Machinability Investigation and Optimization of Process Parameters in Cryogenic Assisted Sustainable Turning of AISI-L6 Tool Steel

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Abstract: The application of cutting fluid is significantly increased in the machining sector to improve productivity. However, the inherent characteristics of cutting fluids on ecology, environment, and society shift the interest of researchers to work on environmentally friendly cooling conditions such as cryogenic cooling. Here, the effect of cutting speed and feed rate on the machining performance of the AISI-L6 tool steel is investigated under cryogenic cooling conditions. Then, the L9 Taguchi based grey relational analysis (GRA) is conducted to investigate the essential machining indices such as cutting energy, surface roughness, tool wear, and material removal rate (MRR). The results indicate that the cutting speed of 160 m/min and feed rate of 0.16 mm/r are the optimum parameters that significantly improves the machining performance of AISI-L6 tool steel.

Key words: sustainable manufacturing; cryogenic machining; hardened steel; energy consumption; tool life

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0 Introduction

Tool steel is famous for manufacturing cutting tools, hot dies, chisels, hammers, etc. The other application of this material involves the various manufacturing operations like deep drawing, wire drawing, and die casting, respectively[1]. In service, most tools are subjected to high and rapidly applied loads. Therefore, they must have the resistance to softening at elevated temperature, wear, deformation, and breakage[1-2]. The increased percentage of nickel, along with chromium and vanadium, enhances the hardenability of this material. These characteristics make it difficult to machine and reduce the tool life. Due to the long production times, the manufacturing costs are increased[3]. Most researchers were focused on machinability of materials, where cutting simulation was regarded as an important approach[4]. Recently, various cooling conditions have been applied to improve machining performance. The cutting fluids increase the efficiency of the cutting process. In addition, they provide better service quality and increase tool life. The cutting fluids have certain disadvantages as well. The conven-

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tional cutting fluids are a source of environmental pollution and health hazards. The recycling of these cutting fluids is also difficult and expensive[5]. Much research has been done on alternative strategies for cooling and lubrication in machining processes. Krolczyk et al.[6] have reviewed various cooling techniques from an ecological point of view. Five techniques were reviewed in detail during the research, namely dry cutting, minimum quantity lubrication (MQL), cryogenic cooling, high-pressure cooling, and biodegradable oils. According to the research, dry cutting is the best method as it eradicates the cutting fluids and is safe for workers.

Gupta et al.[7] have discussed the machinability of the Inconel-800 superalloy under sustainable cooling conditions for the turning process. They have compared the machining results of the near dry machining (NDM) technique with dry machining. MQL process is used in this research as the NDM technique. During the research, it was discovered that NDM reduced cutting forces by 4% to 9% as compared to the dry machining environment. This may occur due to the reduction in friction as a result of the reinforcement of lubrication provided by the cutting fluids.

The surface roughness was reduced by 3% to 10% under NDM conditions due to a reduction in gradient temperature in the cutting area, reduction of friction due to enhanced lubrication and prevention of early damage of the tooltip. Tool wear was reduced by 4% to 11% in NDM as compared to dry machining. This is because cutting fluid in combination with compressed air has almost abolished the crater on the rake surface. NDM generates small fragments of chips, whereas dry machining produced some unbroken, very long continuous chips. Moreover, NDM produced dry chips, which are a favorable result for cleaner production. The application of liquid nitrogen (LN_2), commonly called cryogenic cooling, is a lubrication technique that is under focus from a sustainable manufacturing point of view. It improves machinability by decreasing the cutting zone temperature. After being sprayed on the cutting zone, liquid nitrogen evaporates into the environment. Therefore, it has no health hazards and disposal problems, unlike conventional coolants[8]. Islam et al.[9] have investigated machining performance of hardened EN 24 steel under cryogenic cooling in comparison with dry and flood cooling conditions. During the study, it was discovered that the surface roughness was reduced under cryogenic cooling as compared to other conditions. This is due to the preservation of tool sharpness and better chip removal process. Mia et al.[10] have studied the influence of single and double cryogenic jets on machinability characteristics in turning of Ti-6Al-4V alloy. During the study, it was concluded with a single cryogenic jet, there was a reduction in specific cutting energy, chip-tool interface temperature, and surface roughness by 8%, 5%, and 8%, respectively. Mia[11] investigated the machining parameters under cryogenic cooling conditions. The study concluded that cryogenic cooling reduced cutting force, specific cutting energy, and improved surface finish as compared to dry cutting and conventional cutting oil applications. In another work of Mia et al.[12], the benefits in terms of cutting forces and surface roughness of cryogenic cooling were investigated during turning of Ti-6Al-4V alloy. Kursuncu et al.[13] discussed the effect of cryogenic treatment in the machining of Inconel 718 alloy. Koneshlou et al.[14] have studied the effect of cryogenic treatment on microstructure, mechanical, and wear behaviors of AISI H13 tool steel. During the study, they observed that cryogenically treated samples of the aforementioned tool-steel showed less wear as compared to untreated ones. Huang et al.[15] discussed the microstructure of cryogenic treated M2 tool steel. Revuru et al.[16] have reviewed the performance of cutting fluids in the machining of titanium alloys. According to the review, cryogenic cooling is an effective alternative to conventional cutting fluids and MQL. It reduces cutting forces, helps to increase tool life, reduces friction, and improves the surface quality of the finished products. Moreover, the cryogenic cooling process results in active chip breaking and smaller chip contact length.

