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ORIGINAL ARTICLE

Performance enhancement of AISI 5160 milling using SiO_2-based NF-MQL: a taguchi–regression approach

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Abstract

The present study investigates the parametric influence of machining and nanofluid-assisted minimum quantity lubrication (NF-MQL) variables on surface roughness and cutting force during the milling of AISI 5160 steel. A structured experimental design based on the Taguchi approach was employed to evaluate the effects of cutting speed, feed rate, depth of cut, MQL air pressure, nanofluid flow rate, and nanoparticle concentration. Surface roughness and cutting force were selected as key performance indicators to assess surface integrity and machining load, respectively. Statistical analyses were carried out using signal-to-noise ratio analysis, analysis of variance (ANOVA), and regression modelling to identify significant factors and establish predictive relationships. The results reveal that surface roughness is predominantly influenced by feed rate and cutting speed, whereas cutting force is strongly governed by depth of cut, followed by cutting speed and nanofluid flow rate. NF-MQL parameters, particularly fluid flow rate, play a vital role in enhancing tribological conditions, leading to reduced friction, lower cutting forces, and improved surface finish. The developed regression models exhibit high predictive accuracy, with coefficients of determination exceeding 96% for surface roughness and 99% for cutting force. Residual diagnostics confirm the models' validity and robustness. Optimal machining conditions were identified that simultaneously minimise surface roughness and cutting force, whereas poor performance was associated with low cutting speeds, high feed rates, large depths of cut, and insufficient lubrication. Overall, the study shows that NF-MQL is a viable lubrication strategy for improving machining performance in the milling of high-strength AISI 5160 steel. Furthermore, the research will contribute to the development of optimised NF-MQL parameters and predictive machining models for a material that has received little attention in the existing literature.

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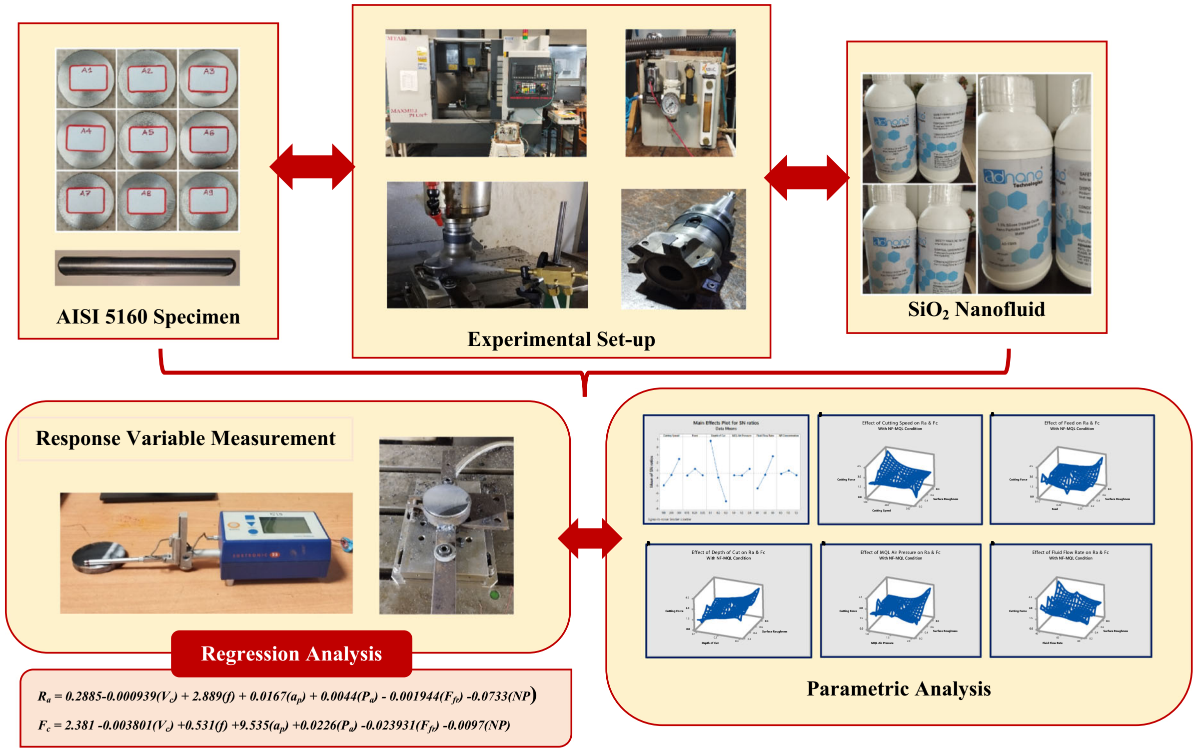
Graphical abstract



Keywords AISI 5160 · Face milling · Minimum quantity lubrication (MQL) · Silicon dioxide (SiO_2) · Nanofluid (NF)

1 Introduction

In the industrial sector, machining is critical for producing the appropriate size, shape, and surface quality by removing unwanted material in the form of tiny chips. Products produced by the manufacturing industry come in a variety of shapes, sizes, and materials. Cutting and shaping operations, such as turning, drilling, and milling, produce a finished surface with the desired shape and dimension by removing a layer of chips from the parent workpiece [19]. Milling involves loading the work against a spinning multi-point cutting tool that removes the metal. Milling is superior to other machining procedures in terms of precision and surface quality, and it can be used for a wide range of tool room operations. The numerous milling operations performed by the various milling cutters are classified into two types: face milling and peripheral milling. In peripheral milling, a cutter cuts a surface parallel to its rotational axis. In this case, the cutting force exerted by each tooth varies with the length of the cut. The machine's driving mechanism is subjected to a shock, resulting in vibration. Face milling is a machining process used to level and smooth the various surfaces of workpieces, which can be performed with a variety of tools. It is defined as a machining process that uses a large diameter cutter with multiple cutting teeth to create flat surfaces in a variety of applications. Using a cutter with minimal projection from the machine spindle, this process allows for high power to be applied while minimizing deflections. AISI 5160 is a chromium steel alloy known for its exceptional strength and toughness, and it is widely used in spring applications. The potential issues with AISI 5160 include hardness, chip formation, and machining vibration/chatter. Machinability of AISI 5160 is affected by the hardness of ~ 32–40 HRC after hardening. Segmented chips are possible and can impair surface finish and tool life.

Traditional flood cooling systems are becoming increasingly unpopular due to their high environmental impact, high coolant consumption, mist hazards, disposal issues, and rising operating costs. Worldwide, industries are moving toward greener machining practices that are consistent with ISO 14001 environmental management, energy efficiency initiatives, and cost-cutting goals. Although Minimum Quantity Lubrication (MQL) can significantly reduce coolant usage, it still struggles to control heat generation and friction when machining medium-carbon spring steels such as AISI 5160. This leads manufacturers to explore **Nanofluid-Assisted MQL (NF-MQL),** which enhances lubrication and cooling performance through nanoparticles with superior thermal conductivity and tribological behaviour. [15–18]

Developments in this field have resulted in the creation of CO_2-assisted cooling methods, NF-MQL, and vegetable oil-based MQL. Although its thermal stability may be restricted at high cutting temperatures, vegetable oil-based MQL provides biodegradability and adequate lubrication, making it appropriate for environmentally friendly machining applications. Cryogenic and CO_2-assisted cooling techniques offer better cooling performance, especially in high-speed machining, but they come with greater operating costs and specialized infrastructure requirements. On the other hand, NF-MQL improves heat dissipation, decreases tool wear, and improves surface integrity by combining the benefits of traditional MQL with improved thermal conductivity and tribological qualities offered by nanoparticles. These advantages have made NF-MQL a viable strategy for maximizing machining performance without sacrificing sustainability. [16–19, 21]

Thus, the present study is motivated by both industrial necessity and scientific curiosity: the need to reduce the machining challenges associated with AISI 5160 while increasing productivity and sustainability. By investigating the potential of NF-MQL lubrication in face milling, this study hopes to generate new knowledge, optimize machining parameters, reduce environmental impact, and provide industries with reliable data and methodologies for implementing advanced, eco-friendly lubrication technologies.

2 Literature review

A comprehensive review of the existing literature on NF-MQL machining reveals that incorporating nanoparticles into cutting fluids consistently enhances machining performance across a range of metallic materials (Table 1). Studies involving aluminium alloys [1, 2, 9, 11], titanium alloys [13], hardened steels [5, 10, 12], cast irons [4], stainless steels [8], and nickel-based superalloys [6, 7] [14] consistently demonstrate that NF-MQL effectively reduces cutting forces, improves lubrication quality, lowers interface temperatures, and enhances surface finish compared to dry cutting or conventional lubrication conditions [3, 4, 6–13]. Nanoparticles, such as Al_2O_3, MoS_2, TiO_2, and SiO_2, offer superior thermal conductivity, rolling effects, and anti-wear capabilities, contributing to this improvement [3, 4, 6, 8–13]. Existing research suggests that machining under NF-MQL significantly improves the quality of the machined surface by reducing friction at the tool-work interface, resulting in less tool wear and smoother surfaces. Another important finding from the literature is that NF-MQL performance is highly dependent on factors such as nanoparticle type, concentration, MQL airflow pressure, and spray direction. To achieve effective cutting zone wetting, penetration, and cooling, these parameters must be properly optimised. Furthermore, the literature indicates that NF-MQL benefits hard and challenging materials the most due to their higher thermal load and frictional tendencies during machining. Despite these advances, research on medium-carbon spring steels, such as AISI 5160, is limited, and little is known about the impact of NF-MQL on machineability, cutting force behaviour, and surface roughness. As AISI 5160 is widely used in automotive and industrial applications that demand surface integrity, there is a clear need to investigate how NF-MQL can improve its machinability. Overall, the literature suggests that NF-MQL has a high potential to improve machining results, but more material-specific studies, particularly for steels like AISI 5160, are needed to fully comprehend and optimize its benefits. These limitations highlight the need for a systematic and comprehensive study of AISI 5160 machining performance under NF-MQL conditions [15–18]. As a result, a systematic investigation is required to evaluate and optimize the effect of NF-MQL on AISI 5160 milling performance. Thus, this study investigates and optimizes the milling performance of AISI 5160 steel under NF-MQL conditions, with a focus on cutting forces and surface roughness. [20] The reviewed literature demonstrates significant advancements in nano-cutting fluids, hybrid MQL techniques, and optimization methods such as Taguchi [21–23]. However, these studies are largely confined to stainless steels, tool steels, and superalloys, leaving a critical gap in the machining of spring steels like AISI 5160. Therefore, investigating hybrid nanofluid-assisted MQL combined with advanced multi-objective optimisation techniques for AISI 5160 presents a novel and impactful research direction, contributing to both sustainable manufacturing and material-specific machining science.

