OPTIMIZATION OF CNC MILLING PROCESS PARAMETERS WITH CRYO-TREATED WC TOOLS BY RSM

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ABSTRACT

In this work, it is proposed how different levels of cryogenic treatment, such as shallow cryogenic treatment (SCT), which occurs at -110°C, medium cryogenic treatment (MCT), which occurs at -150°C, and deep cryogenic treatment (DCT), which occurs at -175°C, affect the machinability of P20 material. In this paper, an effort is made to optimize the process variables in machining P20 steel with cryogenically treated tungsten carbide (WC) cutting tools in the CNC milling process using the Response surface methodology (RSM) and Taguchi method. Data for this study is gathered using the Box-Behnken design of response surface methodology (RSM). Cutting speed (CS), feed rate (FR), depth of cut (DOC), and the lowering temperatures are considered significant process parameters that are functions of performance measures. The observations revealed that there is a substantial correlation between performance measures and cryogenic treatment, cutting speed, feed, and depth of cut. The purpose of this work is to model the output parameters and optimize the process parameters using RSM.

Keywords: cryogenic treatment, tungsten carbide tools, RSM, NSGA-II, SEM analysis.

INTRODUCTION

Manufacturing sectors have made extensive use of CNC milling equipment. Typically, in CNC end milling processes, tungsten carbide end milling cutting tools are mostly used. The efficiency of the milling operation is greatly improved by the cutting tool life. Since every machining operation depends on tool life, improving the productivity of manufacturing processes is also dependent on it. The main variables in the CNC milling process are MRR, Tool wear rate (TWR), cutting force, power consumption, and surface roughness of the milled work material. To provide the ideal machining conditions, it is necessary to identify and analyse the changes occurring inside the tool materials. Tool life is an important economic factor and a major factor in enhancing efficiency in CNC milling. Higher TWR slows down machining, which increases machining time and reduces milling productivity. Higher MRR and low cutting forces, TWR, and power consumption are critical for improving CNC milling efficiency and reducing surface roughness.

Cryo-treatment, a supplement to the standard heat treatment approach, has been effectively used to reduce tool wear with the goal of improving tool life. The material's mechanical properties, such as heat conductivity and micro-hardness, are improved by the cryogenic treatment, which also refines the grain structure (Jaswin and lal, 2010, Gill *et al*., 2010, Podgornik *et al*., 2016, Yang *et al*., 2016, Sobotova *et al*., 2016). Additionally, a further advantage of cryogenic treatment is that it improves the material's ability to dissipate heat due to better thermal conductivity properties (Perez and Belzunce, 2014, Xie *et al*., 2015, Dieringa, 2017)

Nalbant *et al.* (2007) investigated the impact of cutting tool shape and cutting speed on cutting forces. The findings indicated that increasing cutting speed by 20% causes the major cutting force to increase by 10.4%. While increasing cutting speed by 66.6% causes the major cutting force to decrease by 14.6%. Additionally, they discovered that an increase in cutter tip radius results in an increase in cutting force. Hossein et al. (2007) were able to evaluate the causes of feed rate, cutting speed, radial depth, and axial depth of cut by simulating first and second-order equations of cutting force using the RSM approach. Minitab software was utilised to predict the outcomes. The range between experimental values and projected values is acceptable. By considering the effect of process variables including feed rate, cutting speed, and depth of cut, Shaik and Srinivas (2017) proposed a multi-objective evolutionary algorithm (MOEA), or genetic algorithm, to reduce the Ra and amplitude of tool vibration when milling Al-6061 workpieces using CNC technology. According to the investigation, a smaller vibration amplitude would probably be sufficient to create the conditions for a desirable surface finish. A unique integrated evolutionary-based modelling and multi-objective optimization method for the CNC end milling process was proposed by Kondayya and Krishna (2012). The experiments are planned using the CCD in RSM, and the objective functions are optimised using NSGA-II. For process planning, the Pareto optimal solution set is produced. Oktem *et al.* (2005) proposed an effective approach for attaining the best machining conditions that result in the lowest Ra in CNC milling of mould components by coupling RSM with GA. The findings show that the experimental values and the anticipated values by GA agree very closely. Reddy (2013) proposed a method by integrating the Taguchi approach and ANN method to maximise the Ra and de-lamination damage when using end mills to process GFRP composite material. The depth of cut and cutting speed are determined to have the greatest effects on the replies based on the results of the ANOVA. The projected values and experimental values agree very closely. In addition to the aforementioned, several studies have been accounted for studying the machining execution in CNC turning, EDM, Wire-EDM, and ECM processes and have produced successful results. (Chopra and Sargade, 2015, Li *et al.*, 2013, Li *et al.*, 2016, Ghosh and Rao, 2017)

