RESPONSE SURFACE METHODOLOGY FOR EFFECTIVE LUBRICATION AND REDUCED TOOL WEAR IN TURNING EN24 STEEL

ADALARASAN R.[1*], SANTHANAKUMAR M.[1]

[1]Department of Mechanical Engineering, Saveetha Engineering College, Chennai, Tamilnadu, India
Email: [1]adalarasan@saveetha.ac.in

Abstract

Turning is an important machining process involving quality characteristics like tool wear and finish of the cut surface. The present work is focused towards the application of response surface methodology (RSM) in turning of EN24 steel. The work observes the effectiveness of the application of minimum quality lubricant (MQL) during the process of turning EN24 steel. The selection of parameters like tool type, work speed, depth of cut and type of lubrication is vital to obtain a good finish and reduced tool wear. Taguchi's L_{18} orthogonal array (OA) is used to conduct the turning trials and RSM is applied to predict the optimal turning condition.

Key words: EN24 steel; Optimization; response surface methodology; Taguchi; Surface finish.

I. INTRODUCTION

The EN24 steel finds many applications requiring high strength and wear resistance. The growing industrial application requires a proper study of their machining characteristics. Turning is an important metal removal operation for fabrication of parts in the final stage. However the difficulty in turning EN24 steel has created a good degree of research interest and hence the required drive and motivation. Generally the flank wear of the tool is found to be more at higher cutting speed and feed rate [1]. The effect of various machining parameters can be visualized from the quality characteristics observed in the machined surfaces including tool wear [2-5].

The methods used for solving the multi response problems include the principal component analysis (PCA), grey relational analysis (GRA), technique for order of preference by similarity to ideal solution (TOPSIS), neural networks, genetic algorithm (GA), response surface methodology (RSM) and desirability analysis [6-10]. Taguchi's technique employing the concepts of the grey theory is effectively used to identify the grey relational grade. It is used as the performance measure to find the optimal setting of input parameters [11, 12]. Taguchi based method is found to be effective in single response optimization, however a practical situation requires multi response optimization [13, 14]. Taguchi based desirability analysis is observed to predict the optimal variables in different manufacturing operations [15, 16]. The hybrid technique of grey based PCA can be applied to solve problems with a finite number of options. It combines the merits of both the techniques adopted for prediction of optimal variables [17]. The response surface methodology is a numerical technique employed along with the desirability analysis to find the optimal input condition. The technique is used to generate the desirability plots and identify the relation between the variables and observed quality characteristics [18, 19].

From the review of literature, it is observed that optimization of the turning characteristics and a study of lubrication effectiveness is limited in literature, particularly with EN24 steel. Hence the present work is focused towards applying the RSM to identify the optimal turning condition for EN24 steel.

II. EXPERIMENTATION AND DESIGN OF TURNING TRIALS

The EN24 steel rods of diameter 25 mm are subjected to turning under defined conditions. A center lathe with required accessories and attachments is used for experimentation and a new insert is used during different trials. The input parameters like type of lubrication, tool type, work speed and depth of cut is taken for the study and their levels are found out by pilot trials. The number of input variables and their levels are indicated in Table 1.

Taguchi L_{18} orthogonal array is used to conduct the turning trials and two replicates are obtained for each of the responses. The responses like tool wear and surface finish are studied as the quality characteristics. The surface finish is measured by using Talysurf recorder for a cut-off length of 0.8 mm. The width of the flank wear land is observed to evaluate the wear of the tool using a video measuring system inbuilt with a high resolution camera. The responses obtained during the trials are listed in Table 2. The trials were conducted randomly to reduce the effects of extraneous factors available during experimentation.