Several statistical techniques are used to design the experiments such as response surface methodology (RSM) based central composite design

(CCD)[17], Box-Behnken design (BBD), artificial neural network (ANN)[18], and factorial method (full-factorial, half-factorial)[19], grey relational analysis (GRA), and Taguchi method[20], etc. Among several techniques applied for the design of experiments, Taguchi has got attention due to ease in application, having the capability to provide a minimum combination of experiments accommodating several parameters having different levels of parameters. Also, GRA has the capability to find the optimal combination of parameters having multiple performance measures.

Much focus in recent times has been on sustainable development through cooling techniques that can achieve near dry machining[21]. However, not much research work can be found on the optimization of cutting parameters for tool steels from the sustainability point of view. Even less research work can be identified for low alloy L series tool steels. Patel et al.[22] have performed analysis and modeling of surface roughness based on cutting parameters and tool nose radius in turning of AISI D2 steel. During their research, they found a linear relationship of surface roughness with cutting speed, feed, and nose radius. High surface quality was achieved for low feed value, high cutting speed, and large nose radius. Pathak et al.[23] have optimized cutting parameters in dry turning of AISI A2 tool steel for surface roughness and cutting force components. The research concluded that optimum results are obtained at minimum values of cutting speed, feed, and depth of cut.

From the literature, it was identified that the machining sector is searching for a sustainable and environmentally friendly cooling system to cope up with the low productivity, surface quality, and energy consumption type challenges. Cryogenic LN_2 is reported as efficient for the machining of hard-to-cut AISI-L6 steel. Also, literature depicts that optimization techniques to determine the optimum level of parameters are useful to achieve the actual experimental conditions. In this study, an attempt has been made to machine AISI-L6 tool steel under cryogenic LN_2. Also, Taguchi based GRA was used for multi-response optimization to get the optimal experimental conditions. The controllable parameters are cutting speed and feed rate, whereas performance measures are surface roughness, tool wear, energy consumption, and material removal rate.

1 Experimental Setup

Tool steel AISI-L6 is being taken as a workpiece material having hardness about 58 HRC. The chemical, physical, and mechanical properties of workpiece material are provided in Tables 1,2.

The length of the workpiece was 100 mm, and the diameter was 50 mm. All the turning tests were performed by using CK 4060CNC turning machine having a maximum spindle speed of 12 000 r/min and equipped with an 8 kW drive motor. The uncoated carbide tool number YG-8 and CNMG tool holder assembly were used. The tool geometry was as follows: the rake angle was $-1°$, and the tool clearance angle was $10°—12°$[24]. The new tool was used for every cut.