3 Experimental procedure and set-up

3.1 Materials and methods

AISI 5160 is a high-carbon, chromium spring steel widely used in the automotive, aerospace, agricultural machinery, defence, and tooling industries for its excellent combination of strength, toughness, and fatigue resistance. This steel is commonly used to make automotive leaf springs, suspension components, crankshafts, blades, wear-resistant tools, and high-stress machine elements. The industries require high-dimensional accuracy, superior surface finish, and long tool life during machining to ensure component reliability and safety. In industrial practice, components manufactured from AISI 5160 are often machined in the normalized condition to achieve dimensional accuracy before final quenching and tempering. Normalized AISI 5160 presents notable machining challenges, including increased cutting forces, accelerated tool wear, and heightened sensitivity of surface integrity to cutting parameters. Consequently, the application of advanced lubrication strategies and systematic parameter optimisation is essential to ensure sustainable, reliable machining performance in normalised AISI 5160 steel .

AISI 5160 steel was selected as the workpiece material for the present study. It was used in a normalized (or partially tempered) condition with an average hardness of 38 HRC. The experiment samples (27 in number) were prepared as round bars (Ø = 60 mm, L = 310 mm). For subsequent experimental runs, the round bars were converted into 27 equal pieces (11 mm thickness at each division) using a scriber for milling on an MTAB Maxmill VMC, and then cut along the marked lines with a band saw, as shown in Fig. 1. The chemical composition of AISI 5160 steel (Table 2) complies with ASTM A29/A29M standards

3.2 Machine tool, equipment and workpiece

All of the experiments in this study were carried out at Walchand College of Engineering's Advanced Manufacturing Lab using Vertical Machining Centre (VMC) milling. Experiments were carried out using the high-speed precision MAXMILL Plus (MTAB) VMC (speed 100–8000 rpm, motor 7 KW). The experiment focused on using the design of experiment method to optimize process parameters in AISI 5160 VMC milling with NF-MQL mode, using a combination of cutting force and surface roughness performance measures. The BT 40 FMB27-45L tool holder used in this experiment holds an 80 mm face milling cutter with 7 teeth and an SDMT 12 (Wadia) carbide insert.(Figs. 2, 3, 4, 5, 6 and 7).

This study considers input cutting variables such as cutting speed (V_c), feed rate (f), depth of cut (a_p), and MQL process parameters such as air pressure (P_a), fluid flow rate (F_{fr}), and nanoparticle concentration (NP), based on previous experiments, the tool manufacturer's recommendation, and industry practices. The factors and levels to be tested are chosen based on the experimental design. The design matrix L27OA contains three values for each input parameter, namely V_c, f, ap, P_a, F_{fr} and NP, while the nozzle distance of 12.5 cm and nozzle angle of 20° are optimized values chosen for experimental purposes. Table 3 shows the input parameters and their respective levels.

3.3 Response variable measurement

For this experiment, two output parameters were recorded: surface roughness (R_a) and cutting force (F_c). Cutting force is directly related to tool wear, machine tool power requirements, self-excited vibrations, and the aesthetics and ergonomics of the machined surface. R_a is also an important factor in determining the quality of a machined workpiece surface. The R_a of the face-milled surface was measured using the Taylor Hobson surface roughness tester. The Taylor Hobson precision surface roughness tester is a handheld, portable instrument that measures surface parameters using a diamond stylus. The device used a motorized traverse to move the stylus across a surface, with its vertical movement detected by a piezoelectric pickup and converted to digital signals by a microprocessor to display roughness results on a color LCD screen. The Surtronic 25 is a portable, self-contained instrument for measuring surface texture used in these experiments. The R_a of the face-milled circular specimen is measured nine times: three from the left peripheral area, three from the central region, and three from the right peripheral area, to capture potential variations in surface texture across the specimen's face. At each location, the Taylor Hobson instrument's stylus traces the surface profile over a defined sampling length, applying standard-compliant filtering to distinguish roughness from waviness. The arithmetic average roughness (R_a) is calculated for each trace. The nine R_a values are then averaged to produce a representative average Ra for the surface, indicating the overall surface finish achieved through face milling. This technique provides spatial coverage by sampling at various locations (left, centre, and right) to capture variation across the surface and provide a representative value for overall surface roughness. Because face milling produces patterns, measurements are taken in the direction of feed or perpendicular to it. This is practically reasonable for obtaining an average R_a.

The F_c forces were monitored using a Kistler (5233A1) dynamometer, which is a high-precision force-measuring instrument that measures three types of cutting force: feed (F_x), normal (F_y), and passive (axial) (F_z) during face milling. A fixture holds the workpiece in place on this dynamometer, allowing for real-time force measurement and data collection for analysis. The Kistler dynamometer with a charge amplifier was used, and the cutting forces were recorded as a graphical signal that DynoWare software analyzed. The resultant force, F_c, has been calculated from Eq. (1)

$$Fc = \sqrt{Fx^2 + Fy^2 + Fz^2} \tag{1}$$

Every measurement used in this investigation was done with calibrated equipment. To guarantee measurement accuracy, calibration was carried out before experimentation in compliance with manufacturer guidelines using standard reference specimens. To reduce signal drift and electrical noise, force measurements were conducted with appropriate zeroing and reliable signal acquisition techniques. Consistent measurement techniques and controlled laboratory circumstances were used for the experiments.

Fig. 1 AISI 5160 round bar and AISI 5160 Sample specimen (27 Nos.)

Table 2 The chemical composition (Wt.%) of AISI 5160

Element	(C)	(Cr)	(Mn)	(Si)	(P)	(S)	(Fe)
Weight %	0.57	0.70	0.84	0.16	0.035	0.039	97.656%

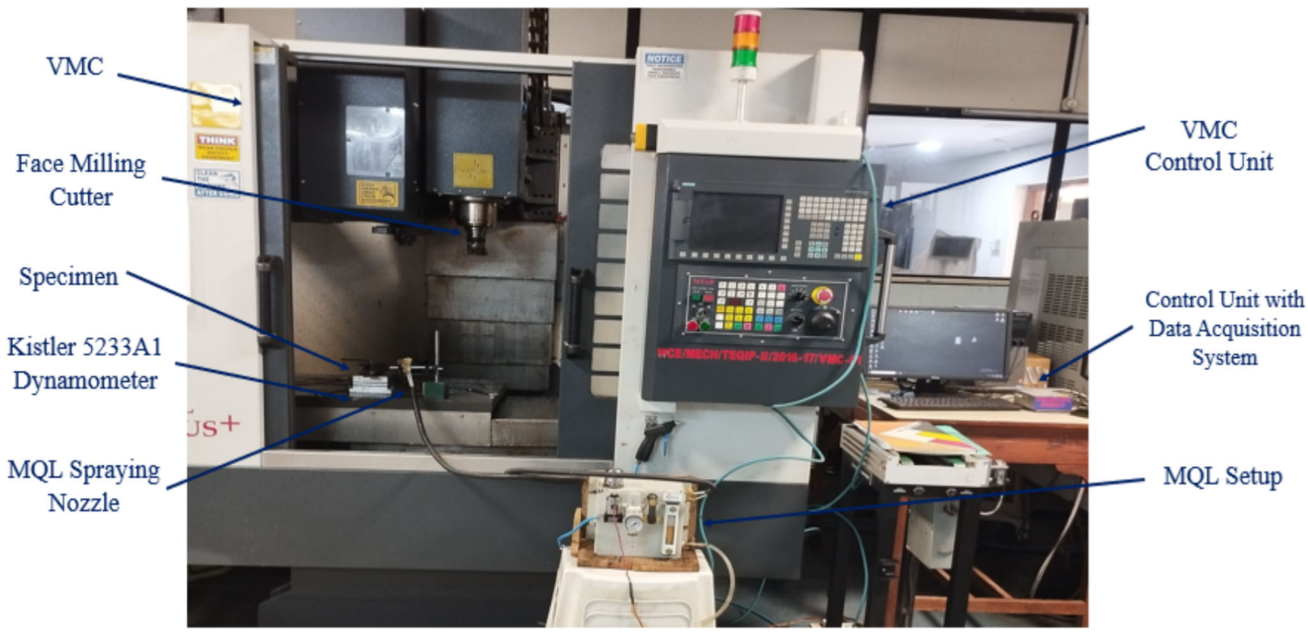


Fig. 2 Experimental set-up

The face milling cutter rotates at a fixed spindle speed while feeding across the AISI 5160 specimen. The coolant nozzle, set at a 20-degree angle, delivers nanofluid to the cutting zone, reducing friction and heat generation. The magnetic stand keeps the nozzle properly aligned throughout the operation. The arrangement helps in understanding how machining parameters and coolant application affect the cutting performance and surface quality. The collected data is later used to analyze machining performance, cutting efficiency, and tool wear characteristics.

3.4 Minimum quantity lubrication setup

The Kenco MQL systems used in this experiment typically operated at 1.5–3 kg/cm^2. The driving force that atomizes the fluid is air pressure, which in this experiment was set at 1, 1.5, and 2 bar. The fluid flow rate used in this study was 40, 60, and 80 mL/hr by manually adjusting the control screw based on air pressure.

3.5 Nanofluid preparation

Nanoparticle concentrations in nanofluids typically range from 0.1 to 5 vol.%. The optimal concentration of nanoparticles is determined by the specific application and desired

