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Efficient Machining of AISI4140 with Minimum Quantity Lubrication: Optimization

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Abstract

The advantages of minimum quantity lubrication (MQL) in machining include good lubrication, cleanliness, lower costs, and manageability; nevertheless, MQL's poor cooling characteristic is a severe drawback. However, effective machining depends heavily on picking the right process parameters and cutting fluid. In addition, technicians must have access to a straightforward optimization approach that allows them to quickly and simply identify the optimal parameter combinations for every given production procedure. The total machinability can be improved by considering optimization simultaneously for selecting optimal conditions. According to our findings, thickness ratio of chip (rc), cutting temperature (T), and while Material Removal Rate (MRR) can be maximized, while cutting force (F) and roughness (Ra) may be minimized, respectively. Deliver the best outcomes with Taguchi-based principal component analysis (PCA)-Grey relational analysis (GRA) optimization. MQL with cutting oil at 360 m/min and a feed rate of 0.11 mm/rev were found to be the optimum process conditions. The PCA-GRA approach can be useful, but only in certain situations, such as when there are competing goals to consider.

Keywords

Lubrication, Cooling, Force, Temperature, Surface roughness, Material removal rate

Introduction

Hardened AISI4140 is widely utilized in the defense sector and in the production of toughened forging dies, shafts, bearings, gears, and railway components due to its high hardness and toughness for its high chromium and molybdenum content [1]. However, the tremendous heat generated by turning such hardened metals compromises the quality of the machined object (about 80 %). Since MQL requires less cutting fluid than flood cooling, it has been utilized for years to increase machinability [2]. Many articles have been written extolling MQL, with researchers stating that it outperforms conventional machining techniques for a broad variety of metals and alloys. AISI 1045 steel was turned dry at speeds between 200 and 350 m/min to determine MQL [3]. The testing results demonstrated a contact length between 6 and 28% of chip tool, decrease in cutting temperature, and as well as cutting force, when the MQL surface quality was enhanced. Wet machine reduces power consumption by 8.5%, tool wear by 16.1%, and surface roughness by 10.4% when compared to dry machine of Inconel

825 alloy. In addition to enhancing quality of the surface and life of the tool when milling AISI4140 steel, pulse jet MQL was found to have a positive effect on turning tough-to-cut titanium alloy over external MQL and dry turning [4, 5].

For turning AISI4140 steel, the effect of MQL with nano graphite on T and tool wear was investigated. Nanofluids concentrated to 0.3% by weight can reduce cutting temperature and tool wear by as much as 80% when compared to flood cooling. Based on our research, MQL appears to be a viable strategy for improving machine readability. Surface roughness, cutting pressures, and tool wear were analysed during the turning of AISI4140 steel to determine the impact of MQL flow rates on machinability [6]. Increased flow rates in MQL have been proven to decrease cutting forces and tool wear without significantly altering surface roughness. Selecting values for the input process parameters within a given range is essential for turning such hardened components. Optimization of process parameters influencing T, Ra, F, MRR, r_c, and wear is essential for achieving optimum outcomes. To make the procedure more automatable, it is necessary to carefully examine many responses simultaneously [7, 8]. Multi-attribute decision making (MADM) methods have been extensively studied for their potential to optimize turning process parameters. When there are several competing findings, MADM technologies let users choose the best combination of inputs to reach a consensus [9]. Taguchi's experimental design is used in a variety of machining processes to get the required output at the intended price and in the desired amount of time.

Milling processing factors were optimised using a Taguchi L27 orthogonal array to minimize F and Ra [10]. The Taguchi technique may be used to maximize the value of a particular parameter. Combining the Taguchi approach with grey relational analysis (GRA) can broaden its use for multi-objective optimization in practical issues with varying features. Popular among industrial advanced data management (MADM) tools is Taguchi-GRA [11]. In a problem of multi-objective optimization, not all solutions are created equal. Taguchi-GRA-PCA has been shown by researchers [12] to reduce cutting temperature and pressures without sacrificing surface quality in the hard turning process. Cutting speeds, feed rates, and coated tool materials for machining duplex stainless steel were the topic of a Taguchi-GRA-PCA optimization study [13].