Table 1 Chemical composition of AISI-L6 tool steel

C	Mn	Si	Cr	V	Ni	Mo
0.65—0.75	0.25—0.8	0.25	0.6—1.2	0.2—0.3	1.25—2	0.5 (max)

Table 2 Physical and mechanical properties of AISI-L6 tool steel

Property	Value
Modulus of elasticity / ($10^3 N \cdot mm^{-2}$)	215
Density / ($g \cdot cm^{-3}$)	7.84
Specific heat capacity / ($J \cdot (g \cdot K)^{-1}$)	0.46
Elastic modulus / GPa	190—210
Thermal conductivity / ($W \cdot (m \cdot K)^{-1}$)	36.0
Electric resistivity / ($\Omega \cdot mm^2 \cdot m^{-1}$)	0.30
Poisson's ratio	0.27—0.30
Hardness	58 Rockwell C

The machining process chosen for our research was turning, and the cooling environment was cryogenic cooling. The tests were performed with three values of cutting speed, i.e., 100, 130, and 160 m/min, three different levels of feed rate, which were 0.08, 0.12 and 0.16 mm/r and a constant depth of cut equal to 1 mm. The range of cutting conditions was selected from the recommendations of the manufacturer's handbook. In this study, Taguchi's L9 orthogonal array (OA) is used from Minitab. The orthogonal array used has nine rows and three columns. The rows represent the number of tests, whereas the columns indicate the process parameters along with levels. The first, second, and third columns in this paper represent cutting speed, feed rate, and cooling conditions, respectively.

2 Measurement of Responses

Three parameters were measured, which are surface roughness, cutting energy, and tool wear. Surface roughness is a significant quality indicator of the machining process. In the current research, the surface roughness values were measured at different locations through Mehr Perthometer SJ-410 on the workpiece, and then meant the value of the surface roughness was calculated. This method helped to increase the accuracy of the results. Cutting energy is another important parameter that is related to the machining efficiency of the product. Cutting energy in the present work was measured through PPC current clamps. The MRR is another critical parameter in machining, which needs to be maximized to achieve the optimum results. It is the product of cutting speed, feed rate, and depth of cut. The tool wear is a crucial machining parameter that directly affects production time and the overall cost of the product. The tool wear is decided based upon three criteria: (1) Average width of flank wear (VBavg), (2) maximum flank wear (VBmax), and (3) notch wear at the depth-of-cut-line (VB-notch or VNmax)[5]. In this study, maximum flank wear (VBmax) is only considered as the parameter of wear. The measurements were carried out on workpiece material until the experimental process was completed, and finally, an average value of tool wear was calculated.

3 Results and Discussion

This section describes the surface roughness, cutting energy, MRR, and tool wear. The subsequent analysis is presented in the sections below. The summary of the experimental results is presented in Table 3.

Table 3 Taguchi L9 array depicting the effect of parameters on performance measures

No.	Cutting speed/ $(m\cdot min^{-1})$	Feed rate/ $(mm\cdot r^{-1})$	Surface roughness Ra	Cutting energy/J	MRR/mm^3	Tool wear/ nm
1	100	0.08	1.33	296 842	8 000	182
2	100	0.12	1.45	341 265	12 000	148
3	100	0.16	1.71	406 852	16 000	116
4	130	0.08	1.22	376 852	10 400	156
5	130	0.12	1.35	437 387	15 600	131
6	130	0.16	1.54	495 261	20 800	102
7	160	0.08	1.1	469 582	12 800	126
8	160	0.12	1.22	521 268	19 200	109
9	160	0.16	1.41	576 592	25 600	78

3.1 Taguchi method

Taguchi developed a statistical approach to design the experiments[25]. This technique has accumulated the design of experiments from different world statisticians and different fields to mold it according to the requirements in the manufacturing field. Also, it was made easy for the practitioners to apply, considering fewer experimental designs, providing a clear understanding of performance measures variation at different levels of parameters, accommodating the economic burden of all the combination increases the number of experiments. Under the manufacturing domains, following design are applied:

(1) Design any process/product and robust by considering the real conditions.

(2) Design any process/product and robust considering each component variation on target.

(3) Decrease the alterations across target value.

During system design, engineering and scientific knowledge is applied to produce a prototype design. It includes product design, process design, and optimization stage. At the process design stage, optimization of the range of parameters to improve their effect on performance measures under optimal values. Besides, it is assumed that the optimal range of process parameters are insensitive to environmental conditions or noise factor. Classical full factorial design[26] provides a large number of experiments, while Taguchi uses an orthogonal array to design the smallest number of experiments considering the entire parameter space. After deciding the appropriate orthogonal array, the Taguchi loss function is defined to determine the deviation of performance measure from the desired value. The orthogonal array has the flexibility to accommodate multiple process parameters, with each having different parameter levels. The loss function is simply transformed to signal to noise ratio (S/N-ratio).

