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Effects of Minimum Quantity Lubrication (MQL) on Surface Roughness in Milling Al Alloy 383 / ADC 12 Using Nano Hybrid Cutting Fluid

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Abstract: This work aims to investigate and assess the beneficial function and feasibility of nanofluids in minimum quantity lubrication (MQL) assisted machining. The goal is to develop newly generated CNT based nano hybrid cutting fluid and demonstrate its effect on surface roughness of Al alloy. Moreover, the fabricated nano hybrid cutting fluid will eventually reduce cutting fluid consumptions and maintain an eco-friendly environment. Three conditions were used to perform the machining process such as dry condition, conventional oil and Al_2O_3/CNT nanoparticle with EVO oil as base fluid. The lowest surface roughness achieved for nanofluid and the maximum surface roughness for the dry condition. In terms of looking for optimum parametric combination, Artificial Neural Network (ANN) and Response Surface Methodology (RSM) have been used. The ANN technique has proved its efficiency since its correlation coefficients, mean prediction errors (MPEs), and root mean square errors (RMSEs) are small compared to the RSM approach.

Keywords: Minimum quantity lubrication (MQL), Nano-fluid, ANN- RSM comparison, Aluminum Die casting, Al383, Surface roughness, Milling.

1. Introduction

Close to 20% of machining expenses are attributed to lubrication in traditional manufacturing processes[1,2]. Complete lubricant removal may affect tool wear and part quality. The machining lubricant has been discovered to have a significant impact on thermal deformation and surface inaccuracy[3]. Reducing coefficient of friction and wear protection is crucial in any machining[4]. Another environmental benefit of MQL metal cutting is the substitution of mineral oils with environmentally friendly vegetable oils[5]. High cutting velocity, feed rate, and depth of cut is used for large -volume machining for which, generates a lot of heat. In addition, it reduces tool life and surface veracity. Thermal dynamics of hard-to-machined components during manufacturing contributes to micro defects and Residual Stresses in final products and overheating on machine tools, where temperature plays a critical role in the study of the tool-workpiece interface [6]. Edge damage characteristics present tiny cracks and serrated continuous edge breakage. The main causes of the edge damage were explored regarding the edge residual stress, microstructure, and the change of element content[7]. The final state of RSes in a workpiece depends on its material and on the employed cutting parameters/conditions[8]. There are several cutting parameters and conditions that affect the generation of RS, so understanding the relationship between the RS generation and those parameters to minimize the induced tensile RS is a crucial issue[9]. As a result of this ineffective heat removal, conventional fluid functions cannot penetrate the chip-tool interface. Incorrect cutting fluid handling causes harm to soil and water resources. Cutting fluids can also cause skin and respiratory issues for machine operators[10]. A lot of researches have been conducted where MQL was applied to reduce lubricant usage. The cutting area gets extremely hot while hardening rough fabrics at high speed[11]. The poor structure, adhesion, abrasion, and chemical alteration are all caused by this excessive heat output. Thus, in intermittent operations on dry condition machining MQL is considered as well performer. The nature of lubricant and its concentration has huge influence on the performance of machining[12]. Tungsten carbide solid lubricant-assisted nano-finishing fluids was used in the AISI 4340 steel using a limited volume lubrication technique for TiCN/Al2O3/Tin chemical vapor deposition[13]. For providing better outcomes during MQL application, low viscosity fluids were found. The findings lead to safer and efficient processing aimed at waste reduction/omission and environmentally responsible practices. When MQL process is used, the surface finishes get better due to less wear and tear [14].

Using more eco-friendly and biodegradable materials would help reduce pollution. Demand for ecologically friendly lubricants is expected to expand 7–10% over the next few years, compared to barely 2% for the whole lubricant market [15]. In general vegetable oil is a liquid that is combination of triglycerides which is nonpolar. These glycerol molecules attached with three fatty acids chain along with the hydroxyl group. Fatty acids are found in vegetable oil which create bond to each of the three carbons of glycerol molecule. Because of this long chain of fatty acid, there's a possibility for providing good strength lubricant to the rotating metallic surfaces. Generally vegetable oil is draw out from various types of fruits, seeds, grains, nuts. In plants, soybean, sunflower, cottonseed is admired for using in different types of operation[16]. Vegetable oils are eco-friendly for its decomposable quality and it is also industrial friendly for high friction co efficient and higher strength than produced by mineral oil. Vegetable oil occurs less wear scars that's why it has more potential for working as a lubricant. Also, it contains viscosity-temperature characteristics [17].

Nano hybrid cutting fluids are made up of nano-sized particles, which provided good results in improving warm characteristics. This is the age of working liquids, set to replace their conventional companions. Nanoparticles have recently been introduced to base fluids to boost lubrication performance in order to increase the effectiveness of MQL thanks to their thermo-physical characteristics[18]. A nano-liquid is defined as a liquid formed by the scattering of metallic or non-metallic nanoparticles or nanofibers within a size of less than 100 nanometres into a base cutting liquid [19]. It had been noticed that an ascent of nanoparticle fixation improves both, the heat conductivity and consistency[20]. Setti et al.[21] in their study, used water-based Al_2O_3 and precious stone nanofluids in MQL granulating measure and the results were contrasted with those of pure water. The outcomes indicated the advantages of lessening crushing powers, improving roughness. Nano-added substances can be ordered into a few kinds which are non-metallic, blending metallic, carbon, and earthenware nanoparticles. Multi-divider carbon nanotubes and Al_2O_3 nanoparticles are among the nano-added substances that have predominant warmth, mechanical, and tribological properties [22]. Padhan et al.[23] in his work investigates the comparative performance of four cooling/lubrication techniques: dry cutting, wet, minimum quantity lubricant (MQL) and compressed-air modes in turning Nitronic 60 steel using a new-generation SiAlON ceramic inserts.

Das et al.[24] justified the use of an artificial neural network to construct a link between cutting process parameters and surface roughness while milling Al-4.5Cu-1.5TiC metal matrix composites. Furthermore, Palavar et al.[25] found that utilizing ANN to forecast aging effects on the wear behavior of Inconel 706 super alloy can yield useful results, and that the approach can be utilized to calculate weight loss values in the identified parameters with a high coefficient of determination value. Ammar H. et el.[26] in his paper developed hybrid machine learning (ML) models are developed to predict the induced residual stresses (RSes) during turning of Inconel 718 alloy. Bingöl et al.[27] agreed on root mean square error (RMSE), coefficient of determination (R2), and absolute average deviation (AAD) as comparison criteria between RSM and ANN. A batch sorption technique was used to remove lead ions from aqueous solution using Nigella sativa seeds (black cumin), a unique and natural biosorbent, using the following process variables: pH, biosorbent mass, and temperature. They came to the conclusion that the ANN model had a better predictive power than the RSM model.

Surface roughness predicting is critical for industrial processes. A good modelling strategy for these output parameters is needed. Many studies have compared the accuracy of response surface methods with artificial neural networks and the final results were mixed. Between these two models, ANN perform better at predicting surface roughness and workpiece vibration in stainless steel boring, according to Venkata and Murthy[28], who used statistical models to find the relationship between cutting parameters and these two outputs. Other researchers, on the other hand, have discovered that RSM outperforms the ANN technique in a variety of inquiries and studies. In case of multi-input and multi-output (MIMO) scenario, ANN model is the most effective as it doesn't require any linearization[29]. Indeed, Lakshminarayanan and Balasubramanian[30] made a conclusion after predicting friction stir-welded joints tensile strength of AA7039 aluminum alloy that RSM has a major advantage over ANN, which is the ability to calculate the factor contributions from the regression model's coefficients, as well as the ability to identify unimportant main factors, interaction factors, and insignificant terms in the model.

Over the last few years, a large amount of study has been done on MQL. The majority of them use the same lubricant in different conditions, such as dry machining, wet machining, and MQL. However, in this study, surface roughness was measured using standard oil and Nano hybrid cutting fluid as lubricants in diverse conditions. Finally, a comparison between RSM and the ANN has made. This Nano hybrid cutting fluid is eco-friendly and besides it will reduce the consumption of cutting fluid which eventually help to minimize the overall cost of the machining and maintain a sustainable environment.

The objectives of this investigations are as follows

- To prepare of CNT based nano-fluid by

confirming the uniform dispersion to increase the cooling property.