Table 1. Variables and their levels

Symbol	Input Parameters	Level 1	Level 2	Level 3
A	Tool type	WC insert	TiN insert	-
B	Type of lubrication	Dry machining	Conventional lubrication	MQL
C	Work speed (rpm)	200	400	600
D	Depth of cut (mm)	0.4	0.6	0.8

Table 2. L18 OA and responses

Trials	Parameters				outputs	
	A	B	C	D	Surface roughness (μm)	Flank wear (mm)
1	1	1	1	1	0.693	0.0376
2	1	1	2	2	0.706	0.0372
3	1	1	3	3	0.722	0.0421
4	1	2	1	1	0.663	0.0342
5	1	2	2	2	0.689	0.0362
6	1	2	3	3	0.726	0.0393
7	1	3	1	2	0.674	0.0356
8	1	3	2	3	0.640	0.0375
9	1	3	3	1	0.626	0.0373
10	2	1	1	3	0.678	0.0376
11	2	1	2	1	0.682	0.0346
12	2	1	3	2	0.662	0.0358
13	2	2	1	2	0.615	0.0367
14	2	2	2	3	0.652	0.0382
15	2	2	3	1	0.632	0.0352
16	2	3	1	3	0.572	0.0375
17	2	3	2	1	0.521	0.0366
18	2	3	3	2	0.543	0.0410

III. RESPONSE SURFACE METHODOLOGY

The centre-line average surface roughness value (Ra) is generally employed to characterize the turned surface. The tool wear is a measure of machinability. The studied responses are optimized using the various steps listed below.

Step 1: Calculate the *S/N ratio* as a part of data pre-processing using the *lower-the-better* characteristic [3].

Step 2: Perform data normalization and calculate the normalized *S/N ratio* [4, 7].

Step 3: Determine the values of grey relational coefficient and grey relational grade (GRG) by taking appropriate value of distinguishing coefficient [8, 11].

Step 4: Find the mathematical relationship between the turning variables and GRG to study the behaviour in experimental domain [18].

Step 5: Supplement with proper analysis of variance (ANOVA) to find the contribution of turning parameters [3, 9].

Step 6: Plot the 3D graphs to observe the influence of turning variables on responses and apply the desirability analysis.

IV. RESULTS AND DISCUSSION

A. Conversion of responses (surface roughness and flank wear) into GRG

The S/N ratio and normalized S/N ratio are found out as a part of data pre-processing. Both the tool wear and surface roughness are analyzed as *smaller-the-better* responses with a desired target of zero. The values of normalized *S/N ratio* and GRG are listed in Table 3. The calculation of GRG value permits the conversion of a multi response optimization problem into optimization of a single response.

B. Mathematical modelling

The quadratic models (polynomial equations of second order) are generated to indicate the mathematical relationship between turning variables and responses. The quadratic model relates the responses in terms of GRG with the turning variables. A L18 OA is used to reduce the number of machining trials. The design expert software is used to generate the models (Equations (1-6)).

Tool type : WC insert
Type of lubrication : Dry machining

Table 3. Normalization and GRG values

Trials	S/N ratio		Normalized S/N ratio		Grey relational coefficient		GRG
	Ra	FW	Ra	FW	Ra	FW	
1	3.185	28.496	0.140	0.544	0.368	0.523	0.445
2	3.024	28.589	0.084	0.595	0.353	0.553	0.453
3	2.829	27.514	0.017	0.000	0.337	0.333	0.335
4	3.570	29.319	0.274	1.000	0.408	1.000	0.704
5	3.236	28.826	0.158	0.727	0.372	0.646	0.509
6	2.781	28.112	0.000	0.331	0.333	0.428	0.381
7	3.427	28.971	0.224	0.807	0.392	0.721	0.557
8	3.876	28.529	0.380	0.562	0.446	0.533	0.490
9	4.069	28.566	0.447	0.582	0.475	0.545	0.510
10	3.375	28.496	0.206	0.544	0.386	0.523	0.455
11	3.324	29.213	0.188	0.941	0.381	0.895	0.638
12	3.583	28.922	0.278	0.780	0.409	0.694	0.552
13	4.222	28.707	0.500	0.661	0.500	0.596	0.548
14	3.715	28.359	0.324	0.468	0.425	0.484	0.455
15	3.986	29.069	0.418	0.861	0.462	0.783	0.622
16	4.852	28.519	0.719	0.557	0.640	0.530	0.585
17	5.663	28.730	1.000	0.674	1.000	0.605	0.753
18	5.304	27.744	0.875	0.127	0.800	0.364	0.582

