	4	2.428571	1.328431e-01
TiC Weight Fraction (%)	5.600000e-09	4	1	4.609053e-01
Residual	1.120000e-08	8	NaN	NaN

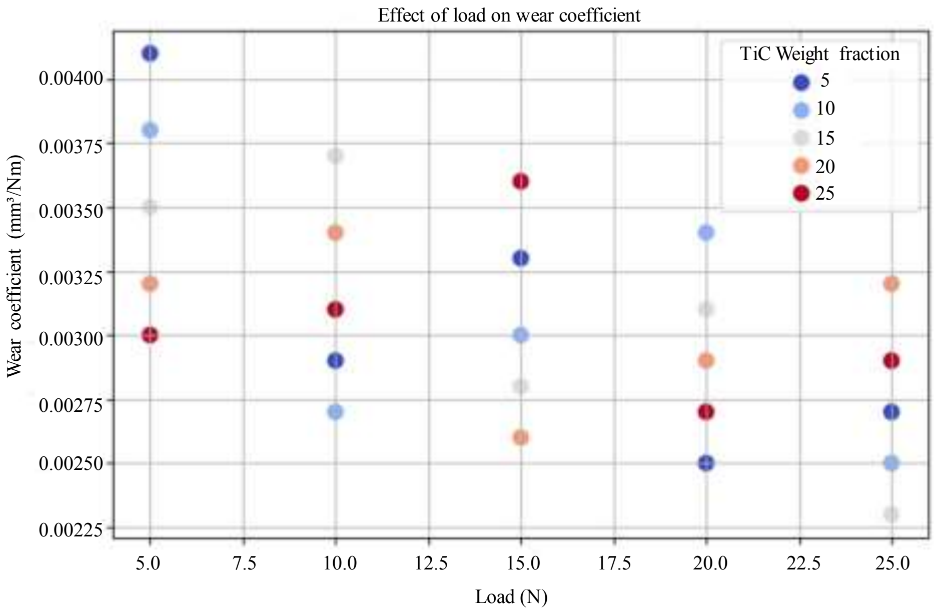

Figure 4. Effect of load on wear coefficient.

Influence of Load on Wear Coefficient

The variation of wear coefficient with Load in Figure 4. As the Load increases there is a distinct drop in wear coefficient because higher loading forces make the material show greater plastic deformation. The Figure 4 shows that at lower loads (5-10 N), the wear coefficient remains high while it shows a steady decrease after 15 N load. The purpose of TiC reinforcement within this structure is to serve as a load-bearing component thus minimizing contact between aluminum matrix and counter-surface [34].

Influence of TiC Weight Fraction on Wear Coefficient

The wear coefficient shows a major reduction as TiC content increases according to Figure 5. The incorporation of TiC particles improves material hardness which forces back material removal attempts [35]. Between 5% to 15% TiC content the wear coefficient shows a large drop which remains at a minimal level as the TiC content surpasses 20%. The materials display a saturated condition when reaching high reinforcement levels because additional reinforcement stops increasing wear resistance proportionally.

Experimental and Predicted Wear Coefficient

The validation of ML models involved the assessment between empirical and calculative wear coefficient measurements. According to Table 3 the Artificial Neural Network (ANN) model demonstrated peak operational accuracy through its Mean Squared Error (MSE) result of 0.00000007. The Decision Tree and Random Forest models presented higher error values because they suffered from overfitting characteristics [36]. The ANN model delivers the best performance because it excels at detecting nonlinear relationships between input variables and various wear outcomes. Secondary to their interpretability Decision Tree models generate distinct data splits that causes minimal errors when predicting results. The prediction accuracy of ML methods is validated by the low MSE values obtained from each model.