For the analysis of parameters, S/N ratio is calculated according to the desirability/performance characteristic of the performance measure, such as lower-the-better, nominal-the-better, and higher-the-better. Regardless of the performance characteristic, the larger S/N ratio corresponds to better performance. Therefore, the highest S/N ratio is a desirable level in the analysis. Furthermore, analysis of variance (ANOA) is done to evaluate which parameter has contributed to what percentage. Also, mathematical models for each specific performance measure can be determined considering all the parameters simultaneously. The 3D surface plots can be achieved to calculate the simultaneous response of two parameters on the performance measure.

The effect of cutting speed and feed rate on surface roughness, cutting energy, MRR, and tool wear are presented, respectively.

3.2 Surface roughness

The surface roughness of the machined surface is one of the most important parameters in the machinability of materials. The effect of machining parameters on surface roughness is evaluated using a portable spectrometer, as shown in Fig.1.

Fig.1 Surface roughness during the turning process

From Fig.2, it can be seen that surface roughness is inversely proportional to the cutting speed. So, by increasing the cutting speed from 100 m/min to 160 m/min. There is a decrease in surface roughness, resulting in better surface quality at higher cutting speeds. The straight-line slope shows that the relation between these two factors is linear. This can be attributed to the fact that at lower cutting speeds, the tool has a high amount of wear owing to an earlier wear cycle. Secondly, at lower cutting speeds, BUE and BUL areas on the tool's cutting-edge form a protrusion in the cutting directly from the tool to the workpiece, these coating layers of materials result in changes to the depth of cut and tool geometry. As a result, the irregular geometry contacts with the material being machined, causing surface roughness to increase. On the other hand, the feed rate is directly proportional to the surface roughness. By increasing the feed rate from 0.08 mm/r to 0.16 mm/r, the surface roughness is

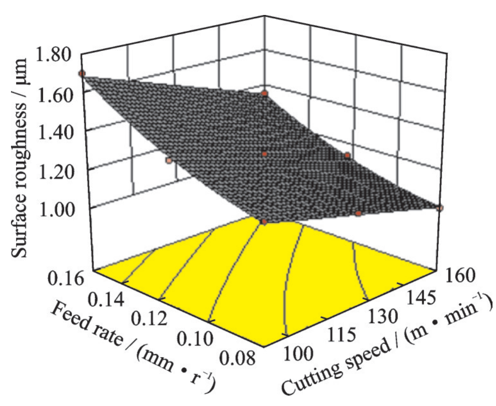

Fig.2 3D response surface of feed and cutting speed on surface roughness increased. For all three levels of cutting speed, the increment in surface roughness from 0.08 mm/r to 0.12 mm/r is small as compared to the increment from 0.12 mm/r to 0.16 mm/r. The increase in surface roughness with the increase in feed rates can be attributed to the fact that the increase in feed rate caused an increase in feed force and volumes of material removed[26]. Sarikaya et al.[26] have also evaluated cutting parameters and cooling/lubrication methods in turning of Haynes 25 superalloy. According to their results, under dry, there was a decrease in surface roughness with an increase in cutting speed from 15 m/min to 45 m/min, and a slight increase in surface roughness from 45 m/min to 60 m/min, under dry, wet cooling and MQL conditions. Sarikaya et al.[27] have analyzed machining parameters in CNC turning under MQL conditions for AISI 1050 steel by using the Taguchi design and response surface methodology (RSM) method. They have performed cutting experiments under dry, wet cooling and MQL conditions. They have calculated surface roughness at cutting speeds from 80 m/min to 200 m/min and have also observed the best surface quality at the highest level of cutting speed. The results of the literature support current research result that surface roughness is inversely proportional to cutting speed.

