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Multi response optimization of turning operation with self-propelled rotary tool

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Abstract

The purpose of the study is to determine the cutting performance of self-propelled rotary tool (SPRT) in the turning operation of hardened EN24 steel by optimizing the cutting conditions. Parameters such as horizontal inclination angle of the SPRT, depth of cut, feed rate and spindle speed were chosen while two conflicting factors; surface roughness (Ra) and metal removal rate (rMMR) were decided as performance criteria. Regression model was used to determine the quantitative relationships between the process variables in terms of performance parameters. Then, Technique for Order Preference by Similarity to Ideal Solution (TOPSIS), Non-dominated Sorting Genetic Algorithm-II (NSGA-II)-TOPSIS Hybrid Model and Goal Programming methods were employed to obtain the optimum conditions. In the analyses, optimization was determined by minimizing the Ra and maximizing the rMMR. Consequently, Goal Programming produced better results among the applied models. Optimum cutting conditions help operators and engineers to make decisions in the turning operations.

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Keywords: Self-Propelled Rotary Tool; Multi Objective Optimization; TOPSIS; Goal Programming

1. Introduction

Machining of the hardened materials is always problematic in manufacturing industry. For this reason, different kinds of new methods are introduced to improve the machining operations. Self-propelled rotary tool method is one of these methods developed for turning operations. This method uses a circular cutting tool rotating around its own

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principle axis during the cutting process as seen in Figure 1. Rotation of the tool changes vicinity of the tool edge, where contacts with the work piece, for each instant of cutting period (Dessoly, Melkote, & Lescalier, 2004). This action profoundly affects the physical and mechanical properties of the cutting tool. In the conventional turning operations, generated cutting heat is accumulated on a very small area of the cutting tool. Therefore, high temperature triggers the thermal softening effect for the cutting tool. Softening results in an accelerated wear mechanism which reduces the tool life and surface quality of the work piece. However, in SPRT turning, thermal softening effect is greatly reduced since the rotary tool provides a rest time to cool down for the cutting edge (Rao, Krishna, Katta, & Krishna, 2015). In the operation, rotary motion is actuated by the effect of the chip formation during the cutting process. Besides, rotation of the tool can be driven by a power source to make certain of the tool motion (Armarego, Karri, & Smith, 1994).

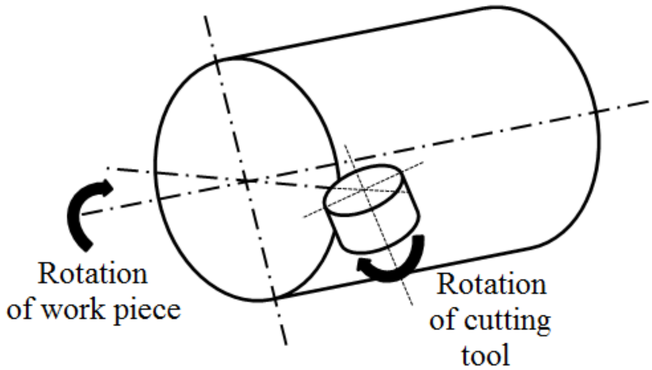

Figure 1. Schematic of SPRT turning operation

In the earlier studies, researchers compared this method with the conventional turning operations. It is commonly stated that rotary tool applications have extensive benefits over the cutting tool life. Furthermore, statements say that wear mechanism of the cutting tool changes by using SPRT method. Crater type wear is not effective in SPRT method while it is dominant in conventional turning operations. Moreover, diffusion wear is reduced since the cutting temperature is lowered. However, abrasion and distributed flank wear are the main wear mechanisms for the tools in SPRT turning operation (Kishawy & Wilcox, 2003). Studies with different work piece materials show that this method increases wear resistance obviously. Ezugwu (2007) studied tool wear in SPRT method by machining nickel and titanium based superalloys which are very hard and refractory materials. It is proven that cutting temperature is reduced and tool life is improved against the wear with SPRT method. Lei et al. (2002) studied titanium alloy Ti64 and Venuvinod et al. (1981) studied mild steel machining with SPRT method. Both studies revealed that tool life increase due to the cutting temperature reduction is the main advantage of the process. Investigation of the method is also conducted with different aspects such as cutting force and coefficient of friction. Increase in the rotational speed of the tool reduces the cutting force slightly while accelerating the wear on the tool (Lei & Liu, 2002). On the other hand, coefficient of friction between chip and tool decreases when the feed and the cutting speed are increased. It is also stated that feed and cutting speed have identical impact level on the coefficient of friction (Li & Kishawy, 2006), (Kishawy, Pang, & Balazinski, 2011). SPRT method is also adapted to milling operations. Dabade et al. (2003) studied face milling operation with self-propelled rotary inserts to investigate the method response by using Taguchi method. Optimization is realized to observe the response variables as surface roughness and chip cross sectional area. It is shown that the inclination angle of the insert is the most important parameter over the response variables. Another face milling operation with SPRT is studied by Patel et al. (2006). In the study, Design of Experiment (DOE) method is used to observe the effect of parameters in the operation. It is shown from the analysis of variance (ANOVA) that maximum cutting force significantly depends on inclination angle, cutting speed, depth of cut and feed rate. There are limited multi objective optimization studies about this process. Therefore, this research attempts to determine optimum cutting conditions in SPRT method. Operators and engineers will benefit from the results of the study to obtain desired surface finish and material removal rate.