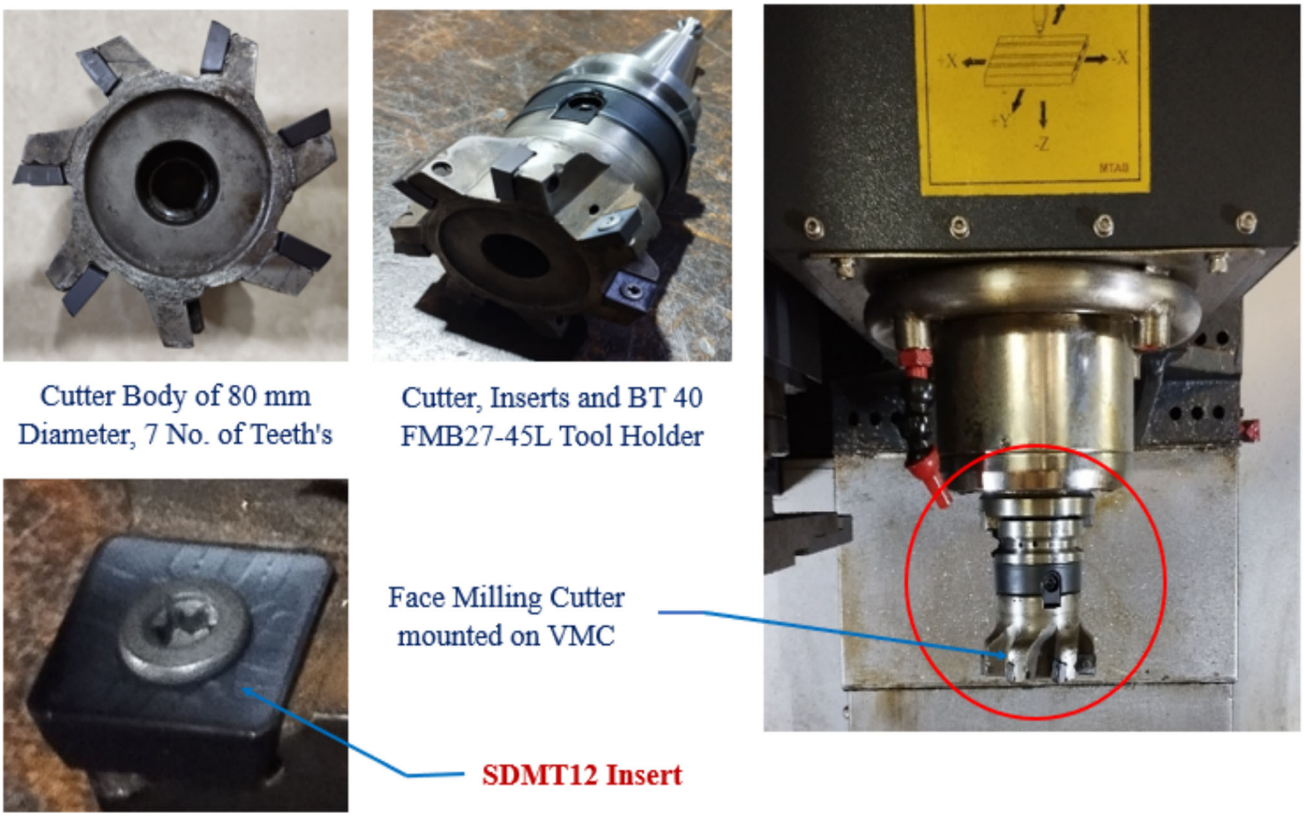


Fig. 3 Cutting tool used in experimentation

nanofluidic properties. Thermal conductivity and tribological properties of nanofluids can vary depending on concentration. Several factors, such as tribological properties, heat transfer, and machining performance, should be considered when determining the nanoparticle concentration for SiO_2 in the proposed study. Nanoparticle concentration can affect machining performance, such as R_a, F_c and tool wear. In the current study, Silicon Dioxide (SiO_2) of the sizes and purities listed in Table 4 are chosen based on their previous literature and nanoparticle properties, which are suitable for milling AISI 5160, to investigate their effects on R_a and F_c. The nanoparticles were purchased from Adnano Technologies, Pvt. Ltd. in Bengaluru, ensuring stable nanoparticle dispersion through controlled ultrasonication and (SDS) surfactant addition. Before use, the nanofluid was gently agitated to maintain uniformity and stored under regulated conditions to preserve dispersion stability and reduce agglomeration during experiments. Deionised water (0.995 g/cm3) serves as the base fluid in this study. During the nanofluid preparation with a two-step technique, 0.5%, 1%, and 1.5% by volume of SiO_2 nanoparticles were added to deionised water.

During the investigation, the supply air pressure was set to 1, 1.5, and 2 bar, with a cutting fluid flow rate of 40, 60, and 80 ml/hr. For each test, the nozzle elevation angle and stand-off distance remained constant at 20° and 12.5 cm.

Fig. 4 Taylor hobson surface roughness tester (Surtronic 25)

4 Parametric analysis of NF-MQL milling of AISI 5160

The present experimental investigation on NF-MQL machining in milling was systematically designed using a Taguchi-based Full-Factorial OA to efficiently study the influence of multiple process parameters on machining performance. Milling experiments were conducted by considering six

Table 1 A review of studies that used NF-MQL methods in various milling operations for challenging materials. [19]

Investigators	Material	Machine/tooling	Lubrication method	Operation	Input variables	Responses	Methodology Used	Key Results / Conclusions
Ojolo et al. (2015) [1]	Al 6061	CNC, HSS Cutter	MQL	End Milling	V_s, f, a_p	Ra	RSM, ANOVA	MQL improved Ra ≈ by 20%; Feed most dominant factor
Safiei et al. (2018) [2]	AA6061-T6	CNC	MQL	End Milling	V_s, f, a_p	Ra	Taguchi + ANOVA	Optimized MQL settings reduce Ra significantly
Duc et al., (2021) [3]	60Si2Mn	CNC, Carbide Tool	NF-MQL (Al_2O_3, MoS_2)	Hard Milling	V_c, f, a_p, Air Press. Flow Rate	Fc, Ra, Tool wear	Factorial DOE + ANOVA	MQL-Al_2O_3 lowered forces, improved Ra
Bülent et al., (2020) [4]	EN-GSJ 700–02	VMC, Coated Carbide	NF-MQL MoS_2	Climb Milling	V_c, f, a_p Air Press. Flow Rate, Nanoparticle concentration	Ra, Tool Wear	Comparative experiments	MoS_2 MQL reduced Ra & wear significantly
Duc et al., (2020) [5]	SKD11	VMC, Carbide	MQL + MQCL	Hard Milling	-	Ra	DOE	Parameters showed low influence; MQL generally better
Günan et al. (2020) [6]	Hastelloy C276	CNC, Carbide	NF-MQL (Al_2O_3)	Side Milling	Vs, f, F_{fr}, Spray Angle, P_a, NP	Ra, Tool Wear, Tool Life	Taguchi	Al_2O_3 NF-MQL improves Ra & wear vs base-oil MQL
Singh et al., (2019) [7]	Inconel 625	CNC, PVD Coated carbide	NF-MQL	Face Milling	V_c, f, a_p, P_a, Nozzle angle, Nozzle distance, F_{fr}	Ra, Tool Wear	RSM	NF-MQL gives better surface finish & wear
Xiufang et al. (2021) [8]	Grade 45 Steel	CNC	NF-MQL (Al_2O_3)	Plain Milling	Vs, f, a_p, F_{fr}, P_a, Nozzle Position, NP	Ra, Fc, Tool Wear	Parametric study	An optimal Al_2O_3 concentration exists for the best machining
Sayuti et al. (2014) [9]	AA6061-T6	VMC, HSS	NF-MQL, (SiO_2)	End Milling	Vc, f, ap, NP concentration	Ra, Fc, Cutting Temp	Surface microscopy	Better surface morphology using SiO_2 NF-MQL
Muthusamy et al., (2015) [10]	AISI 304	CNC, Tin Coated Carbide	NF-MQL (TiO_2)	End Milling	Vc, f, ap, NP	Tool Life, Tool wear	Wear analysis	TiO_2 nanofluid reduces wear vs conventional coolant

Table 1 (continued)

Investigators	Material	Machine/tooling	Lubrication method	Operation	Input variables	Responses	Methodology Used	Key Results / Conclusions
Rahmati et al. (2013) [11]	AL6061-T6	VMC, Tungsten Carbide	NF-MQL (MoS_2)	Slot Milling	P_a, Orientation	Ra, Fc, Cutting Temp	Taguchi, DOE	MoS_2 nano-lubrication significantly improves machinability
Uysal et al. (2015) [12]	AISI 420	CNC	NF-MQL (MoS_2)	Side Milling	V_c, f, ap, F_{fr}, P_a, Nozzle Angle,	Ra, Tool Wear	Experimental comparison	Nano-MoS_2 MQL improves surface quality & tool life
Okokpujie & Tartibu, (2021) [13]	TI-6AL-4 V-ELI Alloy	CNC, Carbide	NF-MQL (TiO_2)	Face Milling	V_c, f, ap	Fc	Taguchi Design	TiO_2 Nano lubricant lowered cutting forces vs dry & oil
Mohanraj et al. (2022) [14]	Inconel 625	CNC	NF	Face Milling	V_s, f, ap, NP	Ra, MRR	TOPSIS	Nanofluid bio-lubricant optimized performance
Dennison et al. (2024) [21]	Various materials (review)	Various	NCF (Al_2O_3, MoS_2, CNTs, hybrid)	General machining (review)	Review-based	Tool wear, Temp., Friction	Review study	Compared to traditional fluids, hybrid nanofluids greatly improve tribological performance, lower tool wear, and improve cooling
Vu Minh Hung et al. (2024) [22]	SKD11 steel	CNC Milling, Carbide tool	Dry, Wet, Conventional	Hard Milling	Vc, f, ap	Ra	Taguchi method	Lubrication enhances R_a, V_c, and f are key variables
Chohan et al. (2025) [23]	Heat-resistant Superalloys	CNC, Coated tool	Hybrid NF-MQL	Milling	Vc, f, NP Concentration	Tool wear, Temp., Ra	Experimental and Comparative Analysis	Hybrid NF-MQL greatly lowers tool wear and temperature while increasing sustainability

Data compiled from published literature [19]

Fig. 5 MQL spraying nozzle spraying mist on specimen

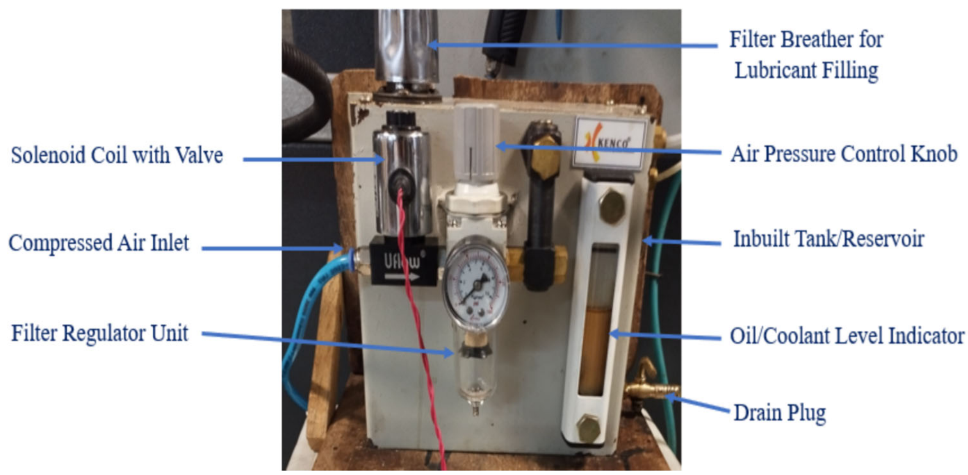


Fig. 6 Kenco MQL set up

Fig. 7 SiO_2 NF dispersed in water with NP of 0.5, 1, and 1.5 (2 Lit. each)