- To investigate the impact of CNT based nano-fluid in respect of surface roughness.
- To reduce surface roughness during machining aluminum alloy in milling by using fabricated nano-fluid.
- To develop a comparative analysis of two predictive models for predicting surface roughness during milling Al alloy.

Author contribution: Conceptualization- M.S.H.; experiment- M.S.H, Fu. A, S.A; Data Analysis- Fu. A; writing - original draft preparation, Fu. A; writing- review and editing, M.S.H, S.K, Fu. A, supervision, Fa. A.

2. Experimental investigation

2.1 Experimental equipment

The experiment was performed using Universal knee type milling machine Model - X6132A showed in **Fig.1**, High Speed Steel (HSS) side milling cutter (Inner dia-22mm, Outer dia-80mm, Thickness-10mm) showed in **Fig.2**, and HP-TR2 Side Feed Dual Action Trigger Airbrush nanofluid spray system.

Fig. 1: Universal knee type milling machine

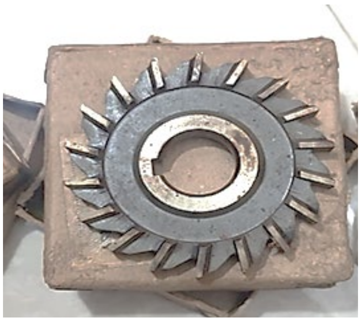


Fig. 2: Side milling HSS cutter

2.2 Workpiece material

When more detailed components with greater die filling properties are required, Aluminum Alloy 383 (ADC12) die casting is a superior option. It has advantages such as simplicity of casting, superior mechanical properties, dimensional accuracy, and greater corrosion resistance. Moreover, it has been using in making different parts of a cars, like transmission cases, converter housings, and cylinder blocks. Chemical composition of Al 383 is given in Table 1.

Table 1: Chemical Composition of Al 383 (ADC_{12})

Al	Bal.
Cu	2.0-3.0
Mg	0.1
Iron (max)	1.3
Sn (max)	0.15
Ni (max)	0.3
Zn	3
Mn	0.5
Si	9.5-11.5
Others	0.5

2.2.1 Preparation of workpiece material

This Al alloy was prepared in Bangladesh Industrial Technical Assistance Centre (BITAC). **Fig. 3** shows the prepared material. Material was prepared by stir casting process. firstly, the matrix material Aluminum heated to the melted temperature 800°C in the electric furnace at a speed of 600 rpm and stirred for 2 minutes followed by degassing using argon. In the meantime, reinforcement materials are preheated at 620°C to remove moisture and then added to the liquid matrix. The mixture is continuously stirred at 600 rpm for 15 minutes. Then the mixture is poured to the mold that is already preheated. Mold was used to create a metal ingot (600 x 90 x 40 mm) for the stir casting sample. Lastly solidification occurred.

Fig. 3: Preparation of Aluminum 383

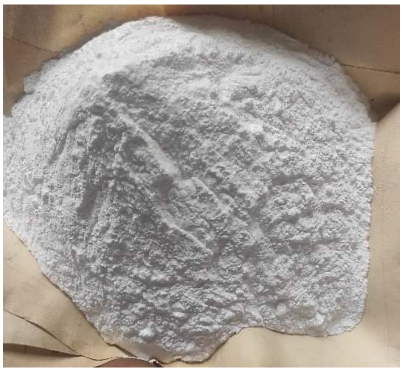
2.3 Preparation of nano-fluid

CNT and Al_2O_3 nanoparticles, and extra virgin olive oil were used to make hybrid nanofluids. Extra virgin olive oil used as a base fluid. Aluminum oxide nano particles and CNT is presented in **Fig.4 (a) and (b)**, respectively. To prepare nanofluid samples with steady dispersion, ultrasonication and magnetic stirring were used.

The diameter of the CNT and Al_2O_3 were 15 nm and 20 nm respectively. By dispersing a certain amount of CNTs – Al_2O_3 in the extra virgin olive oil, CNTs and Al2O3 with solid volume fractions of 0.3%, 0.5%, 1% were prepared. The ultrasonic homogenizer and magnetic stirrer are used to decrease nanoparticle aggregation and sedimentation.

To achieve uniform dispersion of nanoparticles in base fluid, nanofluids of various volume concentrations were stirred continuously for 30 minutes to 1 hour using a magnetic stirrer. Following that, the nanofluids were sonicated continuously for 1-2 hours with a UP200SHielscher ultrasonicator set to 20-25 kHz and 150 W of output power to uniformly scatter the nanoparticles.

In case of conventional cutting fluid, it is consisted of 10% volume of Aquates 3180. When Aquates 3180 is combined with water, it produces a milky white emulsion. This is a popular cutting fluid used during many machining operations because of it effective heat transfer abilities. Besides it reduces the friction between tool and workpiece as a result tools lifespan get increase.


(a)


(b)

Fig. 4: (a) Al_2O_3 nano particle (b) MWCNT

2.3.1 Stability analyses of nanofluids:

The study of stability is a key aspect in determining the properties of nanofluids for usage. The sticking together of particles, known as agglomeration, causes the dispersed particles to settle. When nanoparticles aggregate over an extended period of time, they can block microchannels and reduce the thermal conductivity of nanofluids[31]. Stability may be assessed using a variety of techniques, such as sedimentation, spectral absorbency analysis, and zeta potential analysis. Among these techniques Zeta potential technique has been performed in this study.

Zeta potential is the difference between the potential of the dispersion fluid and the layer of stationary to the surface of the dispersed particles. It represents the degree of repulsion between particles that are similarly charged. The Zeta potential measurement was carried out on the samples at two distinct times: immediately after preparation and seven days later. Absolute Zeta potential values of less than 30 mV are thought to have poor

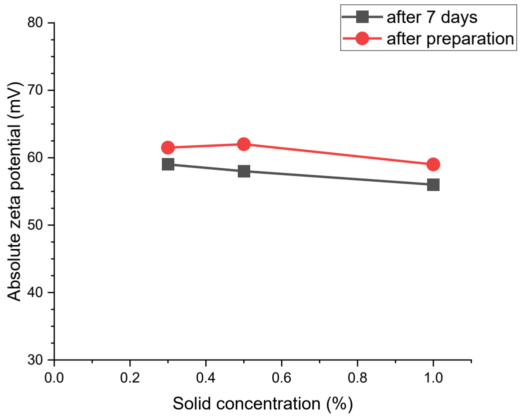


Fig. 5: Zeta potential analysis in different concentrations

stability, 30 mV to 45 mV are considered reasonably good, and more than 45 mV demonstrate excellent stability with some sedimentation [32,33].

In **Fig. 5**, the absolute Zeta potential values of the samples at different solid concentrations are shown

2.4 Experimental setup:

During the operation, the atomized nanofluid was projected across the rake face by minimum lubrication along the auxiliary cutting edge. Air atomization is selected by means of an atomized ultrasound, as it is less effective in lowering the temperature impact of Leiden frost [34]. The nanofluid spray system is shown in **In Fig. 7**. The MQL setup shown in **Fig. 6** consists of a container for gravity feeds and two diameter coaxial nozzles which sprayed nanofluid droplets under high pressures to the cutting zone. The orifice diameter of the primary nozzle was 0.3 mm, and a maximum air pressure of 6 bar was chosen for greater nanofluid penetration into the chip-tool interface. For improved droplet dispersion and spread angle, the nanofluid spray system was adjusted with a 30º impingement angle, a 35 mm spray distance, and a 120 ml/hr. flow rate.

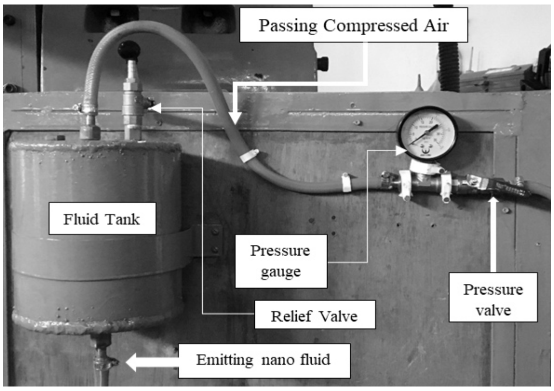


Fig 6: MQL Setup

Fig. 7: Nano-fluid spray system

2.5 Experimental procedure

The cooling state was used as an output to research the performance of lubrication and their effect on the studied outputs, and Box-Behnken design (BBD) was used to make the tests. They had three levels and four factors. Here the maximum and minimum values are putted first in design of expert software and a mid-value generated from them. The 27 turning tests were conducted under traditional dry conditions, conventional oil, and employing a nano fluid as a MQL approach for cooling.

