Research on Engineering Structures & Materials
www.jresm.org
Research Group

Research Article

Machine learning and Taguchi optimization technique for wear rate analysis of Al 2024/ SiC/CNT based hybrid metal matrix composites

M N Rajesh [1,a], C Siddaraju [2,b], T Ram Prabhu [3,c], T S Sachit [4,d], R. Suresh [*,4,e]

[1]*GITAM (deemed to be) University, Bangalore-561203, Karnataka, India*
[2]*M S Ramaiah Institute of Technology, Bangalore-560054, Karnataka, India*
[3]*DRDO, Bangalore-560093, Karnataka, India*
[4]*MS Ramaiah University of Applied Sciences, Bangalore-560058, Karnataka, India*

Article Info

Article History:

Received 08 Apr 2025
Accepted 06 June 2025

Keywords:

Aluminium AL2024 alloy;
Silicon carbide;
Carbon nano tubes;
Wear rate;
Taguchi approach;
Machine learning

Abstract

This study focuses on the development and wear performance analysis of an aluminum alloy-based hybrid metal matrix composite (HMMC) reinforced with Silicon Carbide (SiC) and Carbon Nanotubes (CNTs). The composite was fabricated using the stir casting method, and it's mechanical and wear properties were evaluated. The Taguchi method was employed to design experiments, and ANOVA was used to identify significant factors affecting wear rate. Results indicated that applied load had the greatest influence (84.33%), followed by reinforcement content (10.36%) and sliding speed (2.31%). Wear surface morphology was examined using optical microscopy and scanning electron microscopy (SEM). To enhance predictive capabilities, machine learning (ML) models were applied to estimate the wear rate of Al2024/SiC/CNT composites. Five ML algorithms such as K-Nearest Neighbours (KNN), Support Vector Machine (SVM), Decision Tree, XGBoost, and Gradient Boosting were evaluated. XGBoost achieved the highest accuracy (99%) due to its ensemble learning and regularization features. Decision Tree and Gradient Boosting also performed well (96–97%), effectively modelling key variable interactions. SVM attained 92% accuracy, while KNN lagged at 79%, likely due to limitations in capturing complex relationships. This integrated approach of experimental analysis and ML modelling offers a reliable method for optimizing and predicting wear behavior in hybrid composites.

1. Introduction

During Particularly in sectors like aircraft and automotive where performance, fuel economy, and load-bearing capacity are critical, lightweight materials are increasingly important in modern engineering applications. Although Aluminum alloys—especially Al2024—have a better strength-to----weight ratio than others, they show flaws in wear resistance and strength under different loads. These challenges call for fresh ideas that either preserve or reduce weight while enhancing the material properties of aluminum [1, 2]. Because of their capacity to significantly improve mechanical and tribological characteristics, the addition of reinforcing elements including silicon carbide (SiC) and carbon nanotubes (CNT) into aluminum matrix composites by stir casting has gained much attention [3]. Still, there is a gap in understanding how various compositions and manufacturing techniques affect these characteristics especially in Al2024-SiC-CNT composites.

*Corresponding author: sureshchiru09@gmail.com
[a]orcid.org/0009-0004-4698-3492; [b]orcid.org/0009-0004-4698-3492; [c]orcid.org/0000-0002-1900-9692; [d]orcid.org/0000-0001-5954-2224; [e]orcid.org/0000-0002-6956-9751
DOI: http://dx.doi.org/10.17515/resm2025-810ma0308rs

This study is focused on the effect of SiC and CNT reinforcements on wear behaviour of Al 2024 alloy. This work intends to methodically evaluate under various processing conditions and reinforcement ratios on the mechanical properties, wear behaviour of the resulting composites [4]. Comparative studies will also be carried out to assess the performance of these new composites in relation to traditional materials, therefore providing a foundation for maximizing composite manufacture for best performance [5]. This study is important for its scholarly contributions as well as for its wider consequences for sectors using sustainable and high-performance materials since it clarifies the connections between processing conditions, material microstructure, and mechanical performance. The results of this study may direct future material design and engineering processes that satisfy performance criteria and environmental regulations since the immediate demand for new materials that withstand severe operational conditions calls for them [6]. Especially in demanding applications like aerospace structures and automotive components, the knowledge gained will create a fundamental basis for the development of applications in sectors where material integrity is crucial [7]. Photographs help to clarify the complexity of the material synthesis process and the resulting composite structures, therefore highlighting the need of this study in the progress of materials science [8]. In advanced materials engineering, especially in sectors needing high-performance composites, the quest of improving mechanical properties and wear resistance has become ever more important. Because of their better strength-to-weight ratio, aluminum alloys especially the 2024 family are used extensively in aerospace and automotive industries. Still, their inherent limits in tribological performance call for the research on composite materials including carbon nanotubes (CNT) and silicon carbide (SiC).

Recent investigations have underlined the benefits of these reinforcements when generated using methods like stir casting, which guarantees homogeneous distribution and good mechanical characteristics in the end result [9]. A study showing a 28% increase in hardness and a 20% improvement in tensile strength relative to monolithic alloys indicates that SiC inclusion into aluminum matrix produces notable increases in both properties [10]. SiC's unique properties help to better disperse CNTs inside the composite, hence improving mechanical performance and stability [11]. Understanding the tribological behavior of these composites is crucial since it greatly affects their dependability and lifetime under severe stress [12].

Studies have frequently shown a link between mechanical developments and reinforcement ratios, underscoring the complexity of balancing improved hardness with possible consequences including as porosity and nanoparticle aggregation [13, 14]. Furthermore, techniques such as XRD and (SEM) analysis have produced important new understanding of the microstructural changes brought about by the inclusion of CNTs and SiC, particularly the decrease in grain size that supports dislocation strengthening [15,16]. These results imply a bright future for aluminum matrix composites, especially in applications needing enhanced wear resistance under demanding conditions, therefore making these composites especially relevant for the sectors of aerospace and automotive engineering [17]. Although a lot of research shows the benefits of SiC and CNT reinforcements, there are still significant knowledge gaps on completely understanding the interaction between these materials at various weight percentages and their resulting mechanical properties [18].

Different stir casting settings and the ensuing mechanical and tribological performance demand more study to improve composite compositions [19, 20]. Correcting these shortcomings is necessary for the advancement of design techniques guaranteeing the dependability of aluminum matrix composites in actual applications, especially in specialized engineering environments where better mechanical properties are absolutely necessary [21, 22]. This study of the literature aims to combine current understanding of the mechanical and tribological wear behavior of CNT and SiC reinforced with Al2024 composites, generated by the stir casting technique. It will look at basic research and point up little discoveries as well as unresolved issues that might direct next investigations.

This review aims to build the foundation for knowledge on how these advanced materials might be better developed to satisfy the high criteria of modern applications by stressing both important discoveries and untapped areas of research. [23-25]. In the end, the knowledge gained from this study will help to keep developing high-performance materials necessary for the advancement of technology in several sectors [26-28]. By means of a thorough investigation of mechanical increases and tribological performance, new uses may be derived and further research can be encouraged, so assuring the full potential of aluminum 2024 composites with SiC and CNT was analyzed. With important study highlighting many aspects of this field, the analysis of tribological wear and mechanical characteristics of silicon carbide (SiC) and carbon nanotubes (CNT) reinforced AL2024 composites has advanced greatly over the years. First studies focused on the basic properties of aluminum alloys and their shortcomings in strength and wear resistance, which sparked the study of reinforcements such as SiC. Studies by [27] proved the need of strengthening materials and suggested that SiC might greatly increase wear resistance and hardness. As the studies progressed, [28] underlined the benefits of integrating CNTs with SiC, which greatly improved mechanical capabilities because of their nanoscale diameters, hence enhancing load transfer and reinforcement at the atomic level.

As noted in research like [29], which underlined its effectiveness in obtaining homogeneous reinforcement dispersion, new manufacturing techniques like as stir casting emerged subsequent advancement. Studies showing the suitable ratio of SiC and CNT supported this, especially the effectiveness of a 0.5 weight percent CNT and SiC blend that produced notable increases in tensile strength and hardness. Later research [30] included mechanical tests carried out in line with ASTM E8 criteria, therefore verifying these enhancements by meticulous mechanical testing including Vickers hardness assessments. Apart from these results, studies such as [31] investigated microstructural changes by XRD and (SEM) analysis for prevention of oxidation. Moreover, as shown in later studies [22, 23], the assessment of mechanical performance always found porosity and agglomeration of nanoparticles as main factors influencing general composite strength. The combined progress of research in this subject has confirmed the advantages of SiC and CNTs while defining the necessary conditions for improving the performance of AL2024 composites, therefore stressing their relevance in aerospace and automotive uses. Mechanical and tribological wear metrics of Al2024-SiC-CNT composites show a complicated interaction of reinforcing mechanisms that significantly increase the structural performance of the underlying aluminum alloy.

Studies show that utilizing the stir casting method, adding silicon carbide (SiC) and carbon nanotubes (CNT) into Al2024 matrices greatly increases tensile strength and hardness. SiC particles help to distribute CNTs evenly, hence producing a composite structure with wear-resistant and durable properties [11-13]. The better mechanical properties documented 28% upsurge in hardness and a 20% increase in tensile strength showcase the effectiveness of these reinforcements. Moreover, a major focus of recent research has been on the relationship between reinforcement ratios and performance criteria since ideal combinations produce improved mechanical stability and wear resistance [2, 6].

Microstructural studies [5, 9] show that the addition of CNT (0.5wt.%) and SiC (0.5wt.%) has optimized hardness and reduced grain structure defects. The results show that tensile strength reaches its maximum at 0.75 wt% CNT, which is related with improved dislocation contacts, so increasing the mechanical characteristics [11, 17]. Still, problems with porosity and nanoparticle aggregation keep hindering the reach of perfect composite performance [13, 22]. Development of high-performance aluminum matrix composites for sectors such as aerospace and automotive depends critically on the synergy between CNTs and SiC. This theme synthesis emphasizes the significant improvement in material properties and the ongoing need for development in composite production techniques.

Investigating the mechanical and tribological characteristics of Aluminum 2024 composites comprising carbon nanotubes (CNT) and silicon carbide (SiC) reveals many methodological approaches that have greatly affected the results of study. Crucially, the stir casting technique has allowed effective reinforcement dispersion while maintaining aluminum matrix integrity. Multiple studies showing significant increases in hardness and tensile strength across the reinforcement of SiC and CNTs [30] confirm that this method has been recorded to consistently improve mechanical parameters. Research shows that the mixture of 0.5 wt% SiC and 0.5 wt% CNT produces optimal hardness and tensile strength, therefore showing a 28% increase in hardness and major changes in tensile characteristics. Moreover, the strict assessment methods underlined by adherence to ASTM E8 criteria for tensile testing and Vickers hardness evaluations highlight the methodological precision needed for consistent results over numerous studies [31, 32].