Table 3 Factors and levels used in experimental investigation

Factor	Investigated variables	Levels			Response variables
		Low	Medium	High	
A	Cutting Speed (V_c) (m/min)	100	200	300	Surface Roughness (R_a) (μm) Cutting Force (F_c) (N)
B	Feed (*f*) (mm/rev)	0.15	0.20	0.25	
C	Depth of Cut (a_p) (mm)	0.10	0.20	0.30	
D	Air Pressure (P_a) (Bar)	1	1.5	2	
E	Fluid Flow Rate (F_{fr})(mL/hr)	40	60	80	
F	NP Concentration (Wt.%)	0.5	1	1.5	

Table 4 Nanoparticle (NP) properties

S.N	Parameter	NP 1	NP 2	NP 3
1	SiO_2 NP Content	0.5% (Wt.% %)	1% (Wt.% %)	1.5% (Wt.% %)
2	Base Fluid	Deionized Water	Deionized Water	Deionized Water
3	Average Particle Size	20–50 nm	20–50 nm	20–50 nm
4	Physical Form	Liquid	Liquid	Liquid
5	Morphology of Dispersed Nano Particle	Near Spherical	Near Spherical	Near Spherical
6	Color	White	White	White
7	Purity	> 99%	> 99%	> 99%

controllable input parameters, each varied at three levels, while evaluating their effect on two critical output responses, namely R_a and F_c. The selected L27 array was derived from the standard L27 (3^{13}) orthogonal array, with columns 1–6 assigned to the six input parameters. This ensured a balanced representation of factor levels and reduced confounding effects, allowing for independent evaluation of each parameter's impact on output responses. The results were analyzed using MINITAB 17 statistical software. Table 5 shows the measured F_c and R_a values for the machined surfaces from all experimental trials. Based on the extensive parametric and statistical analysis of milling AISI 5160 steel under NF-MQL conditions, a clear comparative understanding of surface roughness (R_a) and cutting force (F_c) can be established, highlighting how each input parameter influences both responses differently.

The experimental results and Taguchi signal-to-noise (S/N) analysis show that F_c and R_a have distinct sensitivities to machining and NF-MQL parameters. The Taguchi response Table 6 (smaller-is-better criterion) indicates that a_p is the most influential parameter (Rank 1, Delta = 7.8603), followed by F_{fr} (Rank 2) and V_c (Rank 3). F_c, on the other hand, is primarily determined by a_p, F_{fr}, and V_c, as evidenced by regression coefficients and ANOVA results (Tables 7, 8 and 9).

4.1 Signal-to-noise analysis for R_a and F_c

The combined effects of V_c, *f*, a_p, MQL P_a, F_{fr}, and NP concentration on the machining responses, specifically Ra and Fc, under the "smaller-is-better" signal-to-noise (S/N) ratio criterion were assessed using the Taguchi analysis. Since both reactions must be minimised, a higher (less negative) S/N ratio indicates better machining performance with lower variability. Taguchi S/N ratio analysis reveals that a_p is the most critical parameter affecting R_a and F_c, followed by F_{fr} and V_c. Parameters related to the NF-MQL system, such as P_a and NP**,** play a supportive but comparatively less dominant role. These results provide a clear guideline for selecting optimal machining and lubrication conditions to achieve superior surface quality and reduced cutting forces in NF-MQL milling.

Using the "smaller-is-better" criterion, the main effects plot for signal-to-noise (S/N) ratios, Fig. 8, shows how machining parameters affect the robustness of R_a under NF-MQL settings. Higher S/N ratio values in this plot are associated with less variable R_a. The sharpest slope and largest variance in S/N ratio throughout its levels show that the a_p has the most influence of all the parameters. As the a_p grows from 0.1 to 0.3 mm, the S/N ratio drops dramatically,

Table 5 Experimental results of R_a and F_c under NF-MQL conditions in face milling

Run	V_c	f	a_p	P_a	F_{fr}	NP	R_a	F_c
A1	100	0.15	0.1	1	40	0.5	0.55	2.214
A2	100	0.15	0.1	1	60	1	0.47	1.549
A3	100	0.15	0.1	1	80	1.5	0.4	1.146
A4	100	0.2	0.2	1.5	40	0.5	0.63	2.958
A5	100	0.2	0.2	1.5	60	1	0.54	2.613
A6	100	0.2	0.2	1.5	80	1.5	0.48	2.108
A7	100	0.25	0.3	2	40	0.5	0.86	4.195
A8	100	0.25	0.3	2	60	1	0.76	3.566
A9	100	0.25	0.3	2	80	1.5	0.69	3.096
A10	200	0.15	0.2	2	40	1	0.39	2.547
A11	200	0.15	0.2	2	60	1.5	0.33	2.257
A12	200	0.15	0.2	2	80	0.5	0.36	1.836
A13	200	0.2	0.3	1	40	1	0.5	3.56
A14	200	0.2	0.3	1	60	1.5	0.44	3.182
A15	200	0.2	0.3	1	80	0.5	0.48	2.662
A16	200	0.25	0.1	1.5	40	1	0.65	1.843
A17	200	0.25	0.1	1.5	60	1.5	0.58	1.347
A18	200	0.25	0.1	1.5	80	0.5	0.66	0.729
A19	300	0.15	0.3	1.5	40	1.5	0.27	3.272
A20	300	0.15	0.3	1.5	60	0.5	0.31	2.804
A21	300	0.15	0.3	1.5	80	1	0.22	2.285
A22	300	0.2	0.1	2	40	1.5	0.41	1.312
A23	300	0.2	0.1	2	60	0.5	0.42	0.895
A24	300	0.2	0.1	2	80	1	0.36	0.424
A25	300	0.25	0.2	1	40	1.5	0.6	2.366
A26	300	0.25	0.2	1	60	0.5	0.59	1.88
A27	300	0.25	0.2	1	80	1	0.51	1.366

Table 6 Response table for signal-to-noise ratios *(Smaller is better)*

Level	V_c	f	a_p	P_a	F_{fr}	NP
1	− 4.9631	− 3.7016	0.8326	− 3.6387	− 5.3680	− 3.4507
2	− 3.6251	− 2.8004	− 3.9427	− 3.6993	− 3.5863	− 3.0450
3	− 1.5496	− 3.6358	− 7.0277	− 2.7998	− 1.1834	− 3.6421
Delta	3.4135	0.9012	7.8603	0.8995	4.1845	0.5971
Rank	3	4	1	5	2	6

suggesting a notable decline in surface finish and process robustness at a higher a_p.

4.2 ANOVA results for R_a and F_c

Analysis of Variance (ANOVA) is a computational method used to assess the design parameters and pinpoint those that significantly affect machining performance. ANOVA aids in identifying the relative contributions and interaction effects of different parameters that affect the output responses of the experiments, which are carried out using a structured design. The number of experiments required is significantly influenced by the matrix's design. As a result, having an appropriate experiment design is crucial. To determine the variables influencing the R_a and F_c displayed in Tables 10 and 11, the experimental results were analyzed using ANOVA.

Table 7 Analysis of variance for R_a

Source	DF	Adj. SS	Adj. MS	F-Value	P-Value
Regression	6	0.585789	0.097631	105.25	0.000
Cutting Speed	1	0.158672	0.158672	171.06	0.000
Feed	1	0.375556	0.375556	404.87	0.000
Depth of Cut	1	0.000050	0.000050	0.05	0.819
MQL Air Pressure	1	0.000089	0.000089	0.10	0.760
Fluid Flow Rate	1	0.027222	0.027222	29.35	0.000
NP Concentration	1	0.024200	0.024200	26.09	0.000
Error	20	0.018552	0.000928		
Total	26	0.604341			

Table 8 Analysis of variance for F_c

Source	DF	Adj. SS	Adj. MS	F-Value	P-Value
Regression	6	23.1035	3.8506	670.72	0.000
Cutting Speed	1	2.6000	2.6000	452.88	0.000
Feed	1	0.0127	0.0127	2.21	0.153
Depth of Cut	1	16.3649	16.3649	2850.55	0.000
MQL Air Pressure	1	0.0023	0.0023	0.40	0.535
Fluid Flow Rate	1	4.1232	4.1232	718.21	0.000
NP Concentration	1	0.0004	0.0004	0.07	0.789
Error	20	0.1148	0.0057		
Total	26	23.2183			

Table 9 Model summary for R_a and F_c under NF-MQL

Response	S	R-sq (%)	R-sq.(adj.) (%)	R-sq.(pred.) (%)
R_a	0.0304564	96.93	96.01	94.29
F_c	0.0757691	99.51	99.36	99.06

4.2.1 ANOVA for R_a

The combined and independent impacts of V_c, f, a_p, P_a, Ffr and NP on Ra during milling under NF-MQL conditions were assessed using regression analysis. A high F-value of 105.25 and a P-value of 0.000 in the analysis of variance results show that the overall regression model is extremely significant. This demonstrates that, under NF-MQL machining, the chosen machining parameters taken together have a statistically significant impact on R_a.

With the largest adjusted sum of squares (0.375556), a very high F-value of 404.87, and a P-value of 0.000, 'f' stands out as the most significant factor among the individual factors. Even with adequate NF-MQL lubrication, higher feeds result in more feed marks and surface imperfections, suggesting that feed rate is a major factor in controlling R_a. With an F-value of 171.06 ($P = 0.000$) and an adjusted sum of squares of 0.158672, V_c is found to be the second most important factor. V_c's substantial statistical significance emphasizes how crucial it is for improving surface quality by fostering stable cutting conditions and efficient nanofluid interaction at the tool–workpiece interface. R_a is also significantly impacted by the F_{fr} and NP, with P-values of 0.000 and F-values of 29.35 and 26.09, respectively. These results emphasise the critical role of adequate nanofluid supply and optimized nanoparticle concentration in improving lubrication, heat dissipation, and surface integrity under NF-MQL conditions. Increased flow rate ensures better delivery of the nanofluid, while appropriate nanoparticle concentration enhances the tribological performance at the cutting zone. On the other hand, as demonstrated by their extremely low F-values (0.05 and 0.10) and high P-values (0.819 and 0.760), a_p and MQL P_a did not affect surface roughness throughout the studied range. This implies that the impacts of P_a and a_p on R_a are successfully reduced under NF-MQL circumstances, perhaps as a result of the nanofluid's increased lubricating and cooling effectiveness. The comparatively small error sum of squares (0.018552) in relation to the overall sum of squares (0.604341) suggests

