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Experimental Investigations and Optimization of Machining Parameters in CNC Turning of SS304 Using Coolant at 0 °C

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Abstract: During the machining process, coolant is utilized to remove chips and tiny abrasive particles created during the machining process as well as to lessen heat concentration and friction between tools and chips. The machining performances, such as tool life, surface roughness, cutting forces, retention of mechanical properties of the work material, etc., are also desired to be retained or improved at the same time. This presented research work's main goal is to investigate and analyze the impact of coolant at 0 °C on input machining parameters when turning SS304 (an austenitic stainless steel of the 300 series with high corrosion resistance) on a CNC lathe and to optimize the input variable factors, such as feed rate, cutting speed, and depth of cut for the best machining conditions, and each input cutting parameter is given a weight using the analytic hierarchy process (AHP) technique. A novel experimental setup is created to decrease the temperature of emulsion coolant and to use it in control conditions during machining operation. To research and assess the impact on the workpiece surface roughness, forces produced during actual cutting operations, the rate of tool wear, and the rate of material removal, twenty-seven sets of experiments using the partial factorial design approach are devised and carried out. Prioritizing the many optimal solutions accessible for this work is done using the technique for the order of preference by similarity to ideal solution (TOPSIS) and grey relation grade (GRG) approaches. Further, the surface finish of the workpiece after machining, rate of tool wear, cutting force generated during machining, and material removal rate from the workpiece were compared with traditionally/conventionally used input parameters with newly obtained optimized parameters through this work. Approximately a 30% improvement is observed in output parameters compared with using traditional parameters, and was close to the 50% of the result obtained through cryogenic machining. The work piece's chip morphology along with tool wear was observed in form of SEM images, and it supports the claim of the surface finish and tool wear. The material removal rate was physically observed during machining. SEM pictures were used to physically validate the changes in tool wear. It has also been shown that keeping the coolant temperature at 0 °C significantly improves a number of work quality and machining characteristics. This method offers a substitute for cryogenic machining, making it useful for the manufacturing sectors.

Keywords: low temperature; decision making; optimization; chip morphology; surface roughness

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1. Introduction

The use of more advanced engineering materials, such as stainless steel, super alloys, high resistance temperature alloys, titanium-based alloys, composites, etc., that have superior engineering properties, such as high strength, superior fracture toughness, high wear resistance, the ability to withstand high temperatures, etc., has become more pragmatic over the past decade [1]. The problems associated with the machining of SS304 is the presence of chromium carbide fiber, which has resistance to plastic deformation during cutting, and nickel's heat resistance, which limits thermal conductivity and causes heat concentration zones to form in the cutting zone, which causes strain hardening in materials.

These are issues with the machining of materials such as SS304. Widespread uses of the aforementioned materials are now possible thanks to advancements in the machining industry, such as improved work–tool heat dissipation, high-speed machining center, and greater feed rates with more precision and better surface polish. Cutting velocity, feed rate, depth of cut, coolant pressure, and coolant temperature are input variables in the machining process that are essential for achieving the best surface finish, greatest dimensional accuracy, lowest tool wear rate, and highest metallurgical stability of workpiece material, among other output parameters [2].

Cryogenic machining is utilized in reality to have a greater heat dissipation rate while machining. Liquid Nitrogen/Oxygen gas is used as a coolant in cryogenic machines to dissipate the heat generated during the machining process. When splattered over the task, the gas has a temperature of less than −100 °C. Although cryogenic machining has been employed, its use is limited by safety and economic concerns since it requires expensive equipment and technology, which drives up manufacturing prices [3]. As a result, industries are hesitant to embrace traditional machining methods with advanced machining capabilities, such as cryogenic machining due to the increase in the job's overall cost. This research gap is filled by the current research work and it provides a viable solution. A little effort has been made through this research work to develop an affordable and practical option, such as a coolant refrigeration machine, to lower the temperature of the coolant that is stored in the main tank and to use this refrigerated coolant during machining operation. It is proposed through this research to use low temperature (0 °C) coolant to determine its impact on the output responses while machining with SS304. Furthermore, investigations had been carried out to determine the optimum input parameters at 0 °C to have better output responses and compare it with responses actually available now using the current input parameters. In the current study, all input cutting parameters were optimized to their best values. Along with physical abrogation, sufficient rationale, and good logic, recommendations for new parameters are also made in this work. Additionally, using recognized scientific multi-criteria decision-making techniques, the optimized parameter ranking has also been validated in this research.

In the case of hard materials, such as stainless steel, titanium alloys, or super alloys, the output responses of machining processes, such as tool wear, metallurgical stability of workpiece, surface roughness, and fume generations from coolants, primarily depend upon the temperature generated during the machining, and better heat dissipation capability of the machining process through the coolant. The material removal rate and tool wear rate were also affected by the temperature generated in the work–tool interface area and cutting forces [4,5].

When a variety of options are offered to researchers, multi-criteria decision-making (MCDM) approaches are scientific instruments that help them choose the optimal option based on their preferences [6]. The many alternative solutions to the problems have been ranked using MCDM techniques, such as the technique for an order of preference by similarity to ideal solution (TOPSIS), preference ranking organization method for enrichment of evaluations (PROMETHEE), and grey relation grade (GRG) [7]. These methods were used in the current research to select the optimal solution from the pool of available, optimized input parameters. Additionally, the rankings produced by each approach are contrasted with one another in order to confirm and provide a clear justification for employing a suggested set of parameters.

The research work presented in this paper offers a reliable and workable approach as a substitute for the cryogenic system. To support the findings, the multi-attribute optimization of the machining parameters and its ranking using the TOPSIS and GRA methods are carried out. High-resolution images of tools and chips were obtained using a scanning electron microscope (SEM), which was then utilized to confirm the physical cause and valid reasoning, and to ascertain the causes and modes of tool failure. It is advised to use the newly improved input parameters in place of the traditional ones because they will have a favorable and sizeable effect on the output machining parameters. Finding the optimal input variable optimization to obtain the lowest tool wear rate, the highest surface finish, the best dimensional stability, and the fewest fluctuations in cutting forces has been an honest and promising endeavor.