GRG = +0.39256 + 6.09196E-004 * Work speed - 0.098977 * Depth of cut +2.99037E-004 * Work speed * Depth of cut -1.27442E-006 * Work speed^2 (1)

Tool type : WC insert
Type of lubrication : Conventional machining

GRG = +0.89832 +6.09196E-004 * Work speed - 0.75428 * Depth of cut +2.99037E-004* Work speed * Depth of cut -1.27442E-006 * Work speed^2 (2)

Tool type : WC insert
Type of lubrication : MQL

GRG = +0.76446 +6.09196E-004 * Work speed - 0.53218 * Depth of cut +2.99037E-004 * Work speed * Depth of cut -1.27442E-006 * Work speed^2 (3)

Tool type : TiN insert
Type of lubrication : Dry machining

GRG = +0.59343 +6.09196E-004 * Work speed - 0.098977 * Depth of cut +2.99037E004 * Work speed * Depth of cut -1.27442E-006 * Work speed^2 (4)

Tool type : TiN insert
Type of lubrication : Conventional machining

GRG = +0.92069 +6.09196E-004 * Work speed - 0.75428 * Depth of cut +2.99037E-004 * Work speed * Depth of cut -1.27442E-006 * Work speed^2 (5)

Tool type : TiN insert
Type of lubrication : MQL

GRG = +0.90236 +6.09196E-004 * Work speed - 0.53218 * Depth of cut +2.99037E-004 * Work speed * Depth of cut -1.27442E-006 * Work speed^2 (6)

C. Fitness and adequacy

.The analysis of variance is performed on the GRG (Table 4) and F-ratio test results are presented to prove model adequacy. The model F-value (14.13) proves its significance. The probability of model F-value reaching higher value due to noise factors is about 0.01%. The influence of various model terms is proved by the p-value in the ANOVA table. The insignificant terms are removed from the model during reduction.

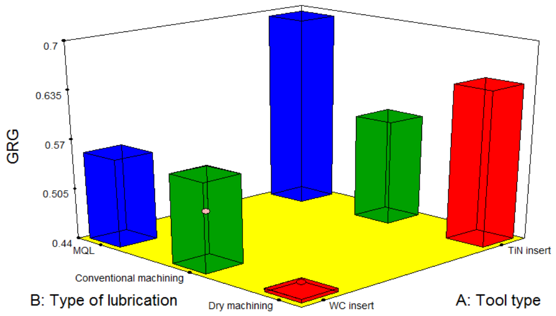
Table 4. Analysis of variance

Source	Sum of squares	Degrees of freedom	Mean sum of square	F-value	p-value	Remarks
Model	0.21	11	0.019	14.13	0.002	significant
A-Tool type	0.044	1	0.044	32.63	0.0012	
B-Type of lubrication	0.024	2	0.012	8.85	0.0162	
C-Work speed	0.019	1	0.019	14.04	0.0095	
D-Depth of cut	0.06	1	0.06	44.58	0.0005	
AB	0.019	2	9.64E-03	7.11	0.0261	
BD	0.023	2	0.012	8.56	0.0175	
CD	6.55E-04	1	6.55E-04	0.48	0.5129	
C^2	8.96E-03	1	8.96E-03	6.62	0.0422	
Residual	8.13E-03	6	1.36E-03			
Cor Total	0.22	17				

