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Optimization of End Milling Process Parameters for Minimization of Surface Roughness of AISI D2 Steel

Pankaj Chandna, Dinesh Kumar

***Abstract*—**The present work analyses different parameters of end milling to minimize the surface roughness for AISI D2 steel. D2 Steel is generally used for stamping or forming dies, punches, forming rolls, knives, slitters, shear blades, tools, scrap choppers, tyre shredders etc. Surface roughness is one of the main indices that determines the quality of machined products and is influenced by various cutting parameters. In machining operations, achieving desired surface quality by optimization of machining parameters, is a challenging job. In case of mating components the surface roughness become more essential and is influenced by the cutting parameters, because, these quality structures are highly correlated and are expected to be influenced directly or indirectly by the direct effect of process parameters or their interactive effects (i.e. on process environment). In this work, the effects of selected process parameters on surface roughness and subsequent setting of parameters with the levels have been accomplished by Taguchi's parameter design approach. The experiments have been performed as per the combination of levels of different process parameters suggested by L9 orthogonal array. Experimental investigation of the end milling of AISI D2 steel with carbide tool by varying feed, speed and depth of cut and the surface roughness has been measured using surface roughness tester. Analyses of variance have been performed for mean and signal-to-noise ratio to estimate the contribution of the different process parameters on the process.

***Keywords*—**D2 Steel, Orthogonal Array, Optimization, Surface Roughness, Taguchi Methodology.

I. Introduction

MILLING is one of the most widely used metal removal processes in industry and milled surfaces are largely used to mate with other parts in die, aerospace, automotive, and machinery design as well as in manufacturing industries [1], [2] (Fig. 1). Surface roughness is an important measure of the quality of a production and also influences the machining cost. The mechanism behind the formation of surface roughness is very dynamic, complicated, and process dependent; it is difficult to calculate surface roughness value through theoretical analysis [3]. Therefore, usually most of machine operators applied "trial and error" approaches to set-up milling machine cutting conditions in order to achieve the desired surface roughness. However, it is not effective and efficient and the success rate for repetitive desirable value is very low. The dynamic nature and widespread usage of milling operations in practice have raised a need for a systematic approach that can help to set-up milling operations in comparatively lesser time and also achieve the desired surface roughness quality. Due to high tolerances and good surface finish values that milling can deal, it is ideal for adding precision features to a part whose basic shape has already been formed [4].

Fig. 1 End Milling Operation on D2 steel

II. Literature Review

Application of Taguchi parameter design requires the identification of factors affecting targeted quality characteristics. Relevant literature must be reviewed thoroughly to find out the most important among different factors or conditions affecting surface roughness in milling operation. The end milling process is a widely used machining process in aerospace industries and many other industries ranging from large manufacturers to a small tool and die shops, because of its versatility and efficiency. The reason for being widely used is that it may be used for the rough and finish machining of such features as slots, pockets, peripheries and faces of components [5]. As milling is a multi-point machining process, more potential variability makes it even harder to obtain a surface roughness model in milling operations compared with single point machining [3]. Tsai et al. stated that the feed rate, cutting speed, depth of cut, cutter geometry, and cutter run out, tool wear, and the cutter force and vibration under dynamic cutting conditions were found to be possible factors affecting surface finish [3]. Fuh and Wu included cutting speed, feed rate, depth of cut, tool nose radius, and flank as control factors for the creation of a statistical model to predict surface roughness for aluminum parts in end milling operations using Taguchi design [6].

Pankaj Chandna is with the Department of Mechanical Engineering, National Institute of Technology, Kurukshetra, 136118, India (e-mail: pchandna08@gmail.com).
Dinesh Kumar is with the Department of Mechanical Engineering, JCDM College of Engineering, Sirsa, 125055, India (e-mail: dinesh30@rediffmail.com).