2. Experimental Setup

2.1. Machine, Material, and Tooling Arrangements

Stainless Steel 304 (SS304) ASTM A276 in cylindrical form is selected as a workpiece for investigation during this research work. The cross-sectional diameter of the bar was chosen as 50 mm, and length as 150 mm for operational easiness. The detailed chemical composition of the given workpiece is described in Table 1. The material has a minimum tensile strength of 515 MPa and minimum yield strength of 205 MPa. A unique system is designed to investigate the effect of change in coolant temperature on output machining characteristics. The castor oil-based coolant was used with its 5% weight proportion, the rest being water. Coolant coming from the refrigeration system is splashed on the tool–work interface area with the help of a convergent nozzle with a tip diameter of 2 mm, and the distance of the nozzle from the workpiece is fixed at 15 mm. The chips were prevented from entangling with the nozzle using chip breakers provided on the tool. The coolant flow from the pump is fixed at a flow rate of 8 kg/min, using a flow control valve with a pressure of 10 bar. The trials are performed on Ace Micromatics LT-16-500 LM turning center. For this research work, only turning operations are considered. Tungsten carbide inserts coated with TiAlN, whose designation is CNMG120404, are used for turning operations. An ISO designate tool holder is used for this experimentation. Additionally, for each set of the experimental run, a new cutting edge of the insert is chosen, and the time of each run is fixed at 300 s.

Table 1. Chemical composition of the specimen.

Elements	Cr	Ni	Mn	Si	C	Fe
(%)	18.2	8.5	1	1	0.08	Balance

The "MITUTOYO" surface roughness tester was used to measure the surface roughness (Ra) of the machined workpiece. The surface roughness was measured three times at 15 mm intervals, and the arithmetic mean of those measurements is used as the true surface roughness. Using a Kistler photoelectric dynamometer, the cutting forces produced during the machining process are measured. The weight loss method, which compares the weight before and after machining, was used to calculate the rate of material removal. The weight was determined using a digital scale called a "HOFFEN", which has a 0.001 g per kilogram accuracy. The adhesion and wear volume of failed inserts were measured using a three-dimensional confocal microscope. Using an optical microscope of the "ZEISS" brand, tool wear on the insert cutting edge was measured. To examine the precise microstructure of the workpiece and chip morphology, a scanning electron microscope (SEM) by the brand VEGA, Tesca, was utilized.

2.2. Refrigeration System

A vapor compression cycle (VCC)-based cooling system is designed and fabricated to remove the sensible heat from the liquid coolant, i.e., to reduce the liquid coolant temperature to approximately 0 °C. A stainless steel container of 50-L capacity is surrounded by the refrigeration evaporative coil, whose surface temperature is maintained at −10 °C. The cooling capacity of the refrigeration system is 2.2 TON, and R134a refrigerant is used as a medium. The system consists of a centrifugal pump with a variable flow unit to control the flow, and a pressure adjustment unit to control the coolant pressure and flow supplied to the work–tool interface area. A control panel is provided for setting the parameters, such as coolant temperature, coolant pressure, and coolant flows as per our requirement, and monitoring the working parameters, such as power consumed, temperature, and pressure of the liquid coolant. The co-efficient of performance (COP) of the system is found to be 2.8.

It has been noted that the system requires 26 min to get 50 L of coolant from 30 °C to 0 °C. Figure 1 is the pictorial view of the system, designed for cooling.

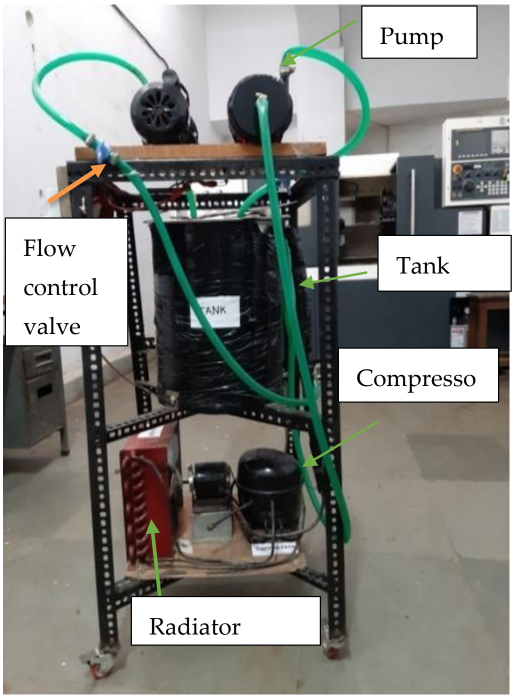

Figure 1. Refrigeration system for coolant cooling.

3. Research Methodology

3.1. Design of Experiment

The cutting velocity, feed rate, depth of cut, type of coolant, coolant temperature, cutting tool, ambient parameters, and machine condition, etc. are the main input variables usually considered when machining stainless steel alloy. The surface finish (Ra), material removal rate (MRR), tool wear rate (TWR), cutting forces (Fc), temperature produced at the work–tool interface area, etc. are typical output reactions, in contrast to input parameters. The individual components and their interactions together with input factors determine the output reactions. A partial factorial degree of experimentation technique has been used to reduce the number of experiments since it is more logical and focuses on the high and low levels of each factor [8]. The critical factors to be considered for experimentation along with three levels are shown in Table 2. Each input process parameter is taken into account using a three-level factor. Each level's value is fixed and is determined using the parameters that are currently in use as well as publicly accessible in the literature. The minimum and maximum levels are chosen to have good accuracy, and their mean value is set at level 2.

Table 2. Important factors considered for experimentations.

Symbol	Process Parameter	Unit	Level		
			1	2	3
v	Cutting velocity	m/s	78	160	235
f	Feed rate	mm/min	100	200	300
t	Coolant temperature	°C	15	10	0
d	Depth of cut	mm	0.5	1.0	1.5
p	Coolant pressure	N/cm^2	5	10	15

The main emphasis of the fundamental research is to analyze the effect of the coolant temperature on output responses; it was essential to decide the level logically, improving the output parameters. The dip in temperature of the coolant to 0 °C can be obtained with the designed system easily, and further heat removal will only decrease latent heat, which will change the phase from liquid to solid and will be of no use; hence, 0 °C is the lower level for experimental purposes. On the higher side, a temperature of 15 °C is selected, as the temperature above it will be close to ambient temperature in any tropical country and will lead to no improvement. Therefore, the mean of 0° and 15 °C is selected as level 2 (i.e., 8 °C).

