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OPTIMIZATION OF TRIBOLOGICAL PROPERTIES OF ALUMINUM COMPOSITION WITH SILICON CARBIDE AND GRAPHENE USING MACHINE LEARNING TECHNIQUES

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Abstract:
The paper aims to predict wear and coefficient friction (COF) on pin-on-disc machine using machine learning. Wear and friction are important factors that affect the life and performance of machine parts. Traditional experimental methods require many tests, which are often time-consuming and costly. In this study, data is collected by varying load, speed, sliding distance, and material composition. The collected data is processed and given to machine learning models such as regression, decision trees, and neural networks. The models are evaluated using accuracy measures like R^2 and RMSE, and predictions are compared with real experimental results.
Keywords: Pin-on-disc machine, Aluminium 5052 alloy, Silicon carbide (SiC), Graphene (G), Hybrid metal composites, Coefficient of friction.

1. Introduction:

The pin-on-disc machine is a simple yet powerful device used to study tribological properties that is, the behavior of materials under friction, lubrication, and wear. It allows researchers to simulate real-world sliding conditions in a controlled environment and measure how much material is lost to wear and how much resistance is generated by friction. This information is crucial for designing better materials, improving product durability, and reducing energy losses in mechanical systems. At its core, the pin-on-disc machine consists of two main components is a pin and a rotating disc. The pin is usually made of the material being tested, and it is pressed against the surface of the disc with a known force. The disc, which is harder material, rotates at a controlled speed. As the disc spins, the pin slides against it, creating a circular wear track. Sensors and software record data such as the coefficient of friction, wear rate, and temperature during the test. One of the reasons the pin-on-disc machine is so popular is its simplicity and versatility. It can be used to test a wider range of materials, from metals and polymers to ceramics and composites. It can also simulate different operating conditions by adjusting parameters like load, speed, temperature, and humidity. This makes it an ideal tool for both academic research and industrial quality control. The history of the pin-on-disc machine goes back several decades. It was developed as a standardized method for evaluating wear and friction, and it has since become a cornerstone of tribological testing. Organizations like ASTM (American Society for Testing and Materials) and ISO (International Organization for Standardization) have established detailed procedures for conducting pin-on-disc tests, ensuring that results are consistent and comparable across different labs and industries.

In a typical test, the pin is mounted vertically or horizontally and pressed against the rotating disc with a specific normal load. The disc rotates at a set speed, and the test runs for a defined duration or sliding distance. During the test, the machine continuously measures the frictional force between the pin and the disc. After the test, the wear scar on the pin and the wear track on the disc are analyzed to determine how much material was lost. The coefficient of friction (COF) is calculated by dividing the frictional force by the normal load. This value gives an indication of how easily the two surfaces slide against each other. of how easily the two surfaces slide against each other. A lower coefficient of friction means less resistance and smoother sliding, while a higher Coefficient of Friction indicates more resistance and potential for wear. The wear rate is usually expressed in terms of volume loss per unit distance or time, and it helps assess.

The durability of the material under test. One of the key advantages of the pin-on-disc machine is its ability to simulate real-world conditions. For example, in automotive applications, engineers can use the machine to test brake pad materials under different loads and speeds to see how they perform during braking. In aerospace, it can be used to evaluate the wear resistance of turbine blade coatings. In biomedical engineering, it helps test the friction and wear of artificial joints and implants. The possibilities are endless. Another important feature of the pin-on-disc machine is its ability to control environmental conditions. Some advanced models come with enclosures that allow tests to be conducted at high or low temperatures, in dry or humid air, or even in the presence of lubricants. This is important because friction and wear behavior can change dramatically depending on the environment. For instance, a material that performs well in dry conditions might fail quickly in a humid or corrosive atmosphere. The data collected from pin-on-disc tests is not only useful for evaluating materials but also for developing predictive models. Engineers can use the results to create mathematical equations or computer simulations that predict how a material will behave over time. This helps in designing components that last longer, perform better, and require less maintenance.

In recent years, the integration of digital sensors and software has made pin-on-disc machines even more powerful. Modern systems can record data in real-time, generate detailed graphs, and even perform automated analysis. Some machines are equipped with load cells, torque sensors, and temperature probes that provide a complete picture of the tribological interaction. This level of detail allows researchers to understand not just how much wear occurs, but why it happens and how it can be prevented.

