STUDY ON MECHANICAL AND MACHINING PERFORMANCE OF CARBON NANOTUBE REINFORCED ALUMINUM METAL MATRIX COMPOSITE

By

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It is hereby declared that this thesis or any part of it has not been submitted elsewhere for the award of any degree or diploma.

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ABSTRACT

In modern material science, engineers are constantly attracting and striving to develop nanohybrid Aluminum based Metal Matrix Composite (AMMC) materials due to their outstanding tribological, microstructural and mechanical qualities like lightweight, ductile, highly conductive, superior malleability, high strength and high specific modulus. Moreover, the demand for Aluminum based Metal Matrix Composite is increasing day by day because of their massive applications in various automobile, military, aviation, aerospace, structural, transportation, marine and other manufacturing industries due to their high stiffness, high strength-to-volume portion, deterioration resistance, and exceptional wear resistance. Nano particles like CNTs, Silicon Carbide and Alumina have created a great impact to produce advanced engineering composites. The mechanical and thermal property upgrades accomplished by expansion of CNT in Aluminum metal lattice frameworks. The addition of Carbon Nanotubes potentially helps in further improving the tensile strength of the metal matrix composite. So, Metal matrix composite with nano tubing provide enhanced mechanical features compared to traditional reinforcement.

In this research work, mechanical properties and machinability of carbon nanotube reinforced aluminum metal matrix composite has been compared with traditional aluminum metal matrix. Moreover, turning operation of carbon nanotube reinforced aluminum metal matrix composite was performed under both dry and MQL cooling condition. Cutting speed, feed rate and depth of cut have been considered as input cutting parameters whereas resultant outputs are cutting temperature, surface roughness, cutting force and tool wear. It is found that application of MQL resulted in maximum 16.62%, 31.28%, and 27.58% lesser cutting temperature, surface roughness, and cutting force by than machining without any fluid. Using response surface methodology, optimum cutting condition has been found while machining fabricated composite under MQL condition, the optimum cutting parameters which yielded the desired surface roughness R_a = 1.03μm, is follows: 1 mm of t, 168 m/min of V_c and 0.103 mm/rev of feed rate. Finally, A predictive model of surface roughness was developed using artificial neural network (ANN) which has been validated against the experimentally found results. For ANN developed model, regression value is found to be 0.98 for carbon nanotube reinforced aluminum metal matrix composite under MQL condition which is very close to 1, thus justifying the efficacy of the developed model.

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List of Abbreviations

MMC	:	Metal Matrix Composite
AMMC	:	Aluminum Metal Matrix Composite
CNT	:	Carbon Nano Tube
MWCNT	:	Multi Walled Carbon Nano Tube
MQL	:	Minimum Quantity Lubrication
SEM	:	Scanning Electron Microscope
RSM	:	Response Surface Methodology
ANN	:	Artificial Neural Network
ANOVA	:	Analysis of Variance

List of Symbols

V_c	:	Cutting Speed
S_0	:	Feed rate
t	:	Depth of Cut
T	:	Cutting Temperature
R_a	:	Average Surface roughness
Pz	:	Main cutting Force

Chapter-1

Introduction

1.1 Introduction

A Composite material is a material made from two or more constituent materials with significantly different physical properties, when combined, produce a material with characteristics different from individual one. Many natural and artificial materials are of this nature, such as: reinforced rubber, carbon, filled polymers, mortar and concrete, alloys, porous and cracked media, aligned and chopped fiber composites, polycrystalline aggregates (metals), etc. This type of composite is used extensively throughout our daily lives. Common everyday uses of fiber reinforced metal composites include: Aircraft, Boats and marine, Sporting equipment, Automotive components, Wind turbine blades, Aerospace and space industry (landing gears and aircraft brakes) Catalysts, Sensors. [**Hashin Z. 2009**]. Metal matrix composite materials (MMC) represent a good solution for environmental problems caused by the emissions of vehicles and reduce their overall weight by increasing specific mechanical properties of structural materials. In the last years, aluminum is one of the most studied structural materials to produce MMC due to its large use in different industrial sectors like: aeronautical, nautical and automotive in which the low weight of vehicles is very important [**Alam and Kumar 2016**]. Aluminum is a very useful structural metal employed in different industrial sectors, in particular it is used in large quantities in automotive, aeronautic and nautical industries. The main reasons of its wide use are: a very good oxidation resistance, excellent ductility, low melting temperature and low density. However, the demand for aluminum and its alloys having some much higher technological properties is increasing massively [**Bavasso et al. 2016**]. Different type of reinforcements can be used to produce Al-composites that can be different in chemical composition, structure and size. Nanotechnology is a rapidly expanding field which is developing in different sector, due to the high reactivity of materials in nanoscale, for example a number of studies on nanotechnology applications in environmental pollution have originated. [**Verdone and Palma, 2017**]. In particular, carbon is one of the mostly used reinforcement, that now a day, is available in different structure and size, like microfibers (CMFs), nanoplatelets (CNPs) and nanotubes (CNTs) [**Bartolucci et al. 2011**]. Aluminum Metal Matrix Composite (AMMCs) with nano tubing have some outstanding tribological, microstructural and mechanical qualities like lightweight, ductile, highly conductive, superior malleability, high strength and high specific modulus. Moreover, the demand of Aluminum based Metal Matrix Composite is increasing day by day because of their superior and applications in various automobile, military, aviation, aerospace, structural, transportation, marine and other manufacturing industries [**Maurya R et al. 2016**].

In recent years, CNTs have created a great impact to produce advanced engineering composites, with the development of CNTs reinforced polymer, ceramic and metal composites. CNT possesses outstanding mechanical qualities, better young modulus, higher strength and low thermal expansion, which have resulted in increased attention in CNT-matrix composite research and metal matrix composites possesses higher specific strength, higher wear resistances, low density compared to currently available alloys [**R. Raja et al. 2021**]. Metal matrix composite with carbon nano tubing should also provide enhanced features such as higher specific strength, exceptional strength, increased hardness in combination, low weight, exceptional strength, and rigidity, and an increased hardness in combination with or replacing traditional reinforcement. compared to currently available alloys [**Chen M et al. 2018**]. Carbon nanotube-based alumina nanocomposites had better hardness due to the CNTs' load-bearing capacity and increased fracture toughness. Due to strong Van der Waals forces between the atoms, CNT nano particles tend to clump together, making it harder to dampen and overcome the matrix's surface tension [**Zhou M et al. 2017**]. Compared to 2024Al base material fabricated young’s modulus of the composite, tensile strength, were improved massively if a small amount of CNTs were added to the matrix also microstructure characteristics can be changed too [**Cha et al. 2005**]. The injection of 2.0 wt.% CNTs to the 2024 aluminum alloy resulted in significant grain refinement. The wear rate of independently reinforced n-Al2O3 composites was lower than that reinforced CNTs, although the coefficient was larger. Also, the MWCNTs (Multi walled Carbon Nanotube) largely improve matrix strength and hardness, hence achieving improved resistance to plastic deformation and reducing the plowing impact of the matrix reinforcement [**Kurita et al. 2011**]. Carbon Nanotubes (CNT) have novel attributes that make them an appropriate strengthening operator in

Aluminum (Al) Metal Matrix framework. Strengthening with CNT prompts increment in quality without significant increment in weight. The mechanical and thermal property upgrades accomplished by expansion of CNT in Aluminum metal lattice frameworks. When Silicon Carbide and Alumina is added it helps in furthering the thermal conductivity and melting point properties of Aluminum in addition to improving its hardness. The addition of Carbon Nanotubes potentially helps in further improving the tensile strength of the metal matrix composite.

There are different types of CNTs and they can be classified in single walled carbon nanotubes (SWCNT), double walled carbon nanotube (DWCNT) and multi walled carbon nanotube (MWCNT). The SWCNT consist of a single plane of graphene wrapper to create a cylindrical structure with a diameter of 1-2 nm. The DWCNT and the MWCNT consist of two or more SWCNT to form a coaxial cylindrical structure can be produced via several techniques like electrolysis, laser ablation, chemical vapor deposition arc discharge and son chemicals [**Marini et al. 2017**]. Carbon nanotube (CNT) has been considered as an excellent nano particle which have maximum thermal conductivity (3000 W/m-K) than any other nano particles used so far [**Sadri et al. 2014**]. CNTs based metal matrix composite has a broad range of current and future applications. Young's modulus of the composite, tensile strength and wear resistance were improved massively if a small amount of CNTs added to the matrix also microstructure characteristic. Nanohybrid materials are typically selected for engineering applications since they have a correct organization of mechanical qualities. Metal Matrix Nano Composites (MMNCs) are obtaining large applications in aerospace, marine, defense, and automobile markets due to their high stiffness, high strength-to-volume portion, deterioration resistance, and exceptional wear resistance. The advantages of Carbon nano tube reinforced aluminum metal matrix composite include (i) Higher specific strength than traditional composite (ii) higher wear resistances and rigidity, (iii) Low density and low weight (iv) Low thermal expansion and (v) Increased hardness and better young modulus. Some potential applications of carbon nano tube reinforced aluminum metal matrix composite are shown in **Table 1.1**

Table 1.1 Potential applications of Carbon nano tube reinforced aluminum metal matrix composite. [**S.R. et. al 2010**]

Areas	Advantages
Automobile industry: gears, brake pads, piston rings and cylinder liners.	Higher specific strength, higher wear resistances and rigidity.
Electronic packaging industry: Solders and heat sinks for thermal management.	Low thermal expansion.
Sports industry: badminton and tennis rackets and light weight bicycles.	Low density, low weight, exceptional strength.
Aerospace and space industry: landing gears, aircraft brakes, structural radiators and high gain antenna boom.	Better young modulus, higher strength
MEMS and sensors battery and energy storage: hydrogen storage materials, micro-beams and micro-gears, anodes and anode coatings.	Increased hardness and resistance.
Other Applications: Military, Structural Marine, turbine blades, etc.	Light weight with excellent strength

Stir casting and powder metallurgy has been the most common and preferred CNT-AMC production method mainly due to agglomeration and floating because of density issues. However, liquid state production is cheaper for bulk production and intricate parts compared to others. In order to achieve optimal performance for the composite, an exceptional and homogenous matrix of interfacial bonding plus good reinforcement are very crucial. The mixture has to be electromagnetically stirred and later ultrasonically vibrated [**Xiang et al. 2017**]. Basically, the production of CNT-AMC can be grouped into five categories:

- Solid state (powder metallurgy)
- Liquid state (stir casting)
- Thermal spray
- Electro-chemical deposition
- other novel techniques

Metal cutting is a process of material removal in which the loss of materials is caused by effecting a relative motion between tool and work piece. It involves complex thermo-mechanical phenomena, such as high strain rate at the primary shear zone frictional contact interaction between the chip and tool at the secondary shear zone and elevated temperature in the chip induced by mechanical energy dissipation. Cutting performance can be improved enormously by controlling the chip tool interfacial temperature rise and frictional effects using a coolant/lubricant [**Kramar and Kopac 2009**].

In this research work, carbon nanotube reinforced aluminum metal matrix composite has been developed by stir casting process where different weight percentages of CNTs, Silicon carbide and aluminum oxide dispersed in pure aluminum bar. The most difficulties in the preparation of this type of composite are represented by the low wettability between metallic matrix and fillers and the possibility of the oxidation of metal during melting with consequent decreasing of mechanical proprieties. Then, different mechanical properties such as tensile strength, impact strength, flexural strength, and hardness of the fabricated composite has been carried out with a view to studying the effects on the mechanical performance of the composite. Moreover, different machining performances of carbon nanotube reinforced aluminium metal matrix composite were investigated asmachining play’s important role in producing product from different types of material ranging from soft to hard. Though, the characteristics that make composite material parts perform so effectively also make the materials more difficult to machine. Manufactured products qualities are determined by their surface quality. The high friction between tool and work piece leads to high temperatures, tool wear, and poor surface quality. Turning operation has been performed at different speeds, feed, and depth of cut. Then different output parameters such as cutting temperature, cutting force, tool wear and surface roughness recorded with the help of thermocouple, dynamometer, scanning electron microscope, and surface roughness tester respectively. Machining parameters optimized using the RSM model where the statistical significance of each cutting parameter and their interaction also studied in turning offabricated composite material. Finally, A standard multilayer feed-forward back propagation hierarchical neural network method was applied for the prediction of surface roughness. So, the whole thesis can be divided into four basic parts. In the first part, fabrication of carbon nano tube reinforced aluminum metal matrix composite for this research work has been presented. In the second part, mechanical properties of carbon nano tube reinforced aluminum metal matrix composite tested. In the third part, experimental investigation of the machining of composite material conducted under dry and MQL machining environments. In the final part, for predicting surface roughness an artificial neural network model will be developed and machining parameter will be optimized using response surface methodology (RSM).

1.2 Literature Review

Composite materials have been developed by several sectors over the past few decades in response to rising demand for materials that may enhance the overall performance of marine, aircraft, and automobile components. Aluminum is one of the most studied structural materials for making Metal Matrix Composites (MMC) because it is used so often in above mentioned industries. However, their usage is restricted in particular applications because to their low hardness and subsequently low wear resistance. Particulate reinforcements in aluminum metal matrix composites (Al-MMCs) are regarded as the most promising approach to improving these drawbacks. A review of the literature connected with the work is presented in this section. The topics covered also highlight the latest developments in the areas related to the present work. The advantages of nanoparticles-based aluminum metal matrix composite in mechanical properties and optimization of machining parameters using different tools are presented. A brief review of some of the interesting and important contributions in the closely related areas is presented in this section.

1.2.1 Research on Aluminum based Metal Matrix Composite

A great number of researchers have analyzed the various properties and applications of aluminum-based composites using a variety of reinforcing materials. Dwivedi et al. [**2014**] discovered the hardness, tensile strength and fatigue failure of Al356-SiC composites. It was found that varying the SiC ceramic particle size increases the hardness, tensile strength, toughness, and fatigue life. The tribological behavior of aluminum nanocomposites was evaluated by Suresh et al. It was discovered that the wear characteristics of AA7075, such as wear rate and friction coefficient, decrease with the addition of Al_2O_3 and SiC powder [**Suresh S et al. 2019**]. In their study, Gayathri et al. [**2021**] created an aluminum metal matrix composite using stir casting method and uses waste alumina catalyst and nano Al_2o_3 as dual reinforcement. The composites underwent thorough microstructural analysis using a scanning electron microscope in order to test their hardness and tensile strength. It was discovered that the composites have better mechanical characteristics than pure aluminum. Shakil et. el. in their study aluminum-based, hybrid metal matrix composite was developed by stir casting method. As reinforcement materials, the amount of Al2O3 is always 1 wt.%, and the amount of SiC can be 0, 2, 4, 6, or 8 wt.%. Samples have been studied for their microstructure, mechanical properties, and how they wear. The results show that adding Al_2O_3 and SiC reinforcements to the aluminum Al-6103 grade matrix made the material harder and more resistant to wear. The hardest AMCs are those with 8 wt.% SiC and 1 wt.% Al2O3 [**Hossain S et al. 2019**].

Among different types of reinforcements, one widely utilized reinforcement in particular is carbon, which is now accessible in a variety of sizes and structures, including nanoplatelets, nanotubes, and microfibers (CNTs) [**Bartolucci SF et al. 2011**]. Since their discovery, CNTs have drawn a lot of attention from scientists, and their exceptional mechanical, electrical, and thermal properties are the main drivers of this interest. Manjunath in his research work created a hybrid Aluminum/Gr-CNT material with two nanoscale reinforcements (Graphene and CNT). Hybrid composites with varying weight percentages of graphene (1, 2, 3, and 5 Wt.%) and a fixed CNT content of 2 wt.% were made via stir casting [**Naik H R M et al. 2021**]. Deng et al. [**2007**] have worked on a cold isostatic press followed by a hot extrusion process, created a 2024Al matrix composite reinforced with 1.0 wt.% carbon nanotube (CNT). The composite's elongation does not change, but its tensile strength and Young's modulus are significantly improved. The exceptional mechanical qualities of CNTs and their bridging and pulling-out functions in the Al matrix composite are too responsible for the increase. Reddy and Anand [**2019**] by altering the CNT reinforcement weight percentage (0.4%, 0.7%, and 1.1%) of size 30 nm in Al 5056 matrix, nanocomposite materials are created using the stir method. With an increase in the weight percentage of reinforcement, it is discovered that the properties of Nano composites are significantly impacted. Gowda et al. [**2017**] have studied the wear characteristics of aluminum/B4C/CNT hybrid composites under different load conditions. The result shows that the reinforcement of aluminum by B4C and CNT, keeping B4C constant and increasing the percentage of CNT from 0 to 2% leads to significant improvement wear. The manufacture, microstructure, and tribological behavior of carbon nanotube reinforced aluminum composites against pure aluminum have been tested and showed that the CNT reinforced composites displayed lower wear rate and friction coefficient compared to the pure aluminum under mild wear conditions [**Manikandan et al. 2016**]. Uniaxial tensile tests were performed by Laha et al. [**2009**] with plasma spray formed (PSF) Al–Si alloy reinforced with multiwalled carbon nanotubes (MWCNTs). The elastic modulus of the composite increases by 78% as a result of the addition of CNTs. The tensile strength of the CNT reinforced composite slightly increased, while the strain to failure decreased by 46%. Due to its high strength-to-weight ratio, aluminum/carbon nanotube composite is a strong candidate material for aerospace applications. The dispersion of carbon nanotubes (CNTs) in molten metal is challenging due to their low density. Mansoor in his work investigated induction melting, a fairly distinct approach to facilitate the dispersion of CNTs in molten aluminum. A simultaneous increase in yield strength, tensile strength, ductility and hardness was observed [**Mansoor et al. 2016**]. Pham et el. [**2018**] prepared SiCp/CNT/Al6061 hybrid composites by spark plasma sintering. Mechanical properties and wear resistance of the hybrid composites were enhanced. The enhancement dues to the synergistic strengthening effect of hybrid reinforcements. A comparative study on the surface properties of Al−SiC−multi walled carbon nanotubes (CNT) and Al−SiC−graphene nanoplatelets (GNP) hybrid composites fabricated via friction stir processing (FSP) was observed and found that microstructural characterization reveals a more homogeneous dispersion of GNPs in the Al matrix as compared to CNTs [**Sharma et al. 2019**]. Shetty et al. [**2021**] carried out LM-12 aluminum alloy reinforced with different weight percentage of SiO2 and carbon nano tubes hybrid metal matrix composite development using stir casting method with sand mold technique. Further, heat treatment was carried out. it has been observed that expansion of particulates essentially enhances tensile strength and hardness. Saheb and Mohammad [**2016**] in their work synthesized Al2O3-SiC-CNTs hybrid nanocomposites by ball milling, sonication, and spark plasma sintering (SPS) at 1500 °C for 10 min. The influence of SiC nanoparticles and CNTs on the microstructure, densification, hardness, and fracture toughness of the composites was investigated.

In a critical review Thirugnanasambantham et al. [**2021**] concluded that CNT as support for Al lattice will enhance the thermal and mechanical properties such as elastic modulus, hardness, creeps and damping capabilities of the material. Al-CNT regarded as the next generation structural material for many functional engineering design applications. Their critical review investigation introduced here would be influential for fabricating a novel high-quality Al–CNT composites. Bakshi et al. [**2010**]. have focused on the critical issues of CNT-reinforced MMCs that include processing techniques, nanotube dispersion, interface, strengthening mechanisms and mechanical properties. Composites of carbon nanotubes (CNTs) dispersed in aluminum were fabricated by Marini et al. The most difficulties in the preparation of this type of composite are represented by the low wettability between metallic matrix and fillers and the possibility of the oxidation of metal during melting with consequent decreasing of mechanical proprieties. Young's modulus was evaluated at different temperature and correlated with the different CNTs percentage [**Marini et al. 2017**]. The effect of the CNT radius and content on the mechanical properties of CNT-Al composites was observed by Myung Eun Suk in his novel work using a series of molecular dynamics simulations, particularly focusing on MMCs with a high CNT content and large CNT diameter. As the CNT content increased, the strength and stiffness increased; however, the fracture strain was not affected [**Myung Eun Suk 2021**]. Herzallah et al. [**2020**] have examined how the size and quantity of CNT and SiC particles affect the mechanical characteristics of Al matrix composites. They discovered that adding more SiC and CNT results in a decrease in the relative density and an increase in the hardness and compressive strength of Al-SiC and Al-CNT composites. Moreover, multi-walled carbon nanotubes (0.166, 3.33%) and 5% SiC was used for the reinforcement to fabricate aluminum alloy 5083 by stir casting process and tensile strength was discovered to have increased by 18% [**Jannet et al. 2020**].

1.2.2 Mechanical Behavior of Aluminum Metal Matrix Composite

In today's modern world the need for more efficient material is very significant for the development of new products. For these composites play a major role as it has strong load carrying material embedded in weaker material. Reinforcement provides strength and rigidity to help and support the structural load. Researchers have observed various results in production of Al-CNT composites, some have obtained significant increase of strength [**Mokdat et al. 2016**], other ones have observed irrelevant increase or decrease of some properties of composite [**Simões et al. 2015**]. Many of these different results depends on the quality of fillers dispersion, composite fabrication process and interfacial interaction between matrix and fillers. Filler's dispersion is another one crucial problem in preparation of Al-CNT composites, due to the tendencies of CNT to form agglomeration due to the Van der Waals interaction. In this work, the MMC were obtained by the aid of an induction furnace with centrifugal casting and atmosphere control system to avoid the metal oxidation. It was demonstrated that the induction melting allows to obtain a good dispersion of fillers in the melting matrix [**Mansoor and Shahid, 2016**]. Furthermore, to prevent the agglomeration problem, the nanotubes were functionalized by superficial treatment in order to decrease the interaction forces. Metal matrix composites are widely used for outstanding mechanical properties. Novel hybrid composite, like MWCNT coated SiC as the reinforcement in A356 enlighten that the accumulation of the precise amount (1.5%) of carbon nanotubes significantly improved the tensile strength (229 MPa), hardness (305 MPa), impact strength (4J) and elongation percentage (6.1%) by the semi-solid stir casting process. In addition, the combination of 10% of SiC and 1.5% of MWCNT with the A356 have increased tensile strength by 189.25%, hardness by 133.83%, elongation by 186.54% and impact strength by 200% as compared with base alloy [**Sangeetha et al. 2021**].

To determine the effect of a variety of embedded optical fibres on the properties of carbon/epoxide composite systems a programme of mechanical testing has been carried out. Both the polyimide and acrylate coated fibres with diameters of approximately 100µm had little adverse effect on the mechanical properties of any of the composites, except in longitudinal compression were up to 26% reduction in strength was seen in some systems [**Roberts and Davison 2021**]. Imran and Khan [**2021**] have focused on mechanical properties, tribological properties and corrosion behaviour of Al-7075 metal matrix composites (AMMCs) by the addition of desirable reinforcements. These particulate reinforcements Sic, Al_2O_3, Gr, TiO_2, bagasse ash etcetera is incorporated in the stir casting method. Corrosion resistance and superior wear, low coefficient of thermal expansion as compared to conventional base alloys revealed the significant improvement in mechanical properties. The mechanical investigation and fabrication of Al alloy, alumina and boron carbide metal matrix composites are dealt with whereas reinforcements, aluminium which is the matrix metal having properties like light weight, high strength and ease of machinability, alumina which as better wear resistance, high strength, hardness and boron carbide which has excellent hardness and fracture toughness are added. Mixing the required quantities of additives into stirred molten aluminium, the fabrication is done by stir casting. The samples are prepared and tested to find the various mechanical properties after solidification. By using Scanning Electron Microscope (SEM) the internal structure of the composite is observed [**Vijaya Ramnath et al. 2021**]. By hot extrusion of elemental Al powder blended with different amounts of metallic glass reinforcements Al-based metal matrix composites were synthesized through powder metallurgy methods. By controlled milling of melt-spun $Al_{85}Y_8Ni_5CO_2$ glassy ribbons the glass reinforcement was produced. At temperatures within the supercooled liquid region the composite powders were consolidated into highly dense bulk specimens. By the addition of the glass reinforcements the mechanical properties of pure Al are improved. For the samples with 30 and 50 vol.% of glassy phase the maximum stress increases from 155 MPa for pure Al to 255 and 295

MPa, respectively. Composites exposition appreciative ductility with a strain at maximum stress ranging between 7% and 10%. Glass-reinforced composites can be modelled by using the iso-stress Reuss model [**Scudino S. et al. 2021**].

Mechanical properties, fabrication techniques and surface texture of aluminium matrix composites (AMCs) reinforced by silicon carbide (SiC). varying SiC content in AMCs is (0,5,10,20 Wt.%) were fabricated by stir casting process. Hardness, Tensile strength, Toughness and Microstructure of composites were analysed as mechanical properties. Reinforcement of silicon carbide into Al matrix increased tensile strength and hardness, maximum tensile strength shows at 20 Wt.% SiC reinforced in AMCs, which increase the porosity into the composites and also decrease the ductility [**Shukla et al. 2021**]. The composites Al6061-SiC & Al6061-SiC/Graphite hybrid were prepared using stir casting method in which amount of reinforcement is varied from 5-15% in steps of 5Wt.%. Uniform distribution of the particles in composites with clustering at few places were revealed by the microphotographs of the composites. The tensile strength of the composites was enhanced because of the contribution of dispersed graphite and SiC in Al6061 alloy. Without any voids samples indicated uniform distribution of the reinforcement particles in the matrix [**Krishna et al. 2021**]. By varying the treatment parameters (temperature & duration), heat treatment has potential to produce a desired combination of properties in aluminium graphitic composites. It is possible to optimize the properties of metal matrix composites by choosing the balance of the reinforcing phases, together with some technology parameters of the manufacturing process. The composites were made by Vortex casting and based on a commercial aluminium alloy, with either single-phase or two-phase (hybrid) reinforcing particles which are graphite and silicon carbide, concentrations up to 10 vol.%.

By powder metallurgy Al based metal matrix composites consisting of pure Al reinforced with different amounts of mechanically alloyed $Zr_{57}Ti_{8}Nb_{2.5}Cu_{13.9}Ni_{11.1}Al_{7.5}$ glassy powder were produced. In order to take advantage of the viscous flow behaviour of the glassy powder the samples were consolidated into highly dense bulk specimens at temperatures within the supercooled liquid region. While retaining appreciable plastic deformation with a fracture strain between 70% and 40%, compression tests show that the addition of the glass reinforcement increases the strength of pure Al from 155 to 250 MPa. Such composites containing a high-volume fraction of glassy particles were accurately modelled using a shear lag model [**Scudino S. et al. 2021**]. Boopathi [**2021**] have crated compositions of aluminium-Sic-fly ash were added up to the ultimate level and stir casting method was used for the fabrication of aluminium metal matrix composites. X-ray diffraction studies and optical microscopy was used for the micro structural studies. The density of the composites, elongation of the hybrid metal matrix composites in comparison with unreinforced aluminium was decreased and the hardness, tensile strength was increased in the presence of Sic and fly ash [SiC (5%) + fly ash (10%) and fly ash (10%) + SiC (10%)] with aluminium. Instead of aluminium-SiC and aluminium-fly ash composites, aluminium in the presence of SiC (10%)-fly ash (10%) was the hardest. The mechanical properties of pure Al were remarkably improved by the β-Al_3Mg_2. While retaining appreciable plastic deformation ranging between 45% and 15%, the composites with 20 and 40vol.% reinforcement display yield and compressive strengths exceeding that of pure Al by a factor of 2-3. For affecting the properties of the composites modelling of the mechanical properties reveals that the matrix ligament size plays a dominant role. The specific strength of the composites was increased by the addition of low-density β-Al_3Mg_2 particles [**Scudino S. et al. 2021**]. By uniaxial hot-pressing Al-based composites reinforced with Mg-based metallic glass particles were synthesized. Within the supercooled liquid region of the metallic glass reinforcement the composite powders were consolidated into highly dense bulk specimens. Incorporating the matrix-strengthening mechanism the relationship between the mechanical properties and the structure was investigated and described by a modified shear lag model [**Wang et al. 2021**]. By the stir casting method Al alloy matrix composites reinforced with hybrid can be successfully synthesized. The important process parameters are for synthesizing of hybrid composite by stir casting process, stirrer design and position, melting and pouring temperature, particle incorporation rate, reinforcement particle size and amount, stirring speed and time, particle-preheating temperature, mould type and size. The hardness, toughness, strength, corrosive and wear resistance of the composite will be increasing with the hybrid reinforcement instead of single reinforcement [**Krishnan et al. 2021**].