Table 2 present the results of combining the BBD parameters with the measured surface roughness. For each test, the values of surface roughness are the average of three measured values.

Table 2: 4-Factors and 3-levels used in the experimental plan.

Levels	Vc (m/min)	T.f (mm/rev)	Ap (mm)	N.p
1	17	22	0.5	1
2	19	33	0.75	2
3	21	44	1	3

Outputs from orthogonal plans are used to predict material machinability using response surface methodology (RSM) and artificial neural networks (ANN). The following formulas are used to compare the RSM and ANN techniques.:

$$R^2 = \frac{\sum_{i=1}^{n}(y_{i.pr}-y_{i.ex})}{(y_{i.pr}-y_{average})} \qquad (1)$$

$$MPE(\%) = \frac{100}{n}\sum_{i=1}^{n}\left|\frac{(y_{i.ex}-y_{i.pr})}{y_{i.ex}}\right| \qquad (2)$$

$$RSME = \sqrt{\frac{\sum_{i=1}^{n}(y_{i.ex}-y_{i.pr})^2}{n}} \qquad (3)$$

where n is the number of tests, $y_{i,ex}$ is the experimental value, $y_{i,pr}$ is the predicted value, and $y_{average}$ is the average of the experimental values.

3. Modeling method

3.1 Response surface methodology

RSM is a collection of mathematical and statistical procedures for determining the functional relationship between a response and its interest. This method is a set of mathematical procedures that are based on fitting empirical models to experimental data collected in accordance with the experimental design.

The following is a relationship between machining factors and cutting conditions:

Y = F (Np, Vc, Tf, ap)

Using the following equation, the second-order model's response surface may be fit:

$y_{cc} = \beta_0 + \beta_1.x_1 + \beta_2.x_2 + \beta_3.x_3 + \beta_4.x_4 + \beta_5.x_5.x_2 + \beta_6.x_1.x_3 + \beta_7.x_1.x_4 + \beta_8.x_2.x_3 + \beta_9.x_2.x_4 + \beta_{10}.x_3.x_4 + \beta_{11}.x_1^2 + \beta_{12}.x_2^2 + \beta_{13}.x_3^2 + \beta_{14}.x_4^2$ … … … (4)

where 'y' stands for the relevant response (Ra), and 'cc' stands for the corresponding cooling condition, and x_1, x_2, x_3, x_4 the turning parameters. The term β is the regression coefficient. From Eq. (4) the relationship is defined between the studied output and the turning parameters as given below:

$y = \beta_0 + \beta_1.Vc + \beta_2.Tf + \beta_3.ap + \beta_5.Vc.Tf + \beta_6.Vc.ap + \beta_7.Vc.Np + \beta_8.Tf.ap + \beta_9.Tf.Np + \beta_{10}.ap.Np + \beta_{11}.Vc^2 + \beta_{12}.Tf^2 + \beta_{13}.ap^2 + \beta_{14}Np^2$ … … … (5)

Table 3: Experimental Result

Number	Cutting speed	Table Feed	Depth of cut	No Of Passes	Dry	conventional	Nano
	Vc	T. f	ap	N. p	Ra.	Ra.	Ra.
1	17	22	0.75	2	3.7757	2.9186	2.5194
2	21	22	0.75	2	3.2640	2.7175	2.0821
3	17	44	0.75	2	3.8403	3.0342	2.4406
4	21	44	0.75	2	3.3319	2.7340	2.0098
5	19	33	0.5	1	3.2544	2.6928	2.1533
6	19	33	1	1	3.5615	2.9403	2.3357
7	19	33	0.5	3	3.4930	2.7648	2.1628
8	19	33	1	3	3.8275	3.0384	2.3592
9	17	33	0.75	1	3.5715	2.7933	2.4158
10	21	33	0.75	1	3.1613	2.6724	2.0314
11	17	33	0.75	3	3.9097	3.0456	2.4750
12	21	33	0.75	3	3.4342	2.7777	2.0587
13	19	22	0.5	2	3.3140	2.6959	2.1157
14	19	44	0.5	2	3.5095	2.8311	2.1690
15	19	22	1	2	3.5845	2.9103	2.3476
16	19	44	1	2	3.7503	3.0188	2.3214
17	17	33	0.5	2	3.5675	2.7058	2.3451
18	21	33	0.5	2	3.1457	2.6028	1.9541
19	17	33	1	2	3.9509	3.1404	2.5653
20	21	33	1	2	3.5296	2.9224	2.1735
21	19	22	0.75	1	3.2721	2.7127	2.1854
22	19	44	0.75	1	3.4885	2.8683	2.2297
23	19	22	0.75	3	3.5707	2.8413	2.2017
24	19	44	0.75	3	3.8077	3.0139	2.2770
25	19	33	0.75	2	3.5224	2.8482	2.2470
26	19	33	0.75	2	3.6073	2.8943	2.2878
27	19	33	0.75	2	3.5209	2.8469	2.2463

3.2 Artificial neural network technique

Artificial neural network (ANN) is based on the human brain's ability to process and model data. It was created in an effort to model the learning process mathematically. Even when applying expert system rules is difficult, ANN can be quite helpful in classification and function approximation problems [35]. A trained neural network can be considered an "expert" in the category of data it has been assigned to examine. This expert can then make projections in response to new scenarios of interest and respond to "what if" questions. In situations when rules like classification and function approximation problems found in an expert system cannot be efficiently implemented, ANNs can be a great help. Neural computing demands the connection of a large number of neurons into a neural network. Neurons are divided into layers. Each neuron in a network is typically a basic processing unit that receives one or more inputs and produces an output. Each input has a weight assigned to it by each neuron, which affects the intensity of the input.

MATLAB and the neural network tools were used to develop artificial neural networks in this study. In order to find the optimal architecture, activation function, and training algorithm, a number of ANN models were developed and compared to each other. All network models MPE, RSME, and R^2 values (for training, validation, and testing) were the most important considerations.

4. Result and discussion

4.1 Cooling effect on machining factors

During machining, the surface roughness improves dramatically when MQL cooling is used. When certain combinations of cutting settings are employed during dry machining, the lowest surface quality is achieved during turning. A comparison graph for Ra under various cooling conditions employed in the experiments is shown in Table 4. The MQL mode also generates better surface quality; this strategy improves not only product quality but also the environment by reducing lubricant consumption, which leads cheaper machining costs because some turning operations require lubrication.

4.2 RSM modeling

ANOVA is a way to figure out how important a factor or interaction factor is to a certain response based on data from experiments. In this example, it breaks down how much each part of the response contributes to the total variability of how the response looks. It also looks at how much error there is. The F-ratio is used to quantify the importance of each parameter. In instance, when the F value rises, the concrete parameter's importance rises as well. Besides The p-value is a measure of how strong the evidence is against the null hypothesis. For this work ANOVA analysis has been carried out employing using Design Expert 13 software.

In the machining process planning, surface roughness is a major constraint on the selection of cutting settings. Tables 4, 5, and 6 show that cutting velocity (v_c) is the most important parameter in dry, conventional and nano hybrid cutting fluid conditions with a contribution of 49.58 percent and 26.122 percent and 79.53 percent respectively. Regression equations are given bellow:

$$Ra_{Dry} = 4.08 - 0.071 \times Vc + 0.007 \times T.f + 0.723 \times ap + 0.341 \times N.p + 0.00004 \times Vc \times T.f + 0.00023 \times Vc \times ap - 0.0082 \times Vc \times N.p - 0.0027 \times T.f \times N.p + 0.00047 \times T.f \times N.p + 0.0273 \times ap \times N.p - 0.0008 \times Vc^2 + 3.10 \times 10^{-6}\, T.f^2 - 0.0354 \times ap^2 - 0.019 \times N.p^2 \quad \dots\dots\dots (6)$$

$$Ra_{conventional\ oil} = -1.197 + 0.287 \times Vc + 0.0246 \times T.f + 1.639 \times ap + 0.428 \times N.p - 0.0011 \times Vc \times T.f - 0.058 \times Vc \times ap - 0.018 \times Vc \times N.p - 0.0024 \times T.f \times ap + 0.0.00039 \times T.f \times N.p + 0.026 \times ap \times N.p - 0.0058 \times V.c^2 + 0.00005 \times T.f^2 + 0.0271 \times ap^2 - 0.0111 \times N.p^2 \quad \dots\dots\dots (7)$$

$$Ra_{nano\ fluid} = 4.031 - 0.159 \times Vc + 0.011 \times T.f + 0.664 \times ap + 0.123 \times N.p + 0.00008 \times Vc \times T.f - 0.00039 \times Vc \times ap - 0.0039 \times Vc \times N.p - 0.0072 \times T.f \times N.p + 0.000704 \times T.f \times N.p + 0.014 \times ap \times N.p + 0.0017 \times Vc^2 - 0.000123 \times T.f^2 - 0.0303 \times ap^2 - 0.017 \times N.p^2 \quad \dots\dots\dots (8)$$

Here Vc means cutting velocity, T.f table feed, ap depth of cut and N.p number of phases.

