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RESEARCH ARTICLE

Multi-response optimization for AISI M7 Hard Turning Using the utility concept

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Abstract

The utility idea is used to optimize AISI M7 hard turning in the present study. This study uses the Taguchi optimization approach to examine the effects of insert nose radius and machining parameters such as cutting speed, feed rate, and depth of cut on surface roughness (Ra) and material removal rate (MRR) in a turning operation. The signal-to-noise (S/N) ratio is used to analyze the performance characteristics in the turning of AISI M7 employing nose radius of 0.4, 0.8, and 1.2 mm carbide inserts on CNC turning centre in a three-level, four-parameter design of experiment using L9 orthogonal array using MINITAB 17. Every trial is held in a dry setting. According to the results of the current investigation, feed rate and nose radius are the most important variables affecting surface roughness and material removal rate.

Keywords: Optimization Algorithm, Overcurrent Relay, Protective Zone, Real-Time Coordination.

Introduction

The technology of CNC turning machines has substantially evolved in recent years to match the high standards in a variety of production sectors, particularly in the precision metal cutting business. Turning is a basic machining operation among the several CNC industrial machining techniques. It is extensively used throughout several industrial sectors. Surface roughness (Ra) and material removal rate (MRR) are crucial controlling variables in machining processes. MRR serves as a productivity indicator. Ra is a metric for excellence. The process of choosing the best cutting speed, feed rate, depth of cut, and insert nose radius decreases the Ra value and increase the MRR value.

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Literature Survey

This section includes some selected articles for an in-depth investigation to find a research gap or further extension of research in the area of hard turning. The selected papers for the study are as follows:

Alok, A., & Das, M. (2019) "executed a new type of coating material, HSN2 with 12 μm thickness on carbide insert by using physical vapor deposition technique for machining hard AISI 52100 steel of hardness 55 HRC is evaluated. DSC and TGA also characterize the coated carbide insert's thermal and oxidative stability. The primary cutting, radial and feed pressures, maximum flank wear, and surface quality of the workpiece are all related to the input process parameters of cutting speed, feed rate, and depth of cut. The impact of cutting parameters on machinability is studied statistically. Also, regression models are created to link input and output process characteristics. A response surface optimization and validation test follow this. Percentage errors for main cutting force, radial force, feed force, surface roughness (%), and flank wear (%) were identified in the confirmation test. The greatest tool wear recorded is 292 m, which is acceptable under ISO 3685. Among all output parameters, cutting speed is shown to be the most effective. The current effort is unique in that it involves machining AISI 52100 steel with a 55 HRC hardness at 102–287 m/min with a new coating material HSN2 with a 12 m thickness".

Aouici, H., *et al*. (2012) "investigated experimentally the effects of cutting speed, feed rate, workpiece hardness and depth of cut on surface roughness, and cutting force

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components in the hard turning. To mill the AISI H11 steel, Sandvik used cubic boron nitride (CBN 7020), which is a mix of 57 percent CBN and 35% TiCN. Using ANOVA, we used four-factor (cutting speed, feed rate, hardness, and depth of cut) and three-level fractional experiment designs. This technique generated mathematical surface roughness and cutting force components (RSM) models. While the depth of cut and workpiece hardness have the greatest impact on cutting force components, both feed rate and workpiece hardness have statistical relevance on surface roughness. Finally, optimal cutting conditions range for industrial production are recommended".

Aouici, H., *et al.* (2011) "investigated turning conditions of hardened AISI H11 (X38CrMoV5-1), and the effects of cutting parameters on flank wear (VB) and surface roughness (Ra) using the CBN tool. The response surface approach is used in the machining trials (RSM). In this study, the combined impacts of three cutting parameters are investigated (cutting speed, feed rate, and cutting duration) on two performance outputs (VB and Ra) (ANOVA). The optimal cutting conditions for each performance level are derived using a quadratic regression model. The data suggest that cutting time affects flank wear the most, followed by cutting speed. Also, the feed rate seems to mainly influence workpiece surface roughness".