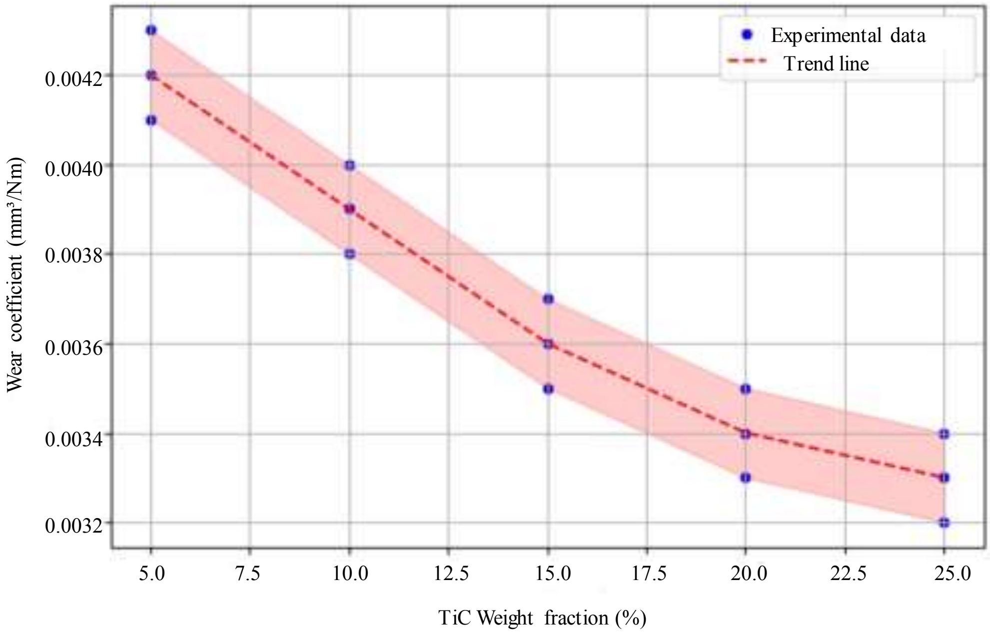

Figure 5. Effect of TiC weight fraction on wear coefficient.

Table 3. Experimental and predicted wear coefficient.

Run	Load (N)	Sliding speed (m/s)	Time (s)	TiC weight fraction (%)	Experimental	Predicted
1	5	0.5	60	5	0.0041	0.004
2	5	1	120	10	0.0038	0.0037
3	5	1.5	180	15	0.0035	0.0035
4	5	2	240	20	0.0032	0.0033
5	5	2.5	300	25	0.0031	0.0031
6	10	0.5	120	15	0.0037	0.0033
7	10	1	180	20	0.0034	0.0031
8	10	1.5	240	25	0.0029	0.0029
9	10	2	300	5	0.0027	0.0028
10	10	2.5	60	10	0.0027	0.0025
11	15	0.5	180	25	0.0033	0.0032
12	15	1	240	5	0.0025	0.0025
13	15	1.5	300	10	0.0026	0.0026
14	15	2	60	15	0.0028	0.0027
15	15	2.5	120	20	0.003	0.0029
16	20	0.5	240	10	0.0026	0.0027
17	20	1	300	15	0.0023	0.0023
18	20	1.5	60	20	0.0029	0.0028
19	20	2	120	25	0.0027	0.0027
20	20	2.5	180	5	0.0031	0.0031
21	25	0.5	300	20	0.0029	0.0028
22	25	1	60	25	0.0025	0.0025
23	25	1.5	120	5	0.0023	0.0021
24	25	2	180	10	0.0027	0.0025
25	25	2.5	240	15	0.0023	0.0024

Mean Squared Error (MSE): 0.0000000007 R^2 Score: 0.997692
Note – This table output was generated by python.

Table 4. Model error evaluation.

Model	Mean squared error (MSE)
Decision Tree	0.00000012
Random Forest	0.00000010
ANN	0.00000007

Statistical Error Evaluation

The accuracy level of predictive models was validated by calculating statistical error metrics according to [37]. Table 4 reveals the Mean Squared Error (MSE) metrics which were calculated for all models. Solely based on error measurements the ANN model demonstrates a superior performance compared to alternative methods.