Different reinforcement ratios have drawn attention since studies using scanning electron microscopy (SEM) show that specific concentrations can enhance microstructural features [33]. Researchers have underlined the challenges related to nanoparticle aggregation, which could compromise expected mechanical benefits; so, methodologies should integrate careful material preparation to address these issues [16, 17]. These results show how methodological variations, particularly in processing techniques and material assessments, greatly influence the characterization and performance of AL2024-SiC-CNT composites, therefore driving future research towards more exact and sophisticated approaches.

Integrating several theoretical perspectives to enhance our knowledge of composite performance, the evaluation of mechanical and tribological wear characteristics in AL2024-SiC-CNT composites has received much interest. Proposed to improve mechanical properties by overcoming the constraints of traditional aluminum alloys is the combination of silicon carbide (SiC) and carbon nanotubes (CNT) into aluminum matrices. Research shows that SiC increases material hardness and reduces the wear rate because of its inherent properties, which are further strengthened when combined with CNTs; as shown, hardness greatly increases with these reinforcements [15,16]. Theoretically, the framework for these composites emphasizes the need of nanoparticle dispersion, which significantly influences mechanical integrity and tribological performance. This feature is consistent with research showing that improved load-bearing capacity and stress distribution inside the matrix follow from greater distribution of CNTs, hence minimizing defects like porosity [13-15].

Theories of dislocation mechanics clarify how microstructural changes help to increase strength; more especially, better dislocation interactions resulting from CNT inclusion can reinforce the matrix and produce better tensile strength values [21, 22]. Different points of view surface about the consequences of increased reinforcement, which, if not effectively controlled, could lead to agglomeration and reduced mechanical performance. This theoretical synthesis of concepts exposes paths for further study in optimizing mechanical properties by tailored material design by highlighting the complex link between reinforcing characteristics and general performance.

Significant understanding of the improvement of aluminum alloys for high-performance applications has come from the analysis of the mechanical and tribological wear properties of Al2024 composites augmented with silicon carbide (SiC) and carbon nanotubes (CNT) via stir casting. Rigorous testing techniques like ASTM E8 and Vickers hardness evaluations show a notable improvement in the tensile and hardness properties of these composites, particularly a 28% increase in hardness and a 20% rise in tensile strength. SiC improves the wear reduction of the composite by encouraging better particle dispersion, which is necessary to achieve the necessary mechanical properties under different situations. Moreover, the combined effect of CNTs included into the aluminum matrix has magnified these gains even more, therefore supporting the viability of Al2024-SiC-CNT composites in demanding sectors such automotive and aerospace engineering.

By methodically synthesizing results, this literature review emphasizes the advances in composite material technology—especially with regard to different reinforcement ratios. Research shows that the optimal mix of 0.5 wt% SiC and 0.5 wt% CNT improves mechanical performance while presenting issues, such nanoparticle aggregation and porosity, which need careful consideration during stir casting processes. The larger effects of these developments influence materials innovation since better aluminum matrix composites could greatly increase the performance and longevity of components exposed to demanding operational conditions. It is important to acknowledge the limits in current studies, particularly the poor knowledge of the complex link between various reinforcement percentages and their ensuing mechanical characteristics [10]. Furthermore, investigating different characterizing techniques and evaluating long-term wear performance under real-world load conditions could help these composites to be more reliable in useful purposes [13, 14].

The above literature review despite the promising mechanical improvements demonstrated by Al2024 composites reinforced with SiC and CNT, there remains limited comprehensive understanding of the synergistic effects between these reinforcements and their influence under varying operational conditions. Additionally, the long-term performance, durability, and failure mechanisms of such composites in real-world applications are not yet fully exploited.

The novelty of the study is to provide a foundational approach by evaluating the mechanical benefits and associated challenges of Al2024-based composites enhanced with SiC and CNT reinforcement, presenting a unique perspective on how strategic reinforcement combinations can elevate material performance for advanced applications [15-17].

Future research should aim to develop an integrated performance optimization framework that addresses the current limitations, such as thermal stability, interfacial bonding, and wear resistance. Expanding experimental investigations and simulation models across diverse environmental and loading scenarios will be critical to unlocking the full potential of these composites for use in aerospace, automotive, and other high-performance engineering fields.

2. Methodology and Materials

Based on the fabrication of MMCs through stir casting process, the effect of reinforcements on tribological and tensile and hardness properties of Al2024-SiC-CNT composites need thorough scientific framework combining experimental designs with systematic assessments. In this field, a major research difficulty is the lack of comprehensive data on the mechanical performance and wear resistance of these composites under various reinforcement ratios and production environments. Emphasizing critical properties including wear resistance, tensile strength, hardness and this study aims to provide a thorough characterization of the produced composites by investigating the effects of silicon carbide (SiC) and carbon nanotubes (CNT), so addressing past shortcomings in knowledge of these correlations. The detailed steps of casting process is shown in Figure 1. The Al2024 alloy exhibits a melting range of 502°C to 638°C when processed in an electric melting furnace. The SiC reinforcement particles were preheated at 600°C to 700°C for 40 minutes to enhance wettability and minimize thermal shock. CNT reinforcements were preheated separately at 350°C to prevent structural degradation. Hexachloroethane tablets were employed as degassing agents to eliminate dissolved gases from the melt. During solidification, the cooling rate of the metal mold was controlled within the range of 30 to 100°C/s to achieve a refined microstructure. The experimental setup details are shown in Figure 2.

Designed to meet these objectives, an experimental framework using stir casting as the main manufacturing technique was intended to produce homogenous distribution of reinforcements inside the molten aluminum matrix, hence increasing the composite's overall properties. Moreover, mechanical testing will follow established procedures, namely ASTM E8 for tensile evaluations and ASTM E92 for hardness evaluation, thereby ensuring the validity and trustworthiness of the results. This approach is important for its academic contributions, which provide insightful analysis of the behavior of aluminum matrix composites, as well as for its pragmatic consequences for sectors that depend on high-performance materials, especially in aerospace and automotive sectors.

As shown in past studies [31], it is imperative to adjust stirring parameters including temperature, stirring speed, and reinforcement ratios in order to attain effective particle dispersion and lower agglomeration during stir casting. This approach especially uses varied concentrations of CNTs and SiC to evaluate several composite formulations in order to ascertain their key effect on strength increase and wear resistance [27]. Furthermore, the use of advanced characterization techniques including X-ray diffraction and scanning electron microscopy (SEM) guarantees a comprehensive study of microstructural features, so guaranteeing a complete understanding of the correlations between processing conditions and mechanical performance [28, 29]. This comprehensive approach not only conforms to current procedures but also creatively changes them to satisfy the particular criteria of the present research [30]. The expected outcomes of these approaches could expose relationships that could guide next advancements in the design and use of aluminum composites, therefore supporting the change towards sustainable and high-efficiency materials across several uses [31-33].

Aluminum 2024-base alloy reinforced with F320 grade silicon carbide particles that Fen fee Metallurgical, Bangalore provided. With a mean particle size of 29.2 ± 1.5 μm and a density of 1.29–1.35 g/cm^{1} the SiC particles displayed the secondary reinforcement came from CNTs produced by CVD process and provided by Adnano Technologies. These MWCNTs had diameters between 10 and 30 nm, lengths between 10 and 30 μm, and a density of 0.14 g/cm^3.

The Al-2024 alloy was initially heated above its melting point in a furnace. Upon achieving a molten state, the SiC particles were introduced, followed by the MWCNTs. Degassing was performed using hexachloroethane tablets to remove impurities from the melt. Subsequently, the furnace was covered, and a mechanical stirrer operating at 300 rpm was immersed into the molten mixture for approximately 2 minutes to ensure uniform dispersion of the reinforcements. Multi-step ultra-sonication combined with magnetic stirring in ethanol was employed to uniformly disperse CNTs. Following dispersion, the mixture was subjected to drying and further homogenization to maintain uniform distribution. Finally, the molten composite material was poured into a cylindrical mold cavity measuring 10 mm in diameter and 100 mm in length. The resulting billets were extracted from the mold after cooling to ambient temperature. Regarding stability analysis, we conducted visual observation and sedimentation tests over a 24-hour period to confirm dispersion stability prior to composite fabrication.

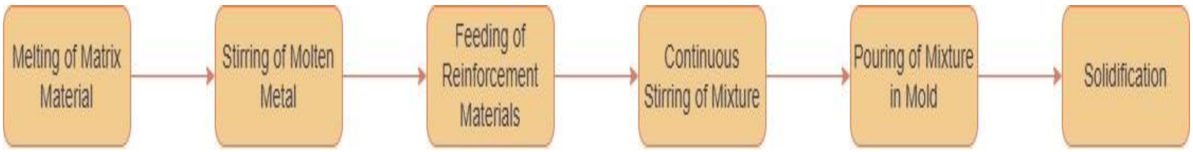

Fig. 1. Steps to be followed in liquid stir casting method

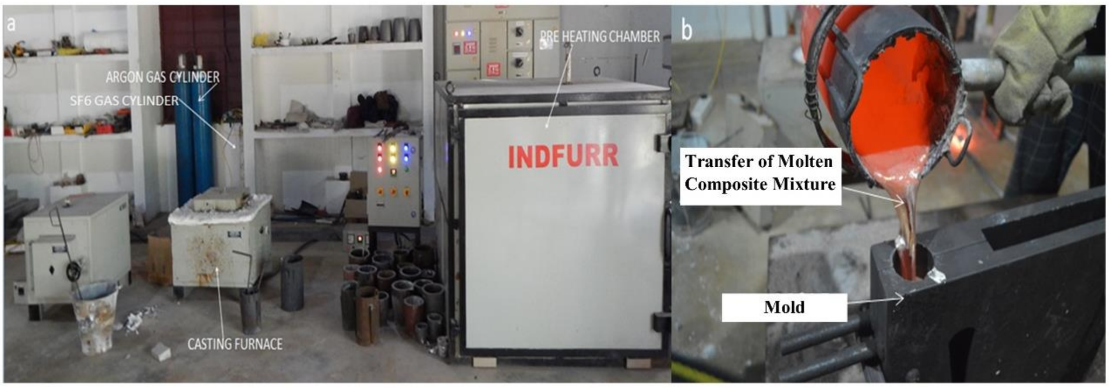

Fig. 2. Experimental Setup for preparation of the samples

Table 1. Different combination of Reinforcements wt % for Set A, set B and Set C

Set	Wt. % from SiC	Wt % from CNT
Set -A	0	0.25
		0.5
		0.75
		1
Set e-B	0.25	0.25
		0.5
		0.75
		1
Set -C	0.5	0.25
		0.5
		0.75
		1