Azizi, M. W., *et al.* (2012) "investigated the effect of cutting parameters (cutting speed, feed rate, and depth of cut) and workpiece hardness on surface roughness and cutting force components. On AISI 52100 steel with coated Al2O3 + TiC mixed ceramic cutting tools. The experiment was planned using Taguchi's L27 orthogonal array. The response table and ANOVA enabled us to test the linear regression model's validity and identify relevant factors impacting surface roughness and cutting forces. The statistical study shows that the depth of cut, workpiece hardness, and feed rate have a statistically significant influence on the cutting force components than the cutting speed. Empirical models were created to connect cutting parameters and workpiece hardness with surface roughness and cutting forces. The desired function technique for multiple response factor optimization was used to find the optimal machining settings to create the lowest surface roughness with the least cutting force components. Finally, validation experiments were conducted to validate the proposed empirical models".

Azizi, M. W., *et al.* (2020) "optimized machining parameters to achieve the desired technical parameters such as surface roughness, tool radial vibration, and material removal rate using response surface methodology (RSM). The hard turning of EN19 alloy steel with GC3015) cutting tools was examined. In order to achieve the needed surface finish quality and production rate, manufacturers of hard and high-precision components confront a major challenge. RSM can handle this issue by creating a mathematical model and conducting tests. The statistical study employed a face-centered central composite design (FCCD) with cutting parameters (cutting speed, feed rate, and depth of cut). It was shown that cutting parameters correlated with surface roughness, tool vibration, and material removal rate. Using a desirability function, numerical and graphical optimization was used to find the best cutting settings for reducing surface roughness, tool vibration, and material removal rate. Finally, validation experiments were conducted to validate the mathematical models".

Bouzid, L., *et al.* (2015) "attempted to statistically model the relationship between cutting parameters (speed, feed rate, and depth of cut), cutting force components (Fx, Fy, and Fz), and workpiece absolute surface roughness (Ra). A chemical vapor deposition–coated carbide tool is used to machine martensitic stainless steel (AISI 420). A full-factorial design (43) is used to examine the experimental findings using both ANOVA and RSM. The optimal cutting conditions are obtained utilizing mutually responsive surfaces and desire functions, with residual values checking the model's adequacy. The findings show that depth of cut (Fx: 86%) dominates (Fy: 58%) and feed rate (Fz: 81%) influences surface roughness behavior (Ra: 81 percent). Also, the anticipated and actual cutting force components and surface roughness were in excellent agreement. The findings are also tested for mistakes (Fx: 6.51 percent, Fy: 4.36 percent, Fz: 3.59 percent, and Ra: 5.12 percent). Finally, ideal cutting ranges for industrial production are anticipated".

Cakir, M. C., *et al.* (2009) "examined the effects of cutting parameters (cutting speed, feed rate, and depth of cut) onto surface roughness through the mathematical model developed by using the data gathered from a series of turning experiments performed. A second study was conducted to assess the impact of two well-known coating layers on surface roughness. The trials were performed for two CNMG 120408 (ISO designation) carbide inserts with the same geometry and substrate but varied coating layers to assure identical cutting conditions. Cold-work tool steel AISI P20 was machined. A thin TiAlN layer (31micro m) is PVD coated on Insert 2, while a TiCN underlayer, an Al2O3 intermediate layer, and a TiN outer layer are all deposited by CVD on Insert 1. The overall average error of the model was 4.2 percent for Insert 1 and 5.2 percent for Insert 2, proving the equations' dependability".

Chinchanikar, S., *et al.* (2013) "investigated the performance of coated carbide tool considering the effect of work material hardness and cutting parameters during turning of hardened AISI 4340 steel at different levels of hardness. Multiple linear regression models were used to identify relationships between cutting parameters and performance metrics such as cutting forces, surface roughness, and tool life in the area of cutting parameters, the created models are trustworthy and may be utilized successfully to anticipate reactions. An ANOVA was used to identify highly significant parameters (ANOVA). According to experimental evidence, less cutting force is necessary to machine tougher materials. The depth of cut influences cutting forces, then feed rate. Surface roughness is influenced by cutting speed, feed, and depth of cut. Particularly when working with tougher materials, cutting speed and depth of cut become the most important elements affecting tool life. RSM and Desirability Function establish ideal cutting conditions. Cutting pressures, surface roughness, and tool life was found to be reduced by using lower feed rates, deeper cuts, and restricting cutting speeds to 235 and 144 m/min for 35 and 45 HRC work materials, respectively".