A survey of published studies demonstrates the widespread usage of MADM strategies for optimizing process parameters in a wide range of manufacturing operations. It is difficult to locate a research in the literature [14] that compares Taguchi, GRA, and PCA for optimizing turning process parameters. Researchers have been able to fill up this information gap by determining the best values for T, F, Ra, r_c, and MRR while turning AISI4140 steel utilizing the decision-making approaches. This study adds to our understanding by providing evidence that Taguchi-PCA-GRA is useful for optimization.

Experimentation

Material

For this experimental study, AISI4140 was turned on a lathe. Table 1 displays the work material's chemical composition and size.

Cutting tool material and geometry

Experiments in turning have made use of a coated tungsten carbide insert. The necessary working tool geometry has been achieved by installing the insert into a PSBNR 2525 M12 toolholder. Table 2 displays the many types and geometries of cutting tools.

Cooling and machining conditions

The KL-3280 C/2000 lathe was used for the turning experiment, and its maximum spindle speed was 1400 rpm. Experiments have been conducted using a range of parameters, including cooling process, cutting speed, and feed rate. For this study, we didn't alter the depth of cut to see how that would affect the results. Depths of cut, cutting speeds, and feed rates, have been determined through experimentation based on industry standards and manufacturer recommendations. The selected parameter levels for milling AISI4140 alloy steel were validated by comparison to the ranges used by other researchers [15, 16]. Turning tests have been conducted in both dry and MQL cooling environments. Straight cut oil of ISO VG 68 and vegetable oil have both been utilized as cutting fluid for MQL. The cutting zone in MQL is sprayed with a fine mist of fluid, as is well known. The mist is produced when cutting fluid and compressed air are mixed in a separate chamber. A nozzle connected to the chamber impinged the mist on the chip-tool interface. Table 3 displays the machining and cooling parameters.

Response

This research takes a close look at several process reactions, including T, F, Ra, MRR, and r_c. Calibrated thermocouples in the cutting tools were used to determine the average cutting temperature [17].

The cutting force was determined by utilizing a KISTLER 9257B three-dimensional dynamometer and a data collection system. Talysurf (Surtronic 3+) measurements were acquired

Table 2: Specification of tungsten carbide (WC) as a tool for cutting.

Auxiliary cutting edge angle	15°
Cutting tool geometry Inclination angle	-7°
Principal cutting edge angle	75°
Tool holder	PSBNR 2525 M12
Orthogonal clearance angle	6°

Table 1: Properties of material.

Material	C	Cr	Fe	Mn	Mo	Si	Hardness	Density	Size
AISI4140	0.43%	1.10%	97.77%	1.0%	0.25%	0.30%	197 BHN	8.03 Mg/m^3	Φ 170 × 510 mm

Table 3: Cooling and machining conditions.

Machining tool	7.5 kW (Lathe)
Oil pressure	2.5 MPa
Oil flow rate	150 ml/hr
MQL supply air pressure	2.3 MPa
Nozzle angle	30°
Setting	Dry MQL with vegetable oil (MVO) and MQL with VG 68 cutting oil (MCO)

at a sample length of 0.8 mm to determine the surface roughness of the machined material following each step. The machining condition has both direct and indirect effects on chip thickness, which is a measure of the nature of chip-tool interaction. During both dry and MQL machining, samples of chips were collected. By adjusting the cutting speed, feed rate, and depth of cut, one may determine the MRR. The study's input parameters and their associated ranges are shown in table 4.

Taguchi's L9 (3^3) orthogonal array design was constructed using the MINITAB 17 after the processing inputs and its levels for optimization were selected. OA design is a method used to develop multiple-variable controlled experiments. This method can help you model and optimise the process's parameters with fewer experiments and less lost information [18]. This means less money and time will be spent on experiments. The experiments have been conducted, and data on various responses have been gathered for each trial. The experimental setup and results are given below.

Methodology

Parameter optimization for a process that considers competing (or complementary) outcomes. The reactions may also be helpful or harmful. Several methods, and their results, have been used for optimization. The Taguchi technique allows for the optimization of a process's parameters while focusing on a single goal (Table 5).

