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MACHINING OF COMPOSITE MATERIALS: CHALLENGES, ADVANCES AND AI-DRIVEN SOLUTIONS

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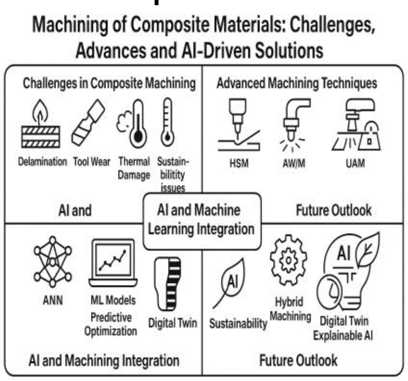
Graphical abstract



Abstract

The demand for composite materials is increasing across industries like energy storage, aerospace, automotive, and healthcare, driven by their exceptional attributes such as high strength-to-weight ratios and resistance to corrosion. However, machining these materials presents significant challenges due to their heterogeneous and anisotropic structures, leading to complex tool-workpiece interactions, rapid tool wear, poor surface quality, and environmental concerns. This review explores recent advancements in machining techniques for composite materials, with a particular focus on addressing key challenges and leveraging artificial intelligence (AI) solutions. It serves as a comprehensive resource to enhance machining practices in modern composite manufacturing by optimising machining parameters. The paper concludes by pinpointing significant research gaps in hybrid machining and AI-driven strategies, suggesting promising avenues for enhancing high-precision surface machining of fibre-reinforced composites and propelling the field forward.

Keywords: Composites, machining, delamination, sustainable machining strategies, AI-driven machining optimisation

Abstrak

Permintaan terhadap bahan komposit semakin meningkat dalam pelbagai industri seperti penyimpanan tenaga, aero-angkasa, automotif, dan kesihatan, didorong oleh nisbah kekuatan dan ketahanan terhadap kakisan. Pemesinan bahan-bahan ini menghadapi cabaran besar disebabkan oleh struktur heterogen dan anisotropik yang menyebabkan interaksi kompleks antara mata alat dan bahan. Kerosakan mata alat yang cepat, kualiti permukaan yang kurang memuaskan, serta isu-isu alam sekitar memerlukan perhatian yang teliti. Kajian ini meneroka kemajuan terkini dalam teknik pemesinan bahan komposit, dengan penekanan khusus pada menangani cabaran utama dan memanfaatkan penyelesaian berasaskan kecerdasan buatan (AI). Ia berfungsi sebagai sumber rujukan untuk meningkatkan amalan pemesinan dalam pembuatan bahan komposit moden dengan mengoptimumkan parameter pemesinan. Kajian ini juga mengenal pasti jurang penyelidikan yang ketara dalam pemesinan hibrid dan strategi berasaskan AI, serta mencadangkan kajian pada masa hadapan yang membantu untuk meningkatkan pemesinan permukaan berketepatan tinggi bagi komposit bertetulang gentian dan memacu kemajuan dalam bidang ini.

Kata kunci: Komposit, pemesinan, cabaran, kemajuan, kecerdasan buatan

1.0 INTRODUCTION

Composite materials are transforming industries like energy storage, aerospace and biomedical engineering, thanks to their exceptional strength-to-weight advantages. Yet, their true potential remains untapped due to the difficulties involved in machining them [1, 2, 3, 4]. In general, there are several types of composites available including polymer matrix composites (PMC), metal matrix composites (MMC), and ceramic matrix com-posites (CMC) [5, 6, 7]. To transform these composites into useful products, machining processes such as milling, drilling, and turning are applied [8]. Machining complex geometries is not a straightforward process because it relies on trial-and-error methods or static parameter settings, which are insufficient for optimizing cutting conditions. This method typically takes a longer time and is unable to adapt to real-time changes in material behaviour or tool wear [9]. Moreover, high energy consumption and the ex-tensive use of cooling lubricants contribute to environmental concerns [10, 11].

Composites also present unique challenges in machining due to their heterogeneous structure and anisotropic nature [12, 13, 14]. This issue leads to unpredictable tool-material interactions, making machining difficult to optimise, hence causing delamination, fibre pull out and thermal damage to composites. For instance, drilling glass fibre-based composites could accelerate rapid tool wear because of the abrasive nature of the material [15, 16]. Researchers have been working to address these challenges by introducing process optimisations tailored to the unique demands of composite materials [17]. Several well-known techniques, such as high-speed machining, ultrasonic-assisted machining, laser-assisted machining, and abrasive water jet machining, have been applied to improve machining efficiency and quality. As a result, tool wear and surface defects can be reduced. Likewise, innovations in tool materials and coatings, such as polycrystalline diamond (PCD) [18] and coated carbide tools [19], are widely used to withstand the high abrasiveness and thermal sensitivity of compo-sites. The aim, once again, is to extend tool life and enhance performance.

Lately, the integration of artificial intelligence into composites machining has become increasingly popular. This has led to a new area of research focus, the integration of data-driven methods. Machine learning and artificial intelligence are widely used to optimise machining parameters and predict tool wear and material behaviour [20, 21].

There are many advantages to the machine learning approach. For instance, this approach enables real-time adjustments, reduces trial-and-error, and minimises defects, which is particularly valuable for complex geometries and high-precision applications. Additionally, sustainable machining practices, including cryogenic cooling and minimum quantity lubrication (MQL), are gaining traction to reduce the environmental impact of composite machining and improve workplace safety [22]. Current research includes an innovative longitudinal-torsional ultrasonic cryogenic cooling created with a focus on environmental sustainability [23]. This system includes a novel mechanical structure to enhance both the amplitude of longitudinal-torsional ultrasound and the efficiency of heat dissipation. Additionally, a high-power cryogenic cooling device utilising a vortex tube was developed by researchers, and a distinctive wireless power supply system was employed, enabled the formulation of a design approach for integrating multiple transducers with a single longitudinal-torsional composite hollow horn.

Although numerous papers have been published on the integration of AI and ML in composites machining, comprehensive reviews in this area remain relatively scarce. This paper provides a comprehensive review of recent advances in composite material machining, focusing on AI driven solutions. It examines the latest developments in composite material machining, highlighting ML application in process parameter optimization, and the integration of automation and smart manufacturing concepts to address the integral challenges of machining composites.

Unlike most previous reviews, which focus mainly on conventional machining challenges and improvements, our review extensively explores the integration of AI and machine learning (ML) to optimize machining parameters, predict tool wear, and improve process efficiency.

While prior studies have examined AI in general composite machining, they rarely discuss its real-time implementation. Additionally, our review introduces Digital Twin technology, where AI-driven simulations predict and optimize machining conditions before physical trials. This review also explores the role of Explainable AI (XAI) in ensuring transparency in machining parameter selection.

Figure 1 shows a growing interest in composites machining research, especially from 2015-2024, with a peak in recent years.

The trend indicates that composites machining is becoming an increasingly popular area in materials science and engineering. Despite minor fluctuations, this upward trajectory highlights the field's growing importance in modern manufacturing and materials science.