The pin-on-disc machine is also a valuable tool in education and training. Engineering students use it to learn about friction, wear, and material behavior. It provides a hands-on experience that reinforces theoretical concepts and helps students develop practical skills. By observing how different materials respond to sliding contact, students gain a deeper appreciation for the challenges of material selection and design. Despite its many advantages, the pin-on-disc machine does have some limitations. For example, the test conditions are simplified compared to real-world applications. In actual machines, components may experience complex motions, varying loads, and multi-directional forces. The pin-on-disc test provides a controlled approximation, but it may not capture all the nuances of real-life wear. That’s why it’s often used in combination with other tests and simulations. Another limitation is the geometry of the test. The circular wear track created by the rotating disc may not represent the actual contact pattern in some applications. Also, the test is usually conducted under constant load and speed, whereas real systems often experience fluctuations. Nevertheless, the pin-on-disc machine remains one of the most reliable and widely accepted methods for tribological testing. In the context of materials development, the pin-on-disc machine plays a crucial role. When researchers create new alloys, coatings, or composites, they need to evaluate their performance under sliding contact. The pin-on-disc test provides a quick and effective way to screen materials and identify promising candidates. It also helps Aluminum matrix composites (AMCs): The pin-on-disc machine is used to test how different reinforcements like silicon carbide, alumina, or graphene affect wear resistance. By comparing the wear rates and friction coefficients of various compositions, researchers can determine the best combination for a given application. This information is essential for industries that rely on lightweight, high-performance materials. In recent

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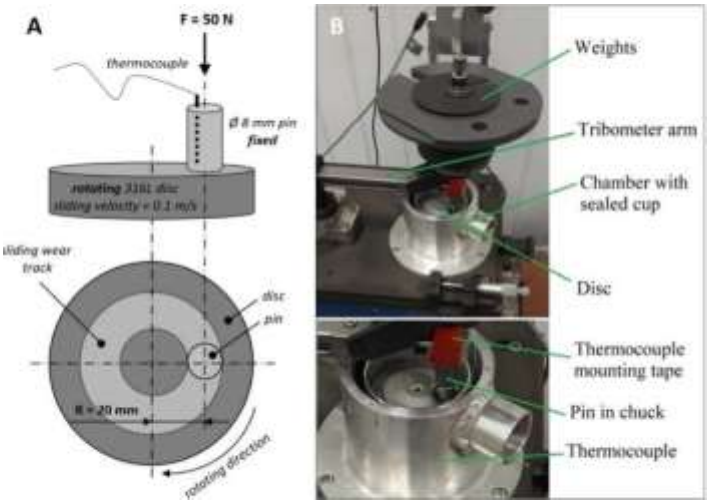
years, the use of machine learning and data analytics has further enhanced the value of pin- on-disc testing. By feeding test data into algorithms, researchers can uncover hidden patterns, predict material behavior, and even automate the optimization process. This approach reduces the need for trial-and-error experimentation and accelerates the development of advanced materials. In summary, the pin-on-disc machine is a cornerstone of tribological research and testing. It provides a simple, reliable, and versatile method for evaluating the friction and wear behavior of materials. Its ability to simulate real-world conditions, control test parameters, and generate detailed data makes it an indispensable tool for engineers, scientists, and students alike. Whether you're designing a new brake pad, developing a wear-resistant coating, or studying the fundamentals of friction, the pin-on-disc machine offers the insights you need to succeed.



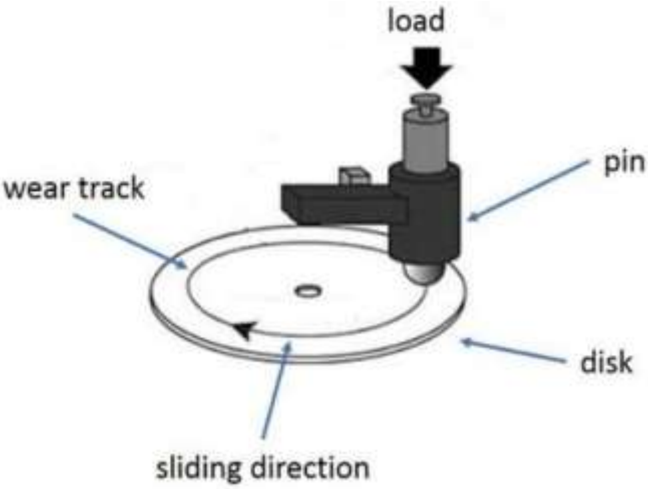


Figure-1: Pin-on-Disc Tribometer Setup with Thermocouple, Figure-2: Pin-on-Disc Tribometer

