Triboinformatics: Combining Machine Learning with studies of friction and wear of Al/Gr MMCs

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1. Introduction

- Tribology remains an empirical, and data-driven scientific discipline due to the absence of mathematical derivations from physical or chemical first principles of physics and chemistry to characterize friction and wear [1].
- The traditional tribological analysis through isolated experimental observations, often fails to generate proper interpretation of tribological behaviors.
- Data-driven analysis and Machine Learning (ML) algorithms can offer novel insights into tribology. In particular, the area of so-called Triboinformatics (sometimes called "Intelligent Tribology) has been suggested [1, 2].
- The objective of the study is to develop and analyze the performance of ML algorithms to predict the COF and wear behavior of Al/Gr MMCs. Additionally, we present a comparative analysis of different material and tribological test parameters influencing the friction and wear behavior of these MMCs.

2. Methodology

2.1. Data collection

Experimental data of dry friction and wear test of Al/Graphite MMCs from different sources available in literature was collected for analysis. For modeling different ML algorithms to predict COF, and wear rate, 533 and 852 sample data points were used respectively [3].

2.2. Input and output parameters

Eleven material and tribological variables namely graphite content, hardness, ductility, processing procedure, heat treatment, silicon carbide content, yield strength, tensile strength, normal load, sliding speed, and sliding distance were considered as the input parameters or features. COF, and wear rate were the two output parameters.

2.3. Machine learning algorithms

Five different ML algorithms: Artificial Neural Network (ANN), K Nearest Neighbor (KNN), Random Forest (RF), Support Vector Machine (SVM), and Gradient Boosting Machine (GBM) were developed using Python programming language and its built-in "scikit-learn" toolkit.

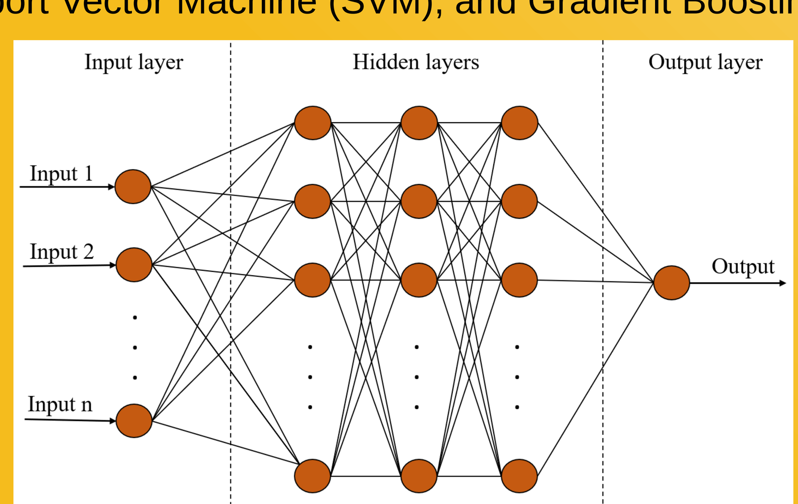

Fig.1. Artificial neural network architecture

2.4. Parameter optimization of the ML algorithms

The grid search method, and the five-fold cross validation were used to find the optimal parameters of the ML algorithms by assessing model performance for different parameter combinations.

3. Results and discussion

3.1. Performance evaluation

The coefficient of determination (R^2 $value$) is the most important performance metrics for ML regression algorithms. Mean squared error (MSE), root mean squared error (RMSE), and mean absolute error (MAE) are other metrics to evaluate the performance of an ML model.

Table 1: Performance of the ML methods in predicting COF

ML Model	MSE	RMSE	MAE	R^2 value
ANN	0.0037	0.0611	0.0403	0.8630
KNN	0.0066	0.0816	0.0460	0.7561
RF	0.0037	0.0612	0.0332	0.8626
SVM	0.0064	0.0802	0.0547	0.7644
GBM	0.0028	0.0538	0.0360	0.8941

Performance metrics of the ML algorithms in **Table 1** indicate satisfactory model execution in COF prediction with the R^2 value ranging from 0.7561 to 0.8941 and significantly low values of MSE, RMSE, and MAE.