Both of these factors increase surface roughness. Kumar et al.[28] have verified the effect of feed rates on surface roughness for five materials for the CNC turning process. The feed rate range for their experiments was from 0.05 mm/r to 0.15 mm/r. The value of spindle speed was kept in the range from 339 r/min to 980 r/min. In most materials, surface roughness increased with increase and especially at high levels of spindle speeds and in the range of feed rates from 0.1 mm/r to 0.15 mm/r. Therefore, the study concluded that high surface quality could be achieved at high spindle speeds and low feed rates. Bashir et al.[3] have studied the effect of feed rate on surface roughness for surface milling. According to their research, surface roughness was found to increase with an increase in feed rate from 22 m/min to 68 m/min under dry and MQL conditions, and the best surface quality was achieved at 22 m/min. The established results are in accordance with current research results concerning the relationship between surface roughness and feed rate.

3.3 Cutting energy

From Fig.3, it can be observed that cutting energy is directly proportional to the cutting speed. The cutting energy increases with the increase in cutting speed and feed rate. At all levels of feed rate, the relation between cutting speed and cutting energy is almost linear, the increments in cutting energy from 100 m/min to 130 m/min and from 130 m/min to 160 m/min are almost the same. From Fig.3, it can be observed that cutting energy is directly proportional to the cutting speed and feed rate. The relationships of cutting speed and feed rate with cutting energy are almost linear. At higher cutting speeds and feed rates, the axis motor needs to move faster. This results in an increase in cutting energy[10].

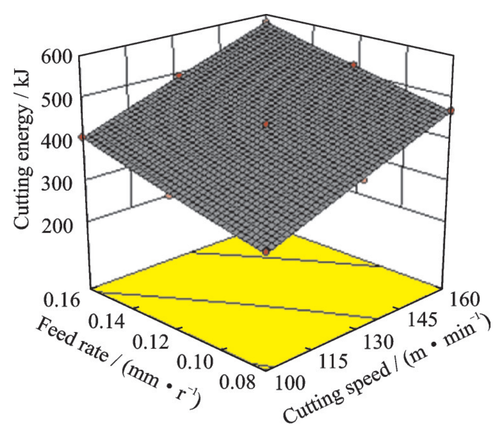

Fig.3 3D surface of feed and cutting speed on cutting energy

3.4 Material removal rate (MRR)

MRR is an output perimeter that is derived from cutting speed and feed rate. The mathematical relation between MRR and cutting parameters is provided in Eq. (1).

$$\mathrm{MRR} = V_c \times f \times a_p \tag{1}$$

where V_c is the cutting speed, f the feed rate, and a_p the the depth of cut. Theoretically, MRR is directly proportional to cutting speed, feed rate, and depth of cut, and the relationship is linear. In this paper, the depth of cut is constant, so the focus of this work is on the relationship of MRR with cutting speed and feed rate. The MRR is calculated from Eq. (1) for all experiments. Fig.4 shows that MRR is directly proportional to the cutting speed and feed rate. It is found to increase linearly with the increase of cutting speeds at all levels of feed rate, and vice versa.

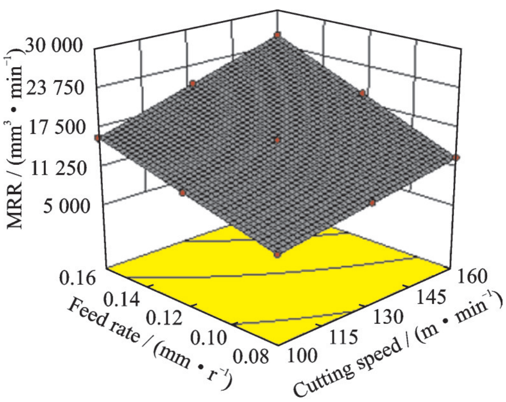

Fig.4 3D response surface of feed and cutting speed on MRR

According to the researches published by Mia et al.[29] and Gadekula et al.[30], MRR was found to be directly proportional to cutting speed and feed rate. The results of the literature on the effect of cutting speed and feed rate on MRR support the current research work.

3.5 Tool life

From Fig.5, it can be inferred that tool wear is inversely proportional to the cutting speed and feed rate. By increasing the cutting speed and feed rate, tool wear is decreased, and vice versa. The straight-line slope in both cases indicates that the relation of tool wear with cutting speed and feed rate is inversely linear. Tool wear here was flank wear, as shown in Fig.5.