Cutting tools are repeatedly subjected to cryogenic temperatures (i.e., below 190 °C) as an alternative to heat treatment in order to eliminate residual stresses and improve steel's wear resistance. Cryogenic treatment results in a significant improvement in hardness and toughness. Tool life can be extended by 35 to 50 percent (Özbek *et al.*, 2015). Cryogenic treatment also increases thermal conductivity, which aids in transferring heat away from the tool. In addition, cryo-treated materials have increased dimensional stability and grain refinement (Shaik and Srinivas, 2017, Su and Hou, 2008).

The process variables involved in cryo-treatment include lowering the temperature, soaking period, quenching and tempering, heating and cooling rates, and more. According to a few studies, lowering temperature has a greater impact than the soaking period (Kondayya and Krishna, 2012, Li *et al.*, 2015, Arokiadass, 2015). However, there are very few references in the literature that discuss the impact of the cryo-treatment soaking period on the milling process performance indicators. Few researchers have examined the cryogenic cooling impact in machining using liquid nitrogen as a coolant over the past ten years (Qu *et al.*, 2016, Zhang et al., 2016, Lv *et al.*, 2013, Reddy *et al.*, 2013, Raju *et al.*, 2011, Yang *et al.,* 2011, Milfelner *et al.*, 2005). However, the study found that compared to dry machining, utilising liquid nitrogen as a coolant in the machining zone did not significantly increase tool life or surface morphology. Additionally, whenever the tool's material comes into direct touch with liquid nitrogen, it may become brittle and develop micro cracks and flank wear at higher machining rates.

DCT has developed as a novel machining method in recent years as a means of reducing tool wear in the CNC turning process (Özbek *et al.*, 2015, Chetan *et al.*, 2017). However, there hasn't been a reported much about CNC end milling till now. Extensive studies used approaches like artificial neural networks (ANN), genetic algorithms (GA), fuzzy logic, etc. attempted to determine the optimal level of process parameters for the milling process (Ozcelik *et al.*, 2005, Yang *et al.*, 2011, Lv *et al.*, 2013, Zhang *et al.*, 2016). For improved machining performance, numerous researchers have optimised frequently used machining parameters such as feed rate, cutting speed, depth of cut, etc (Tsai *et al.*, 2005, Oktem *et al.,* 2005, Kant and Sangwan *et al.*, 2015, Chopra and Sargade, 2015, Li *et al.*, 2013, Li *et al.*, 2016, Ghosh and Rao, 2017).

However, little research has been done up to this point to determine the ideal level of process parameters by using a cryogenic treatment soaking period and a lowering temperature.

EXPERIMENTAL WORK

The Box Behnken design from RSM is used to design the experimental runs. To machine, a P20 steel workpiece with dimensions of 200x200x12mm, and a 40mm-long (ISO standard) tungsten carbide end mill cutter with four flutes was purchased. P20 steel has the following chemical makeup: silicon 0.2-0.8 percent, manganese 0.6-1 percent, chromium 1.4-2 percent, molybdenum 0.3-0.55 percent, sulfur 0.03 percent (maximum), and iron balance. (Vardhan *et al.*, 2018).

Three tungsten carbide tools were procured and they were shallowly cryogenically treated (SCT), mediumly cryogenically treated (MCT), and deeply cryogenically treated (DCT) tools. Cutting tools undergo cryogenic treatment, where they are kept at -110°C, -150°C, and -175°C for 36 hours while being cooled for 5 hours and warmed up for 9 hours before being returned to room temperature. The cryo treated tools are shown in Figure-2. The cryo-system's details are described in the section below.

A cryogenic treatment unit made of stainless steel is the main component of the cryogenic treatment system. It contains an additional liquid nitrogen delivery system that enables it to preserve the soaking duration, cooling rate, and warm-up period by delivering a controlled volume of pressurized LN_2 into the chamber. A solenoid valve in the liquid nitrogen delivery chamber is coupled to the proportional integral derivative (PID) controller shown in Figure-1.