It is shown in **Fig.** 8 how roughness value changes depending on the cutting speed, table feed rate and depth of cut.

In Fig. 8(a), increasing cutting speed surface roughness significantly decreasing in dry machining condition and MQL condition. But there is no considerable change happening in conventional oil condition. On the other hand, there is no considerable amount of change in surface roughness happening for decrease or increase table feed rate in all the three conditions.

The cutting speed and depth of cut plot in Fig. 8(b) shows that when the cutting speed increases, the surface roughness decreases and decreasing depth of cut roughness value decreasing. In Fig. 8(c) table feed and depth of cut plot no significant change happening due to table feed. But by decreasing depth of cut roughness value get reduced

Table 4: Anova analysis for dry condition.

Source	Sum of Squares	df	Mean Square	F-value	p-value	
Model	1.27	14	0.0904	31.98	< 0.0001	significant
A-Vc	0.6297	1	0.6297	222.67	< 0.0001	
B-T.f	0.0748	1	0.0748	26.44	0.0002	
C-ap	0.3073	1	0.3073	108.65	< 0.0001	
D-N.p	0.2504	1	0.2504	88.55	< 0.0001	
AB	2.767E-06	1	2.767E-06	0.0010	0.9756	
AC	5.456E-08	1	5.456E-08	0.0000	0.9966	
AD	0.0011	1	0.0011	0.3781	0.5501	
BC	0.0002	1	0.0002	0.0778	0.7850	
BD	0.0001	1	0.0001	0.0374	0.8499	
CD	0.0002	1	0.0002	0.0664	0.8011	
A²	0.0000	1	0.0000	0.0171	0.8980	
B²	7.534E-07	1	7.534E-07	0.0003	0.9872	
C²	0.0000	1	0.0000	0.0093	0.9249	
D²	0.0020	1	0.0020	0.6981	0.4198	
Residual	0.0339	12	0.0028			
Lack of Fit	0.0291	10	0.0029	1.19	0.5401	not significant
Pure Error	0.0049	2	0.0024			
Cor Total	1.30	26				

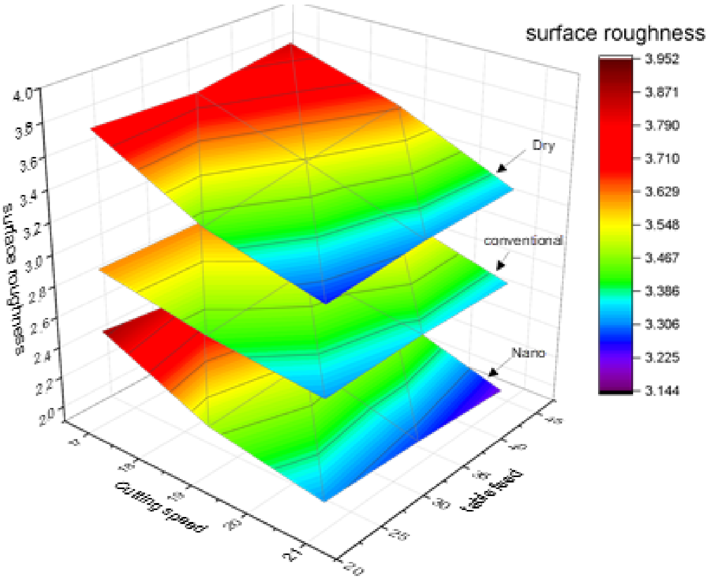
Table 5: ANOVA analysis for conventional oil.

Source	Sum of Squares	df	Mean Square	F-value	p-value	
Model	0.4678	14	0.0334	12.73	< 0.0001	significant
A-Vc	0.1222	1	0.1222	46.58	< 0.0001	
B-T.f	0.0413	1	0.0413	15.74	0.0019	
C-ap	0.2345	1	0.2345	89.36	< 0.0001	
D-N.p	0.0536	1	0.0536	20.43	0.0007	
AB	0.0025	1	0.0025	0.9347	0.3527	
AC	0.0033	1	0.0033	1.26	0.2836	
AD	0.0054	1	0.0054	2.06	0.1771	
BC	0.0002	1	0.0002	0.0673	0.7997	
BD	0.0001	1	0.0001	0.0274	0.8712	
CD	0.0002	1	0.0002	0.0646	0.8037	
A²	0.0029	1	0.0029	1.09	0.3161	
B²	0.0002	1	0.0002	0.0683	0.7983	
C²	0.0000	1	0.0000	0.0058	0.9404	

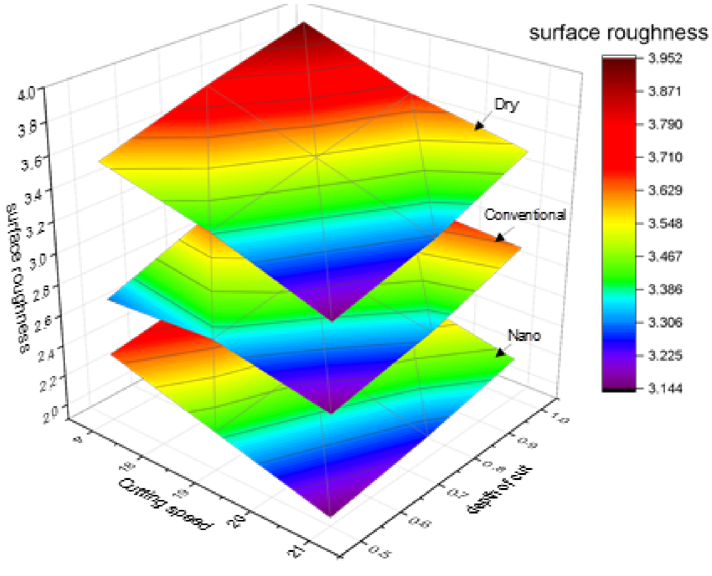
D²	0.0007	1	0.0007	0.2502	0.6260	
Residual	0.0315	12	0.0026			
Lack of Fit	0.0300	10	0.0030	4.13	0.2108	not significant
Pure Error	0.0015	2	0.0007			
Cor Total	0.4993	26				

Table 6: ANOVA analysis for nano fluid

Source	**Sum of Squares**	**df**	**Mean Square**	**F-value**	**p-value**	
Model	0.6298	14	0.0450	38.75	< 0.0001	significant
A-Vc	0.5009	1	0.5009	431.53	< 0.0001	
B-T.f	1.541E-06	1	1.541E-06	0.0013	0.9715	
C-ap	0.1206	1	0.1206	103.86	< 0.0001	
D-N.p	0.0028	1	0.0028	2.41	0.1467	
AB	0.0000	1	0.0000	0.0093	0.9248	
AC	1.586E-07	1	1.586E-07	0.0001	0.9909	
AD	0.0003	1	0.0003	0.2194	0.6479	
BC	0.0016	1	0.0016	1.36	0.2667	
BD	0.0002	1	0.0002	0.2066	0.6576	
CD	0.0000	1	0.0000	0.0420	0.8410	
A²	0.0002	1	0.0002	0.2018	0.6613	
B²	0.0012	1	0.0012	1.01	0.3349	
C²	0.0000	1	0.0000	0.0165	0.8999	
D²	0.0015	1	0.0015	1.26	0.2844	
Residual	0.0139	12	0.0012			
Lack of Fit	0.0128	10	0.0013	2.27	0.3446	not significant
Pure Error	0.0011	2	0.0006			
Cor Total	0.6437	26				



(a)



