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Preliminary communication

OPTIMIZATION OF MACHINING PARAMETERS IN FACE MILLING USING MULTI-OBJECTIVE TAGUCHI TECHNIQUE

Yusuf FEDAI, Funda KAHRAMAN, Hediye KIRLI AKIN, Gokhan BASAR

Abstract: In this research, the effect of machining parameters on the various surface roughness characteristics (arithmetic average roughness (*Ra*), root mean square average roughness (*Rq*) and average maximum height of the profile (*Rz*)) in the milling of AISI 4140 steel were experimentally investigated. Depth of cut, feed rate, cutting speed and the number of insert were considered as control factors; *Ra*, *Rz* and *Rq* were considered as response factors. Experiments were designed considering Taguchi L_9 orthogonal array. Multi signal-to-noise ratio was calculated for the response variables simultaneously. Analysis of variance was conducted to detect the significance of control factors on responses. Moreover, the percent contributions of the control factors on the surface roughness were obtained to be the number of insert (71.89 %), feed (19.74 %), cutting speed (5.08%) and depth of cut (3.29 %). Minimum surface roughness values for *Ra*, *Rz* and *Rq* were obtained at 325 m/min cutting speed, 0.08 mm/rev feed rate, 1 number of insert and 1 mm depth of cut by using multi-objective Taguchi technique.

Keywords: milling; optimization; surface roughness; Taguchi

1 INTRODUCTION

Machining processes like turning, milling, drilling and grinding, etc., have been commonly used in the manufacturing industries. Milling is one of the basic machining processes using rotary tools to remove material from a workpiece by feeding the tools into the workpiece at a certain direction [1]. Milling is a system consisting of a workpiece, cutting tool, machine tool, fixture and cutting parameters. The machinability of a material is defined by measuring factors such as tool life, cutting force and surface roughness. Surface roughness is a commonly encountered problem in machined surfaces. The quality of the surface plays a very important role in the performance of the milling as a milled surface of good quality significantly improves fatigue strength, corrosion resistance or creep life. Surface roughness is determined using *Ra*, *Rz* and *Rq* measurements [2, 3].

At the present time, there have been many investigation progressions in surface roughness modeling and optimization of the machining parameters. Kıvak [4] studied the effect of cutting tools, cutting speed and feed rate on the surface roughness and flank wear in milling of Hadfield steel using Taguchi method (TM). Stipkovic Filho et al. [5] developed a mathematical model for surface roughness as a function of cutting speed, feed and cutting depth in face milling of AISI 4140 hardened steel using response surface methodology (RSM). Sarıkaya et al. [6] researched the influence of machining parameters on surface roughness and tool life in face milling process of AISI D3 steel with carbide coated inserts using TM. Ghani et al. [7] optimized machining conditions in end milling process AISI H13 hardened steel using TM. Gopalsamy [8] used TM to find optimal process parameters on surface roughness and tool life for end milling hardened steel. Ab. Rashid et al. [9] applied artificial neural network and multiple regression method for modeling and optimizing of surface roughness. Patwari et al. [10] modelled and optimized machining parameters for surface roughness in end milling of medium carbon steel by using RSM and genetic algorithm. Baek et al. [11] optimized machining parameters in face milling operation of AISI 1041 steel. Benardos and Vosniakos [12] predicted surface roughness in CNC face milling using neural networks and Taguchi's design of experiments. Routara et al. [13] investigated the influence of cutting parameters: spindle speed, depth of cut and feed rate on the surface roughness of aluminum, brass and AISI 1040 steel in CNC end milling using RSM. Chhabada and Ambekar [14] used grey relational analysis to multi-response optimization of machining parameters on CNC milling of EN 19 alloy steel with TiAlN coated cutter. Mansour and Abdalla [15] used RSM for modeling surface roughness in end milling of EN 32 case hardening steel. Gologlu and Sakarya [16] investigated the effects of cutter path strategies on surface roughness of pocket milling of 1.2738 steel based on TM. Gupta and Sood [17] studied the effects of machining parameters on cutting force and surface roughness in turning of AISI 4340 steel using uncoated carbide insert. Taguchi technique and the utility concept were used for the determination of the optimal performance characteristics. They found that cooling condition has a dominant effect on the performance characteristics.

In this study, the effect of machining parameters on the various surface roughness characteristics; *Ra*, *Rq* and *Rz* in the milling of AISI 4140 steel with TiAlN+TiN, PVD-coated, R 390-11 T308M-PM 1030 solid carbide insert were experimentally investigated. Optimal machining parameters were determined using multi-objective Taguchi technique and a confirmation experiment was conducted to test the success of the optimization.