The solenoid valve, which is managed by a PID controller with preset values, controls the flow of liquid nitrogen. Platinum Resistance Temperature Detectors (RTD) are used to measure the temperatures of the work materials. A data acquisition system continuously stores the temperature data of the samples that PID has read during the cryogenic treatment cycle. Figure-1 depicts the cryo-treatment cycle. A similar type of equipment is used elsewhere. (Vardhan *et al.*, 2017).

Figure-1. Cryogenic treatment setup.

Figure-2. Different cryo-treated tools.

The main goal of the experiment is to examine how cryogenically treated tungsten carbide cutting tools perform during machining. Table-1 displays the process parameters that were used.

Table-1. Machining parameters used.

Parameters	Levels		
	L1	**L2**	**L3**
Feed Rate (mm/tooth)	0.1	0.15	0.5
Cutting Speed (m/min)	75	85	95
Depth of cut (mm)	0.5	1	1.5
Lowering Temperatures (^oC)	-110	-150	-175

According to the Box Behnken design in RSM (Vardhan *et al*., 2017), 29 tests must be carried out for the selected levels, which are listed in Table-2. After ten minutes of machining operation, the machining time is recorded. The workpiece weight and cutting tool weight were determined using electronic weighing equipment. The weights of the workpiece & cutting tool are recorded before and after machining to analyze MRR & TWR.

$$TWR = 1000 * \Delta WT/(\rho * T) \quad (1)$$

$$MRR = 1000 * \Delta Ww/(\rho * T) \quad (2)$$

where ΔW_w= change in weight of workpiece (grams), ρ = density (kg/m^3), T = machining time (mins)

Some other source has reported on a calculation of a similar type (Vardhan *et al.*, 2017, Mohanty et al., 2014). A Taylor Hobson Surtronic 3+ stylus instrument is used to measure the surface roughness (Ra) of the machined work material. The workpiece's average Ra values are noted, after which the same process is carried out four more times, resulting in a tabulated average of the four readings of Ra values.

RESULTS AND DISCUSSIONS

Table-2 displays the experiment's results. The relationship between process parameters and performance measures was established experimentally, and the most influential parameters were discovered using ANOVA at a significant threshold of 0.05.

After the irrelevant parameters were removed, the ANOVA for MRR is displayed in Table-3. The most significant parameters are determined to be the input parameters depth of cut, feed rate, cutting speed, and cryogenic lowering temperature, as well as the interaction terms feed rate x cryogenic lowering temperature, cutting speed x cryogenic lowering temperature, and square terms cutting speed x cutting speed (Vardhan *et al*., 2018).

For MRR, the adjusted and unadjusted coefficients of determination (R2) values are 81.79 and 88.29 percent, respectively. It is discovered that the lack of fit does not effect on any of the output responses.

VOL. 17, NO. 24, DECEMBER 2022 ISSN 1819-6608
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Table-2. Experimental results.

S. No	A:CS (m/min)	B:FR (mm/tooth)	C:DOC (mm)	D:lowering temperature (^{o} C)	MRR (mm^3/min)	TWR (mm^3/min)	Ra (microns)
1	75	0.15	1	-1	44325.6	46.7173	1.48
2	85	0.2	1	-1	55300.4	50.63	1.5
3	85	0.15	1.5	-1	64503.5	58.0591	1.78
4	85	0.15	0.5	-1	54023.3	53.2911	1.3
5	85	0.1	1	-1	47963.1	55.4008	1.2
6	95	0.15	1	-1	60884.1	56.1814	1.15
7	75	0.15	1	1	58843.8	26.097	0.68
8	85	0.15	1.5	1	80326.2	40.0844	0.44
9	85	0.1	1	1	63929.2	35.865	0.69
10	85	0.2	1	1	80003.9	42.1941	0.58
11	85	0.15	0.5	1	65460.1	29.5359	0.48
12	95	0.15	1	1	78562.2	48.5232	0.36
13	75	0.1	1	0	48131.3	44.3038	1.48
14	75	0.15	0.5	0	50403.4	45.9198	1.35
15	75	0.2	1	0	55124.5	51.4135	1.54
16	75	0.15	1.5	0	49612	48.5232	1.6
17	85	0.15	1	0	63605.1	50.5232	1.38
18	85	0.15	1	0	63605.1	50.5232	1.38
19	85	0.15	1	0	68605.1	50.5232	1.38
20	85	0.1	0.5	0	52403.4	36.0844	0.72
21	85	0.15	1	0	63605.1	50.5232	1.38
22	85	0.2	1.5	0	84806.9	62.0717	1.45
23	85	0.2	0.5	0	68219.7	58.7426	1.05
24	85	0.15	1	0	63605.1	55.5232	1.58
25	85	0.1	1.5	0	72085.8	68.2911	1.22
26	95	0.2	1	0	72085.8	64.1814	1.25
27	95	0.1	1	0	62757.1	58.962	0.85
28	95	0.15	1.5	0	72583.3	72.346	1.15
29	95	0.15	0.5	0	60884.1	52.3038	0.9