The paper has four parts. First, it reviews the extant literature. Then, single-multi objective optimization methods are presented. Next, SPRT turning operation of hardened EN24 steel was investigated. Machining performance parameters which were decided as surface roughness and metal removal rate were observed to determine the optimum process variables. In the operation, process parameters were chosen as horizontal inclination angle of the SPRT, depth of cut, feed rate and spindle speed. Experimental data was taken from Rao et al.'s (2015) study. Optimization was run by using three different methods as TOPSIS, NSGA-II-TOPSIS hybrid model and Goal Programming. Optimum condition was defined as the work piece with minimum Ra and the operation with maximum rMMR. The paper concludes with a discussion and direction for further research.

2. Single-Multi Objective Optimization Methods

Single-Multi-objective optimization problems are very popular in many disciplines such as economics, engineering, healthcare, biology. In multi-objective problems, there is a tradeoff between the different objectives. Response Surface Methodology (RSM) and NSGA-II are common optimization methods in this area. Response Surface Methodology (RSM) is a design of experiment method to define the relationship between independent variables and response variables. The purpose of the method is to attain an optimal response by using series of designed experiments. It is widely applied for machining and manufacturing processes to form quadratic models. NSGA-II is widely used method for machining operation. It is an upgraded model of NSGA. NSGA-II has many different points from NSGA such as usage of elitist strategy technique and non-dominated sorting procedure. Manipulated parameters are not required for NSGA-II which makes the algorithm independent from the user (Konak, Coit, & Smith, 2006).

Multi-Criteria Decision analysis is one of the solution methods of multi-objective problems. The analysis has seen an incredible amount of use in recent years. Its role in different application areas has increased significantly. TOPSIS and Goal Programming have common use in the analysis. TOPSIS compares the alternative ways by evaluating the weight of each criterion and produces score rankings. Goal Programming is extensively employed due to the compatibility for nonhomogeneous units of measure. The method can be divided into two sides as priority decision and objective function in the applications. Initially, Goal Programming model is built if the goals are easily listed and deviation variables are listed. Then, weighted Goal Programming model make the total weighted deviations minimized (Velasques & Hester, 2013).

3. Comparative Study of Multi Objective Optimization Methods for SPRT Turning

Rotary turning is a complicated method which has various cutting and tool parameters including cutting tool speed, insert diameter, inclination angle and the other process parameters. The geometry and material of the work piece have an effect on the efficiency of the process. The inclination angle is the most critical factor which influences the performance of rotary turning significantly.

Based on Rao et al.'s (2015) study, depth of cut (X1), inclination angle of rotary tool (X2), feed rate (X3), and spindle speed (X4) were process parameters. The levels of the parameters are given in Table 1. Each of the parameters has three levels.

Table 1. Parameters and their levels (Rao, Krishna, Katta, & Krishna, 2015)

	Levels		
Parameters	-1	0	1
Depth of cut (mm)	0.2	0.4	0.6
Inclination angle (^{o})	10	30	50
Feed rate (mm/rev)	0.56	0.96	1.36
Spindle speed (rev/min)	150	200	250

Response Surface Methodology was applied to decrease the number of experimental runs and the design matrix was chosen a three level four factor central composite rotatable factorial design consisting of 27 sets of experimental runs by Rao et al. (2015). Surface roughness and metal removal rate were responses to measure. The design matrix was given in Table 2. It was observed that Ra and rMMR are two conflicting responses.