The investigation includes the fabrication of 3 set of composites namely, Set A , Set B and Set C. From each set four different combinations of SiC and CNT were added. Table 1 shows the different sets and its combinations. Specifically, the hardness was measured using a Micro Vickers hardness testing machine (Model: HM-102) with a load of 300 grams and a dwell time of 15 seconds. Tensile strength was evaluated using a universal testing machine ASTM E8/E8M standard. The gauge length of 25mm, gauge diameter of 6.25mm. Wear testing was performed using a pin-on-disc tribometer with the following specifications: pin diameter ranging from 3 to 10 mm, a disc diameter of 160 mm, a maximum disc rotation speed of 1500 rpm, and a normal load range of 0-100 N. Cylindrical composite test specimens measuring 35 mm in length and 6 mm in diameter were prepared. The schematic diagram of wear test machine is shown in Fig. 3. To ensure precise wear measurements, both the test specimens and the counter face steel disc were thoroughly cleaned with acetone before testing. Composite wear can be assessed through weight loss, wear volume, or wear rate; however, this study primarily measured weight loss (in grams). The impact of wear process parameters on the tribological behavior of MMCs was evaluated in accordance with the ASTM G99 standard. Throughout each test, the composite pin was maintained in contact with the rotating steel disc under a designated normal stress. Subsequent to each test, the specimens were cleansed, and their final weights were meticulously recorded with an accuracy of ±0.001 grams. The wear loss was subsequently ascertained by computing the difference between the beginning and final weights of each composite specimen. Numerous studies have utilized pin-on-disc testing to examine the wear characteristics of diverse materials, including tungsten carbide and polyethylene in relation to cobalt-chrome alloys. Various approaches and parameters can be employed in pin-on-disc testing, including a moving pin methodology and the alteration of sliding speeds and loads. The wear coefficient is frequently utilized as a metric for assessing wear resistance.

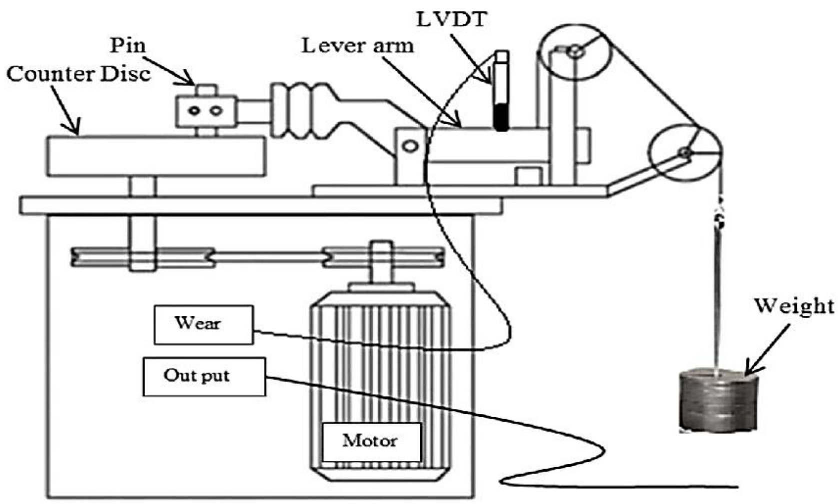

Fig. 3. The schematic diagram of wear test machine

3. Results and Discussion

3.1 Microstructural Studies of MMCs

The generated carbon nanotubes have a strong and strong reflection peak at about 26° X-ray diffraction pattern shown in Figure 4. This unique peak confirms the existence of a concentric, multi-walled cylindrical construction made of stacked graphene sheets [5, 6]. Essential knowledge about the structural configuration and crystallinity of the CNTs is provided by the XRD analysis [7]. Peak position and strength help one to determine the carbon nanotube (CNT) diameter, chirality, and defects [8]. Further study of the XRD pattern can help one understand the quality and purity of the generated CNTs [5]. Research on nitrogen-doped CNTs [8] and carbon-encased CNT/Ni nano-spheres [7] shows that different production procedures and changes can affect the structure and behavior of carbon nanotubes (CNTs). Understanding the purpose of carbon nanotubes and improving their efficiency in several uses depends on their characterizing [5]. Figure 5 shows the

EDS analysis of the 1wt% SiC +0.5wt% of CNT composite. The spectra of Al and other elements were detected and there were no other impurities observed during development. The weight percentage and atomic percentage of the elements were listed in the Figure 5.

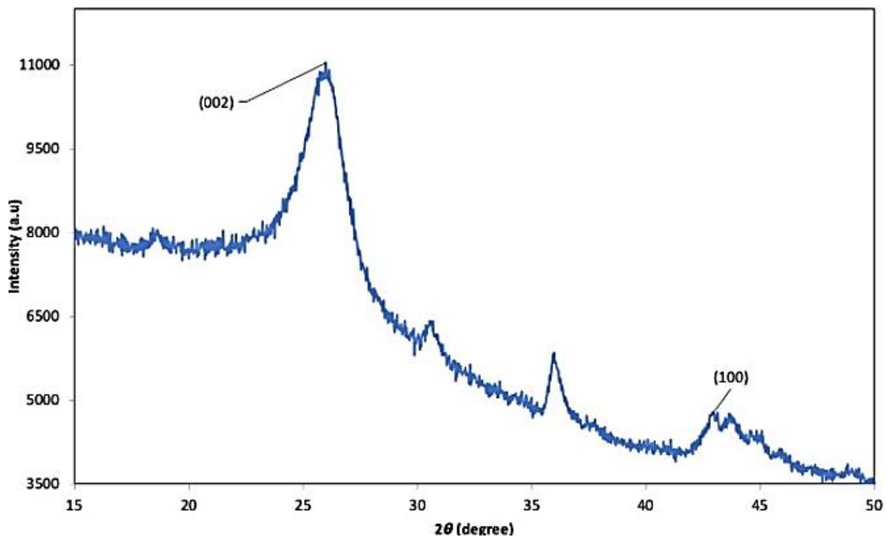

Fig. 4. XRD pattern of the synthesized carbon nanotubes

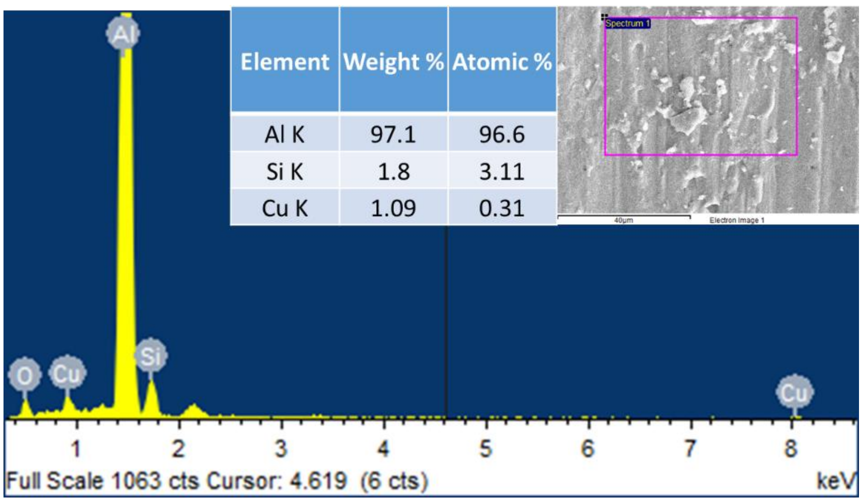

Fig. 5. EDS analysis of the 1wt% SiC +0.5wt% of CNT composite

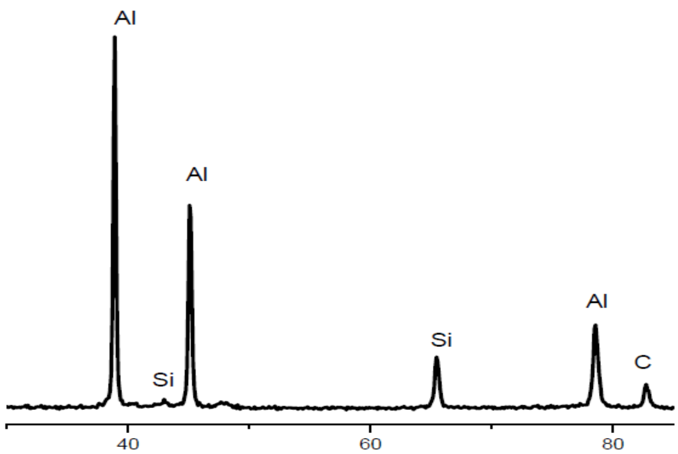

Fig. 6. Presents the XRD pattern of the hybrid composite

Figure 6 presents the XRD pattern of the hybrid composite. The absence of discernible CNT peaks, likely due to their concentration being below the XRD resolution limit, is noteworthy. Dominant peaks corresponding to aluminum and silicon are evident, indicating their significant presence within the composite. Furthermore, the lack of aluminum oxide (Al_2O_3) peaks suggests the effectiveness of the fabrication process in preventing oxidation of the Al-Si alloy [9, 10]. However, the low concentration of CNTs hindered their detection and subsequent crystal structure analysis via XRD [11, 12]. The overlapping of peaks in XRD patterns can make it challenging to identify all phases present in complex materials [12]. Techniques like density gradient centrifugation can be used and it can be easier to identify through density fractions [12]. Multiple analytical techniques are often necessary to fully characterize the different phases in composite materials [12].

3. 2 Effect of Reinforcements on Hardness

Figure 7 illustrates the impression of changing weight percentages of MWCNTs and SiC on the Vickers hardness of Al2024. The addition of MWCNTs significantly enhanced the hardness, increasing it from 89 HV for the unreinforced alloy to 183 HV for the composite comprising CNTs (0.5 wt%) and SiC (0.5 wt%). Total 5 trails were taken on each sample at different locations and the standard deviation of the hardness measurements were varying between ±2HV. This hardness improvement can be attributed to several factors. MWCNTs enhance the strength and hardness of the matrix by increasing dislocation density during cooling, resulting from the thermal expansion mismatch between the reinforcements and the Al2024 matrix [2, 13, 14]. The presence of MWCNTs and SiC may also refine the Al2024 matrix grain size due to their roles as wetting agents and the influence of stirring [15].