After deleting unnecessary parameters, the analysis of variance tables for MRR and TWR is provided in Table-3 and Table-4. The most significant variables influencing the responses are those with p-values lower than 0.05. Cutting speed, DOC, feed rate, and cryogenic lowering temperature have more influence on all of the responses.

For TWR, the results for the coefficient of determination (R2) and the corrected R2 are 97.55 percent and 95.72 percent, respectively. It is discovered that all of the output responses are unaffected by the lack of fit.

Table-5 displays the ANOVA for Surface roughness after removing unnecessary factors. The most significant factors influencing the responses are those with p-values lower than 0.05. Cutting speed, depth of cut, feed rate, and cryogenic lowering temperature is shown to be the process variables that have the most influence on all of the responses. For Surface Roughness, the coefficient of determination (R2) and adjusted R2 values are 97.19 and 95.62 percent, respectively. The lack of fit is found to have no effect on any of the output responses.

Table-3. Analysis of variance for MRR.

Source	Sum of Squares	dof	Mean Square	F Value	p-value Prob> F	
Model	8.291E+009	11	9.431E+008	13.57	< 0.0001	Significant
A-CS	3.244E+009	1	2.224E+009	31.12	< 0.0001	
B-FR	7.698E+008	1	6.788E+008	9.63	0.0060	
C-DOC	1.602E+009	1	1.712E+009	24.34	0.0001	
D-Lowering Temp	4.102E+009	1	3.112E+009	44.57	< 0.0001	
AC	2.784E+008	1	1.794E+008	2.46	0.1266	
AD	9.614E+008	1	9.734E+008	13.89	0.0025	
BD	3.105E+008	1	2.815E+008	4.21	0.0603	
CD	8.311E+007	1	8.321E+007	1.21	0.2889	
A^2	5.116E+007	1	5.136E+007	0.64	0.4046	
C^2	2.235E+008	1	2.245E+008	3.11	0.0905	
Residual	1.258E+009	18	6.981E+007			
Lack of Fit	1.178E+009	14	8.427E+007	4.22	0.0866	not significant

Table-4. Analysis of variance for TWR.

Source	Sum of Squares	dof	Mean Square	F Value	p-value Prob> F	
Model	4315.08	11	366.26	52.13	< 0.0001	significant
A-CS	618.36	1	628.36	90.13	< 0.0001	
B-FR	61.24	1	61.24	8.79	0.0091	
C-DOC	613.49	1	613.49	88.04	< 0.0001	
D-Lowering Temp	2974.80	1	2934.80	415.80	< 0.0001	
AC	18.10	1	16.80	2.51	0.1324	
AD	81.16	1	81.66	11.49	0.0039	
BC	70.21	1	72.21	10.06	0.0059	
B^2	51.29	1	51.29	7.10	0.0170	
C^2	8.83	1	8.83	1.36	0.2781	
D^2	14.11	1	13.81	1.96	0.1802	
Residual	112.32	16	7.18			
Lack of Fit	100.52	12	8.29	2.62	0.1827	not significant
Pure Error	12.80	4	3.20			

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Table-5. Analysis of variance for surface roughness.