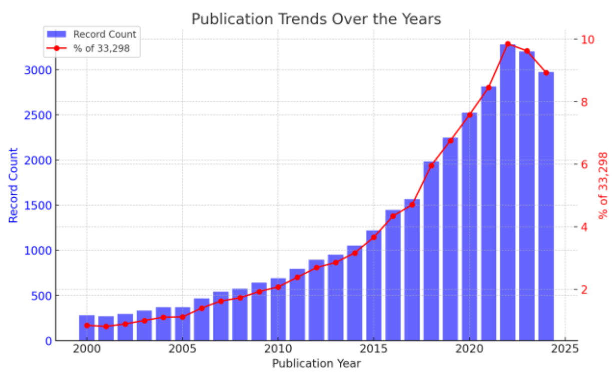


Figure 1 Number of publications from 2015 to 2024 using the keywords ''machining of composites'' obtained from Web of Science

2.0 COMPOSITE MATERIALS

A composite is a material made by combining two or more distinct materials, typically resulting in properties that surpass those of its individual components. In the case of polymer composites, which are the focus of this paper, the matrix is commonly combined with fibres to facilitate load transfer, resulting in a material that is both lightweight and strong [24]. Another type of composite family commonly found in industries includes metal matrix composites and ceramic matrix composites. Their applications are prevalent in the energy, automotive, aerospace, and medical sectors.

In addition to being lightweight and strong, composite materials offer several other advantages, including corrosion and fatigue resistance, excellent thermal stability, and an outstanding strength-to-weight ratio [25, 26]. These additional properties make them suitable for electronics and construction [27, 28, 29, 30].

Composites can be manufactured through several processes. Common methods employed are hand lay-up, autoclave moulding, compression moulding, pultrusion, and filament winding. These processes enable the fabrication of composite parts that are tailored to their near-net shape, underscoring the versatility and capabilities inherent to this material class. To achieve excellent surface quality and dimensional accuracy, machining processes such as turning, milling, and drilling are employed. Additionally, selecting the appropriate tool geometry, cutting speed, and feed rate is crucial in machining. These choices ensure a good surface finish, maintain dimensional accuracy, minimise tool wear, manage excessive heat and stress during machining, and, most importantly, prevent defects. However, due to heterogeneous and anisotropic characteristics of composite materials, machining these materials can lead to various problems. These include including delamination, hole shrinkage, and fibre pull-out.

2.1 Types of Composite Materials

Composites combine diverse elements, capitalizing on their strengths while ad-dressing weaknesses [31]. By optimizing, designers break free from traditional materials, using customizable, stronger, and lighter options tailored to requirements. This flexibility enables complex, cost-effective, and superior solutions when reimagining designs with composites. Composites typically have a two-phase structure, with a matrix material containing dispersed particles or fibres [32]. Figure 2 depicts composite materials, which are divided into three main categories: Polymer Matrix Composites (PMCs), Metal Matrix Composites (MMCs), and Ceramic Matrix Composites (CMCs) [33,34]. Each type of composite has specific subtypes based on the matrix material used, such as glass, carbon, aluminium, magnesium, silicon carbide, and zirconia [35].

2.2 Polymer Matrix Composites (PMCs)

Polymer composites use strong, stiff fibres embedded in a polymer matrix. The fibres carry most of the load, but the matrix is crucial as it bonds the fibres together, distributes forces evenly, and transfers loads to the fibres [36]. Additionally, the matrix material's characteristics significantly influence the composite's properties. Therefore, the performance of the fibres, matrix, and their interface directly impacts the overall composite performance. Comprising a polymeric matrix, often derived from thermoset or thermoplastic resins, these materials incorporate reinforcing fibres like glass, carbon, or aramid [37, 38]. The unparalleled design and processing versatility of polymer matrix composites has made them highly advantageous and invaluable across a wide range of diverse sectors, from automotive and aerospace to sports equipment and marine applications. These composites offer exceptional flexibility and adaptability, allowing for tailored solutions and enabling innovative developments in numerous industries.

•Glass Fibre Reinforced Polymer (GFRP): GFRPs are strong, lightweight, and resistant to corrosion and impact [39]. They are widely used in the construction industry, automotive parts, and consumer goods [40, 41, 42, 43].

•Carbon Fibre Reinforced Polymer (CFRP): CFRPs offer exceptional strength, stiffness, and lightweight properties, making them highly suitable for ap-plications where high performance is crucial, such as aerospace compo-nents, high-end automotive parts, and sporting goods [44].

•Aramid Fibre Reinforced Polymer (AFRP): Known for their high toughness and impact resistance, AFRPs are often used in ballistic applications, protective gear, and aerospace [45].

2.3 Metal Matrix Composites (MMCs)

Metal matrix composites consist of a metal matrix—such as aluminum, magnesium, or titanium—reinforced with materials like ceramics (silicon carbide, aluminum oxide) or fibres (carbon) [46]. The addition of these reinforcements enhances the mechanical and thermal properties of the base metal, improving its strength, wear resistance, and performance at high temperatures [47]. MMCs are primarily used in ap-plications where high strength, thermal conductivity, and wear resistance are required, such as in automotive brake components, aerospace structures, and electronic packaging.

•Aluminum Matrix Composites: Known for their lightweight properties and improved strength, aluminum-based MMCs are widely used in the aero-space and automotive industries for parts like engine components and structural parts [48, 49].

•Magnesium Matrix Composites: Magnesium MMCs offer excellent strength-to-weight ratios and are commonly used in applications where weight reduction is critical, such as in the automotive and defense industries [50].

•Titanium Matrix Composites: Due to their high strength, corrosion re-sistance, and thermal stability, titanium MMCs are often used in demanding aerospace applications, including turbine blades and airframe components [51, 52, 53].

2.4 Ceramic Matrix Composites (CMCs)

Ceramic matrix composites are composed of a ceramic matrix—such as silicon carbide, alumina, or zirconia—reinforced with fibres, typically carbon or ceramic fibres. CMCs are valued for their ability to withstand extremely high temperatures, chemical stability, and resistance to wear, which makes them suitable for applications in high-stress environments. They are commonly used in the aerospace, defence, and energy sectors, particularly in applications such as turbine blades, heat shields, and engine components where traditional metals would fail under high heat and stress.

•Silicon Carbide Composites: Known for their high strength, thermal shock resistance, and oxidation resistance, silicon carbide-based CMCs are commonly used in high-temperature applications, such as gas turbines and engine components [54].

•Alumina Composites: Alumina-based CMCs offer excellent wear resistance and chemical stability, making them ideal for use in chemical processing equipment and medical implants [55, 56, 57].

•Zirconia Composites: With superior toughness and thermal stability, zirconia composites are used in applications requiring both high thermal resistance and durability, including cutting tools and biomedical applications [58, 59, 60].