2 MATERIALS AND METHODS

Experiments were conducted in dry cutting conditions by using a SPINNER MVC1000 model CNC milling machine. The workpiece material used was AISI 4140 steel in the form of a 260 × 150 × 25 mm block. The chemical composition and mechanical properties of AISI 4140 steel are given in Table 1. R 390-020B20-11M tool holder and a TiAlN+TiN, PVD-coated, R 390-11 T308M-PM 1030 solid carbide insert were used. The experimental set up is displayed in Fig. 1. The surface roughness characteristics; Ra, Rz and Rq values of workpieces were measured by MITUTOYO SJ-400 transportable surface roughness tester. The cut off length and evaluation length were constant at 0.8 mm and 4 mm respectively. Surface roughness measurements were made three times on the surfaces of workpieces, and their average roughness parameters were determined. Experiments were conducted according to the Taguchi L_9 orthogonal design matrix and the results were evaluated using Minitab 17 software.

Table 1 The chemical compositions and mechanical properties of AISI 4140 workpiece material

Chemical compositions (wt.%)					
C	Si	Mn	P	S	Ti
0.378	0.223	0.688	0.015	0.007	0.007
Al	Cr	Mo	Ni	V	Co
0.018	0.970	0.199	0.032	0.010	0.009
Mechanical properties					
Tensile strength	Yield strength	Elongation (%)	Brinell Hardness	Elastic modulus	Poisson ratio
655 MPa	415 MPa	25.70	197 HB	190-210 GPa	0.27-0.30

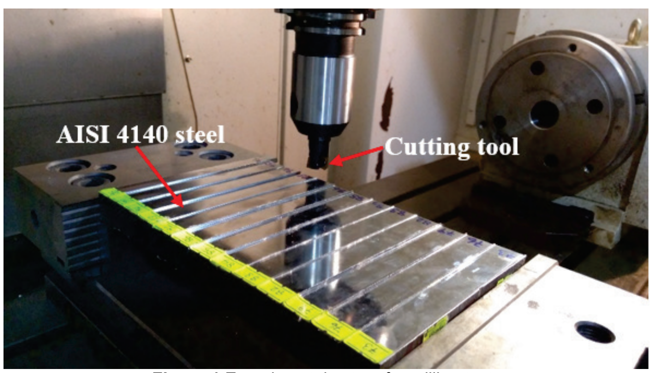

Figure 1 Experimental set up for milling tests

3 EXPERIMENTAL RESULTS AND DISCUSSION

Taguchi technique has been widely used in engineering analysis. This technique exhibits a systematic way that is simple and effective in order to optimize designs for cost, performance and quality [18, 19]. Although the traditional Taguchi technique is successfully applied in the optimization of single response problems, it is not used to solve multi-response problems [20, 21].

Multi objective Taguchi method was proposed by Tong et al. [22] and Anthony [23]. This method transforms multiple responses to single response by simply adding normalized quality loss values for analyzing multiple quality characteristics together. Fig. 2 demonstrates the flow chart for the multi objective optimization.

In this study, depth of cut (mm), feed rate (mm/rev), cutting speed (m/min) and number of insert (pieces) were chosen as input parameters; the surface roughness characteristics *Ra* (μm), *Rq* (μm) and *Rz* (μm) were chosen as output parameters. Specified parameters and their levels are given in Tab. 2. Taguchi L_9 orthogonal array and experimental results were given in Tab. 3.