Ghani et al. conducted a study to optimize cutting conditions for hardened steel under semi-finish and finish conditions [7]. Applying cutting speed, feed rate, and depth as control factors, they used measured responses (i.e., surface roughness and resultant cutting force) and their calculated signal-to-noise ratio to determine the optimal cutting condition. Bouzid et al. did research to obtain optimal cutting parameters such as cutting speed, feed per tooth, and cutting depth for surface roughness in down face milling operations by using duplex stainless steel and carbon steel compositions as samples [8]. Also applying these three cutting parameters as control factors, Lin studied multiple characteristics including removed volume, surface roughness, and burr height, and in this research a weighted value was used to optimize the cutting condition for face milling operations [9]. Oktem et al. developed a Taguchi optimization method for low surface roughness for milling an aluminum alloy [10]. The studies reviewed above indicated although applied in various working conditions for solving different, specific problems, they all selected the three commonly applied machining parameters – feed rate, cutting speed, and depth of cut – as controllable input factors. These studies indicated that the technique of Taguchi parameter design worked well in optimizing cutting parameters to achieve the surface finish result. This study includes feed rate, spindle speed, and depth of cut as control variables. The determination of optimal cutting parameters has significant importance for economic machining in minimizing of particular operating mistakes like tool fraction, wear, and chatter.

Taguchi design method has been applied in the present work. Taguchi design was developed by Dr. Genichi Taguchi of Nippon Telephones and Telegraph Company, Japan. It is a set of methodologies by which the inherent variability of materials and manufacturing processes are taken into account at the design stage. The application of this technique had become widespread in many US and European industries after the 1980s. In this technique multiple factors can be considered at once and seeks nominal design points that are insensitive to variations in production and user environments to improve the yield in manufacturing and the reliability in performance of a product [11]. Therefore, controlled factors along with noise factors may be considered in this approach. Although similar to design of experiment (DOE), the Taguchi design only conduct the balanced (orthogonal) experimental combinations, which makes the Taguchi design even more effective than a fractional factorial design. By using the Taguchi techniques, industries are able to greatly reduce product development cycle time for both design and production, therefore reducing costs and increasing profit. Moreover, Taguchi design allows looking into the variability caused by noise factors, which are usually ignored in the traditional DOE approach.

III. Design of Experiment

Experiments have been performed by investigators in almost all fields of inquiry, usually to discover something about a particular process or system. In this experimental work the following settings has been used.

A. Material Used

In this work hardened AISI D2 steel (hardness 50-70 HRC) has been used as the work piece material and coated Tungsten carbide is being used as the tool material. The chemical arrangement of AISI D2 tool steel is given in Table I. AISI D2 is recommended for tools requiring very high wear resistance, combined with moderate toughness (shock-resistance) like Dies, Punches, Forming Rolls, Knives, and Slitters etc. AISI D2 can be supplied in various finishes, including the hot-rolled, pre-machined and fine machined condition.

TABLE I
Chemical Composition of AISI D2 Steel

Name of the Component	% Composition
Carbon	1.55 %
Silicon	0.30 %
Manganese	0.35 %
Chromium	12.00 %
Molybdenum	0.75 %
Vanadium	0.90 %

B. Machine Used

Machining was carried out on CNC machine at CTR, Ludhiana shown in Fig 2. Specifications of the vertical milling machine are shown in Table II.

TABLE II
Specifications of Vertical CNC Milling Machine

Property	Specification
Table Size	915 * 356 mm
Table Load	341 KG
Power	3 phase, 60 Hz
Control	GE FANUC 211
X Axis Travel	560 mm
Y Axis Travel	406 mm
Z Axis Travel	508 mm
Spindle Speed	100 RPM Direct Drive
Spindle Diameter	65 mm
Spindle Taper	ISO-40
Tool Taper	BT-40
Magazine Capacity	22 Tools
Maximum Weight of Tool Holder	50 KG
Maximum Tool Length	254 mm

C. Steps in Taguchi Methodology

1) Identify the main function, side effects, and failure mode
2) Identify the noise factors, testing conditions, and quality characteristics
3) Identify the objective function to be optimized
4) Identify the control factors and their levels
5) Select the orthogonal array matrix experiment
6) Conduct the matrix experiment
7) Analyze the data, predict the optimum levels and performance
8) Perform the verification experiment and plan the future action

D. Process Parameters of End Milling

The selected end milling process parameters are presented in Table III. The range of speed is selected as 796 rpm to 1194 RPM; the depth of cut is selected as 0.25mm to 0.75 mm; whereas the range of feed is considered as 508 mm/min to

1100 mm/min.

E. Experimental Procedure

The experimental region has been decided as per Taguchi design approach. The number of levels for each controllable process parameter has been defined by Table III. A wide experimental region has been covered so that sensitivity to noise factors does not alter with small changes in these factors settings and to obtain optimum regions for the process parameters. Therefore, each parameter was analyzed at different levels of the process parameters. The work-piece has been machined to the size of 100×100×25 mm by cutter. Three main machining parameters are considered to predict surface roughness of D2 material using carbide tool. Among the range of spindle speed, feed, and depth of cut accessible possible in the machine the following three levels are considered as shown in Table III. The machining is carried out by selecting proper spindle speed and feed rate during each experimentation as per OA selected. Table IV shows the design matrix used in this work.