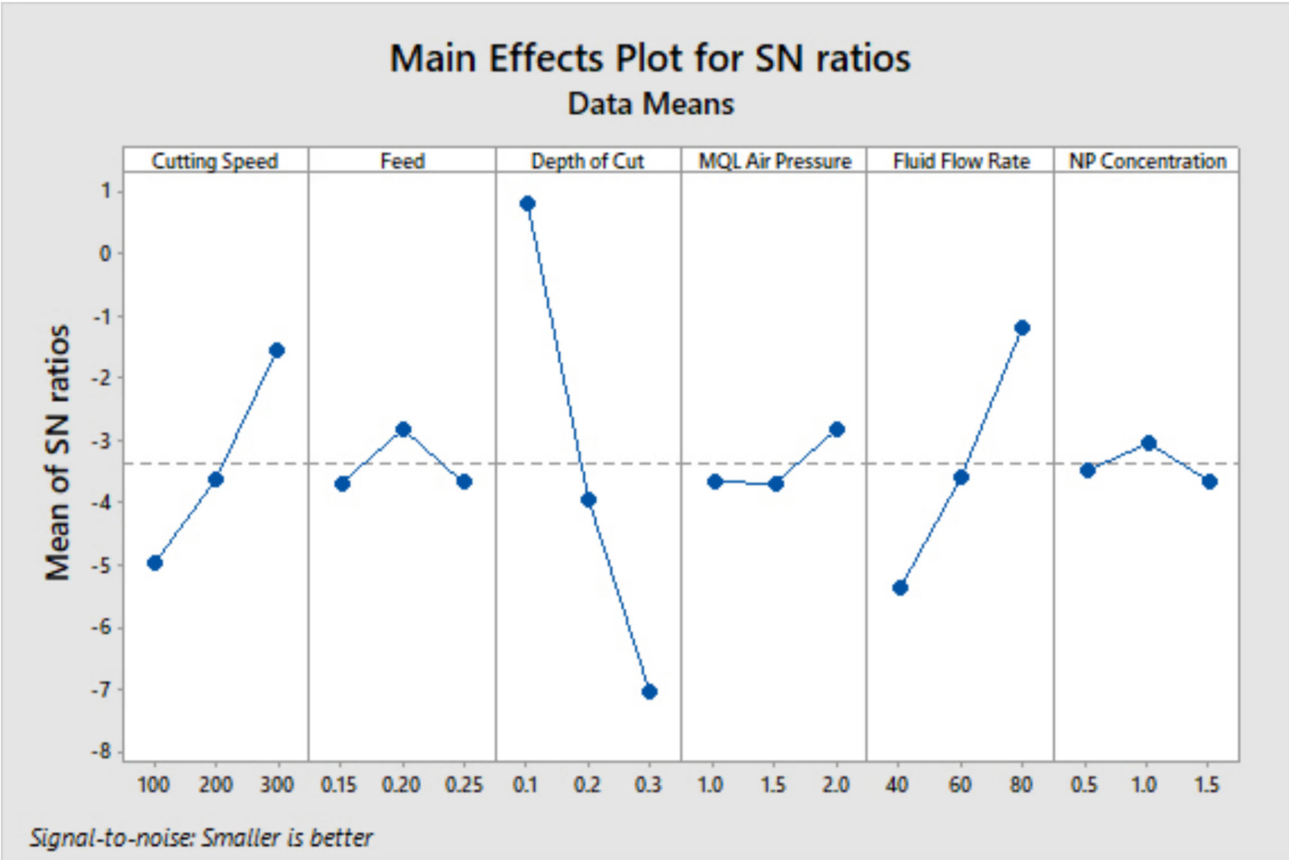


Fig. 8 Main effects plot for S/N ratios under NF-MQL condition

Table 10 Optimum performance runs: *(Low surface roughness and low cutting force)*

Run	V_c	f	a_p	P_a	F_{fr}	NP	Ra	Fc	Performance remark
A24	300	0.20	0.10	2.0	80	1.0	**0.36**	**0.424**	Best overall performance
A21	300	0.15	0.30	1.5	80	1.0	0.22	2.285	Best Ra, moderate force
A18	200	0.25	0.10	1.5	80	0.5	0.66	0.729	Very low cutting force
A23	300	0.20	0.10	2.0	60	0.5	0.42	0.895	Good surface finish

Table 11 Poor performance runs: *(High surface roughness and high cutting force)*

Run	V_c	f	a_p	P_a	F_{fr}	NP	Ra	Fc	Performance remark
A7	100	0.25	0.30	2.0	40	0.5	**0.86**	**4.195**	Worst overall performance
A8	100	0.25	0.30	2.0	60	1.0	0.76	3.566	Very high Ra and Fc
A9	100	0.25	0.30	2.0	80	1.5	0.69	3.096	Poor machining condition
A4	100	0.20	0.20	1.5	40	0.5	0.63	2.958	High force and roughness

minimal unexplained variation and strong model adequacy. Overall, the regression ANOVA confirms that the statistically significant factors influencing R_a in NF-MQL milling are f, V_c, F_{fr}, and NP; a_p and P_a have little effect within the parameter ranges under study.

4.2.2 ANOVA for F_c

The effects of V_c, f, a_p, MQL P_a, F_{fr}, and NP on cutting force during NF-MQL machining were assessed using regression analysis. An extremely high F-value of 670.72 and a P-value of 0.000 in the analysis of variance results show that the overall regression model is highly significant. This demonstrates that, under NF-MQL settings, the chosen machining parameters together have a statistically significant impact on cutting force.

Among the individual parameters, a_p is identified as the most dominant factor affecting F_c, with the highest adjusted sum of squares (16.3649) and an extremely large F-value of **2850.55** ($P = 0.000$). This result indicates that F_c increases substantially with increasing a_p due to the larger material removal cross-section and higher resistance offered by the workpiece material. The second most important parameter is F_{fr}, which has a substantial F-value of 718.21 ($P = 0.000$). The significant impact of F_{fr} emphasizes how crucial efficient nanofluid delivery is to lowering F_c by enhancing lubrication and reducing friction at the tool–chip interface. F_c is similarly statistically significantly impacted by V_c, with an F-value of 452.88 and a P-value of 0.000. This suggests that V_c is a significant factor in altering cutting mechanics, with higher speeds typically reducing F_c because of improved tribological conditions under NF-MQL and thermal softening of the workpiece material. In contrast, f exhibits a relatively low F-value of **2.21** with a P-value of **0.153,** suggesting that its effect on F_c is statistically insignificant within the investigated range. Similarly, **MQL $\mathbf{P_a}$** and NP show negligible influence on F_c, as reflected by their very low F-values (0.40 and 0.07) and high P-values (0.535 and 0.789). These findings show that under NF-MQL settings, P_a and NP may have an impact on lubrication quality and surface integrity, but they have little direct effect on F_c. The regression model's adequacy is confirmed by the small error sum of squares (0.1148) in relation to the total sum of squares (23.2183), which shows little unexplained variation. Overall, the ANOVA results demonstrate that a_p**, $\mathbf{F_{fr}}$, and $\mathbf{V_c}$** are the primary parameters governing F_c in NF-MQL machining, while f, P_a, and NP have comparatively minor effects within the studied parameter ranges.

4.3 Regression modelling and predictive capability

To determine quantitative correlations between the input parameters and the responses, regression models (Table 9) were created. Excellent model accuracy is demonstrated by the R_a model's coefficient of determination (R^2) of 96.93% and the cutting force model's even better R^2 value of 99.51%. The close agreement between R^2, adjusted R^2, and predicted R^2 values confirms the robustness and generalizability of both models. The regression coefficients further reinforce the ANOVA findings. For R_a, f and V_c have strong and significant coefficients, whereas for F_c, a_p and F_{fr} dominate the response. The low standard error values for both models indicate minimal prediction error and high reliability.

4.4 ANOVA model validation using residual diagnostics and interaction analysis

Through interaction effect analysis and residual diagnostics for both R_a and F_c under NF-MQL circumstances, the appropriateness and statistical validity of the ANOVA models created using the L27 orthogonal array were thoroughly confirmed. The L27 design's basic premise of factor independence was supported by the interaction plots, which showed mostly parallel patterns across the control factors, suggesting negligible interaction effects.

Additionally, both responses and their normal probability plots of residuals (Fig. 9) demonstrated a near alignment of data points along the reference straight line, supporting the residuals' normal distribution. The Anderson–Darling normality criterion (p-value > 0.05) is met by this observation, confirming the normality assumption necessary for trustworthy ANOVA inference.

Furthermore, the residuals against fitted values plots (Fig. 10) confirmed homoscedasticity and the suitability of the regression models by showing a uniform and random scatter around the zero line without any obvious pattern or funnel shape. The residuals versus observation order plots (Fig. 11) confirmed the independence of errors and the stability of experimental circumstances by showing a random distribution of residuals devoid of trends or autocorrelation.

These statistical diagnostics demonstrate that the assumptions of normality, constant variance, and independence are met satisfactorily, confirming the robustness, reliability, and predictive capability of the developed models and validating the applicability of the L27 orthogonal array design for analyzing machining performance of AISI 5160 steel under NF-MQL conditions.

4.5 Final regression equation in terms of coded factors for R_a and F_c

A mathematical model was created using the study's findings. Multiple regression analysis was chosen for this, and the models were created using Minitab 17 software. Equations (2) and (3) gave the linear Surface Roughness and Cutting Force models by considering the impact of all major factors (i.e., Vc, f, ap, Pa, Ffr, NP). The developed regression equation for R_a and F_c quantitatively describes the relationship between the selected machining parameters during NF-MQL milling.

$$\mathbf{R_a} = \mathbf{0.2885 - 0.000939\,(V_c) + 2.889\,(\mathit{f}) + 0.0167\,(a_p) + 0.0044\,(P_a) - 0.001944\,(F_{fr}) - 0.0733\,(NP)} \tag{2}$$

$$\mathbf{F_c} = \mathbf{2.381 - 0.003801\,(V_c) + 0.531\,(\mathit{f}) + 9.535\,(a_p) + 0.0226\,(P_a) - 0.023931\,(F_{fr}) - 0.0097\,(NP)} \tag{3}$$