The experiment is conducted using four shortlisted factors, including cutting velocity, feed rate, depth of cut, and coolant temperature, in order to have more realistic, practical solutions. As the coolant pressure depends upon pressure generating device and if range is limited to narrow range, the factor has to be neglected as it has less effect compared to other factors [9]. The current system pressure range is only 15 bar and hence neglected. As a result, 27 trials are conducted using four components and three levels for each element in the experiment. Each set of experiments is carried out twice to ensure consistency in the results. The experiment had a run of three times, if the reading discrepancy reached a level of 10% in the initial two runs. The experiment's third measured value is regarded as the final one. As indicated in Table 3, controllable input process parameters are arranged as per the partial factorial rule. The output response, i.e., experimental results values obtained for each of those combinations, is tabulated.

Table 3. Experimental results for the set of combinations of input process parameters.

Exp. Run	Controllable Input Process Parameters				Experimental Results			
	t	*v*	*f*	*d*	R_a (μm)	F_c (N)	TWR (μm)	MRR (gm/min)
1	15	78	100	0.5	2.5	660	154	51
2	15	78	200	1.0	2.62	690	156	56
3	15	78	300	1.5	2.76	720	162	62
4	15	160	100	1.0	2.38	760	158	61
5	15	160	200	1.5	2.48	780	165	67
6	15	160	300	0.5	2.30	790	184	78
7	15	235	100	1.5	2.02	930	190	73
8	15	235	200	0.5	2.2	945	198	75
9	15	235	300	1.0	2.12	985	232	80
10	8	78	100	1.0	2.26	685	157	68
11	8	78	200	1.5	2.5	725	150	60
12	8	78	300	0.5	2.32	698	156	68
13	8	160	100	1.5	1.92	760	162	70
14	8	160	200	0.5	1.96	760	176	76
15	8	160	300	1.0	2.09	810	182	83
16	8	235	100	0.5	2.0	875	172	68
17	8	235	200	1.0	1.9	970	190	76
18	8	235	300	1.5	2.32	985	220	91
19	0	78	100	1.5	2.1	685	146	78
20	0	78	200	0.5	1.8	685	150	80
21	0	78	300	1.0	1.5	795	158	80
22	0	160	100	0.5	1.5	795	165	74
23	0	160	200	1.0.	1.7	785	175	80
24	0	160	300	1.5	1.75	829	215	86
25	0	235	100	1.0	1.7	868	186	86
26	0	235	200	1.5	1.72	990	212	87
27	0	235	300	0.5	1.78	950	200	88

3.2. Weight Assigning Using the Analytic Hierarchy Process (AHP)

The AHP method explains the inter-relative structured relations of the performance determining criteria (PDC) in MCDM problems. The basic steps adopted in assigning weights for the input process parameters are discussed further:

Step 1: *Hierarchy structure*: In the beginning, a hierarchy of input parameters is formed for a given multi-criteria decision-making task with pre-determined alternatives and pre-defined criteria. The pre-determined criteria are based on the relative importance of one parameter compared to other parameters. Then, the entire hierarchic structure is grouped into three different levels as: (a) objective of process at the top; (b) criteria at the middle; (c) low weightage or sub-criteria at the bottom level [10].

Step 2: *Comparative matrix*: After forming the entire hierarchy structure, the preferential procedure is initiated to allot weight to the pre-defined criteria. The allocation of weight to the various criteria concerning the objective is calculated by comparing a typical pair and allotting the weight concerning its importance in the given problem and achieving the objective. A standard scale of nine is selected for pair-wise comparison [11].

Let $X = \{X, j = 1, 2, \ldots\ldots N\}$ a group of pre-defined criteria, then the formation of the comparison matrix (D) will be $R \times R$, and D_{ij} describes the relative usefulness of i^{th} criteria concerning j^{th} criteria.

$$D_{RR} = \begin{bmatrix} D_{11} & D_{12} & \cdots & D_{1R} \\ D_{21} & D_{22} & \cdots & D_{2R} \\ \vdots & \vdots & \ldots & \vdots \\ D_{M1} & D_{M2} & \cdots & D_{MR} \end{bmatrix}, \ D_{ii} = 1, \ D = \frac{1}{D_{ji}}, D_{ji} \neq 0 \quad (1)$$

The comparison matrix is given in Table 4 for different output parameters as represented below for a given problem.

Table 4. Comparison matrix.

Attributes	R_a	F_c	TWR	MRR
R_a	1	3	2	1
F_c	1/3	1	1/2	1/2
TWR	1/2	2	1	1/2
MRR	1	2	2	1

Step 3: *Determination of weight***:** The weight ($\overline{\omega}_i$) of every pre-determined criterion is calculated by applying the Equation (2):

$$\overline{\omega}_i = \frac{\left\{\prod_{j=1}^{N} D_{ij}\right\}^{\frac{1}{N}}}{\sum_{i=1}^{N}\left\{\prod_{j=1}^{N} D_{ij}\right\}^{\frac{1}{N}}}, \ i = 1, \ 2, \ \ldots .n \quad (2)$$

The weight calculated by the above equation for our case is shown in Table 5.

Table 5. Attributes and allocations of weight.

Attributes	Assigned Weights
R_a	0.35
F_c	0.13
TWR	0.20
MRR	0.32

Step 4: To determine the difference in the achieved results of the weight calculations, the actual measured value of variation is defined as consistency variation.

$$CR = \frac{CI}{RI} \quad (3)$$

The value of random consistency is determined from Table 6. It depends upon the maximum eigenvalue of the selected matrix and the total number of elements present in the matrix. The consistency index (CI) is calculated using Equation (4) and is found to be 0.0152.

$$CI = \frac{\lambda_{max} - N}{N - 1} \quad (4)$$

Table 6. Random consistency index.