Source	Sum of Squares	dof	Mean Square	F Value	p-value Prob> F	
Model	4.21	11	0.43	62.19	< 0.0001	significant
A-CS	0.65	1	0.56	78.75	< 0.0001	
B-FR	0.12	1	0.12	15.88	0.00085	
C-DOC	0.13	1	0.13	20.61	0.00035	
D-Lowering Temp	3.26	1	3.28	470.74	< 0.0001	
BD	0.077	1	0.088	12.56	0.0013	
CD	0.14	1	0.14	18.16	0.0004	
A^2	0.021	1	0.012	1.61	0.2233	
B^2	4.026E-003	1	4.028E-003	0.59	0.4569	
C^2	0.020	1	0.011	1.51	0.2351	
D^2	9.772E-003	1	9.783E-003	1.42	0.2514	
Residual	0.13	17	6.937E-003			
Lack of Fit	0.12	15	7.953E-003	2.34	0.2129	not significant
Pure Error	0.024	3	3.371E-003			
Cor Total	4.42	27				

Figure-3 displays a surface variation plot for the MRR between feed and cutting speed. MRR tends to rise along with rising feed rate and cutting speed. This is because more heat is generated in the cutting zone as the cutting speed rises. As a result of this high heat, the metal softens, and the MRR increases (Mohanty *et al.,* 2014), Vardhan *et al.,* 2018).

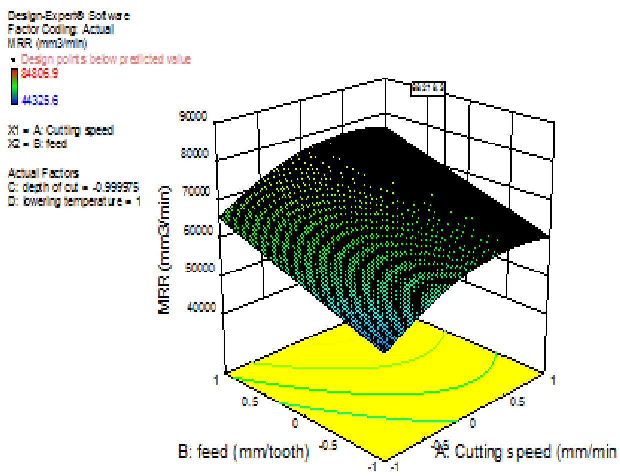

Figure-3. Surface plot for variation MRR with CS vs FR.

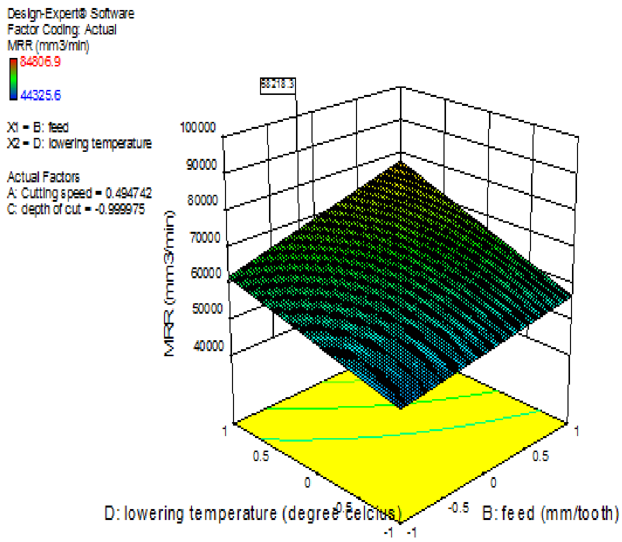

Figure-4. Surface plot for variation MRR with lowering temperature vs. feed.

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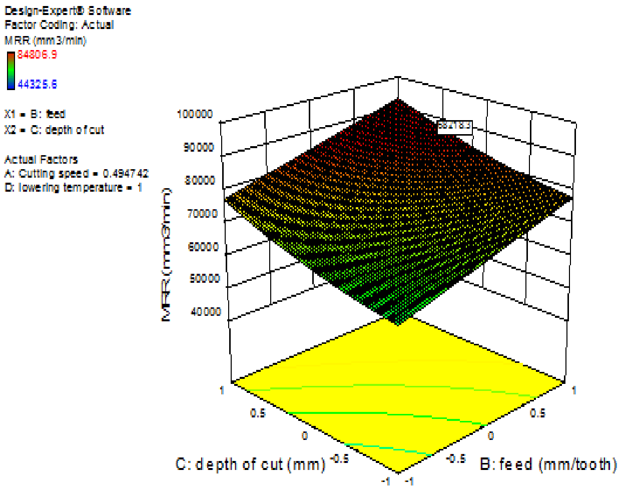

Figure-5. Surface plot for variation MRR with depth of cut and feed.