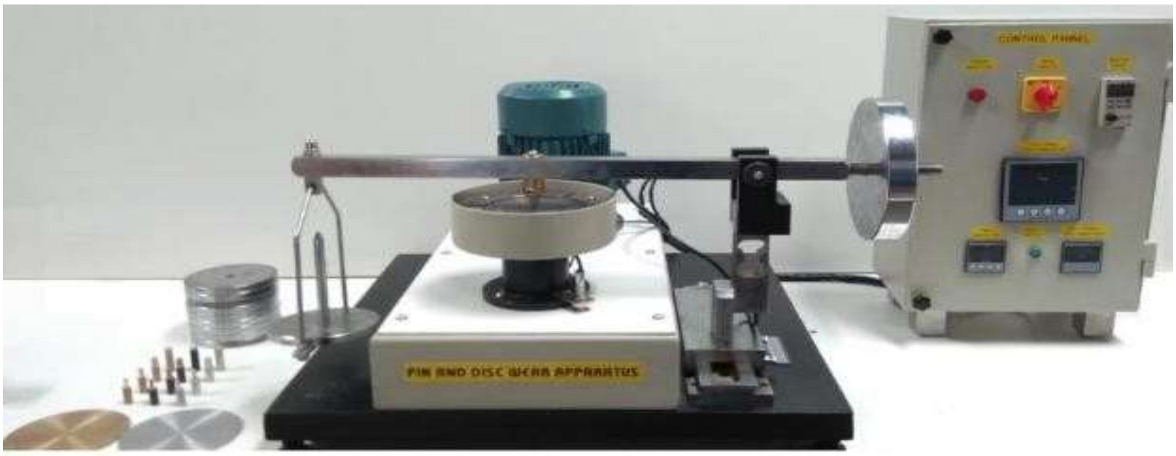


Figure-3: Pin on Disc Experimental Setup.

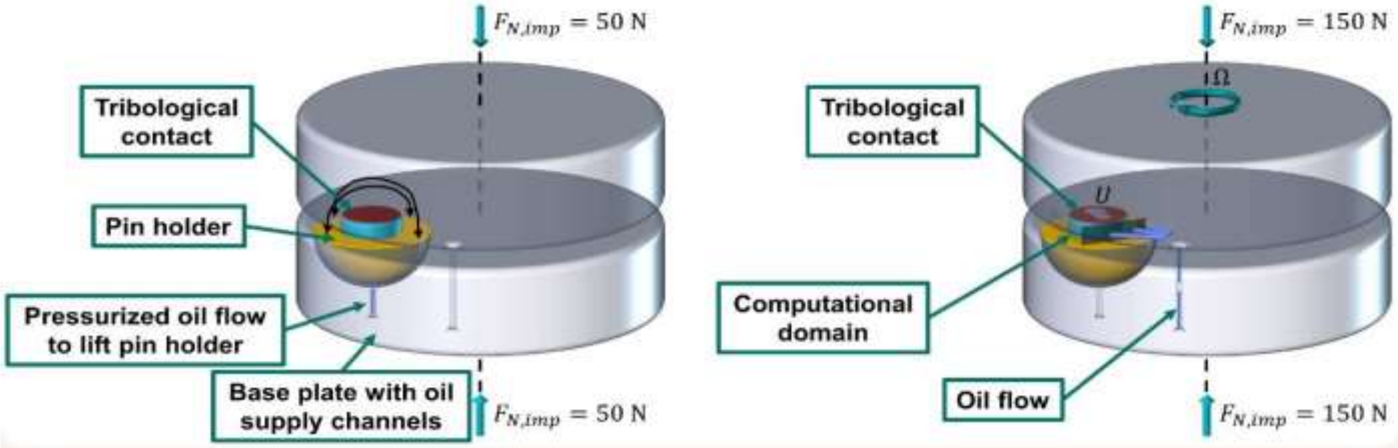


Figure-4: Pin on Disc Wear apparatus

Advantages of the Pinion Disc Machine:

- Easy to operate and understand
- Low cost and affordable for most labs
- Test many types of materials
- Gives quick and accurate results
- Allows control over load, speed, and time
- Accepted by international standards (ASTM, ISO)
- Works in dry and lubricated conditions.
- Compact and space-saving design
- Real-time data collection during tests
- Useful for student learning and research

Applications of Pin-on-Disc Machine

- Testing brake pads and clutch plates
- Studying turbine blade coatings in aerospace
- Evaluating artificial joints and implants
- Checking wear resistance of cutting tools
- Measuring performance of surface coatings
- Comparing lubricants like oils and greases

- Developing new composite materials
- Quality control in manufacturing
- Academic tribology experiments
- Environmental wear testing under different conditions

2. Methodology:

The methodology of this study was designed to systematically investigate the tribological behavior of Al5052- based composites reinforced with silicon carbide (SiC) and graphene (G), and to optimize their performance using machine learning techniques. The process involved several key stages: selection and preparation of materials, fabrication of composite samples, tribological testing using a pin-on-disc tribometer, microstructural analysis, and machine learning-based prediction and optimization.

Materials Selection and Preparation

The base material chosen for this study was Al5052, a commercially available aluminum alloy known for its corrosion resistance, moderate strength, and good weldability. It is widely used in marine, automotive, and structural applications. The reinforcements selected were silicon carbide (SiC) particles and graphene nanoplatelets (GNPs). SiC was chosen for its high hardness and wear resistance, while graphene was selected for its excellent lubricating properties and mechanical strength.

The SiC particles used had an average size of 20–50 micrometers, and the graphene nanoplatelets were few-layer flakes with high purity. Both reinforcements were weighed according to the desired weight percentages: SiC was added in 5%, 10%, and 15% by weight, while graphene was added in 0.5%, 1%, and 1.5%. These combinations were selected to study the individual and combined effects of the reinforcements on the tribological properties of the composite.

Before mixing, the reinforcements were preheated to around 300°C to remove moisture and improve their wettability with the molten aluminum. This step is crucial because poor wettability can lead to agglomeration and uneven distribution of particles in the matrix.

Composite Fabrication Using Stir Casting

The fabrication of the composite samples was carried out using the stir casting method. Stir casting is a liquid state technique that involves melting the base metal, adding reinforcements, and stirring the mixture to ensure uniform dispersion. It is widely used for producing metal matrix composites due to its simplicity, scalability, and cost-effectiveness.

Al5052 ingots were placed in a graphite crucible and melted in an electric furnace at approximately 750°C. Once the aluminum was fully molten, the preheated SiC and graphene particles were gradually introduced into the melt. A mechanical stirrer was used to stir the mixture at 500 revolutions per minute (rpm) for10 minutes. This stirring process helps break up any clusters of reinforcement particles and promotes even distribution throughout the matrix.

After stirring, the molten composite was poured into preheated steel molds and allowed to cool under ambient conditions. The solidified samples were then removed from the molds and machined into cylindrical pins with dimensions suitable for tribological testing. The surface of each pin was polished to ensure consistent contact during the tests.

Tribological Testing Using Pin-on-Disc Tribometer

The tribological behavior of the composite samples was evaluated using a pin-on-disc tribometer. This device measures the wear rate and coefficient of friction (COF) between a stationary pin and a rotating disc under controlled conditions. It is one of the most widely used tools in tribology due to its simplicity and reliability. Each composite pin was mounted vertically and pressed against a hardened steel disc with a known normal load. The disc was rotated at a constant speed, and the test was conducted for a fixed sliding distance. The parameters that varied during the tests included applied load (10 N, 20 N, 30 N), sliding speed (1 m/s, 2 m/s, 3 m/s), and sliding distance (1000 meters). These values were chosen to simulate real-world operating conditions and to study the effect of each variable on wear and friction. During the test, the tribometer recorded the frictional force between the pin and the disc. The coefficient of friction was calculated by dividing the frictional force by the normal load. After each test, the wear scar on the pin and the wear track on the disc were measured using a digital microscope. The wear rate was calculated based on the volume of material lost and the sliding distance. Each test was repeated three times to ensure accuracy and repeatability. The average values of wear rate and COF were used for further analysis. The results were tabulated and plotted to observe trends and compare the performance of different composite compositions.