Das, D. K., *et al.* (2014) "investigated surface roughness during hard machining of EN 24 steel with the help of coated carbide insert. The test was done in dry circumstances. The process parameters were optimized using the Grey-based Taguchi method. The adequacy of the surface roughness prediction models constructed using regression analysis was also tested. Hard machining produces a surface roughness of 0.42 microns. The best depth of cut (Ra) and cutting speed (Rz) for the grey-based Taguchi technique were found to be 0.4 mm, 0.04 mm/rev, and 130 m/min, respectively. Feed is the most important parameter for both Ra and Rz. The prediction models have strong R2 values (0.993 and 0.934). This shows a better model fit and is very significant".

Das, S. R., *et al.* (2015) "investigated the dry hard turning of AISI 4140 steel using PVD-TiN coated Al2O3+TiCN mixed ceramic inserts. In this study, the combined influence of cutting parameters (cutting speed, feed, and depth of cut) on performance variables including surface roughness and flank wear is investigated (ANOVA). Cutting feed, followed by cutting speed, is shown to have the greatest impact on surface roughness. Although the depth of cut is not statistically significant, flank wear is a function of the depth of cut. SEM observations are done on the machined surface and worn tool to establish the procedure. In the examined range, abrasion was the predominant wear mechanism. Tool wear and surface roughness were also investigated. It was used to anticipate the appropriate surface roughness and flank wear. Based on RSM, mathematical surface roughness (Ra) and flank wear (VB) models were established with 95% confidence. Finally, under optimal cutting circumstances (obtained via response optimization), tool life was tested to justify coated ceramic inserts in hard turning. Because TiN-coated ceramic has a longer tool life (51 minutes), it has a lower projected machining cost per item (Rs. 12.31)".

Das, S. R., *et al.* (2017) "addressed surface roughness, flank wear, and chip morphology during dry hard turning of AISI 4340 steel (49 HRC) using CVD (TiN/TiCN/Al2O3/TiN) multilayer coated carbide tool. The influence of cutting settings on tool and workpiece flank wear and surface roughness were studied using Taguchi's L9 Orthogonal array (OA) and ANOVA. SEM was used to examine the surface topography of machined workpieces, wear processes of worn coated carbide tools, and chip morphology of produced chips (SEM). Thus, multiple regression analysis was used to create a mathematical model for each answer, and numerous diagnostic tests were run to ensure the model's validity and usefulness. Finally, a cost study based on Gilbert's method was done to demonstrate the economic viability of coated carbide tools in hard turning (suggested by the response optimization technique). The findings reveal that feed and cutting speed affect surface roughness and flank wear statistically. Faster-cutting speed improved surface polish and increased flank wear. Tool wear is generated by abrasion from the flank land rubbing on the machined surface and high cutting temperatures. Chip morphology indicates saw-tooth chip formation with severe serration produced by cyclic fracture propagation driven by plastic deformation. The overall machining cost per item for hardened AISI 4340 steel with a coated carbide tool is $0.13 (i.e. Rs. 8.21 in Indian rupees). The research concluded that a multilayer TiN/TiCN/Al2O3/TiN coated carbide tool for hard turning in dry cutting conditions is a cost-effective alternative to standard cylindrical grinding. It also provides cheaper alternatives to CBN and ceramic tools".

Davoodi, B., *et al.* (2015) "investigated the effects of cutting parameters on tool life of PVD TiAlN-coated carbide tools, and volume of workpiece material removed during the machining of the N-155 iron–nickel-base superalloy is evaluated. Cutting factors included cutting speed and feed rate at five levels. RSM was used to model the interactions between machining parameters and output variables (RSM). ANOVA was used to test the mathematical model and its variables. Overall, the findings demonstrated excellent agreement between observed tool life, material eliminated, and model predictions. The cutting tool inserts were also SEM investigated, and wear processes were studied at different cutting speeds. The most common tool failure mechanism was adhesion. Finally, the desired function technique was used to optimize tool life and material removal for optimal productivity".