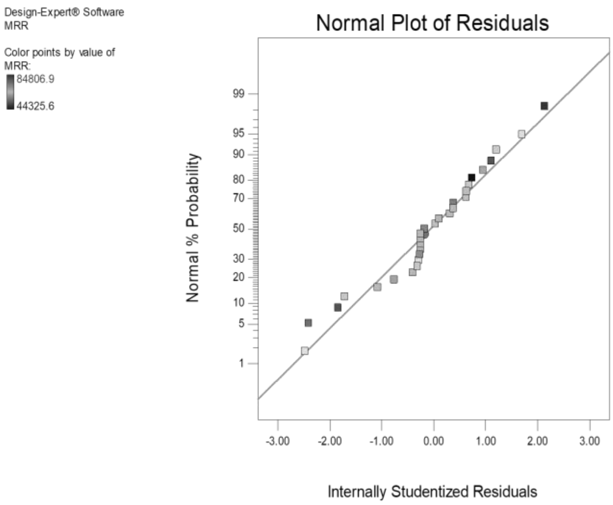

Figure-6. Normal plot of residual for MRR.

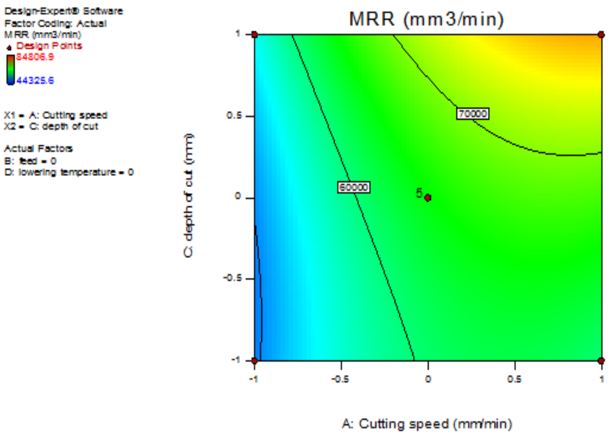

Figure-7. Contour plot for MRR.

The following equations (3) to (5) express the results of regression analysis in terms of actual components

$$\mathbf{MRR} = +64465.14 + 8443.00 \text{ x } A + 5689.27 \text{ x } B + 6043.64 \text{ x } C + 8343.78 \text{ x } D + 3122.65 \text{ x } A \text{ x } C + 2184.35 \text{ x } B \text{ x } D - 5621.36 \text{ x } A^2 + 2017.96 \text{ x } C\text{^}2 \quad (3)$$

$$\mathbf{TWR} = +52.13 + 7.46 \text{ x } A + 2.53 \text{ x } B + 6.12 \text{ x } C - 8.17 \text{ x } D + 4.36 \text{ x } A \text{ x } C + 3.24 \text{ x } A \text{ x } D - 7.22 \text{ x } B \text{ x } C + 2.77 \text{ x } B \text{ x } D + 2.34 \text{ x } B^2 + 1.98 \text{ x } C^2 - 8.35 \text{x } D\text{^}2 \quad (4)$$

$$\mathbf{Surface\ roughness} = +1.42 - 0.21 \text{ x } A + 0.10 \text{ x } B + 0.15 \text{ x } C - 0.43 \text{ x } D + 0.085 \text{ x } A \text{ x} B - 0.10 \text{ x } B \text{ x } B - 0.13 \text{ x } C \text{ x } D - 0.078 \text{ x } A^2 - 0.11 \text{x } B^2 - 0.12 \text{ x } C^2 - 0.35 \text{ x } D\text{^}2 \quad (5)$$