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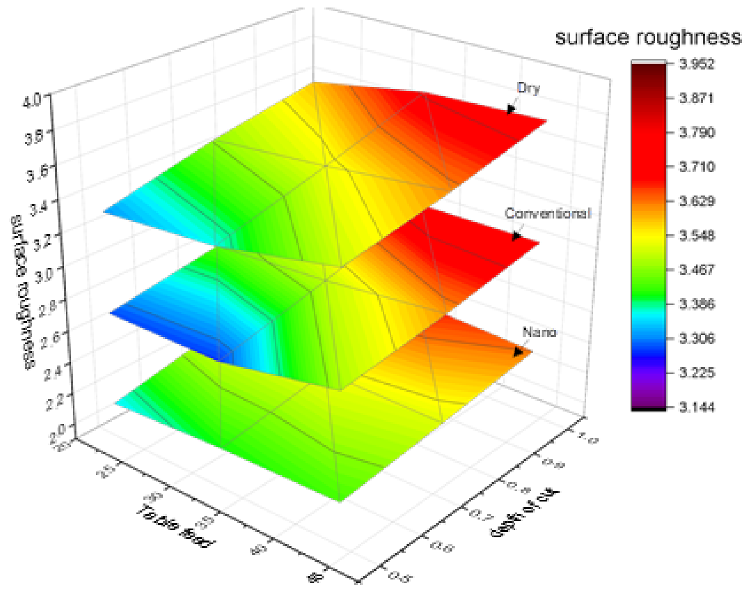


(c)

Fig. 8: Effects of different cutting parameters on surface roughness

Table 7: Obtained optimization values of RSM

Condition	Cutting Speed	Table Feed	Depth Of Cut	No of Passes	Surface Roughness,	Desirability
Dry	20.987	22.263	0.816	1.013	3.144	1.000
conventional	20.961	26.478	0.527	1.221	2.598	1.000
Nano	20.982	26.939	0.537	1.245	1.954	1.000

Table 8: Optimization of response parameters

Condition	Goal	Lower limit	Upper limit
Cutting Speed (mm/min)	Is in range	17	21
Table Feed (mm/min)	Is in range	22	44
Depth Of Cut (mm)	Is in range	0.5	1
No of Passes	Is in range	1	3
(a) Dry condition			
R_a (µm)	Minimize	3.14	3.95
(b) Conventional oil			
R_a (µm)	Minimize	2.60	3.14
(c) Nano hybrid cutting fluid			
R_a (µm)	Minimize	1.95	2.57

4.2.1 Optimization process

The idea of desirability was suggested by Myers and Montgomery[36)], the RSM's desirability function strategy employed for improving the studied output. For each cooling setting, this method looks for a combination of factor values that results in the lowest possible surface roughness. The use of the desirability function yields better results than most other methods. The desirability function between 0 and 1 was calculated using the gradient approach. The desirability function is used to evaluate the acceptance of optimization. If the desirability value approaches 0, the response should be rejected totally, whereas if it approaches or equals 1, the response should be accepted.

The goal of the optimization method was to find the parameter that produced the least amount of surface roughness (shown in Table 7). Numerical optimization is the process of optimizing a set of goals that can be applied to either factors or responses. All goals include target, maximization, minimization, within range, none (for responses only), and setting to an exact value (for factors alone). Using Design Expert 13.0 software optimization process was performed. Table 8 displays the optimization conditions.

4.3 ANN modeling:

The back-propagation algorithm was used as a learning algorithm. As training algorithm, the Levenberg-Marquadt (TRAINLM) was selected. LM algorithms are quick and don't take up a lot of memory. For adaption learning function and performance function LEARNGDM and MSE selected respectively. As an activation function, the hyperbolic tangent sigmoid transfer function (TANSIG) was utilized. A feed forward neural network with two hidden layers of ten neurons was proven to be the best network for reliable findings shown in **Fig. 9/**

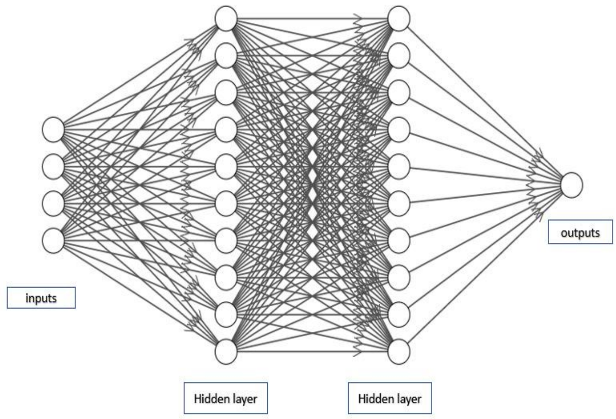
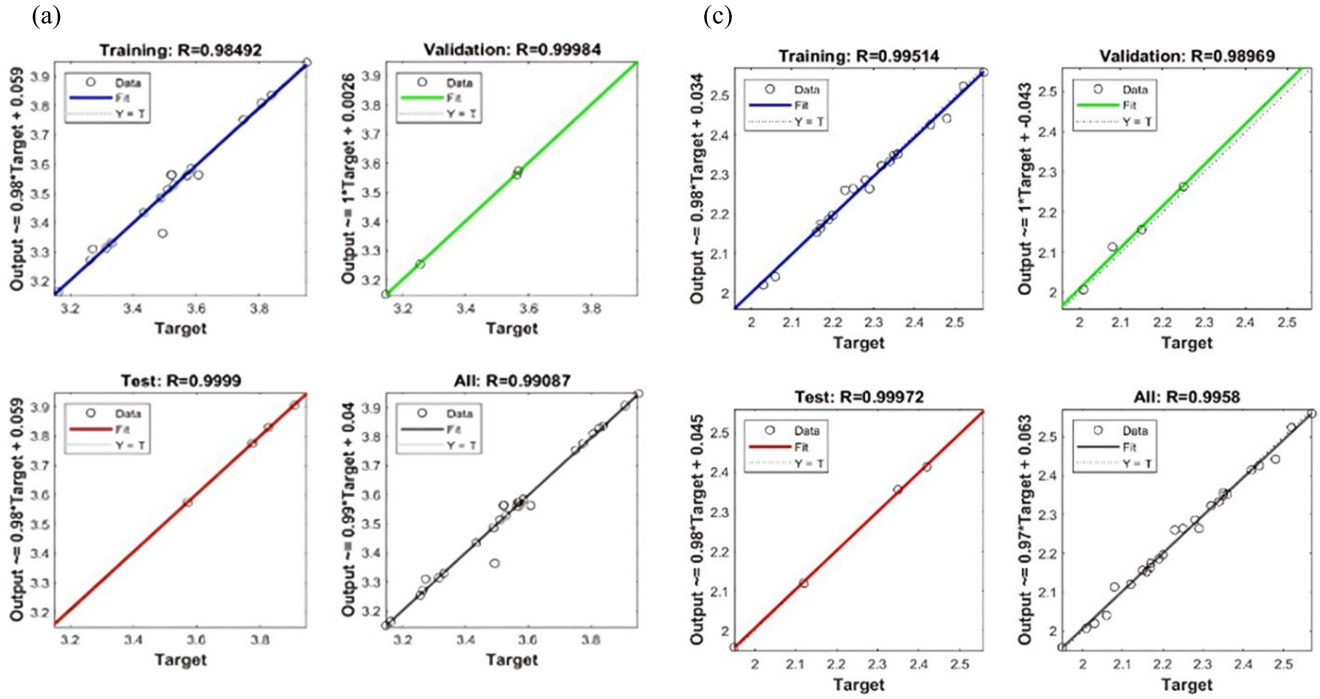


Fig 9: Optimal architecture for output modelling

Training the neural network is crucial and without it, the ANNs become inefficient and may produce erroneous predictions. For Training, validation and testing we randomly divide up the 27 samples. For training, validation and testing 70% ,15% and 15% data used respectively. For the surface roughness, the determination coefficients (R^2) of the developed predictive models are surface roughness, their R^2 are 98.18%, 98.19%, and 99.16%, respectively, for the dry, conventional, and nano-fluid conditions prediction models. The correlation coefficient for training, validation, testing and their combined effect are analyzed. The value of R is so close to 1. There is a better analysis when the value of R is close to 1.