TABLE III
LEVELS OF INPUT CONTROL PARAMETERS

Factors	Levels	Factor Level values
Speed (RPM)	3	796, 995, 1194
Depth of Cut (mm)	3	0.25, 0.50, 0.75
Feed (mm/min)	3	508, 800, 1100

TABLE IV
ORTHOGONAL ARRAY L9

Sample No.	Spindle Speed (rpm)	Feed Rate (mm/min)	Milling Depth (mm)
1	1	1	1
2	1	2	2
3	1	3	3
4	2	1	2
5	2	2	3
6	2	3	1
7	3	1	3
8	3	2	1
9	3	3	2

TABLE V
PROCESS PARAMETER DESIGN

Pieces	Speed (rpm)	Depth of Cut (mm)	Feed (mm/min)
1	796	0.75	500
2	796	0.50	800
3	796	0.25	1100
4	995	0.75	800
5	995	0.50	1100
6	995	0.25	500
7	1194	0.75	1100
8	1194	0.50	500
9	1194	0.25	800

Taguchi's designs aimed to allow greater understanding of variation than did many of the traditional designs. Taguchi contended that conventional sampling is inadequate here as there is no way of obtaining a random sample of future conditions. Taguchi projected extending experimentation with an outer array or orthogonal array should simulate the random atmosphere. In the present work the experiments have been performed on the combinations of levels of factors defined by L9 orthogonal array.

Taguchi orthogonal array is designed with three levels of three milling parameters. Orthogonal array design of experiment has been found suitable in the present work. It considers three process parameters (without interaction) to be varied in three discrete levels. The experimental design has been shown in Table V.

IV. ANALYSIS AND INTERPRETATION

The experiments are conducted thrice for the same set of parameters for a piece. The surface finish values have been measured for each trial and shown in Table VI. Surface roughness average parameter (Ra) is the most extended index of product quality and has been used in this study. The average roughness (Ra) can be defined as the area between the roughness profile and its mean line or integral of absolute value of the roughness profile height over the evaluation length. The experimental data for the surface roughness values with mean value is shown in Table VII.

TABLE VI
MEASURED SURFACE ROUGHNESS

Pieces	R_{a1} (μm)	R_{a2} (μm)	R_{a3} (μm)
1	0.201	0.175	0.18
2	0.372	0.385	0.379
3	0.382	0.375	0.369
4	0.605	0.621	0.602
5	0.306	0.309	0.321
6	0.355	0.371	0.352
7	0.821	0.839	0.822
8	0.398	0.41	0.389
9	0.244	0.253	0.248

TABLE VII
MEAN SURFACE ROUGHNESS

Pieces	Speed (v) (rpm)	Depth of Cut (d) (mm)	Feed (f) (mm/min)	Mean Surface Roughness (μm)
1	796	0.75	500	0.18
2	796	0.50	800	0.38
3	796	0.25	1100	0.37
4	995	0.75	800	0.61
5	995	0.50	1100	0.31
6	995	0.25	500	0.36
7	1194	0.75	1100	0.83
8	1194	0.50	500	0.40
9	1194	0.25	800	0.25

TABLE VIII
MEASURED S/N RATIO & MEANS BY TAGUCHI OPTIMIZATION

Pieces	Speed (rpm)	Depth of Cut (mm)	Feed (mm/min)	S/N Ratio	Mean
1	796	0.75	500	14.89	0.18
2	796	0.50	800	8.40	0.38
3	796	0.25	1100	8.636	0.37
4	995	0.75	800	4.293	0.61
5	995	0.50	1100	10.17	0.31
6	995	0.25	500	8.873	0.36
7	1194	0.75	1100	1.618	0.83
8	1194	0.50	500	7.958	0.40
9	1194	0.25	800	12.04	0.25

To study the process parameters characteristics and optimum setting signal-to-noise ratio has been calculated instead of average in Taguchi method for the results obtained based on orthogonal array. Optimal performance and minimal variance can be designed by S/N quantity. Table VIII lists the S/N ratio and means value. Average and the variation of the quality characteristics both are replicated by S/N ratio. Since the problem is of minimization of surface roughness, the relation “smaller is better” is selected to calculate S/N ratio.