MICRO-STRUCTURAL ANALYSIS

The metallographic microstructure of ASM Metal Handbook (Sanathanam *et al.*, 2004) has the following phases. (a) WC is represented by the α-phase, and (b) cobalt binder is represented by the β-phase. (c) γ-phase represents numerous carbides of tungsten and at least one metal binder. (d) η-phase represents carbides of the cubic lattice (TaC, TiC, etc.). The η-phase is not significant in the current work because the chosen grade contains just a few additional carbides. The obtained microstructure reveals that only α, β & η phases have been seen, but lack of TiC and TaC prevents the formation of the gamma phase. The rigid Alpha grains' shape, is incompletely produced as a result of the deposition of several grains. The usual size of the α-phase grains in the microstructure of DCT tungsten carbide tools is larger than that of the SCT tools, as seen in Figure-8 and Figure-9. The hard α-phase grains reach their most stable state during the cryo-treatment process. It makes the hard α-phase grain structure rigid and stress-free, which reduces stress-induced fractures and increases the life of the cutting tool (Vardhan *et al.*, 2018). Figure-10 shows the EDS report on spot 1.

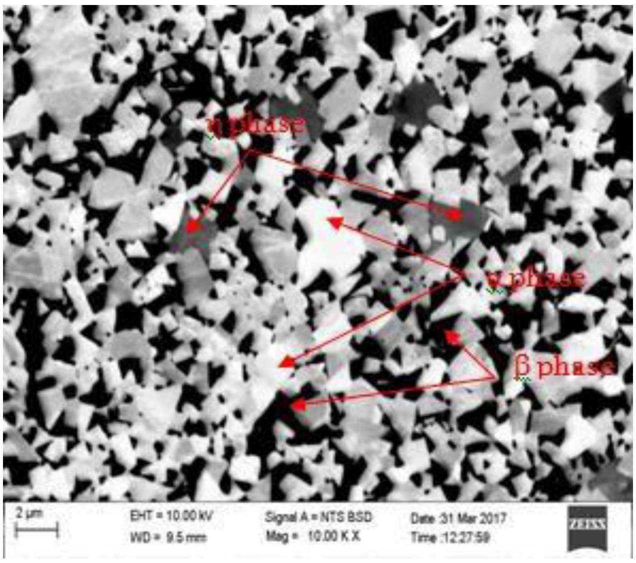

Figure-8. Microstructure of tungsten carbide tools.

VOL. 17, NO. 24, DECEMBER 2022 ISSN 1819-6608
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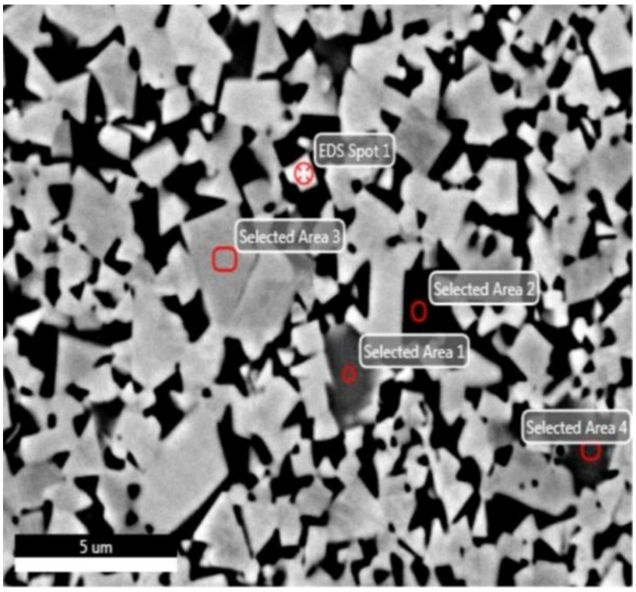

Figure-9. Microstructure of DCT tungsten carbide tools.

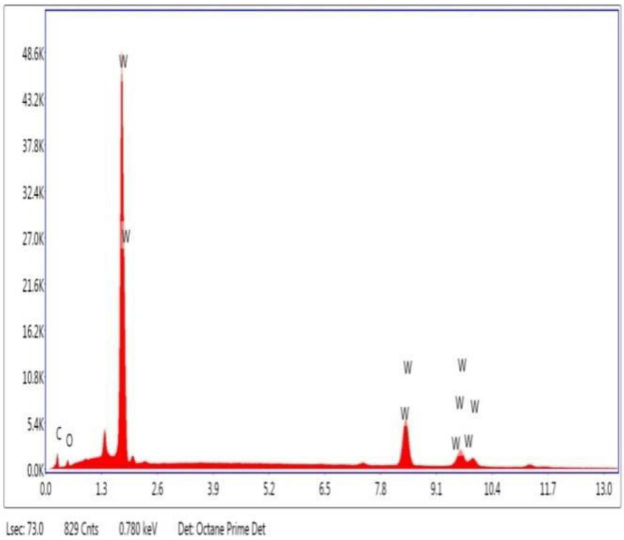

Figure-10. EDS report on spot 1.