2.5 Hybrid Composites

Hybrid composites combine two or more types of reinforcing fibres or matrices to enhance specific properties [61, 62, 63, 64]. For instance, combining carbon and glass fibres within a polymer matrix can balance the cost and weight benefits of glass fibres with the high strength and stiffness of carbon fibres. Hybrid composites are increasingly used in high-performance and cost-sensitive applications across industries like automotive, aerospace, and sports equipment. In summary, each type of composite material offers unique advantages suited to specific environments and functional requirements. Through judicious selection of matrix and reinforcement components, engineers can create materials optimised for performance under specific operational stresses, enabling applications requiring high performance, durability, and weight efficiency.

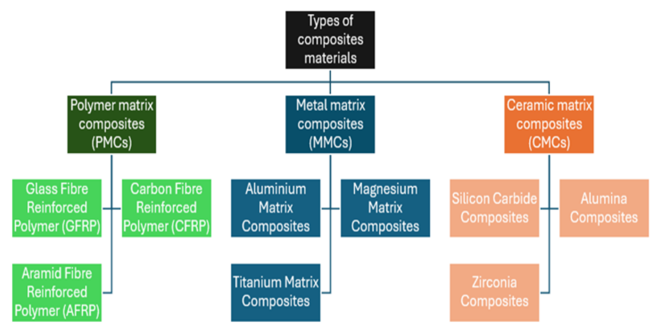


Figure 2 Main categories of composite materials [65,66,67,68,69]

3.0 MACHINING CHALLENGES IN POLYMER COMPOSITE MATERIALS

The general methodology of machining process is outlined in Figure 3. This flowchart provides a structured approach to machining operations, ensuring efficiency, precision, and quality in manufacturing.

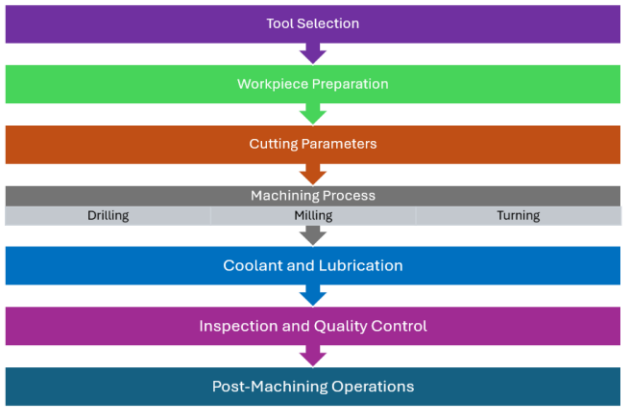


Figure 3 Machining process workflow

Despite the advantages of composite materials, there are significant challenges associated with their machining processes. Unlike homogeneous metals, composite materials are inherently heterogeneous and anisotropic, with properties that depend on the direction and distribution of their fibres and matrix components. As a result, conventional machining methods often encounter difficulties that can compromise the efficiency of manufacturing processes and the quality of the machined components. Figure 4 shows the challenges associated with composites machining.

A key challenge faced when machining composite materials is the problem of layer separation, known as delamination. This is a common issue with fibre-reinforced composites, where the individual layers can start to peel apart under the mechanical forces encountered during drilling or milling, especially at the points where the tool enters and exits the material.

Delamination is one of the most critical challenges encountered in the machining of composite materials due to their layered structure and anisotropic properties. Delamination refers to the separation of composite layers at the fibre-matrix interface, leading to structural weakness, poor surface integrity, and reduced mechanical performance. This phenomenon commonly occurs in drilling, milling, and turning operations, particularly when machining fibre-reinforced polymer composites (FRPs) such as carbon fibre-reinforced polymers (CFRPs) and glass fibre-reinforced polymers (GFRPs). The core challenge lies in the complex interplay between the cutting tool and the composite's fibre-matrix interface, which can give rise to uneven cutting forces and ultimately lead to the undesirable separation of the individual layers. The wide variety of composite materials contributes to uneven cutting forces during machining, with each type requiring specific cutting parameters to address this issue effectively. To address delamination, researchers have developed specialized cutting tools, backing support, and process optimizations. The use of step drills and brad & spur drills can reduce cutting forces and distribute loads more evenly, thereby minimizing entry and exit delamination. The application of polycrystalline diamond (PCD) and diamond-coated tools is also effective in reducing tool wear and preventing excessive mechanical damage. Sacrificial backing plates can be used on composite materials to absorb exit forces and prevent push-out delamination. Lastly, process parameter optimization, including lower feed rates and higher cutting speeds, is effective in reducing thrust forces that contribute to delamination.

Composite materials containing abrasive fibers like GFRP (Glass Fibre Reinforced Polymer) or CFRP (Carbon Fibre Reinforced Polymer) often cause rapid wear on cutting tools and thermal damage. These fibers are typically harder than the primary matrix material, leading to significant damage and wear on standard cutting tools. As a result, tool lifespan is reduced, dimensional accuracy declines, and production costs increase. Furthermore, the machined composite component may exhibit other adverse outcomes, including diminished dimensional precision, inferior surface quality, and fibre pullout, which can stem from the detrimental effects on cutting efficiency.

Another issue in composite machining is the thermal challenge posed by intense heat generated from high-speed cutting, which can damage the polymer matrix. Unlike metals, which dissipate heat quickly, composite materials have poor thermal conductivity. This results in localized heat exposure, leading to degraded mechanical properties in those areas. To address this, researchers have suggested methods like cryogenic cooling and minimum quantity lubrication (MQL) to target the cutting area. However, these solutions can significantly increase overall processing costs. In addition, there are concerns regarding air pollution and the challenges associated with lubricant disposal. The additives in lubricants are hazardous to the environment and can lead to long-term pollution. To address this issue, vegetable oils are increasingly being used as biodegradable and sustainable alternatives to petroleum-based metalworking fluids (MWFs) in machining operations. They offer non-toxic, renewable lubrication while maintaining effective cooling and chip removal. To enhance the performance of vegetable oils and MQL systems, nanomaterials have been introduced as additives to improve their tribological properties, thermal stability, and lubrication efficiency. Nanoparticles such as Al_2O_3, MoS_2, TiO_2, graphene, and carbon nanotubes (CNTs) are incorporated into vegetable oils, forming hybrid nano-lubricants that exhibit superior heat dissipation, anti-wear characteristics, and friction reduction. These nano-lubricants create a protective boundary layer at the tool-workpiece interface, reducing cutting forces, tool wear, and surface roughness.

Due to their inherent heterogeneity, composites do not behave uniformly during machining, making it challenging to optimise machining parameters. This is where machine learning algorithms can be applied to predict optimal parameters, providing an efficient alternative to the traditional trial-and-error approach, which is both time-consuming and reliant on manual adjustments.