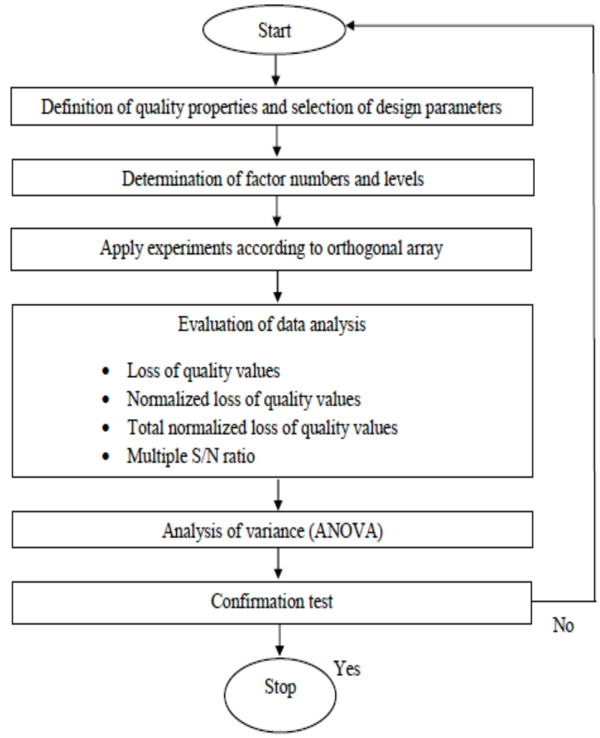

Figure 2 Flow chart for multi-objective optimization

Table 2 Control factors and their levels

Symbol	Factor	Unit	Level 1	Level 2	Level 3
A	doc	mm	0.5	1	1.5
B	f	mm/rev	0.08	0.12	0.16
C	V	mm/min	175	250	325
D	N	(pieces)	1	2	3

Evaluation of data analysis:

Multiple responses are transformed to single response using the Taguchi quality loss function. This optimization procedure is given below and explained.

1. Compute the quality loss (L_{ij})

Quality loss can be classified into three categories: “larger-is-better”, “smaller-is-better” and “normal-is-better”. In this study, the “smaller-is-better” category was selected for obtaining optimum machining parameters. Quality loss values for these responses were calculated using Eq. (1) and shown in Tab. 4.

$$L_{ij} = \frac{1}{n_i}\sum_{k=1}^{n_i} {y_{ijk}}^2 \qquad (1)$$

where n_i is the number of experiment repetition for the i^{th} response, y_{ijk} is the observed value for the i^{th} response in the k^{th} repetition of the j^{th} experiment and L_{ij} is the loss function of the i^{th} response in the *j* experiment.

2. Establish the multi S/N ratio (MSNR):

Step 1: Calculation of Normalized Quality Loss

$$C_{ij} = \frac{L_{ij}}{L_i^*} \tag{2}$$

$$L_i^* = max\left\{L_{i1}, L_{i2} \ldots, \ L_{ij}\right\}$$

where C_{ij} is the Normalized Quality Loss, L_{ij} is the quality loss and L_i^* is the maximum quality loss among the experimental runs. Normalized quality loss values for these responses were computed by using Eq. (2) and summarized in Tab. 5.

Step 2: Calculation of Total Normalized Quality Loss

$$TNQL_j = \sum_{i=1}^{m} w_i C_{ij} \tag{3}$$

where $TNQL_j$ is Total Normalized Quality Loss, w_i is the weight of i^{th} a normalized response (i = 1, 2, ..., m). m is the number of response factors.

Table 3 L_9 orthogonal design matrix and experimental results for *Ra*, *Rz* and *Rq*

Trial No	*doc* (mm)	*f* (mm/rev)	*V* (m/min)	*N* (pieces)	*Ra* 1 (µm)	*Ra* 2 (µm)	*Ra* 3 (µm)	Ave. *Ra* (µm)	*Rz* 1 (µm)	*Rz* 2 (µm)	*Rz* 3 (µm)	Ave. *Rz* (µm)	*Rq* 1 (µm)	*Rq* 2 (µm)	*Rq* 3 (µm)	Ave. *Rq* (µm)
1	0.5	0.08	175	1	0.19	0.16	0.20	0.183	1.35	1.39	1.36	1.367	0.24	0.24	0.26	0.247
2	0.5	0.12	250	2	0.25	0.27	0.30	0.273	1.90	1.95	1.85	1.900	0.31	0.36	0.38	0.350
3	0.5	0.16	325	3	1.20	1.22	1.21	1.210	4.90	5.00	5.10	5.000	1.34	1.38	1.36	1.360
4	1	0.08	250	3	0.46	0.52	0.50	0.493	2.32	2.47	2.41	2.400	0.54	0.60	0.61	0.583
5	1	0.12	325	1	0.13	0.16	0.14	0.143	0.90	0.82	0.88	0.867	0.16	0.18	0.20	0.180
6	1	0.16	175	2	0.48	0.53	0.47	0.493	2.70	3.00	2.90	2.867	0.61	0.60	0.65	0.620
7	1.5	0.08	325	2	0.22	0.23	0.21	0.220	1.60	1.55	1.45	1.533	0.28	0.30	0.27	0.283
8	1.5	0.12	175	3	1.03	1.08	1.06	1.057	4.40	4.35	4.25	4.333	1.15	1.25	1.13	1.177
9	1.5	0.16	250	1	0.29	0.28	0.31	0.293	1.90	1.80	2.00	1.900	0.38	0.35	0.40	0.377