Davoodi, B., *et al.* (2014) "investigated the effects of cutting speed and undeformed chip thickness on cutting and feed force components, and tooltip temperature was experimentally investigated in order to remove the cutting fluid. AA5083-O wrought alloy with high Mg content (4.5%) was machined dry and wet using coated carbide tools. Using ANOVA, they used two-factor (cutting speed and undeformed chip thickness) and five-level fractional experiment designs. This method was used to construct mathematical models for cutting and feed force components and tool tip temperature (RSM). The results reveal that the undeformed chip thickness affects the output variables. AA5083 may be machined without cutting fluid at high cutting speed and low undeformed chip thickness. In dry and wet machining, cutting speed and chip thickness have statistical relevance on the cutting and feed force components. Finally, suitable turning conditions for industrial production were provided".

Devi, K. D., *et al.* (2015) "studied an optimization problem that seeks the identification of the best process condition or parametric combination for the said manufacturing process. Single-objective optimization refers to problems involving just one quality feature. It is difficult to pick the ideal option that meets all quality standards concurrently when more than one character is considered. The current research used Response Surface Methodology to solve a Multi-Objective Optimization issue by straight turning brass bar. The research sought to determine the ideal process environment for both quality and productivity. Finally, the research examines the impact of four input factors on output parameters: cutting speed, feed, depth of cut, and coolant type. The estimated ideal setting minimized surface roughness and maximized MRR, tool life, and machinability index. The confirmatory test validated the ideal outcome".

Dureja, J. S., *et al.* (2009) "attempted to model the tool wear and surface roughness, through response surface methodology (RSM) during hard turning of AISI-H11 steel with TiN-coated mixed ceramic inserts. The influence of machining parameters such as cutting speed, feed rate, depth of cut, and workpiece hardness was explored by analyzing the response factors of flank wear and surface roughness using ANOVA and factor interaction graphs in the RSM. This model best fits the experimental data. Optimization of numerous response components using a desirability function. The validation trials predicted response factors within 5% error. Surface roughness is influenced by feed rate and workpiece hardness, whereas flank wear is influenced by feed rate and depth of cut. The tool wear was monitored using a toolmaker's microscope, and some of the typical inserts were characterized by SEM-EDX. There is abrasion, notch wear, and chipping of the tool surface from rubbing and impingement of hard particles in the work material".

Dureja, J. S., *et al.* (2014) "attempted to investigate tool wear (flank wear) and surface roughness during finish hard turning of AISI D3 steel (58HRC) with coated carbide (TiSiN-TiAlN coated) cutting tool. The Taguchi L9 (3)3 orthogonal array was used for design. They used the S/N ratio and ANOVA to find important factors impacting tool wear and surface roughness. Cutting speed and feed influenced tool wear (flank wear), and feed influenced surface roughness (Ra). Regression analysis was used to generate mathematical models for tool wear and surface roughness. The confirmation trials using Taguchi's optimum parameter combination predicted the response factors with less than 5% error. To decrease tool wear and surface roughness, the Desirability function module in RSM was used. The optimum solution via desirability function optimization was compared to the optimal Taguchi set of parameters. Both strategies provide similar optimization outcomes".

Kaladhar, M., *et al.* (2013) "attempted to explore the influence of machining parameters on the performance measures, surface roughness, and flank wear in turning of AISI 304 austenitic stainless steel with a two-layer chemical vapor deposition (CVD) coated tool. The Taguchi method was used to accomplish this. The data show that cutting speed affects surface roughness and flank wear the most. Also projected are ideal process parameter settings and performance measure ranges".

Kaladhar, M., *et al.* (2010) "studied the optimization of machining parameters in turning AISI 202 austenitic stainless-steel using CVD-coated cemented carbide tools. A number of process factors are investigated throughout the experiment including speed, feed, depth of cut, and nose radius. The trials were done on a CNC lathe utilizing complete factorial design in the Design of Experiments. ANOVA was also used to examine process factors' effect and their interaction during machining. The research shows that the feed affects the surface roughness the greatest, followed by the nose radius. An effort was made to forecast surface roughness. Validation trials validate the projected values".