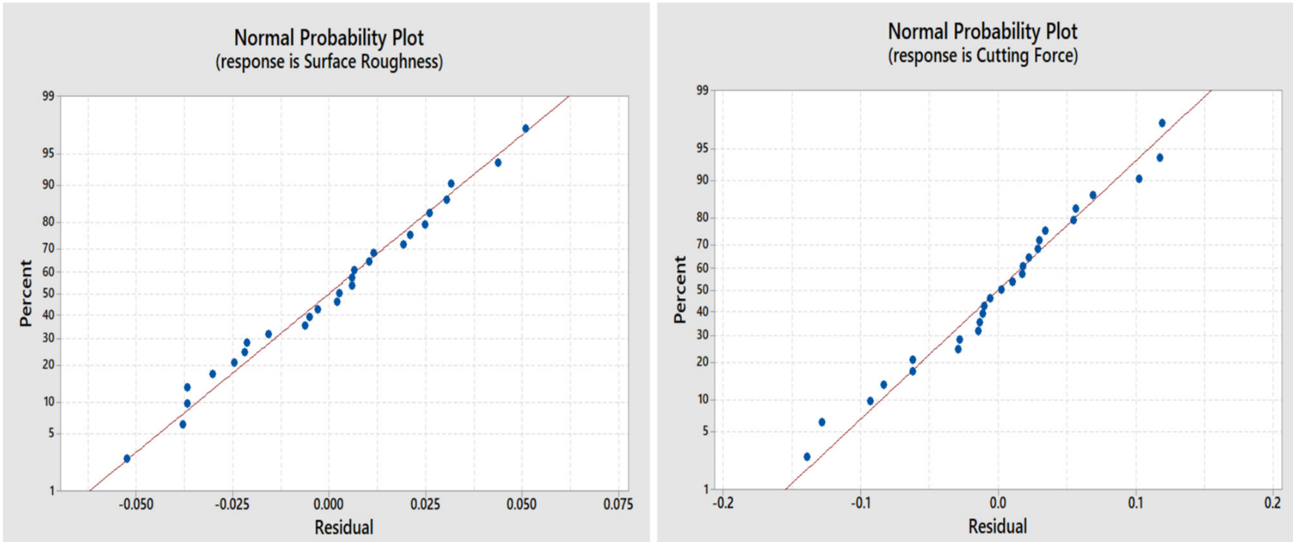


Fig. 9 Normal probability plot of residuals for the R_a and F_c model

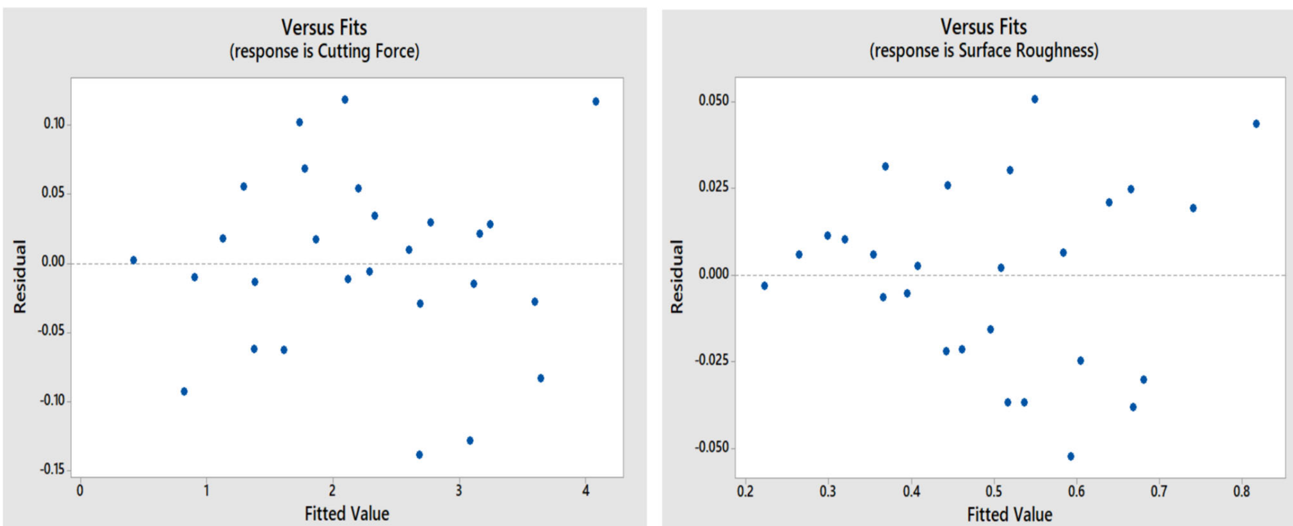


Fig. 10 Residuals versus fitted values plot for R_a and F_c model

5 Results and discussion

The experimental, statistical, and regression results from the milling of AISI 5160 steel under NF-MQL conditions are thoroughly examined in this section. Taguchi signal-to-noise analysis, analysis of variance, and regression modelling are used to examine the combined impact of machining parameters and NF-MQL variables on R_a and F_c. The findings are interpreted in terms of machining mechanics, tribological behaviour, and lubrication effectiveness. The three-dimensional surface plot from the section below illustrates the influence of the selected process parameters on R_a and F_c under nano-fluid minimum quantity lubrication (NF-MQL) conditions.

5.1 Influence of process parameters on R_a and F_c

One important measure of the surface integrity and functional performance of machined parts is R_a. Based on the smaller-is-better criterion, the Taguchi signal-to-noise ratio analysis shows that a_p has the largest delta value, followed by F_{fr} and V_c. However, with p-values significantly below 0.05, ANOVA results show that f and V_c are statistically the most important factors influencing R_a. F_c represents the mechanical load experienced by the cutting tool and directly affects tool life, dimensional accuracy, and energy consumption. ANOVA results indicate that depth of cut is the most influential parameter affecting F_c, with an extremely high F-value of 2850.55. Feed is extremely significant ($F = 404.87$,

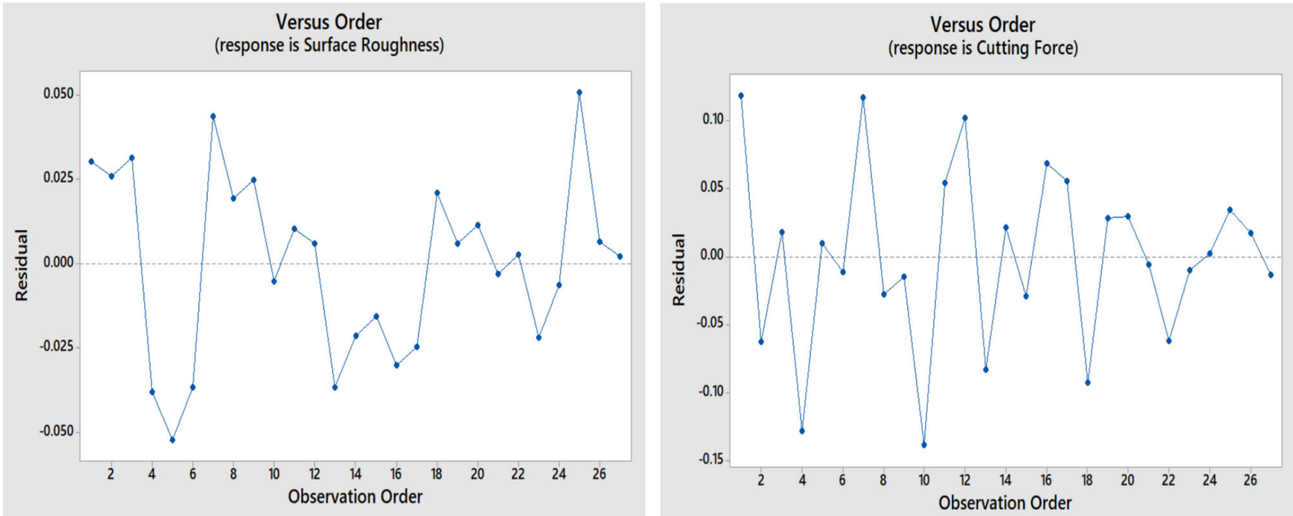


Fig. 11 Residuals versus observation order plot for R_a and F_c model

$p = 0.000$) in the ANOVA for surface roughness, meaning that an increase in feed significantly raises R_a because of larger tool marks and more material deformation per tooth. However, feed is statistically insignificant for F_c ($p = 0.153$), indicating that, within the chosen experimental range, its contribution to F_c fluctuation is comparatively minimal when compared to lubricating parameters and a_p. This highlights that 'f' should be carefully optimized primarily for surface finish control rather than force reduction. The response surface reveals that 'f' remains a critical machining parameter affecting both surface quality and F_c, even in the presence of enhanced lubrication and cooling provided by NF-MQL. The surface plot showed a moderate increase in F_c and R_a when the '*f*' climbed to 0.20 mm/rev. The surface plot demonstrates a more noticeable rise in F_c and R_a at the maximum 'f' of 0.25 mm/rev. While Fc increases dramatically, Ra values get closer to their upper range. Nanoparticles help reduce friction at the interface by causing rolling effects, but their impact decreases with increasing chip thickness and cutting load. The following surface plot illustrates how each separate input variable affects the output response:

5.1.1 Effect of 'V_c' on R_a and F_c under NF-MQL condition

F_c and R_a are strongly influenced by V_c. V_c is statistically significant ($p = 0.000$) for both R_a and F_c, according to ANOVA results. Because of the higher lubrication efficiency under NF-MQL conditions and the thermal softening of AISI 5160, increasing V_c results in a decrease in F_c. Simultaneously, higher V_c improve surface finish by reducing built-up edge formation and ensuring smoother chip flow, as reflected in the lower R_a values at 200–300 m/min. Thus, V_c positively contributes to both reduced F_c and improved surface quality. Under nano-fluid minimum quantity lubrication (NF-MQL) conditions, the three-dimensional surface plot (Fig. 12) shows how V_c affects R_a and F_c. R_a values varied between about 0.40 and 0.86 µm at the lowest V_c of 100 m/min, while the F_c varied between 1.15 and 4.20 N. Both F_c and R_a significantly decreased as the V_c rose to 200 m/min. Both the F_c and the Ra values declined to roughly 0.73–3.56 N and 0.33–0.66 µm, respectively.

At the highest V_c of 300 m/min, the surface plot shows the minimum R_a and F_c values. Ra was reduced to as low as 0.22 µm, while the F_c decreased significantly, reaching values as low as 0.42 N. The pronounced downward trend along the V_c speed axis indicates that higher V_c, when combined with NF-MQL, are highly effective in minimizing F_c and surface irregularities. The response surface reveals a clear dependence of both output responses on V_c, while simultaneously highlighting the effectiveness of NF-MQL in reducing machining forces and improving surface quality.

5.1.2 Effect of '*f*' on R_a and F_c under NF-MQL condition

Feed rate (*f*) has a significant impact on Ra but a relatively little impact on Fc. '*f*' is extremely significant ($F = 404.87$, $p = 0.000$) according to the ANOVA for R_a, meaning that an increase in feed significantly raises Ra because of larger tool marks and more material deformation per tooth. However, for F_c, f is statistically insignificant ($p = 0.153$), suggesting that within the selected experimental range, its contribution to Fc variation is relatively small compared to depth of cut and lubrication parameters. This highlights that f should be carefully optimized primarily for surface finish control rather than force reduction. R_a and F_c data were comparatively low at lower feed rates (0.15 mm/rev). The F_c remained quite modest, and the R_a values were typically less than 0.55 µm.