Table 2. The design matrix of the experiments (Rao, Krishna, Katta, & Krishna, 2015)

Experiment no.	Parameters and levels				Ra	rMMR
	X1	X2	X3	X4	(μm)	(g/min)
1	-1	-1	-1	-1	1.83	1.766
2	1	-1	-1	-1	2.58	3.432
3	-1	1	-1	-1	1.98	1.758
4	1	1	-1	-1	2.65	3.465
5	-1	-1	1	-1	2.15	3.582
6	1	-1	1	-1	2.89	6.568
7	-1	1	1	-1	2.29	3.254
8	1	1	1	-1	3.05	6.758
9	-1	-1	-1	1	1.59	3.056
10	1	-1	-1	1	2.24	4.722
11	-1	1	-1	1	1.65	3.088
12	1	1	-1	1	2.35	4.765
13	-1	-1	1	1	2.02	4.922
14	1	-1	1	1	2.53	7.888
15	-1	1	1	1	1.95	4.524
16	1	1	1	1	2.75	7.928
17	-1	0	0	0	1.65	2.625
18	1	0	0	0	2.45	5.101
19	0	-1	0	0	1.95	4.507
20	0	1	0	0	2.15	4.273
21	0	0	-1	0	1.88	2.668
22	0	0	1	0	2.28	5.165
23	0	0	0	-1	2.25	4.242
24	0	0	0	1	1.95	4.322
25	0	0	0	0	2.09	4.285
26	0	0	0	0	2.06	4.427
27	0	0	0	0	2.04	4.267

3.1. DOE-TOPSIS hybrid model

TOPSIS method was performed using DOE results to determine the best point of two responses. The criteria are surface roughness and metal removal rate. The alternatives are 27 experimental runs. The weights of the criteria (Ra and rMMR) are taken 0.5 and 0.5 according to the experts which have experience in this process. The results of the model are shown in Table 3. Optimum cutting and tool geometry conditions are achieved in 14th run. The TOPSIS Score is 0.794. Optimum depth of cut (mm), inclination angle (^{o}), feed rate (mm/rev) and spindle speed (rev/min) are 0.2, 10, 1.36 and 250 respectively.

Table 3. The results of the DOE-TOPSIS model

Experiment no.	TOPSIS Score	Experiment no.	TOPSIS Score	Experiment no.	TOPSIS Score
1	0.255	10	0.636	19	0.651
2	0.501	11	0.578	20	0.609
3	0.453	12	0.628	21	0.521
4	0.498	13	0.677	22	0.668
5	0.555	14	0.794	23	0.596
6	0.706	15	0.652	24	0.636
7	0.515	16	0.771	25	0.617
8	0.703	17	0.548	26	0.632
9	0.584	18	0.645	27	0.621

3.2. NSGA-TOPSIS hybrid model

TOPSIS method was performed using 100 NSGA points to classify and select the optimum point. NSGA model results are taken from Rao et al.'s (2015) study. The criteria are surface roughness and metal removal rate. The alternatives are 100 NSGA points. The weights of the criteria (Ra and rMMR) are taken 0.5 and 0.5 according to the experts which have experience in this process. The results of the model are given in Table 4.

Table 4. The results of the NSGA-TOPSIS model

Point no.	Score	Point no.	Score	Point no.	Score	Point no.	Score	Point no.	Score
1	0.768	21	0.202	41	0.655	61	0.548	81	0.742
2	0.632	22	0.215	42	0.655	62	0.416	82	0.810
3	0.212	23	0.811	43	0.208	63	0.202	83	0.610
4	0.800	24	0.233	44	0.206	64	0.488	84	0.269
5	0.761	25	0.813	45	0.207	65	0.224	85	0.633
6	0.508	26	0.589	46	0.297	66	0.359	86	0.193
7	0.810	27	0.666	47	0.809	67	0.198	87	0.762
8	0.806	28	0.688	48	0.569	68	0.527	88	0.578
9	0.336	29	0.518	49	0.217	69	0.818	89	0.699
10	0.813	30	0.804	50	0.316	70	0.199	90	0.249
11	0.192	31	0.407	51	0.254	71	0.343	91	0.280
12	0.193	32	0.507	52	0.374	72	0.600	92	0.374
13	0.805	33	0.258	53	0.343	73	0.460	93	0.329
14	0.527	34	0.818	54	0.498	74	0.752	94	0.424
15	0.803	35	0.815	55	0.753	75	0.441	95	0.818
16	0.432	36	0.195	56	0.811	76	0.191	96	0.269
17	0.258	37	0.710	57	0.382	77	0.236	97	0.390
18	0.469	38	0.280	58	0.816	78	0.304	98	0.315
19	0.568	39	0.731	59	0.721	79	0.197	99	0.195
20	0.285	40	0.786	60	0.665	80	0.310	100	0.192

Optimum point is obtained in 34th point. The TOPSIS Score is 0.818. Optimum depth of cut (mm), inclination angle (^{o}), feed rate (mm/rev) and spindle speed (rev/min) are 0.2, 15, 0.67 and 248 respectively.