Keblouti, O., *et al.* (2017) "investigated the effects of cutting parameters and coating material on the performance of cutting tools in turning AISI 52100 steel. Uncoated and coated (with TiCN-TiN coating layer) cermet tools were compared. The inserts had the same substrate composition and shape. It was used to build a mathematical model (RSM). The influence of cutting settings on machining surface quality and cutting forces was studied using ANOVA. The findings suggest that feed rate is the most important factor. However, cutting depth affects cutting force components. The coating layer influence on surface quality was also evaluated. Using PVD (TiCN-TiN) coated inserts reduced surface roughness. A second-order regression model with 95 and 97% correlation coefficients was created".

Keblouti, O., *et al.* (2017) "presented work concerning an experimental study of turning with coated cermet tools with TiCN-TiN coating layer of AISI 52100 bearing steel. The major goals are to investigate the impact of cutting settings and coating materials on cutting tool performance. Second, use a multi-objective optimization to reduce surface roughness (Ra) and increase the material removal rate. It was used to build a mathematical model (RSM). The impact of cutting parameters on machining surface quality and material removal rate was quantified using ANOVA. The results show that feed rate has the greatest impact on surface quality. They also look at how coating layers affect surface quality. The PVD (TiCN-TiN) coated insert has a reduced

Figure 1: Workpiece Samples of AISI M7

surface roughness than the uncoated tool. This paper also provides the root mean square deviation and correlation coefficient between theoretical and experimental data, with a maximum computed inaccuracy of 2.65%".

Research Gap and Objectives of Research

Research Gap

By studying various research articles, it can be concluded that optimization of cutting parameters such as cutting speed, feed rate, and depth of cut are not done for hard AISI M7 material with coated carbide tool using the utility concept of multi-response optimization (Figure 1). The material hardness will be 62 to 64 HRC during the turning process in dry conditions.

Objectives of Research

The basic objectives of the research are as follows:

- To find the optimum value of MRR.
- To find the optimum value of Ra.
- To find the combined effect of MRR and Ra using the utility concept. (Multi-response Optimization).

Methodology

In the first phase of research, I initially finalized the research area and then collected and studied the articles closely related to the research area. I have done industrial visits to find the problem so I can correlate my work to industrial problems. In this phase, I have finalized the hard material AISI M7 with hardness 62-64 HRC (Figure 2). The machining parameters such as cutting speed, feed rate, depth of cut, and quality characteristics such as MRR and surface roughness (Ra) are selected for investigation.

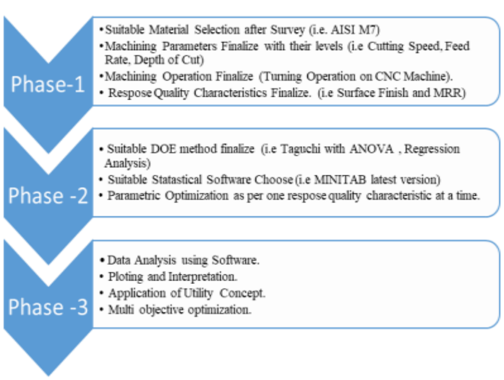

Figure 2: Methodology implemented

Figure 3: Experimental unit

In the second phase of research, I have finalized the Design of Experiment (DOE) method such as the Taguchi Method with ANOVA and Regression Analysis. For statistical analysis, I have used MINITAB 17 Software. I have done parametric optimization separately for each response characteristic.

In the third phase of research, I plotted results for surface roughness and MRR quality characteristics and applied multi-response optimization by the utility concept.

Experimentation

AISI M7 is taken for machining and their weight before machining and after machining was precisely recorded and cycle time is recorded from the screen (Figure 3). The MRR is calculated by using the formula:

$$MRR= (W_i - W_f) / \rho * t \quad (1)$$

Where, W_i = Initial weight of workpiece in *gm*
W_f = Final weight of workpiece in *gm*
t = Machining time in seconds
ρ = Density of AISI M7
= (7.95 x 1000 Kg/m^3)

and surface roughness value is recorded with the help of Make–Strumentazione, Model-RT10G, L.C.0.001 μm (Figure 4).