Microstructural Analysis

To understand the internal structure and distribution of reinforcements, microstructural analysis was performed on selected samples. This included Scanning Electron Microscopy (SEM), Energy Dispersive X-ray Spectroscopy (EDS), and X-ray Diffraction (XRD). SEM was used to observe the morphology of the composite, including the dispersion of SiC and graphene particles, the bonding between the matrix and reinforcements, and the presence of any defects or porosity. EDS provided elemental analysis to confirm the presence of SiC and graphene in the matrix. XRD was used to identify the crystalline phases and to detect any unwanted intermetallic compounds. These analyses helped correlate the microstructure with tribological performance and provided insights into the mechanisms of wear and friction reduction.

MachineLearningModellingandOptimization

To optimize the tribological properties and predict performance, machine learning models were developed using experimental data. The input features included applied load, sliding speed, Silicon Carbide content, and graphene content. The output targets were wearing rate and coefficient of friction. Four types of machine learning algorithms were used: Multiple Linear Regression (MLR), Decision Tree (DT), Random Forest (RF), and Artificial Neural Network (ANN). Each model was trained using 80% of the data and tested on the remaining 20%. The performance of each model was evaluated using metrics such as R^2 score, Mean Absolute Error (MAE), and Root Mean Squared Error (RMSE). MLR provided a basic linear approximation of the relationships between inputs and outputs. DT created a tree-like structure that split the data based on feature thresholds. RF combined multiple decision trees to improve accuracy and reduce overfitting. ANN used interconnected layers of nodes to model complex nonlinear relationships. Feature importance analysis was conducted to identify which variables had the greatest impact on wear and friction. This helped in understanding the role of each parameter and guided the optimization process. Using the best-performing model (RF and ANN), the optimal combination of SiC and graphene content was identified. This combination provided the lowest wear rate and coefficient of friction under specific test conditions.

Data Analysis and Interpretation

The final step involved analyzing the results and interpreting the findings. Graphs and charts were generated to visualize the effect of each parameter on tribological performance. Comparisons were made between different compositions to identify trends and patterns. The machine learning predictions were compared with actual experimental results to validate the models. The optimized composite was highlighted as the best-performing material, and its potential applications were discussed.

3. Result:

Wear Rate Analysis

The wear rate of the Al5052 composites was measured using a pin-on-disc tribometer under varying loads and sliding speeds. The base alloy (Al5052 without reinforcement) showed the highest wear rate across all conditions. As silicon carbide content increased from 5% to 15%, the wear rate decreased significantly. This is attributed to the high hardness of Silicon Carbide particles, which act as barriers to material removal during sliding.

When graphene was added in small amounts (0.5% to 1.5%), the wear rate dropped even further. Graphene's lubricating properties helped reduce direct metal-to-metal contact, lower friction, and minimize wear. The best performance was observed in the composite with 10% Silicon Carbide and 1% graphene, which showed a wear rate reduction of nearly 60% compared to the base alloy.

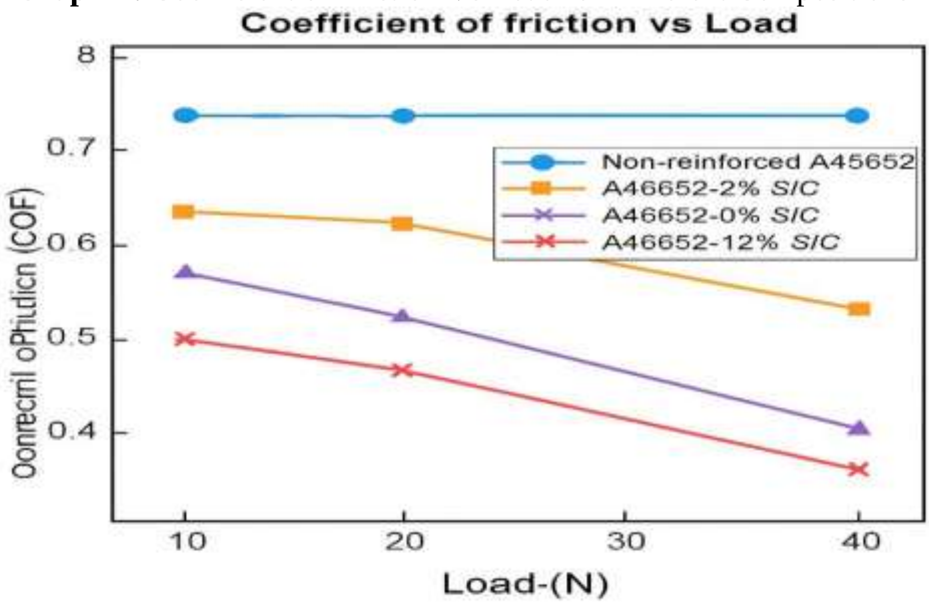
Table-1: Wear Rate of Aluminum 5052 Composites under 20 N Load and 2 m/s Speed