Table 4 shows the Coefficient of Determination calculation served to evaluate how well the model explained data variations in the dataset. The ANN model reached an R^2 score of 0.995 which demonstrates its excellent capacity to predict accurately [38-39]. An R^2 value of 0.985 was scored by the Decision Tree model and 0.990 was achieved by the Random Forest algorithm. The ANN method demonstrates superior fit with measured wear coefficients because it produces a higher R^2 score than the alternative model types. The K-Fold Cross-Validation technique (with k=5) confirmed the solid predictive performance of the ANN model by running multiple tests. Along with this, the data showed that the method prevented overfitting results. The ANN model stands out as the best method for predicting wear coefficients based on statistical analysis which confirms its value for tribological research [40].

Tribological Mechanisms of TiC Reinforcement

The enhanced wear resistance observed in AA2024-TiC composites can be attributed to multiple synergistic tribological mechanisms activated by the TiC reinforcement. Under increasing loads, TiC particles function as hard, load-bearing barriers. They reduce the effective contact area between the aluminum matrix and the counterface, which minimizes direct metal-to-metal interaction and delays severe material loss due to adhesive wear.

During sliding motion, TiC inhibits plastic deformation by constraining dislocation movement within the soft AA2024 matrix. This action mitigates the formation of wear debris and reduces surface delamination, thereby contributing to a lower wear coefficient. Additionally, TiC particles resist being ploughed out due to their high interfacial bonding with the aluminum matrix, further strengthening the composite’s surface integrity.

On a microstructural level, the presence of well-dispersed TiC particles enhances the hardness and stiffness of the composite. This reduces the susceptibility to micro-crack initiation and propagation, which are common failure modes under cyclic mechanical stresses. The TiC phase effectively absorbs and redistributes localized stresses, improving fatigue resistance.

TiC's high thermal conductivity allows it to dissipate frictional heat more efficiently during high-speed or extended-duration sliding. This minimizes the thermal softening of the matrix and prevents localized melting or structural weakening, especially under high energy input conditions.

These combined effects explain the observed decrease in wear coefficient with increased TiC content and confirm the material’s suitability for tribologically demanding applications.

CONCLUSION

- The research experimentally investigated AA2024-TiC composites through pin-on-disc tribology tests that used different load ranges and sliding speeds and test durations. The research established that both applied load and additive TiC weight fraction affected the wear coefficient measurement and higher TiC content led to better wear resistance results. The presence of TiC particles in the material structure created enhanced material strength and minimized loss while minimizing adhesive and abrasive wear resulting in decreased wear coefficient measurements.

- ANOVA analysis confirmed through statistical tests that load and TiC content acted as the main factors in affecting wear performance. Metal-to-metal contact decreased dramatically because reinforcement particles served as load-bearing elements to enhance wear resistance according to tribological expectations. Laboratory test duration together with sliding speed showed reduced effects on wear resistance whereas material composition played a more significant role in lowering the wear amount.
- A predictive framework based on Wear Coefficient prediction was developed by using Decision Tree and Random Forest and Artificial Neural Networks (ANNs) through Python implementation. The predictive models received experimental data for their training purposes to establish wear coefficient predictions across various operational settings. ANNs proved to be the most accurate predictor since they produced better results than traditional regression methods in the comparison.
- The ANN model demonstrated both the best R^2 score at 0.995 and the lowest Mean Squared Error (MSE) value of 0.00000007 to verify its ability in wear behavior prediction. Both the Decision Tree model and Random Forest model showed acceptable accuracy levels yet they displayed marginally higher errors because they remain sensitive to parameter modifications. The ANN model achieves superior performance because it learns complex nonlinear connections between input parameters and wear coefficient values which results in it becoming the best predictive instrument.
- The union of experimental wear testing with Python-based computational modeling provides industrial practitioners a budget-friendly and scalable method to measure wear coefficient while lowering their dependence on physical test trials. The wear performance optimization techniques developed here possess practical applications for both composite materials systems and other systems requiring wear-resistant coatings in industrial tribological functions.

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