N	1	2	3	4	5	6	7	8	9	10
RI	0	0	0.58	0.9	1.12	1.24	1.32	1.41	1.45	1.49

In the AHP method, the maximum value limit for CR is 0.1, and in case the obtained value is more than 0.1, then to obtain better consistency, the entire procedure has to be repeated [12].

The random consistency index (RI) is given in Table 6.

Using Equation (3), CR is calculated as 0.0169. As the value of CR is less than 0.1, the weight assigned is consistent and can be used to solve the given problem.

3.3. Multi-Objective Optimization Using the TOPSIS Approach

TOPSIS is a technique of MCDM which helps determine and select the best suitable optimal solution from several available solutions available for the given problems. The guiding principle is that the shortlisting criteria should have smallest geometric distance from positive solution and largest from the least negative solution [13]. The TOPSIS method involves the various steps discussed below.

Step 1: The formation of a decision matrix with 'n' attributes and 'm' alternatives and is shown in the form of a matrix as given by Equation (5):

$$R_m = \begin{bmatrix} p_{11} & p_{12} & p_{13} & \cdots & \cdots & p_{1n} \\ p_{21} & p_{22} & p_{23} & \cdots & \cdots & p_{2n} \\ p_{31} & p_{32} & p_{33} & \cdots & \cdots & p_{3n} \\ \vdots & \vdots & \vdots & \ddots & \ddots & \vdots \\ \vdots & \vdots & \vdots & \ddots & \ddots & \vdots \\ p & p & p_{m3} & \cdots & \cdots & p_{mn} \end{bmatrix} \quad (5)$$

Furthermore, p_{ij} is the result of i^{th} alternative concerning the j^{th} attribute.

Step 2: The normalized matrix can be obtained by using the following expression as shown in Equation (6):

$$s_{ij} = \frac{p_{ij}}{\sqrt{\sum_{i=1}^{m} p_{ij}^2}} \quad j = 1,\ 2, \ldots, n. \quad (6)$$

where, s_{ij} is the normalized value of i^{th} alternative concerning the j^{th} attribute.

Step 3: The value assigned to each attribute is assumed to be $w_j(j = 1, 2, \ldots, n)$. After the application of assigning weights, the weighted normalized decision matrix $U = [s_{ij}]$ can be obtained as:

$$U = w_j s_{ij} \quad (7)$$

where, $\sum_{j=1}^{m} w_j = 1$.

Step 4: To obtain the best possible positive and negative ideal solutions using the following expression:

$$X^{+} = \left\{ \left(\sum_i^{max} u_{ij} | j \in J \right), \left(\sum_i^{min} | j \in J | i = 1, 2, \ldots\ldots m \right) \right\} \\ = \left\{ u_1^{+}, u_2^{+}, u_3^{+}, \ldots\ldots\ldots, u_n^{+} \right\} \tag{8}$$

$$X^{-} = \left\{ \left(\sum_i^{min} u_{ij} \middle| j \in J \right), \left(\sum_i^{max} | j \in J | i = 1, 2, \ldots\ldots m \right) \right\} \\ = \left\{ u_1^{-}, u_2^{-}, u_3^{-}, \ldots\ldots\ldots, u_n^{-} \right\} \tag{9}$$

Step 5: The difference between positive alternative solution given by the expression (10):

$$S_i^{+} = \sqrt{\sum_{j=1}^{n} \left(x_{ij} - x_j^{+} \right)^2}, \ i = 1,\ 2,\ \ldots,\ m \tag{10}$$

The difference between alternatives for the negative alternative solution is given by Equation (11):

$$S_i^{-} = \sqrt{\sum_{j=1}^{n} \left(x_{ij} - x_j^{-} \right)^2}, \ i = 1,\ 2,\ \ldots,\ m \tag{11}$$

Step 6: The relative closeness of the ideal solution to the far away distinct value is calculated by the equation:

$$P_i = \frac{S_i^{-}}{S_i^{+} + S_i^{-}} \ i = 1,\ 2,\ \ldots,\ m \tag{12}$$

Step 7: The P_i value is arranged in descending order to mark the most preferred and least preferred solutions [14].

Based on the above steps, the 27 sets of experiments are ranked by applying the TOPSIS technique, and it is found that experiments performed with coolant temperatures close to 0 °C have high ranks compared with coolants used at higher temperatures. Table 7 shows the experimental details and ranking of different sets of experiments derived by the TOPSIS method.

Table 7. Ranking by TOPSIS method.

Sr. No	Controllable Process Parameter				Experimental Results				TOPSIS			
	t	*v*	*f*	*d*	R_a (μm)	F_c (N)	TWR (μm)	MRR (gm/min)	Si+	Si-	Pf	Rank
1	15	78	100	0.5	2.5	660	154	51	0.05	0.02	0.288	25
2	15	78	200	1.0	2.62	690	156	56	0.05	0.02	0.28	26
3	15	78	300	1.5	2.76	720	162	62	0.051	0.02	0.273	27
4	15	160	100	1.0	2.38	760	158	61	0.043	0.02	0.344	22
5	15	160	200	1.5	2.48	780	165	67	0.043	0.02	0.34	23
6	15	160	300	0.5	2.3	790	184	78	0.037	0.03	0.444	17
7	15	235	100	1.5	2.02	930	190	73	0.036	0.03	0.466	15
8	15	235	200	0.5	2.2	945	188	75	0.039	0.03	0.416	21
9	15	235	300	1.0	2.12	985	232	80	0.04	0.03	0.44	18
10	8	78	100	1.0	2.26	685	157	68	0.036	0.03	0.435	19
11	8	78	200	1.5	2.5	725	150	60	0.046	0.02	0.327	24
12	8	78	300	0.5	2.12	698	156	68	0.038	0.03	0.416	20
13	8	160	100	1.5	2.32	760	162	70	0.031	0.04	0.532	12
14	8	160	200	0.5	1.96	760	176	76	0.03	0.04	0.546	10
15	8	160	300	1.0	2.09	810	182	83	0.031	0.04	0.534	11