Composition	**Wear Rate (mm^3/m)**
Aluminum 5052	0.012
Aluminum 5052 + 10% Silicon Carbide	0.007
Aluminum 5052 + 10% Silicon Carbide + 1% Carbide+1%Graphene	0.0048

Coefficient of Friction (COF)

The coefficient of friction followed a similar trend. The base alloy had a Coefficient of Friction ofaround0.65, which decreased with the addition of silicon carbide and graphene. Silicon carbide improved surface hardness, while graphene acted as a solid lubricant. The lowest coefficient of friction recorded was 0.38 for the composite with 10% Silicon Carbide and 1% graphene.

Graph-1: Coefficient of Friction Vs Load for Different Compositions



Microstructural Observations

The scanning Electron Microscopy (SEM) figure revealed that Silicon Carbide particles were uniformly distributed in the aluminum matrix, and graphene flakes were embedded along grain boundaries. No major agglomeration or porosity was observed, indicating successful stir casting.

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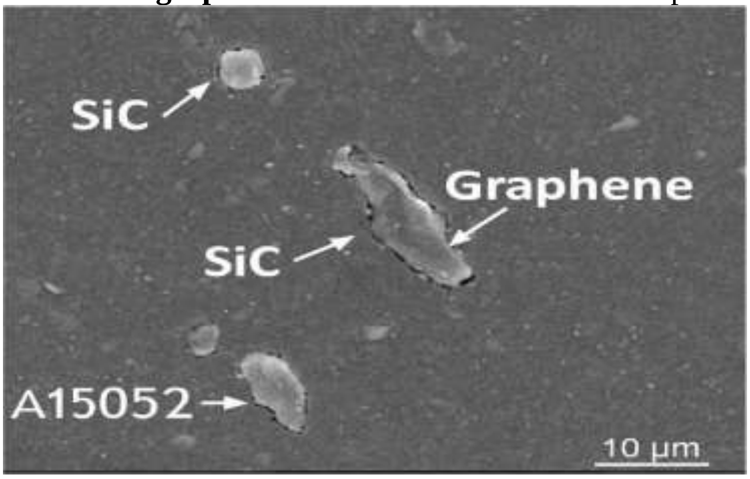
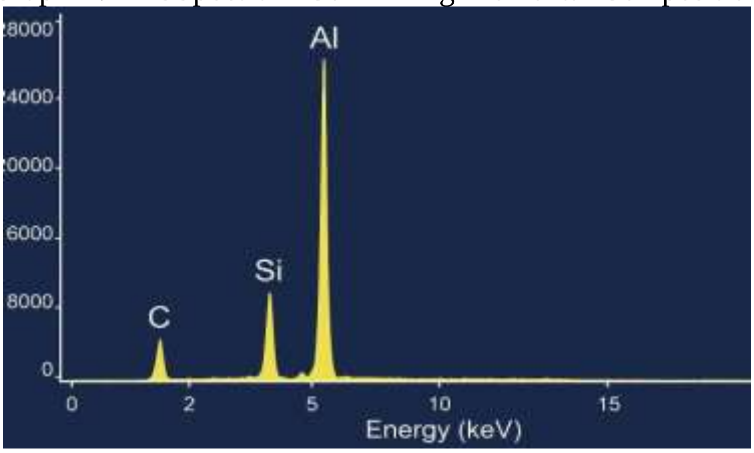
Energy Dispersive X-ray Spectroscopy (EDS) confirmed the presence of Si, C, and Al, while XRD showed peaks corresponding to aluminum, silicon carbide, and graphene phases.