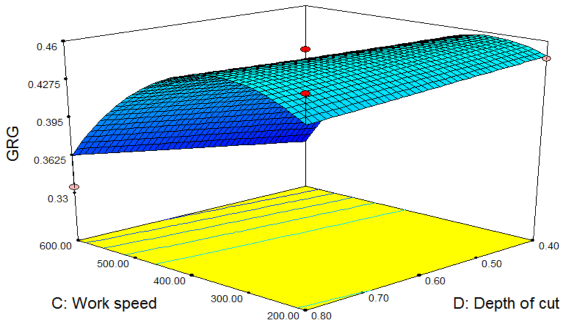
The value of R-squared is 96.28% and it proves the closeness among the values predicted by the mathematical model and the experimental data (Table 5). The higher R-squared value indicates the accuracy of model coefficients. The predicted R-squared value and adjusted R-squared value are in realistic agreement with each other. Hence the polynomial equation can be deemed fit and adequately precise in predicting the responses. The response surface plots are generated to study the effect of turning variables on the GRG (Figure 1).

Table 5. R-squared and adequate precision table

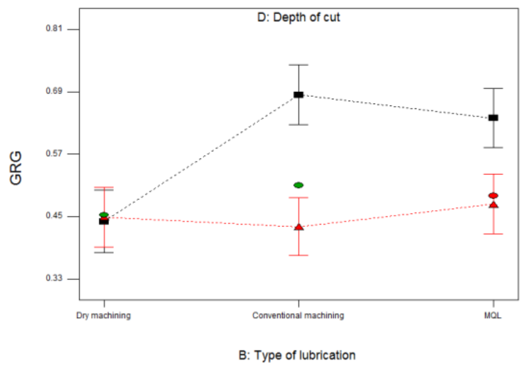
Std. Dev.	0.0368	**R-Squared**	0.9628
Mean	0.5346	**Adj R-Squared**	0.8947
C.V. %	6.8852	**Pred R-Squared**	0.5484
PRESS	0.0988	**Adeq Precision**	14.3718



(a)



(b)



(c)

Fig. 1 3D plots

D. Desirability analysis

The *larger-the-better* type desirability function is used in the analysis with GRG values. The turning condition representing the largest value of desirability is chosen as the optimal condition (Table 6). The optimal turning parameters is found out as: lubrication type: MQL, Tool type: TiN insert, work speed: 285.73 rpm and depth of cut: 0.4 mm. The ramp graph of desirability displays the necessary level of turning parameters (Figure 2). A dot on each ramp and its height indicates the amount of desirability. The optimal value located at the top ascending part of ramp graph and it represents a desirability value of one. In Figure 3, most of the values appear close to the center line indicating the normal distribution of errors.

Table 6 Optimal turning condition

Factor	**Name**	**Level**	**Low Level**	**High Level**
A	Tool type	TiN insert	WC insert	TiN insert
B	Type of lubrication	MQL	Dry machining	MQL
C	Work speed	285.73	200	600
D	Depth of cut	0.4	0.4	0.8
Response	**Prediction**	**SE Mean**	**95% CI low**	**95% CI high**
GRG	0.7937	0.036	0.7	0.88