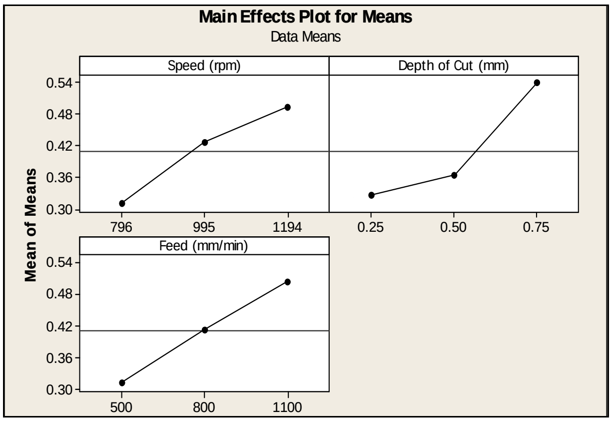

Fig. 3 Effects Plot for Means

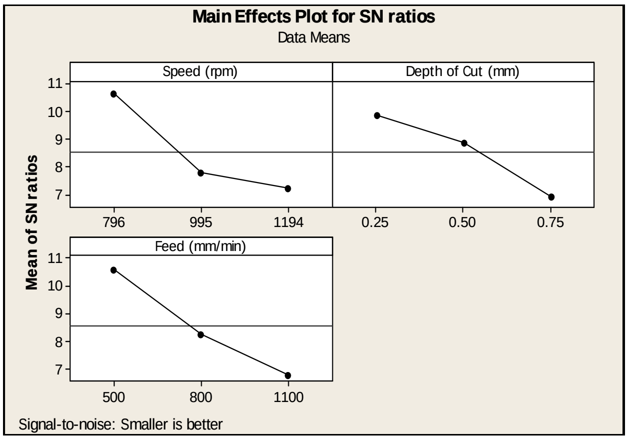

Fig. 4 Effects Plot for S/N Ratio

For lower-the-better performance characteristic, S/N Ratio calculated by (1)

$$\text{S/N ratio} = -\log_{10}\left(\frac{1}{n}\right)\sum_{i=1}^{n} {y_{ij}}^2 \quad (1)$$

where n: Number of replications; yij: Observed response value:

i=1, 2.…. n; j=1, 2.…k.

The result of S/N ratio analysis for the surface roughness values, these values have been calculated using Taguchi process is shown in Table VIII.

Figs. 3 and 4 show the main effects plots for means and S/N ratio respectively for the average of three trials of surface roughness for end milling process. An optimum level of the process parameters have been obtained from these plots i.e. the third level of the parameter speed (v3), the third level of the parameter depth of cut (d3) and the third level of the parameter feed (f3).

The Taguchi method is a simple and effective solution for parameter design and experimental planning [12], [14]-[15]. Signal-to-noise (S/N) ratio is used to signify a performance characteristic in which the smaller value of the S/N ratio is required.

A. ANOVA for Mean and S/N Ratio

A better feel for the relative effect of the different factors can be found by decomposition of variance, which is commonly called ANOVA. The parameters such as sequential sum of squares (SS), variance, degree of freedom, Fisher’s ratio (F) and percentage contribution has been calculated.

TABLE IX
ANALYSIS OF VARIANCE FOR S/N RATIO INCLUDING PERCENT CONTRIBUTION

Source	DF	SS	Variance	F	% Contribution
Speed	2	20.33	1016	0.31	16.71
D.O.C.	2	13.17	6.58	0.2	21.82
Feed	2	21.66	10.83	0.33	17.8
Error	2	66.51	33.26		43.67
Total	8	121.67			