In summary, machining is evolving towards more sustainable practices to protect the environment and reduce health risks for workers. While the use of biodegradable lubricants is becoming increasingly popular, it does not address all the associated challenges. In addition, techniques such as cryogenic cooling and minimum quantity lubrication (MQL) are being applied to reduce heat and tool wear, supporting both efficiency and sustainability in machining processes but these methods also have limitations and do not solve all challenges associated with the composites machining process. Emulsion coolant expenses including production, usage, and disposal can represent as much as 15% of total manufacturing costs [70]. This has spurred the advancement of more sustainable options, such as minimum quantity lubrication (MQL) and sub-zero cooling methods that utilise liquefied gases like nitrogen (LN2) or carbon dioxide (LCO2).

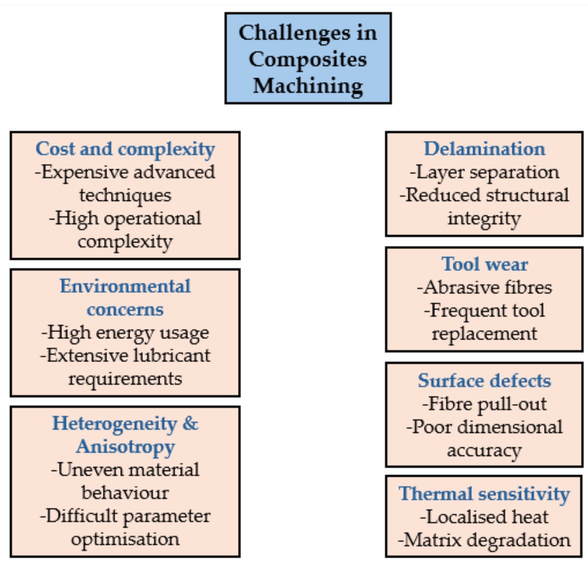


Figure 4 List of challenges associated with composites machining [70]

4.0 RECENT ADVANCES IN MACHINING TECHNIQUES FOR COMPOSITE MATERIALS

In the past decade, numerous studies have reported significant advances in machining techniques. Key among these advancements are high-speed machining, ultrasonic-assisted machining, laser-assisted machining, and abrasive water jet machining. Each of these methods contributes uniquely to overcoming specific machining challenges posed by composites.

High-Speed Machining (HSM) is increasingly popular for its potential to improve material removal rates and surface quality in composite machining. Babu *et al*. specified high-speed machining as 10,000–15,000 rpm and very high-speed machining as 15,000–50,000 rpm [71]. The transition ranges are 8,000–12,000 rpm (low to high speed) and 12,000–20,000 rpm (high to very high speed) [72].

By operating at higher spindle speeds and feed rates, HSM minimizes heat generation, which is critical since composites typically have low thermal conductivity. This method, however, demands advanced, high-cost machinery and careful optimization of cutting parameters to avoid issues like tool wear and delamination, especially in materials like carbon fibre-reinforced polymers (CFRPs). Although this method is a popular approach in machining, it often results in undesirable vibrations, particularly when working with flexible fibre materials. Future research should focus on mitigating this issue to enhance tool lifespan and machining quality [73].

Workpiece materials exhibit different dynamic behaviours during high-speed machining compared to their static properties due to the high loading rate. Chip morphology evolves from continuous to serrated and fragmented as cutting speed increases, which is linked to the variation in material dynamic properties. Ultra-high-speed machining in the brittle regime can reduce cutting energy consumption by over 19% compared to high-speed machining in the ductile regime [74].

High-speed machining can produce varied surface characteristics compared to lower-speed machining [75]. Specific ranges of high cutting speeds can result in fewer surface defects and lower surface roughness, though the optimal speed depends on the workpiece material, cutting method, and tool used. HSM can also cause severe plastic deformation, leading to an ultrafine grain layer and phase changes on the machined surface. As cutting speed increases, larger compressive residual stresses may develop deeper in the subsurface due to greater plastic deformation. However, a thin superficial layer can exhibit very high tensile residual stresses, potentially causing issues in service. Optimising the cutting speed is necessary to balance the surface quality parameters. Slamani *et al*. analysed the cutting forces, surface roughness, and delamination during slotting tests on FFRP composite materials, revealing that fibre orientation significantly affects cutting forces, defects, and surface quality, with 90° orientation providing the best surface finish and feed rate being the most influential cutting parameter [76]. In case of composites machining, the equation for delamination factor can be expressed as follow.

$$F_D = D_{max}/D_o \qquad (1)\ [77]$$

Where F_D (delamination factor), D_{max} (maximum delamination diameter) and Do (hole diameter)

The cutting force can be reduced within the HSM speed range, due to thermal softening from chip plastic deformation, which weakens material resistance. Brittle fracture of the removed material can also help keep the cutting force low when reaching the ultra-high-speed machining range. The tool-chip friction coefficient tends to decrease as cutting speed increases. Severe tool wear under the extreme conditions of HSM is a critical challenge for industrial application. Understanding tool wear behaviour and mechanisms can guide the design and fabrication of cutting tools suitable for HSM and recommend appropriate tools for specific workpiece materials [78, 79]. Figure 5 illustrates the development and adoption of high-speed machining (HSM), highlighting significant advancements in speed, material removal rates, and application capabilities from 1820 to 2010. The following equation describes the correlation involving cutting speed (V) and tool life (T). This can be written as:

$$VT^n=C \qquad (2)\ [80]$$

Where V (cutting speed), T (tool life) n, C (Constants dependent on material and machining conditions)

HSM has been successfully deployed in manufacturing various mechanical components, offering advantages for removing large volumes of material. Advancements in ultra-hard cutting tools have enabled higher speed ranges to be used industrially [81, 82]. However, the development of advanced engineering materials with greater strength and toughness presents further challenges for high-speed machining applications [83]. The current research focuses on optimising tool geometry, developing more advanced lubricants, and designing innovative materials for cutting tools. The primary goal is to enhance durability and performance when machining composites in demanding environments.