3.3. DOE-Goal Programming model

Goal programming method was applied using DOE results. Software products of LINGO and MINITAB were used to solve the model. Analysis of variance for material removal rate is presented in Table 5. The model is consistent at 5% significance level. All coefficients of the model are consistent at 10% significance level.

Table 5. Analysis of variance for material removal rate

Source	DF	Seq SS	Contribution	Adj SS	Adj MS	f-value	p-value
Regression	6	62.6427	98.07%	62.6427	10.4405	169.05	0.000
X1	1	27.0162	42.29%	0.2217	0.2217	3.59	0.073
X2	1	0.0220	0.03%	0.7002	0.7002	11.34	0.000
X3	1	26.5696	41.59%	0.6538	0.6538	10.59	0.004
X4	1	5.9973	9.39%	5.9973	5.9973	97.11	0.000
X2*X2	1	0.6783	1.06%	0.6783	0.6783	10.98	0.003
X1*X3	1	2.3593	3.69%	2.3593	2.3593	38.20	0.000
Error	20	1.2352	1.93%	1.2352	0.0618		
Lack-of-Fit	18	1.2198	1.91%	1.2198	0.0678	8.82	0.107
Pure Error	2	0.0154	0.02%	0.0154	0.0077		
Total	26	63.8779	100.00%				

Model Summary

S	R-sq	R-sq (adj)	PRESS	R-sq (pred)
0.248513	98.07%	97.49%	1.94068	96.96%

The regression equation after analysis of variance for material removal rate is obtained as;

$$r_{MMR}.(X5) = -0.900 + 1.518X1 - 0.0522X2 + 1.117X3 + 0.01154X4 + 0.000841X2X2 + 4.800X1X3 \quad (1)$$

Analysis of variance for 1/average surface roughness is given in Table 6. The model is consistent at 5% significance level. If at least half of the coefficients are consistent at 5% significance level, model is consistent according to the coefficients. Therefore, the coefficients are consistent.

Table 6. Analysis of variance for 1/average surface roughness

Source	DF	Adj SS	Adj MS	f-value	p-value
Regression	8	0.151779	0.018972	66.15	0.000
X1	1	0.003983	0.003983	13.89	0.002
X2	1	0.002302	0.002302	8.02	0.011
X3	1	0.000895	0.000895	3.12	0.094
X4	1	0.009549	0.009549	33.29	0.000
X4*X4	1	0.006900	0.006900	24.06	0.000
X1*X3	1	0.001864	0.001864	6.50	0.020
X1*X4	1	0.000595	0.000595	2.07	0.167
X3*X4	1	0.000618	0.000618	2.15	0.159
Error	18	0.005163	0.000287		
Lack-of-Fit	16	0.005093	0.000318	9.15	0.103
Pure Error	2	0.000070	0.000035		
Total	26	0.156942			

Model Summary

S	R-sq	R-sq (adj)	R-sq (pred)
0.0169360	96.71%	95.25%	93.25%

The regression equation after analysis of variance for 1/average surface roughness is obtained as;

$$1/R_a(X6) = 0.023 - 0.375X1 - 0.000565X2 - 0.0855X3 + 0.00658X4 - 0.000014X4X4$$
$$+0.1349X1X3 - 0.000610X1X4 - 0.000311X3X4 \quad (2)$$

Goal programming model:

Objective function:

$$MinZ = P_s.d_s^- + P_m.d_m^- \quad (3)$$

Constraints:

$$-0.900 + 1.518.X1 - 0.0522.X2 + 1.117.X3 + 0.01154.X4 + 0.000841.X2.X2 +$$
$$4.800.X1.X3 + d_s^- - d_s^+ = 4.8 \quad (4)$$

$$0.023 - 0.375.X1 - 0.000565.X2 - 0.0855.X3 + 0.00658.X4 - 0.000014.X4.X4 +$$
$$0.1349.X1.X3 - 0.000610.X1.X4 - 0.000311.X3.X4 + d_m^- - d_m^+ = 0.45 \quad (5)$$

Bounds:

$$X1 \leq 0.6 \quad (6)$$
$$X2 \leq 50 \quad (7)$$
$$X3 \leq 1.36 \quad (8)$$
$$X4 \leq 250 \quad (9)$$
$$X1 \geq 0.2 \quad (10)$$
$$X2 \geq 10 \quad (11)$$
$$X3 \geq 0.56 \quad (12)$$
$$X4 \geq 150 \quad (13)$$
$$d_S \geq 0 \quad (14)$$
$$d_S + \geq 0 \quad (15)$$
$$d_m - \geq 0 \quad (16)$$
$$d_m + \geq 0 \quad (17)$$
$$P_S = 1 \quad (18)$$
$$P_m = 1 \quad (19)$$

The GP model was solved and the model determined the optimal combination as follows.