The choice of a certain orthogonal matrix from the common orthogonal array is determined by:

- Number of controlling variables
- Amounts for each control factor's levels (Table 1)
- The total amount of factor freedom

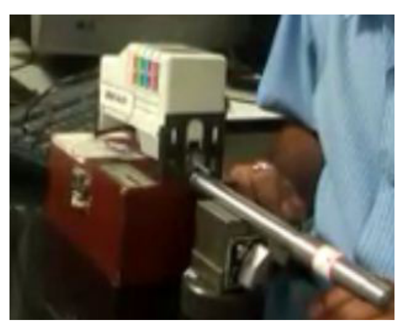

Figure 4: Make–strumentazione, model-RT10G

Table 1: Control factors and their levels

Levels	Control factors			
	Cutting speed (m/min)	Feed rate (mm/rev)	Depth of cut (mm)	Nose radius (mm)
Level 1	150	0.15	0.5	0.4
Level 2	220	0.22	0.75	0.8
Level 3	300	0.28	0.8	1.2

Table 2: Experiment to collect MRR values

Exp. No	MRR (Trial1) mm^3/sec	MRR (Trial 2) mm^3/sec	Mean MRR mm^3/sec	S/N Ratio dB
1	205.011	212.79	208.901	46.39
2	307.51	328.53	318.020	50.03
3	368.90	368.90	368.900	51.33
4	218.87	232.51	225.690	47.05
5	305.96	323.08	314.520	49.94
6	375.60	363.15	369.375	51.34
7	225.91	224.21	225.060	47.04
8	308.29	313.74	311.015	49.85
9	345.90	337.28	341.590	50.66

According to MINITAB 17, the best orthogonal array for the current study work's four parameters—cutting speed, feed rate, depth of cut, and nose radius—which are employed at three levels—is L9 (3^4).

- Condition of S/N ratio for surface roughness: smaller is better

$$\eta = -10 \log \frac{1}{n} \sum_{i=1}^{n} yi^2 \tag{2}$$

- Condition of S/N ratio for Material removal rate: larger is better

$$\eta = -10 \log \frac{1}{n} \sum_{i=1}^{n} 1/yi^2 \tag{3}$$

Where, η - Signal to Noise (S/N) Ratio, Yi –an i^{th} observed value of the response, n - Number of observations in a trial, y - Average of observed values (responses) s – Variance
Let T= average results for 9 runs of MRR (Table 2).

Table 3: Experiment to collect Ra values

Exp. No	Ra (Trial1) µm	Ra (Trial 2) µm	Mean Ra µm	S/N Ratio dB
1	2.10	2.50	2.300	-7.2673
2	2.68	2.63	2.655	-8.4817
3	2.35	2.32	2.335	-7.3659
4	0.95	0.45	0.700	2.5767
5	3.10	3.60	3.350	-10.5250
6	3.50	3.38	3.440	-10.7325
7	1.35	1.32	1.335	-2.5102
8	1.20	1.31	1.255	-1.9812
9	4.10	3.53	3.815	-11.6541

$$T' = \frac{\sum_{i=1}^{9} M}{9} = 298.119 \text{ mm}^3/\text{sec} \tag{4}$$

$MRR_{optimum} = T' + (A_2 - T') + (B_3 - T') + (C_3 - T') + (D_2 - T')$ [Ross, 1988]

$MRR_{optimum}$ = 298.119+ (302.2 -298.119) + (360.0 -298.119) + (302.8 – 298.119) + (304.2 – 298.119)

$MRR_{optimum}$ = 375.842 mm3/sec (Predicted value) (5)

Let T= average results for 9 runs of Ra

$$T' = \frac{\sum_{i=1}^{9} Ra}{9} = 2.53 \ \mu\text{m} \tag{6}$$

$Ra_{optimum} = T' + (A_3 - T') + (B_1 - T') + (C_2 - T') + (D_3 - T')$ [Ross, 1988]

$Ra_{optimum}$ = 2.35+ (2.135 – 2.53) + (1.445 – 2.53) + (2.390– 2.53) + (1.430 – 2.53)

$Ra_{optimum}$ = 0.350 µm (Predicted Value) (7)

The correlation among the factors i.e. cutting speed, feed rate, depth of cut and nose radius and performance measure (Ra) and (MRR) is obtained. The polynomial model was obtained as follows:

- Ra = 1.65 - 0.00216 (Cutting Speed) + 13.9 (Feed Rate) - 0.146 (Depth of Cut) - 2.16 (Nose Radius) R-Sq.