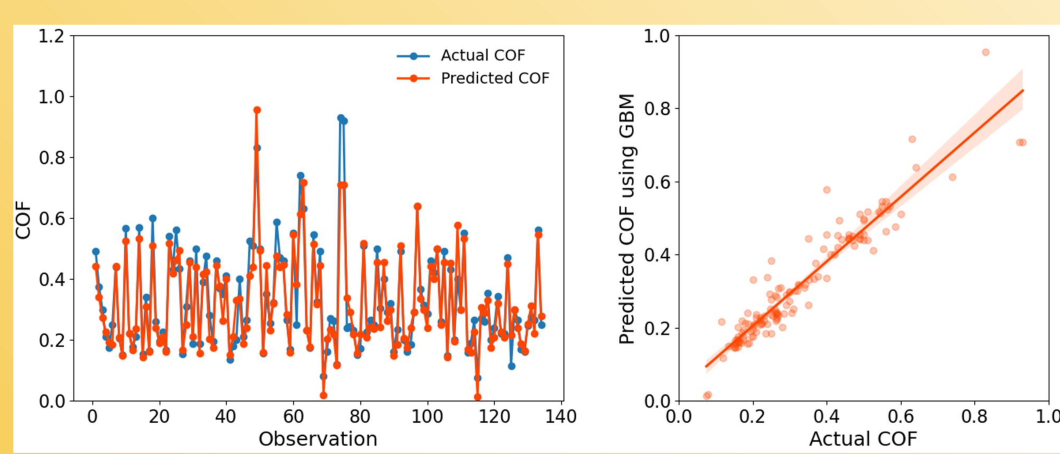

Fig.2. Predicted COF using GBM vs actual COF

Decision tree based GBM outperformed other algorithms as the boosting mechanism effectively handled complex COF data with less variation and could predict the COF with 89.41% accuracy (**Fig.2.**).

Table 2: Performance of the ML methods in predicting wear rate

ML Model	MSE	RMSE	MAE	R^2 value
ANN	0.0031	0.0558	0.0181	0.7395
KNN	0.0017	0.0422	0.0114	0.8512
RF	0.0014	0.0374	0.0093	0.8832
GBM	0.0016	0.0408	0.0123	0.8607

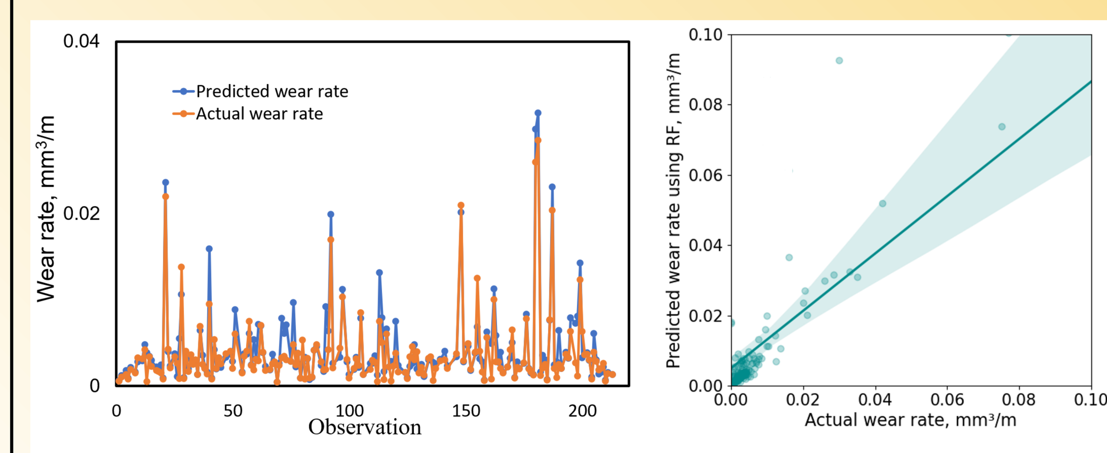

Fig.3. Predicted wear rate using RF vs actual wear rate

The R^2 value ranging from 0.7395 to 0.8832 and significantly low values of MSE, RMSE, and MAE indicate satisfactory model execution of the ML algorithms in wear rate prediction.

The decision tree based RF algorithm outperformed others in wear rate prediction as its bagging mechanism is robust against variability and outliers. With an R^2 value of 0.8832, the RF algorithm could predict the wear rate of Al/Gr MMCs with 88.32% accuracy (**Fig.3.**).

3.2. Feature importance analysis

The feature importance chart of decision tree based RF algorithm (**Fig.4.**) identified hardness and graphite content as the most important material variables in predicting the COF of Al/Gr MMCs.