Table 7. *Cont.*

Sr. No	Controllable Process Parameter				Experimental Results				TOPSIS			
	t	*v*	*f*	*d*	R_a (μm)	F_c (N)	TWR (μm)	MRR (gm/min)	Si+	Si-	Pf	Rank
16	8	235	100	0.5	2.00	875	172	68	0.035	0.03	0.467	14
17	8	235	200	1.0	1.9	970	190	76	0.034	0.04	0.511	13
18	8	235	300	1.5	2.32	985	220	91	0.041	0.04	0.465	16
19	0	78	100	1.5	2.1	685	146	78	0.029	0.04	0.557	9
20	0	78	200	0.5	1.8	685	150	80	0.023	0.04	0.65	2
21	0	78	300	1.0	1.5	795	158	80	0.024	0.05	0.671	1
22	0	160	100	0.5	1.5	795	165	74	0.027	0.05	0.637	3
23	0	160	200	1.0.	1.7	785	175	80	0.026	0.04	0.63	4
24	0	160	300	1.5	1.75	829	215	86	0.029	0.04	0.599	6
25	0	235	100	1.0	1.7	868	186	86	0.027	0.05	0.628	5
26	0	235	200	1.5	2.72	990	212	87	0.032	0.04	0.581	8
27	0	235	300	0.5	2.78	950	200	88	0.031	0.04	0.59	7

3.4. Multi-Objective Optimization Using the GRG Technique

The GRG technique is well-known for making optimum use of the resources at hand by adhering to the best possible combinations of input process parameters [15]. The individual setting of the input parameter, at its best conditions for a defined response output parameter, may not be favorable for the rest of the other parameters; hence, optimization of multi-objective input parameters was carried out. All the input parameter values are normalized with the minimum value as zero and maximum as one and converted into a single problem in this technique. The system's overall performance is calculated, known as the GRG, and the overall ranking depends on the GRG score [16]. This technique can easily solve a multi-attribute input process optimization. The highest obtained value of GRG will be considered as the optimal solution with combinations of input parameters. The 'higher the better' principle in the grey relation technique is explained in mathematical form in the given Equations (13) and (14) as:

$$x_i(p) = \frac{y_i(p) - miny_i(p)}{maxy_i(p) - \ miny_i(p)} \tag{13}$$

The 'lower the better' condition is specified as:

$$x_i(r) = \frac{maxy_i - y_i(r)}{maxy_i(r) - miny_i(r)} \tag{14}$$

where, $\mathrm{x_i}(p)$ is calculated as GRG and $min\ y_i\ (p)$ is the minimum numeric value of $y_i(p)$ for the i^{th} response and the value $max\ y_i(p)$ is the maximum value for the i^{th} response, where p = 1, 2, 3, 4 for the various output responses considered in the experiment. The values obtained after normalization are shown in Table 8. The GRG is calculated to establish a correlation between the data obtained by the normalized procedure and the finest data. The GRG is calculated as given in Equation (15):

$$\xi_i(I) = \frac{\Delta_{min} + \Psi\Delta_{max}}{\Delta_{oi}(I) + \Psi\Delta_{max}} \tag{15}$$

where, $\Delta_{oi}(p) = |x_0(p) - x_i(p)|$, Ψ value is between $0 \leq \Psi \leq 1$. Δ_{min} is the lowest value for Δ_{oi} and Δ_{max} is the highest value for Δ_{oi} [17]. The final equation of GRG is represented in the form of Equation (16):

$$\gamma_\mathrm{i} = \frac{1}{\mathrm{n}}\sum_{1=1}^{\mathrm{n}} \xi_\mathrm{i}(\mathrm{I}) \tag{16}$$

Table 8. Ranking by GRG method.

Sr. No	Controllable Process Parameter				Experiment Results				Ranking	
	t	*v*	*f*	*d*	Ra (µm)	Fc (N)	TWR (µm)	MRR (gm/min)	GRG Value	Rank
1	15	78	100	0.5	2.5	660	154	51	0.405408	8
2	15	78	200	1.0	2.62	690	156	56	0.347549	18
3	15	78	300	1.5	2.76	720	162	62	0.329532	19
4	15	160	100	1.0	2.38	760	158	61	0.322827	20
5	15	160	200	1.5	2.48	780	165	67	0.30351	23
6	15	160	300	0.5	2.3	790	184	78	0.313928	21
7	15	235	100	1.5	2.02	930	190	73	0.274642	25
8	15	235	200	0.5	2.2	945	188	75	0.260159	27
9	15	235	300	1.0	2.12	985	232	80	0.265834	26
10	8	78	100	1.0	2.26	685	157	68	0.413587	6
11	8	78	200	1.5	2.5	725	150	60	0.3666	13
12	8	78	300	0.5	2.32	698	156	68	0.394966	10
13	8	160	100	1.5	1.92	760	162	70	0.361912	14
14	8	160	200	0.5	1.96	760	176	76	0.352312	15
15	8	160	300	1.0	2.09	810	182	83	0.351373	16
16	8	235	100	0.5	2.0	875	172	68	0.308119	22
17	8	235	200	1.0	1.9	970	190	76	0.291863	24
18	8	235	300	1.5	2.32	985	220	91	0.395687	9
19	0	78	100	1.5	2.1	685	146	78	0.502661	4
20	0	78	200	0.5	1.8	685	150	80	0.58433	2
21	0	78	300	1.0	1.5	795	158	80	0.611209	1
22	0	160	100	0.5	1.5	795	165	74	0.568309	3
23	0	160	200	1.0.	1.7	785	175	80	0.422897	5
24	0	160	300	1.5	1.75	829	215	86	0.387907	11
25	0	235	100	1.0	1.7	868	186	86	0.408177	7
26	0	235	200	1.5	1.72	990	212	87	0.379891	12
27	0	235	300	0.5	1.78	950	200	88	0.348573	17

Table 8 shows the preference ranking obtained by the GRG method; the value of GRG is calculated based on Equation (16). The experiment runs no. 21 (machining with the coolant at 0 °C, cutting velocity at 78 m/min, feed rate at 300 mm/min, and depth of cut at 1.0 mm) is the preferred rank for the given set of input parameters. The recommended parameters are quite distinct from the currently used parameter (machining with the coolant at 0 °C, cutting velocity at 78 m/min, feed rate at 300 mm/min, and depth of cut at 1.0 mm), but are matching with the optimized parameters recommended by TOPSIS, as it also suggests experiment run no.21 as the best optimized input parameters.