Four different combinations of composites ($AlSi_7Mg$ + alumina; scrap aluminium alloy + alumina; $AlSi_7Mg$ + spent alumina catalyst; scrap Al alloy + spent alumina catalyst) were produced for the purpose of comparison through the stir-squeeze casting process. Four composites the reinforcement formed a mixture in the eutectic silicon phase of the matrix alloy was influenced by the alumina particles size and content ratio. Among the four composites the scrap aluminium alloy + alumina exhibited the lowest porosity

(7.3%) and abrasive wear loss (0.11 mg for the finest abrasive), highest hardness (58.5 BHN) and second highest ultimate tensile strength (125 MPa) and ultimate compressive strength (312 MPa). When using alumina as reinforcement superior mechanical properties were obtained and better mechanical properties can mainly be attributed to the morphology of the reinforcement and silicon eutectic phase mixture [**Tjong 2021**]. Kumar et al. [**2021**] have processed for nanocomposites include aluminium and magnesium can be classified into ex-situ and in-situ synthesis routes. Ex-situ nanocomposites reinforced with very low loading levels of nanoparticles exhibit creep resistance and higher yield strength than their micro composite counterparts filled with much higher particulate content. Using appropriate processing techniques better dispersion of ceramic nanoparticles in metal matrix can be achieved. By adding ceramic nanoparticles mechanical strength and ductility can be obtained readily in aluminium or magnesium. For the nanocomposites reinforced with in-situ nanoparticles similar beneficial enhancements in mechanical properties are observed. Density and hardness of the AA5052/ZrB_2 composites increases with increase in the amount of reinforcement. With increase in the volume fraction of ZrB_2 particles up to 9 vol.% ultimate tensile strength and 0.2% yield strength improved continuously but beyond this composition strength reduced. An improvement in ductility was observed with dispersion of ZrB_2 particles in base alloy [**Kumar et al. 2021**]. Optimum amount of reinforcement and casting temperature were determined by evaluating the density and mechanical properties of the $A_{356}Al/ZrO_2$ composites. Reinforcing the Al matrix alloy with ZrO_2 particles, improved the hardness and ultimate tensile strength of the alloy to the maximum values of 70 BHN and 232 MPa. The highest mechanical properties were obtained by the specimen including 15% of ZrO_2 produced at 750^oC [**Abdizadeh and Baghchesara 2021**].

Lo S. et al. [**2021**] evaluated the mechanical properties of a Zn-Al alloy reinforced with alumina fibres tensile, compression and impact properties were determined at 25, 100 and 150°C. Although fibre reinforcement did result in some improvement of tensile and compression properties at elevated temperatures, the composites had poor toughness and ductility. Impairing the performance of the reinforced materials, the presence of a brittle SiO_2 layer at the fibre interfaces resulted in fibre decohesion under tensile loading. For the composite materials some improvement in wear resistance was noted but in fatigue resistance fibre reinforcement did not yield significant improvement. With different weight percentages of B_4C and 3 Wt.% of coconut shell fly ash (CSFA) the samples of Al7075 hybrid aluminium matrix composites (HAMC) were fabricated. The homogeneously distributed B_4C and CSFA particles added as reinforcement to improve the hardness, tensile strength and impact strength of the composites. By reinforcements of 12 Wt.% B_4C and 3 Wt.% CSFA in Al7075 alloy hardness of the composites increased 33%. By the addition of 9 Wt.% B_4C and 3 Wt.% CSFA in Al7075 alloy the tensile strength of the composites increased 66%. While increasing B_4C and CSFA reinforcements in the matrix elongation of the composites decreased. With 9 Wt.% B_4C and 3Wt.% CSFA addition in Al alloy the impact energy of the composites increased up to 2.3J. By a proprietary process metal matrix composites have been made by the addition of 10 µm diameter TiC particles to molten Al. Homogeneous and extensive grain refinement were observed by the resultant reinforcement distribution in commercial purity Al and 2XXX alloy matrices. Per volume percent of reinforcement added, the elastic modulus increases which are greater for Al-TiC composites. By the nucleation of solid Al on the Tic particle surfaces which were attributed to efficient load transfer in this system due to strong interfacial bonding [**Karantzalis et al. 2021**]. A model which was successful in predicting the experimentally observed strength and fracture toughness values of the Al_2O_{24}-SiC MMCs was proposed to suggest that the strength of the Al_2O_{24}-SiC metal matrix composite could be estimated from the load transfer model approach that takes into consideration the extent of clustering. It is suggested that the strength of particulate-reinforced MMCs maybe calculated from the relation: $\sigma_y = \sigma_m V_m + \sigma_r (V_r - V_c) - \sigma_r V_c$, where σ and V represent the yield strength and volume fraction, respectively and the subscripts m, r and c represent the matrix, reinforcement and clusters respectively [**Hong et al 2021**].

Harichandran and Selvakumar [**2021**] fabricated the micro and nanocomposites containing different weight % of B_4C particles using stir and ultrasonic cavitation assisted casting process and characterized by SEM and an X-ray diffractometer. The properties of the samples containing up to 6% nano B_4C reinforced composites were better than the micro B_4C reinforced composites according to the tensile test results. The ductility and impact energy of the nanocomposites were better than the micro B_4C particle reinforced composites. When the B_4C content was increased up to 8% of addition the wear resistance of the nanocomposite significantly increased, which was more pronounced. The in situ formed ZrB_2 particles enhanced the mechanical properties of AA6061 alloy and refined the microstructure. From 0 to 10 in steps of 2.5 the weight percentage of ZrB_2 was varied.

With the increase in ZrB_2 content improvement of hardness, ultimate tensile strength and wear resistance of AA6061 alloy was observed [**Dinaharan et al. 2021**].

1.2.3 Machining of AMMC under Minimum Quantity Lubrications

Minimum Quantity Lubrication (MQL) is a technique where the lubrication cost is minimized, for which total manufacturing cost or operational cost is reduced. It is a type of micro lubrication that allows for near-dry machining. This has been noticed through various studies on drilling, turning, and grinding operations. The lubricant reduces the friction between the cutting tool and the wok piece reducing the amount of heat generated in the process. Different type of material and composite can be machined through by MQL. Metals can be used as alloy components, but carbon, a nonmetal yet essential component of steel, can also be used for MQL condition. The aluminum alloy composite as a work piece which machined by lathe machine. The composite aluminum alloy made by following some specific step. Generally dry, flooded, MQL condition are applied for machining operation. In most of the case better surface roughness has been obtain in MQL condition. A combination of compressed air and a little amount of oil is referred to as minimum quantity lubrication or MQL [**Bashir et al. 2018**]. It replaces a significant amount of water and mineral oil-based cutting fluid with a small amount of water-based environmentally friendly lubricant. The performance of machining processes is affected by cutting fluid functions such as lubrication, cooling, and chip reddening. By this MQL method the lubricant is sprayed directly into the cutting zone, that’s why it provides high cutting performance without requiring a large amount of fluid flow. It’s improved the tool life and surface finish. In the case of MQL the lubricant has to be environmentally friendly [**Sharmin et al. 2020**]. The soil and water resources are harmed as a result of improper cutting fluid treatment, notwithstanding the significant benefits of utilizing the MQL approach. Cost reduction, energy efficient, waste reduction, management health and safety resource efficiency and green environment are the main sustainability objectives for MQL technique. The result shows that high range of effectiveness of sustainability is achieved by MQL nano fluid rather than other conventional/classical MQL method. For sustainability assessment there have no other condition without MQL technique. For MQL technique the cutting tool temperature is reduce there for the here reduce the tool wear [**Khan et al. 2009**].

Laghari et al. [**2018**]demonstrated modeling and optimization of tool wear and surface roughness in turning of Al/SiCp using response surface methodology. The experimental work is consisting of turning Al/SiCp (45%SiCp) weight with uncoated Carbide tools. The results reveal that the machining criteria like tool life and surface roughness are dominantly influenced by various process parameters. The optimal combination of machining parameters obtained, the maximum tool life is 10.511 (min) speed of 6.283 m/min, feed of 0.01 mm/rev, and 0.2 mm of depth and minimum surface roughness is 0.044 lm cutting speed 18.85 m/min, feed rate mm/rev 0.015 and depth of cut 1.5 mm and 45% of silicon carbide. The experimental values of turning Al/ SiCp 45 wt.% were compared with the obtained projected values and found the minimum error. Machining Characteristics on Surface Roughness of a Hybrid Aluminum Metal Matrix Composite (Al6061-SiC-Al_2O_3) indicates that the increase of cutting speed reduces the surface roughness and vice versa. The minimum surface roughness is achieved at a cutting speed of 60 m/min, feed rate of 0.20 mm/rev and a depth of cut of 0.50 mm [**Sasimurugan, T., & Palanikumar, K. 2011**]. In order to obtain reduced average surface roughness, it is recommended to use medium cutting speed, minimum feed rate and lower depth of cut [**Mia et al. 2017**].

Bansal & Upadhyay [**2016**] presented the effect of machining parameters on tool wear, surface roughness and metal removal rate of Alumina Reinforced Aluminum Composite has been observed in turning operation. Hardness and tensile strength increase with the reinforcement ratio. Tool wear increases with the process variables whether it is coated or uncoated tool, however tool wear is less in coated tool as compared to uncoated due to the coating. Surface Roughness increase with the process variables except the speed, speed made adverse effect on surface roughness. MRR increases with the process parameters except the concentration of reinforced particles due the presence of hard ceramic particles. The machinability of 2024 aluminium alloy reinforced with Al_2O_3 particles using varying size and weight fraction of particles up to 30 wt.% by a vortex method was carried out at different cutting conditions. The optimum surface roughness was obtained at a speed of 160 $mmin^{-1}$ while the maximum surface roughness value was found in the machining of the 10% Al_2O_3 composites with particle size of 16 mm. The surface roughness also increased with the increasing weight percentage of the particles [**Sahin et al. 2002**]. Kumar et al. [**2014**] made an effort to find out the effect of machining parameters on cutting force and surface roughness and also investigated the feasibility and dry turning characteristics of in situ Al–4.5%Cu/TiC metal matrix composites using uncoated ceramic inserts. When the wt.% of TiC reinforcement was increased, the tensile strength and hardness of Al–4.5%Cu/TiC MMCs improved better with reduced ductility. The formation of BUE was more prominent when the lower cutting speed was provided which is 40 m/min and continued to decrease with increasing cutting speed. Executing less than 10% of TiC reinforcements, mostly helical and C-types chips were produced at relatively higher cutting speed but in case of 10% of TiC reinforcements, discontinuous and short length chips were produced during the machining.

Cutting speed and depth of cut are the major cutting parameters affecting wear rate in carbide X500 and PCD inserts. Surface roughness R_a was not affected by the cutting parameters used when using PCD insert. Promising tool wear rates also were recorded under low levels of cutting speed and high levels of feed rate when using carbide insert X500 [**Kamalizadeh et al. 2019**]. Higher TiB_2 reinforcement ratio produces higher tool wear, surface roughness and minimizes the cutting forces. & Machinability of in situ MMC is different from traditional MMC, because of the presence of fine and uniformly distributed reinforcement, which reduces flank wear. When machining the in situ MMCs with high-speed causes rapid tool wear due to generation of high temperature in the machining interface. At high cutting speed machining will minimize chip tool contact length and build-up edge formation, which reduce the cutting force and surface roughness. The rate of flank wear, cutting force, and surface roughness are high when machining with a higher depth of cut. An increase in feed rate increases the flank wear, cutting force and surface roughness [**Anandakrishnan & Mahamani 2011**]. Siva et al. [**2013**] developed aluminum metal-matrix composite (AMC) is using a novel in-situ ceramic composite, converted from waste colliery shale (CS) material by heat treating in a plasma reactor under neutral atmosphere. The developed AMC has shown improved mechanical properties as compared to Al-Al_2O_3 and Al-Al_2O_3-SiC composites. The present study encompasses the machinability of the developed AMC as well as the other two composites. Plasma treated colliery shale has enabled development of in-situ ceramic composite comprising Al_2O_3-SiC-C. The AMC made with in-situ ceramic composite has shown better machinability in comparison to other AMCs made with Al_2O_3 and Al_2O_3-SiC for the same volume percentage. The graphite particles present on CS have helped in enhancing machinability. Minimum surface roughness is observed for Al-CS composite for all test conditions in comparison to other AMCs made with and Al_2O_3-SiC. The extent of tool wear is less for Al-CS composite in comparison to other AMCs made with Al_2O_3 and Al_2O_3-SiC [**Siva et al. 2013**]. The porosities of the fabrication of Al-4wt% Mg–

graphite and/or silicon carbide (SiC) particulate composites bars were found to expand with the increase of graphite and/or SiC content because of the vortex found because of the stirring action, which enhances the dissolution of gases and causes more bubbles to be formed inside the melt. In the case of SiC addition it was found that the Rockwell hardness was increased with an increase in the SiC content due to its high hardness. The surface roughness (Ra) of the cast composite bars was improved with the increase of the volume percentage of the graphite particles. This is due to the structure and lubricating action of the graphite particles. The addition of SiC particles causes the Ra of the composites to increase [**Hassan et al. 2007**].

Razavykia et al. [**2015**] has done an experimental investigation to find out the evaluation of cutting force and surface roughness in the dry turning of Al–Mg_2Si in-situ metal matrix composite inoculated with bismuth using design of experiment approach. The multilevel factorial design was used to examine the effect of cutting speed and feed rate which were set as 0.1–0.2 mm/rev and 70–210 m/min respectively and Bi addition on cutting force and surface roughness of Al–20%Mg_2Si in-situ composite. The result shows that the recommended optimum cutting conditions in machining of Al–20%Mg_2Si composite is found to be: cutting speed at 210 m/min and feed rate at 0.1 mm/rev in the presence of Bi. Predictive models for cutting force and surface roughness are statistically significant as p-value is less than 0.05 at 95% confidence level. An abrasive water jet turning of the newly developed hybrid MMC of A359/B_4C/Al_2O_3 produced by electromagnetic stir casting method and its main focus is to discuss the effect of process parameters of abrasive water jet machining on outcomes such as surface roughness and metal removal rate. Abrasive water jet turning processes can be successfully applied for the turning of hybrid MMC workpiece. The surface roughness is found in the range of 6.0545 μm to 8.3825 μm, which is quite higher. This is due to the plough nature of AWJ process with full of furrows and cutting traces which leads to the significantly higher surface roughness. Another reason of higher surface roughness is the dislodgment of reinforcement particles which are not able to cut during turning operation. The minimum and maximum MRR found in AWJ turning process is 434.72 mm^3/min and 565.02 mm^3/min, respectively. So, MRR varies from 434.72 mm^3/min to 565.02 mm^3/min [**Srivastava et al. 2019**]. In situ Al–Cu/TiB_2 MMCs are successfully synthesized using stir casting furnace. It is identified that tangential forces are decreasing due to the increase in temperature while increasing the cutting speed for MMCs and base alloy. In all cases, the surface roughness for MMCs was found to be less than the base alloy, except at low cutting speed due to the formation of BUE. Minimal BUE formation is observed at high speed for both MMCs and base alloy. It is observed that chip breakability improved due to the presence of reinforcement. The segmented chips are formed at higher feed. Both MMCs and base alloy exhibited almost similar chip shapes in all conditions considered in this investigation [**Senthil et al. 2013**]. Lin et al. [**2019**] made an effort to find out effect of tool nose radius and tool wear on residual stresses distribution while turning in situ TiB_2/7050 Al metal matrix composites. In order to have a deeper understanding of the residuals stress distribution during machining metal matrix composites, this paper investigates the effect of tool nose radius and tool wear on the residual stress distribution during turning TiB_2/7050 Al composites. Due to the existence of TiB_2 particles, the residual stress on the machined surface is always compressive. With the increase of tool nose radius, the surface residual compressive stress has a trend to decrease and the residual stress penetration layer becomes deeper. The tool wear has more significant effect on the residual stress distribution than the tool nose radius. The rate of flow of liquid on developed composite AA6061-ZrO_2 is the most influential factor which affected surface roughness and tool wear as their contributions were 43.58% and 39.1% respectively. The most optimal machining parameters and sequence to obtain minimum tool wear was cutting speed: 30 m/min, feed rate: 0.15 mm/rev, depth of cut: 0.5 mm, rate of flow of oil: 50 mL/h, and % reinforcement of ZrO_2: 5. This work also contributes to the development of a low-weight, high-strength composite material with the help of AA 6061 and ZrO_2 [**James & Annamalai 2018**].

Kannan et al. [**2020**] presented a study on surface roughness, tool wear and cutting force in turning of hybrid (Al7075 + SiC + Gr) metal matrix composites. This paper presents a detailed study on optimization of turning parameters of Al7075/SiC/ Gr metal matrix composites that are used for structural applications widely. For achieving minimum Ra, speed of 40 m/min and a moderate feed rate of 0.100 mm/rev and high depth of cut of 0.3 mm and material composition of 3%SiC + 7%Gr are found to be the optimal condition for the turning of the Al7075/SiC/Gr hybrid composite specimens. Ra, VB and F values were drastically reduced by 16%, 22% and 32% respectively due to the addition of 7wt% Gr with Al7075. The confirmation test revealed the improvement in surface finish as 16.02% while the tool wear and cutting force are reduced by 22% and 32.30% respectively. The wear rate of extruded Al-Al_2O_3 Composites increased rapidly with increasing the cutting parameters: cutting speed, feed and depth of cut, however cutting speed is shown to be more effective. Sudden breakage of tool inserts occurred when the experiment started at high cutting speed [**Fathy et al. 2012**]. Coated tools can increase the tool life with more than 3.3 times of uncoated tools, at cutting speed of 80 m/min. Wear rate of cutting tool increased as weight fraction of reinforcement particles was increased. Wear rate of cutting tool has also increased by increasing extrusion ratio from 4.4 to 9.5. However, the effect of weight fraction is more pronounced than extrusion ratio. Surface roughness of reinforcement composites has much lower values compared to matrix commercial purity alloy alone. Surface roughness of composites has slightly decreased as weight fractions of reinforcement particle are increased.

The effect of Al_2O_3, TiN and Ti (C, N) based CVD coatings on tool wear in machining metal matrix composites containing 10 wt.% SiC particles produced by liquid metallurgy was investigated at different cutting conditions. The results showed that the tool life decreased considerably with increasing particle size and cutting speed in machining the particle reinforced composite. The wear performance of TiN-coated tool was considerably lower than that of Al_2O_3-coated tool in machining the composites with various particle sizes. Cutting speed was also found to be more effective in machining the composite. Moreover, it was observed that mild abrasive was the main responsible mechanism for wear of the tool. Cast composites consisting of 10 wt.% SiCp with various sizes produced successfully by liquid metallurgy method. For cutting tools, tool A showed better performance than that of tool B. It was found that tool wear decreased considerably with increasing the particle sizes. It is shown that the tool life decreased with increasing cutting speeds in all cutting conditions. A lower cutting speed can be used for the machining of coarse particle- reinforced composites while a higher cutting speed can be allowed for the machining of fine particle- reinforced composites. It is observed that the major wear form of the tool was the abrasion on the flank face of the tool [**Sahin & Sur 2004**]. Tool wear increases with cutting speed (450 m/min) when machining AlSi/AlN metal matrix composite using uncoated carbide cutting tool. While at high cutting speed, the surface finish improves. It was found that the cutting speed of 750m/min was optimum condition for obtaining smooth finish and longer tool life. For the medium cutting speed (450m/min) is clearly showed that highest flank wear. The flank wear will occur in the beginning of cutting and increase during machining. We found the surface roughness is good for the high cutting speed (750m/min). The cutting tool was design for high-speed machining. Over all this insert is suitable for machining Al/AlN MMC for good surface finish in high speed machining as suggested manufacture [**Said et al. 2014**]. An experimental exploration on chip formation, surface roughness and cutting force measurement throughout the CNC milling operation of Al–4.5%Cu/TiC MMCs produced by the in-situ practice and compared the results with those for Al–4.5%Cu/SiC MMCs produced by ex situ technique and with Al–4.5Cu master alloy. Cutting force increases with the increase in the percentage of TiC and SiC particles in the composites. It was found that in machining Al–4.5Cu–SiC composites, cutting forces are comparatively higher as compared to those for Al–4.5Cu–TiC composites. Whereas in the case of Al–4.5Cu master alloy cutting forces developed are maximum. In machining Al–Cu–TiC composites no built-up edge formations was found, whereas in the case of Al–Cu–SiC light built-up edge and in machining of Al–Cu alloy built up edge formations was noted. Surface roughness of Al–Cu alloy was found to be maximum and in the case of both the metal matrix composites surface roughness increases as the quantity of TiC and SiC particles increases in the composites. In the case of Al–Cu–TiC composites surface roughness was found less as compare to Al–Cu–SiC composites [**Das et al. 2016**].

Machining characteristics of a silicon carbide particle reinforced magnesium metal matrix composite (SiCp/Mg MMC) has been studied. Abrasive wear of the flank face was observed to be the dominant tool-wear mechanism for all conditions within this study. It was observed that a greater depth of cut reduced the amount of tool wear for a given volume of material removed. Surface roughness values were within the range of 0.2–3.0μm. The chips formed from facing magnesium metal matrix composite with SiC particle reinforcement (3–4 μm) were saw tooth, continuous or semi-continuous chips. The primary wear mechanism on the tool was abrasion wear of the tool flank. The SiC reinforcement particles did not fracture during the machining conditions within this study. Achieved average surface roughness values were in good agreement with theoretical surface roughness [**Pedersen & Ramulu 2006**].An experimental study on tool wear behavior in micro milling of nano Mg/Ti metal matrix composites has been studied. This study exhibits an investigation on tool wear in micro milling of magnesium based MMCs reinforced with 1.98 Vol.% of nano-sized titanium particles using 0.5mm diameter two-flute tungsten carbide micro endmills. The tool wear was characterized both quantitatively and qualitatively by observing tool wear patterns and analyzing the effect of cutting parameters on flank wear, reduction in tool diameter, cutting forces, surface roughness, and burr formation. The results indicated that the main wear mechanisms were identified as flank wear and edge chipping due to abrasive wear and chip adhesion in uncoated micro endmills. It was also observed that the largest tool wear was occurred at smallest feed per tooth (0.75μm/tooth) and smallest wear was occurred at largest feed per tooth (3μm/tooth). At 3 μm/tooth feed per tooth and depth of cut of 100 μm, built-up edge (BUE) was found at the cutting edge in particular at the cutting speed of 125.6m/min. And a smaller tool wear along with the highest surface roughness was observed when compared to that at 62.8m/min and 31.4m/min [**Yu, W., Ramanathan, R. and Nath 2017**]

Jamil et al. [**2020**] made an effort to have less energy consumption, tool wear, surface roughness in the face milling of hard-to-cut titanium alloy (Ti-6Al-4V) using hybrid alumina and multi-walled carbon nanotube (Al203-MWCNT) which is nano additive based minimum quantity lubricant (MQL). The milling operations are executed on CNC milling machine with a micro grains coated carbide milling tool that has a multi-layer coating of TiN+TiAlN. Different methodologies including Taguchi, multi objective optimization, RSM, ANOVA, Sensor topography, KEYENCE digital microscope integrated VHX software, SEM, EDX are applied to find out different machining parameters and performance measures. Hybrid nano fluid is found to be one of the most effective strategies to have the better wettability, conductivity and lubrication capability of MQL. As per acquisition outcome: better surface quality, higher material removal rate (MRR) is achieved with maintaining desired productivity. Though Inconel 718 has the drawback of low MRR and high tool wear, it has excellent oxidation and corrosion properties so they chose 718 as a workpiece material and vegetable oils as biodegradable lubricants to grind Ni-Cr alloy under nano fluid technique to understand and analyze several results such as: surface quality, heat transfer rate, wetting property, G ration, MRR and lubrication phenomenon. The surface grinding operation is performed on CNC surface grinder machine with the grinding wheel that is made of Al2O3 and six-point diamond dresser is also used. SEM, EDS methods are applied. After having all the results, the outputs are compared to pure oil and flood cooling techniques. Different parameters are found to be more effective and enhancing under biodegradable oil-based nano fluid MQL strategy that ensures the environment friendly machining and it makes the process greener as well [**Virdi et al. 2020**].

Abbas et al. [**2019**] carried out an experimental investigation on surface roughness and power consumption characteristics under Al2O3 assisted MQL nano hybrid strategy. In the experiment, AISI 1045 steel is selected as workpiece material and uncoated tungsten carbide (WC) as cutting tool to perform turning operation on a CNC turning center machine. Several methods including surface roughness tester named Tesa Rough Surf 90 G, optical microscope (Olympus BX51M), classical desirability approach, regression modeling, sustainability assessment model is implemented to check out for dry, flood and Al2O3 nano fluid condition to analyze the result of surface quality and power consumption including cost of machining, management of waste and environmental impact [**Mia and Dhar 2019**].

Borade and Kadam [**2016**] presented a comparison of vegetable oil based MQL and Al2O3 nano fluid based MQL behavior on surface roughness and temperature. EN 353 steel (Case hardening material) is chosen as workpiece material with cutting tool inserts of cubic boron nitride (CBN CNMG 7075) material to perform turning operation on high-speed precision CNC lath (HASS-MAKE). Surf Tester, Infrared thermometer, Taguchi's L9 array method with OVAT, ANOVA methodologies are executed in this experiment. Surface roughness and temperature are the significant reduction achieved under Al203 based MQL nano fluid rather than vegetable oil based MQL. An experimental investigation to determine the characteristics and outcomes of several nano cutting fluids as for example: Al203, molybdenum disulfide (MoS2) and graphite under MQL technique and differentiated these three fluid types [**Zaman et al. 2019**]. CNC lath machine is used to execute turning operation of Inconel-800 (Ni-based alloy) with CBN cutting tool. The TelC made lathe tool dynamometer associated with XKM 2000 software, standard Mitutoyo's make toolmaker's microscope, Mitutoyo make SJ301 surface roughness tester, SEM, Box-Behnken RSM, CDA, ANOVA approaches are applied. They found that when it comes to high cutting speed values issue then M_oS_2 and graphite based nano fluids provide better enhancement but when it comes to good lubrication, cooling properties and machining characteristics, graphite based nano fluid shows the better performance because of its tribological property. Interestingly, in terms of Inconel 800, better machining characteristics are achieved when small amount of graphite is added in vegetable oil [**Gupta et al. 2019**]. Another experimental investigation on sustainability assessment demonstrated to observe the performance of nano-additive MQL with machining quality characteristics. CNC lath machine is used for turning Ti-6Al-4V with the use of standard carbide turning inserts and tool holders (CNMG 120416 MR ISO) under the vegetable oil based MQL nano fluid coolant. Surface quality, tool wear, power consumption is considered. Analysis methods including RSM, ANOVA are used in a wise way. Cost reduction, energy efficient, waste reduction, management health and safety resource efficiency and green environment are the main sustainability objectives. The result shows that high range of effectiveness of sustainability is achieved by MQL nano fluid rather than other conventional/classical MQL method [**Kishawy et al 2019**].