PCA may be used to assign weights to each response in an optimization problem with variable importance.

PCA for weight calculation

In PCA, a set of possibly correlated variables is transformed into a set of linearly uncorrelated variables using an orthogonal transformation. Since the principal components are listed from most variance to least, the first component explains most of the variation in the data. PCA is used to assign relative importance to each answer. The weights are calculated using the following steps [19]:

Step 1: Evaluation of signal-to-noise (S/N) ratio

The S/N is the objective function in the optimization issue; it is the logarithmic function of the process response value that places a focus on variance. The Taguchi technique has been popular for optimizing complex industrial processes in recent years due to its ability to determine the optimal quantities of process parameters for a given response [20]. The following formulae were used to determine Taguchi's S/N ratio using the criterion.

$$S/N(B) = -10\log\ 10\left[\frac{1}{n}\sum_{i=1}^{n}\frac{1}{y_i^2}\right] \quad (1)$$

$$S/N(NB) = -10\log\ 10\left[\frac{1}{n}\sum_{i=1}^{n} y_i^2\right] \quad (2)$$

The best S/N ratio represents the sweet spot for a given set of process controls.

Step 2: Matrix formation

Using a new matrix, we may create classifications of the S/N ratio [21]:

$$X = \begin{bmatrix} x_1(1) & x_1(2) & \cdots & x_1(n) \\ x_2(1) & x_2(2) & \cdots & x_2(n) \\ \vdots & \vdots & \ddots & \vdots \\ x_m(1) & x_m(1) & \cdots & x_m(n) \end{bmatrix} \quad (3)$$

$$i = 1,2,\ldots,9;\ j = 1,2,\ldots,5.$$

Where (x-i,(j)) is the grey relational coefficient for each response variable and (m, n) is the total number of trials.

Table 4: Processing factors and their levels.

S. No	Factors	Factors code	Level 1	Level 2	Level 3
1	Cooling/lubrication method	A	Dry	MVO	MCO
2	Cutting speed (m/min)	B	180	270	360
3	Feed rate (mm/rev)	C	0.11	0.13	0.15

Table 5: Design of experiments.

S. No.	Input factor			Experimental results				
	A	B (m/min)	C (mm/rev)	Cutting temperature (°C)	Cutting force (N)	Roughness (μm)	MRR (cm^3/min)	Chip thickness ratio
1	Dry	180	0.11	875	449	1.16	22.8	0.8
2	Dry	270	0.13	910	457	1.18	34.94	0.88
3	Dry	360	0.15	959	477	1.29	54.58	0.96
4	MVO	180	0.13	851	449	1.18	26.3	0.86
5	MVO	270	0.15	891	474	1.23	39.88	0.94
6	MVO	360	0.11	884	384	0.96	40.5	0.91
7	MCO	180	0.15	844	489	1.26	29.8	0.94
8	MCO	270	0.11	830	384	0.96	30	0.9
9	MCO	360	0.13	874	391	0.94	47.54	0.92

Step 3: Production of a matrix of correlation coefficients

The variety of correlation coefficients is estimated according to the following standards [22]:

$$Rjl = \left(\frac{Cov\,(x_i(j), x_i(l))}{\sigma_{x_i(j)} \times \sigma_{x_i(l)}}\right) \tag{4}$$
$$j = 1,2, \ldots, n;\ 1 = 1,2, \ldots, n.$$

Where

$\sigma_{x_i(1)}$ standard deviation of $x_i(j)$ and $x_i(l)$

$Cov\,(x_i(j),)x_i(l)$ covariance of sequences $x_i(j)$ and $x_i(l)$; $\sigma_{x_i(j)}$

Step 4: Evaluating the eigenvalues and eigenvectors

The array of correlation coefficients may be used to calculate the Eigenvalues and Eigenvectors by following these steps:

$$(R - \lambda_k I_m)V_{ik} = 0 \tag{5}$$

Where

λ_k are the Eigenvalues

$\sum^n \lambda_k = n, k = 1,2, \ldots, n.\ V_{ik} = [a_{k1}\ a_{k2} \cdots a_{kn}]^T$ are the eigenvectors corresponding to the λ_k.