Fig.6 shows that flank wear is directly proportional to the cutting speed and feed rate. The straight-line slope in both cases indicates that the relationship of tool wear with cutting speed and feed rate is linear. This can be attributed to thermal softening of tool material at higher cutting speeds and feed rates[11]. However, the effect of feed rate is more pronounced than the effect of cutting speed on tool wear.

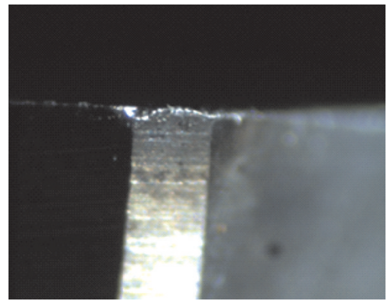

Fig.5 Flank wear patterns during the turning process

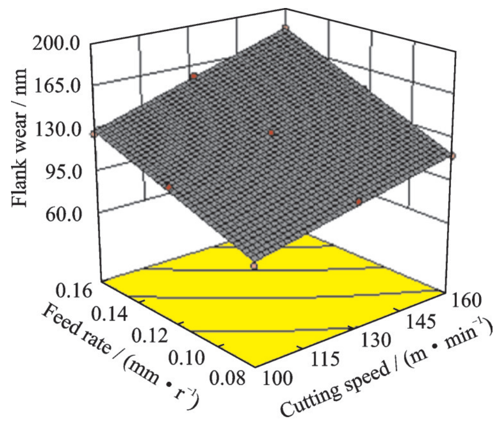

Fig.6 3D response surface of feed and cutting speed on flank wear

4 Grey Relation Analysis

When the performance measures are determined in different units owing to different attributes, it can influence the contribution of some performance measure. It will occur if some performance measures have substantial values, and some have the least. Besides, their goals (maximum, minimum), and direction are different, thereby leading to wrong interpretation or analysis. Therefore, it is essential to consider all the performance measures to a comparable sequence in terms of normalization. This process is named grey relational analysis (GRA). It analyzes a complicated uncertainty in several performance measures and optimizes it towards the target objective.

The response optimization is generally used for optimization problems. However, this method cannot be used when dealing with problems involving optimization of more than one parameter. For such problems, Taguchi based grey relational analysis (GRA) is used. The output parameters in this paper are surface roughness, cutting energy, MRR, and tool wear. The purpose of the GRA is to optimize all parameters, which means minimizing surface roughness, cutting energy and tool wear, and maximizing MRR. Taguchi based GRA is basically a statistical method, which includes a relational analysis of the uncertainty in the system model and lacks of information. It involves a correlation analysis of sequences with uncertainty and discrete data. It determines the degree of approximation through grey relational grade (GRG)[3]. In this work, GRG was determined in the first step after the normalization of the experimental results. By normalization, we mean that we make the range of each of the parameters from 0 to 1. This is known as grey relational generating. Three criteria are used in GRA, which are "larger-the-better" "smaller-the-better", and "nominal-the-best". In the current research, we aim to maximize the value of MRR. So, we use the "larger-the-better" criterion for MRR, which is represented by Eq. (2).

$$x_i(p)=\frac{x_i^p(p)-\min(x_i^0(p))}{\max(x_i^0(p))-\min(x_i^0(p))} \tag{2}$$

The aim of this paper is to minimize the value of cutting energy, surface roughness, and tool wear. Here, we use the "smaller the better" criterion for these factors, which are governed by

$$x_i(p)=\frac{\max(x_i^0(p))-x_i^0(p)}{\max(x_i^0(p))-\min(x_i^0(p))} \tag{3}$$

where $x_i(p)$ is the value after grey relational generation, $\max(x_i^0(p))$ and $\min(x_i^0(p))$ are the largest and the smallest values of $x_i^0(p)$ for the pth response, respectively. For better response, values of normalized results should be as large as possible with the best possible value equal to one. The grey relational coefficient (GRC) denoted by $\varepsilon_i(p)$, provides the relation between desirable and real experimental normalized data. GRC is defined by

$$\varepsilon_i(p)=\frac{\Delta_{\min}+\zeta\Delta_{\max}}{\Delta_{0i}(p)+\zeta\Delta_{\max}} \tag{4}$$