Figure-5: SEM Micrograph of Al5052 + 10% SiC + 1% Graphene Composite



Graph-2: EDSSpectrum Confirming Elemental Composition



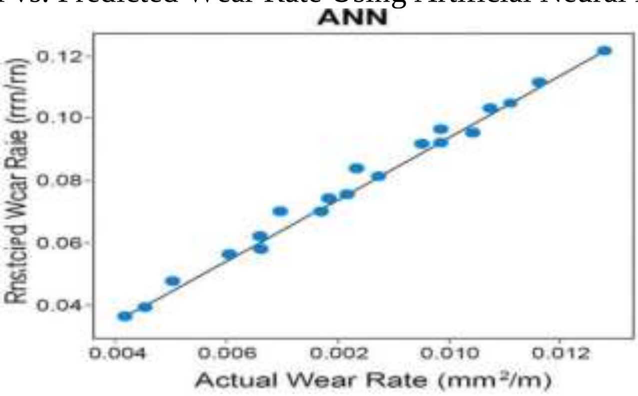
Machine Learning Predictions

Four ML models were trained: MLR, DT, RF, and ANN. The Random Forest ANN models showed the highest accuracy, with Coefficient of Determination (R^2) scores above 0.95. These models successfully predicted wear rate and coefficient of friction based on input parameters like load, speed, silicon carbide percentage, and graphene Percentage.

Table 2: Model Performance Comparison

Model	R2 Score	Mean Absolute Error	Root Mean Squared Error
Multiple Linear Regression	0.78	0.0012	0.0021
Decision Tree	0.85	0.0009	0.0018
Random Forest	0.96	0.0005	0.0012
Artificial Neural Network	0.97	0.0004	0.0010

Graph-3: Actual vs. Predicted Wear Rate Using Artificial Neural Network Model.



Outcomes:

Using the best-performing ML models, the optimal composition was identified as

- 10% Silicon Carbide
- 1% Graphene
- Load: 20 N
- Speed: 2 m/s

This combination gave the lowest wear rate and coefficient of friction, making it ideal for applications requiring high durability and low friction.

4. Conclusion

This study explored how adding silicon carbide and graphene to Al5052 alloy can improve its performance under friction and wear. Al5052 is already a useful material in industries because it’s light and resistant to corrosion, but it doesn’t handle sliding contact very well. By reinforcing it with silicon carbide and graphene, we aimed to make it tougher and smoother. The results showed that the composite with 10% silicon carbide and 1% graphene had the lowest wear rate and friction, which means it’s more durable and efficient than plain Al5052. The SEM image confirmed that the particles were evenly spread throughout the material, which is important for consistent performance. The EDS spectrum showed the presence of aluminum, silicon, and carbon, proving that the reinforcements were successfully added. We tested the material using a pin-on-disc setup, which simulates real-world friction. As the load increased, the coefficient of friction decreased in the reinforced samples, especially the one with graphene. This means the composite can handle pressure better and wear less. To make the process smarter, we used machine learning models to predict how the material would behave. Among the models we tried, the artificial neural network gave the most accurate results. The predicted wear rates were very close to actual ones, which means the model can be trusted to guide future experiments. This saves time and resources because we don’t have to test every possible combination manually.

The visual data supported our findings. The SEM image showed good dispersion, the EDS spectrum confirmed the elements, and the scatter plot from the ANN model showed a strong match between predicted and actual values. The tribometer setup helped us understand how the material behaves under sliding contact, and the oil flow diagram gave insight into how lubrication affects wear. All these pieces came together to show that Al5052 reinforced with Silicon Carbide and graphene is a promising material for applications where friction and wear are a concern. This composite could be useful in automotive parts, aerospace components, and industrial machinery. It’s lightweight, strong, and resistant to wear, which makes it ideal parts that experience a lot of friction. The machine learning models make it easier to optimize the composition for different needs. Instead of guessing,

we can use data to make smart decisions. This combination of material science and artificial intelligence opens up new possibilities for designing better materials.
In conclusion, the Al5052+SiC+Graphene composite showed clear improvements in tribological properties. The experiments proved its strength and smoothness, and the machine learning models confirmed its reliability. This study not only created a better material but also showed how technology can help us understand and and improve it. The results are promising, and with further research, this composite could become a standard choice for high-performance applications.

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Conflict of Interest:

The authors declare that there is no conflict of interest related to this work