Step 5: Principal components calculation

$$Y_{mk} = \sum_{i=1}^{n} x_m(i) \cdot V_{ik} \tag{6}$$

The above formula may be used to extract the primary components that are independent of one another, such as Ym1, Ym2, and so on. Each response's weight is based on an eigenvector element connected to the first principal component, as the first PC always reflects the highest variance in the data.

GRA analysis

The GRA approach was developed as a popular technique for studying known unknowns. The following are some of the many stages involved in GRA [23]:

Step 1: GRA generalize/normalize response (NR)

All responses were normalized linearly between 0 and 1 for the first step of GRA, GRG, so that they are all comparable. Because some of the replies needed to be minimized, they were normalized using the following equation, which is based on the principle of "smaller is better."[24].

$$x_i(k) = \frac{\max x_i(k) - x_i(k)}{\max x_i(k) - \min x_i(k)} \tag{7}$$

īThe following equation was used to normalise the answers that required to be maximised in accordance with the "bigger is better" criterion:

$$x_i(k) = \frac{x_i(k) - \min x_i(k)}{\max x_i(k) - \min x_i(k)} \tag{8}$$

$i, k = 1,2,3 \ldots \ldots, 32, 4$ respectively.

Step2: GRC calculation

The GRC now stands in for the connection between the theoretical and empirical outcomes of an investigation [25].

$$GRC, \zeta_i(k) = \frac{\Delta\min + p\Delta\max}{\Delta x_i(k) + p\Delta\max} \tag{9}$$

Where

$\Delta x_i(k)$ sequence deviation (SD),

$x_0(k)$ absolute variation of the reference sequence

$x_i(k)$ comparability sequence should be obtained by using the following formula:

$$\Delta x_i(k) = |x_0(k) - x_i(k)| \tag{10}$$

and the maximal and the minimal variations should be found.

$$\Delta\min = \min_{\forall i}\min_{\forall k}\Delta x_i(k) \tag{11}$$
$$\Delta\max = \max_{\forall i}\max_{\forall k}\Delta x_i(k)$$

The variance of the GRC is controlled by the differentiating coefficient ($0 \le p \le 1$). Since a value of 0.5 often yields modest differentiating effects and good stability, this is the default setting for the distinguishing coefficient p.

Step3: Grey relational grade (GRG) calculation

The weighted-GRG for each experiment was determined using this method. Instead of using complex multi-objective response variables, GRG may be utilized as a performance index in optimization.

$$GRG = \sum_{i=1}^{n} [w_i(k) GRC(k)] \tag{12}$$

In equation 8, n is the total no of behaviour characteristics, and $w_i(k)$is the relative importance of those qualities. PCA was used to establish the relative importance of the performance indicators.

Results and Discussion

Since there are five possible solutions to this problem and the Taguchi approach has already been applied for process input optimization, PCM-GRA techniques have been integrated with Taguchi. PCA was used to determine weights for each response, which was an additional step in this procedure.

Weightage evaluation for results through PCA

Table 6 displays the computed S/N ratios for each response and each experimental run. Next, the PCA approach was used to the S/N values obtained in order to assign weights.

Table 7 displays the estimated eigenvalues, related eigenvectors, liability proportions, and explained variations for each PC. Maximum data variance is always explained by the first main component. The first principle component here contributed 45.2% of the total variance. Table 8 shows the weights assigned to each response based on the eigenvector values of the first principal component. The S/N was used to determine the eigenvector of each answer in MINITAB. The square of an eigenvector is a measure of its importance to the process. The results of a main components analysis are shown

Table 6: Evaluation of experimental output.