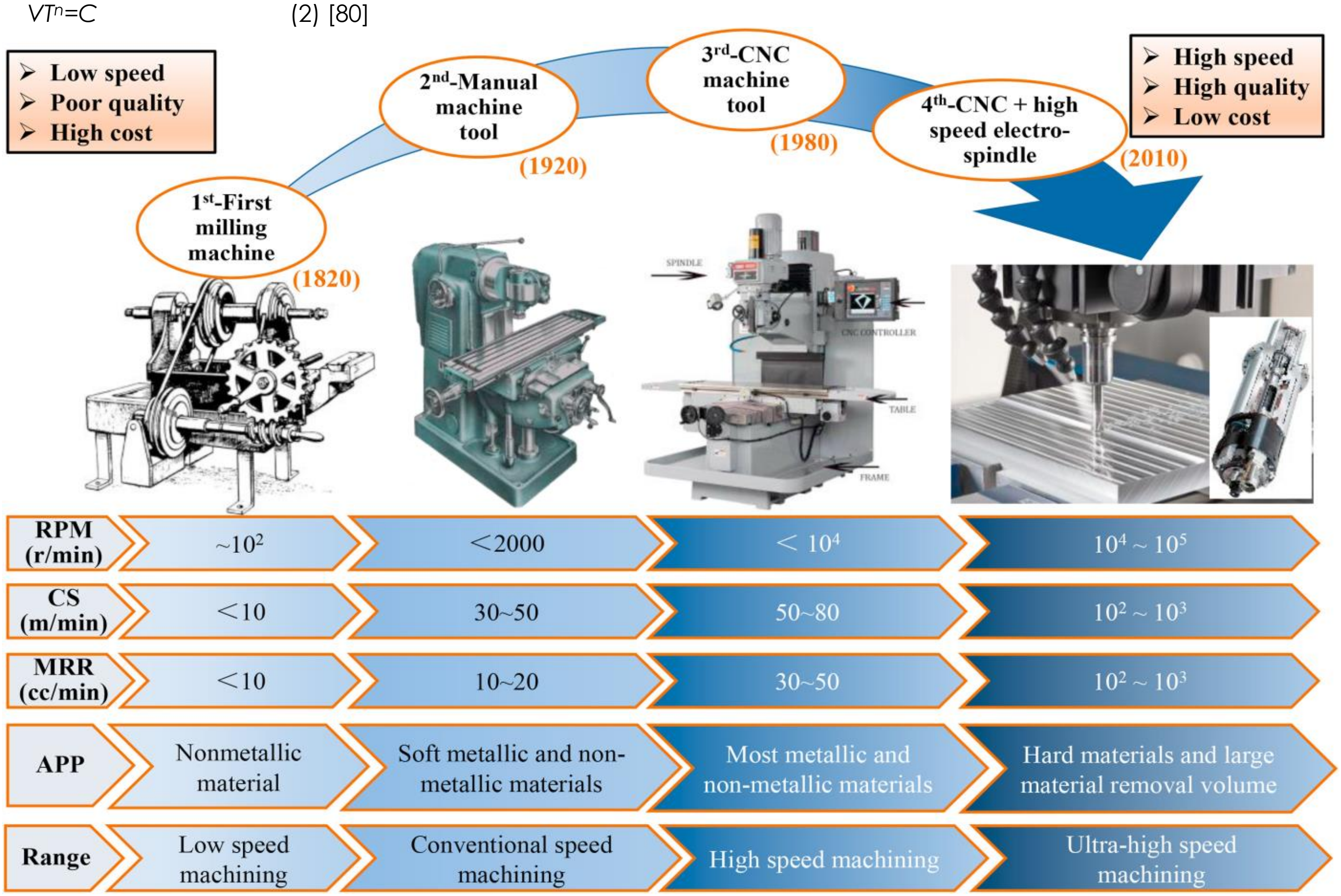


Figure 5 High-speed cutting development and use. Note: (CNC-Computer Numerical Control, RPM-revolutions per minute, CS-cutting speed, MRR-material removal rate, APP-application) [74]

Ultrasonic Assisted Machining (UAM) has evolved significantly over the last 60 years, building on the concept introduced as early as 1927 and patented in 1945 [84]. UAM applies ultrasonic vibrations to conventional machining, enhancing efficiency and reducing residual stress on the workpiece's surface, particularly beneficial for brittle materials [85]. While early ultrasonic machining was limited by low material removal rates and primarily used for finishing, advances in ultrasonic transducers and tool design have broadened its application across various machining processes [86, 87, 88].

One important method in UAM is Conventional Ultrasonic Machining (USM) [89]. It relies on abrasive slurry impacts to shape brittle materials, and UAM itself, which integrates high-frequency vibrations directly into traditional machining operations like turning, milling, and drilling. In UAM, vibration can be applied either to the cutting tool (Actuated Tool System, ATS) or the workpiece (Actuated Work System, AWS), creating a cyclical tool–workpiece interaction that enhances material removal efficiency. As illustrated in Figure 6, the vibrations result in a cyclic four-step movement, known as approach, contact, immersion, and withdrawal, at the cutting tip. This enhances cutting precision and extends tool lifespan by reducing continuous tool-workpiece contact. This advancement in ultrasonic machining represents a significant breakthrough in processing hard-to-machine materials [90].

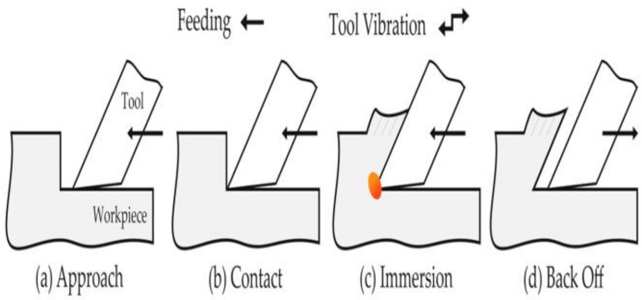


Figure 6 Essential tool movement in a vibration cycle [91]

Laser-Assisted Machining (LAM) uses laser heating to enhance machining of hard, brittle materials [92]. It has two main approaches which include pre-heat LAM and in-situ LAM [93]. In pre-heat LAM, a laser softens the workpiece surface before it contacts the cutting tool, improving material removal in processes like turning, milling, and grinding [94, 95, 96]. Research shows that factors like laser power and scan speed significantly influence surface quality and tool wear in materials like hardened steel and fused silica. In contrast, in-situ LAM directly heats the cutting zone in real-time, ideal for ultra-precision machining with diamond tools [97]. By focusing the laser on the contact point between the tool and workpiece, in-situ LAM enhances ductility, allowing for smoother cuts in materials. This method increases the ductile-brittle transition (DBT) depth, enabling more ductile removal and reducing residual stress. Studies on in-situ LAM of glass-ceramics have explored optimization of cutting parameters to lower cutting forces, employing methods like response surface methodology (RSM) and artificial neural networks (ANN) for parameter prediction. In-situ LAM offers improved efficiency, reduced machining costs, and higher surface quality for challenging materials like thermoset and thermoplastic composites. Figure 7 illustrates a laser-assisted machining process (LAM). This is a two-step process for creating a final hole using mechanical drilling. The first step involves machining a pilot hole, either by laser machining (red dashed line) or a conventional drilling tool, followed by the second step, where a larger drill (blue dashed line) is used to complete the final hole. By using LAM, lower cutting forces are required during the machining operation, and tool life can be extended; however, the laser can damage the polymer matrix. Additionally, the laser tends to create a heat-affected zone, which can alter the mechanical properties of the composite, making it undesirable for the manufactured products or components.