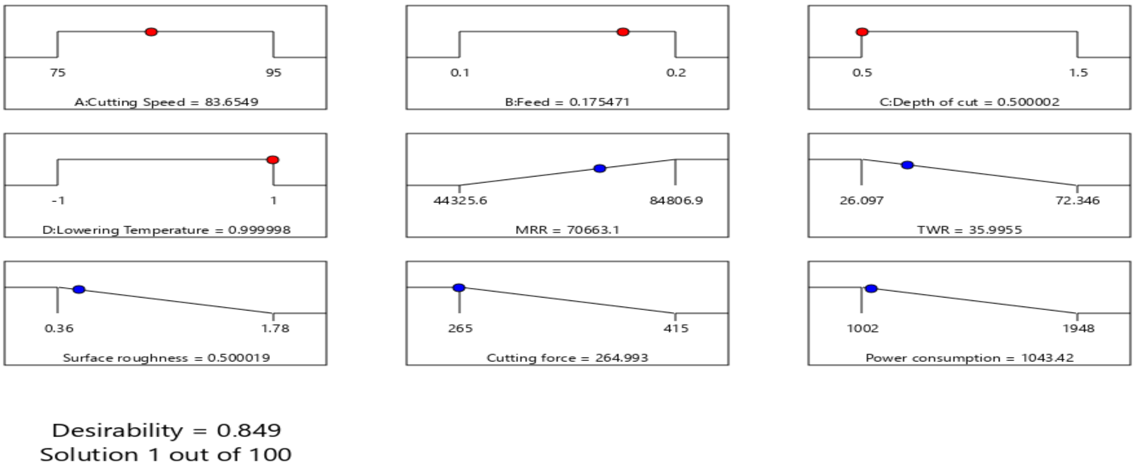

Figure-11. Solution with the desirability.

Table-6. Optimized values of process parameters.

S. No	Cutting Speed	Feed Rate	Depth of cut	Lowering Temp.	MRR	TWR	Surface roughness	Desirability
1	83.655	0.175	0.500	1.000	70663.075	35.996	0.500	0.849

OPTIMIZATION USING RSM METHODOLOGY

The goal of this study is to maximise MRR and reduce TWR, Ra, cutting forces, and power consumption by applying RSM methodology to optimise the machining parameters. The optimum parameter values derived via RSM are shown in Table-6. The best combination of the machining parameters that affect performance measurements should be selected from the primary desirability plots to increase the productivity of the CNC end milling operation. The optimised process parameter for improving the end milling process performance measures is shown in Table-6. The ideal mixing of the resultant machining parameters is found to be within the proposed mathematical model and process parameter ranges. Figure-11 shows the solution's desirability graph.

CONCLUSIONS

This study and investigation examine the impact of input parameters on the CNC milling performance measures for the machinability of high-strength materials. The analysis leads to the following conclusions:

a) The end mill carbide cutting tools' life was greatly increased by the cryogenic treatment. When compared to other treatments like SCT and MCT, deep cryogenic treatment has the greatest impact on tool wear.

b) When using a DCT-treated tool at -175 ° c temperature, it was found that MRR increased by 24.53 percent, TWR, Ra, cutting force, and power consumption decreased by 31.03 percent, 75.28 percent, 29.62 percent, and 13.37 percent, respectively, compared to a tool that had undergone SCT treatment.

c) According to SEM analysis, surface quality on the machined surface with the DCT tool has increased when compared to other treated tools.

d) Cutting speed, depth of cut, and cryogenic lowering temperature, feed rate was determined to be the important factors for all the responses.

e) From the analysis, it is observed that the DCT cutting tool is preferable to MCT and SCT-treated cutting tools while machining P20 steel to achieve higher MRR, lower TWR, and Ra.

f) To optimize the process for various materials, it is necessary to analyze factors such as different coatings on cutting tool materials, wet and dry machining, cooling temperature, and tempering cycle.

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