Run No.	Cutting temperature (°C)	S/N ratio			
		Cutting force (N)	Roughness (µm)	MRR (cm^3/min)	Chip thickness ratio
1	-58.8402	-53.0449	1.28916	27.1587	-1.93820
2	-59.1808	-53.1983	1.43764	30.8665	-1.11035
3	-59.6364	-53.5704	2.21179	34.7407	-0.35458
4	-58.5986	-53.0449	1.43764	28.3991	-1.31003
5	-58.9976	-53.5156	1.79810	32.0151	-0.53744
6	-58.9290	-51.6866	-0.35458	32.1491	-0.81917
7	-58.5268	-53.7862	2.00741	29.4843	-0.53744
8	-58.3816	-51.6866	-0.35458	29.5424	-0.91515
9	-58.8302	-51.8435	-0.53744	33.5412	-0.72424

Table 7: Eigen-values and explicated difference for PCA.

	First	Second	Third	Fourth	Fifth
Eigenvalue	2229.0	1092.9	38.0	0.0	0.0
Proportion	0.663	0.325	0.011	0.000	0.000
Cumulative	0.663	0.989	1.000	1.000	1.000

Table 8: Eigenvectors for PCA.

Variable	PC1	PC2	PC3	PC4	PC5
Cutting temperature (°C)	0.635	-0.739	-0.226	-0.000	-0.001
Cutting force (N)	0.769	0.633	0.089	0.003	-0.002
Roughness (µm)	0.003	0.002	-0.001	-0.741	0.671
MRR (cm^3/min)	0.077	-0.230	0.970	0.004	0.006
Chip thickness ratio	0.000	-0.000	0.007	-0.671	-0.741

in table 9; this analysis ranked the relative importance of the T, F, Ra, MRR, and r_c.

Optimization through GRA-PCA

Table 10 displays the results of our application of equation

Table 9: Impact on the first PC for each process response.

Factors	Contribution
Cutting temperature (°C)	0.31
Cutting force (N)	0.28
Roughness (µm)	0.29
MRR (cm^3/min)	0.15
Chip thickness ratio	0.07

7 and equation 8 to derive the normalized response for the GRA technique. The deviation sequence and grey relationship coefficient calculated using equation 9 and equation 10, are shown in table 11. Once weights have been established by PCA, the weightage GRG for each iteration may be calculated using equation 12. Higher concentrations of GRG are associated with better overall performance.

Table 12 of the response for S/N ratios reveals that the Cooling/Lubrication technique has the greatest impact, followed by feed rate and lastly cutting speed. The S/N ratio values were used to find the optimal parameter combination, as seen in the major effect plot of figure 1. A3B3C3 suggests a cutting speed of 360 m/min and a feed rate of 0.13 mm/rev when utilising MQL and cutting oil.

Table 10: The Taguchi-GRA-PCA optimization method necessitates the calculation of a normalized response.

Factors			Responses					Normalize response				
A	B	C	Cutting temperature (°C)	Cutting force (N)	Roughness (µm)	MRR (cm^3/min)	Chip thickness Ratio	Cutting temperature (°C)	Cutting force (N)	Roughness (µm)	MRR (cm^3/min)	Chip thickness ratio
Dry	180	0.11	875	449	1.16	22.80	0.80	0.6512	0.3810	0.6286	0.0000	0.0000
Dry	270	0.13	910	457	1.18	34.94	0.88	0.3798	0.3048	0.6857	0.3820	0.5000
Dry	360	0.15	959	477	1.29	54.58	0.96	0.0000	0.1143	1.0000	1.0000	1.0000
MVO	180	0.13	851	449	1.18	26.30	0.86	0.8372	0.3810	0.6857	0.1101	0.3750
MVO	270	0.15	891	474	1.23	39.88	0.94	0.5271	0.1429	0.8286	0.5374	0.8750
MVO	360	0.11	884	384	0.96	40.50	0.91	0.5814	1.0000	0.0571	0.5570	0.6875
MCO	180	0.15	844	489	1.26	29.80	0.94	0.8915	0.0000	0.9143	0.2203	0.8750
MCO	270	0.11	830	384	0.96	30.00	0.90	1.0000	1.0000	0.0571	0.2266	0.6250
MCO	360	0.13	874	391	0.94	47.54	0.92	0.6589	0.9333	0.0000	0.7785	0.7500

Table 11: Evaluation of PCA-based grey relational grades.