Patole and Kulkarni [**2018**] have developed a predicted model on surface roughness and cutting force in terms of turning of AISI 4340 workpiece which is performed on CNC lath machine with cutting insert of tungsten carbide (WC) coated CCMT 090308 using response surface methodology. The cutting fluid is composed of ethylene glycol and multi-walled carbon nano tube (MWCNT) nano particles since MWCNT has better cutting performance. Analysis methods including RSM, MINITAB software, ANOVA are applied for different purposes. As per outcome, appropriate cooling phenomenon and better surface finish result are the acquirements through the response surface methodology. An effort for performing drilling hole operation of AISI 304 Stainless steel (Cr-Ni SS) on CNC drilling machine using simplified MQL with RQL (point sprayer and compressor) technique. The drill bit used in this experiment is tungsten carbide (WC) which is cryogenically treated. Several methodologies for instance: SEM, XRD, Linear intercept method using SEM image, micro Vickers hardness testing machine, Taylor Hobson Sardonic, SRM are applied in such a wise way [**Naveena et al. 2017**]. An optimization approach for sustainable drilling operation of Al 6061-T6 plate with HSS uncoated drill bit which is performed on CNC vertical machining center. Two techniques of lubricant are used here including MQL with nano fluid (MoS2+canola biodegradable oil) and MQL with RHVT in NOGA MINI setup. Analysis methods including Mitutoyo SJ301 roughness tester, Dynamometer, electric power measurement device, SIEMEN 802 D CNC controller, RSM, ANOVA, multi objective optimization, desirability approach, PSO, BFO, TLBO, MATLAB are executed for different purposes [**Singh et al. 2018**]. Using CNC surface grinding machine they compare three cooling methods conventional flood cooling, dry grinding, and MQL grinding, and proved that, under specific conditions, MQL can compete with or outperform conventional flood cooling delivery. A general-purpose alumina wheel is used to grind common steels EN8, M2, and EN31A. Lubricant L50 MQL system is used to deliver pure synthetic oil Castrol Care cut ES1 for MQL grinding. Through their research, they claim that MQL workpiece accuracy is comparable to and can build upon WET efficiency [**Barczak et al. 2010**]. CBN type and three conventional wheel models are evaluated in presence of fluid, air-jet, and 11 different forms of coolant lubricants and dry conditions. Due to the plastic deformation in the contact region, it has been found that surface finish and consistency are considerably finer with the application of the MQL technique for grinding of hardened steel 100Cr6 [**Tawakoli et al. 2011**].

Sharma et al. [**2016**] have worked on AISI 1040 steel as a workpiece, lathe as a machine tool, Uncoated cemented carbide inserts as a cutting tool under different machining environments like wet, dry, conventional cutting fluid mist, and 1% Al2O3 nanofluid mist using MQL system. Using different lubrication environments in turning, the use of nano-cutting fluid reduced cutting force, tool wear, the average surface roughness of machined part is recorded compared to dry, conventional mist, and wet machining. With increasing nanoparticle concentrations, thermal conductivity, viscosity, and density of nanofluids increase, while real heat decreases. The process efficiency of MQL grinding using oil-based nano lubricants and the accuracy of their friction reduction results. The nano lubricants which are made with multicomponent organic-inorganic nano additive composed of MoS2 nanoparticles, triglycerides and phospholipids, and Paraffin oil and soybean oil were used as the base fluids. Here basic capacity, grinding friction coefficient, and G-ratio are used as measurands to determine process efficiency under different conditions. On average, soy-based and paraffin-based nano lubricants demonstrated better process performance in near-dry grinding of EN24 steel and cast iron, respectively, based on the investigation coefficient of grinding and specific energy [**Kalita et al. 2012**]. An aluminum oxide (Al_2O_3) grinding wheel and tempered and annealed ABNT 4340 steels are used for investigation, MQL technique led to lower roughness values, highest residual stress value, and no negative effect on the surface integrity [**Roberto et al. 2007**].

Sharmin et al. [**2020**] designed a modified nozzle to increase the effectiveness of MQL in grinding operations. The nozzle has multiple holes and acted as the mixer of air and fluid that’s why proper divergence and convergence sections are designed properly. AISI 201 Alloy Steel is used as workpiece material and MQL with vegetable oil as cutting fluid. The modified nozzle ensures that the cutting fluid is delivered to the entire tool-work contact area, while the standard nozzle only delivers the fluid to a small area. That’s why grinding temperature is reduced. Face milling of Ti-6Al-4V alloy (100mm x 100mm x 50mm) with dry, wet, MQL with and without nano platelets, cryogenic cooling and the combination of MQL and cryogenic cooling are done in Mori Seiki (NVD 4000).

Dynamometer and amplifier Multichannel manufactured by Kistler Instrument Corp., xGnP are used as analysis methods. The cutting tool is Uncoated insert (R245 12T3M-KM(H13A) with a face mill cutter [**Park et al. 2017**].

Rahmati et al. [**2014**] used Machine Mitsuki Seiki Vertical Type 3A for investigating the optimum molybdenum disulfide (MoS2) nano lubrication parameters in CNC slot milling of aluminum AL6061-T6 (40mm x 40mm x 100mm). Ordinary lubricant oil, Nano lubricant, ECOCUT HSG 905S neat cutting oil are used in the methods which are Taguchi optimization, standard orthogonal array, single to noise (S/N) response analysis, Pareto ANOVA. Lastly, End mill cutter (Tungsten Carbide AE302100) is used as cutting tool. Hybrid cryogenic MQL, Conventional flooding, MQL, Cryogenic are used as lubricant for improving tool life in machining of Ti-6Al-4V alloy (50mm x 50mm x 150mm). ANOVA (Analysis of Variance) method is used in Bridge VMC 610xp milling centre and for the end milling operation, the cutting tool is Solid carbide end mill [**Shokrani et al. 2019**]. Technique for order preference by similarly to ideal solution model (TOPSIS), Pareto based hybrid multi objective optimization using Vegetable oils, pure castor oil mists for end milling operation is performed and used Gene expression programming (GEP), Non dominated sorting genetic algorithm- II (NSGA- II) programming languages. Uncoated carbide tool is used for Inconel 690 (90mm x 30mm x 20mm) by the machine called MTAB CNC milling machine (3 axes). Radial basis functions, support vector regression, Kriging, multivariate adaptive regression methods have been used [**Sen et al. 2019**]. They used CNC assisted three axis milling machine where the lubricants are Al2O3 and palm oil mixed nano fluids. Milling operation (eco benign milling) is done on Inconel 690 by the cutting tool which is uncoated carbide tool. In this operation Fuzzy interference system (FIS) and Multi performance characteristics index (MPCI) are the methods and have been compared with Conventional Lubrication Technology.

Muaz and Choudhury [**2019**] implemented Multi objective genetic algorithm (MOGA) and Taguchi analysis, Taguchi- Gray relational analysis (TGRA) of MQL assisted flat end milling process for finishing of AISI 4340 steel is performed. EMCO Concept mill 250 machining centre is used and the cutting tool is Milling cutter having 90° approach angle where the lubricants are Pure emulsion, Boric acid dissolved in the emulsion, Graphite suspended in the emulsion, Hybrid solid liquid minimum quantity lubrication. Scanning Electron Microscopy (SEM) (0.02:0.5) and Energy dispersive X-ray spectroscopy (EDS analysis) methods applied using Water PEG solution, 0.02 wt.% Go lubricant, 0.50 wt.%

SiO2 lubricant, 0.02/0.50 wt.% Go/SiO2 lubricant as cutting fluid. End milling operation is performed on AISI-304 stainless steel (210mm x 105mm x 110mm) by using the cutting tool TAP400R C32-35-200L, Juhai tools, China (Diameter- 35 mm, three teeth) and the machine is VDF-850 vertical milling center China [**Lv et al. 2018**].

1.2.4 Modeling of Surface Roughness

Surface roughness, cutting force, temperature and tool wear use as important factors to consider the performance of machining process and it also reflects the quality of the product. It is considered that the product quality increases with a decrease in surface roughness, cutting force, temperature and tool wear. Controlled parameters such as cutting condition and non-controlled parameters such as work-piece non-homogeneity, tool wear, machine motion errors, chip formation and other random disturbances; all have effects on surface roughness. On the other hand, cutting force, temperature and tool wear increases with the increase of the material strength, shear strength to be specific. Increase in the cutting force during machining is always detrimental as it decreases the tool life and increases the surface roughness. That is why many researchers have been studied to identify the required machining parameters for optimum surface roughness.

A comparison between the ANN (Artificial Neural Network) and RBF (radial basic function) approach has been presented for investigate the capability of the ANN to predict the effect of the hot deformation parameters on the strength of Al-base metal matrix composites [**Mia and Dhar 2016**]. In the first investigation they worked their RBF model then, using the ANN's trained model, predict the behavior of the Al-base metal matrix composite deformed under the same conditions as the RBF technique. They found out a nonlinear variation on the second training and errors still outside the 10% range. Then the last phase the error was 5% range and that was acceptable. In this experiment they used three time filter the ANN result while for the RBF approach was done in one shot. They show that for objective more accuracy ANN perform better. In this experiment it was discovered that the filtrated ANN outperforms RBF in predicting the hot deformation behavior of Al–12 vol. % Al_2O_3 [**Jalham 2003**]. R. Kumar & Chauhan [**2015**] have done an experimental investigation in Al hybrid composite under different machining parameters for better roughness testing. Here RSM and ANN are used to evaluate experimental results and anticipate system behavior under any circumstance within the operational range. For the ANN the network was trained using the implemented feed-forward Bach prop, with the goal of lowering the Mean square error (MSE) between the predicted and experimental outputs to an acceptable threshold, thereby minimizing the performance of the MSE function. After 102 iterations, a successful training is completed with an MSE error of 0.0022678 and 6 validating tests. RSM and ANN are multivariate regression modeling methods that can address both linear and nonlinear problems. In this experiment the RSM and ANN models were constructed out of the experimental data and correlated fairly well. The results indicate that the ANN prediction has a greater deviation than the RSM prediction. Other hand RSM is powerful in identifying the insignificant main factors and interaction factors or insignificant cubic terms in the model. Surface roughness has been considerably influenced by the interplay between feed rate and cutting speed. In this experiment compare to RSM the ANN model creates more error. To confirm the data acquired during testing and to anticipate the behavior of the system under any circumstance within the operational range, response surface methodology (RSM) and artificial neural networking (ANN) are used. The research shows that feed rate has a greater impact on both materials and approach angle than speed and approach angle [**R Kumar and Chauhan 2015**]. A multiple-layer feed-forward ANN model for the tribological behavior of short alumina fiber reinforced zinc–aluminum (Zn-Al) composites was formed. With the help of the ANN training sets, specific wear rate and friction coefficient were tasted [**Mia and Dhar 2019**]. Two artificial neural networks are presented as the foundation for building a model that predicts the tribological characteristics of alumina fiber reinforced zinc–aluminum alloy matrix composites based on load, fiber volume percentage, and fiber orientation in this research. In this experiment, back propagation (BP) was used to train an algorithm for multilayer perceptions that minimized the error for a particular training pattern. The input variables in the ANN model in this work were applied load, fiber volume percentage, and fiber orientation, while the output or dependent values were frictional coefficient and specific wear rate. The modeling findings validate the ANN's practicality and its strong connection with the experimental data. In this experiment it was well trained that result ANN was excellent analytical tool. Here degrees of accuracy of the prediction were good and considerable time costs were comparatively low. They graphically and experimentally decide that a well-trained neural network can extract more meaningful information from limited experimental databases, resulting in significant cost and time savings [**Genel et al. 2003**].

Hayajneh et al. [**2009**] used ANN for predicted wear loss quantities of aluminum-copper-silicon carbide (Al-Cu-SiC) composite. In computer programming, the sigmoid function is the most popular activation function for ANN. Depending on the value of the input, it mixes nearly linear, curvilinear, and nearly constant behavior. It accepts any real-valued input and provides an output that is bounded between real and imaginary values, often known as a squashing function. Back propagation neural networks represent a supervised learning approach in this experiment, needing a large number of full records, including the goal variables. The mass loss amounts of several Al–Cu–based composite materials reinforced with SiC have been predicted using a neural network. Here the findings of the experiments reveal that copper and/or silicon carbide increase the wear resistance of Al–4 wt% Mg alloys. Before being used in the training and testing of ANN, the experimental values of mass loss of the worn specimens were first coded. In the fields of composite material characterization and tribology, ANN might be an effective prediction approach [**Mia et al. 2017**].

Recycled PVC composites varying different weight percentages were predicted and optimized using ANN modeling. The composite elements, which represent the input factors to the ANN, were: virgin PVC in powder form with a K-value, stearate-acid coated $CaCO_3$, and virgin PVC in powder form with a K-value. For that the tensile strength and ductility which were received from the UTM were picked as the outputs of the network in addition to the density of the extrudate which was chosen as the third output. In this experiment the network is divided into three layers: an input layer with six input nodes, an output layer with three output nodes, and a hidden layer with three output nodes. In this work, 15 architectures, 4 activation functions, and 5 training procedures were used to execute a huge number of tests in order to find the optimum ANN model/s parameters. The first step was to conduct single and multi-factorial analysis. The PVC composite characteristics were then optimized using one of the finest ANN models available. Multi factorial analysis, ANOVA, three factors were also playing important role in this process. Artificial neural networks were used to model the link between the composition of PVC composites and their mechanical characteristics. The model employed in this experiment was able to determine the best weight proportion of materials to accomplish any desired attribute. Here the results also demonstrate that ANN modeling may be used to determine the best weight percentages of different PVC composite ingredients to obtain a desired composite quality[**Altarazi et al. 2018**]. The surface roughness of Al–SiC (20 p) was investigated by rotating the composite bars with a coarse grade polycrystalline diamond (PCD) insert under various cutting circumstances. Experimental data ware tasted with analysis of ANOVA and ANN. Metal matrix composites (MMC) materials have a higher specific strength and stiffness than traditional structural materials, and are widely employed in autos, recreational equipment, and aerospace applications. Here The alloy A356/SiC/20p aluminum with 7.5 % silicon, 2.44 % magnesium, and 20 % volume silicon carbide (SiC) particles was put to the test. A medium-duty lathe was used to process the work material at five different cutting speeds. They used a back propagation network algorithm and create a flow chart than could be help for reached the final step. The ANN model was evaluated using the training data, and graphs with anticipated and tested values were displayed. Here the ANN model was effectively used to MMC composite machining parameters and suitable tool, which was used to predict the surface roughness in machining process. Surface roughness data was gathered on a lathe using a PCD coarse grade cutting insert under varied cutting conditions for various combinations of cutting speed, feed rate, and depth of cut. ANOVA and ANN were used here and the ANN technique provides a systematic and effective tool for optimization [**Muthukrishnan & Davim 2009**]. A 'Feed Forward Back Propagation' artificial neural network model was created for the study and prediction of surface roughness, the link between cutting and process factors in Al, Cu, TiC Metal Matrix Composites in this paper. The experiment was carried out in a dry environment with a CNC lathe machine and 3D profilometer has been used to measure surface roughness parameters. They collect data and the trained Artificial Neural Network was simulated to anticipate the output response based on the input process variables data. Their data shows that all the predicted forecast values were almost equal to the experimental value. A back propagation type neural network was employed for this purpose. The cutting circumstances and surface roughness parameters had a non-linear relationship. In this experiment they got good result from ANN modeling [**Das et al. 2015**]. Regression analysis (RA) and artificial neural network (ANN) used in this research for predicting the surface roughness with a hard turning of AISI 52100 steel. Taguchi orthogonal array, ANOVA also used here. Correlation and confirmation experiments were done to investigate the effect of cutting parameters on surface roughness and to check the correctness of the created regressive model. Based on MSE and AEP values for the data sets analyzed in this study, the optimal ANN design was established. The performance of the constructed network was evaluated using the correlation coefficient (R-value) for both training and testing data in an ANN model for surface roughness prediction. The RA and

ANN model projected findings show a high agreement between expected values and experimental results. Compared to RA and ANN RA generate maximum error that was almost double compare to ANN. The employment of RA and ANN models as an efficient and alternative strategy for experimental investigations could save time and money by reducing the number of experimental runs. Moreover, the correlation coefficient between ANN model predictions and experimental data was more than that of the RA model, indicating that ANN model predictions were quite accurate [**Maheshwera Reddy Paturi et al. 2018**]. Using ANN, RSM methods the relationship between the hardness and wear behaviour, process parameters of friction stir processing were evaluated. The process parameters had significant effect hardness and wear behaviour of Al 6061/Al_2O_3-TiB_2, experimentally. As alternative methods to compute the hardness and weight loss for given process parameters the developed ANN, RSM models could be employed. The estimated values for the hardness and wear behaviour of the processed zone had an error less than 0.60%, which indicated reliability [**Vahid M et al. 2021**]. For modelling the process output characteristics that influence by weight fraction, speed, feed rate, cutting depth, face centred central composite experimental design coupled with RSM was used. Experimental result imply that surface roughness criteria were found to increase with increase of feed, roughness decreases at higher cutting speed during machining. RSM showed an accuracy of 95% with the help of Minitab software, good agreement between experimental and predicted values of surface roughness and cutting force was observed [**Ghosal and Patil 2021**].

The RSM was utilized for modelling and optimizing the impact on surface roughness for input parameters of Al metal composites. For formative the greatest conditions for a basic surface roughness response surface curve lines were made. With reducing the feed and lifting the cutting speed and depth of cut the surface roughness was begin to decrease [**Venkatesan et al. 2021**]. Using RSM the optimization of roller burnishing parameters of silicon carbide particles-reinforced Al composites of metal matrix base was carried out. By changing speed of the burnishing tool and number of passes experiments were conducted in dry condition. In order to evaluate its influence on output responses such as roughness and hardness of the surface, the input parameters were changed at different levels. Using RSM the optimization was carried out [**Shankar et al. 2021**]. RSM is an effective tool for prediction of wear behaviour under combined sliding and rolling action. The wear of MMC is much lower than hardened, tempered AISI 4340 steel and rolling speed had the most maximum influence in wear of both materials under investigation [**Mandal et al. 2021**].

Cutting force model was developed and optimized through RSM and compared for two different percentages of components SiC_p/Al 45% and SiC_p/Al 50%. The plots show that during increment with depth of cut in proportion with feed rate are able to cause increments in cutting forces. Because of higher cutting speed increases, higher cutting speed shows a positive response in both the weight percentage of SiC_p by reducing the cutting force. With increasing SiC_p weight percentages a very fractional increasing trend of cutting force was observed. Error percentages found in an acceptable range with minimal error percentages [**Laghari et al. 2021**]. The second order model of cutting force had been established by RSM to analyse the effect of actual processing conditions on the generation of cutting force for the turning process of SiC_p/Al composite with different cutting parameters, such as feed rate, depth of cut, cutting speed. Predicted parameters by the RSM were in close agreement with experimental results with minimal error percentage. Higher cutting speed shows a positive response by reducing the cutting force. For the model of SiC_p/Al components had been compared to the cutting force of SiC_p/Al 45 Wt.% between predicted and experimental results [**Sap E. et al. 2021**].

To optimize the machining parameters including depth of cut, feed and speed in accordance to Box-Behnken design in Minitab 17, the contour plots the surface plot and response optimizer had to made to study the influence of machining parameters and their interactions. RSM was used to optimize the machining parameters, found more than 95% confidence level [**Laghari et al. 2021**]. To optimize the process parameters in casting, welding and machinability studies of composite materials RSM is used. To design the experiments and minimizes the number of experiments for specific number of factors and its levels RSM is used, conduct experiments as per the design and responses are recorded. To identify the factors which influence the response analysis of variance is used [**Kamruzzaman et al. 2017**]. For obtaining a specific objective function response and process parameters are optimised where regression equations are developed [**Chelladurai et al. 2021**]. To analyse the cutting variables RSM with central composite rotatable design matrix was employed. For predicting the output responses second order regression models were developed. For the specified range of input parameters using overall desirability index the optimal parameters for multiple responses were arrived [**Nataraj et al. 2021**]. RSM and other models were used for modelling and multi objective optimization of

Al6351/Egg Shell Reinforced Composite. The properties of the composite optimized were toughness and hardness whose values vary in response to changes in production process variables namely- stirring speed, preheat temperature and stirring time. To develop an RSM model for modelling the variations in the mechanical properties of the fibreboard in response to variations in process parameters an experimental design using Box-Behnken Design was used. Results of the study showed that RSM effectively modelled the properties of the composite [**Nwobi-Okoye and Uzochukwu 2021**]. An attempt had been made through the RSM in machining of 10%-micron Al_2O_3 LM25 Al MMC manufactured through stir casting method. On the basis of three performance characteristics of tool wear (VB), surface roughness (Ra) and cutting force (Fz) with the combined effects of three machining parameters including cutting speed, feed rate and depth of cut were investigated. To study the effect of process parameters as well as their interactions the contour plots were generated. Using desirability-based approach RSM process parameters were optimized [**N. et al. 2021**]. Using RSM with central composite design (CCD) experimental work was carried out Al matrix composite (A413-9% B_4C) with zinc coated copper wire. A systematic approach for modelling and analysis of machining characteristics of Micro-Wire Electric Discharge Machining (Micro-WEDM) process was presented using RSM. The effect of various input parameters, such as voltage, capacitance and feed rate on machining, performance of MRR, kerf width and surface roughness were investigated. The optimized values of MMR, KW and SR parameters were found to be 0.259943 mm^3/min, 87 µm and 0.97 µm, respectively [**Taylor and Francis 2021**]. Through the response surface methodology in machining of homogenized 20% SiC_p LM_{25} Al MMC manufactured through stir cast route to model the machinability evaluation. The contour plots were generated to study the effect of process parameters including cutting speed (s), feed rate (f), depth of cut (d) and machining time (t) which were optimized using response surface methodology on the basis of two performance characteristics of flank wear (VB_{max}) and surface roughness [**Taylor and Francis 2021**].

In order to obtain the best surface finish and material removal rate (MRR) the input parameters of nano powder mixed electric discharge machining (NPMEDM) were optimized using central composite rotatable design (CCRD) based on response surface methodology (RSM). The surface finish had been improved by 46.06% and MRR had been increased by 38.22% [**Gopalakannan et al. 2021**]. Modelling of the machining process (EDM, WEDM, USM, high speed machining), finite element modelling, simulation and optimization of soft computing methods in MMCs were focused on this review. The study would emphasize on ANN, RSM, fuzzy logic, Taguchi method as soft computing optimization methods [**Srivastava et al. 2021**]. As the influencing parameters cutting speed, depth of cut and weight percentage of SiC_p were selected. Through stir casting route the application of response surface methodology and face centred composite design for modelling, optimization and an analysis of the influences of dominant cutting parameters on tangential cutting force, axial cutting force and radial cutting force of Al MMCs were produced. Using the developed model's mathematical models were developed and tested for adequacy using analysis of variance and other adequacy measures. In the turning of Al MMCs the predicted values and measured values were fairly close, which indicate the developed models could be effectively used [**Seeman et al. 2021**]. To develop mathematical model for specific wear rate and coefficient of friction RSM was employed because capability of the RSM was good in prediction of results and results were very closer to the measured value. Considering five machining parameters (gap voltage, pulse-off-time, discharge current, flushing pressure, pulse-on-time) based on Box-Behnken's design of experiments (BBDOEs), the methodology for predictive modelling and multi-response optimization of machining accuracy and surface quality to enhance the hole quality on Al-SiC based MMC, employing response surface methodology (RSM) and desirability function approach (DFA).In order to estimate the machining characteristics such as MRR, EWR and SR a mathematical model had been formulated by applying RSM [**Li, J and Laghari 2021**].

An application of RSM and Particle swarm optimization (PSO) technique for optimizing the process parameters such as feed rate, spindle speed and depth of cut on the cutting force, surface roughness and power consumption of milling and provides a comparison study among desirability and PSO techniques was illustrated. To study the relationship between the input and output responses the process parameters were analysed using RSM central composite face-centred design. Using the desirability approach and the PSO technique optimized process parameters were acquired through multi-response optimization, results obtained from PSO were closer to the desirability function approach which achieved significant improvement [**Malghan et al. 2021**]. Experiments were conducted in the better composition material to identify the optimized turning parameters such as spindle speed, feed rate and depth of cut with bio lubricants as cutting fluid using RSM method. As the optimized input machining parameters spindle speed of 275 rpm, a feed rate of 0.2 $mmrev^{-1}$ and depth of cut of 0.75 mm were identified. The study made by RSM derived the regression equation for the turning parameters. For mathematical modelling and optimization of process parameters such as peak current, pulse on time and duty cycle were used by RSM. Between input process parameters and responses such as Material Removal Rate (MRR), Electrode Wear Rate (EWR) and Surface Roughness (SR) mathematical model was developed. The effects of peak current, wire tension, spark gap set voltage, pulse on time and pulse off time were investigated experimentally on MRR and Ra. For investigation of process variable affecting MRR and Ra RSM was employed. The confirmatory results had shown a significant improvement in MRR and Ra due to process optimization, predicted optimal values of MRR and Ra are 1.7509 g/h and 0.50 µm respectively [**Shahadev et al. 2021**].

Benardos and Vosniakos [**2002**] developed the neural network modeling approach for the prediction of surface roughness in CNC face milling. Gaitonde et al. [**2011**] added time and cutting tools as inputs with cutting speed and feed; and acquired 20.57% prediction accuracy in surface roughness. Apart from turning, ANN has been adopted in boring operation to anticipate the surface roughness and by doing so, a 4.52% error rate was found [**Rao et al. 2014**], while in milling Zain et al. [**2010**] found satisfactory results with ANN and made an attempt to improve prediction of surface roughness and cutting force by using Artificial Neural Networks (ANN) technique. The effects of the process inputs, namely cutting speed, depth of cut, feed rate, and tool nose radius on the output responses are evaluated using response surface methodology (RSM). Manna A. and Bhattacharyya B. [**2004**] used Taguchi method to optimize the cutting parameters for the effective turning of Al/SiC-MMC using a fixed rhombic tooling system. Lo also used adaptive neuro-fuzzy inference system (ANFIS) to predict the surface roughness in end milling process. The independent parameters for the cutting were spindle speed, feed rate, and depth of cut. The ANFIS model was done using triangular and trapezoidal membership functions. The average error of prediction of surface roughness for triangular membership function was found around 4%. Chen and Savage [**2001**] used fuzzy net-based model to predict surface roughness under different tool and work piece combination for end milling process. The input parameters included cutting speed, feed, depth of cut, vibration, tool diameter, tool material, and work piece material for the fuzzy system. While validating the model it was found that the predicted error was within 10%. Kumunan et al. have performed series of end milling operations with varying cutting speed, feed, depth of cut and vibration. Their work proposed two different hybrid intelligent techniques namely ANFIS and radial basis function neural network- fuzzy logic (RBFNN-FL) for predicting surface roughness during end milling. An experimental data set was obtained with speed, feed, depth of cut and vibration as input parameters and surface roughness as response variable. The input-output data set was used for training and validation of the proposed techniques. After being validated, those techniques were forwarded in order to predict surface roughness. Both the hybrid techniques were found superior over their respective individual intelligent techniques when computational speed and accuracy were in concern predicting surface roughness. In hard turning, Sharma et al. [**2008**] formed ANN model of surface roughness in terms of speed, feed, depth of cut and approaching angle and found 76.4% accuracy. Karayel [**2009**] derived surface roughness, by ANN, close to actual values. Azouzi and Guillot [**1997**] examined the feasibility of neural network-based sensor fusion technique to estimate the surface roughness and dimensional deviations during machining. This study concludes that depth of cut, feed rate, radial and z-axis cutting forces are the required information that should be fed into neural network models to predict the surface roughness successfully.