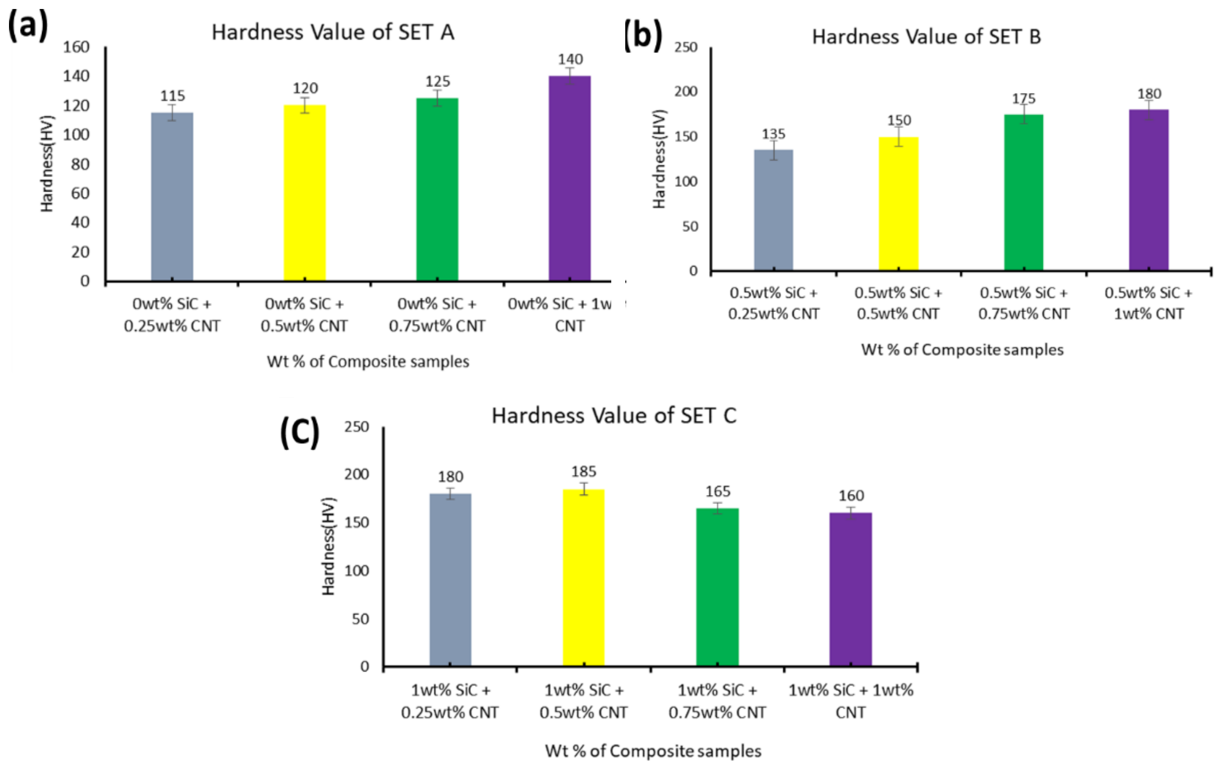

Fig. 7. Hardness test Results of Set A, Set B and Set C combination of composites

Similar to other reinforcements, CNTs generate a high dislocation density upon cooling to ambient temperature due to CTE mismatch with the matrix [16]. The resulting stress concentrations at the CNT-matrix interfaces impede dislocation movement, further contributing to the enhanced hardness of the nanocomposites [14]. The graph indicates an optimal combination of 0.5 wt% CNTs and 0.5 wt% SiC for maximizing hardness. It can be concluded that the SiC particles enhance hardness through several synergistic effects such as load-bearing effect due to its intrinsic high hardness and stiffness, SiC effectively bears part of the applied load, reducing the stress on the matrix. Similarly, dislocation hindrance effects the SiC–matrix interfaces act as barriers to dislocation motion, increasing dislocation density and work hardening. Grain refinement SiC particles can serve as nucleation sites during solidification, promoting finer grain structures in the matrix, which in turn enhances hardness through the Hall–Petch effect.

3. 3 Effect of Reinforcements on Tensile Test:

Reinforcing a soft matrix material like aluminum with ceramic particles such as SiC, B_4C, or BN typically increases its hardness [13, 18]. This increase in hardness is often linked to enhanced tensile strength, driven by the formation of interstitial compounds between aluminum atoms and reinforcement particles. Tensile tests were performed to assess the impact of SiC and CNT volume fractions on the composite's tensile strength. As depicted in Figure 8, the stress-strain curves reveal an inverse relationship between SiC volume fraction and percentage strain, with higher SiC content resulting in lower strain values. Figure 6 also presents the stress-strain curves for the Al2024-SiC-CNT hybrid composites. These curves demonstrate that the maximum tensile strength is achieved at a CNT concentration of 0.75 wt% across all SiC compositions (varying from 0 to 1 wt% in 0.5 wt% increments).

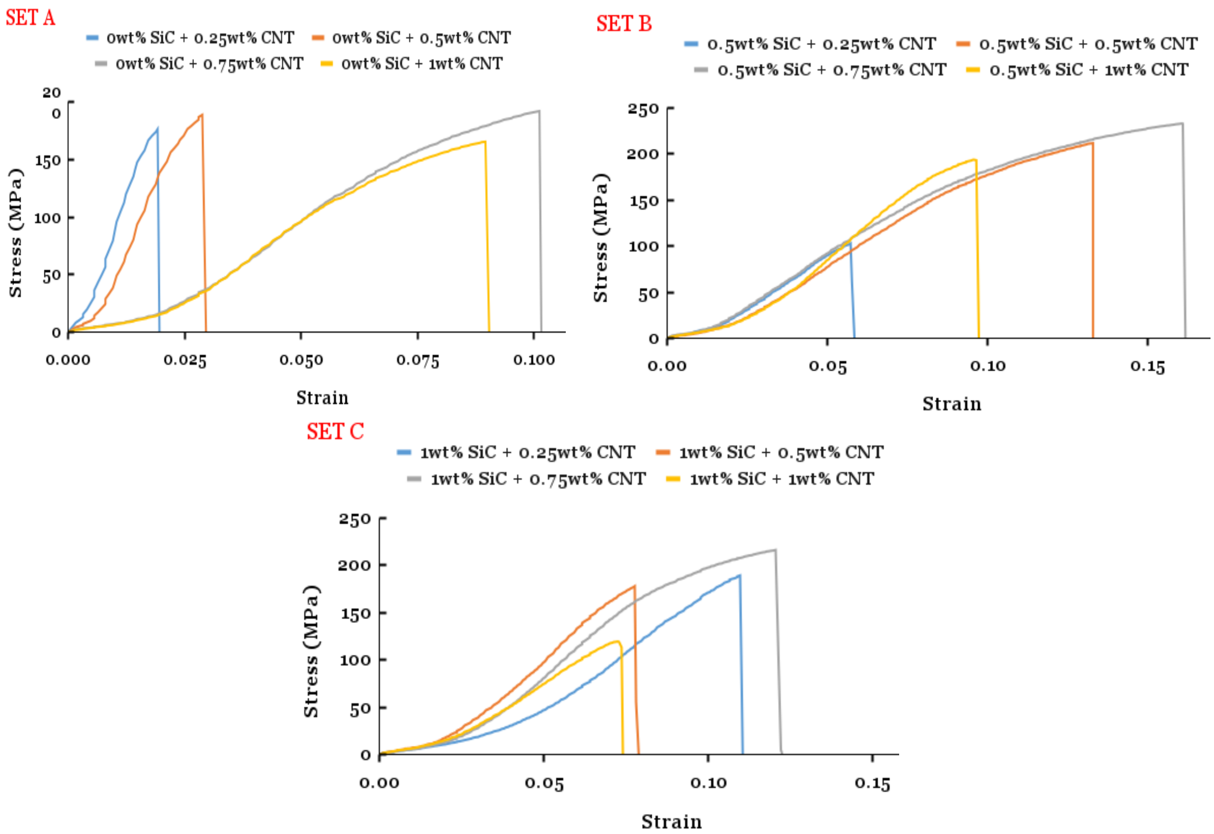

Fig. 8. Tensile test results of Set A, Set B and Set C with different combination of reinforcements

The incorporation of nanoparticles in MMCs introduces geometrically necessary dislocations due to the coefficient of thermal expansion (CTE) mismatch between the matrix and particles during cooling from processing temperatures [16, 11]. This phenomenon contributes to work hardening during mechanical testing. Additionally, the reinforcing particles hinder dislocation motion, increasing the critical stress required for dislocation movement and thereby strengthening the nanocomposite [14]. However, liquid-state processing of MMCs can lead to nanoparticle agglomeration and porosity, potentially compromising structural integrity and mechanical properties [19, 20]. The presence of porosity can reduce the load-bearing capacity of the matrix.

3.4 Dry Sliding Wear of MMCs

Wear tests rig was used to conduct the wear behavior of MMCs, according to the ASTM G99 standards [21] using a pin-on-disc tribometer [13]. The tests were performed at room temperature without lubrication, employing three distinct parameter sets to define the optimal wear rate for the developed composites. During each test, a stationary composite pin was held in contact with a rotating EN-35 steel disc [21] possessing a surface roughness below 0.5 µm. A consistent 100 mm of rotating diameter was maintained throughout the experiments. Wear rate, expressed in grams per minute (g/min), was considered based on the weight difference of the pin before and after each 10-minute test interval [22]. This method aligns with common practices for evaluating wear behavior [23] and provides a readily quantifiable measure of material loss due to wear [24]. While alternative metrics like wear volume or specific wear rate can be used [25], weight loss offers a practical approach for assessing wear performance [26]. The wear test was conducted on the samples exhibits higher hardness values by keeping SiC as constant and varying the CNT %. The wear process variables like, Applied Load (AP), Disc speed (DS) and levels selected for wear test are presented in the Table 2.