Each network performance was judged by the correlation coefficient between network predictions and actual results, which was calculated by comparing the training, validation, and test datasets to figure out how well each network did. Results from the surface roughness prediction model's tests, training, and validation datasets are shown in **Fig. 10 (a, b, c).**



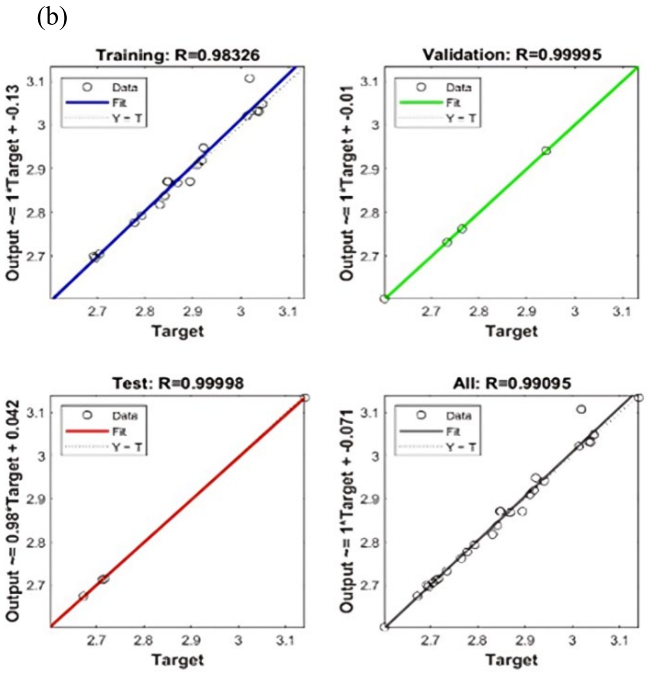


Fig. 10: Correlation of surface roughness between predicted and experimental data using training, validation, and test data sets for (a) dry, (b) conventional oil (c) MQL conditions.

Table 9: Under dry, conventional, and MQL conditions, comparison of experimental and prediction outcomes for RSM and ANN

Existing experimental data			**RSM predicted data**			**ANN predicted data**		
Dry	Conventional	Nano	Dry	Conventional	Nano	Dry	Conventional	Nano
3.78	2.92	2.52	3.70	2.86	2.46	3.77	2.92	2.52
3.26	2.72	2.08	3.24	2.71	2.05	3.27	2.72	2.11
3.84	3.03	2.44	3.85	3.03	2.45	3.84	3.03	2.43
3.33	2.73	2.01	3.40	2.78	2.05	3.33	2.73	2.01
3.25	2.69	2.15	3.23	2.65	2.13	3.25	2.70	2.16
3.56	2.94	2.34	3.54	2.92	2.32	3.56	2.94	2.33
3.49	2.76	2.16	3.51	2.77	2.15	3.36	2.76	2.15
3.83	3.04	2.36	3.84	3.07	2.36	3.83	3.03	2.35
3.57	2.79	2.42	3.60	2.83	2.43	3.57	2.79	2.41
3.16	2.67	2.03	3.17	2.70	2.04	3.16	2.67	2.02
3.91	3.05	2.48	3.92	3.03	2.48	3.91	3.05	2.44
3.43	2.78	2.06	3.43	2.76	2.05	3.43	2.78	2.04
3.31	2.70	2.12	3.30	2.67	2.12	3.31	2.70	2.12
3.51	2.83	2.17	3.47	2.80	2.16	3.51	2.82	2.17
3.58	2.91	2.35	3.64	2.96	2.36	3.59	2.91	2.36
3.75	3.02	2.32	3.78	3.06	2.32	3.75	3.11	2.32
3.57	2.71	2.35	3.61	2.77	2.37	3.57	2.71	2.35
3.15	2.60	1.95	3.16	2.63	1.96	3.15	2.60	1.96
3.95	3.14	2.57	3.93	3.11	2.57	3.95	3.13	2.56
3.53	2.92	2.17	3.48	2.85	2.16	3.53	2.95	2.16
3.27	2.71	2.19	3.31	2.74	2.22	3.31	2.71	2.19
3.49	2.87	2.23	3.46	2.85	2.21	3.49	2.87	2.26
3.57	2.84	2.20	3.59	2.86	2.24	3.56	2.84	2.20
3.81	3.01	2.28	3.76	2.99	2.25	3.81	3.02	2.29
3.52	2.85	2.25	3.55	2.86	2.26	3.56	2.87	2.26
3.61	2.89	2.29	3.55	2.86	2.26	3.56	2.87	2.26
3.52	2.85	2.25	3.55	2.86	2.26	3.56	2.87	2.26

Table 10: RSM and ANN prediction results comparison

	For Dry condition				For Conventional oil				For Nano - fluid			
Number	Predicted surface roughness		Absolute prediction error (%)		Predicted surface roughness		Absolute prediction error (%)		Predicted surface roughness		Absolute prediction error (%)	
	RSM	ANN	RSM	ANN	RSM	ANN	RSM	ANN	RSM	ANN	RSM	ANN
1	3.70	3.77	2.00	0.02	2.86	2.92	2.01	0.04	2.46	2.52	2.36	0.16
2	3.24	3.27	0.73	0.24	2.71	2.72	0.27	0.06	2.05	2.11	1.54	1.52
3	3.85	3.84	0.25	0.08	3.03	3.03	0.14	0.05	2.45	2.43	0.38	0.60
4	3.40	3.33	2.04	0.03	2.78	2.73	1.68	0.05	2.05	2.01	2.00	0.13
5	3.23	3.25	0.75	0.01	2.65	2.70	1.59	0.27	2.13	2.16	1.08	0.16
6	3.54	3.56	0.60	0.03	2.92	2.94	0.69	0.04	2.32	2.33	0.67	0.12
7	3.51	3.36	0.49	3.69	2.77	2.76	0.19	0.07	2.15	2.15	0.59	0.47
8	3.84	3.83	0.33	0.06	3.07	3.03	1.04	0.23	2.36	2.35	0.03	0.30
9	3.60	3.57	0.80	0.08	2.83	2.79	1.31	0.02	2.43	2.41	0.59	0.07
10	3.17	3.16	0.27	0.08	2.70	2.67	1.03	0.09	2.04	2.02	0.42	0.56
11	3.92	3.91	0.26	0.10	3.03	3.05	0.51	0.11	2.48	2.44	0.20	1.33
12	3.43	3.43	0.12	0.02	2.76	2.78	0.64	0.02	2.05	2.04	0.42	0.85
13	3.30	3.31	0.42	0.01	2.67	2.70	0.96	0.00	2.12	2.12	0.20	0.22
14	3.47	3.51	1.12	0.09	2.80	2.82	1.10	0.46	2.16	2.17	0.41	0.24
15	3.64	3.59	1.55	0.03	2.96	2.91	1.71	0.00	2.36	2.36	0.53	0.37
16	3.78	3.75	0.79	0.05	3.06	3.11	1.36	2.94	2.32	2.32	0.06	0.04
17	3.61	3.57	1.19	0.19	2.77	2.71	2.37	0.02	2.37	2.35	1.06	0.16
18	3.16	3.15	0.45	0.15	2.63	2.60	1.05	0.01	1.96	1.96	0.30	0.24
19	3.93	3.95	0.53	0.07	3.11	3.13	0.97	0.20	2.57	2.56	0.18	0.25
20	3.48	3.53	1.40	0.01	2.85	2.95	2.48	0.90	2.16	2.16	0.62	0.41
21	3.31	3.31	1.16	1.15	2.74	2.71	1.01	0.00	2.22	2.19	1.59	0.03
22	3.46	3.49	0.82	0.07	2.85	2.87	0.64	0.02	2.21	2.26	0.88	1.36
23	3.59	3.56	0.54	0.26	2.86	2.84	0.66	0.10	2.24	2.20	1.74	0.24
24	3.76	3.81	1.25	0.05	2.99	3.02	0.79	0.26	2.25	2.29	1.18	0.40
25	3.55	3.56	0.78	1.16	2.86	2.87	0.41	0.80	2.26	2.26	0.58	0.75
26	3.55	3.56	1.59	1.22	2.86	2.87	1.18	0.80	2.26	2.26	1.21	1.05
27	3.55	3.56	0.83	1.20	2.86	2.87	0.46	0.85	2.26	2.26	0.61	0.78

4.4 ANN and RSM comparison

To evaluate the prediction accuracy of RSM and ANN predictive models, this study employed the coefficient of determination (R^2), mean predicted error (MPE), and root mean square error (RSME). The prediction value of these two methods are compared in Table 9.