- X1 (Depth of cut): 0.39 mm
- X2 (Inclination angle): 10^o
- X3 (Feed rate): 1.15 mm/rev
- X4 (Spindle speed): 249 rev/min

4. Discussion

Three models are compared each other in Table 7. In three models, inclination angle and spindle speed levels are nearly same, whereas depth of cut and feed rate levels are different.

Table 7. Comparison of three model according to cutting conditions and geometry

Models	Depth of cut (mm)	Inclination angle (°)	Feed rate (mm/rev)	Spindle speed (rev/min)
DOE-TOPSIS	0.6	10	1.36	250
NSGA-TOPSIS	0.2	15	0.67	248
DOE-Goal Programming	0.39	10	1.15	249

Effects of geometry and cutting parameters on surface roughness and material removal rate are shown in Figure 2 and Figure 3.

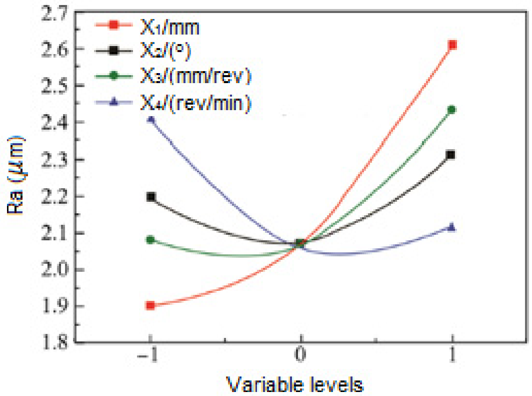

Figure 2. Main effects of parameters on Ra (Rao, Krishna, Katta, & Krishna, 2015)

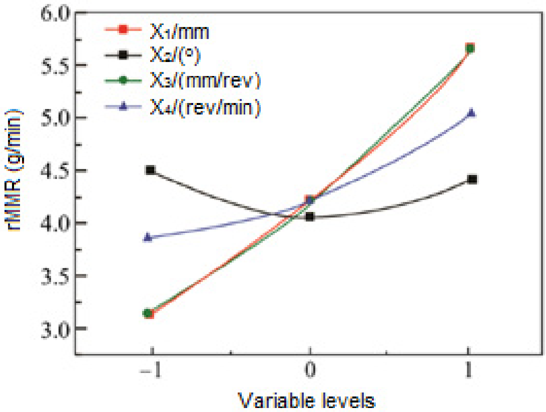

Figure 3. Main effects of parameters on rMMR (Rao, Krishna, Katta, & Krishna, 2015)

When Figure 2 and Figure 3 are compared;

- There is a tradeoff between surface roughness and metal removal rate for depth of cut. Optimal Ra is observed with level -1 however, optimal rMMR is observed with level +1 for depth of cut Therefore, it is better to apply mean value of the levels which is about 0.4 mm for this situation.
- There is a tradeoff between surface roughness and metal removal rate for inclination angle. It is seen that the range between inclination angle levels of -1 and 0 is applicable for optimal results. Therefore, inclination angle range of 10^o - 30^o can be selected for the operation.
- There is a tradeoff between surface roughness and metal removal rate for feed rate. It is observed that optimal range of the levels is between 0.96 and 1.36 mm/rev.
- Optimal level range for spindle speed locates in the range of 0 and +1. It means that values between 200 and 250 rev/min are applicable for optimal results.

By considering proposed three methods for optimization, each method is observed with proper results. However, the main difference arises from depth of cut. Among the methods, goal programming offers the closest value of depth of cut for optimal conditions. As a result, Goal programming model produces better results according to the other models.

5. Conclusion

In this article, three different multi-objective models were used to determine optimum cutting and geometry parameters of SPRT turning operation. The effect of depth of cut, inclination angle, feed rate and spindle speed on surface roughness and metal removal rate was investigated. It was seen from the results that Goal Programming method produces better results compared to the other models. This research provides a framework for the determination of optimum cutting conditions in the industrial area and helps operators to obtain desired surface properties. A limitation of this study is that more data is required to determine the optimum cutting conditions effectively. In further studies, different multi-objective methods might be used and sensitivity analysis based on criteria weights can be performed.

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