Table 4 Quality loss values for *Ra*, *Rz* and *Rq*

Exp. No	Quality Loss (dB)		
	Ra	Rz	Rq
1	0.0339	1.8767	0.0609
2	0.0751	3.6967	0.1239
3	1.4642	25.0467	1.8499
4	0.2448	5.7867	0.3423
5	0.0217	0.7667	0.0343
6	0.2459	8.3667	0.3882
7	0.0485	2.3800	0.0804
8	1.1186	18.8067	1.3873
9	0.0869	3.6367	0.1432

$TNQL_j$ values have been determined by using Eq. 3. Then for each response, a weight (w_i) was assigned, to indicate its importance relative to other responses. In this case each response has a different importance and weight. Weighting factors have been selected as $w_1 = 0.333$, $w_2 = 0.333$, $w_3 = 0.333$ for surface roughness. Multi signal-to-noise ratio ($MSNR$) was calculated by using Eq. 4. $TNQL_j$ and $MSNR_j$ values were given in Tab. 6.

Table 5 Normalized quality loss values for *Ra*, *Rz* and *Rq*

Exp. No	Normalized quality loss values		
	Ra	Rz	Rq
1	0.0232	0.0749	0.0329
2	0.0513	0.1476	0.0670
3	1.0000	1.0000	1.0000
4	0.1672	0.2310	0.1850
5	0.0148	0.0306	0.0185
6	0.1679	0.3340	0.2099
7	0.0331	0.0950	0.0435
8	0.7640	0.7509	0.7499
9	0.0593	0.1452	0.0774

Step 3: Determine the multi S/N ratio (MSNR)

$$MSNR_j = -10\log\left(TNQL_j\right) \tag{4}$$

Table 6 *TNQL* and *MSNR* values

Exp. No	*TNQL*	*MSNR* (dB)
1	0.0437	13.598
2	0.0886	10.524
3	1.0000	0.000
4	0.1944	7.113
5	0.0213	16.713
6	0.2373	6.248
7	0.0572	12.426
8	0.7549	1.221
9	0.0940	10.269
Average *MSNR*		8.679

Table 7 Main effects of factors on *MSNR*

Factor	*MSNR* (dB)			
	Level			
	1	2	3	Max-Min
doc	8.041	**10.024***	7.972	2.052
f	**11.045***	9.486	5.506	5.540
V	7.022	9.302	**9.713***	2.691
N	**13.527***	9.733	2.778	10.749
*Optimal level				

3. Determine the optimal factor/level combinations

The effect of the control factors on the MSNR was obtained from Tab. 7. For the surface roughness parameters *Ra*, *Rz* and *Rq*, the MSNR graphs of the control factors are shown in Fig. 3. The best factor / level combination was identified as $A_2B_1C_3D_1$. The optimum levels of different control factors minimum surface roughness are A at level 2

(1 mm) and B at level 1 (0.08 mm/rev), C at level 3 (325 m/min), D at level 1 (1).

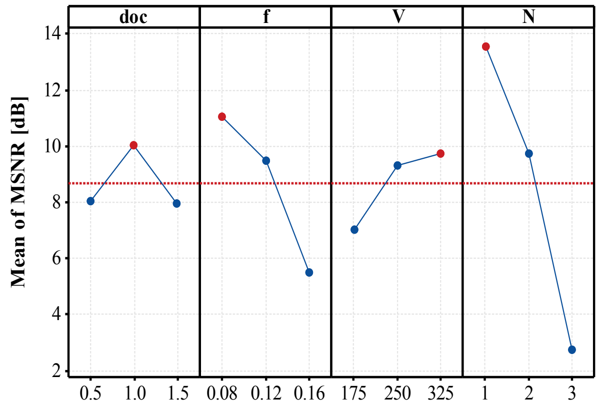

Figure 3 *MSNR* graph of control factors

4. Variance analysis (ANOVA)

ANOVA was performed to calculate the effective factors on the surface roughness results and the contribution of these factors in the milling process (Tab. 8). From the ANOVA chart, the surface roughness parameters *Ra*, *Rz* and *Rq* appear to be the most important factor in the feed rate. When the effect of the factors as a percentage is examined, it is seen that the effect of number of insert is 71.89%, the effect of the feed rate is 19.74%, the effect of the cutting speed is 5.08%, and the effect of the depth of cut is 3.29%. In conclusion, according to the ANOVA table, the most important factor to consider for surface roughness has been found to be the number of insert.