where $\Delta_{0i}(p)$ is the difference between the absolute values of $x_0(p)$ and $x_i(p)$ whereas $\Delta_{\min}$ and $\Delta_{\max}$ are the minimum and the maximum values of the absolute differences between all comparing sequences, respectively. ζ is the distinguishing or identification coefficient. It helps to minimize the effect of $\Delta_{\max}$; when its value is too large or too small, its value lies between 0 and 1. It also enhances the difference significance of GRC. Most researchers take its value equal to 0.5, so in our work, the value of ζ is taken as 0.5. The GRC for all responses were calculated using Eq. (5). GRG is a weighted sum of the GRC and is calculated by

$$\gamma_i=\frac{1}{n}\sum_{p=1}^{n}\varepsilon(p) \tag{5}$$

where n is the number of performance characteristics, here, n is 4. The higher value of GRG indicates that the corresponding process parameter combination is closer to the optimal. Table 4 provides a summary of GRC and GRG measurements. In Table 4, the ninth experiment gives the highest value of GRG, which means that it has the best multi-performance characteristics, i.e., optimum values of all output parameters among all experiments.

Table 4 GRC and GRG for each experimental run

Speed/(m·min^{-1})	Feed rate/(mm·r^{-1})	GRC SR	GRC CE	GRC MRR	GRC TW	GRG
100	0.08	0.570 1	1.000 0	0.333 3	0.333 3	0.559 2
100	0.12	0.465 6	0.759 0	0.392 8	0.426 2	0.510 9
100	0.16	0.333 3	0.559 8	0.478 3	0.577 8	0.487 3
130	0.08	0.717 6	0.636 1	0.366 7	0.400 0	0.530 1
130	0.12	0.549 5	0.498 8	0.468 1	0.495 2	0.502 9
130	0.16	0.409 4	0.413 5	0.647 0	0.684 2	0.538 5
160	0.08	1.000 0	0.447 4	0.407 4	0.520 0	0.593 7
160	0.12	0.717 6	0.384 0	0.579 0	0.626 5	0.576 8
160	0.16	0.496 0	0.333 3	1.000 0	1.000 0	0.707 3

4.1 ANOVA for GRG

Analysis of variance (ANOVA) is a statistical method used to examine the interactions of all the control factors under consideration[3]. We use ANOVA to identify the significant factors. ANOVA is with a 95% confidence level and a 5% significance level. The ANOVA analysis results are shown in Table 5. The results show that the model is significant. Also, cutting speed (A), feed rate (B), the combination of A and B denoted by AB, A^2, and B^2 are all significant factors and have a severe impact on GRG values. This is because the corresponding P values for all these factors are lower than 0.05. The value of R-square is 0.996 9, and the adjusted value of R-square is 0.991 8. Both these values are very close to each other, which shows the reliability of data.

Table 5 ANOVA for GRG

Source	Sum of squares	Degree of freedom	Mean square	F-value	p-value prob > F
Model	0.029 415	5	0.005 883	22.650 030	0.013 8
A	0.004 133	1	0.004 133	15.911 83	0.028 2
B	0.012 095	1	0.012 095	46.566 510	0.006 4
AB	0.007 126	1	0.007 126	27.436 270	0.013 5
A^2	0.004 390	1	0.004 390	16.900 73	0.026 1
B^2	0.001 671	1	0.001 671	6.434 825	0.084 9
Residual	0.000 779	3	0.000 260		
Cor total	0.030 194	8			

4.2 Calculation of GRC and GRG

After using the equations, GRC and GRG are calculated and depicted in Table 5.

The 3-D plot for GRG in ANOVA is presented in Fig.7. It can be deduced that GRG values initially decrease with an increase in cutting speed, but eventually, the relationship becomes directly proportional at higher cutting speeds. So, GRG decreases with increasing cutting speed from 100 m/min to 130 m/min and then increases with an increase in cutting speed from 130 m/min to 160 m/min, attaining a maximum value of 160 m/ min. On the other hand, GRG is directly proportional to feed rate, which means that by increasing the feed rate, GRG is increased and vice versa. The relation between GRG and feed rate exponentially results in very high GRG values at large values of feed rates.