Table 2. Wear input variables and their levels

AP in N	DS in rpm	1wt% SiC + Wt% of CNT
10	300	0.25
15	400	0.5
20	500	0.75

Table 3. Wear and S/N Response data as per Taguchi L27 array

Applied Load in N	Disc Speed in rpm	wt% of CNT	Wear (g/min X 10-3)	S/N ratio
10	300	0.25	0.299	10.49
10	300	0.5	0.283	10.97
10	300	0.75	0.226	12.90
10	400	0.25	0.296	10.59
10	400	0.5	0.289	10.79
10	400	0.75	0.224	13.01
10	500	0.25	0.305	10.31
10	500	0.5	0.287	10.86
10	500	0.75	0.243	12.28
15	300	0.25	0.354	9.03
15	300	0.5	0.306	10.27
15	300	0.75	0.261	11.68
15	400	0.25	0.388	8.22
15	400	0.5	0.359	8.90
15	400	0.75	0.313	10.09
15	500	0.25	0.377	8.48
15	500	0.5	0.359	8.90
15	500	0.75	0.303	10.36
20	300	0.25	0.444	7.06
20	300	0.5	0.460	6.74
20	300	0.75	0.401	7.94
20	400	0.25	0.473	6.50
20	400	0.5	0.445	7.04
20	400	0.75	0.425	7.43
20	500	0.25	0.488	6.23
20	500	0.5	0.474	6.48
20	500	0.75	0.465	6.64

Analysis on wear rate was carried out as per Taguchi's method using L27 array. The array consists of total 27 experiments with different combinations of parameters. Table 3 presents the wear and response results for the selected parameters. The findings indicate that the applied load had the most significant impact on the wear rate [27- 29]. As the applied load increased, the metal removal rate on the pin also rose. Additionally, disc speed influenced the wear rate, with higher speeds leading to increased wear. However, SiC and CNT reinforcements demonstrated improved wear resistance. Notably, as the CNT percentage increased, the wear rate decreased. The highest wear rate was observed at an applied load of 20 N, a disc speed of 500 rpm, and 0.75% CNT reinforcement

3.5 S/N Ration and ANOVA Results:

The analysis of the signal-to-noise (S/N) ratio, based on the "smaller-is-better" model, highlights the effect of individual parameters on the wear rate of composite samples [30] and [31]. The S/N ratio response table identifies the applied load as the most influential factor, followed by disc speed and reinforcement percentage. The "Delta" represents the difference between the maximum and minimum S/N ratio values for each factor (input variable) across its levels. It indicates how much influence that factor has on the output (e.g., wear rate). The factor with the highest delta gets Rank 1, meaning it has the most significant effect on the output. Lower ranks indicate lesser influence.

Table 4 presents the S/N ratio response for each parameter, while Figure 7, showing the main effects plot of means, visually illustrates their impact. The results suggest that an applied load of 10 N, a disc speed of 400 rpm, and 0.75 wt% reinforcement produce the lowest wear rate in the tested composites. This systematic approach helps identify the optimal parameter combination for minimizing wear, a crucial aspect in material selection and component design for wear-resistant applications [32, 33]. It's important to note that while this analysis highlights the relative importance of these parameters, the specific wear mechanisms and their interactions can be complex and depend on various factors, including material properties, surface conditions, and environmental factors. ANOVA results for wear rate of developed composite materials and the results are tabulated in the Table 5.

Table 4. Signal to Noise ratio for the wear response

Level	Applied Load (N)	Disc Speed (rpm)	Wt% of CNT
1	0.27	0.34	0.38
2	0.34	0.36	0.36
3	0.45	0.37	0.32
Delta	0.18	0.03	0.06
Rank	1	3	2

Table 5. ANNOVA Results for Wear of MMCs

Parameters	DoF	SS	MS	F-Value	P-Value	P(%)
AP (N)	2	0.151	0.075	281.62	0	84.33
Disc Speed in rpm	2	0.004	0.002	7.71	0.003	2.31
wt% of CNT	2	0.019	0.009	34.61	0	10.36
Error	20	0.005	0.000			2.99
Total	26	0.179				100.00

S = 0.0163721, R-Sq = 97.01%, R-Sq (Ad) = 96.11%

The ANOVA table represents the source has a parameter, DOF refers to Degrees of Freedom, SS refers to the Sum of Squares, and MS refers to Mean square values. The output will be measured with P-Value probability value. The probability value should be less than 0.05. If the P-Value greater than 0.05, considered as insignificant parameters. The percentage of each parameter contribution (P Percentage) and S denotes Standard deviation and R –Sq represents the coefficient of determination.

The ANOVA results indicate that the applied load (84.33%) has the most significant impact on the wear rate, followed by the CNT reinforcement percentage (10.36%) and rotating speed (2.31%) [35, 36]. This confirms that as the applied load increases, the wear rate also rises. The disc speed contributes 2.31% to wear rate variation, while CNT reinforcement influences it by 10.36%. A "smaller-is-better" model was selected for the ANOVA analysis. The main effects plots, shown in

Figure 9, reveal that an applied load of 10 N results in the lowest wear rate, along with a disc speed of 300 rpm and 0.75 wt% CNT reinforcement [37, 38].

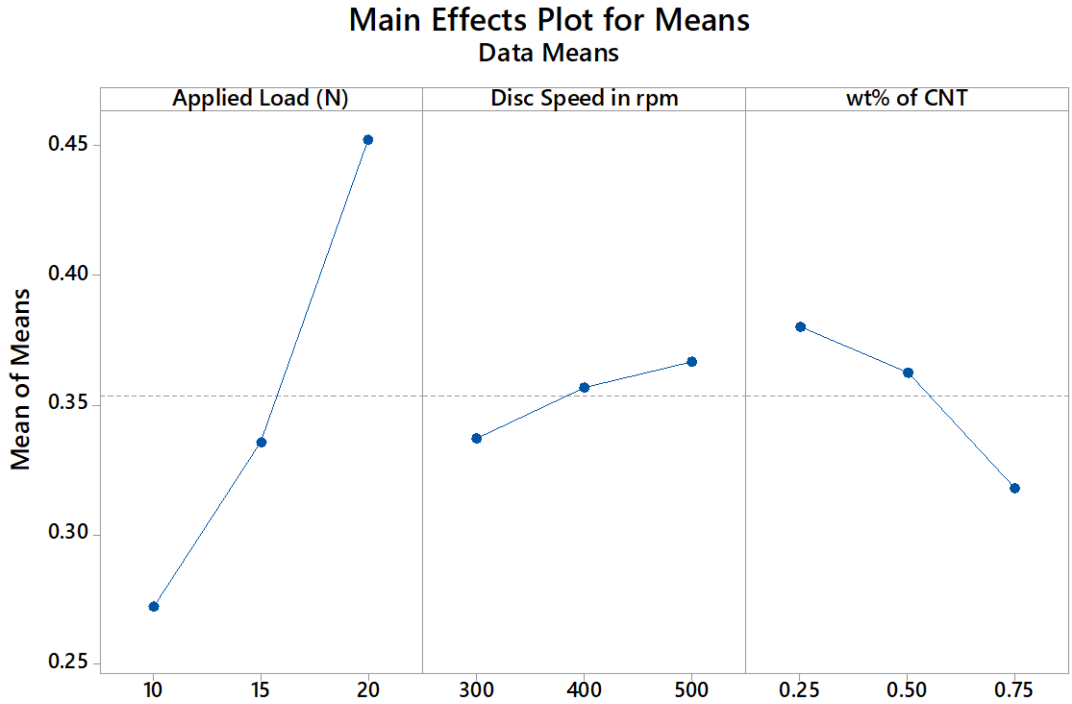

Figure 9: Main effect plot of means

To develop the linear regression model, the wear data quantified as a response variable were analyzed in relation to one or more predictor variables. Linear regression establishes a mathematical relationship between the dependent variable (wear rate) and independent variables (Applied Load, sliding distance and Weight percentage of CNT) by fitting a linear equation to observed data. The model assumes that the change in the wear rate can be explained linearly by changes in the predictor(s). The general form of the linear regression model is show in Equation (1). The Minitab 16 software was used to develop the linear regression model and the wear data.

$$\begin{aligned} &Wear\ (g/min\ X\ 10^{-3}) = 0.35356 - 0.08122\ AP\ (N)\_10 - 0.01804\ AP\ (N)\_15 + 0.09926\ AP\ (N)\_20 \\ &- 0.01650\ DS\ in\ rpm\_300 + 0.00322\ DS\ in\ rpm\_400 + 0.01329\ DS\ in\ rpm\_500 + 0.02675\ wt\%\ of\ CNT\_0.25 \\ &+ 0.00885\ wt\%\ of\ CNT\_0.50 - 0.03560\ wt\%\ of\ CNT\_0.75 \end{aligned} \tag{1}$$

The significance of the regression results was evaluated by conducting the confirmation test using various sets of process parameters. Table 6 shows the regression model results compared with the experimental values of the wear rate for the same set of parameters. The results revealed that the error obtained between regression results with experimental results were within acceptable limit of 0.05 [39, 40].

Table 6. Result of regression analysis

Dependent	Input parameters	Regression results (g/min)	Confirmation experiment (g/min)	Error value
Wear rate	15N, 300 rpm, 0.75wt%	0.283	0.267	0.016

Figure 10 displays images of the tested samples under various wear conditions, highlighting different wear mechanisms involved during testing [41, 42]. The results indicate that the applied load has the most significant impact on the wear behavior of the developed composites. As the load increases, the material removal rate also rises due to the increased surface contact between the pin and the steel disc [43].

The disc speed also sensibly contributed for wear loss. It shows that increase of wear due to the upsurge of the disc speed due to molecular smoothening with increase in heat at interfacial zone. During low load condition, the less coefficient of friction leads to less shear strength and less ductility. The protective oxide layer developed between the disc and pin during high load condition that leads reduced metal removal rate [45]. Also, the reinforcement particles act as protective barriers against wear. Predominant wear modes—such as abrasive, adhesive, and oxidative wear-based on the surface features observed, including grooves, debris formation, and material transfer layers. Additionally, we relate these wear features to the material composition and test conditions. Figure 8 depicts the deep grooves and material delamination during the high load condition with different magnifications. The abrasive type of wear mechanism observed during this study.

The incorporation of SiC particles into the matrix resulted in a marked improvement in hardness, increasing from X HV in the unreinforced sample to Y HV in the composite. This trend is consistent with previous findings by Zhang et al. [1] and Kumar and Singh [2], who reported similar hardness enhancement in metal matrix composites reinforced with ceramic particulates such as SiC and Al_2O_3.