Table 8 ANOVA for *MSNR*

Factors	Degree of freedom (DOF)	Sum of squares (SS)	Mean square (MS)	Percent contribution (PC)
doc	2	8.150	4.075	3.29
f	2	48.964	24.482	19.74
V	2	12.607	6.303	5.08
N	2	178.300	89.150	71.89
Total	8	248.020		100

5. Confirmation experiment

The final step of the optimization process is to test the condition giving the optimal values to verify that the proposed improvement has been met. Verification test results are given in Tab. 9. In this work, the optimum result for the surface roughness as a result of milling process was reached under the experimental conditions $A_2B_1C_3D_1$ test conditions. Eq. (5) was used to calculate *Ra*, *Rz* and *Rq* of surface roughness values at optimal milling conditions determined by Taguchi technique. The estimated value of the *MSNR* at the optimum parameter levels (η_{opt}) is calculated.

$$\eta_{opt} = \eta_m + \sum_{i=1}^{p}(\eta_{mi} - \eta_m) \tag{5}$$

where η_{opt} is the predicted MSNR, η_m is the overall average of the MSNR, η_{mi} is the average MSNR at the optimum level, and p is the number of the input factors that significantly influence the quality characteristic.

Table 9 Confirmation test results

Surface roughness	Random parameters	Optimum process parameters	
		Predicted	Experimental
Level	$A_2B_1C_2D_3$	$A_2B_1C_3D_1$	$A_2B_1C_3D_1$
Ra (µm)	0.493		0.117
Rz (µm)	2.400		0.933
Rq (µm)	0.583		0.143
MSNR (dB)	7.113	18.273	17.359

It is seen that an improvement of 10.246 (dB) in the MSNR when the optimal process parameter ($A_2B_1C_3D_1$) is used instead of the random parameter ($A_2B_1C_2D_3$). The results obtained from the confirmation experiments reflect the success of the multi-response optimization.

4 CONCLUSIONS

This study presented multi objective Taguchi technique to optimize performance parameters of AISI 4140 steel. The multiple quality characteristics were considered simultaneously using Taguchi quality loss function. The findings of the investigation are summarized as follows:

- The optimal levels of the machining parameters for minimum surface roughness for *Ra*, *Rz* and *Rq* values were obtained to be 325 m/min cutting speed, 0.08 mm/rev feed rate, 1 mm depth of cut and 1 number of insert.
- *Ra*, *Rz* and *Rq* have been decreased down to 0.117 µm, 0.933 µm and 0.143 µm, respectively against the random values of *Ra*, *Rz* and *Rq* of 0.479 µm, 2.400 µm and 0.583 µm, respectively.
- The percent contribution of the control factors on the multiple quality characteristics was obtained to be number of insert (71.89%), feed rate (19.74%), cutting speed (5.08%), and depth of cut (3.29%) with ANOVA. The results show that the number of insert was found to be the significant factor among process parameters. The confirmation test conducted to determine optimal combination of machining parameters of AISI 4140 steel.
- Confirmation test results show that the increase of the MSNR ratio from the random input parameters to the optimal performance parameter was obtained to be 10.246 dB. These results show that the multi response optimization technique by using a Taguchi quality loss function can significantly improve the quality performance characteristics of the milling process.

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Authors' contacts:

Yusuf FEDAI, Assist. Prof. Dr.
Osmaniye Korkut Ata University
Department of Manufacturing Engineering,
80000, Osmaniye, Turkey
E-mail: yusuffedai@osmaniye.edu.tr

Funda KAHRAMAN, Assoc. Prof. Dr.
Mersin University
Department of Mechatronics Engineering,
80000, Mersin, Turkey
E-mail: fkahraman@mersin.edu.tr

Hediye KIRLI AKIN, Assist. Prof. Dr.
Osmaniye Korkut Ata University
Department of Manufacturing Engineering,
80000, Osmaniye, Turkey
E-mail: hediyeakin@osmaniye.edu.tr

Gokhan BASAR, Res. Assist.
Osmaniye Korkut Ata University
Department of Manufacturing Engineering,
80000, Osmaniye, Turkey
E-mail: gokhanbasar@osmaniye.edu.tr