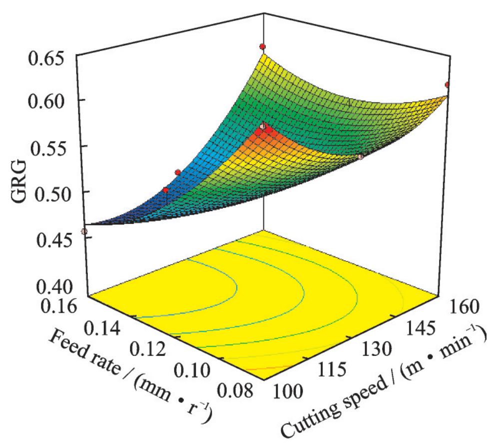

Fig.7 3-D plot for grey relational grade

4.3 Confirmation experiments

At the last stage of research, confirmation experiments of the control factors are performed at optimal and random levels to verify the accuracy of optimized results and find the improvement in overall output value. These experiments are conducted three times. The estimated GRG can be calculated by

$$\gamma_{\text{estimated}} = \gamma_{\text{m}} (\gamma_i - \gamma_{\text{m}}) \tag{6}$$

where $\gamma_{\text{estimated}}$ is the GRG, which predicts the optimal machining parameters, γ_{m} the total mean GRG, γ_i the average GRG at the optimal level, and o the number of design parameters that significantly affect the quality characteristics. Table 6 compares the estimated GRG calculated by Eq. (6) with the experimental value. In Table 6, the estimated GRG value is 0.710 6, and the experimental GRG value is 0.711 2. The close difference between these two values validates both the expected and experimental results. The improvement in GRG from initial factor combination (V3-F2) to optimal factor combination (V3-F3) was 0.113 9, thus showing a percentage improvement of 19.07%.

Table 6 Results of the confirmation experiment

Initial cutting conditions		Optimal cutting conditions	
		Predicted results	Experimental results
Level	V3-F2	—	V3-F3
Surface roughness	1.54	—	1.4
Cutting energy	495 261	—	576 590
MRR	208 00	—	256 98
Tool wear	102	—	77
GRG	0.597 3	0.710 6	0.711 2

Several researchers have performed multi-response optimization for machining parameters through GRA[5, 31-34]. In a nutshell, we can say that the performance parameters, which are surface roughness, cutting energy, MRR, and tool wear, are significantly optimized through Taguchi based GRA. It is evident from literature results that Taguchi based GRA helps to improve the optimization process. The current study also provided an improvement in GRG, as described in the optimization results. It can, therefore, be safely concluded that literature results verify the findings of current research regarding GRA.

5 Conclusions

The cutting parameters are optimized by Taguchi based GRA with the multiple-performance outputs. The conclusions are summarized as follows:

(1) It is concluded from ANOVA results that both cutting speed and feed rate are significant factors affecting the cutting performance.

(2) According to the ANOVA results for GRG, the percentage contribution of flow rate and cutting speed are 46.57% and 15.91%, respectively. Therefore, the flow rate is the most significant control factor on GRG for minimization of surface roughness, cutting energy and tool wear, and maximizing MRR.

(3) Taguchi based GRA directly combines the multiple responses into a single performance characteristic known as GRG. The GRG results depict that the best combination values are cutting speed of 160 m/min and feed rate of 0.16 mm/ r.

(4) The improvement in GRG from initial factor combination (V3-F2) to optimal factor combination (V3-F3) is 0.113 9, thus showing a percentage improvement of 19.07%.

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AISI-L6低温辅助车削可持续加工性与工艺参数优化

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摘要: 为提高生产效率,近年来切削液在机械加工领域的应用显著增加。然而,考虑到切削液对生态、环境和社会有影响,研究人员转向了对环境更友好的冷却条件,如低温冷却。为分析切削速度和进给速度对AISI-L6工具钢在低温冷却条件下的加工性能的影响,采用L9田口灰度关联分析(Grey relational analysis, GRA)分别对切削能量、表面粗糙度、刀具磨损和材料去除率(Material removal rate, MRR)等关键加工指标进行了实验研究。结果表明,切削速度160 m/min和进给速度0.16 mm/r是最优切削参数,能显著提高AISI-L6工具钢加工性能。

关键词: 可持续制造;低温加工;淬火钢;能源消耗;刀具寿命