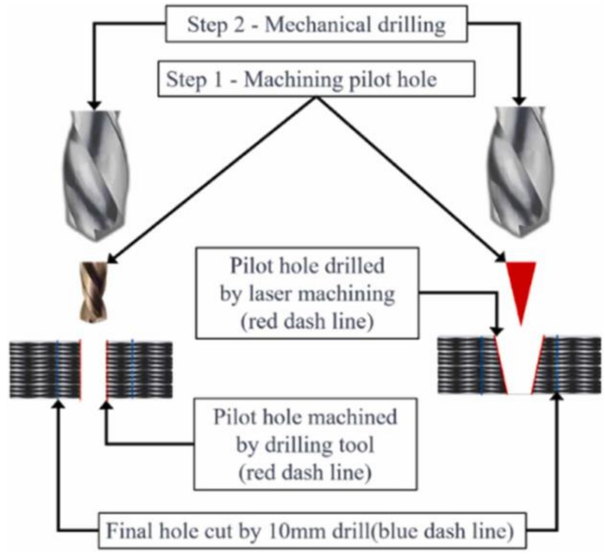


Figure 7 Schematic of laser assisted machining (LAM) [98]

The Abrasive Water Jet Machining (WJM) process is shown in Figure 8. This technique has emerged as a versatile and advanced method suitable for a wide range of materials, including polymer composites. It is also suitable for small-batch production and rapid prototyping. This technique operates as a hybrid mechanism that combines water jet machining (WJM) and abrasive jet machining (WJM). It offers advantages such as precise cutting with minimal heat, prevention of thermal distortion, and preservation of material integrity. In the WJM process, high-speed abrasive particles such as silicon carbide or aluminium oxide, erode material surfaces without generating heat, making it a “cold” machining method. WJM’s flexibility, low power requirement, and durability make it an ideal choice for materials with complex geometries or those sensitive to heat [99,100,101,102]. Key components of WJM systems include a compressor, mixing chamber, nozzle, and pressure gauge, which together allow precise control over cutting, achieving high-quality results across diverse materials.

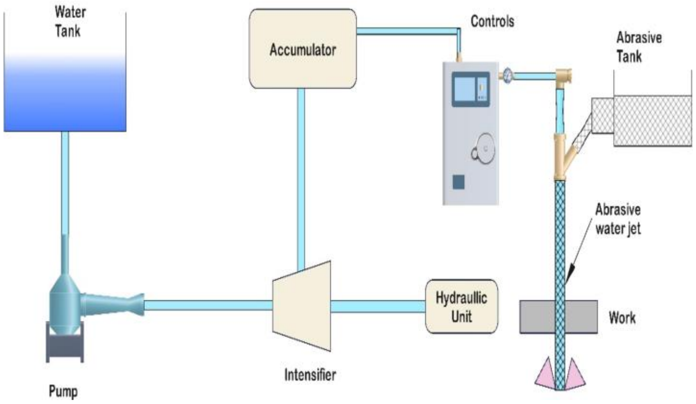


Figure 8 Illustration of water jet machining [103]

5.0 APPLICATIONS OF ARTIFICIAL INTELLIGENCE AND MACHINE LEARNING IN COMPOSITES AND MACHINING

Artificial Intelligence (AI) enables machines to perform tasks intelligently, incorporating human-like psychological skills such as perception, association, prediction, planning, and motor control, with diverse information processing capabilities [104, 105, 106]. Within this field, machine learning (ML) is a subfield that explores algorithms and statistical models enabling computer systems to perform specific tasks, such as classification, regression, and clustering, without explicit programming [107, 108, 109].

Table 1 highlights the increasing reliance on machine learning (ML) and artificial intelligence (AI) for machining composite materials. Among the prevalent methods, Artificial Neural Networks (ANNs) dominate due to their predictive accuracy in modelling complex relationships, such as machining parameters and surface quality. ANNs are computational models inspired by biological neural systems, capable of learning complex patterns by adjusting connections and weights between neurons to minimise errors, typically through backpropagation. They are particularly effective in modelling complex data, predicting outcomes, and optimising processes. Recent literature increasingly highlights their efficiency and reliability in tasks such as image recognition, speech processing, and especially modelling and optimising intricate manufacturing processes.
ANN variations, such as Levenberg–Marquardt (LM) and Particle Swarm Optimization (PSO), demonstrate adaptability for optimisation tasks in water jet machining, turning, and drilling. These approaches effectively address challenges like delamination and tool wear.

Other advanced techniques like Gradient Boosting Machines (GBM), Random Forests (RF), and Support Vector Machines (SVMs) are applied to specific scenarios, especially drilling and turning of fibre-reinforced composites, to enhance parameter prediction and process stability. The use of newer approaches, such as Long Short-Term Memory (LSTM) and Convolutional Neural Networks (CNNs), highlights an interest in real-time, explainable predictions and optimisation.

Despite the increasing trend in the application of AI/ML in composites machining, the inherent complexity of composite materials remains a significant challenge. Accurately modelling the anisotropic and heterogeneous properties associated with composite materials is particularly difficult. Another major issue arises with the availability of high-quality, diverse datasets required for training ML models, as recent research has reported that such datasets are often limited or expensive to obtain. Additionally, machine learning models, such as deep learning, may be overfit, to small or specific datasets reduces their generalisability to broader scenarios.

Despite their utility, simpler algorithms like Linear Regression (LR) and Decision Trees (DT) are still widely used, often in combination with statistical methods like Response Surface Methodology (RSM). This demonstrates a trade-off between computational simplicity and predictive capability. On the positive side, AI/ML techniques can significantly enhance machining accuracy, reduce trial-and-error costs, and contribute to sustainable practices. However, from our review, the choice of a suitable algorithm remains critical for effectively addressing material-specific challenges. Figure 9 depicts the distribution of various modelling techniques used by researchers. Each segment represents a specific method, with the dominant portion illustrating the use of Artificial Neural Networks (ANN).

Table 1 Recent development in composites and machining/simulation integrated with artificial or machine learning

Composite Type	Machining Operation	Cutting Tool	ML Algorithm/Remark	Year and Ref.
Hybrid bio-composites (Nettle and Grewia)	Drilling	Carbide	-Response Surface Methodology (RSM) -Artificial Neural Networks (ANNs)	2024 [110]
CFRP	Abrasive Water Jet	Abrasive particle (Garnet)	-Artificial Neural Networks (ANNs)	2024 [111]
Polyethylene-terephthalate-glycol (PETG)	Turning	Diamond-shaped cutting inserts	-ANN model with a 3-6-1 structure optimized via the Levenberg–Marquardt (LM) training algorithm	2024 [112]
CFRP/Al_2O_3/SiC	Drilling (twist drill, step drill, and core drill)	PVD coated	-Artificial Neural Networks (ANNs) - Random Forest (RF)	2024 [113]
Jute-basalt/epoxy	Turning	Carbide	-Gradient Boosting Machine (GBM) -Adaptive Boosting (AdaBoost) -Extreme Gradient Boosting (XGBoost)	2024 [114]
Hybrid fibre-reinforced polyester	Water jet machining	Water jet	-Response Surface Methodology (RSM) -Artificial Neural Network (ANNs)	2024 [115]
NFRP	Orthogonal cutting	Wedge-shaped	-Convolutional Neural Network (CNN) -Explainable machine learning approach (XML)	2024 [116]
Jute/rattan epoxy	Drilling	High speed steel and carbide (HSS)	-Support Vector Machine (SVM) -Random Forest (RF)	2024 [117]
Banana fibre-reinforced epoxy composites infused with alumina	Water jet	Abrasive particle (garnet)	-Utilised Artificial Neural Network (ANNs) -Long Short-Term Memory (LSTM)	2024 [118]
GFRP	Drilling	High Speed Steel (HSS)	-Linear Regression (LR), Decision Tree (DT), AdaBoost Decision Tree Regressor, XGBRF Regressor	2023 [119]
GFRP	Drilling	High Speed Steel (HSS)	-An Artificial Neural Network (ANNs). -Optimization was performed using a Genetic Algorithm (GA)	2023 [120]
GFRP	Drilling	Carbide	-Artificial Neural Networks (ANN) enhanced by a Particle Swarm Optimization (PSO) algorithm	2023 [121]
GFRP	Milling	Carbide	-Response Surface Methodology (RSM) used to model and optimize machining parameters.	2023 [122]