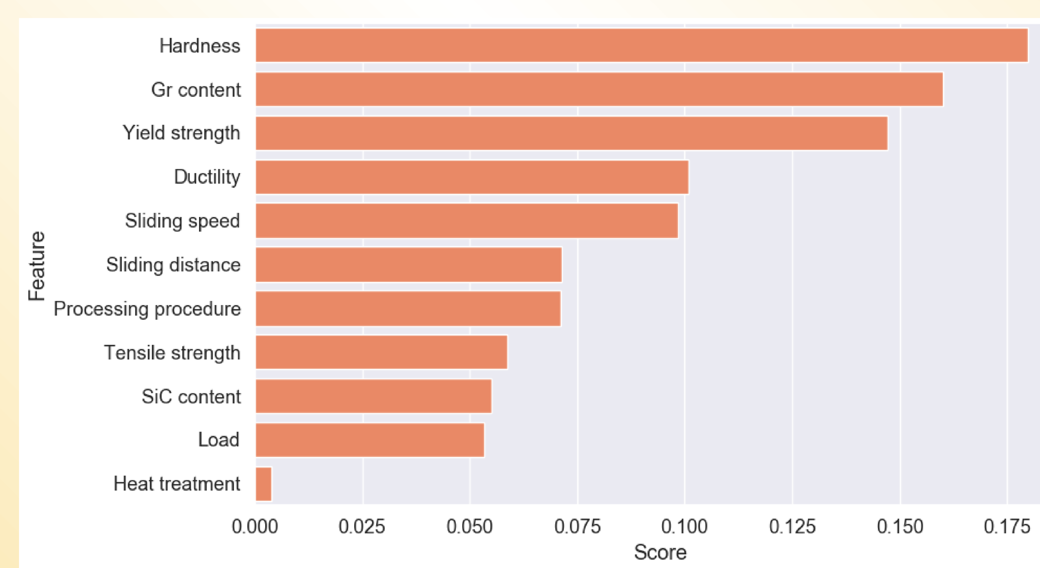

Fig.4. Feature importance in predicting COF

Feature importance chart (**Fig.5.**) shows that the graphite content and the sliding speed had the highest contributions in predicting wear rate of Al/Gr MMCs.

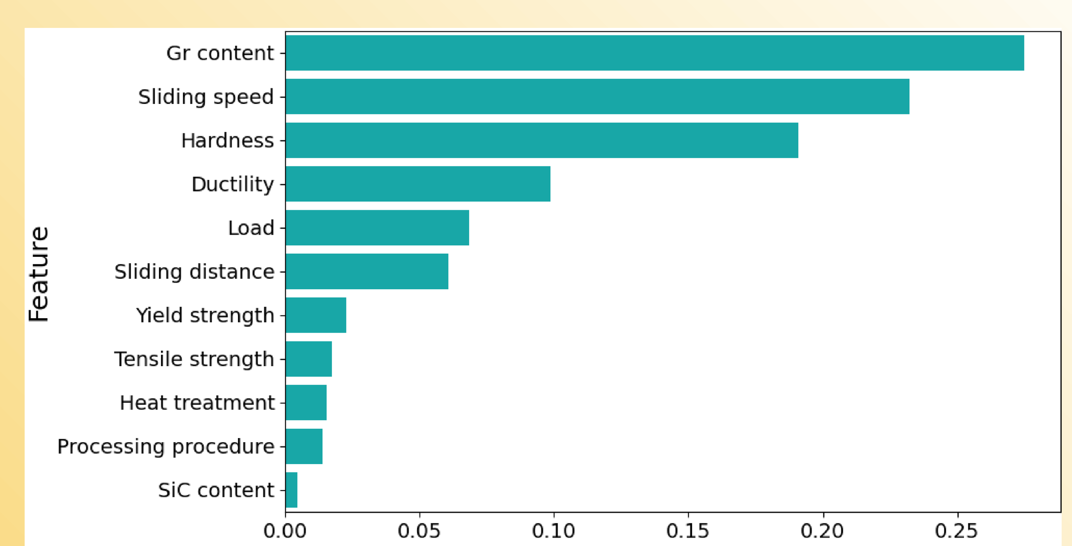

Fig.5. Feature importance in wear rate prediction

4. Conclusions

- Performance metrics indicated that the developed ML algorithms could satisfactorily predict the COF and wear rate of Al/Gr MMCs.
- Decision tree based ensemble ML algorithms (GBM and RF) outperformed others in predicting COF and wear rate.
- GBM uses boosting mechanism in tree building process which can effectively handle complex datasets while RF employs bagging mechanism which is robust against variability and outliers.
- The variability was more prevalent in the wear rate data set than the COF dataset. Consequently, GBM exhibited the best performance in the COF prediction, and RF outperformed GBM in wear rate prediction.
- Hardness and graphite content were identified as the most important parameters in characterizing friction while graphite content and sliding speed were the most influential in wear rate prediction.
- The formation of a thin graphite film over the tribosurface provides lubrication at the mating surfaces and eliminates metal-to-metal contact during sliding. In contrast, with increasing graphite content, crack propagation and delamination of the graphite phase increased due to a weaker bonding with the aluminum matrix.
- Due to these diverse effects, graphite content influenced the friction and wear behavior of Al/Gr MMCs than any other material or tribological variables.

5. References

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For further information

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