RSM models have a good R^2 at initially, however the outcomes show that RSM models have tried to match the data too well in some circumstances, as seen by the prediction results. and avoid making broad generalizations. In the instance of the surface roughness presented in Table 10 the obtained Absolute prediction error value (APE) by RSM (for dry condition) are 2.00, 2.04, 0.33 for tests number 1 ,4 ,8, respectively. These deductions are to be favorably retained in ANN modeling with absolute prediction values of 0.02, 0.03, 0.06 for tests 1, 4 ,8 for dry condition respectively. The ANN, on the other hand, produces excellent outcomes with minimal absolute prediction errors (APE). When comparing the determination coefficients, mean prediction errors (MPE) , root square mean error (RSME) acquired by the ANN models to those obtained by the RSM models in Table 11, the ANN models proved to be more effective.

Table 11: The comparison between RSM and ANN.

cooling condition	**RSM predicted data**		**ANN predicted data**	
	R^2	MPE	R^2	MPE
Dry	0.973	0.855	0.981	0.375
Conventional oil	0.936	1.046	0.981	0.312
nano fluid	0.978	0.795	0.991	0.473

Fig. 11 present comparison between residual. Fig. 11 shows that ANN models had lower residuals in Ra (at various cooling conditions) than RSM models. Besides, the RSME values in Fig. 12 shows that for the investigated material and process, ANN models outperform RSM models in terms of prediction capabilities. Otherwise, under some circumstances, the two methodologies might be used in tandem to improve predictive modeling and optimization

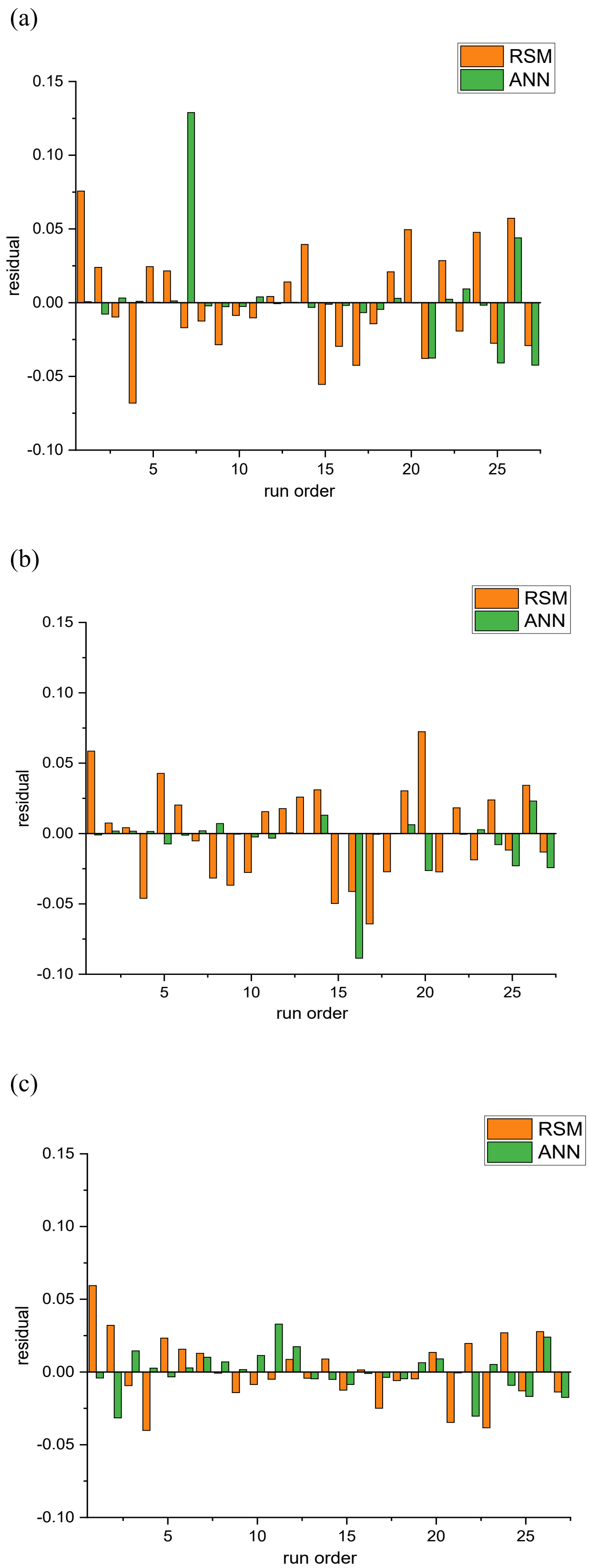


Fig. 11: The comparison between the residuals of the RSM and ANN models for Ra in (a) dry, (b) conventional, and (c) MQL conditions.

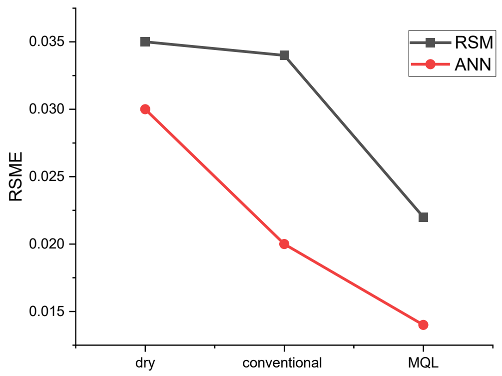


Fig. 12: Comparison of the root mean square error (RSME) results for RSM and ANN models of surface roughness

5. Conclusions

The study yielded the following conclusions:

• Al_2O_3 /CNT nano-particle mixed with EVO oil , make the nanofluid increase heat capacity, thermal conductivity, dynamic viscosity.

• The surface finish was significantly enhanced, owing to the large reduction in temperature at the tool face caused by the use of Nanofluid. Reduction in temperature is obtained due to better lubrication and higher thermal conductivity of the nanofluid which helps in reducing roughness.

• Compared to dry and conventional, Nanofluids significantly reduced the surface roughness.

• The ANN models outperformed the RSM models when it came to predicting surface roughness accuracy in the range where they were trained. The ANN models had a stronger correlation and a lower error rate than the RSM model.

Although employing this fluid improves the entire machining process, it is still pricey when compared to other cutting fluids.

6. Future direction

- Very few investigations have been done into the development of nano cutting fluids for machining applications. More experiments need to be done to identify the optimum ultrasonication time for developing stable CNT-water based nano fluid. Also the effects of several important factors such as particle size and shapes, clustering of particles, temperature of the fluid, and dissociation of surfactant on the stability and thermal conductivity of nanofluids should be studied adequately.
- The performance of the rotary liquid applicator may be improved with more research. Teflon seals and special bearing types can be used to get substantially greater performance.
- Further research may be done on the consumption of nanofluid during a specific period of operation in milling or related processes. Experimental research can be done to evaluate the cost-effectiveness of CNT-based nanofluid as a cooler and lubricant. Nano fluid quantities can be restricted to a particular quantity during experiments, such as the minimal quantity liquid (MQL) system.
- Very few researchers have explored the application of nanofluids specially to machining. More operations (Milling, Drilling, Turning etc.) can be performed using nanofluid as cutting fluid to identify the advantages of nanofluids.
- Other well-known methods like ANFIS, GA, Taguchi, etc. can also be used to model surface roughness and cutting force. These modeling tools can also be used to give a comparative analysis.

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Nomenclature

MQL	Minimum quantity lubrication
BBD	Box-Behnken design
Vc	Cutting speed (m/min)
Ap	Depth of cut (mm)
T.f	Feed rate (mm/rev)
N.p	Number of passes
Ra	Arithmetic mean roughness (µm)
ANN	Artificial neural network
RSM	Response surface methodology
ANOVA	Analysis of variance
DF	Degrees of freedom
MS	Mean squares
SS	Sum of squares
R^2	Determination coefficient
P	Probability of significance
F	Variance ratio
MPE	Mean predicted error
RSME	Root mean square