Deviation sequence					Grey relational coefficient					
Cutting temperature (°C)	Cutting force (N)	Roughness (µm)	MRR (cm^3/min)	Chip thickness Ratio	Cutting temperature (°C)	Cutting force (N)	Roughness (µm)	MRR (cm^3/min)	Chip thickness ratio	PCA based GRG
0.3488	0.6190	0.3714	1.0000	1.0000	0.5890	0.4468	0.5738	0.3333	0.3333	0.4553
0.6202	0.6952	0.3143	0.6180	0.5000	0.4464	0.4183	0.6140	0.4472	0.5000	0.4852
1.0000	0.8857	0.0000	0.0000	0.0000	0.3333	0.3608	1.0000	1.0000	1.0000	0.7388
0.1628	0.6190	0.3143	0.8899	0.6250	0.7544	0.4468	0.6140	0.3597	0.4444	0.5239
0.4729	0.8571	0.1714	0.4626	0.1250	0.5139	0.3684	0.7447	0.5195	0.8000	0.5893
0.4186	0.0000	0.9429	0.4430	0.3125	0.5443	1.0000	0.3465	0.5302	0.6154	0.6073
0.1085	1.0000	0.0857	0.7797	0.1250	0.8217	0.3333	0.8537	0.3907	0.8000	0.6399
0.0000	0.0000	0.9429	0.7734	0.3750	1.0000	1.0000	0.3465	0.3926	0.5714	0.6621
0.3411	0.0667	1.0000	0.2215	0.2500	0.5945	0.8824	0.3333	0.6930	0.6667	0.6340

Table 12: Response table for the Taguchi-PCA-GRA (Larger is better).

Level	Cooling/Lubrication method	Cutting speed	Feed rate
1	-5.249	-5.443	-4.916
2	-4.847	-4.819	-5.285
3	-3.806	-3.640	-3.700
Delta	1.443	1.803	1.585
Rank	3	1	2

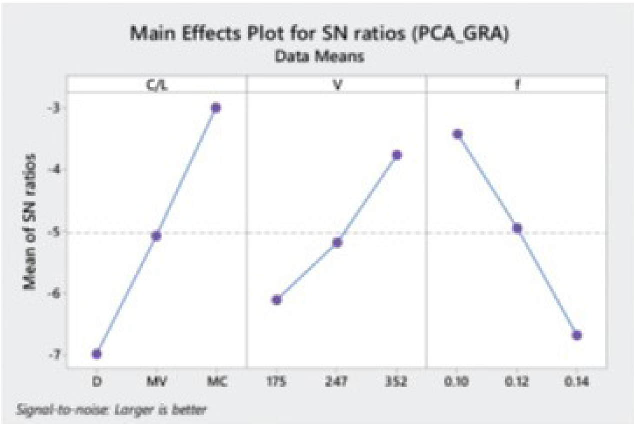

Figure 1: Main effect plot for PCA based GRG.

Conclusions

In this study, dry and MQL methods are used to convert AISI4140 alloy steel. It also provides a methodical overview of three hybrid optimization strategies and their potential utility in multi-response optimization. All process responses were decoupled using PCA, with weights calculated as follows: $W_T = 0.31$, $W_F = 0.28$, $W_{Ra} = 0.29$, $W_{MRR} = 0.15$, and $W_{rc} = 0.07$. The following is a summary of the other significant findings:

The optimum process parameter setting was found using optimization methods; it consists of the following values: MQL in a cutting oil environment (MCO), speed -360 m/min, and feed rate -0.11 mm/rev. The outcome of the test is confirmed by another test, which showed an absolute inaccuracy of less than 5% across the board.

Because it incorporates weight calculation into its procedural phases, Taguchi-GRA-PCA is the simplest approach for optimizing.

The research used PCA-weighted GRG in conjunction with GRA to achieve manufacturing processes optimization. When compared to the Cooling/Lubrication method and the feed rate, the impact of the cutting speed on the PCA-GRA index was rather minor. Cutting oil, a speed of 360 m/min, and a feed rate of 0.13 mm/rev were shown to be optimal conditions for MQL (A3B3C3).

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None.

Conflict of Interest

None.

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