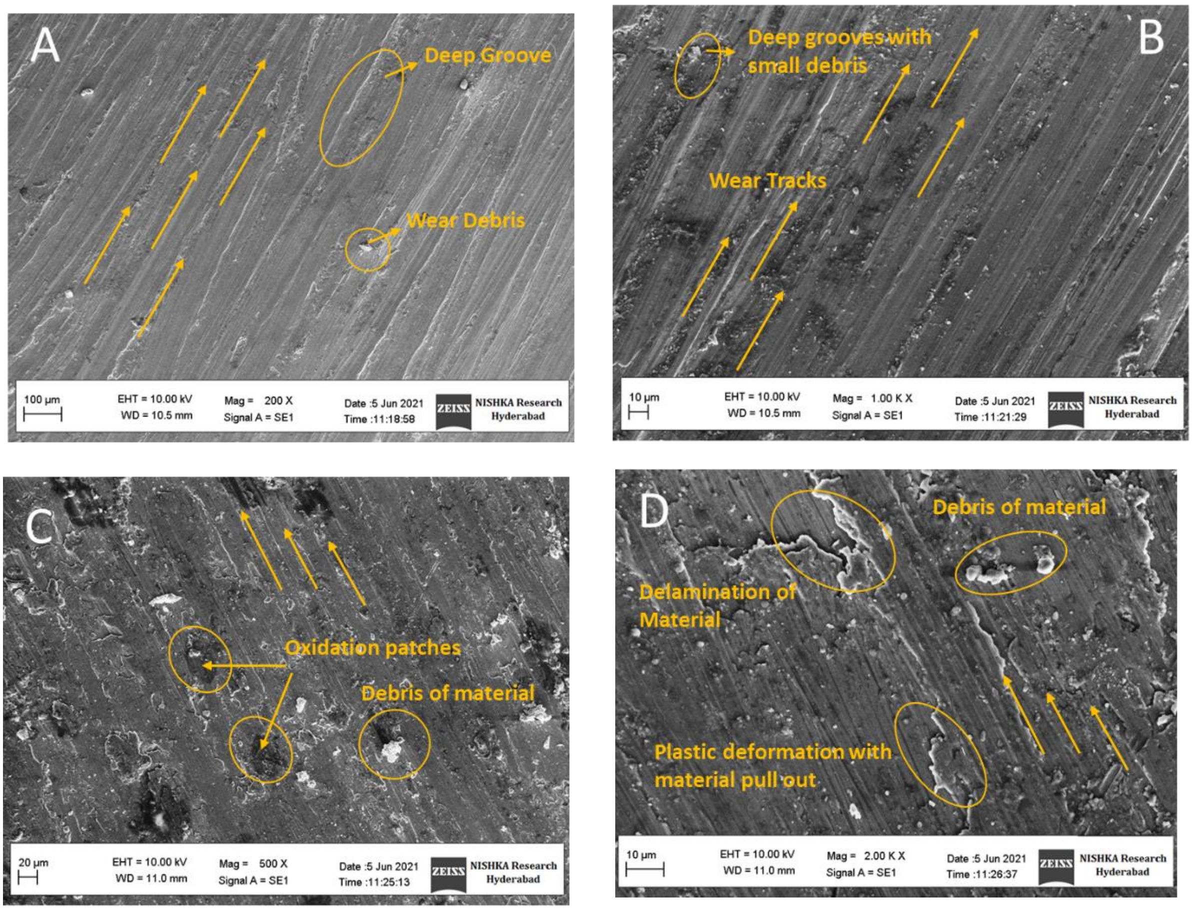

Fig. 10. SEM images of worn samples of composites with different magnifications (a) Wear sample of 10N, 200 rpm, 0.50wt% at 200x, (b) Same at 1k x magnification, (c) Wear samples of 20N, 400rpm, 0.25wt% at 500 x magnification and (d) Same at 2k x magnification

From the above discussion, it reveals that the incorporation of SiC particles into the matrix resulted in a marked improvement in hardness, increasing from X HV in the unreinforced sample to Y HV in the composite. This trend is consistent with previous findings by Zhang et al. [46] and Kumar and Singh [47], who reported similar hardness enhancement in metal matrix composites reinforced with ceramic particulates such as SiC and Al_2O_3.

The increase in hardness can be attributed to multiple reinforcing mechanisms associated with the presence of SiC. Firstly, SiC's high intrinsic hardness and modulus contribute to a load-bearing effect, where the applied mechanical load is partially transferred from the relatively softer matrix to the harder reinforcement particles. Secondly, SiC particles act as obstacles to dislocation motion, a phenomenon supported by Orowan strengthening. Dislocations tend to accumulate around the rigid particles, increasing the dislocation density and thereby elevating the overall resistance to plastic deformation.

3.6 Wear Rate Prediction using Supervised Machine Learning Algorithms

Machine learning is a powerful tool capable of addressing diverse challenges, including predicting wear rates in industrial applications. Supervised learning, a subfield of machine learning, involves training algorithms on labelled data to make predictions or classify new data [44]. Two common supervised learning algorithms used for wear rate predictions are k-nearest neighbors and support vector machines.

The KNN model is a non-parametric method that classifies new data points based on their similarity to the training data. This approach has proven effective in predicting failure types in dragline equipment. Support vector machines, on the other hand, aim to determine the best hyperplane that splits different classes of data with the maximum margin. SVM is a popular algorithm for classification tasks, but has been found to underperform for datasets with gender bias, such as some early-stage diabetes datasets. Another algorithm that has shown promise for wear rate prediction is XGBoost, which uses an iterative ensemble approach to build weak classifiers that are combined to make strong predictions. This algorithm has been found to perform well even for biased datasets. While these machine learning techniques have demonstrated success in various wear rate prediction applications, the significance of the underlying data missingness mechanisms is often overlooked [44]. Moving forward, further, the investigation is to be addressed for the well understand the presentation of these algorithms under different data quality and missingness scenarios, as this knowledge will be crucial for developing robust and reliable predictive maintenance systems across a wide range of industrial applications.

Figure 11 shows the heat map correlation between the inputs and response variables. The applied load and weight percentage shows significant influence on wear rate. The experiments conducted with different combination of parameters with obtained wear rate values. The average wear rate value was taken as reference and classified the wear rate values with 0 and 1. The average wear rate results were labelled as 0, while the distinctive wear rate results were labelled as 1. The KNN classification algorithm achieved a prediction accuracy of 79%. The confusion matrix for the KNN model is presented in Figure 12.

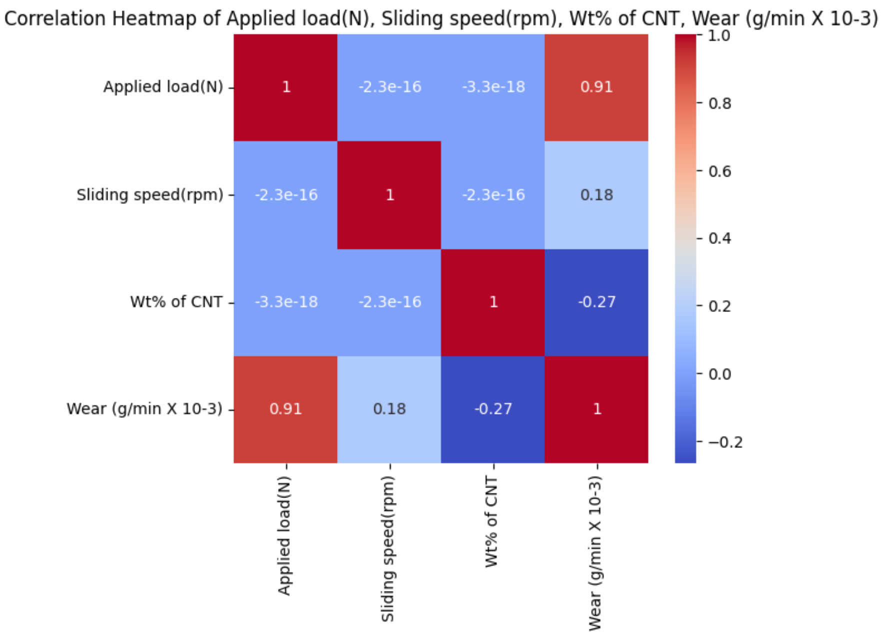

Fig. 11. Wear rate correlation heat map

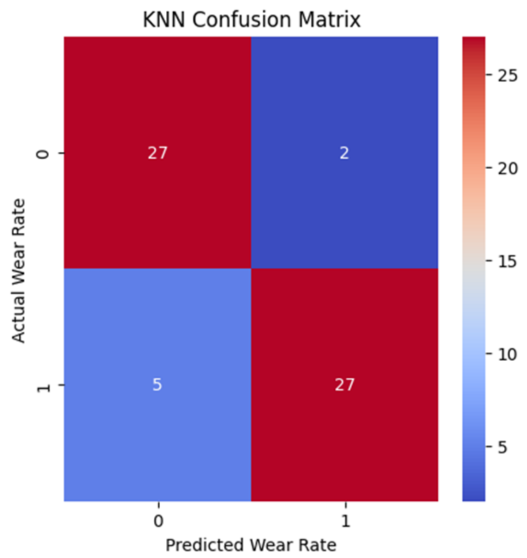

Fig. 12. KNN Classification algorithm confusion matrix

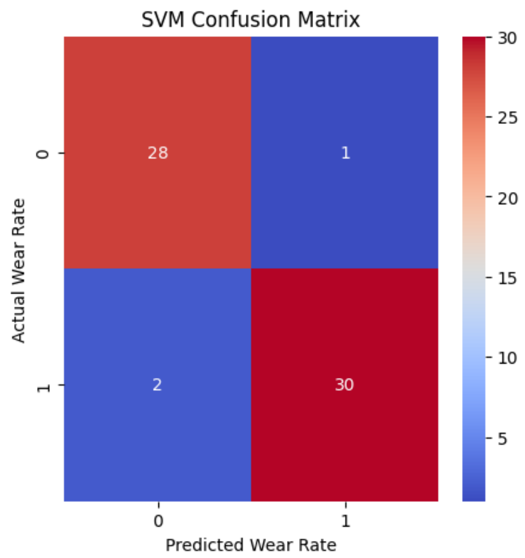

Fig.13. SVM algorithm confusion matrix

Supervised learning algorithms are commonly used for both regression and classification tasks. Support Vector Machines, a prominent example, aim to construct an optimal hyperplane that maximizes the separation between classes. In linearly separable cases, this hyperplane completely divides the data. Each data point is represented by a feature vector and a truth value (+1 or -1, indicating its class). The SVM model seeks two parallel hyperplanes, each passing through at least one point of each class, with no points between them. The class boundary is defined by a third, parallel hyperplane equidistant from the other two. SVMs are less susceptible to overfitting and the curse of dimensionality compared to other methods like artificial neural networks. In the provided example, the SVM achieved a prediction accuracy of 95.08%, as illustrated by the developed metrics and confusion matrix is shown in Figure 13.