The response surface methodology (RSM) allows testing the statistical significance of the model, model terms, and lack of fit and provides 3D plots showing the process inputs effects on the studied responses. Sahin and Motorcu [**2005**] developed a surface roughness model based on cutting speed, feed rate and depth of cut for turning of mild steel with coated carbide tools using response surface methodology (RSM). According to them, feed rate was the least influencing factor on surface roughness. Elbah et al. [**2013**] employed RSM to study the effects of cutting speed, feed rate, and depth of cut on surface roughness criteria during hard turning of AISI 4140 steel (60 HRC) using wiper and conventional ceramic inserts. The Ra regression model of conventional insert was very acceptable with a correlation coefficient of 98.12%. However, the Regression model of wiper insert presented only 87.92% of correlation. Aouici et al. [**2012**] concluded that RSM is useful for investigating the cutting parameters influence on surface roughness and force components when turning hardened AISI H11 steel using cubic boron nitride tool. Nevertheless, the correlation coefficients of the regression models were between 82.14 and 91.43%. Subramanian et al. [**2014**] worked with Al7075-T6 material to develop a surface roughness model during end milling using RSM where the cutting tool was of high-speed steel (HSS). The variables used in the experiment were cutting tool geometry and cutting condition. The cutting speeds were 75 m/min., 95 m/min., 115 m/min., 135 m/min. and 155m/min., the feeds were 0.02 mm/tooth, 0.03 mm/tooth, 0.04 mm/tooth, 0.05 mm/tooth and 0.06 mm/tooth and the used depth of cuts were 1.5 mm, 2 mm, 2.5 mm, 3 mm and 3.5 mm. According to their findings, Surface roughness increased with increasing cutting feed rate and the surface roughness increased with the decrease in cutting speed. The least increase in surface roughness was found at low nose radius, while a decrease in surface roughness was noticed at high nose radius. The surface roughness increased at low radial rake angle and surface roughness decreased at high radial rake angle. The optimal cutting parameters for the minimal surface roughness are $\gamma = 12°$, $R = 0.8$ mm, $V_c = 115$ m/min, $f_z = 0.04$ mm/tooth and $a_p = 2$ mm. It was also possible to predict the roughness of the work material according to the developed second order surface model.

Barman and Sahoo [**2009**] experimentally studied the fractal dimension of aluminum, brass and mild steel in CNC turning and applied both ANN and RSM models to predict the dimension. They concluded that ANN models work better than response surface models to predict accurately. Kumar and Chauhan [**2015**] showed that ANN revealed higher error than RSM in surface roughness measurement. Sahoo et al. [**2015**] revealed the supremacy of ANN over RSM. Furthermore, ANN revealed higher accuracy than Taguchi based surface roughness prediction and also concluded the same result by stating that ANN model gives more accurate Ra prediction values than any other conventional model [**Karabulut 2015**]. ANN is also better than linear regression analysis and utilizes only a few training and testing data set to make an accurate prediction of surface roughness [**Al-Ahmari 2007**].

1.3 Summary of the Review

A review of the study presents that in the modern material science researchers are seeking to fabricate new composite materials to increase tribological, microstructural and mechanical qualities. The conventional materials are not so effective for many applications due to some low properties.

CNTs reinforced aluminum metal matrix composite have excellent mechanical properties like high stiffness, high strength-to-volume portion, deterioration resistance, and exceptional wear resistance which creates the increasing demand of nano particle reinforced aluminum-based Metal Matrix Composite because of their massive applications in various automobile, military, aviation, aerospace, structural, transportation, marine and other manufacturing industries. Advanced engineering composites have been produced in large part thanks to the impact of nanoparticles such CNTs, Silicon Carbide, and Alumina. Therefore, compared to standard reinforcement, metal matrix composite with nano tubing offers improved mechanical properties.

However, very few investigations have been conducted into the development of advanced nanoparticle-based aluminum metal matrix composite. Review of experimental studies clearly demonstrated the effects of advanced reinforcing nanoparticle and its size, shapes and different composition to develop improved metal matrix composite. Necessity of more researches arise to ascertain the effects of these factors. Till now a substantial number of researches fabricated Al metal matrix reinforcing either with CNT or CNT-SIC or CNT- Alumina or SIC-Alumina but an investigation combining all those three reinforcing materials is rare. Problems of nanoparticle agglomeration and settling all need to be investigated thoroughly in the applications. Nevertheless, the high cost of nanoparticles may seem prohibitive and hence minimum requirement of inclusion is estimated.

1.4 Objectives of the Present Work

The objectives of the present work are:

i. Develop a composite material by reinforcing carbon nanotubes with aluminum metal matrix composite

ii. Evaluate different mechanical properties such as tensile strength, impact strength, flexural strength, and hardness of the fabricated composite

iii. Investigate different output parameters such as surface roughness, tool wear, cutting force, and temperature of carbon nanotube reinforced aluminum metal matrix composite to optimize different machining parameters using Response Surface Methodology (RSM).

iv. Develop a prediction model for surface roughness using Artificial Neural Network (ANN) while turning CNT reinforced aluminum metal matrix.

1.5 Scope of the Thesis

The requirement for more effective composite materials is crucial for the creation of new products in the contemporary world. Hence, it has constantly been the drive to develop new metal matrix composite for different outstanding mechanical properties and widespread applications. Among such composites, application of aluminum metal matrix composite with nano tubing is prominent. Nanotubes like CNTs have emerged as a promising solution to produce effective composite materials. The review of the literature motivates to fabricate nanohybrid aluminum metal matrix composite materials instead of conventional composite materials. The present research work has been taken up to prepare carbon nanotube base aluminum metal matrix composite with best composition, evaluate different mechanical properties and investigate the major machinability characteristics in machining (turning) fabricated composite by coated carbide cutting tool under different machining conditions as well as to predict surface roughness in machining when machining under different environmental condition.

Chapter 1 presents the brief description of composite materials, different matrix materials that can be used in metal matrix composite. Furthermore, it also highlights the evolution of CNTs reinforced aluminum-based metal matrix composite and its varieties of application. Moreover, presents the main goals and objectives of machining operation, works that have been previously done on MMC keeping their mechanical properties on thoughts, complications associated with machining of carbon nanotube reinforced aluminum metal matrix composite material, the techniques that are used to model surface roughness of a machined surface. It presents specific objectives of this thesis work and also outlines the methods which have been followed to draw effective results that commensurate with the goals of the thesis.

Chapter 2 presents the development of the carbon nanotube reinforced aluminum metal matrix composite material where three different reinforcing materials i.e., CNT, silicon carbide and alumina have been used to reinforce the matrix material. Pure aluminum ingot has been used as the matrix material in this research work. Moreover, it presents different mechanical properties i.e., tensile strength, flexural strength, impact test and hardness has been carried out of the fabricated composite

Chapter 3 deals with the experimental investigation and findings that have been achieved by carrying out turning operation on the developed composite material under both dry and MQL condition. The composition of sample work piece and complete experimental set up with experimental conditions are briefly describe in this chapter. Finally, the experimental results in terms of temperature, surface roughness, cutting forces and tool wear are represented by different graphs. Effects of minimum quantity lubrications in conventional cutting fluids, relative to dry conditions on temperature, surface roughness, cutting forces and tool wear in turning CNT reinforced aluminum alloy by uncoated carbide cutting tool under different cutting conditions are also discussed.

Chapter 4 explains the theory, structure and also prediction technique of neural network (ANN) and response surface method (RSM) and presents the modeling of surface roughness using Artificial Neural Network and Response surface Methodology. In addition, the chapter also demonstrate the modeling of surface roughness using RSM and ANN of the developed composite under MQL condition. The chapter deals with desirability function analysis to find out optimum machining conditions and concludes with the efficacy of the developed ANN model for predicting surface roughness. The chapter concludes with compare the accuracy of ANN and RSM models for predicting surface roughness in terms of coefficient of determination (R^2), absolute percentage error (APE) and model predictive error (MPE).

Chapter 5 contains the detailed discussions on the experimental results, possible interpretations on the results obtained and artificial neural network model for predicting surface roughness. The reduction of temperature, cutting force and surface roughness due to the usage of MQL are also presented in tabulated form. This chapter also contains the discussion regarding the modeling of surface roughness of carbon nanotube reinforced aluminum metal matrix composite. Finally, a summary of contributions, recommendations for the future work and references are provided at the end.

Chapter-2

Materials and Methods

2.1 Development of Carbon nano tube Reinforced AMMC

Nano hybrid Aluminum Metal Matrix Composite (AMMC) material possesses outstanding tribological, microstructural, and mechanical properties, such as light weight, ductility, high conductivity, superior malleability, high strength, and high specific modulus. Now a days engineers has been constantly trying to develop new composition of AMMC materials.

After researching the literature, I have found that adding CNTs, Al2O3 and SiC reinforcements to the aluminum matrix increases the hardness and strength of the aluminum matrix material which ultimately increases all the mechanical properties as well. Naik H R M et al. [**2021**] during their fabrication of hybrid aluminum-cnt material used a fixed CNT content of 2 Wt.%. Reddy and Anand [**2019**] during their production of nanocomposite materials varied the amount of CNT content (0.4%, 0.7%, and 1.1%) respectively in Al 5056 matrix. Novel hybrid composite, like MWCNT coated SiC as the reinforcement in A356 enlighten that the accumulation of the precise amount (1.5%) of carbon nanotubes significantly improved the tensile strength (229 MPa), hardness (305 MPa), impact strength (4J) and elongation percentage (6.1%) by the semi-solid stir casting process. In addition, the combination of 10% of SiC and 1.5% of MWCNT with the A356 have increased tensile strength by 189.25%, hardness by 133.83%, elongation by 186.54% and impact strength by 200% as compared with base alloy [**Sangeetha et al. 2021**]. Mechanical properties, fabrication techniques and surface texture of aluminium matrix composites (AMCs) reinforced by silicon carbide (SiC). varying SiC content in AMCs is (0,5,10,20 Wt.%) were fabricated by stir casting process [**Shukla et al. 2021**]. Moreover, multi-walled carbon nanotubes were varied from 0.166 to 3.33% and 8-12% SiC was used for the reinforcement to fabricate aluminum alloy 5083 by stir casting process and tensile strength was discovered to have increased by 18% [**Jannet et al. 2020**]. Imran and Khan [**2021**] have focused on mechanical properties, tribological properties of Al-7075 metal matrix composites (AMMCs) by the addition of desirable reinforcements like Sic, Al_2O_3, Gr, TiO_2, bagasse ash etcetera is incorporated in the stir casting method. The mechanical investigation and fabrication of Al alloy, alumina and boron carbide metal matrix composites ended up finding its properties like light weight, high strength and ease of machinability; alumina which as better wear resistance, high strength, hardness and boron carbide which has excellent hardness and fracture toughness are added. Bansal & Upadhyay [**2016**] presented the effect of machining parameters on tool wear, surface roughness and metal removal rate of Alumina Reinforced Aluminum Composite has been observed in turning operation. Hardness and tensile strength increase with the reinforcement ratio. Surface Roughness increase with the process variables except the speed, speed made adverse effect on surface roughness. MRR increases with the process parameters. The machinability of 2024 aluminum alloy reinforced with Al_2O_3 particles using varying size and weight fraction of particles up to 30 wt.% by a vortex method was carried out at different cutting conditions. The optimum surface roughness was obtained at a speed of 160 $mmin^{-1}$ while the maximum surface roughness value was found in the machining of the 15% Al_2O_3 composites with particle size of 16 mm. The surface roughness also increased with the increasing weight percentage of the particles. Till now all of the researchers fabricated Al metal matrix reinforcing either with CNT or CNT-SIC or CNT- Alumina or SIC-Alumina but a few works have been found combining all those three reinforcing materials.

In this work aluminum-based nano hybrid metal matrix composite is developed by stir casting method. Ingot Aluminum and Al_2O_3 content is fixed as 73.5wt% and 15wt% with CNTs content is varied from (0.5, 1, and 1.5) wt.% and Silicon Carbide content is varied from (11, 10.5, and 10) wt.% as reinforcement materials. For the efficient production of aluminum composites, it is vital to choose the right material for the matrix and reinforcing. The commercially available Aluminum ingots were chosen for matrix which is shown in Fig. 2.1.

Fig. 2.1 Photographic view of Aluminium ingot.

Usually, aluminum takes the major proportion in ingot aluminum. The chemical composition and some properties of the experimented ingot Aluminum is listed in Table 2.1 and Table 2.2 respectively.

Table 2.1 Chemical composition (wt.%) of ingot Aluminum.

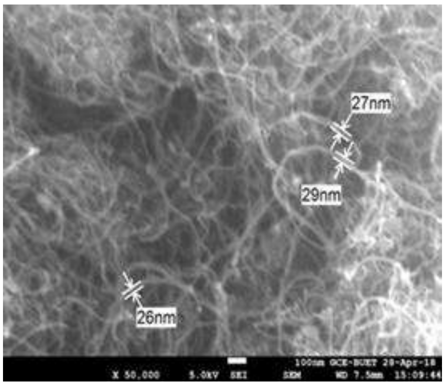
Aluminium	Mg	Si	Mn	Fe	Cu	Zn	Ti
99.6%	0.02	0.08	0.0005	0.289	0.0002	0.00014	0.01

Table 2.2 Properties of ingot Aluminum.

Appearance	Density	Hardness	Tensile Strength	Thermal Conductivity	Melting Point
Silvery white	2.7g/cc	26 HRE	67 MPa	234.2 W/M-K	646.1-675.2 °C

Carbon nanotube, Al_2O_3 and silicon carbide nano-particles were chosen as secondary phase reinforcement materials. Carbon nanotube particles appear as fine black powder. On the other hand, Aluminum oxide is a white odorless crystalline powder whereas pure silicon carbides appear as colorless and transparent crystals. The mixture of Al_2O_3, SiC and MWCNT particles with three different volume percent of MWCNTs (wt.0.5 %, wt.1.0 % and wt.1.5%) and fixed volume percent of Al_2O_3 (wt.15%) and SiC (wt.11%, wt.10.5% and wt.10%) were dispersed in ingot aluminum to fabricate the composite materials. A photographic view and SEM image of carbon nanotube are depicted in Fig. 2.2. (a-b) respectively. The photographic views of Al_2O_3 and Silicon Carbide are provided in the following Fig. 2.2. (c) and Fig. 2.2(d) respectively.

(a)



(b)

(c)

(d)

Fig. 2.2 **(**a-b) Photographic view and SEM image of Carbon nanotube (c) Photographic view of Aluminium Oxide (d) Photographic view of Silicon carbide.

Nano particles like CNTs have created a great impact to produce advanced engineering composites. Different properties of carbon nanotubes are shown in the Table 2.3.

Table 2.3: Properties of CNT.

Aspect ratio	Specific surface area SSA	Purity	Average Outer Diameter	Average Inner Diameter	Number of walls	Length
~1000	350 m2/g	wt.% >97%	20 nm	5nm	5-15	50 Micrometer

Aluminum oxide is amphoteric in nature, and is widely used to make better composite materials as a reinforcing material in various chemical, industrial and commercial spheres. Necessary information regarding the properties of Aluminum Oxide is depicted in the Table 2.4.

Table 2.4: Properties of Aluminium oxide.

Density g/cc	Thermal Conductivity (W/m K)	Diameter	Purity	Young's modulus (GPa)	Thermal Expansion (10-6/K)
3.97	30	<50nm	99%	413	10.8

Silicon Carbide, with the chemical symbol SiC, is a solid industrial mineral crystalline. It is used as a semiconductor and a ceramic, commonly referred to as carborundum. Silicon carbide exists naturally in an extremely rare mineral called moissanite. Some properties of silicon carbide are illustrated in Table 2.5

Table 2.5: Different properties of silicon carbide.

Appearance	Density	Solubility	Molecular mass	Thermal Conductivity
Super black fine powder	3.2 gm/cm^3	Insoluble in water	40.11 g/mol	60-120 W/m. K@25°C.

Many techniques are available in industries for manufacturing of aluminum metal matrix composites such as Solid state (powder metallurgy), Liquid state (stir casting), Thermal spray, Electro-chemical deposition and other novel techniques. Since, stir casting technique is one of the simplest and easiest methods for manufacturing; it has been used to fabricate the composite specimen for testing purpose. Stir casting is suitable due to its simple procedure that are relatively less expensive than other manufacturing process. Two primary difficulties yet with reliable answers are homogeneous dispersion and interfacial bonding of the CNT reinforced metal matrix. Therefore, it is expected that given appropriate processing conditions, CNTs may be dispersed while maintaining their efficient multiwalled structure, and the aluminum matrix's characteristics would be enhanced. Critical issues like processing techniques, nanotube dispersion, interface strengthening mechanism and properties of mechanical should be focused. [**Hashim et. al 2019**]. It is expected that this composite will be beneficial for lightweight material development especially in marine engineering, automobile, military, aviation, aerospace, structural, transportation and other manufacturing industries.

In order to manufacture particle reinforced AMMCs, stir casting is a cost-effective and simple procedure that can be applied. The basic concept of this method is that the reinforcement materials are introduced directly to the molten metal and the particles are consistently dispersed by stirring. Before the reinforcing material is added, the matrix material is heated above its melting temperature. In order to get the greatest possible characteristics, the reinforcement material must be evenly distributed in the matrix material. A variety of parameters must be taken into account while fabricating AMMCs using the stir casting technique, including achieving a homogenous dispersion of reinforcement material, porosity, and good bonding between reinforcement and matrix material. At first some wooden patterns for mechanical testing have been made. Alongside, for machining purpose another cylindrical shaped plastic made pattern has installed. In the Fig. 2.3 stated below, it is shown the patterns prepared for mold cavity in which the molten metals will be poured.

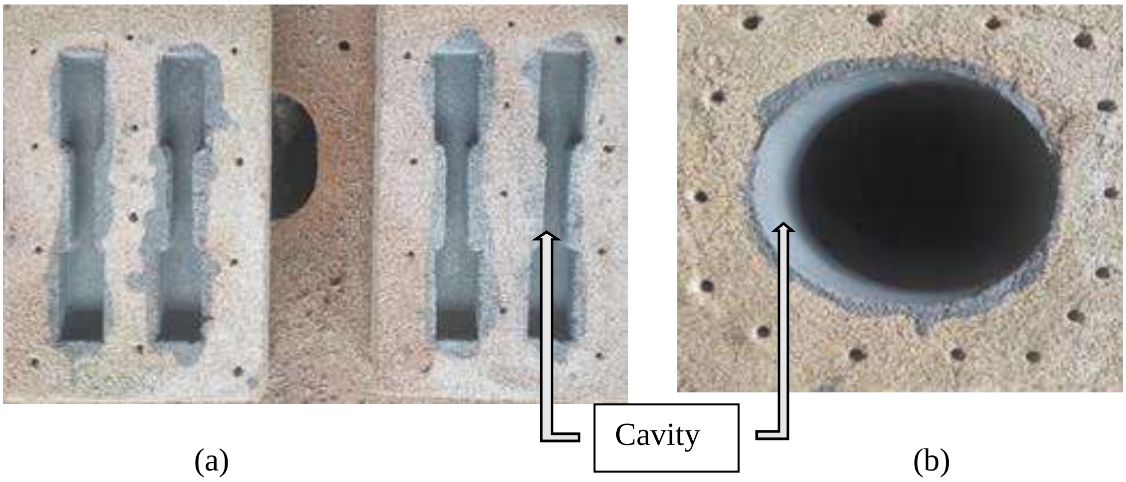
(a)

(b)

(c)

Fig. 2.3 (a) Patterns used to create mould cavity for tensile test (b-c) Pattern used to create mould cavity for making cylindrical shape workpiece.

After making the pattern, using that very pattern mold has been prepared. In the Fig. 2.4 below it is shown the prepared mold using the pattern.



(a) (b)

Fig. 2.4 (a) Mould Preparation by sand casting process for tensile test, (b) Mould Preparation by sand casting process for machining performance.

Titanium carbide mechanical Stirrer and graphite crucible with an electric melting furnace was used for this fabrication process. To fit in the graphite crucible, the aluminium alloy, which was in the form of an ingot, was chopped into small pieces. The crucible was preheated at 500^0C for 30 minutes to remove moisture and prepare for the job. At 800 degrees Celsius, aluminium ingots were melted in the crucible. For better composition and to remove the moisture from reinforcement particles CNT, Al_2O_3 and SiC preheated to a temperature of about 620°C, were added to the molten metal and stirred continuously. 5 minutes were spent stirring melted aluminium. Initial stirring of molten aluminium was done together with the addition of reinforcement components once the reinforcement was pre-heated. The entire melt was again stirred for 5 minutes at 450 rpm. To guarantee adequate mixing of the reinforcements with the molten aluminium matrix, the furnace temperature was raised to 950^0C. To ensure proper mixing, the last stirring took place at 1100^0C for 10 minutes. Experimental setup used in stir casting process is shown in Fig. 2.5.

(a) (b)

Fig. 2.5 (a-b) Preparation of stir casting process using mechanical stir.

2.2 Analysis of Mechanical Properties of Composite Material

After fabrication of the hybrid composite samples, specimens were cut out precisely from fabricated materials per ASTM standards and have been subjected to various mechanical tests. For every type of test, a minimum of three samples were tested to get an average value. Finally, different mechanical properties of prepared samples have been investigated.

Tensile testing is a destructive method used to find out a material's tensile strength and how effortlessly it can be elongated. It measures how much force it requires to break a composite or plastic sample and how much the sample has to stretch or lengthen to break. A total of four specimens were tested having three from each sample for their tensile strength. The composite specimens were cut following the ASTM A370 standard for this test. The tests were conducted using a Universal Testing Machine. The machine was set up with a 10 KN sensor attached to the computer-controlled grip shaft. After setting up the samples were left to break till, they reached their ultimate tensile strength. Four specimens of same dimension were prepared for tensile testing purpose as shown in Fig. 2.6. Length, width and thickness of the specimen were 50, 10 and 15 mm respectively.

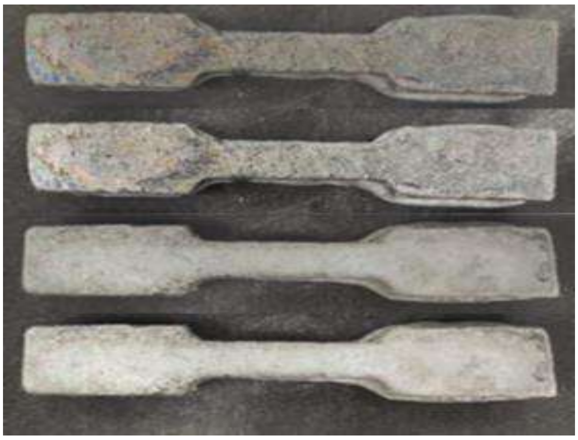


Fig. 2.6 Specimen of carbon nanotube reinforced AMMC for Tensile test.

The entire test was recorded through the sensors under a computerized system and the test results were taken from the computer attached to the universal testing machine. The tensile strength of the composite has shown Fig. 2.7. When SiC, Al_2O_3, CNT reinforce added to the ingot aluminium at 11%, 15%, 0.5 % respectively the composite strength significantly increased than the pure aluminium. The use of SiC, Al_2O_3 and CNTs reinforcement, which has a high strength and stiffness, improved the matrix's local deformation and increased the composites' tensile strength. After increasing the CNT weight percentage to 0.5%. 1%and 1.5% respectively the tensile strength linearly increased.

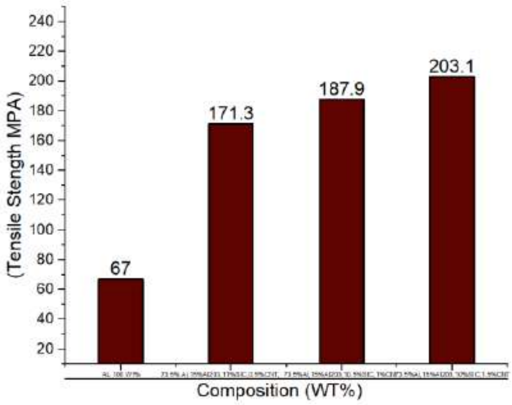


Fig. 2.7 Tensile strength for various weight percentage.

The flexural test method measures how materials behave when they are loaded like a simple beam. For every step of load, the maximum stress and maximum strain are calculated. Following ASTM E290 standards four specimens were cut as samples shown in Fig. 2.8 and then tested to determine their flexural strength. The specimens were set up on the UTM as shown in Fig. 2.9 and pressure was applied on the center point of each of the samples.

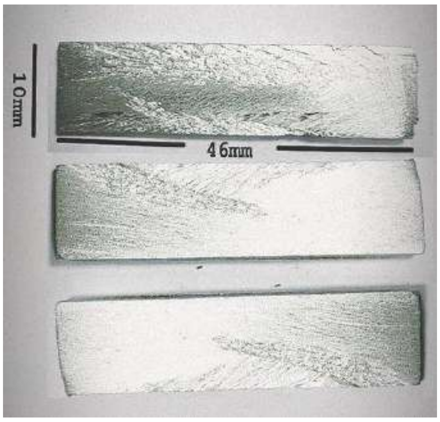


Fig. 2.8 Specimen for Flexural test.

Fig. 2.9 Specimen setup for Flexural test under UTM.

For flexural testing, specimens of different composition were made having dimension of ASTM standard. Flexural strength for pure aluminum was found to be at 162.5 N/mm^2. Maintaining same proportion of Aluminum Oxide, the inclusion of 0.5%, 1%, 1.5% CNT and varying with silicon carbide potentially increases the flexural strength of the material up to 232.9 N/mm^2, 243.3 N/mm^2, 237.7 N/mm^2 respectively which is shown in Fig. 2.10.

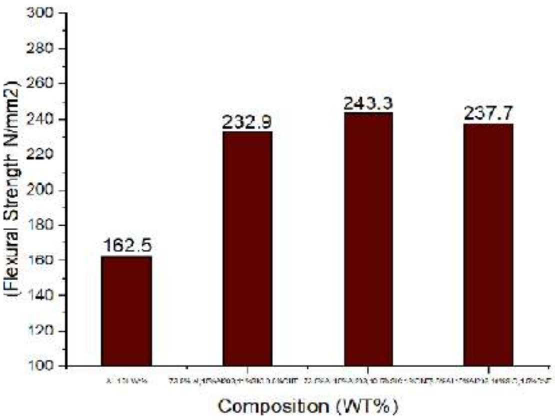


Fig. 2.10 Flexural strength for various weight percentage

Impact test is meant to find out how a sample of a known material will react when a sudden stress is put on it. At ambient temperature, impact strength is determined by letting a pendulum to hit test pieces of AMMCs and measuring the energy absorbed in the break using the benzoid testing machine The test shows if the material is hard or easy to break. The specimens for this test were cutout with ASTM E23 standard and the test was conducted on a Benzoid Impact Tester which is shown in Fig. 2.12. The specimen was set up on the holder and a load was released on it for it to crack at its notch. The amount of force required for creating the crack was recorded. Fig. 2.11 shows the specimens used to test the impact strength. And nest figure depicts the experimental setup of Benzoid Impact Tester.