Composite Type	Machining Operation	Cutting Tool	ML Algorithm/Remark	Year and Ref.
			-An Artificial Neural Network (ANNs) model was developed, using a Back Propagation (BP) approach, and was shown to perform better than RSM for predicting machining force during milling.	
Glass Laminate Aluminium Reinforced Epoxy (GLARE)	Drilling	Carbide	-Multiple linear regression, a supervised machine learning (ML) model, was applied to predict thrust force based on drilling parameters.	2022 [123]
GFRP	Drilling (twist, slot, spur)	Carbide	-LR (Linear Regression)	2022 [124]
CFRP	Milling	Carbide	-Artificial Neural Network (ANNs)	2022 [125]
WGFRE	Drilling	Carbide	-A Hybrid ANN-PSO (Particle Swarm Optimization) model was employed to predict and optimize drilling parameters, focusing on torque and delamination factor outcomes. -Response Surface Methodology (RSM) was also used alongside ANNs-PSO to establish a correlation between drilling parameters and process responses	2022 [126]
CFRP	Turning	Polycrystalline diamond (PCD)	-Fuzzy logic -Artificial neural network (ANNs)	2022 [127]
(HDPE reinforced with Washingtonia filifera fiber	Drilling	High-speed steel (HSS) coated with Titanium Nitride (TiN)	-Response Surface Methodology (RSM) and Artificial Neural Network (ANNs) models	2022 [128]
CFRP	Electrical Discharge Machining (EDM) using aluminum as a fixture plate for guiding the electrode	Copper electrode in EDM	-A Grey Relational Analysis (GRA) approach was utilized for multi-quality analysis. -An Artificial Neural Networks (ANNs) model was implemented and trained using experimental datasets to predict hole quality attributes like circularity, taper, material removal rate, and tool wear rate.	2022 [129]
GFRP	Turning	Tungsten carbide	-Artificial Neural Network (ANNs) model was developed for estimating cutting force and surface roughness during the turning of GFRP.	2022 [130]
CFRP	Edge trimming	Polycrystalline diamond (PCD)	-Statistical model	2021 [131]
Graphite-epoxy laminate	Drilling	Not specified	RNN (Recurrent Neural Network)	2021 [132]

Composite Type	Machining Operation	Cutting Tool	ML Algorithm/Remark	Year and Ref.
GFRP	CO_2 Laser Micro-Milling	CO_2 Laser with variable beam diameters	-Artificial Neural Network (ANNs) with a 3-6-6-3 architecture	2021[133]
NFRP	Orthogonal cutting	Polycrystalline diamond (PCD)	-Random Forest (RF)	2020 [134]
CFRP	Drilling	Tungsten carbide-cobalt	-The study used statistical analysis and empirical modelling (ANOVA, regression models) to relate drilling parameters to outcomes like thrust force and torque.	2020 [135]
Aramid/Phenolic	Milling	High Speed Steel (HSS)	-k-nearest neighbour (kNN) -Decision Trees (DT) -Support Vector Machine (SVM)	2019 [136]
Aramid/phenolic	Milling	High Speed Steel (HSS)	-k-nearest neighbour (kNN) -Decision Tress (DT), -Support Vector Machine (SVM)	2018 [137]
CFRP	Abrasive Waterjet Machining	Waterjet with garnet abrasive	-Adaptive Neuro-Fuzzy Inference System (ANFIS)	2017 [138]
UD-CFRP	Orthogonal Cutting	Carbide	-Artificial Neural Network (ANNs) -Radial Basis Function (RBF)	2016 [139]
CFRP	Helical Milling	Tungsten carbide	-Artificial Neural Networks (ANNs) with back-propagation (BP) learning algorithm	2016 [139]
CFRP	Drilling	Carbide	-Logical Analysis of Data (LAD)	2015 [140]
CFRP	Helical Milling	Tungsten carbide	-Artificial Neural Network (ANNs) with back-propagation learning, used for predicting delamination	2014 [141]
GFRP	End Milling	Cemented carbide end mills (2, 3, 4 flutes)	-Artificial Neural Network (ANNs) with Levenberg-Marquardt (LM) learning algorithm	2013 [142]
Woven Graphite Epoxy	Drilling	Carbide	-Logical Analysis of Data (LAD)	2012 [143]
CFRP	Drilling, milling	Tungsten Carbide, PCD	-Artificial neural network (ANNs)	2011 [144]
CFRP	End milling	Carbide	-Committee Neural Networks (CNNs) was developed to predict specific cutting energies (Kc and Kt) for orthogonal cutting, which was then applied to helical milling.	2010 [145]
GFRP	Turning	Polycrystalline Diamond (PCD)	-The study used Digital Image Processing (DIP) techniques to evaluate surface roughness by analysing images captured during machining.	2009 [146]

Composite Type	Machining Operation	Cutting Tool	ML Algorithm/Remark	Year and Ref.
			-A second-order quadratic model was developed using Response Surface Methodology (RSM) to predict surface roughness (Ra) based on machining parameters. -The average gray scale value (Ga) from images was correlated with Ra values, showing a strong relationship useful	
PEEK with 30% Carbon Fibre	Turning	Cemented Carbide	-ANNs with Error Back-Propagation Algorithm	2008 [147]
CFRP	Drilling	Core drill with diamond grit	-Taguchi Method used for optimizing drilling parameters to reduce thrust force and surface roughness rather than a direct AI or ML model	2007 [148]
GFRP	Turning	Cermet	-Artificial neural networks (ANNs) -RSM	2006 [149]
UD-FRP	Milling	Carbide	-The study utilized non-linear regression and Committee Neural Networks (CNNs) to model cutting forces in FRP materials.	2005 [150]
CFRP	Drilling	Carbide-tipped twist drills	-No specific AI algorithm, the following sensors were used for real-time feedback (Acoustic emission sensors, vibration sensors, force sensors)	2000 [151]