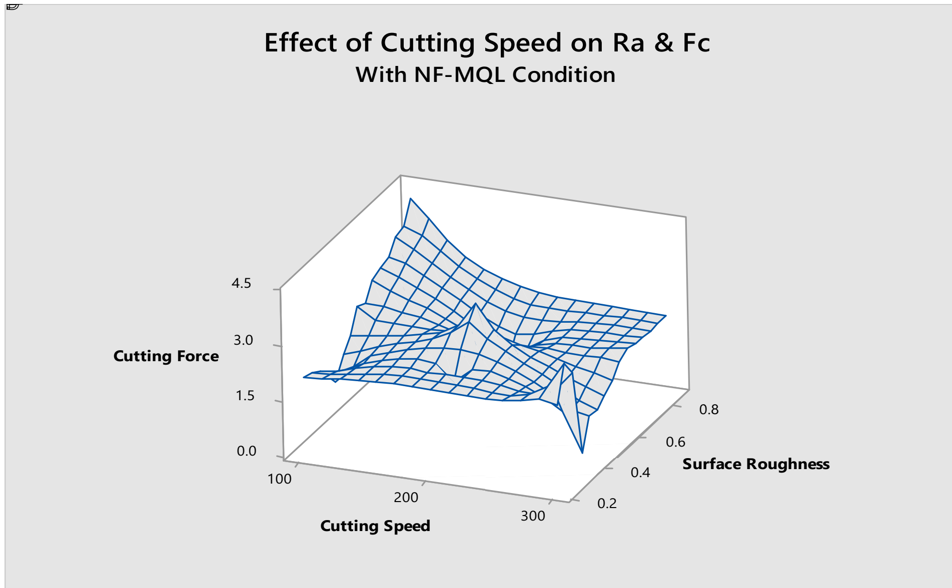


Fig. 12 Influence of cutting speed on Ra and Fc under NF-MQL condition

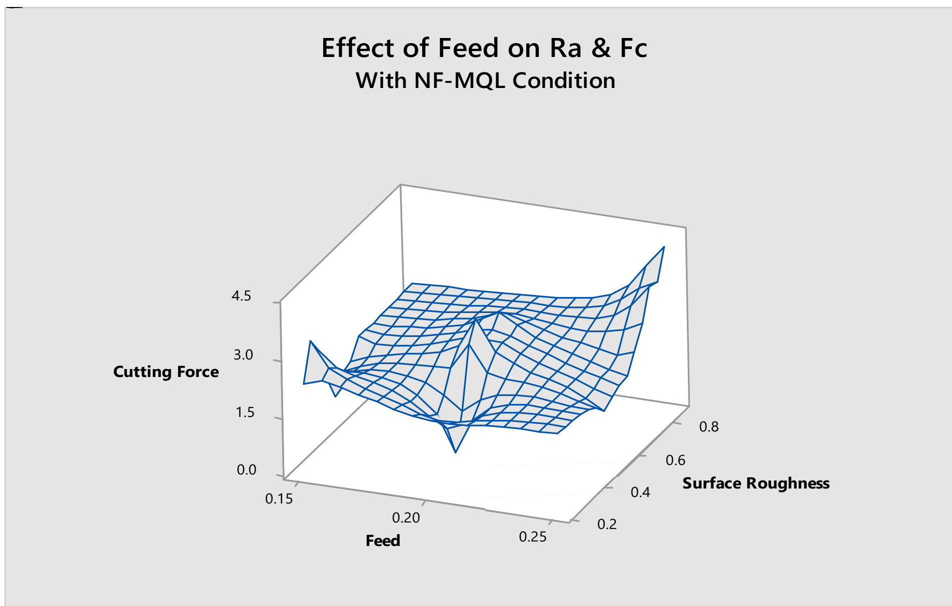


Fig. 13 Influence of feed on R_a and F_c under NF-MQL machining

The surface plot showed a moderate increase in F_c and R_a when the f climbed to 0.20 mm/rev. The surface plot displays a more noticeable rise in F_c and R_a at the maximum 'f' of 0.25 mm/rev. While Fc sharply increases, R_a values get closer to their upper range. Even with NF-MQL's improved lubrication and cooling, feed rate is still a crucial machining parameter that affects F_c and R_a, as the response surface in Fig. 13 demonstrates.

5.1.3 Effect of 'a_p' on R_a and F_c under NF-MQL condition

With a very high F-value (2850.55) and $p = 0.000$, a_p is the most important factor affecting F_c. Because of increased material engagement and resistance at the tool–workpiece interface, increasing the a_p dramatically increases F_c. But under NF-MQL settings, its impact on R_a is negligible and statistically insignificant ($p = 0.819$), suggesting that the a_p has little effect on surface finish. This contrast demonstrates that a_p is a force-dominant parameter rather than a surface-finish-dominant one. The response surface indicates (Fig. 14) that a_p remains a significant machining parameter affecting both surface integrity and F_c, even in the presence of enhanced lubrication and cooling offered by NF-MQL. At lower a_p (0.1 mm), relatively lower F_c and improved R_a were observed. The surface plot shows a moderate increase in both R_a and F_c as the a_p goes to 0.2 mm. The surface plot shows a

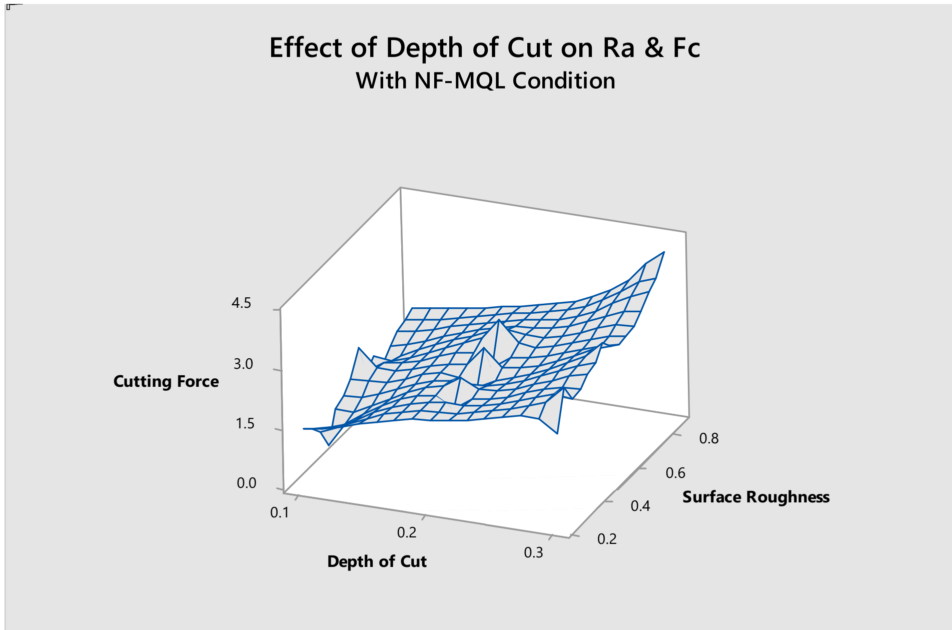


Fig. 14 Influence of depth of cut on R_a and F_c under NF-MQL condition

noticeable increase in F_c and R_a at the maximum a_p (0.3 mm). The advantages of nano-lubrication predominate at lower and intermediate a_p, improving machining performance. But at deeper cuts, the benefits of lubrication are outweighed by the consequences of mechanical deformation, which results in a greater increase in F_c and R_a.

5.1.4 Effect of MQL 'P_a' on R_a and F_c under NF-MQL condition

MQL P_a shows negligible influence on both R_a and F_c, as indicated by high p-values (Ra: 0.760, Fc: 0.535). Although P_a aids in droplet transport and penetration, within the investigated range, it does not significantly alter lubrication effectiveness enough to impact R_a or F_c. This suggests that P_a should be maintained at an optimal level, but does not require aggressive optimization. Frictional behavior and machining performance are directly impacted by MQL P_a, which is essential in controlling the atomization, penetration, and efficient transport of the nano-fluid lubricant into the cutting zone. R_a and F_c measurements were comparatively higher at lower MQL P_a levels (around 1 bar). The surface plot (Fig. 15) showed a discernible decrease in both R_a and F_c as the MQL P_a rose to moderate levels (around 1.5 bar). The surface plot shows a mixed reaction at higher MQL P_a levels (around 2 bar). R_a shows a minor rise in some areas, whereas F_c continues to show a slight decrease or stabilizes at lower values.

5.1.5 Effect of 'F_{fr}' on R_a and F_c under NF-MQL condition

Both responses are strongly and statistically significantly impacted by fluid flow rate (F_{fr}), while the impact on F_c is more noticeable. Because of improved cooling, lubrication, and lower friction at the cutting zone, higher flow rates considerably lower cutting force ($F = 718.21$, $p = 0.000$). Since better lubrication reduces tool wear and results in smoother machined surfaces, F_{fr} is also important for R_a ($p = 0.000$). This demonstrates how important proper nanofluid delivery is for NF-MQL-assisted milling. R_a and F_c measurements were comparatively higher at lower F_{fr} (around 40 ml/h). The surface plot showed a discernible decrease in both R_a and F_c when the F_{fr} climbed to moderate levels (around 60 ml/h). The surface plot (Fig. 16) demonstrates a minor stabilization or slight increase in R_a in some areas at greater F_{fr} (about 80 ml/h), while the F_c stays relatively low.