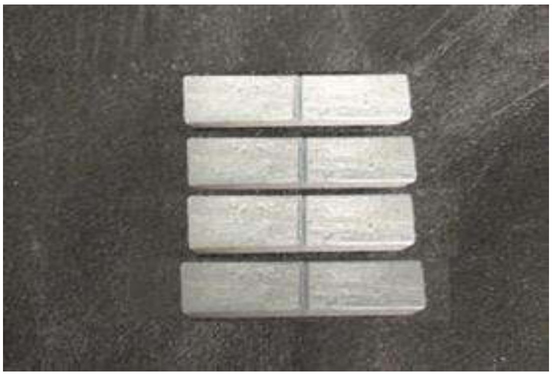


Fig. 2.11 Specimens for Impact test.

Fig. 2.12 Experimental setup for Impact test.

Fig. 2.13 depicts the composite's influence. Ingot Aluminium, SiC, Al2O3, and CNT reinforcement were added to aluminium at 73.25 wt.%, 11wt.%, 15wt.%, and 0.5wt.%, respectively, increasing the composite strength compared to pure aluminium. Impact energy rose linearly as CNT weight percentage was increased to 1% and 1.5%, respectively.

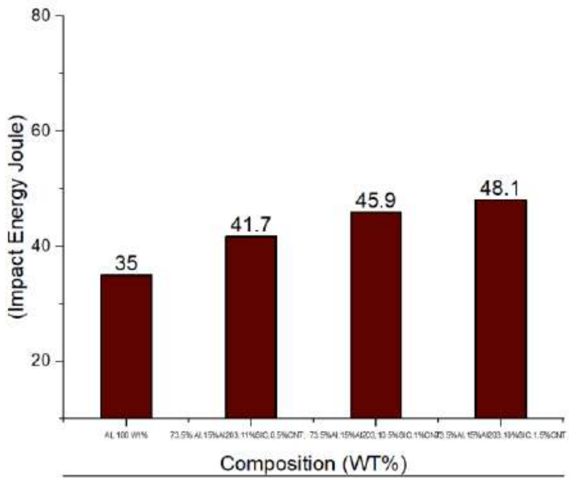


Fig. 2.13 Impact energy for different composition.

Finally, hardness test has been done to find out how hard the fabricated material is. The hardness of a material is the resistance of it while being permanently dented. There are many ways to measure hardness, and each test can come up with different hardness values for the same material. The hardness test was conducted for all sample specimens and the results were noted to take an average value at the end. The test was conducted by placing the sample on a solid hard surface and then using a Rockwell hardness tester. Fig. 2.14 shows an experimental setup of Rockwell Hardness Tester.

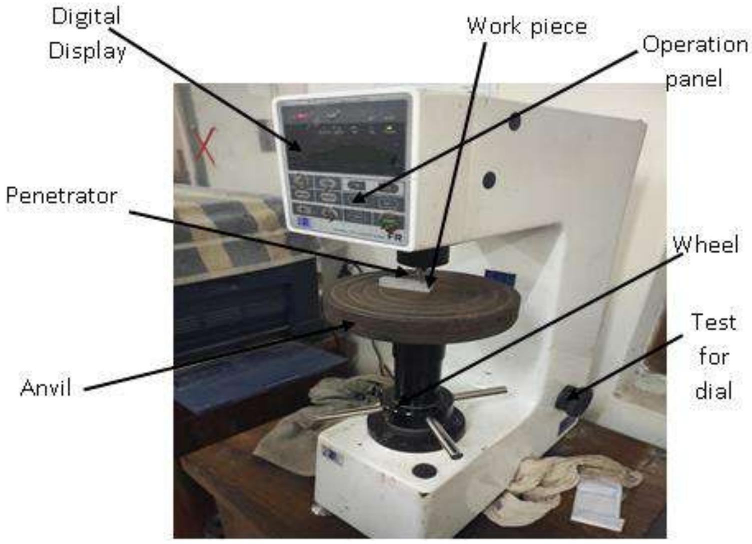


Fig. 2.14 Experimental setup for testing hardness with Rockwell hardness tester.

The Rockwell hardness test method, as defined in ASTM E-18, is the most commonly used hardness test method. The hardness values were tested at three different sites throughout the sample, with average values of 26, 39.3, 37.1, and 36.9 HRA for samples 1, 2, 3, and 4 shown in the Fig. 2.15. Moreover, The Lee rebound hardness test is a non-destructive method used to determine the hardness of materials. In this test, a spring-loaded hammer with a hardened steel tip is allowed to fall from a fixed height onto the surface of the material being tested. The height of the rebound of the hammer is measured by a dial gauge or an electronic sensor and is used to calculate the hardness of the material. During the experiment, six times data were recorded for each composite composition and subjected to the Lee rebound hardness test using a hardness tester and the results were recorded in HL (Lee hardness) units is shown in Fig. 2.15.

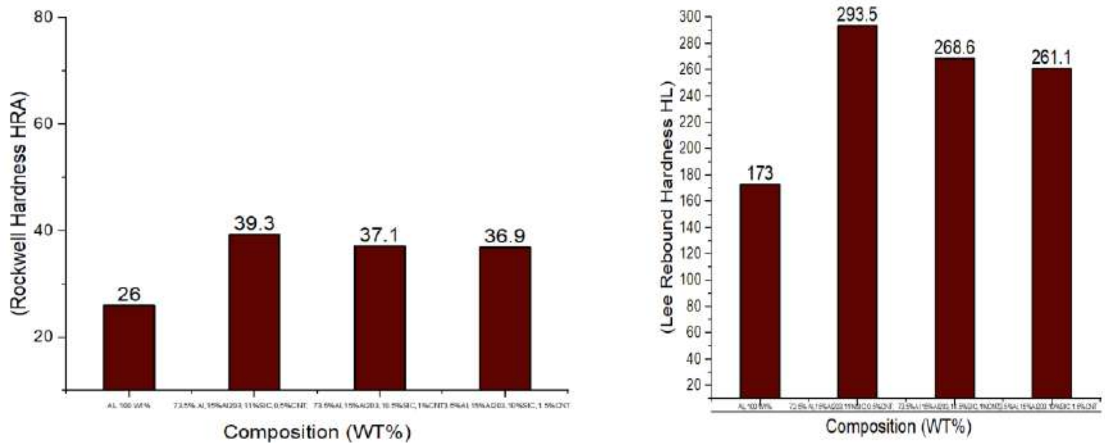


Fig. 2.15 Hardness of AMMC for various weight percentage in Rockwell Hardness and Lee Rebound scale.

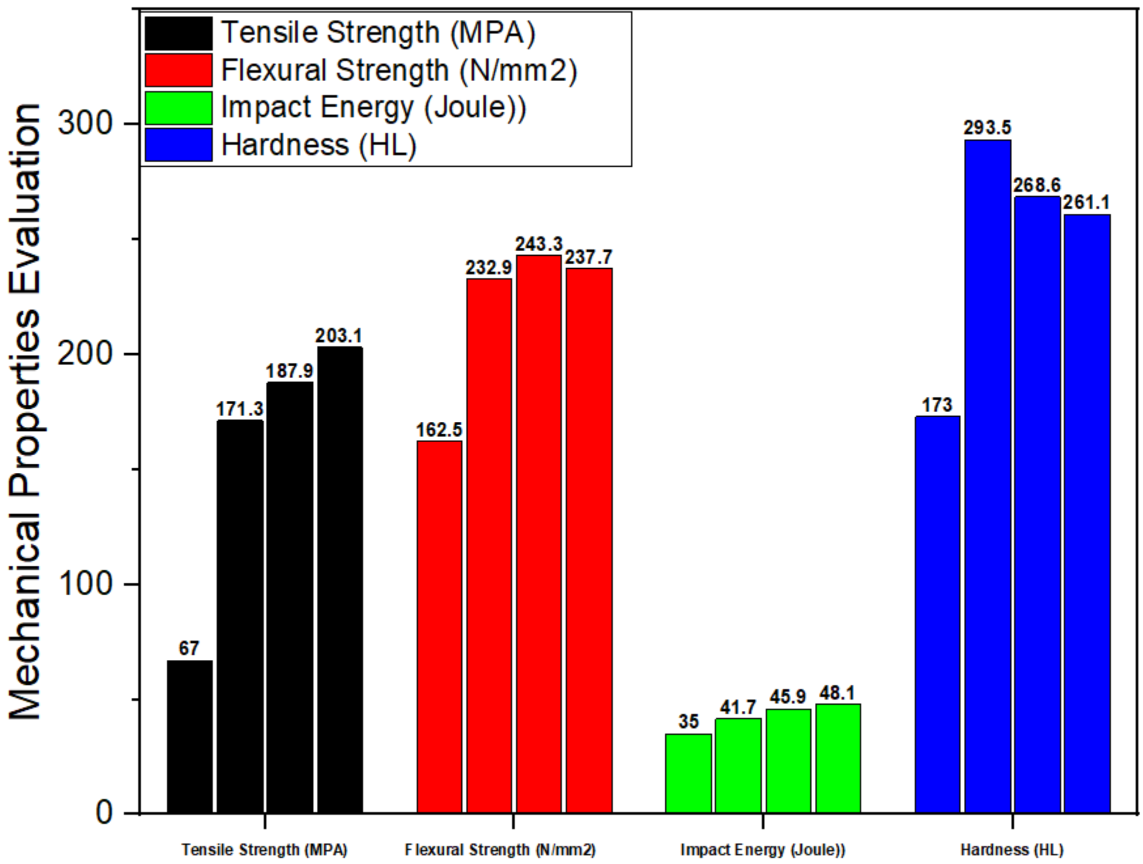


Fig. 2.16 Different Mechanical Properties Analysis for all composition.

After analyzing all the data from mechanical testing, the final result indicates in Fig. 2.16 that incorporation of Al_2O_3, SiC and CNTs reinforcements in pure aluminum improved overall mechanical properties rather than the pure aluminum. Finally, it has been reported that the overall mechanical properties like tensile strength, flexural strength, impact energy and hardness increased massively. In terms of tensile strength and impact energy 73.5 wt.% ingot aluminum, 10 wt.% SiC, 15 wt.% of Al2O3 and 1.5 wt.% of CNTs reinforced AMMC composition resulted the better result than other composition.

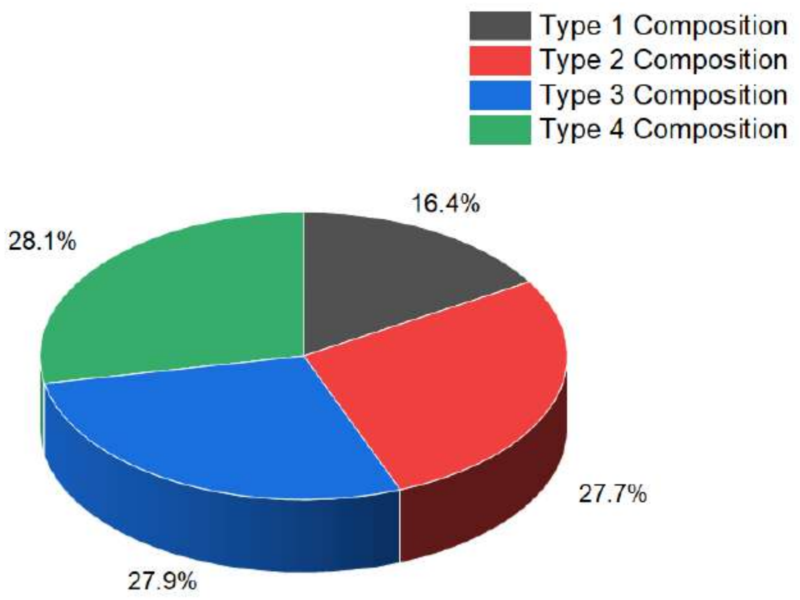


Fig. 2.17 Pie chart of mechanical performance evaluation for all composition.

In Fig 2.17 depicted that the 73.5 wt.% ingot aluminum, 10 wt.% SiC, 15 wt.% of Al_2O_3 and 1.5 wt.% of CNTs reinforced AMMC shows better overall mechanical properties rather than other composition of materials. This study essentially focuses on establishing AMMC as its applications on aerospace and automotive industries because of its admirable properties especially tensile strength and impact energy and compared with the other composition of materials. The tensile strength and impact energy of aluminum metal matrix composites can have a significant impact on their performance in aircraft and automotive industry. Here are some key points to consider:

Tensile Strength: Tensile strength is the maximum stress that a material can withstand before it fractures. In the case of aircraft, high tensile strength is important because it enables the material to withstand the forces and stresses that are exerted on it during flight. Aluminum metal matrix composites have higher tensile strength than conventional aluminum alloys, making them more suitable for use in critical aircraft components such as wing spars, landing gear, and engine components.

Impact Energy: Impact energy is the amount of energy that a material can absorb before it fractures. In aircraft, impact energy is important because it determines the ability of a material to withstand sudden shocks and impacts, such as those that might occur during a hard landing or a bird strike. Aluminum metal matrix composites have higher impact energy than conventional aluminum alloys, making them more resistant to damage from impacts and more suitable for use in aircraft components that are exposed to high stress and impact loads.

Overall, the higher tensile strength and impact energy of aluminum metal matrix composites make them an attractive material for use in aircraft. These materials offer improved performance and durability, which can help to increase the safety and reliability of aircraft components, and reduce maintenance and repair costs. So, considering the all factors as the impact of tensile strength and impact test in aircraft and automotive industry is very crucial, the 73.5 wt.% ingot aluminum, 10 wt.% SiC, 15 wt.% of Al2O3 and 1.5 wt.% of CNTs reinforced AMMC has been selected for machining performances. Finally, a cylindrical bar of composite material was developed by stir casting process using the raw materials i.e., Ingot Aluminum as a matrix, CNT, Silicon carbide and Alumina together in a cylindrical mold for selected composition. The developed work material is shown in Fig. 2.18.

Fig. 2.18 Developed work materials of CNT reinforced aluminum metal matrix composite.

Chapter-3

Experimental Investigation

3.1 Experimental Procedure and Conditions

Composite materials are widely used in diverse applications, and extensive research has been performed to understand the mechanical behavior of such material and develop design procedures for taking maximum advantage of their properties. However, being non-homogenous, anisotropic and reinforced with advanced nanoparticle, these materials are difficult to machine. Significant damage to the work piece may be introduced and high wear rates of the tools are experienced. Traditional machining methods such as drilling, turning, sawing, routing and grinding can be applied to composite materials using appropriate tool design and operating conditions. Generally, nano particle reinforced metal matrix composites are used on a large scale at the production of structure because they have good behavior to mechanical stresses and a high mechanical resistance to weight ratio. From the point of view of the advantages offered by these materials are high toughness, relatively high temperature resistance, and good mechanical resistance, high resistance to corrosion and wear.

In this study, uncoated carbide inserts (SNMG 120404) were used to conduct extensive experimental research on turning carbon nanotube reinforced aluminum metal matrix composite. Investigations have included detailed examinations of the various machining input parameters and their respective responses that result from turning operations. Generation of high cutting temperature during machining is one of the most significant and primary level responses during turning, which not only affects tool life but also degrades the quality of the result. Temperature behavior is proportional to the higher values of cutting process parameters, as well as the increased strength and hardenability of the work piece materials. Cutting force is another primary level machining reaction that is directly proportional to the required quantity of cutting power.

Surface roughness and tool wear are secondary level reactions that depend mostly on the response parameters in terms of temperature and force. Cutting fluids in MQL conditions are commonly used to enhance the performance of machining. However, due to its inefficiency in providing the desired cooling and lubrication, as well as the associated health risks, corrosion, and contamination of the natural environment, a water-soluble cutting fluid under minimum quantity lubrication has been implemented in order to achieve better experimental results.

In this study, a shaft of carbon nanotube reinforced aluminum metal matrix composite which is fabricated considering the best mechanical properties with length of 300 mm length and diameter of 100 mm, was used as the workpiece material to perform turning operation. The cylindrical shaft of composite material was developed by casting the raw materials i.e., Ingot Aluminum as a matrix, CNT (1.5 wt.%), Silicon carbide (10 wt.%) and Alumina (15 wt.%) together in a cylindrical mold. The developed work material after turning 1mm in depth is shown in Fig. 3.1.

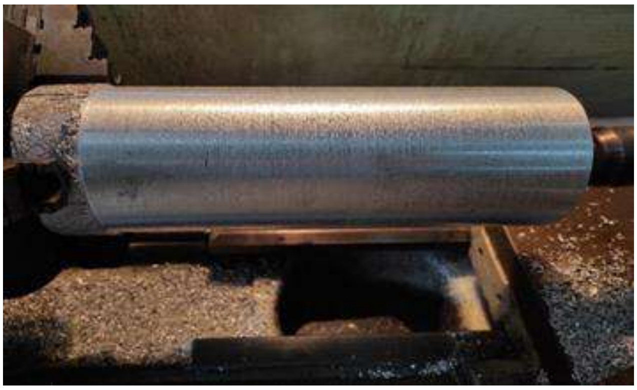


Fig. 3.1 Final product after turning 1mm depth.

The concept of minimum quantity lubrication (MQL) presents itself as a potential solution for hard turn machining in attaining slow tool wear while retaining reasonable cutting forces/power, if the MQL parameters can be set strategically. It has the advantages of a strong stream that can reach the cutting area, strong chip removal, and in some circumstances sufficient pressure for deburring. Not only did the MQL approach reduce temperature, but it also lowered cutting fluid usage.

The primary objective of the present study is to investigate and assess the effect of MQL on the machinability properties of carbon nanotube reinforced aluminum metal matrix composite over dry conditions, particularly in terms of surface roughness, cutting temperature, cutting force and tool wear which influence productivity, product quality, and overall economy.

The machining was performed on a lathe with a main spindle power of 7.5 kW. Fig.3.2 depicts a photographic perspective of the experimental setup to machine the fabricated composite. The nozzle is positioned at a distance of 20.0 mm from the tool tip in order to minimize its interference with the flowing chips and to reach very close to the chip-tool contact zone without avoiding bulk cooling of the tool and the workpiece, which may result in adverse metallurgical changes. After multiple testing, the position of the nozzle tip in relation to the cutting insert has been determined. The ultimate configuration created and utilized is depicted in Fig.3.3. The MQL is guided along the auxiliary cutting edge at a 20^{o} angle in order to reach the major flank and partially under the running chips through the parallel in-built groove.

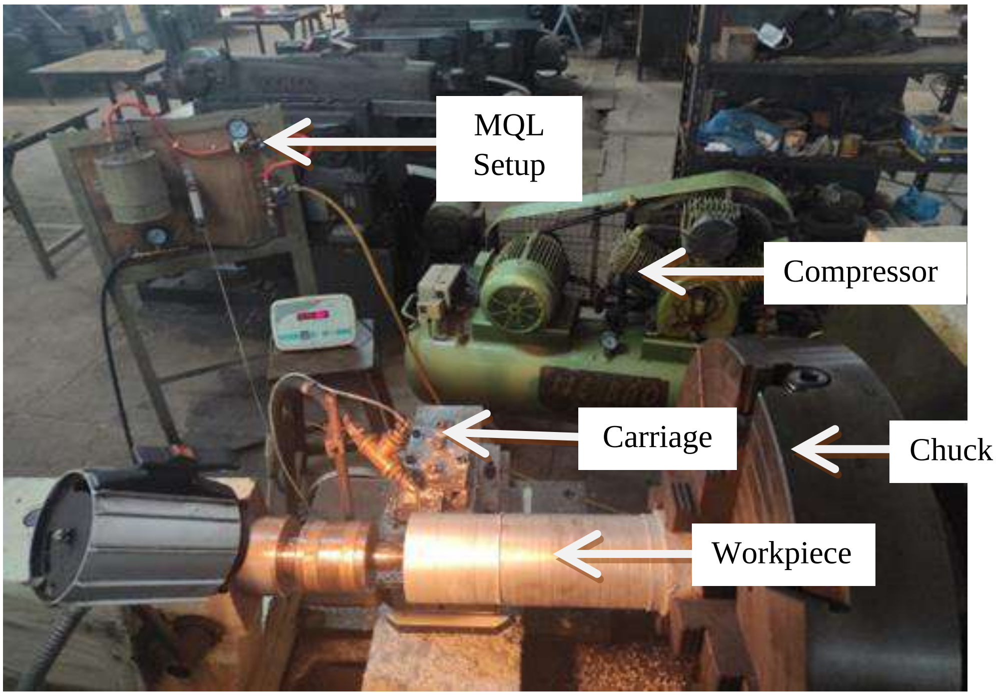


Fig. 3.2 Photographic view of experimental set-up on MQL condition.

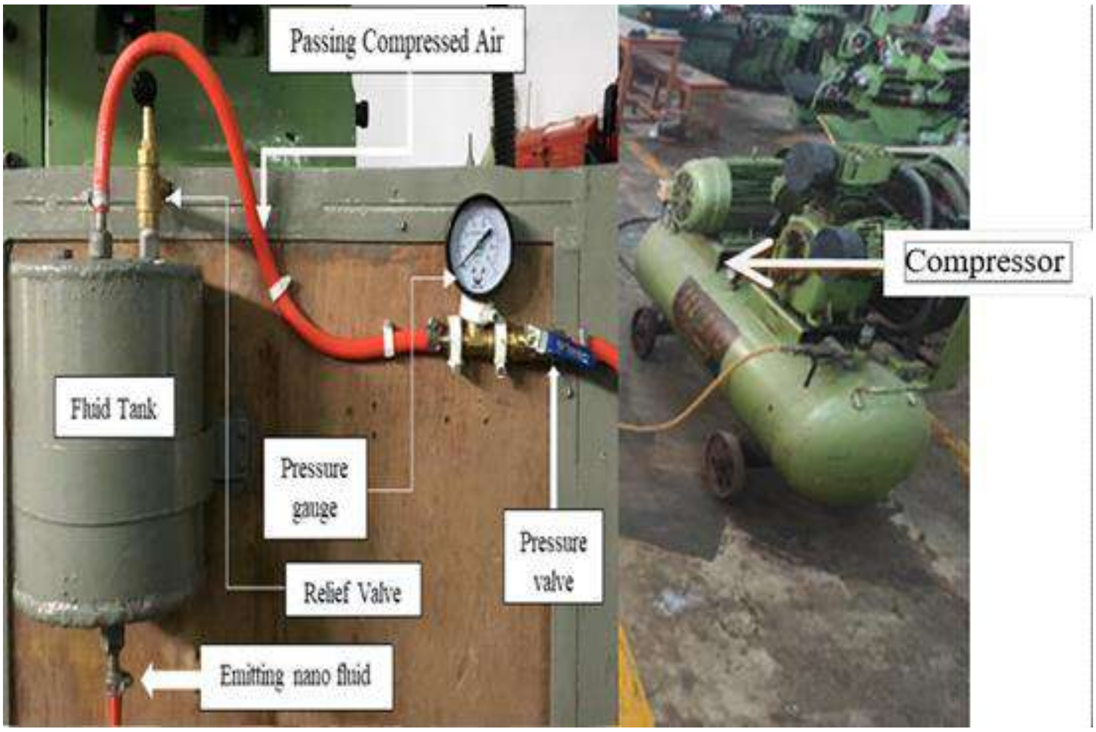


Fig. 3.3 Photographic view of MQL set-up.

Uncoated carbide insert was employed as the cutting tool (ISO specification: SNMG 120404). In addition to 6° side cutting-edge and end cutting-edge angles, the tool holder also positioned at a negative 6° side and back rake angles, respectively. The recommended cutting velocity (V_c), feed rate (S_o) and depth of cut (t) ranges were chosen based on industry standards and tool manufacturer recommendations. Table 3.1 provides a brief summary of the machining test conditions that were used.

Table 3.1: Experimental conditions.

Machine tool	:	Lathe (China), 7.5 kW
Work material	:	Carbon nanotube reinforced aluminum metal matrix composite
Size	:	Length = 300 mm, Diameter = 100 mm
Cutting tool	:	Uncoated Carbide SNMG 120404
Geometry	:	-6°, -6°,6°,6°,15°,75°,0.8 (mm)
Tool holder	:	PSBNR 2525 M12 (ISO specification), Widia
Process Parameters		
Cutting Velocity, (V_c)	:	79,110,168 m/min
Feed rate, (S_o)	:	0.103, 0.137, 0.164 mm/rev
Depth of cut, (t)	:	1, 1.25, 1.5 mm
Environment	:	Dry and Minimum Quantity Lubricant (MQL) condition

In both dry and water-soluble cutting fluid with MQL settings, the cutting temperature, surface roughness, cutting force and tool wear have been measured during short run machining for all the cutting parameter combinations. Under all machining circumstances, the average cutting temperature was determined using a straightforward yet dependable tool-work thermocouple approach with the appropriate calibration. The average value of the major flank wear (VB), which affects cutting forces and temperature and may cause vibration as machining progresses, is typically used to evaluate the life of tools, which finally fail through systematic progressive wear. Surface smoothness and dimensional accuracy of the machined items are impacted by the type and degree of auxiliary flank wear (VS). The temperature and the way that the tool-work interfaces interact, which depend on the machining conditions for specific tool-work pairings, both significantly affect the growth of tool wear.

3.1.1 Cutting Temperature

Machining process becomes productive with the increase of input cutting parameters value, which eventually generate a significant amount of heat, in addition to a high temperature in the cutting zone. If the cutting temperature is not correctly regulated, the cutting tools will suffer from severe flank wear and notch wear, they will lose the sharpness of the cutting edge due to either wear or blunting caused by welded built-up edge, and the quality of the product will suffer as a result. All of these heat sources, when operating under typical cutting conditions, produce the highest temperature at the chip-tool interface. This temperature has a significant impact on the chip formation mode, as well as cutting forces, tool life, and product quality. Machining at high production levels needs to further increase the number of process parameters in order to keep up with the increasing demand and maintain cost competitiveness. As process parameters and the hardness and strength of the work material increase, so does the temperature of the cutting process. Therefore, efforts are made to lower this dangerously high temperature throughout the cutting process. The present study utilized a straightforward but dependable tool-work thermocouple technique with the appropriate level of calibration in order to determine the average cutting temperature for all of the machining situations that were carried out. Photographic view of experimental set-up for measuring cutting temperature is shown in Fig. 3.4.