4. Results and Discussion

4.1. Verification of Results and Effectiveness of Low-Temperature Machining

The primary objective of this research is to analyze the effects of lowering the coolant temperature and optimizing other input parameters to have sizeable positive effect on the output parameters. After implementing the TOPSIS and GRG approaches of preferential ranking systems to determine the best optimization of input parameters, rankings of optimization are highly inclined towards 0 °C suggesting that machining should be performed at 0 °C to achieve better output responses. The first three preference rankings obtained by using both approaches have matched each other, which confirmed that lowering the coolant temperature and using it for machining will be very beneficial compared to using coolant at room temperatures.

Table 9 shows preference ranking obtained by the TOPSIS and GRG methods; both techniques confirm the serial number 21 as the preferred rank. The preferred rank recommends the optimal conditions, which have to be used for obtaining better output responses. The reduction in coolant temperature results in more minor tool wear and better tool life; the abrogation to this is the better heat dissipation from the tool–work contact area. The retention in the tool edge also leads to a better surface finish of the workpiece. The material remove rate has been increased with more minor tool wear as the optimized parameter suggests an increase in cutting velocity and feed rate.

Table 9. Comparison of ranking by TOPSIS and GRG methods.

Exp. run no	Temp (°C)	Velocity (m/min)	Feed (m/min)	Depth of Cut (mm)	TOPSIS Ranking	GRG Ranking
19	0	78	100	1.5	9	4
20	0	78	200	0.5	2	2
21	0	78	300	1.0	1	1
22	0	160	100	0.5	3	3
23	0	160	200	1.0.	4	5
24	0	160	300	1.5	6	11
25	0	235	100	1.0	5	7
26	0	235	200	1.5	8	12
27	0	235	300	0.5	7	17

Table 10 shows the optimal conditions used to date in practice, and a new set of variables recommended by the optimization process. The optimal conditions of the current practice were determined based on the recommendations given by tool manufacturers and experience obtained in the long run for best product quality with minimum cost. There is variation in the recommended and actual values used for machining SS304. The optimization of the available input process parameters, including coolant temperature, is recommended to increase the efficiency of the process. It will result in better process control of the process and will be more economical when compared with the cryogenic machining process. The impact of changes in output parameters is subsequently discussed in Table 11.

Table 10. Comparison of optimized parameters obtained by TOPSIS and GRG methods with conventionally used parameters.

Parameters	Traditionally Used Parameter	Optimal Recommended Process Parameter		Parameter Change Due to Recommendation
		TOPSIS	GRG	TOPSIS/GRG
Temperature (°C)	Ambient temp (28)	0	0	−28
Cutting velocity (m/min)	60	78	78	+18
Feed rate (mm/min)	200	300	300	+100
Depth of cut (mm)	0.8	1.0	1.0	+0.2

Table 11 indicates the differences in the output responses in terms of percentage when the existing input parameters are replaced with new optimal parameters. The results obtained by using modified optimal parameters are highly motivating and has revealed encouraging results, which verified the proposed theory that using coolant close to 0 °C will have excellent results regarding output parameters, such as improvement in surface finish, reduction in tool wear rate, and the simultaneous increase in material removal rate and cutting forces.

Table 11. Percent changes of the optimized parameter with initial parameter setting.

Parameters with Its Unit	Results with Traditionally Used Parameters	Results with Recommended Optimal Process Parameters	Percentage Change in Result at the Optimum Cutting Conditions over Initial Parameter Setting
		TOPSIS and GRG	TOPSIS and GRG
F_c (N)	780	795	15% increase
R_a (μm)	2.3	1.5	34% reduction
TWR (μm)	165	158	4.2% reduction
MRR (gm/min)	67	80	19.4% increase

Furthermore, to analyze the effects of the input process variables on the performance characteristics prioritized using both approaches, i.e., TOPSIS and GRG, an ANOVA with a 95% confidence interval technique is used. MINITAB software is used to verify the result performance with the 'higher the better concept'. Table 12 shows the response table for the preferred solution. It is perceived that the temperature of the coolant, cutting velocity, and depth of cut make significant contributions towards the improvement in the output process parameters. The response table reveals that the cutting velocity, the temperature of the coolant, feed rate, and depth of cut are significant in hierarchal order as per their impact on output response. This justifies that the coolant temperature plays a crucial role in machining the hard materials, such as SS304, and the optimization of other input parameters can result in significant improvement in output parameters.

Table 12. Response table for preferred solution technique.

Level	Cutting Velocity	Temperature	Feed Rate	Depth of Cut
1	0.6265	0.7912	0.8354	0.8125
2	0.8230	0.8325	0.8232	0.7685
3	0.9012	0.6589	0.6925	0.6985
Delta	0.2747	0.1736	0.1429	0.1140
Rank	1	2	3	4

4.2. Tool Wear Rate

The efficacy of any machining process can be enhanced by maximizing the rate of material removal with minimum tool wear. The tool wear rate can be minimized with less erosion of the tool, which is primarily due to crater wear. When tool material comes in contact with the workpiece, chips are formed, eroding the tool's rake face. The chips developed during the process take away 75 percent of the heat generated during the machining process, and the remaining heat is carried away by the tool and coolant used in the machining process. An increase in temperature makes the tool material softer and the tools are easily eroded. Therefore, by providing a more efficient method of heat dissipation by using the low temperature of the coolant, the tool wear rate is reduced considerably, and this is evident from the experimentation carried out in this research work [18]. From the experiment results, it has been confirmed that when machining is done at a 0 °C temperature, the material removal rate is higher with enhanced tool life than that of machining with ambient temperatures. The TOPSIS and grey relation method l ranking systems have also verified the experimentation results by providing the same preference ranking to optimized parameters.