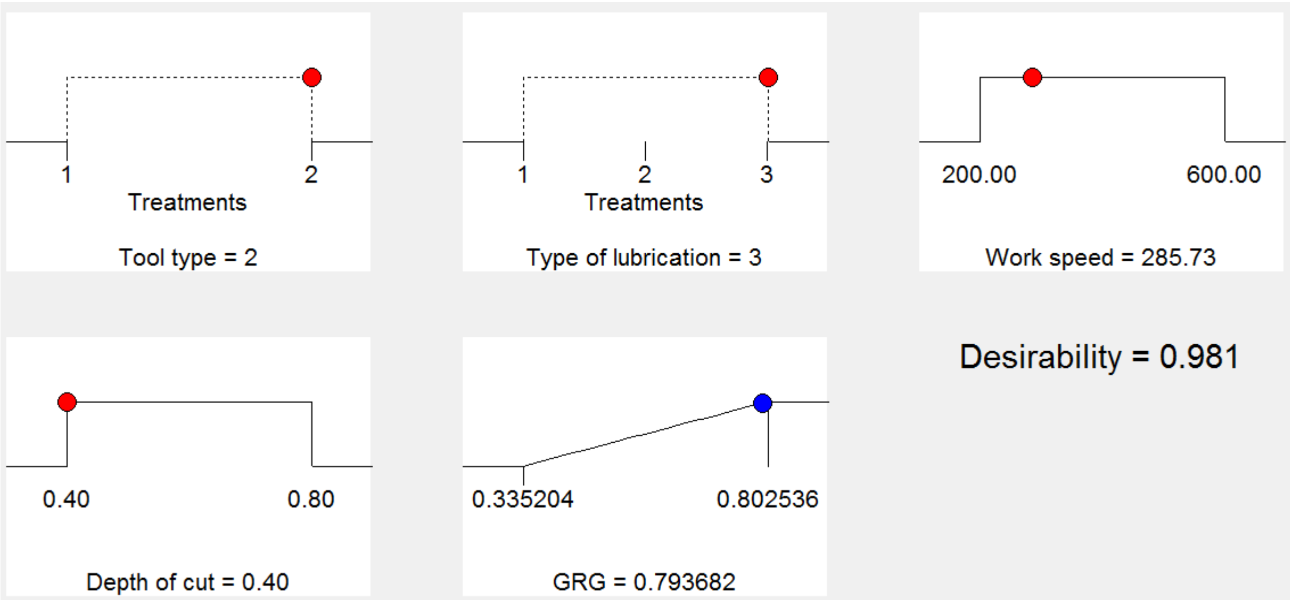


Fig. 2 Desirability graph

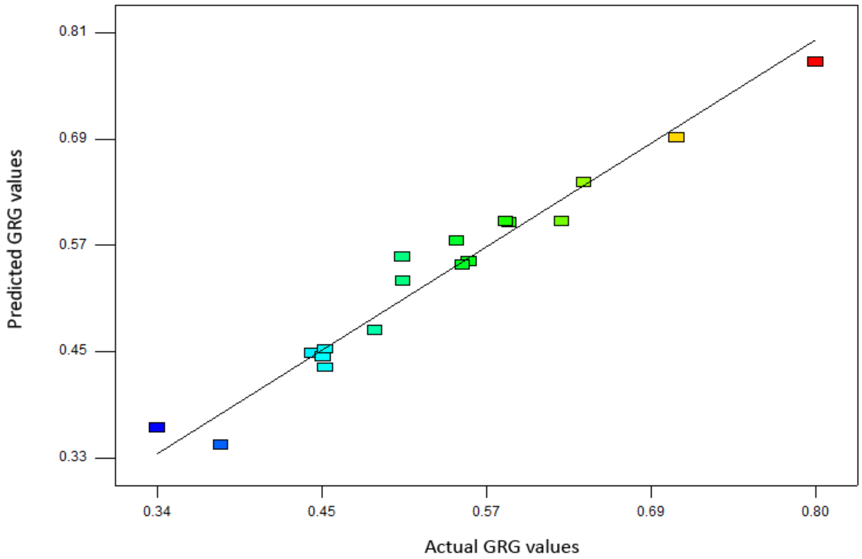


Fig. 3 predicted vs actual GRG values

V. CONCLUSION

The paper discloses the application of RSM to the process of machining (turning) of EN24 steel. The following conclusions are drawn.

- The methodology has combined the merits of GRA and RSM, hence requiring a simple computational effort.
- The optimal combination predicted by RSM is lubrication type: MQL, Tool type: TiN insert, work speed: 285.73 rpm and depth of cut: 0.4 mm
- ANOVA is performed on GRG value to find the major input variables affecting the quality characteristics.

The optimal parameter combination can produce a good finish with a reduced tool wear. Hence this method can be applied to solve multi criteria decision making problems.

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