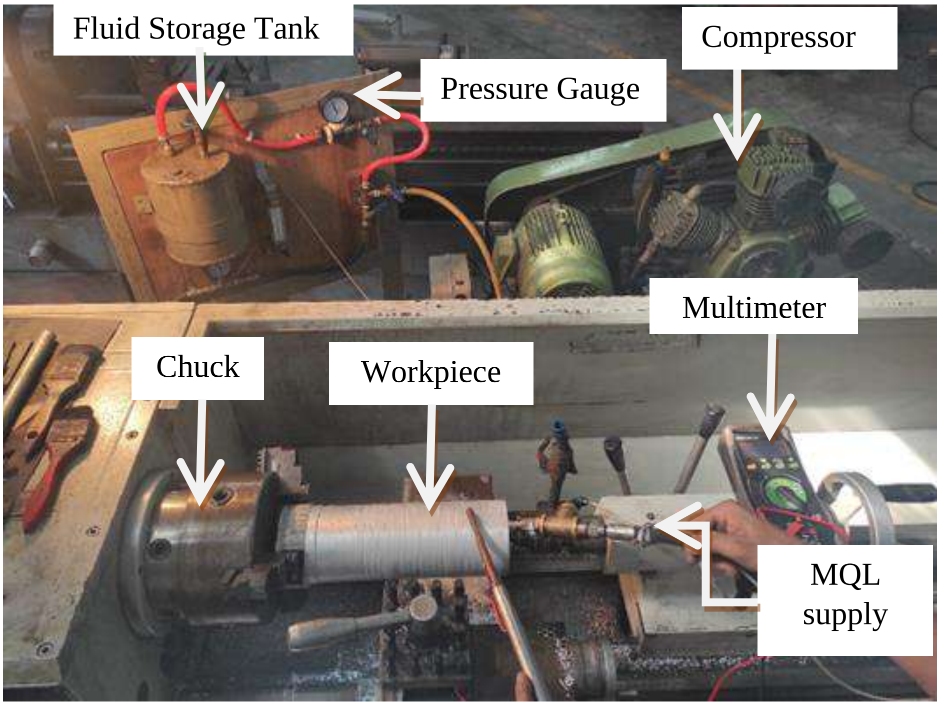
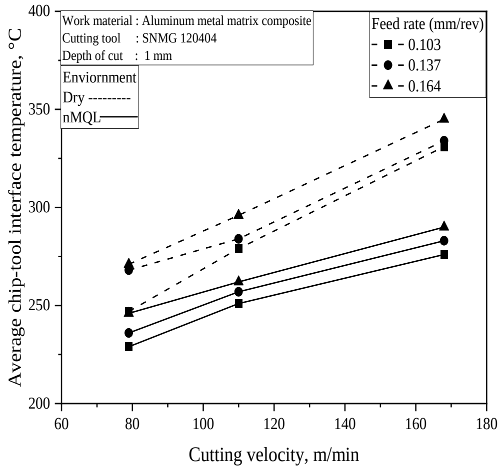
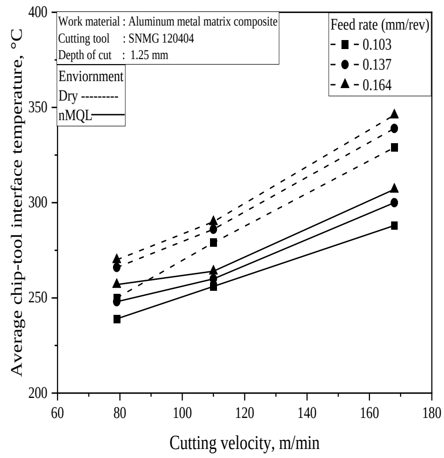


Fig. 3.4 Photographic view of experimental set-up for measuring cutting temperature.

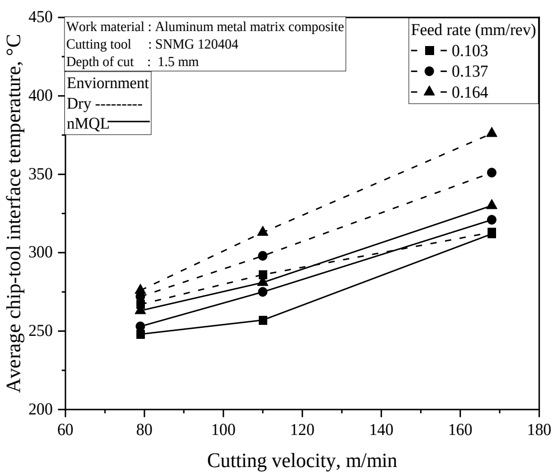
Fig. 3.5 illustrate the evaluated role of water-soluble cutting fluid under MQL and dry condition on the average chip-tool interface temperature during the turning of fabricated composite at various input parameters combinations for depth of cut 1mm, 1.25mm, 1.5mm respectively.



(a)



(b)



(c)

Fig 3.5 (a-c) Variation of average chip-tool interface temperature with cutting speed (V_c) at different feed rate (S_o) in turning of carbon nanotube reinforced aluminum MMC by SNMG insert under dry and MQL conditions.

3.1.2 Surface roughness

The performance and service life of any machined part are largely determined by the quality of that product. The quality of a product is generally evaluated for a given material based on its dimensional and form accuracy as well as its surface integrity in terms of surface roughness, oxidation, corrosion, residual stresses, and surface and subsurface microcracks. Only surface roughness and dimensional deviation on diameter have been examined in this work to determine the proportionate influence that MQL plays on those two primary features. Surface roughness is an important index of machinability that is strongly influenced by the machining environment for any particular tool-work combination and speed-feed conditions. After machining of 100 mm for each experimental run with the sharp cutting edge of the tool, surface roughness was assessed by surface roughness tester and graphical representations at various cutting parameter combinations under dry and MQL conditions are shown in Fig. 3.6 and Fig. 3.7 respectively.

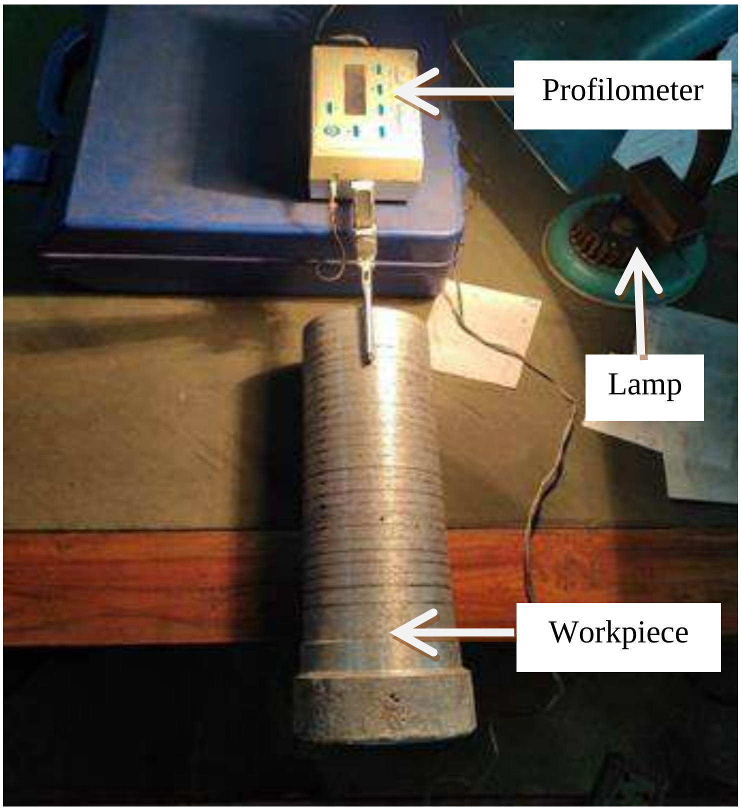
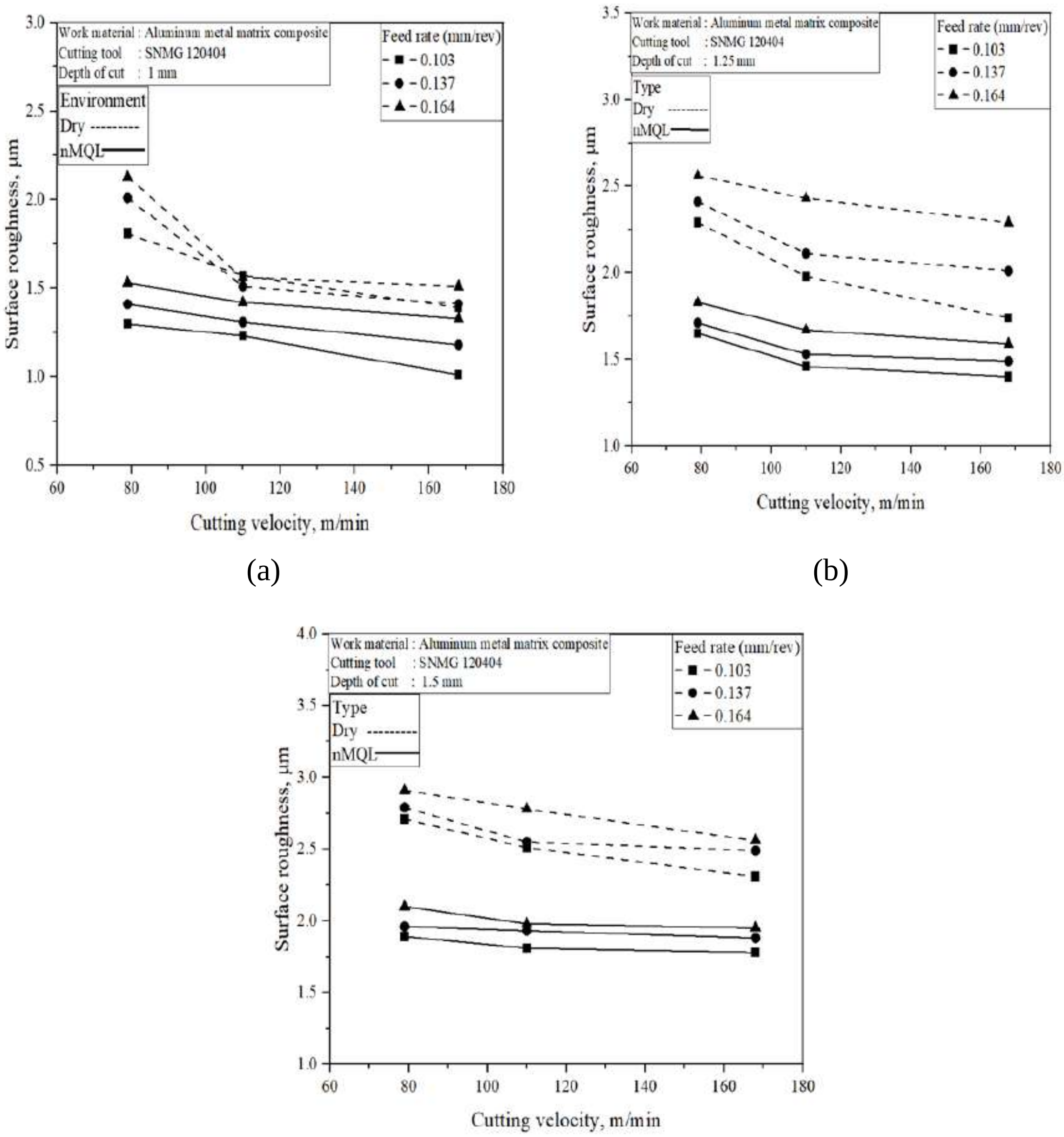


Fig. 3.6 Photographic view of experimental set-up for measuring surface roughness.



(a) (b)

(c)

Fig 3.7 (a-c) Variation of surface roughness with cutting speed, V_c at different feed rate, S_o in turning of carbon nanotube reinforced aluminum metal matrix composite by SNMG insert under dry and MQL conditions.

3.1.3 Cutting Force

Cutting forces for the single point cutting tools being used for the turning operation are characterized by having only one magnitude during machining. But that force is resolved into three components for ease of analysis and exploration resolved into three components namely; tangential force or main cutting force, Pz, axial force or feed force, Px and transverse force, Py. Each of those interrelated forces has got specific significance. In the present work, the magnitude of Pz has been monitored by dynamometer for all the combinations of steel specimens, tool configurations, cutting velocities, feeds and environments undertaken. In the current study, the dynamometer (Kistler) was used to measure the magnitude of Pz for all possible combinations of the fabricated specimen, tool configuration, cutting speeds, feed rates, depth of cut, and working conditions. Photographic view of experimental set-up for measuring cutting force by dynamometer is shown in Fig. 3.8.

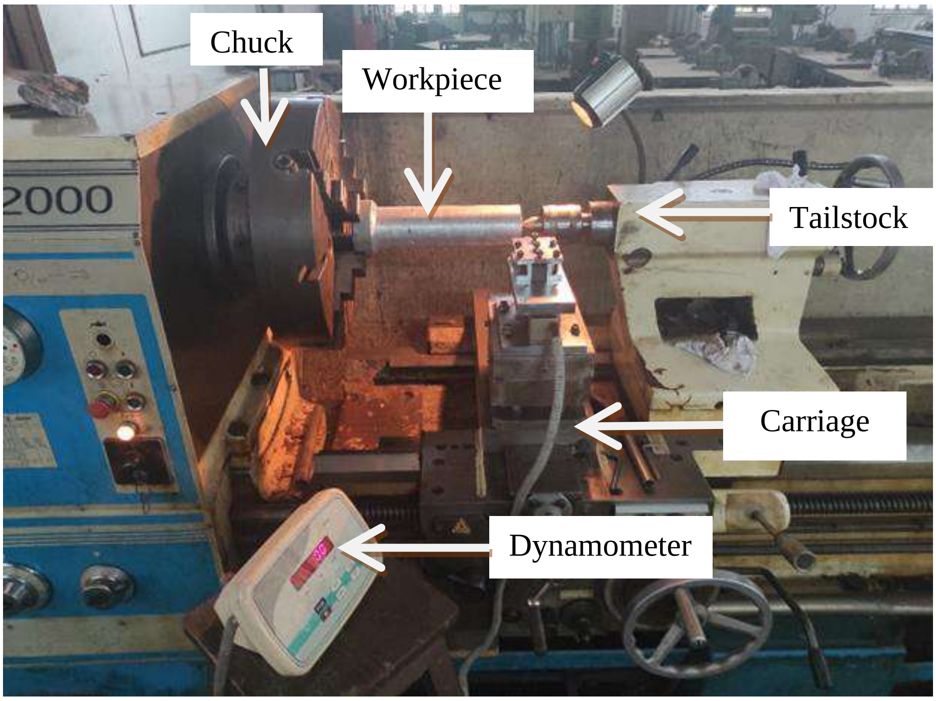
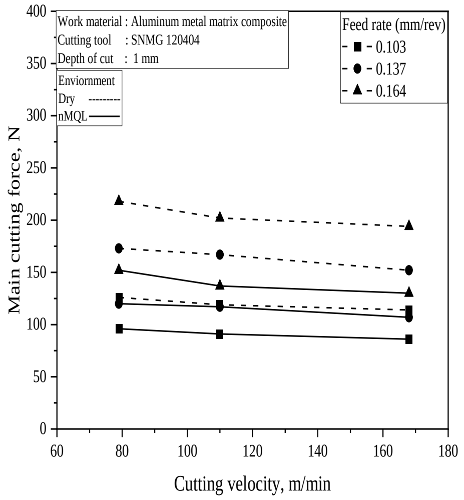
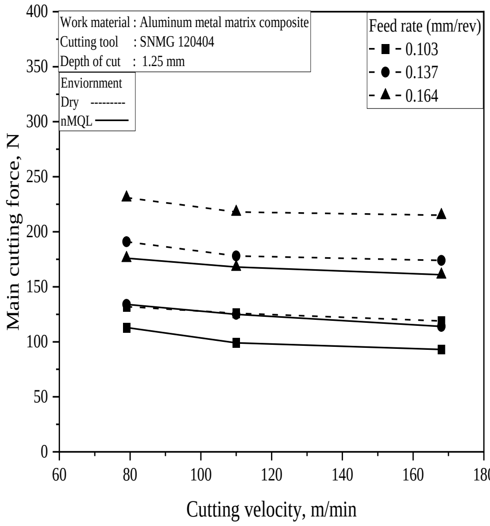


Fig. 3.8 Photographic view of experimental set-up for measuring cutting force by dynamometer.

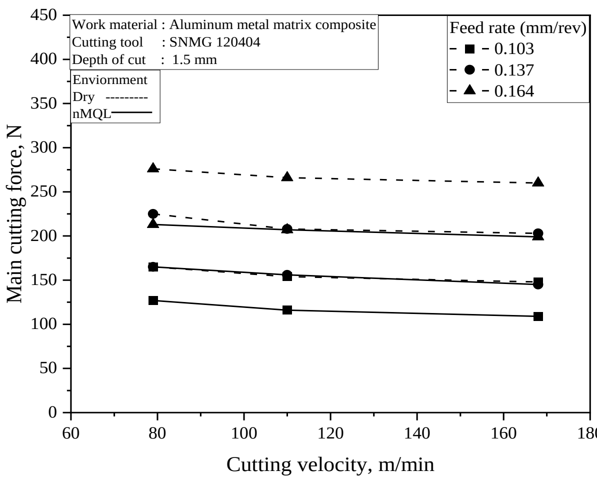
Fig. 3.9 demonstrate visually, respectively, the impact of MQL and dry cutting condition on Pz that was noticed when turning fabricated composite materials by the uncoated carbide insert at various input parameters level. Such a significant decrease in cutting force, Pz, is logically attributed mostly to the cutting tools' ability to maintain their sharpness and to the beneficial change in chip-tool interaction that leads to decreased friction and built-up edge creation. For the other depth of cut and equipment used, outcomes that were more or less comparable were indicated in Fig. 3.9.



(a)



(b)



(c)

Fig 3.9 (a-c) Variation of cutting force with cutting speed, V_c at different feed rate, S_o in turning of carbon nanotube reinforced aluminum MMC by SNMG insert under dry and MQL conditions.

3.1.4 Tool Wear

Depending on the tool-work materials and machining condition, the cutting tools in conventional machining, especially in continuous chip creation operations like turning, typically fail by gradual wear caused by abrasion, adhesion, diffusion, chemical erosion, galvanic action, etc. Due to what is referred to as break-in wear brought on by attrition and micro-chipping at the sharp cutting edges, tool wear initially begins to occur at a relatively faster rate. In addition, cutting tools may fail prematurely, randomly, and catastrophically due to mechanical failure and plastic deformation under adverse machining conditions caused by intense pressure and temperature and/or dynamic loading at the tool tips, especially if the tool material lacks strength, hot-hardness, and fracture toughness. However, in the present experiments involving tools, work material, and machining circumstances, the predominant mode of tool failure was progressive wear. Photographic view of experimental setup for measuring cutting tool wear for fabricated composite is shown in Fig. 3.10. Fig. 3.11 depict the increase of average auxiliary flank wear, VS, with machining time of fabricated composite under both dry and MQL conditions.

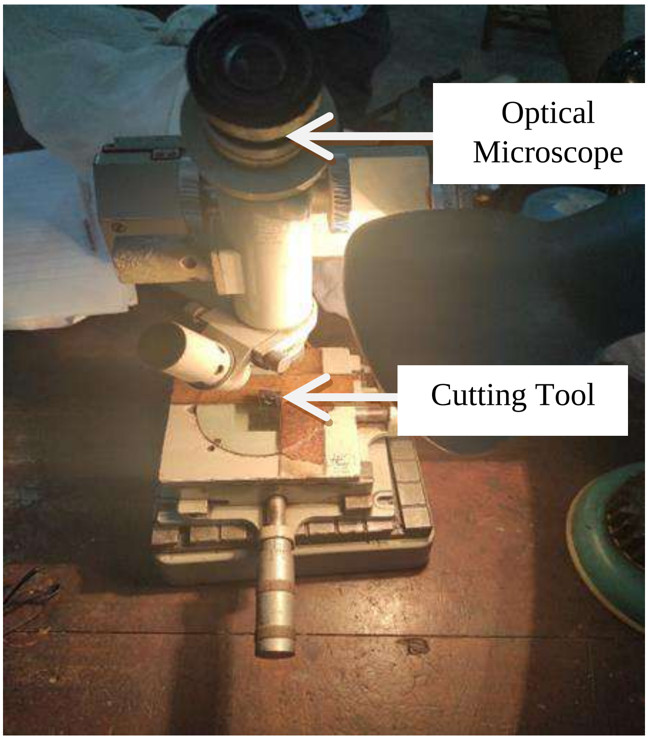


Fig. 3.10 Photographic view of experimental setup for measuring cutting tool wear for fabricated composite.

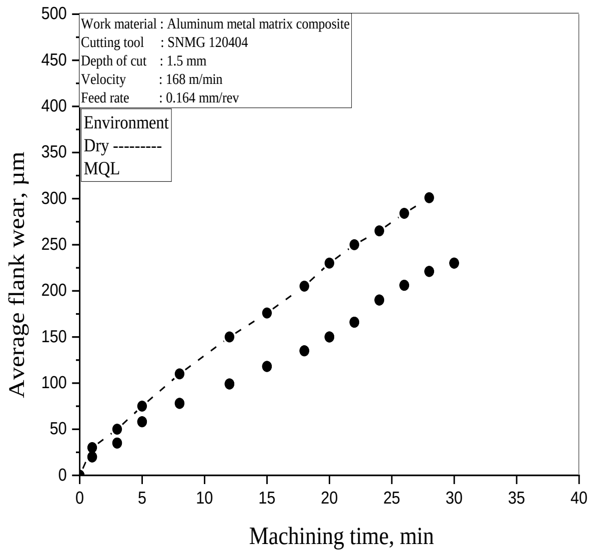


Fig. 3.11 Growth of tool wear with machining time at high cutting speed, (V_c) feed rate, (S_o) and depth of cut in turning of carbon nanotube reinforced Aluminum MMC composite by SNMG insert under dry and MQL conditions.

Under a Scanning Electron Microscope in Figure 3.12 (Philips XL 30, Belgium), the actual effects of different environments on the wear of the carbide inserts of the present two configurations were identified by observing the pattern and extent of wear that developed on the different surfaces of the tool tips after being used for machining hardened carbon steel for an extended period.

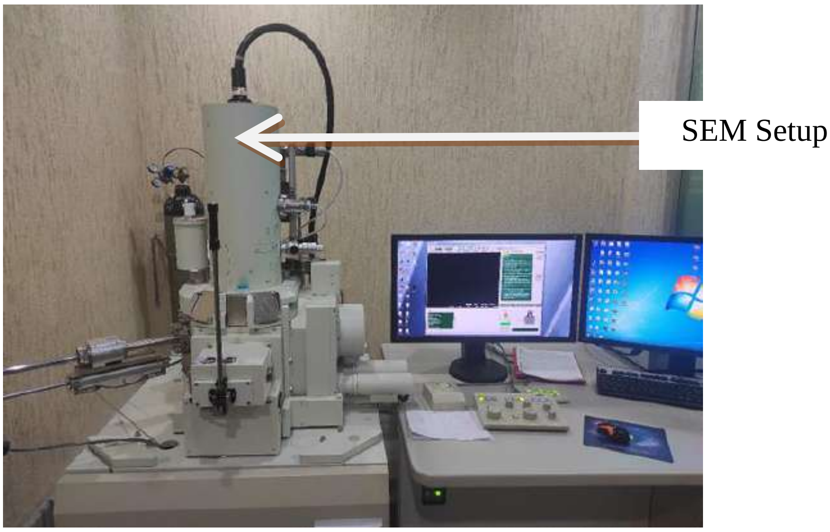
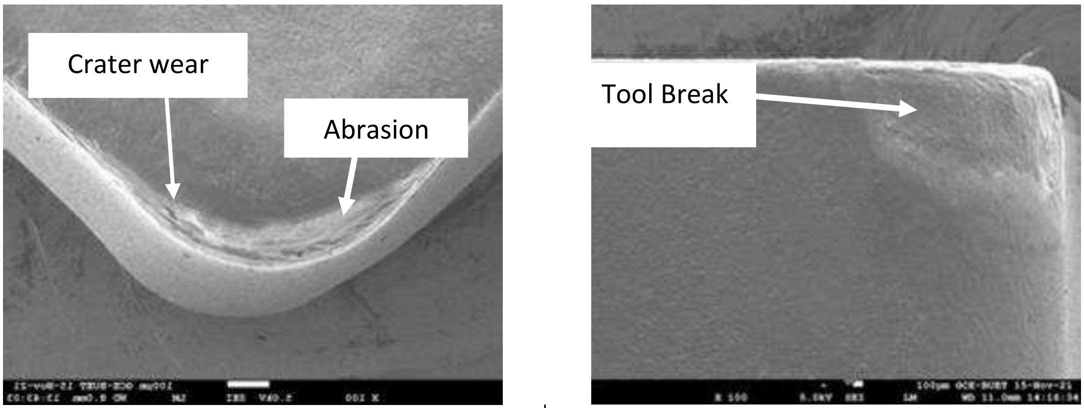
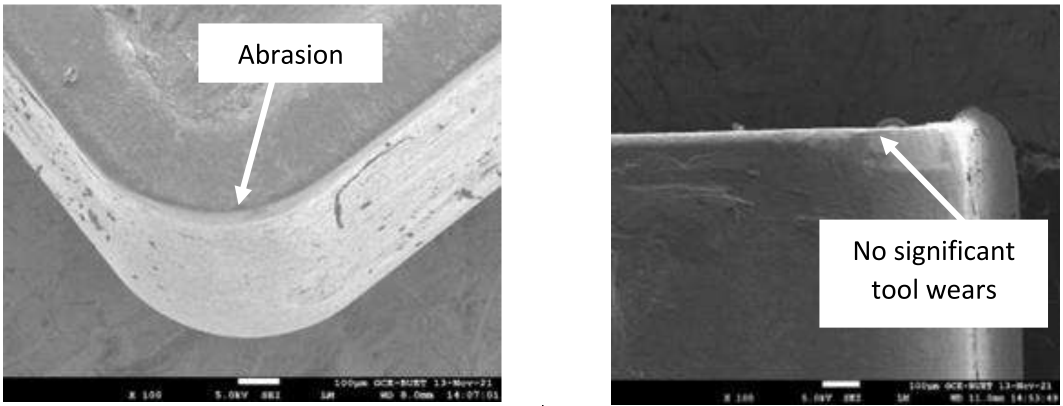


Fig. 3.12 SEM setup for measuring cutting tool wear for developed composite material under both Dry and MQL condition.



(a) (b)

Fig. 3.13 (a-b) SEM views of the worn out SNMG insert [Time 30 min] after machining fabricated materials under dry conditions.



(a) (b)

Fig. 3.14 (a-b) SEM views of the worn out SNMG insert [Time 30 min] SNMG after machining fabricated materials under MQL conditions.

Fig. 3.13 and Fig. 3.14 are scanning electron microscopy (SEM) images of worn-out inserts (SNMG) after machining CNT reinforced aluminum metal matrix composite at Vc = 168 m/min, So = 0.164 mm/rev, and t = 1.5 mm for 30 minutes under dry and MQL conditions.

Chapter-4

Mathematical Modeling by ANN and RSM

Surface roughness modeling has developed into a viable and affordable method in order to characterize the machining environment and the cutting settings that would work best for the material being processed. With the aid of a well-established model of machining responses for a particular material and process, manufacturers may set cutting parameters reasonably accurately, resulting in the optimization of cutting conditions. Numerous techniques, such as the Taguchi method, the adaptive neuro fuzzy inference system (ANFIS), the genetic algorithm (GA), the radial basis neural network (RBN), etc., have been used to conduct extensive research on the modeling of surface roughness for a variety of materials and processes. Numerous techniques, including the Taguchi method, the adaptive neuro fuzzy inference system (ANFIS), the genetic algorithm (GA), the radial basis neural network (RBN), etc., have been utilized in extensive research on the modeling of surface roughness for a wide range of materials and processes. The theory of ANN and RSM must also be thoroughly grasped in order to comprehend the model. The section 1.2.4 includes a review of the relevant literature. Before creating ANN and RSM models to estimate surface roughness, it is necessary to take into account the process performance influencing elements. First, the machining parameters are the cutting speed (Vc), feed rate (S_o) and depth of cut (t) are considered as input parameters. Because these criteria were predetermined, they are regarded as controllable factors. These variables served as input variables for the suggested ANN and RSM model.