To examine the crater wear of the tool, a sample of the tool inserts is examined under SEM. The crater wear of the tool with currently/traditionally used parameters are shown in Figure 2 (machining at ambient temperature, cutting velocity at 60 m/min, feed rate at 200 mm/min, and depth of cut at 0.8 mm), whereas, Figure 3 depicts the crater wear with suggested optimal parameters derived using the TOPSIS or GRG ranking methods (coolant at 0 °C, cutting velocity at 78 m/min, feed rate at 300 mm/min, and depth of cut at 1.0 mm). It is clear from comparing the two images that the current set of parameters causes a significant amount of abrasion wear from the crater surface that results in depression and chipping off of the tool face, whereas the suggested machining parameters value results in a significantly smaller amount of distortion. In a traditional setup, wear is brought on by thermal distortion of the chip face, which makes fine tool segments easily break off. Significantly less distortion of the tool rake face is due to effective heat disposal due to the reduction in coolant temperature [19].

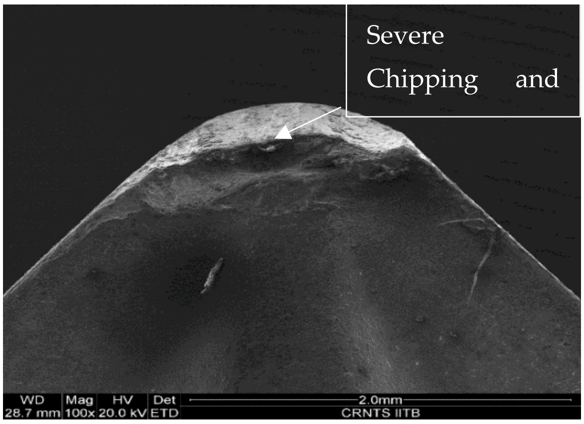

Figure 2. Crater wear with the initial recommended/used parameters.

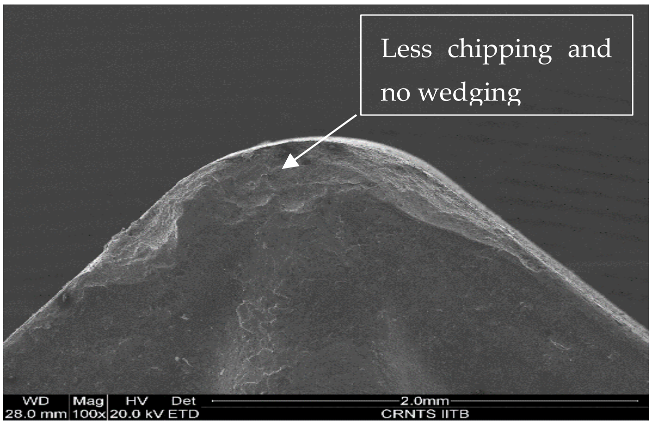

Figure 3. Crater wear with optimized parameters.

The tool's flank wear has a significant impact on both the tool's life and the work piece's surface quality, especially when it comes to strain hardening like the SS304 materials, which are very challenging to machine [20]. The tool flank wear was measured for the inserts, which had machined the sample workpiece for the conventionally recommended parameters, and also for the suggested optimized parameters. It is evident from the above crater wear images that tool life is increased with the optimized parameters when compared to the traditional parameters, as the erosion of the tool is less with the optimized parameters due to better heat dissipation.

4.3. Impact of Input Cutting Parameters on Surface Roughness

The functional performance of any engineering product depends upon the various criteria, and surface finish is one of the most important among them. From the available literature, it is evident that the surface roughness decreases as cutting speed increases, and it increases with an increase in feed rate and depth of cut. Along with cutting speed, built up edge, heat dissipation from the interface zone, and the retention of the tool edge also play a crucial role [4]. The coolant temperature also had a significant impact on the surface roughness value; with a reduction in coolant temperature better surface quality is obtained, especially for difficult-to-cut materials, such as SS304 [21]. Using optimal parameters, as suggested by the TOPSIS and GRG techniques, there is a 34% improvement in surface finish compared with the current parameters, and the abrogation is due to better heat dissipation and low built-up edge on the tool face.

The retention of the cutting edge sharpness plays a vital role in surface finish, and it degrades as machining time is increased due to wear of tool edge. Figure 4 represents the wear and tear of the flank surface of the tool when machined with traditional cutting parameters with coolant at an ambient temperature (machining at an ambient temperature, cutting velocity at 60 m/min, feed rate at 200 mm/min, and depth of cut at 0.8 mm). Figure 5 represents the wear and tear of the flank with optimal parameters suggested by the TOPSIS and GRG ranking techniques (machining with coolant at 0 °C, cutting velocity at 78 m/min, feed at 300 mm/min, and depth of cut at 1.0 mm). The workpiece was found adhered to the tool surface; this is due to the ploughing and spallation effects that usually occur due to improper cooling on the surface, which is not a desired phenomenon during the machining operation as it results in abrasion wear. Furthermore, tool wear results in an inferior surface finish. The adhering phenomenon was not found when the machining is done with coolant at 0 °C and using the suggested optimized parameters by TOPSIS/GRG methods.

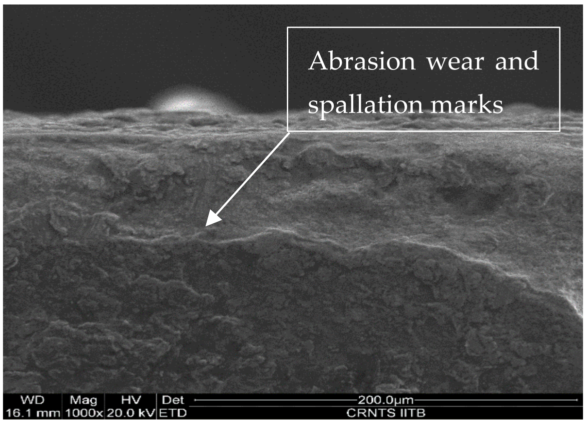

Figure 4. Flank wear of tool with traditional/initial parameters.