References

1) Sharma, A. K., Tiwari, A. K., & Dixit, A. R, "Effects of Minimum Quantity Lubrication (MQL) in machining processes using conventional and nanofluid based cutting fluids: A comprehensive review", *Journal of cleaner production*, **127**, 1-18 (2016).
2) Weinert, K., Inasaki, I., Sutherland, J. W., & Wakabayashi, T., "Dry machining and minimum quantity lubrication", *CIRP annals,* **53** (2), 511-537 (2014).
3) Cozzens, D. A., Rao, P. D., Olson, W. W., Sutherland, J. W., & Panetta, J. M., "An experimental investigation into the effect of cutting fluid conditions on the boring of aluminum alloys", *Journal of Manufacturing science and Engineering,* **121** (3), 434-439 (1999).
4) Jamaluddin, N. A., Talib, N., & Sani, A. S. A., "Performance comparative of modified jatropha based nanofluids in orthogonal cutting process", *Evergreen,* **8** (2), 461-468, (2021).
5) Elsheikh, Ammar H., Mohamed Abd Elaziz, Sudhansu Ranjan Das, T. Muthuramalingam, and Songfeng Lu ''A new optimized predictive model based on political optimizer for eco-friendly MQL-turning of AISI 4340 alloy with nano-lubricants''*,* *Journal of Manufacturing Processes*, **67** (2021).
6) Elsheikh, A. H., Guo, J., Huang, Y., Ji, J., & Lee, K. M. ''Temperature field sensing of a thin-wall component during machining: Numerical and experimental investigations'', *International Journal of Heat and Mass Transfer*, **126**, (2018).
7) Wei, L., Wen-Liang, J., Gui, L., Bo, W., Alsoufi, M. S., Elsheikh, A., & Ibrahim, A. M. M. "Analysis of large edge breakage of WC-Co cemented carbide tool blades emerging in precision grinding process." *Journal of Materials Research and Technology* **19** (2022).
8) Elsheikh, A. H., Ashham, M., Ali, M. K. A., Rashad, M., & Haiou, Z. ''Effect of cutting parameters on surface residual stresses in dry turning of AISI 1035 alloy'', *Journal of the Brazilian Society of Mechanical Sciences and Engineering*, **41 (8)**, (2019).
9) Khoshaim, A. B., Elsheikh, A. H., Moustafa, E. B., Basha, M., & Mosleh, A. O. ''Prediction of residual stresses in turning of pure iron using artificial intelligence-based methods'', *Journal of Materials Research and Technology*, **11**, (2021).
10) Dhar, N. R., Islam, M. W., Islam, S., & Mithu, M. A. H., "The influence of minimum quantity of lubrication (MQL) on cutting temperature, chip and dimensional accuracy in turning AISI-1040 steel", *Journal of materials processing technology*, **171** (1), 93-99 (2006).
11) Said, Z., Gupta, M., Hegab, H., Arora, N., Khan, A. M., Jamil, M., & Bellos, E., "A comprehensive review on minimum quantity lubrication (MQL) in machining processes using nano-cutting fluids", *The International Journal of Advanced Manufacturing Technology*, **105** (5), 2057-2086 (2019).
12) Alib, N., Jamaluddin, N. A., Sheng, T. K., Kiow, L. W., Abdullah, H., Ahmad, S., & Saleh, A., "Tribological Study of Activated Carbon Nanoparticle in Nonedible Nanofluid for Machining Application", *Evergreen,* **8** (2), 454-460 (2021).
13) Muaz, M., & Choudhury, S. K., "Experimental investigations and multi-objective optimization of MQL-assisted milling process for finishing of AISI 4340 steel", *Measurement*, **138**, 557-569 (2019).
14) Hadad, M., & Sadeghi, B., "Minimum quantity lubrication-MQL turning of AISI 4140 steel alloy", *Journal of Cleaner Production*, **54**, 332-343 (2013).
15) Fox, N. J., & Stachowiak, G. W., "Vegetable oil-based lubricants—a review of oxidation", *Tribology international*, **40** (7), 1035-1046 (2007).
16) Syahrullail, S., Kamitani, S., & Shakirin, A. J. P. E. "Performance of vegetable oil as lubricant in extreme pressure condition", *Procedia Engineering*, **68**, 172-177 (2013).
17) Shashidhara, Y. M., & Jayaram, S. R. "Vegetable oils as a potential cutting fluid—an evolution", *Tribology international*, **43** (5-6), 1073-1081 (2010).
18) Ibrahim, Ahmed Mohamed Mahmoud, et al. "Evaluating the effect of minimum quantity lubrication during hard turning of AISI D3 steel using vegetable oil enriched with nano-additives", *Alexandria Engineering Journal*, **61 (12)**, (2022).
19) Ghadimi, A., Saidur, R., & Metselaar, H. S. C. "A review of nanofluid stability properties and characterization in stationary conditions", *International journal of heat and mass transfer*, **54** (17-18), 4051-4068 (2011)
20) Singh, R. K., Sharma, A. K., Dixit, A. R., Tiwari, A. K., Pramanik, A., & Mandal, A. "Performance evaluation of alumina-graphene hybrid nano-cutting fluid in hard turning", *Journal of cleaner production*, **162**, 830-845 (2017).
21) Setti, D., Ghosh, S., & Rao, P. V. "Application of nano cutting fluid under minimum quantity lubrication (MQL) technique to improve grinding of Ti–6Al–4V alloy", *International Journal of Mechanical and Mechatronics Engineering*, **6** (10), 2107-2111 (2012).
22) Hegab, H., Umer, U., Soliman, M., & Kishawy, H. A. "Effects of nano-cutting fluids on tool performance and chip morphology during machining Inconel 718", *The International Journal of Advanced Manufacturing Technology*, **96** (9), 3449-3458 (2018).
23) Padhan, Smita, et al. ''Machinability Investigation of Nitronic 60 Steel Turning Using SiAlON Ceramic Tools under Different Cooling/Lubrication Conditions'', *Materials*, **15 (7)**, (2022).
24) Das, B., Roy, S., Rai, R. N., & Saha, S. C. ''Studies

on effect of cutting parameters on surface roughness of al-cu-TiC MMCs: an artificial neural network approach'', *Procedia Computer Science*, **45**, 745-752 (2015).

25) Palavar, Osman, Dursun Özyürek, and Ali Kalyon. ''Artificial neural network prediction of aging effects on the wear behavior of IN706 superalloy'', *Materials & Design*, **82**, 164-172 (2015).
26) Elsheikh, A. H., Muthuramalingam, T., Shanmugan, S., Ibrahim, A. M. M., Ramesh, B., Khoshaim, A. B., ... & Sathyamurthy, R. ''Fine-tuned artificial intelligence model using pigeon optimizer for prediction of residual stresses during turning of Inconel 718'', *Journal of Materials Research and Technology*, **15**, (2021).
27) Bingöl, D., Hercan, M., Elevli, S., & Kılıç, E. ''Comparison of the results of response surface methodology and artificial neural network for the biosorption of lead using black cumin'', *Bioresource technology*, **112**, 111-115 (2012).
28) Venkata Rao, K., & Murthy, P. B. G. S. N. "Modelling and optimization of tool vibration and surface roughness in boring of steel using RSM, ANN and SVM", *Journal of intelligent manufacturing*, **29**(7), 1533-1543 (2018).
29) Dief, T. N., & Yoshida, S. "System identification for quad-rotor parameters using neural network", *Evergreen,* **3**(1), 6-11 (2016).
30) Lakshminarayanan, A. K., & Balasubramanian, V. "Comparison of RSM with ANN in predicting tensile strength of friction stir welded AA7039 aluminium alloy joints", *Transactions of Nonferrous Metals Society of China*, **19**(1), 9-18 (2009).
31) Yu, W., & Xie, H. "A review on nanofluids: preparation, stability mechanisms, and applications", *Journal of nanomaterials*, **1**, 1-17 (2012).
32) Awais, M., Bhuiyan, A. A., Salehin, S., Ehsan, M. M., Khan, B., & Rahman, M. H. "Synthesis, heat transport mechanisms and thermophysical properties of nanofluids: A critical overview", *International Journal of Thermo-fluids,* **10**, 100086 (2021).
33) Asadi, A., Alarifi, I. M., Ali, V., & Nguyen, H. M. "An experimental investigation on the effects of ultrasonication time on stability and thermal conductivity of MWCNT-water nanofluid: Finding the optimum ultrasonication time", *Ultrasonics sonochemistry*, **58**, 104639 (2019).
34) Leidenfrost, J. G. "On the fixation of water in diverse fire", *International Journal of Heat and Mass Transfer*, **9** (11), 1153-1166 (1966).
35) Ranganathan, S., Senthilvelan, T., & Sriram, G. "Evaluation of machining parameters of hot turning of stainless steel (Type 316) by applying ANN and RSM", *Materials and Manufacturing Processes*, **25** (10), 1131-1141 (2010).
36) Myers, R. H., Montgomery, D. C., & Anderson-Cook, C. M. "Response surface methodology: process and product optimization using designed experiments", *Journal of Quality Technology*, **49** (2), 186-187 (2017).