The parameters for output are surface roughness. The tool geometry, which comprises the nose radius, rake angle, cutting edge angle, and clearance angle, can also be a key factor when selecting a tool for a particular machining process. This machining investigation was conducted using a specific tool-work combination, indicating that the tool geometry was consistent. Consequently, it has not been taken into account in the predicted models for surface roughness. If the used material is manufactured under adequate quality control, the parameters indicating the qualities of the work piece can be regarded as controllable. Due to the fact that the experiment was conducted for a specific combination of tool and work, the chemical and physical properties of machined materials can be regarded constant. Therefore, it was not considered in the predictive models given for surface roughness. If the clamping procedure is carried out correctly, auxiliary equipment such as a clamping system can be said to be under control. Significant vibration generated by inappropriate clamping may compromise the workpiece's structural integrity and damage the machining process. The proposed models do not account for clamping because it was assumed that it would be performed properly throughout the machining process. Vibrations may occur between the workpiece and the machine tool, as well as between the machine tool and the cutting tool. These variables have a substantial effect on the performance of the process. The suggested neural network and response surface model excludes undesired vibration for convenience.

4.1 Modeling by Artificial Neural Network

An artificial neural network (ANN) is a computational model in view of the structure and elements of organic neural systems. As the "neural" some portion of their name recommends, they are mind-motivated frameworks, which are proposed to imitate the way that we people learn. Moreover, ANNs are regarded as modeling techniques for artificial intelligence. Neural systems comprise of input and output layers, and in addition (much of the time) a hidden layer comprising of units that change the input to something that the output layer can utilize. They are great tools for discovering designs that are very intricate or numerous for a human software engineer to concentrate and instruct the machine to perceive. They have a highly interconnected structure comparable to that of brain cells in human neural networks and consist of a large number of simple processing elements known as neurons, which are grouped in different network levels. Data that courses through the system influence the structure of the ANN in light of the fact that a neural system change - or learns, it could be said in view of that input and output. ANNs are viewed as nonlinear statistical information demonstrating tools where the complex relationships between inputs and outputs are displayed or designs are found. Every network has an input layer, an output layer, and one or more hidden layers. In a supervised or unsupervised learning process, ANN is able to learn from the sample set, also known as the training set. This is a well-known advantage of ANN. Once the architecture of a network is specified, the weights are determined through a process of learning so as to provide the desired results.

ANNs have three layers that are interconnected. The primary layer comprises of input neurons. Those neurons send data to the second layer, which in turn sends the output neurons to the third layer. Learning ability and the use of different learning algorithms are the key features of artificial neural network. Best learning algorithm and an optimum number of neurons need to be determined to get a minimal deviation between experimental values and output values. Gradient descent backpropagation (GD), quasi-Newton backpropagation (BFG), Levenberg-Marquardt backpropagation (LM), scaled conjugate gradient backpropagation (SCG), Resilient backpropagation (RP), Conjugate gradient backpropagation with Polak-Ribiére updates (CGP), Bayesian regulation backpropagation (BR) are different types of learning algorithms used in network training process. Validation set is an independent data set that may be applied to trained neural networks if we are experimenting with neural network topologies. The one with the best performance is ultimately selected. After validation, a separate dataset known as the test set is utilized to establish the neural network's performance level, which indicates our level of confidence when employing the neural network. It must be noted that a neural network cannot learn anything that is absent from the training set. Therefore, the size of the training set must be sufficient for the neural network to memorize the features/trends contained in the training set. Alternatively, if the training set contains too many trivial features, the neural network may waste its resources (weights) fitting the noise. Successful implementations of neural networks require a sensible selection and/or representation of the data

Two types of neural networks exist: feed-forward and recurrent. In feed-forward neural networks, signals can only flow from input to output, i.e. an output signal from one layer is always an input signal for the following layer, but never the other way around. The input signals of the first layer are the input signals of the entire network, and the output signals of the network are the output signals of the neurons in the last layer. However, recurrent networks feature feedback loops that permit signals to travel forward and/or backward. Feed-forward neural networks have a simple structure and a straightforward mathematical description. The present thesis uses a multi-layer feed-forward ANN paradigm with a single node in the output layer and three neurons in the input layer for each output response (surface roughness). The network was created progressively by adding nodes and hidden layers until a suitable design was achieved. There may be few or many hidden layers in a network, and their function is to improve network performance. As the number of input neurons increases, so too does the network's requirement for these layers. There is no specific formula to determine the optimal number of hidden layers and neurons. For relatively basic systems, such as the one at hand, the trial-and-error method is often employed to determine the optimal solution to a problem. In Fig. 4.1, a feed-forward neural network is depicted. It consists of an input layer with three input neurons (cutting speed, feed rate and depth of cut), a hidden layer with n neurons, and an output layer with one output neuron (surface roughness).

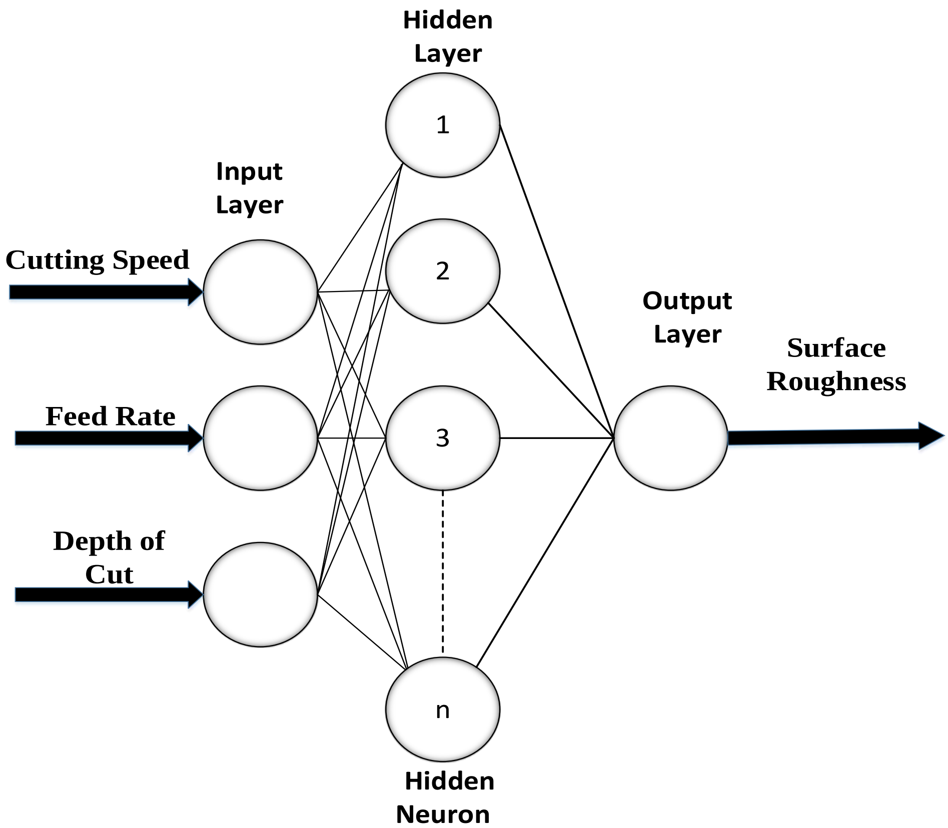
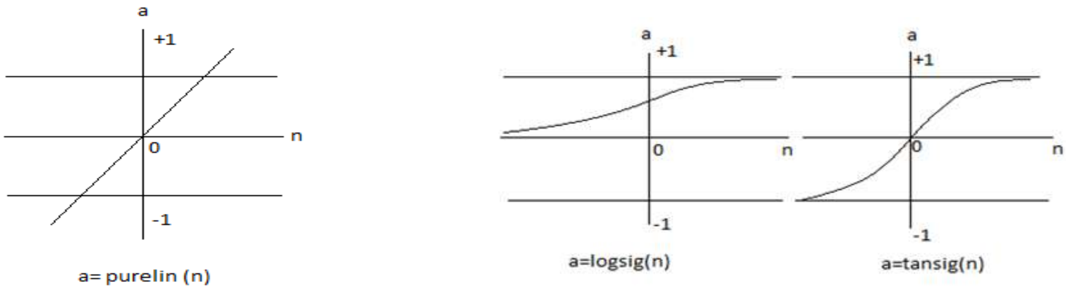


Fig. 4.1 Proposed feed forward neural network.

The log-sigmoid transfer function (LOGSIG), which takes an input and transfers it to the range 0 to 1, is one of the most prominent transfer functions. In the context of neural networks, the hyperbolic tangent transfer function (TANSIG), which delivers an output in the range of -1 to 1, is another popular transfer function. It is important to note that the "tansig" should be selected due to its symmetry [Basheer et al., 2008]. Due to the symmetry of this study, the transfer function of the hidden layer was a hyperbolic tangent sigmoid (tansig), whereas the function of the output layer was a linear function (purelin). Fig. 4.2 illustrates the transfer functions graphically (a-c).



(a) Linear (b) Logsig (c) Tansig

Fig. 4.2 (a-c) Transfer functions.

This approach of machine learning employs two learning strategies with ease. One of these two supervised learning algorithms analyzes the training data and creates an inferred function that can be used to map new samples. The training data consists of a collection of examples for training. Each example in this technique is a pair consisting of an input object and the desired output value. Using supervised learning, the surface roughness for a certain cutting condition has been predicted in this thesis. A neural network was trained in this study using a feed-forward back propagation technique.

In the work, a feed-forward back propagation algorithm was used to teach the neural network how to work. There are two stages of data flow on the network. First, the information from the input layer is sent to the output layer, where it is used to make an output. Then, the error signals caused by the difference between what the network thought would happen and what really happened are sent back from the output layer to the previous layers so that they can adjust their weights. Weights will keep getting changed until the goal for network errors is reached. As a training function, Bayesian Regularization (trainbr) has been used to train the neural network of the MATLAB R2018a toolbox to predict the surface roughness. When there isn't a lot of training data, it can give more accurate results than the Levenberg–Marquardt algorithm.

The number of neurons in the hidden layer is set to five on purpose, and hidden neurons are added to the hidden layer one at a time. The process of adding hidden neurons keeps going until the network's performance doesn't improve much more. Mean squared error (MSE), which compares the actual values for each output node with what was expected, was used to figure out how well the network worked after it was trained. The feedback from this processing is called the "average error" or "performance." When the average error goes below or above the right target, the neural network stops training and is ready for verification.

In this study surface roughness was measured for each depth of cut of 1 mm, 1.25 mm, and 1.5 mm. Three different cutting speeds of 79 m/min, 110 m/min, and 168 m/min, and three feeds of 0.103 mm/rev, 0.137 mm/rev, and 0.164 mm/rev were used to train the neural network. Table 4.1 shows the values for surface roughness under all cutting conditions that were used to predict data. For modeling purposes, values of surface roughness were taken from turning in MQL condition on fabricated composite materials. After the training, the weights are set and the model is put to the test to make sure it is correct. Therefore, in work, the network is evaluated to verify whether it agrees with the results of experiments.

Table 4.1 Actual values of surface roughness for outputs while machining carbon nanotube-based aluminum metal matrix Composite.

Sl No.	Depth of cut t, (mm)	Feed rate S_0, (mm/rev)	Cutting velocity V_c, (m/min)	Surface Roughness (Ra) µm
1	1	0.103	79	1.3
2			110	1.23
3			168	1.01
4		0.137	79	1.41
5			110	1.31
6			168	1.18
7		0.164	79	1.53
8			110	1.42
9			168	1.33
10	1.25	0.103	79	1.65
11			110	1.46
12			168	1.4
13		0.137	79	1.71
14			110	1.53
15			168	1.49
16		0.164	79	1.83
17			110	1.67
18			168	1.59
19	1.5	0.103	79	1.89
20			110	1.81
21			168	1.78
22		0.137	79	1.96
23			110	1.93
24			168	1.88
25		0.164	79	2.1
26			110	1.98
27			168	1.95

While analyzing data for carbon nanotube reinforced aluminum metal matrix composite, optimal network is found at 3-7-1 for MQL cutting condition. Table 4.2 presents the summary of the optimal network architecture.

Table 4.2 Summary of the ANN model for 3-7-1 ANN architecture for surface roughness prediction of CNT reinforced aluminum metal matrix composite.

Type of neural network	:	Multi-layer feed-forward
Input neurons	:	Cutting speed, V_c(m/min.)
	:	Feed rate, S_o (mm/rev.)
	:	Depth of cut, t (mm)
Output neuron	:	Average surface roughness (Ra)
Number of Hidden layers	:	1
Hidden neurons	:	7
Training Function	:	TRAINLM
Adaptive Learning Function	:	LEARNGD
Transfer function	:	Tangent sigmoid (Hidden layer)
	:	Linear transfer function (Output layer)
Sample pattern vector	:	19 (for training) and 8 (for testing)

Among 27 datasets, 19 datasets are taken for training purposes and 8 datasets are taken for testing. To obtain the output closest to the experimental data fabricated composite, the number of neurons in hidden layers is taken as 7 for MQL condition. So, the networks are 3-7-1 for ANN architecture. The proposed ANN structure depicts that it has 3 neurons (depth of cut, cutting speed and feed rate) in the input layer, seven neurons in the hidden layer and one neuron (surface roughness) in the output layer. In order to train and test the network and obtain a respectable predicted roughness with the least average MAPE, the number of neurons in the hidden layer was determined by trial and error using a range of values from 5 to 40. By the end, we had settled on a network of 7 hidden neurons to represent surface roughness. Surface roughness in the proposed network has corresponding representations of 3-7-1.

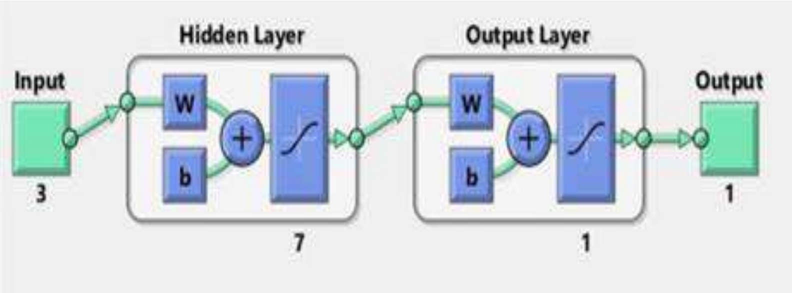


Fig. 4.3 ANN optimum network.

The value of R^2 for surface roughness is found to grow until hidden neuron number 7. After that, mainly the number of test cases begins to drop. The R^2 values achieved during training and testing are highest with a network structure that includes a single hidden layer and seven hidden neurons. Therefore, for this study, the network represented in Fig. 4.3 (containing 7 hidden neurons) was chosen as the best for predicting surface roughness.

The following Fig. 4.4 presents the regression plots for various phases. According to ANN, the value of the Coefficient of correlation (R^2) must be near to 1. In this experiment, the R^2 values of training, validation, testing and all cases range from 0.98 - 0.99 which are close to the 1 that indicates the best predicted output values based on experimental inputs and outputs.

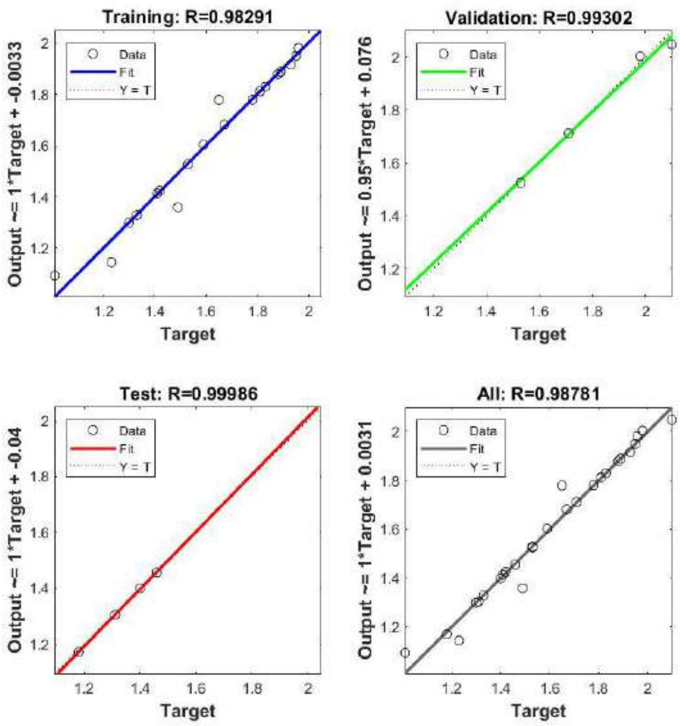


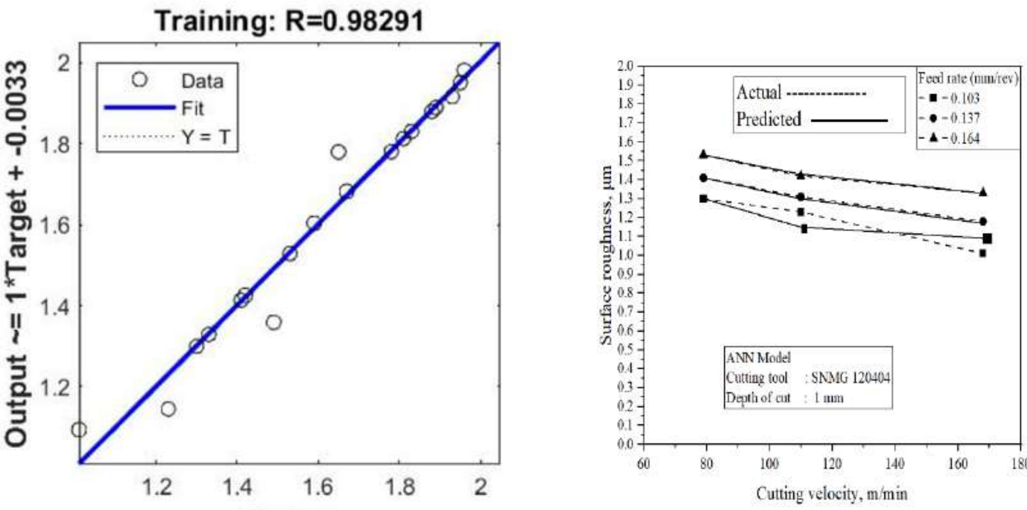
Fig. 4.4 Linear Regression Plot for surface roughness while machining carbon nanotube reinforced aluminum metal matrix composite in MQL Condition.

After the prediction of the values of surface roughness the desired result and error percentages in comparison to the actual value are depicted in the following table 4.3

Table 4.3 ANN predicted values of surface roughness for outputs while machining carbon nanotube-based aluminum metal matrix composite.						
Sl No.	Depth of cut t, (mm)	Feed rate S_0, (mm/rev)	Cutting velocity V_c, (m/min)	Surface Roughness (Ra) µm	Prediction result for ANN	ERROR %
1	1	0.103	79	1.3	1.30	0.02
2			110	1.23	1.15	6.89
3			168	1.01	1.09	8.33
4		0.137	79	1.41	1.41	0.28
5			110	1.31	1.30	0.42
6			168	1.18	1.17	0.80
7		0.164	79	1.53	1.53	0.29
8			110	1.42	1.43	0.40
9			168	1.33	1.33	0.04
10	1.25	0.103	79	1.65	1.78	7.85
11			110	1.46	1.46	0.25
12			168	1.4	1.40	0.02
13		0.137	79	1.71	1.71	0.11
14			110	1.53	1.53	0.08
15			168	1.49	1.36	8.78
16		0.164	79	1.83	1.83	0.03
17			110	1.67	1.68	0.73
18			168	1.59	1.60	0.87
19	1.5	0.103	79	1.89	1.89	0.05
20			110	1.81	1.81	0.13
21			168	1.78	1.78	0.01
22		0.137	79	1.96	1.98	1.08
23			110	1.93	1.92	0.72
24			168	1.88	1.88	0.04
25		0.164	79	2.1	2.05	2.43
26			110	1.98	2.00	1.21
27			168	1.95	1.95	0.03

Coefficient of determination (R^2) and mean square percentage error (MSE) were calculated for each network during training and testing to determine which architecture was more effective. Predictive ability of the BR-trained 3-7-1 model is shown in Fig. 4.5 (a), where the aforementioned metrics are expressed as correlation coefficients (R-value). The average surface roughness prediction is shown on the y-axis and the targets are shown on the x-axis in Fig. 4.5 (a) (measured Ra). Mean sum of squared error (MSE) was used to estimate how well each output node performed relative to its training average, taking into account both the actual and predicted values.

Fig. 4.5 (a) shows the expected surface roughness parameter along the y-axis and the targets along the x-axis. In this graph, the continuous line signifies a good match, while the dashed line indicates that the measured and predicted values are the same. If the R-value is 1, it indicates a perfect correlation, and if it's 0, it implies there's no relationship between the observed and expected values. If the value of R is near to 1, the relationship and fit are satisfactory. The R-value for the network, when subjected to 19 sets of training data on surface roughness, was 0.98291.



(a) Regression line (b) Validation

Fig. 4.5 (a-b) Performance measure of 3-7-1 network.

In this study, the surface roughness of the machined item are the dependent variables of interest, and the ultimate purpose of the model is to produce precise and dependable predictions for these factors. Therefore, it is necessary to assess the accuracy with which a model describes the phenomena being modeled before using that model.

Validating models in this way achieves this goal. The ANN models that have been constructed have also been verified by comparing them to experimental data. Model validity is demonstrated by the figures (4.5b) contrasting experimental and ANN-predicted values.

4.2 Modeling by Response Surface Methodology

Response Surface Methodology (RSM) is a collection of mathematical and experimental techniques that requires sufficient number of experimental data to analyze the problems and to develop mathematical models for several input variables and output performance characteristics. This statistical technique is used to optimize a response (output variable) which is influenced by several independent variables (input variables) in which changes are made in the input variables in order to identify the reasons for changes in the output response. Khuri and Mukhopadhyay mentioned in their research that, RSM model can be utilized to state the degree of correlation between one or more response and some selected control variables. Main purpose is to determine through goodness of fit; statistical significance of the factors connected with a particular response and to determine the optimum settings within the higher or lower level of control variables to minimize or maximize the response of interest **[2010].** The output response is proposed using the fitted second-order polynomial regression model which is called quadratic model. In response surface method a dependent variable Y called the response variable and several independent variables $X_1, X_2, \ldots, X_k$ called independent. Response surface method (RSM) is a combination of experimental, regression analysis and statistical inferences. The optimization and prediction capabilities of RSM are highly appreciated. Bhuiyan, T. and Ahmed, I [**2014]** proposed a prediction model by using the Taguchi method and the Response Surface Method (RSM). The RSM is a practical, economical and relatively easy to use and was employed by many researchers for modeling machining processes [**Hasegawa et al. 1976**]. Both linear and quadratic types of models can be generated by using RSM. Equation 1 shows the first order model and Equation 2 shows the second order model.

$$Y = \beta_o + \sum_{i=1}^{k} \beta_i X_i + \varepsilon \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots (1)$$

$$Y = \beta_o + \sum_{i=1}^{k} \beta_i X_i + \sum_{i=1}^{k} \beta_{ii} {X_i}^2 + \sum_{ij}^{k} \beta_{ij} X_i X_j + \varepsilon \ldots\ldots\ldots\ldots\ldots (2)$$

As shown in Equation 2, the regression coefficients for the linear, quadratic, and interaction terms are denoted by o, ii, and ij, and the estimated response (Y) is based on the quadratic model with interactions. The input variables for cutting speed (Vc), depth of cut (t), feed rate (So), and hardness are all revealed by Xi. A is a random experimental error. Normal probability graphs are presented in Fig. 4.6 to examine the accuracy of the models. It shows that the model is compatible with the data used. The normal probability plot of residuals provides a graphical representation of the model's effectiveness. For this to be a pass, the residuals must behave according to a normal law. The residuals of the model approximating straight lines indicate that normalization is achieved.

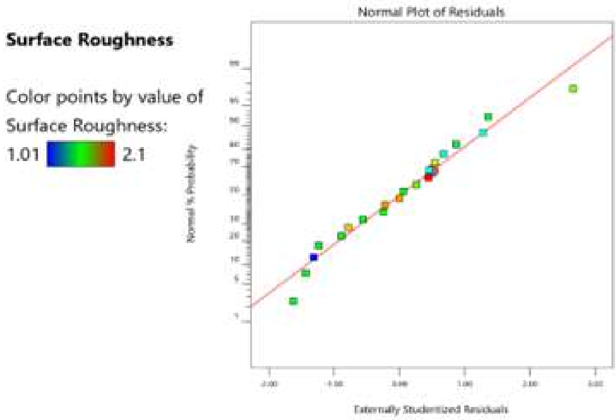


Fig. 4.6 Normal probability plot for Surface roughness.

Here, surface roughness parameters used in the simulation were obtained exclusively through turning in MQL condition of fabricated composite. The Design Expert 12.0 RSM model is then updated with the experimental values of surface roughness for the associated control variables. Table 4.4 illustrates the surface roughness regression coefficient results.

Table 4.4 Regression coefficients of RSM regression models.

Models	R-square (%)	R-square (adjusted) (%)	R-square (predicted) (%)
R_a	97.89	97.37	97.04

Being applied to the cutting process, RSM yields regression models that establish causality between process factors and outputs. Using a central composite design, a full quadratic equation for surface roughness (Eq. 3) is established.

Surface roughness = 1.2921-0.00541 *Cutting Speed+7.22131*Feed rate-1.27911*Depth of cut+0.002584 *Cutting Speed * Depth of cut- 2.78689*Feed rate * Depth of cut +1.04 *Depth of cut^2 ………………… (3)

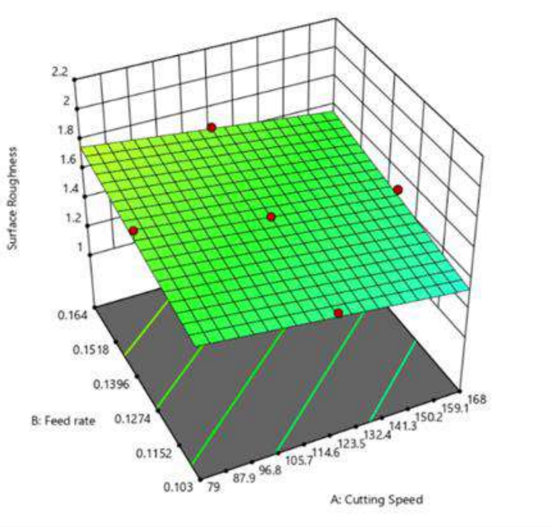
Analysis of variance is used to determine how several independent variables affect the surface roughness (ANOVA). Table 4.5 displays the analysis of variance for regression models of roughness. Values for the sum of squares, the F-value, and the probability-level test (P-value) are listed in order in the ANOVA table. When a factor has a P-value below 0.05, researchers are 95% confident in their finding. The greater the F-value, the greater the proportional importance of that factor.

Table 4.5 Analysis of Variance for Average surface roughness.

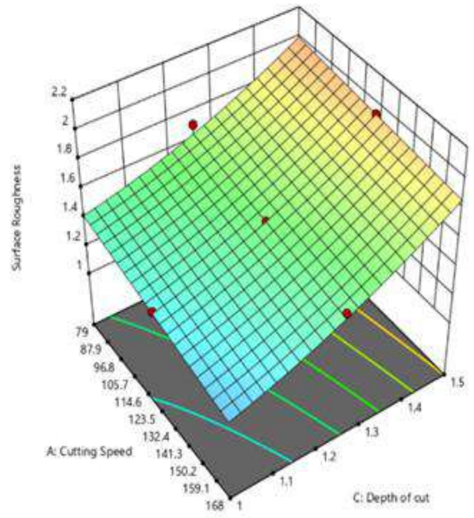
Source	Sum of Squares	DF	Mean Square	F-value	p-value	Remarks
Model	1.26	6	0.21	192.23	< 0.0001	significant
A-Cutting Speed	0.0941	1	0.0941	86.11	< 0.0001	significant
B-Feed rate	0.13	1	0.13	118.94	< 0.0001	significant
C-Depth of cut	1	1	1	919.65	< 0.0001	significant
AC	0.0066	1	0.0066	6.05	0.0287	significant
BC	0.0036	1	0.0036	3.31	0.0921	significant
C^2	0.0211	1	0.0211	19.33	0.0007	significant
Residual	0.0142	13	0.0011			
Lack of Fit	0.0125	8	0.0016	4.45	0.0585	not significant
Pure Error	0.0018	5	0.0004			
Cor Total	1.27	19				

The surface roughness ANOVA data are shown in Tables 4.5. Results of quadratic regression and artificial neural network modeling of technological parameters are summarized in Table 4.5. R^2 measures how well two sets of data fit together by giving weight to the set that is closer to the line of best fit. R^2 values shift from zero to one. A linear relationship between experimental values and network projected values accounts for 95% confidence level has been shown.