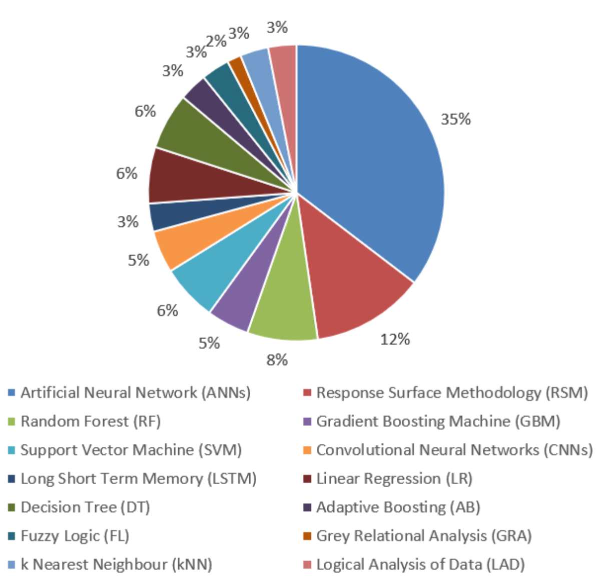


Figure 9 Different type of machine learning and the distribution from this review

6.0 ASSESSING CURRENT ADVANCES

Each of the composite machining techniques discussed has contributed to improvements in how these materials are processed. However, several weaknesses remain that need to be addressed, such as issues with vibration and delamination. High-speed machining, for instance, is often considered economically unviable when the total costs are considered. Similarly, while ultrasonic-assisted machining successfully mitigates heat generation and tool wear, the high tooling costs remain unavoidable. Additionally, achieving precise parameter control is challenging. Laser-assisted machining offers excellent accuracy, but it requires careful management of thermal effects to prevent damage to the polymer matrix. Lastly, water jet machining necessitates post-processing because the rough edges produced by this method are unsatisfactory, despite its well-known versatility.

While there are currently no perfect composite machining techniques, research in this field has shown promising progress. Future studies are expected to incorporate hybrid machining methods, which involve the simultaneous combination of several machining techniques. Hoghoughi *et al*. for instance, [152] evaluates the sustainability of hybrid machining using linear and pit-shaped tool textures with PTFE solid lubricants. This study was focusing on energy consumption, carbon emissions, production rate, cost, and operator health/safety. It was found that a linear textured tool in dry machining conditions was identified as the most sustainable option. The highest Sustainability Index (52.5) was achieved due to its balance of environmental, economic, and social benefits.

Mahbub *et al*. [153] explores hybrid and sequential machining processes, combining conventional and non-conventional techniques like EDM, ECM, and laser machining to enhance precision, productivity, and surface quality for hard-to-machine materials. By integrating methods such as vibration assistance and powder mixing or sequencing EDM with ECM. It was found that significant improvements in machining efficiency, tool life, and surface integrity were observed.

Kumar *et al*. [154] studied milling process of graphene/carbon/epoxy nanocomposites. The study utilised a hybrid optimisation method combining the Grey Relational Analysis (GRA) and Principal Component Analysis (PCA) techniques to optimise multiple conflicting machining responses (material removal rate, cutting force, and surface roughness). By utilising a grey-PCA hybrid optimisation method, optimal parameters (cutting speed, feed, depth of cut, and graphene content) were identified, demonstrating a notable enhancement in machining quality and productivity, with MRR increasing from 3.793 mm^3/min to 17.64 mm^3/min and surface roughness improving from 1.120 μm to 0.750 μm. Additionally, the implementation of machine learning and data analytics is anticipated to reduce reliance on traditional methods for optimizing machining parameters. Real-time data monitoring during machining processes will provide better insights, allowing for more accurate real-time data processing with the assistance of these techniques. Despite the various techniques developed and innovated in composite machining, there is still significant room for improvement, particularly regarding quality and efficiency. Each machining technique relies on finding the right balance between cost, precision, and the desired material properties. Research is ongoing, especially in hybrid machining. With advancements in the field, hybrid machining techniques and data-driven research will undoubtedly be the focal point for the next five years.

7.0 RESEARCH GAPS AND FUTURE RESEARCH

From our review, we found that hybrid machining is emerging as a highly promising research area for enhancing the efficiency, accuracy, and sustainability of composite material machining. Conventional machining techniques, such as milling and drilling, often face limitations such as excessive tool wear, delamination, and heat-induced defects, which reduce the quality and reliability of machined composite components. Future research in composite machining should focus on hybrid machining techniques that combine the benefits of various processes, such as ultrasonic-assisted laser machining and cryogenic water jet cutting, to address key challenges, including delamination, tool wear, and surface roughness. Implementing adaptive AI-driven control systems for real-time adjustments of machining parameters could further enhance process efficiency, especially when working with materials that have complex, anisotropic properties. Advancements in machine learning, particularly deep learning, hold promise for improving predictive modeling of tool wear and surface quality. Incorporating explainable AI (XAI) into these models can clarify the impact of specific variables. For instance, fibre orientation and cutting speed on machining outcomes, enabling more precise parameter optimization.

Another promising avenue is the integration of digital twins, which are virtual models that simulate and predict machining performance in real-time. Combined with machine learning, digital twins could optimize composite machining in a simulated environment before actual production, reducing trial-and-error and enhancing accuracy.

Sustainable approaches are also crucial. Developing AI algorithms that minimize resource usage and emissions could help meet global environmental targets, reducing the ecological footprint of composite manufacturing. Current trends in AI and machine learning in composite machining focus on defect detection, material property optimization, and improved design processes. These technologies are poised to transform the field, providing unprecedented insights and efficiencies that will lead to more accurate and sustainable manufacturing processes.

8.0 CONCLUSIONS

In conclusion, machining composite materials presents three main challenges: thermal sensitivity, tool wear, and delamination. Various approaches have been employed to address these issues, including ultrasonic-assisted machining and water jet machining. Despite these advancements, several limitations remain. Firstly, most machining techniques require specialised equipment with high operational costs, limiting their adoption in smaller manufacturing setups. Secondly, while AI-driven models show promise in optimising machining parameters, their effectiveness depends on high-quality training data, which is often limited due to the complexity and variability of composite materials. Thirdly, environmental concerns, such as coolant disposal and energy-intensive processes, remain a challenge.

Interdisciplinary collaboration among materials scientists, AI specialists, and engineers is crucial for developing customized machining strategies, such as AI-optimized cutting tools for specific composites. The integration of explainable AI promotes transparency, allowing engineers to better understand machining parameters and build trust in AI-driven technologies. Future studies should focus on sustainable machining approaches, optimising resource efficiency, lowering emissions, and enhancing workplace safety. Hybrid machining, combining laser-assisted and ultrasonic-assisted techniques, offers a promising solution to issues like tool degradation and thermal effects. Furthermore, AI-powered sensor systems can enable real-time adaptive machining.

While cryogenic cooling and other alternative solutions show potential, each approach has trade-offs in cost, complexity, and material compatibility. As composite applications expand, research should continue refining these techniques and exploring hybrid approaches that leverage multiple machining strengths. These efforts will be vital in improving efficiency, quality, and unlocking the broader potential of composite materials in high-performance sectors.

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Conflicts of Interest

The authors declare that there is no conflict of interest regarding the publication of this paper.

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