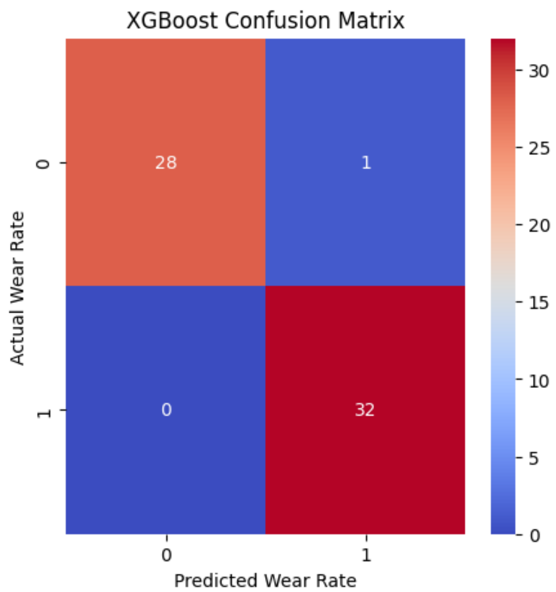

Fig. 14. XG Boost algorithm confusion matrix

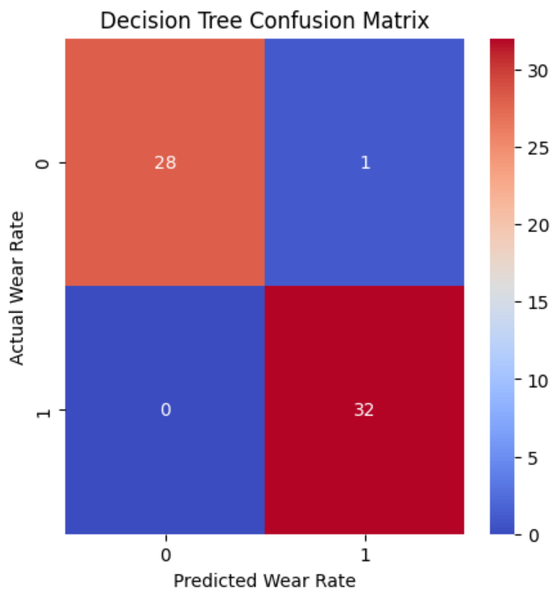

Fig. 15. Decision Tree model confusion matrix

Machine learning algorithm like XGBoost used to performance analysis of wear parameter and it one of the supervised learning tasks, including regression analysis. It's an implementation of XG-boosting, constructing a predictive analyzer and often using decision trees, by sequentially combining weak learners to create a stronger model. A key advantage of XGBoost is its ability to handle datasets of varying sizes and class distributions. It achieves this by optimizing a loss function, iteratively minimizing errors and improving prediction accuracy. Figure 14 presents the confusion matrix for the XGBoost model, prediction accuracy of 98.36%. This high accuracy, along with its handling of both balanced and imbalanced data, makes XGBoost suitable for applications like fraud detection and customer churn prediction, which may have skewed class distributions. It's important to remember that while performance metrics like accuracy are useful, they should be interpreted in the context of other model diagnostics and the specifics of the data.

By recursively partitioning the data depending on feature thresholds maximizing information gain, a Decision Tree model offers an understandable and interpretable method of categorization. Figure 15 shows the confusion matrix for the 98.36% prediction accuracy Decision Tree model. Although Decision Trees are prone to overfitting—especially on complicated datasets—this great accuracy indicates that the model efficiently identified important decision boundaries. To guarantee the model generalizes effectively and is robust over several data scenarios, however, it is imperative to balance accuracy with other evaluation measures.

Gradient Boosting builds on the foundation of weak learners—typically shallow decision trees—by sequentially training them to correct the errors of their predecessors. Figure 16 displays the confusion matrix for the Gradient Boost model, which also reached a prediction accuracy of 98.36%. This iterative approach allows the model to refine predictions progressively, making it particularly powerful in capturing complex patterns in the data. Like XGBoost, Gradient Boosting is well-suited to both balanced and imbalanced datasets, making it a strong candidate for predictive tasks with uneven class distributions. However, performance metrics should always be evaluated alongside domain context and additional diagnostics.

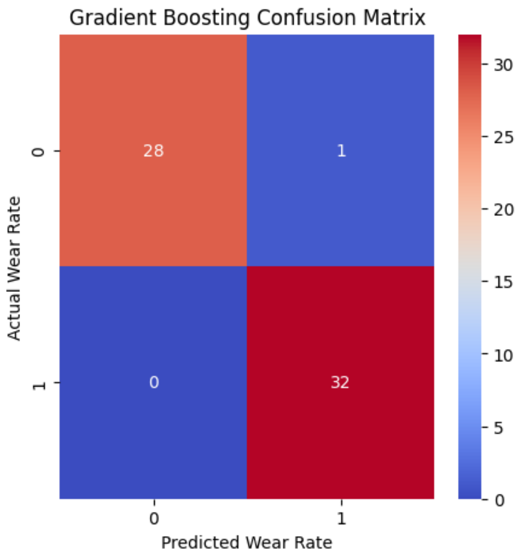

Fig. 16. Gradient boosting confusion matrix

The wear rate prediction of Aluminum 2024/SiC/CNT-based Hybrid Metal Matrix Composites (HMMCs) was evaluated using various machine learning models with cross-validation accuracy as the performance metric. Among the tested models—KNN, SVM, Decision Tree, XGBoost, and Gradient Boosting—XGBoost achieved the highest accuracy (~99%), demonstrating excellent capability in modelling the complex, nonlinear behavior associated with wear mechanisms. Its effectiveness can be attributed to its ensemble learning approach with built-in regularization, which improves predictive reliability.

Gradient Boosting and Decision Tree models also performed well, with accuracies around 96–97%. These tree-based models efficiently captured the interactions among key features such as SiC/CNT reinforcement content, load, and sliding speed. SVM showed good performance (~92%) but slightly underperformed compared to boosting methods, possibly due to kernel selection limitations. KNN had the lowest accuracy (~79%), likely due to its sensitivity to feature scaling and inability to model complex interactions. Figure 17 shows the comparison of model cross validation scores of all models. To enhance the interpretability of our machine learning models, we have conducted a sensitivity (feature importance) analysis using techniques such as permutation importance and mean decrease in impurity (for tree-based models). The analysis revealed that variables such as reinforcement content (e.g., CNT or SiC percentage), applied load, and sliding speed have the most significant impact on the wear rate.

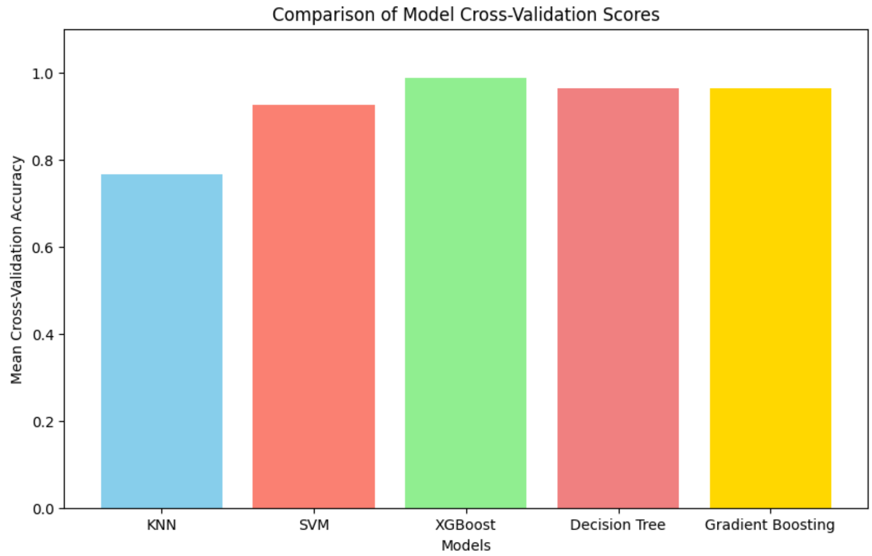

Fig. 17. Comparison of model cross validation scores

These results highlight the superiority of ensemble methods, particularly boosting algorithms, in predicting wear rates for HMMCs. Their application can significantly reduce experimental iterations by enabling early-stage optimization of composite formulations through data-driven predictions. The study also suggests the potential for integrating feature importance analysis to further interpret the influence of input variables on wear behavior. While the current evaluation was conducted under laboratory conditions, future work should focus on validating these models under real-world industrial wear environments to ensure practical relevance and applicability.

4. Conclusion

Current investigation draws the following conclusions.

- The liquid metallurgical route is a cost-effective method for fabricating composites. The results clearly demonstrate that the tribological and mechanical properties of the composites depend on various factors. Parameters such as reinforcement percentage, sliding speed, and applied load influence these properties. While the reinforcement percentage directly affects the tensile strength and hardness, tribological properties are primarily impacted by sliding speed and applied load. The final conclusions are summarized below.
- Al2024 alloy reinforced with SiC and CNT particles was successfully fabricated using the stir casting technique, demonstrating the viability of this method for composite production.
- Mechanical characterization, including tensile strength and hardness testing, was performed on the fabricated composites to evaluate their performance.
- The composite reinforced with 0.5 wt% CNTs and 0.5 wt% SiC exhibited the highest hardness value of 183 HV, outperforming other reinforcement combinations.
- The maximum tensile strength was observed at a CNT concentration of 0.75 wt%, regardless of the SiC content.
- ANOVA analysis revealed that applied load (84.33%) had the most significant effect on wear rate, followed by CNT weight percentage (10.36%) and rotating speed (2.31%).
- Supervised machine learning classification algorithms demonstrated high predictive accuracy for wear rate estimation.

- Among the models, XGBoost and Gradient Boosting algorithms achieved the highest prediction accuracy at 98.36%, followed by SVM (95.08%), Decision Tree (98.36%), and KNN (79%).
- Future research can explore higher reinforcement percentages and the application of additional machine learning algorithms. Enhancing model accuracy through hyperparameter tuning is also recommended.
- As this study was conducted under controlled laboratory conditions, further validation under industrial environments is necessary to assess the composites' real-world performance and generalize the findings.

Reference

[1] Vinodh S, Ramakrishnan TS, Padmanaban R. Wear behaviour of friction surfaced Al-Ni and Al-SiC coatings over mild steel. Mater Res Express.

[2] Yakoub NG. Catalysts of strength: unveiling the mechanical and tribological mastery of Al-2024 MMC with fly ash/TiB_2/SiC reinforcements.Journal of Engineering Science and Sustainable Industrial Technology. 2024; 1-9. https://doi.org/10.21608/jessit.2024.283185.1010

[3] Yang L. Pin-on-disc wear testing of tungsten carbide with a new moving pin technique. Wear. 1999;230(2):122-128. https://doi.org/10.1016/S0043-1648(98)00380-9

[4] Bragdon CR, O'Connor D, Lowenstein JD, Jasty M, Biggs SA, Harris WH. A new pin-on-disk wear testing method for simulating wear of polyethylene on cobalt-chrome alloy in total hip arthroplasty. J Arthroplasty. 2001;16(5):658-665. https://doi.org/10.1054/arth.2001.23718

[5] Chen MY, Breslin MC. Friction behavior of co-continuous alumina/aluminum composites with and without SiC reinforcement. Wear. 2001;251(1-12):1147-1152.