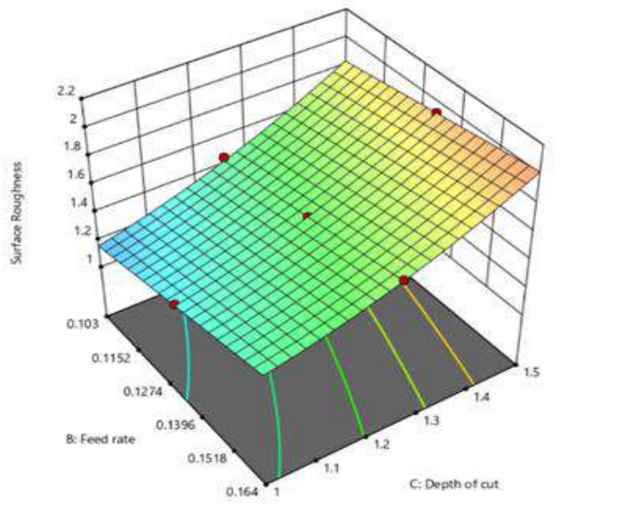
Fig. 4.7 illustrates 3D response surface plots of average surface roughness under MQL cutting condition in terms of cutting speed, feed rate and depth of cut



(a)



(b)



(c)

Fig 4.7 Surface plot of (a) Cutting Speed vs Feed Rate (b) Cutting Speed vs Depth of Cut (c) Feed Rate vs Depth of Cut.

4.2.1. Desirability Function Analysis for carbon nanotube reinforced MM composite

Numerical optimization by desirability function is conducted by employing response surface equations of the machining responses. According to Myers and Montogomery [**Myers et al. 2016**], Desirability function is an objective function (D), the value (d_i) of which ranges from 0 (least) to 1 (most). The function has the capability to search for a point in the specified design space within the constrained levels of factor settings and considering weight and importance which not only suffice all the goal addressed as shown in table 5.14 but it also searches for the highest desirable value possible, $d_i = 1$. During this optimization process, aim is to achieve optimum levels of factor settings, which yield the lowest quantity of average surface roughness.

The optimum solutions for the fabricated composite materials under MQL condition are stated in Table 5.14. According to the best result (desirability = 0.977), the optimum cutting parameters which yielded the R_a = 1.1 µm, are follows: 1 mm of t, 168 m/min of V_c and 0.103 mm/rev of feed rate. For a clear Evaluation, desirability value of each individual factor and responses associated are shown in table 4.6.

Table 4.6 Desirability optimizations solutions for fabricated composite under MQL condition.

Number	Cutting Speed	Feed Rate	Depth of cut	Surface roughness	Desirability	
1	**168**	**0.103**	**1**	**1.035**	**0.977**	**Selected**
2	167.685	0.103	1	1.036	0.976	
3	168	0.103	1	1.036	0.976	
4	167.371	0.103	1	1.037	0.975	
5	168	0.103	1.002	1.037	0.975	

4.3 Comparison between ANN and RSM Model

Table 4.7 displays R^2 coefficients for both ANN and RSM models; however, the ANN models have higher values. Compared to the RSM model values, it is evident that the ANN model has better predictive ability.

Table 4.7 Comparison between ANN and RSM in respect of correlation coefficient.

Models	Correlation Coefficient R^2		
	RSM	ANN training set	ANN validation set
R_a	97.89	98.29	99.30

The performance was evaluated by both absolute percentage error (APE) as shown in Eq. (4) and model predictive error (MPE) as shown in Eq. (5)

$$APE = \left(\frac{|Actual - Predicted|}{Actual}\right) \times 100 \quad \ldots\ldots\ldots\ldots\ldots (4)$$

$$MPE = \frac{1}{N}\sum_{n=1}^{N}\left(\frac{|Actual - Predicted|}{Actual}\right) \times 100 \quad \ldots\ldots\ldots\ldots\ldots (5)$$

The results of RSM and ANN predictions of surface roughness are presented in Tables 4.8. Calculating the corresponding absolute percentage errors (APE). Finally, the model predictive errors (MPE) are calculated and presented in the model. In RSM and ANN modeling of surface roughness, the predicted error of the model was 2.36% and 1.46%, respectively.

Table 4.8 Performance comparison between ANN and RSM models.

Predicted Surface Roughness (μm)				
Experimental	RSM	ANN	RSM-APE (%)	ANN-APE (%)
1.3	1.32	1.30	1.53	0
1.23	1.15	1.15	6.50	6.50
1.01	1.11	1.09	9.90	7.92
1.41	1.42	1.41	0.70	0
1.31	1.3	1.30	0.76	0.76
1.18	1.16	1.17	1.69	0.84
1.53	1.54	1.53	0.65	0
1.42	1.38	1.43	2.81	0.70
1.33	1.34	1.33	0.75	0
1.65	1.81	1.78	9.69	7.8
1.46	1.45	1.46	0.68	0
1.4	1.41	1.40	0.71	0
1.71	1.71	1.71	0	0
1.53	1.55	1.53	1.30	0
1.49	1.35	1.36	9.39	8.72
1.83	1.81	1.83	1.09	0
1.67	1.69	1.68	1.19	0.59
1.59	1.65	1.60	3.77	0.62
1.89	1.88	1.89	0.52	0
1.81	1.83	1.81	1.10	0
1.78	1.79	1.78	0.56	0
1.96	1.99	1.98	1.53	1.02
1.93	1.91	1.92	1.03	0.51
1.88	1.89	1.88	0.53	0
2.1	2.03	2.05	3.33	2.38
1.98	2.01	2.00	1.5	1.01
1.95	1.96	1.95	0.53	0
MAPE			2.36	1.46

Chapter-5

Discussion on Results

5.1 Surface Roughness

Surface integrity and dimensional precision, which regulate the product's performance and service life, are commonly used to evaluate the value of any machined product of a specific material. In the present study, only dimensional accuracy and surface finish were evaluated for evaluating the quality of dry and MQL-machined products. Surface finish is a significant indicator of machinability or grindability due to the fact that the quality of any machined product of a particular material is typically determined by the product's dimensional accuracy and surface integrity, which determine its performance and service life. Generally, if a good surface finish is required, it is obtained through finishing procedures such as grinding, however it is frequently left to subsequent machining. Despite the fact that it is finished by grinding, the surface roughness must be as low as achievable during the preceding machining in order to assist and expedite the grinding process and minimize initial surface defects to the greatest extent possible. The primary sources of surface roughness development in continuous machining processes, such as turning, particularly for ductile metals are:

- Feed marks of cutting tools
- Chatter marks on the workpiece due to vibrations caused during the manufacturing operation
- Irregularities on the surface due to rupture of workpiece material during metal cutting operation
- Surface variations caused due to deformation of workpiece under the action of cutting forces
- Irregularities in the machine tool itself such as lack of straightness of guide ways

From analysis of variance and graphical representation of surface roughness it can be concluded that the surface roughness is significantly affected by depth of cut than cutting speed and feed rate. Surface roughness is the measure of the small-scale deviations of a surface from its ideal shape. In machining CNT reinforced aluminum metal matrix composite, the surface roughness is significantly affected by the depth of cut, rather than the cutting speed and feed rate. This is because of the following reasons:

- Composite Structure: The CNT reinforced aluminum metal matrix composite has a heterogeneous structure, with the CNTs distributed throughout the matrix. The CNTs are more resistant to cutting forces than the aluminum matrix. As a result, a deeper cut will cause more damage to the CNTs, leading to a rougher surface finish.
- Material properties: CNT reinforced aluminum metal matrix composites are a relatively new material and have unique properties compared to traditional metal alloys. The addition of CNTs can increase the hardness and strength of the composite, making it more difficult to machine. A deeper cut can cause more deformation and damage to the material, which can result in a rougher surface finish.
- Chip formation: During machining, chips are formed as the cutting tool removes material from the workpiece. A deeper cut results in larger chips, which can become trapped between the cutting tool and the workpiece, leading to vibrations and chatter. These vibrations can cause irregularities in the surface finish, resulting in increased surface roughness.
- Tool wear: In machining, the cutting tool wears out over time due to the heat generated by the cutting process. A deeper cut puts more stress on the tool, causing it to wear out more quickly. As the tool wears, it becomes less effective at producing a smooth surface finish, which can lead to increased surface roughness.
- Material Removal Mechanism: The material removal mechanism in machining CNT reinforced aluminum metal matrix composite involves the shearing and ploughing of the material. The depth of cut is the primary factor that determines the extent of material removal. A deeper cut will result in more material being removed, leading to a rougher surface finish.

- Tool Chatter: Tool chatter is a vibration that occurs during machining, which can cause irregularities in the surface finish. A deeper cut can increase the amplitude of the tool chatter, leading to a rougher surface finish.

Overall, while cutting speed and feed rate can also affect surface roughness, the depth of cut has a more significant impact in machining CNT reinforced aluminum metal matrix composites due to the unique properties of the material and the challenges associated with chip formation and tool wear. Machining these composites requires careful consideration of these factors to achieve the desired surface finish. In conclusion, the depth of cut has a significant impact on the surface roughness in machining CNT reinforced aluminum metal matrix composite. It is important to optimize the cutting parameters, including the depth of cut, to achieve the desired surface finish while minimizing tool wear and vibration.

It has been demonstrated that the application of cutting fluid during turning improves the surface integrity of the work materials. Due to the enhanced thermal conductivity and lubricating capabilities, a decrease in surface roughness is noticed when employing it. Additionally, owing to the fact of its greater thermal conductivity, conventional fluid removes a greater amount of heat from the cutting zone. As a result, it is able to keep temperatures at a more consistent level, and the tool can keep its edge for a greater amount of time. Additionally, lubrication in MQL setup reduces frictional force and the temperature increase caused by frictional force. Reduced tool wear, lower operating temperature, good fluidity, low viscosity, and high stability in MQL conditions result in enhanced lubrication at the chip-tool interface, which minimizes surface roughness when utilizing conventional fluid. Depending on the work material and cutting circumstances, this improvement in surface finish could be attributable to the prevention or decrease of built-up edge development. This is because the increased thermal conductivity and higher heat transfer capability of fluid in MQL helps to minimize the chip-tool contact temperature. The surface roughness of the CNT reinforced aluminum metal matrix composite after 100 mm of machining for each experimental run with sharp SNMG inserts at different Vc-So combinations under dry and MQL conditions are depicted in Figures 3.7. Surface roughness decreases gradually as cutting velocity increases for both dry and MQL cutting conditions, as is evident from the graphs. Table 5.1 shows the percentage reduction in surface roughness achieved by dry and conventional fluid conditions for different cutting speeds, feed rates, and depths of cut.

Table 5.1 Reduction in surface roughness due to using Dry and MQL in turning CNT reinforced aluminum metal matrix composite.

Sl. NO.	t, mm	S_0, mm/rev	V_c, m/min	Environment		Percentage Reduction in Surface Roughness
				Dry	nMQL	
1	1	0.103	79	1.81	1.3	28.18
2			110	1.57	1.23	21.66
3			168	1.39	1.01	27.34
4		0.137	79	2.01	1.41	29.85
5			110	1.51	1.31	13.25
6			168	1.41	1.18	16.31
7		0.164	79	2.13	1.53	28.17
8			110	1.56	1.42	8.97
9			168	1.51	1.33	11.92
10	1.25	0.103	79	2.29	1.65	27.95
11			110	1.98	1.46	26.26
12			168	1.74	1.4	19.54
13		0.137	79	2.41	1.71	29.05
14			110	2.11	1.53	27.49
15			168	2.01	1.49	25.87
16		0.164	79	2.56	1.83	28.52
17			110	2.43	1.67	31.28
18			168	2.29	1.59	30.57
19	1.5	0.103	79	2.71	1.89	30.26
20			110	2.51	1.81	27.89
21			168	2.31	1.78	22.94
22		0.137	79	2.79	1.96	29.75
23			110	2.55	1.93	24.31
24			168	2.49	1.88	24.50
25		0.164	79	2.91	2.1	27.84
26			110	2.78	1.98	28.78
27			168	2.56	1.95	23.83

5.2 Cutting Temperature

In the machining process, heat generation at the chip-tool interface is of paramount importance. The machining temperature in the cutting zone must be brought down to an optimal level. Shearing of the work material, friction between the moving chips and the rake face of the tool, and friction between the auxiliary flank and the finished surface are the primary sources of heat creation during machining. In turning of various hardened composite material, the magnitude of the cutting temperature increases with the increase of material removal rate, i.e. with the increase of cutting velocity, feed, and depth of cut; as a result, high production machining is restricted by the increasing temperature. This issue intensifies as the strength and hardness of the work materials increases. From Figures 3.5, it is evident that the application of cutting fluid in turning operations facilitates the machining operations by significantly reducing the average chip tool interface temperature. The percentage of reduction in average chip tool interface temperature reached by dry and conventional fluid in MQL cooling conditions for varying cutting velocity, feed rate and depth of has been derived from the preceding data and is presented in Table 5.2.

It has been observed the temperature at chip-tool interface is higher at the higher cutting parameters level both dry and MQL conditions. Cutting fluid in MQL condition achieved better result rather that dry condition. Moreover, the high thermal conductivity and higher heat transfer capability of the cutting fluid dissipates heat from the cutting zone immediately which helps to reduce the cutting temperature during machining. This reduction in temperature is very much appreciable in retaining tool life and product quality.

Table 5.2 Reduction in cutting temperature due to using dry and conventional fluid in turning of CNT reinforced aluminum metal matrix composite.

Sl. NO.	t, mm	S_0, mm/rev	V_c, m/min	Environment		% Reduction in Cutting Temperature
				Dry	nMQL	
1	1	0.103	79	247	229	7.29
2			110	279	251	10.04
3			168	331	276	16.62
4		0.137	79	268	236	11.94
5			110	284	257	9.51
6			168	334	283	15.27
7		0.164	79	271	246	9.23
8			110	296	262	11.49
9			168	345	290	15.94
10	1.25	0.103	79	250	239	4.40
11			110	279	256	8.24
12			168	329	288	12.46
13		0.137	79	266	248	6.77
14			110	286	260	9.09
15			168	339	300	11.50
16		0.164	79	270	257	4.81
17			110	290	264	8.97
18			168	346	307	11.27
19	1.5	0.103	79	267	248	7.12
20			110	286	257	10.14
21			168	313	312	0.32
22		0.137	79	272	253	6.99
23			110	298	275	7.72
24			168	351	321	8.55
25		0.164	79	276	263	4.71
26			110	313	281	10.22
27			168	376	330	12.23

5.3 Cutting Force

The magnitude of the cutting force is a major indication of machinability that influences productivity, product quality, and overall machining economy, as stated in earlier chapters. With an increase in chip load and shear strength of the work material, the cutting forces increase approximately proportionally. In addition to chip load and work material strength, other parameters also determine the magnitude of the cutting forces. However, the cutting forces should always be kept as small as possible without sacrificing the rate of material removal or the quality of the finished product.

Fig.3.9 illustrate how and to what extent the cutting force has lowered under various experimental conditions. As cutting velocity increased, cutting force decreased. Again, it is important that in any machining process, as the cutting speed increases, the shearing of the material becomes much faster. During the experiment, the greater the cutting speed, the easier the shear, and the lower the cutting force. In contrast, the increase in feed rate resulted in a rise in cutting force, despite the use of cutting fluid, due to an increase in energy input. Also, the value of the cutting force increased as the depth of cut increased. As the depth of cut increases, the cutting tool penetrates deeper and removes a larger quantity of material, resulting in an increase in cutting force. The percentage of reduction in cutting force reached by dry and conventional fluid in MQL cooling conditions for varying cutting velocity, feed rate and depth of has been derived from the preceding data and is presented in Table 5.3. From Table 5.3 it is clearly evident that the significant reduction of cutting forces in fabricated composite turning with the application of conventional cutting fluid than dry turning. This may be due the higher surface area of the nano materials which eventually results in the MQL lubrication between the of cutting tool and workpiece interaction.

Table 5.3 Reduction in cutting force due to using dry and conventional fluid in turning of CNT reinforced aluminum metal matrix composite.

Sl. NO.	t, mm	S_0, mm/rev	V_c, mm/min	Environment		Percentage Reduction in Cutting force
				Dry	nMQL	
1	0.5	0.103	71	126	107	15.07937
2			115.5	119	102	14.28571
3			160	114	95	16.66667
4		0.137	71	173	129	25.43353
5			115.5	167	121	27.54491
6			160	152	113	25.65789
7		0.164	71	218	169	22.47706
8			115.5	202	151	25.24752
9			160	194	142	26.80412
10	1	0.103	71	132	121	8.333333
11			115.5	126	111	11.90476
12			160	119	105	11.76471
13		0.137	71	191	146	23.56021
14			115.5	178	137	23.03371
15			160	174	126	27.58621
16		0.164	71	231	188	18.61472
17			108.5	218	180	17.43119
18			160	215	173	19.53488
19	1.5	0.103	71	165	139	15.75758
20			115.5	154	128	16.88312
21			160	148	121	18.24324
22		0.137	71	225	177	21.33333
23			115.5	208	168	19.23077
24			160	203	157	22.6601
25		0.164	71	276	225	18.47826
26			115.5	266	219	17.66917
27			160	260	211	18.84615

5.4 Tool Wear

In general, the wear of cutting tools is quantified by the magnitudes V_B, V_S, V_M, V_{SM}, V_N, etc. The average principal flank wear, V_B, is regarded as the most important parameter, at least in terms of research. Earlier research conducted by the researchers demonstrates that the machining in dry conditions does not aid in reducing tool wear when machining composite materials with coated or uncoated carbide inserts, but can in some instances exacerbate wear. The relationship between an increase in cutting force and temperature and the development of major flank wear (V_B) is proportional. Therefore, of all of the tool wears, the primary flank wear is the one that causes the most concern. The actual machining time after which the average value of its major flank wear reaches a limiting value, such as 300 m, is used to determine the life of carbide tools, which typically fail due to wear. As a result, every effort should be taken to slow the rate of growth of flank wear while maintaining material removal rate (MRR).

The cutting insert has been extracted at regular intervals in order to examine the pattern and extent of wear on the primary and secondary flanks under both dry and MQL conditions. Figure 3.11 presents the gradual increase of V_B, which is the most important parameter for figuring out when a tool has reached the end of its useful life. This was seen when turning CNT reinforced aluminum metal matrix composite with uncoated carbide (SNMG) insert at a cutting speed of 168 m/min, a feed rate of 0.164 mm/rev, and a depth of cut of 1.5 mm, both in dry and nano cutting fluid in MQL conditions. The primary flank wear (V_B) decreases dramatically under MQL conditions, as depicted in Fig. 3.11. Pressurized jet of cutting fluid in MQL conditions has easily been dragged into the plastic contact by its high energy jet, cools the interface. It not only cools the interface but also reduces frictional heat generation by lubricating the friction zones. Fig. 3.13 and 3.14 presents the Scan Electron Microscopic (SEM) condition of carbide tool after machining with dry and cutting fluid in MQL conditions for 30 minutes. From the SEM images it is clearly evident that no significant amount of tool wear and tool breakage found in MQL applications which increases the tool life in hard turning operations. This increased tool life is achieved by lubricating in MQL conditions which reduce in coefficient of friction between the workpiece and cutting tool.

5.5 Prediction of Surface Roughness

Artificial neural networks (ANNs) and Response surface methodologies (RSM) are the largely used predictive modeling techniques based on statistical approach. ANN is currently being used in many fields of engineering for modeling complex relationships which are difficult to describe with physical models. On the other hand, the response surface methodology (RSM) allows testing the statistical significance of the model, model terms, and lack of fit and provides equations to describe a phenomenon. The importance of predicting surface finish in any machining process help the engineers for proper planning, control of machining parameters and optimization of the cutting conditions to minimize production cost, time and manufacturing products of desired quality. The mentioned advantages eventually lead to higher productivity which is the main goal of any production or service-based organization.

In this thesis, ANN and RSM model to predict surface roughness has been constructed for CNT reinforced aluminum metal matrix composite machined under using MQL condition. During the ANN modeling of surface roughness of the machined part, the input layer was chosen to contain three neurons specifically cutting speed, feed rate and depth of cut while the output neuron was surface roughness of the composite materials. In the process of the procedure, a hidden layer was chosen to exist between the input and output layers. The hidden layer could contain different number of neurons and selecting the number of hidden neurons in the hidden layer was the main task to find the optimal neural network structure. Between the input and the output layer, one hidden layer was chosen in the process. The number of hidden neurons in the hidden layer was the most important factor in determining the ideal neural network architecture. The number of hidden neurons was determined through trial and error. The transfer functions utilized in the hidden layer and output layer were the tansig and purelin functions, respectively. As indicated previously, the networks were trained with the number of values surface roughness combinations and tested according model combinations. 3-7-1 network structure with BR trained is recommended for predicting surface roughness based on a higher coefficient of determination (R^2) and lower model predictive error (MPE). As illustrated in Figures 4.4, the network architectures were trained and tested, and their validation was also performed. This validation was performed to verify the accuracy of the ANN model that was constructed. Using the experimental values of surface roughness, and the ANN-predicted values, the graphs depicted in the figures 4.5 are generated. They compared the experimental and anticipated values of surface roughness generated by ANN. It is evident from the figures that ANN can accurately anticipate the experimental values of roughness.

In the present study, a statistical analysis using response surface methodology (RSM) was performed with the objective of analyzing the influence of cutting speed, feed rate and depth of cut on the obtained outputs, which out for a 5% significance level, i.e., for a 95% confidence level. From the statistical analysis of the experimental data, a full quadratic equation for surface roughness has been developed. This equation can be used to make predictions about the response for given levels of each input factor. According to fig. 4.6, the normality is satisfied because the models residuals approximately draw straight lines. For RSM quadratic model, the cutting speed, feed rate and depth of cut, all are statistically significant as P-value less than 0.05. The square terms of cutting speed, depth of cut and feed rate are significant in surface roughness model. The F-value analysis reveals depth of cut as the most important factor followed by the feed rate and cutting speed for surface roughness models.

The question is: which approximation model is more trustable offering better accuracy in fitting experimental data and giving a better optimal solution confirmed by experiment? At this stage, comparison criteria are needed to quantify the difference between values produced by both models and the actual values. In order to test the accuracy of both the ANN and RSM models. The performances of constructed ANN and RSM models were measured in terms of better coefficient of determination (R^2), absolute percentage error (APE) and model predictive error (MPE) for surface roughness. Table 4.8shows that compare the experimental data versus the predicted RSM and ANN values for Ra. It is observed that the deviations of the predicted and experimental data are smaller for ANN model compared with RSM model. Certainly, the obtained R^2 for the surface roughness RSM model is to 0.97 and its value for ANN model is to 0.98. This can clarify the capability of ANN model, as shown in table 4.7, which illustrates, the lower residuals in Ra for ANN model compared with RSM model. In addition, MPE values for the surface roughness RSM model and for the surface roughness ANN model are 2.46% and 1.36 % respectively. So, ANN model presents a good Absolute percentage error (APE) and model predictive error (MPE) compared with RSM model. Based on the lower MPE, the ANN model is suitable; yet, the quadratic model revealed fairly reasonable accuracy. The superiority of the ANN model over RSM model gets justified because ANN forms a complex relation between the input and output corresponding to the necessity of the minimum prediction error, which is not attainable by the RSM as this can only form the quadratic relation between the input and the output. Also, any relation out of quadratic is non-comprehensive to RSM while ANN develops a logical relation there.

Chapter-6

Conclusions and Recommendations

6.1 Conclusions

From the experimental investigation, machining of carbon nanotube reinforced aluminum metal matrix composite and modeling of surface roughness, the following conclusions can be listed as follows:

i. Firstly, in this research CNT reinforced Aluminum metal matrix composite materials have been fabricated where pure aluminum ingots were the matrix material and CNT, SIC and Alumina was reinforcing material. Here Ingot Aluminum and Alumina was constant composition whereas the percentage of CNT varied within .5 wt.%, 1wt.% and 1.5 wt.% with silicon carbide respectively.

ii. Among all these compositions, it was observed that CNT with 1.5% volume shows the best mechanical properties like tensile strength and impact energy. That is why for the further investigation of machining performance, 1.5% volume CNT reinforced aluminum metal matrix composite has been selected.

iii. In depth, analysis of the machinability of CNT reinforced aluminum metal matrix composite has been performed under both dry and MQL cutting condition.

iv. Cutting temperature, surface roughness, cutting force and tool wear are found to improve substantially in MQL cutting condition over dry conditions for the developed composite.

v. All the process parameters are found to possess significant effect on each response as determined through ANOVA analysis.

vi. While machining CNT reinforced aluminum metal matrix composite under MQL cutting condition, the optimum cutting parameters which yielded the output response (surface roughness); R_a =1.03 μm is follows: 1 mm of t, 168 m/min of V_c and 0.103 mm/rev.

vii. Two predictive ANN model and RSM model have been developed for prediction of surface roughness as a function of cutting parameters. These models have been proved to be successful in terms of agreement with experimental results. ANN model provides an optimum network 3-7-1. RSM model provides a quadratic equation for predicting surface roughness. From analysis of variance and graphical representation of surface roughness it can be concluded that the surface roughness is significantly affected by depth of cut than cutting speed and feed rate.

viii. The analysis of the regression coefficients and model predictive error recommended the acceptance of the neural network-based prediction model over response surface model owing to the better capability of ANN model to build an appropriate relation between the input and output.

ix. The approaches used in the present work proved their efficiency in investigating and modeling the machining output parameter as surface roughness. Therefore, the results of this research could be very helpful for scientific researchers as well as for mechanical manufacturing companies.

x. For ANN developed model, regression value is found to be 0.98 for CNT reinforced aluminum metal matrix composite which is very close to 1, thus justifying the efficacy of the developed model.

6.2 Recommendations

i. Very few investigations have been done into the development of advanced nano particle reinforced aluminum metal matrix composite for machining applications. More experiments need to be done to identify the optimum composition for developing CNT reinforced aluminum metal matrix composite. Also, the effects of several important factors such as particle size and shapes, clustering of particles, temperature during casting, and the homogenous dispersion of nano particle should be studied adequately.

ii. Experimental work in different nano particle reinforced aluminum metal matrix composite can be carried out with different weight percentage and manufacturing process.

iii. Apart from dry and MQL cooling condition, machining can be performed out under compressed air or cryogenic cooling environment.

iv. Very few researchers have explored the application of nanofluids specially to machining. More operations (Milling and Drilling) can be performed using nanofluid as cutting fluid to identify the advantages of nanofluids.

v. In the present work, a model has been developed based on artificial neural network. ANFIS, GA, Taguchi etc. may also be used to predict various output responses. Also, a competitive comparison can be presented with these modeling techniques.

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