5.1.6 Effect of 'NP' on R_a and F_c under NF-MQL condition

R_a is moderately affected by nanoparticle concentration ($p = 0.000$), while cutting force is not significantly affected ($p = 0.789$). Increased concentration of nanoparticles enhances tribological performance, resulting in decreased friction and better surface quality. Its low impact on F_c, however, indicates that the concentration of nanoparticles improves surface integrity rather than load-bearing capability during cutting. R_a and F_c readings were comparatively higher at lower NP concentrations (around 0.5 wt.% %). The surface plot (Fig. 17) showed a significant decrease in both R_a and F_c

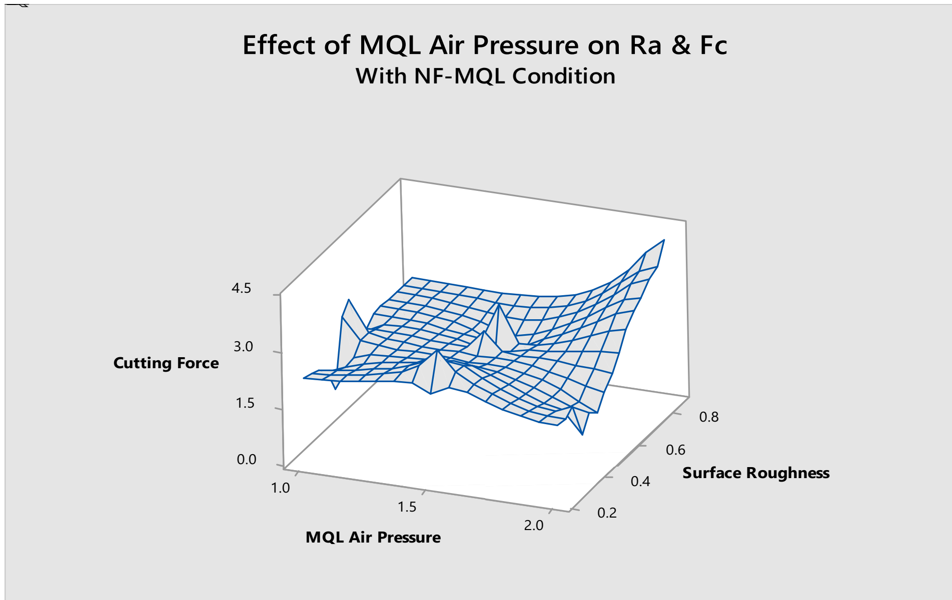


Fig. 15 Influence of MQL air pressure on R_a and F_c under NF-MQL condition

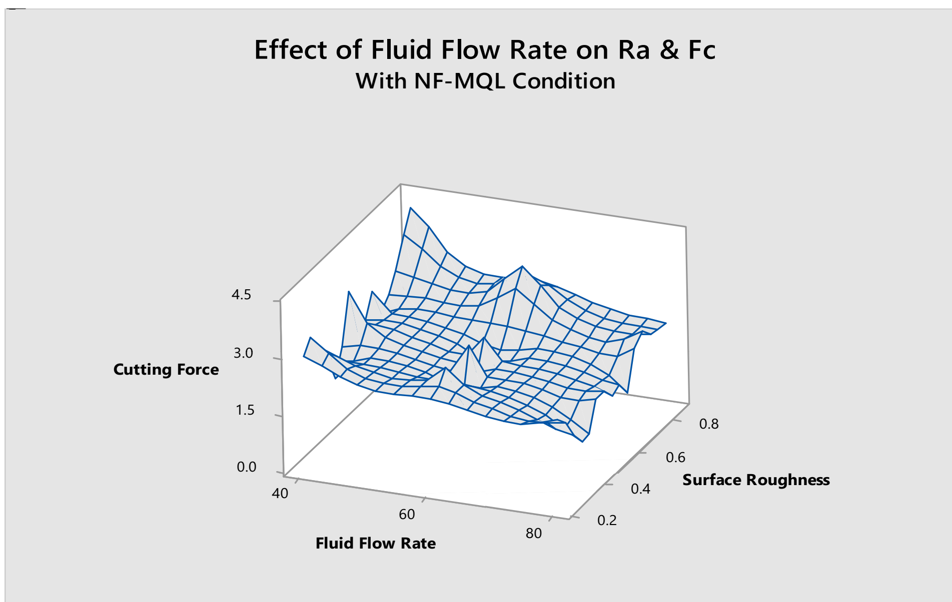


Fig. 16 Influence of fluid flow rate on Ra and Fc under NF-MQL condition

when the NP concentration rose to moderate levels (around 1.0 wt.%). Further increasing the NP concentration to higher levels (approximately 1.5 wt.%) results in a marginal stabilization or slight increase in R_a and F_c in certain regions of the surface plot.

The above observed trends of effects of cutting parameters on R_a and F_c are in good agreement with the normalized condition of AISI 5160 steel and the associated low-force machining regime.

6 Comparative analysis of R_a and F_c

A comparison of F_c and R_a shows that distinct dominant characteristics affect these two responses. While F_c is determined by a_p and F_{fr}, R_a is mostly determined by *f* rate and V_c. This divergence highlights the necessity of multi-objective optimization in milling processes. Optimal machining conditions (Table 10) for achieving minimum R_a involve low feed rates, higher cutting speeds, and increased nanoparticle concentration. In contrast, minimizing cutting force requires reduced depth of cut, higher cutting speeds, and increased

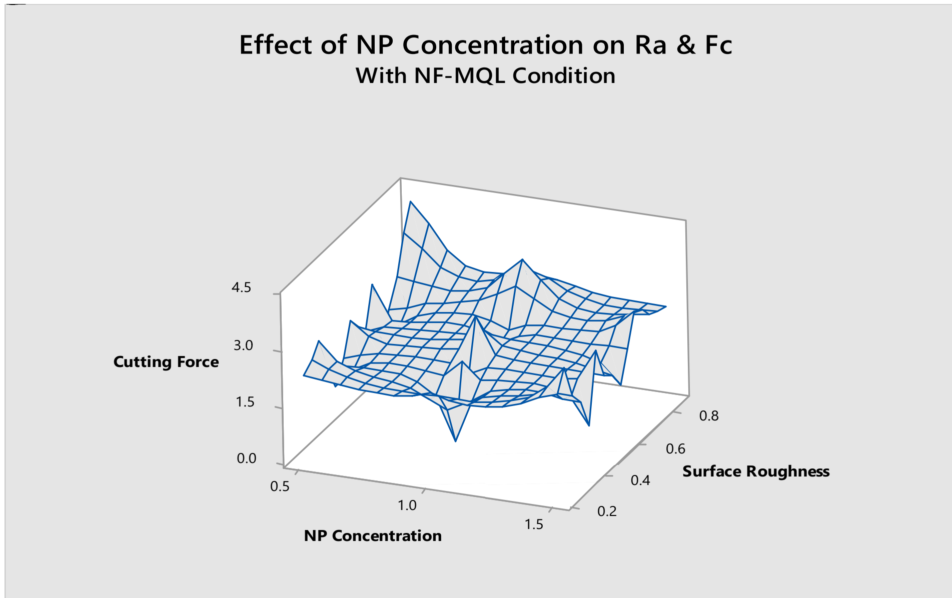


Fig. 17 Influence of NP concentration on R_a and F_c under NF-MQL condition

Table 12 Results of confirmation experiment

Response	V_c	f	a_p	P_a	F_{fr}	NP	Experimental value	Predicted value	Percentage error (%)
R_a	300	0.20	0.10	2	80	1.0	0.38	0.36625	3.62
F_c	300	0.20	0.10	2	80	1.0	0.438	0.42142	3.79

nanofluid flow rate. The identified optimal experimental runs demonstrate that NF-MQL enables a favorable compromise between surface quality and cutting load when appropriate parameter combinations are selected.

Low V_c, high f, a_p, and inadequate nanofluid flow are characteristics of poor performance conditions (Table 11). In these circumstances, high cutting forces and poor surface quality are caused by insufficient lubrication and excessive mechanical engagement.

The result Tables 10 and 11, of optimum and poor runs, clearly highlight the machining conditions that should be **preferred or avoided** for achieving sustainable and high-quality milling of AISI 5160 steel under NF-MQL conditions.

6.1 Confirmation experiment for optimum machining parameters under NF-MQL condition

To confirm the accuracy of the optimal parameters obtained by the orthogonal experiments, the confirmation tests are arranged. The optimum run was selected based on **simultaneous minimization of R_a and F_c,** supported by Taguchi S/N ratio ("smaller-is-better"), ANOVA significance and Experimental response values. From the experimental matrix, **Run A24** shows the **best combined R_a–$F_c$performance**. The identified Optimum Parameter Combination for NF-MQL condition are;

Cutting speed (V_c) = **300 m/min**	MQL air pressure (P_a) = **2 bar**
Feed (f) = **0.20 mm/rev**	Fluid Flow Rate (F_{fr}) = **80 ml/h**
Depth of Cut (a_p) = **0.10 mm**	NP Concentration (NP) = **1.0 wt.%**

Table 12 shows the confirmation experiment results comparing predicted and experimental surface roughness and cutting force at optimal NF-MQL machining conditions. The confirmation experiment was conducted at the optimal NF-MQL parameter combination identified through Taguchi optimization and statistical modeling.

The experimentally obtained surface roughness (0.38 µm) closely matches the predicted value (0.36624 µm), resulting in a percentage deviation of only 3.62%. This low error confirms the high predictive accuracy of the surface roughness regression model under NF-MQL conditions. Similarly, the cutting force achieved from the confirmation experiment (0.438) is excellently consistent with the expected value (0.42142), with a 3.79% deviation. The model accurately reflects the impact of machining and NF-MQL parameters, as evidenced by the high coefficient of determination (R^2 = 99.51%). Minor differences between predicted and experimental results can be attributable to natural experimental variability, such as small fluctuations in aerosol delivery, nanoparticle dispersion stability, and tool-work interface conditions. Nevertheless, all variances are within acceptable bounds for machining tests. Overall, the confirmation test confirms the robustness, reliability, and practical applicability of the optimized approach and regression models for NF-MQL-assisted milling of AISI 5160 steel. NF-MQL significantly improves surface integrity and reduces force.

7 Conclusions

The present investigation demonstrates that NF-MQL is an effective, sustainable lubrication strategy for milling AISI 5160 steel, enabling simultaneous control of surface integrity and cutting load. R_a is predominantly governed by f and V_c, while F_c is overwhelmingly influenced by a_p, followed by V_c and nanofluid flow rate. The NF-MQL parameters, particularly fluid flow rate and nanoparticle concentration, improve tribological conditions by lowering friction and heat generation at the tool-workpiece contact. Higher cutting speeds, lower depths of cut, and enhanced nanofluid flow rates resulted in optimal machining performance, while low cutting speeds, large depths of cut, and inadequate lubrication resulted in unsatisfactory performance. The generated regression models' high predicted accuracy demonstrates their applicability for process optimization and practical use of NF-MQL-assisted milling of high-strength alloy steels. The overall experimental results show that,

High V_c (300 m/min), low a_p (0.10 mm), greater F_{fr} (80 mL/hr), and moderate NP concentration (1%) are typically linked to optimal runs, demonstrating the advantageous effect of NF-MQL in lowering friction and enhancing surface quality.
Low V_c (100 m/min), high f (0.25 mm/rev), high a_p (0.3 mm), and low F_{fr} (40 mL/hr) are the main causes of poor runs. These factors enhance tool–workpiece contact, resulting in increased F_c (4.195 N) and deteriorated R_a (0.86 µm).
The most important factors influencing R_a are f and V_c. The primary factor affecting F_c is the a_p. Under NF-MQL circumstances, F_{fr} considerably lowers F_c and R_a. Although it has little effect on F_c, nanoparticle concentration enhances surface finish.

Overall, the parametric analysis establishes a clear mechanistic understanding of NF-MQL-assisted milling of AISI 5160 steel. The findings provide practical guidelines for selecting machining and lubrication parameters to achieve enhanced surface integrity and reduced cutting forces, supporting the broader adoption of sustainable machining technologies in advanced manufacturing.

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Declarations

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