[6] Herrero C, Álvarez-Méndez J, García JB, Martín SG, Peña RM. Characterization of carbon nanotubes and analytical methods for their determination in environmental and biological samples: a review. Anal Chim Acta. 2014;853:77-94. https://doi.org/10.1016/j.aca.2014.10.008

[7] Sinnott SB, Andrews R. Carbon nanotubes: synthesis, properties, and applications. J Nanosci Nanotechnol. 2001;1(2):137-150.

[8] Mithila SN, Reaz AH, Farhana FZ, Shiddiky MJA, Firoz SH. Magnetically retrievable carbon-wrapped CNT/Ni nanospheres as efficient catalysts for nitroaromatic reduction. RSC Adv. 2024;14:11856-11864. https://doi.org/10.1039/D4RA07815B

[9] Arenal R, et al. Atomic configuration of nitrogen-doped single-walled carbon nanotubes. Nano Lett. 2014;14(9):4822-4829. https://doi.org/10.1021/nl501645g

[10] Bai M, Song B, Reddy L, Hussain T. Preparation of MCrAlY-Al_2O_3 composite coatings with enhanced oxidation resistance through a novel powder manufacturing process. J Therm Spray Technol. 2019;28:157-165. https://doi.org/10.1007/s11666-019-00830-y

[11] Yadav M, Kumaraswamidhas LA, Kumar A, Khan TMY, Baig U. Erosion behavior of Al-SiC and Al-WC MMCs via powder metallurgy under solid particle impingement. Sci Rep. 2024;14:1234. https://doi.org/10.1038/s41598-024-71368-5

[12] Sharma A, Sharma VM, Paul J. A comparative study on microstructural evolution and surface properties of graphene/CNT reinforced Al6061−SiC hybrid surface composite fabricated via friction stir processing. J Mater Process Technol. 2019;274:116291. https://doi.org/10.1016/S1003-6326(19)65108-3

[13] Weiss Z, Crelling JC, Martynková GS, Valášková M, Filip P. Identification of carbon forms and other phases in automotive brake composites using multiple analytical techniques. Carbon. 2005;43(14):2711-2722.

[14] Kumar SM, Vishwanathaiah MK, Roa BA, Basavanappa M, Namadev N, Nagaral M. Impact on casting die diameter size on microstructure and fractographic studies of Al2024 alloy reinforced with fly ash and SiC hybrid composites. Appl Res. 2024;3(4):e202300066. https://doi.org/10.1002/appl.202300066

[15] Ratim S, Ahmad S, Bonnia NN, Yahaya SM. Mechanical properties of hybrid SiC/CNT filled toughened epoxy nanocomposite. IOP Conf Ser Mater Sci Eng. 2017;290(1):012005. https://doi.org/10.1088/1757-899X/290/1/012005

[16] König K, Novak S, Ivekovič A, et al. Fabrication of CNT-SiC/SiC composites by electrophoretic deposition. J Eur Ceram Soc. 2010;30(5):1131-1137. https://doi.org/10.1016/j.jeurceramsoc.2009.07.027

[17] Akbarpour MR, Alipour S, Safarzadeh A, Kim HS. Wear and friction behavior of self-lubricating hybrid Cu-(SiC+ x CNT) composites. Compos Part B Eng. 2019;158:92-101. https://doi.org/10.1016/j.compositesb.2018.09.039

[18] Sandeep B, Laxminarayana P, Kishore K. Microstructure & tribological behavior of hybrid Al 319 metal matrix composite reinforced with SiC & graphene nano powder. J Bio Tribo-Corros. 2025;11(1):14. https://doi.org/10.1007/s40735-024-00934-1

[19] Jagannatham M, Chandran P, Sankaran S, Haridoss P. Tensile properties of carbon nanotubes reinforced aluminum matrix composites: a review. Carbon. 2020;160:14-44. https://doi.org/10.1016/j.carbon.2020.01.007
[20] Esawi AMK, Morsi K, Sayed A, Taher M. Recent advances in the fabrication and properties of aluminum-carbon nanotube composites. J Mater Sci. 2019;54(1):1-20.
[21] Bakshi SR, Agarwal A. An analysis of the factors affecting strengthening in carbon nanotube reinforced aluminum composites. Carbon. 2011;49(2):533-544. https://doi.org/10.1016/j.carbon.2010.09.054
[22] Choi HJ, Shin JH, Bae DH. The effect of milling conditions on microstructures and mechanical properties of Al/MWCNT composites. Compos Part A Appl Sci Manuf. 2012;43(7):1061-1072. https://doi.org/10.1016/j.compositesa.2012.02.008
[23] Habibi MK, Esawi AMK, Gupta M. Dual reinforcement of aluminum with carbon nanotubes and silicon carbide nanoparticles. J Mater Sci. 2012;47(6):2743-2753.
[24] Cha SI, Kim KT, Lee KH, Mo CB, Hong SH. Mechanical and electrical properties of carbon nanotube reinforced aluminum nanocomposites. Mater Sci Eng A. 2007;448(1-2):713-720.
[25] Esawi AMK, El Borady MA. Carbon nanotube-reinforced aluminium strips. Compos Sci Technol. 2008;68(2):486-492. https://doi.org/10.1016/j.compscitech.2007.06.030
[26] George R, Kashyap KT, Rahul R, Yamdagni S. Strengthening in carbon nanotube/aluminium (CNT/Al) composites. Scr Mater. 2005;53(10):1159-1163. https://doi.org/10.1016/j.scriptamat.2005.07.022
[27] Li YL, Zhao YH, Ortalan V. Investigation of aluminum-based nanocomposites with ultra-high strength. Mater Sci Eng A. 2010;527(12):3056-3065.
[28] Bakshi SR, Singh V, Balani K, McCartney DG, Agarwal A. Carbon nanotube reinforced aluminum composite coating via cold spraying. Surf Coat Technol. 2008;202(21):5162-5169. https://doi.org/10.1016/j.surfcoat.2008.05.042
[29] Laha T, Agarwal A, McKechnie T, Seal S. Synthesis and characterization of plasma spray formed carbon nanotube reinforced aluminum composites. Mater Sci Eng A. 2004;381(1-2):249-258. https://doi.org/10.1016/j.msea.2004.04.014
[30] Kwon H, Estili M, Takagi K, Miyazaki T, Kawasaki A. Combination of hot extrusion and spark plasma sintering for producing carbon nanotube reinforced aluminum matrix composites. Carbon. 2009;47(3):570-577. https://doi.org/10.1016/j.carbon.2008.10.041
[31] Tjong SC. Recent progress in the development and properties of novel metal matrix nanocomposites reinforced with carbon nanotubes and graphene nanosheets. Mater Sci Eng R Rep. 2013;74(10):281-350. https://doi.org/10.1016/j.mser.2013.08.001
[32] Esawi AMK, El Borady MA. Carbon nanotube-reinforced aluminium strips. Compos Sci Technol. 2008;68(2):486-492. https://doi.org/10.1016/j.compscitech.2007.06.030
[33] George R, Kashyap KT, Rahul R, Yamdagni S. Strengthening in carbon nanotube/aluminium (CNT/Al) composites. Scr Mater. 2005;53(10):1159-1163. https://doi.org/10.1016/j.scriptamat.2005.07.022
[34] Sachit TS, Bongale A, Kumar S, Jadhav P. Wear performance analysis of B_4C and graphene particles reinforced Al-Cu alloy based composites using Taguchi method. J Mech Behav Mater. 2023;32(1):20220274. https://doi.org/10.1515/jmbm-2022-0274
[35] Li YL, Zhao YH, Ortalan V. Investigation of aluminum-based nanocomposites with ultra-high strength. Mater Sci Eng A. 2010;527(12):3056-3065.
[36] Bakshi SR, Singh V, Balani K, McCartney DG, Agarwal A. Carbon nanotube reinforced aluminum composite coating via cold spraying. Surf Coat Technol. 2008;202(21):5162-5169. https://doi.org/10.1016/j.surfcoat.2008.05.042
[37] Laha T, Agarwal A, McKechnie T, Seal S. Synthesis and characterization of plasma spray formed carbon nanotube reinforced aluminum composites. Mater Sci Eng A. 2004;381(1-2):249-258. https://doi.org/10.1016/j.msea.2004.04.014
[38] Sachit TS, Khan MA. Effect of particle size on mechanical and tribological behavior of LM4/SiCp based MMC. Mater Today Proc. 2018;5(2):5901-5907. https://doi.org/10.1016/j.matpr.2017.12.189
[39] Kwon H, Estili M, Takagi K, Miyazaki T, Kawasaki A. Combination of hot extrusion and spark plasma sintering for producing carbon nanotube reinforced aluminum matrix composites. Carbon. 2009;47(3):570-577. https://doi.org/10.1016/j.carbon.2008.10.041
[40] Kumar PS, Sachit TS, Mohan N, Akshayprasad M. Dry sliding wear behaviour of Al-5Si-3Cu-0.5Mn alloy and its WC reinforced composites at elevated temperatures. Mater Today Proc. 2021;44:566-572. https://doi.org/10.1016/j.matpr.2020.10.351
[41] Sachit TS, Mohan N. Wear behavior of aluminum LM4 reinforced with WC and Ta/NbC hybrid nano-composites fabricated through powder metallurgy technique. FME Trans. 2019;47(3):406-412. https://doi.org/10.5937/fmet1903534S
[42] Tjong SC. Recent progress in the development and properties of novel metal matrix nanocomposites reinforced with carbon nanotubes and graphene nanosheets. Mater Sci Eng R Rep. 2013;74(10):281-350. https://doi.org/10.1016/j.mser.2013.08.001

[43] Song N, Liu H, Fang J. Fabrication and mechanical properties of multi-walled carbon nanotube reinforced reaction bonded silicon carbide composites. Ceram Int. 2016;42(1):351-356. https://doi.org/10.1016/j.ceramint.2015.08.117
[44] Sachit TS, Suresh R, Nagaraj T. Systematic wear rate analysis of Ti-6Al-4V based hybrid composites using Taguchi optimizer and machine learning classifiers. J Inst Eng India Ser D. 2025;1-13. https://doi.org/10.1007/s40033-025-00871-4
[45] Cai Y, Chen L, Yang H, et al. Mechanical and electrical properties of carbon nanotube buckypaper reinforced silicon carbide nanocomposites. Ceram Int. 2016;42(4):4984-4992. https://doi.org/10.1016/j.ceramint.2015.12.011
[46] Zhang Y, et al. Mechanical properties of SiC-reinforced aluminum matrix composites. Mater Sci Eng A. 2017;696:103-111.
[47] Kumar M, Singh R. Hardness and wear behavior of SiC-reinforced metal matrix composites. J Compos Mater. 2018;52(22):3093-3104.