Table 4: Design matrix with multi-response S/N ratio

Exp.	A	B	C	D	η_{obs}
1	150	0.15	0.75	0.4	19.56
2	150	0.22	0.8	0.8	20.77
3	150	0.28	1.5	1.2	21.98
4	180	0.15	0.8	1.2	24.81
5	180	0.22	1.5	0.4	19.70
6	180	0.28	0.75	0.8	20.30
7	300	0.15	1.5	0.8	22.26
8	300	0.22	0.75	1.2	23.93
9	300	0.28	0.8	0.4	19.50

= 97.6% (8)

- MRR = 65.5 - 0.0552 (Cutting Speed) + 1060 (Feed Rate) + 5.1 (Depth of Cut) + 15.7 (Nose Radius) R-Sq. = 96.0% (9)

The elements in the above equation are all relevant. A higher R-squared value is always preferred. This demonstrates the estimated constants' accuracy and the models' applicability (Table 3).

Multi-Response Optimization

The multi-response S/N ratio of the total utility value is given by (Table 4)

$$\eta_{Obs} = W_1\eta_1 + W_2\eta_2 \quad (10)$$

using the utility concept, where W1 and W2 are the weights provided to Ra and MRR. Based on the needs and priorities of the clients, weights are assigned to the performance criteria. Both Ra and MRR are given equal weight in the current work. W1 and W2 thus equal 0.5.

Result and Discussion

Figure 5 shows that the cutting speed =300 m/min, Feed rate =0.15 mm/rev, depth of cut = 0.75 mm, and Nose radius = 1.2 mm are optimum values of process parameters at which both response parameters MRR and Ra give good result in terms of quality. Mean value of η_{obs} at different levels is shown in Table 5.

In this optimization stage, we have given equal importance to both values' Ra and MRR. Here nominal is best, this criterion is used.

The conclusions of multi-objective optimization are:

- Ra and MRR both values increase with the increase in cutting speed.
- Ra and MRR both values decrease with an increase in feed rate.
- Ra and MRR both values increase first and then decrease.
- Ra and MRR both values increase with the increase in nose radius.

Table 5: Mean value of η_{obs} at different levels

Levels	Mean values of η_{obs} for process parameters			
	A	B	C	D
Level 1	20.77	22.21	21.27	19.59
Level 2	21.61	21.47	21.70	21.11
Level 3	21.90	20.60	21.32	23.58

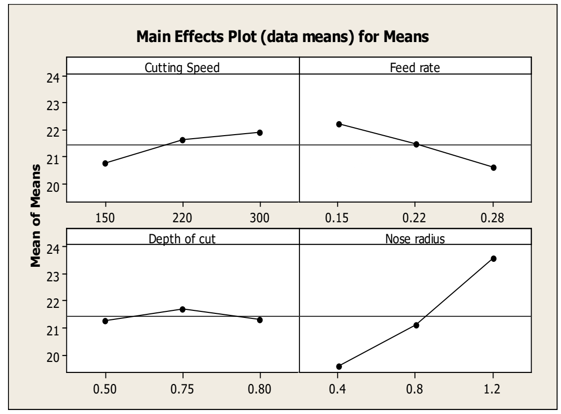

Figure 5: Muti-response optimization

Conclusion

It is discovered that the feed rate and nose radius of the insert substantially influence MRR value and surface roughness (Ra) value. We have applied the utility notion of multi-response optimization. The recent analysis reveals that cutting speed =300 m/min, feed rate =0.15 mm/rev, depth of cut = 0.75 mm nose radius = 1.2 mm delivers the greatest MRR value and least surface roughness (Ra).

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