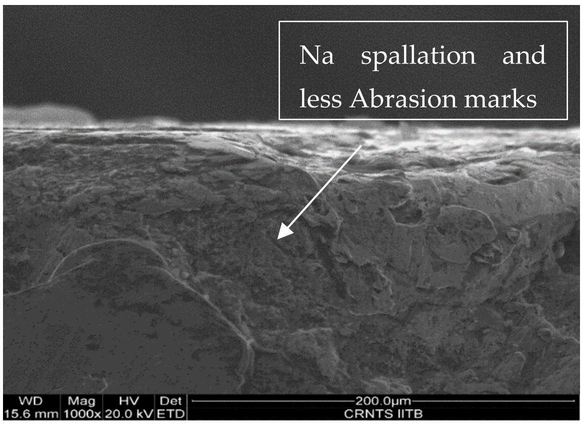

Figure 5. Flank wear of tool with optimized parameters.

The ploughing and spallation effect was observed in the form of fine particle abrogation from the tool surface and the same can be verified from Figure 4; however, this phenomenon is observed to be negligible when machining is done with low-temperature coolant; as observed in Figure 5, there is less abrasion and no spallation mark. Heat dissipation at a faster rate helps retain the cutting edge sharpness, and also, less thermal distortion leads to minimizing the wear of the tool flank surface, resulting in better surface roughness [21].

4.4. Chips Morphology

High cutting forces are needed to process work hardening and high strength alloys, such as SS304, Titanium, and nickel-based alloys, which causes heat concentration in the work–tool zone contact area and increased tool wear and tear, which leads to poor surface finish. Additionally, it contributes to built-up edge chips that is produced during the machining process [22]. The chip generation is influenced by several parameters, such as cutting velocity, feed rate, depth of cut, and temperature generation due to the friction of the tool and workpiece, etc. Since the built-up edge results in a poor surface finish, it should be avoided. Moreover, the tearing of the surface from the workpiece should be uniform, resulting in good quality surface finish [23].

The work piece samples machined with traditional machining parameters and optimized parameters were put to the test under SEM to obtain high-resolution images. Figure 6 depicts the workpiece sample's SEM image, which is machined by using the conventional input parameters, while Figure 7 represents the SEM image of the workpiece sample machined by using the suggested/modified parameters. It is evident that the fracture of surfaces obtained with conventional machining parameters is uneven and highly distorted as crack propagation during plastic deformation is uneven at a fluctuating rate compared with the modified machining parameters, where the propagation of cracks is uniform, leading to an even plastic deformation and generation of a smooth surface. On the other hand, the decrease in thermal distortion and retaining of cutting-edge sharpness also attributes to fine, even surface generation and more uniformity across chip generations [24]. The suggested optimized parameters are providing more affirmative results and are highly recommended for machine SS304 with the given machine conditions.

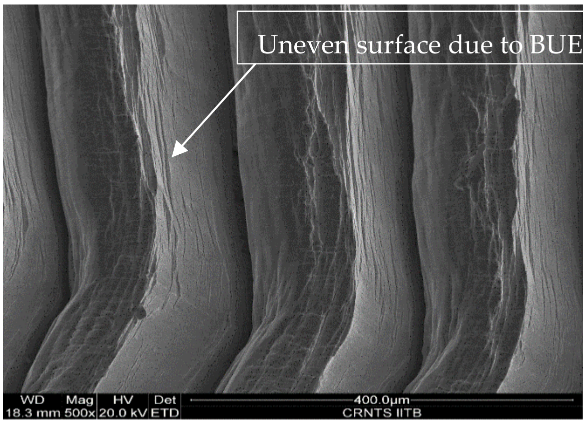

Figure 6. Chips cross-section with initial parameters.

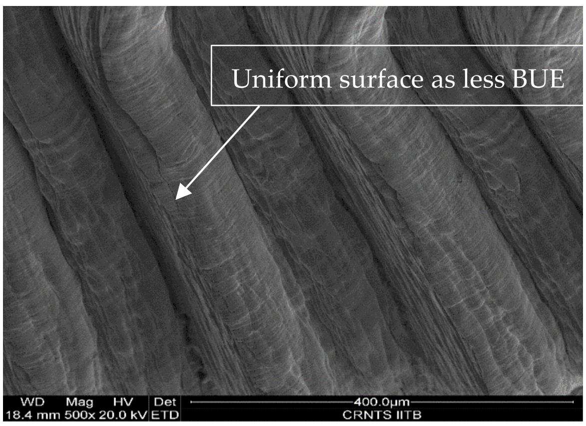

Figure 7. Chips cross-section by using proposed optimized parameters.

5. Conclusions

The literature available in the public domain related to cryogenic machining of SS304 with respect to tool life and the surface finish had eminently established improvement in workpiece properties; however, the machining of materials using a cryogenic coolant has limitations because of safety risk and technical feasibility. The experimental research was conducted with the major objective to investigate the effect of a reduction in the temperature of emulsion coolant on the machining parameters along with the optimization of input machining parameters. The coolant temperature of 0 °C provided the best optimized condition. The limitations of cryogenic machining have been overcome in the current system with a net result of close to 50 percent improvement in output parameters compared with cryogenic machining. The concluding remarks for the work are stated below:

1. The research work suggests that the parameters used on the turning CNC lathe for machining SS304 may be replaced with the recommended parameters, if possible, (machining with coolant at 0 °C, cutting velocity at 78 m/min, feed rate at 300 mm/min, and depth of cut at 1.0 mm), which will result in improvements in the tool life, surface finish, and material removal rate for the given machine conditions.
2. The recommended input parameters are based on optimizing the input parameters and are duly verified by the TOPSIS and GRG preferential ranking techniques.
3. Based on the examinations of the SEM images, it is verified physically that there is a considerable reduction in tool wear with the suggested input parameters compared with the conventional or traditional parameters currently being used.
4. ANOVA revealed that temperature, cutting velocity, feed rate, and depth of cut have more significance as per their serial order mentioned above on machining of SS304.

The outcome of the present research work is highly recommended to the industries that deal with the machining of hard materials since it will improve the machining quality of the jobs and reduce the running costs to machine the hard materials.

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