Variance measures how far a set of numbers is spread out. A variance of zero indicates that all the values are identical. Variance is always non-negative. A small variance indicates that the data points tend to be very close to the mean (expected value) and hence to each other, while a high variance indicates that the data points are very spread out around the mean and from each other. In an ANOVA, the F-ratio is the statistic used to test the hypothesis that the effects are real: in other words, that the means are significantly different from one another. It is used to determine if the variances between the means of two populations are significantly different. If the difference between the means is due only to chance, that is, there are no real effects, then the expected value of the F-ratio would be one (1.00). Seldom will the F-ratio be exactly equal to 1.00, however, because the numerator and the denominator are estimates rather than exact values. Therefore, when there are no effects the F-ratio will sometimes be greater than one, and other times less than one. The percent contribution values reflect the relative portion of the total variation observed in an experiment which is attributed to each factor. It is a function of the sums-of-squares, for each factor, indicating its relative power to reduce the response variation. This is the percentage of sum of squares for that term relative to the total sum of squares. In other words, the percent contribution of a given factor indicates the potential reduction in the total variation that can be achieved, if this factor is controlled precisely. The sequential and adjusted sums of squares in the analysis of variance table also indicate the relative importance of each factor; the factor with the biggest sum of squares has the greatest impact. These results mirror the factor ranks in the response tables. The results of ANOVA for S/N ratio and Means with speed, depth of cut and feed are shown in Tables IX and X. It is clearly illustrated Table X that parameters speed, depth of cut and feed significant affect both the mean and variation in surface roughness. It is found that depth of cut is the most significant parameter, and feed is the next significant parameter for affecting the surface roughness in milling of AISI D2 steel. Therefore, the control factor depth of cut and feed should be carefully set to avoid process variance.

TABLE X
ANALYSIS OF VARIANCE FOR MEANS INCLUDING PERCENT CONTRIBUTION

Source	DF	Seq SS	Variance	F	% Contribution
Speed	2	0.05167	0.02583	0.41	16.67
D.O.C.	2	0.07807	0.03903	0.62	25.18
Feed	2	0.0542	0.0271	0.43	17.48
Error	2	0.12607	0.06303		40.67
Total	8	0.31			

The results obtained by average plot, S/N ratio plot and ANOVA table are not sufficient to find the optimum parameters in order to minimize the surface roughness. Therefore, to be more confident about the optimum combination of process parameters, percent contribution and confidence interval has also been estimated. In addition to this, some conformational experiments have also been performed and check the existence of the results between these intervals.

B. Percent Contribution

The percent contribution is the portion of the total variation observed in an experiment attributed to each significant factor. The percent contribution is a function of the sums of squares for each significant item [13]. The variation due to a factor contains some amount due to error (Verror) and can be obtained by (2)

$$V = V' + V_{error} \tag{2}$$

where, V′ is the expected amount of variation. Expected sum of secure (SS') due to variation in the process parameters and percent contribution for each related parameter is computed with the help of (3)-(6).

$$V = SS_v \tag{3}$$
$$V = SS'_v \tag{4}$$
$$SS' = SS - (V_{error})(v) \tag{5}$$
$$P = \frac{SS'}{SS_T} \tag{6}$$

where P is the percent contribution for each process parameters and SST is the total sum of square. ANOVA table for mean surface finish and S/N ratio including percent contribution has been shown in Tables IX and X respectively.

C. Confidence Interval

Confidence interval (CI) has been calculated for 95% consistency level and some conformational experiments have been conducted at optimum level of the process parameters for testing the adequacy of the Taguchi methodology. This interval has been obtained by (7):

$$\text{CI} = \left[F\,(\alpha, 1, \nu_e) V_e \left\{\frac{1}{\eta} + \frac{1}{r}\right\}\right]^2 \tag{7}$$

where α is the level of risk, Ve is the error variance, νe is the error degrees of freedom, η is the effective number of replications and r is number of test trials.

The 95% confidence interval of the predicted optimum of the surface roughness is:

$$[\mu - \text{CI}] < \mu < [\mu + \text{CI}],\ 0.0499 < \mu < 0.7701$$

where, μ is the mean surface roughness.

V. CONCLUSION

The study proposes an integrated optimization approach using Taguchi method. Optimum combination of process parameters (v3, d3, f3) for minimum surface roughness has been calculated using Taguchi methods. The result also matches with the experiment 7 in Table VIII where S/N ratio is minimum (1.618) for the said combination. It has been found that the depth of cut contributes more than 21% in minimization of surface roughness, whereas, feed and speed affects the surface roughness to 17.8% and 16.7% respectively. The predicted range of surface finish is 0.0499< μ < 0.7701 at 95% consistency level for optimum combination of process parameters. Three conformational experiments have also been performed at the optimum combination of process parameters and all the results (Table XI) are found within the calculated range of surface roughness.

TABLE XI
CONFORMATIONAL TESTS

Pieces	Speed (v3) (rpm)	Depth of Cut (d3) (mm)	Feed (f3) (mm/min)	Surface Roughness (μm)
1	1194	0.75	1100	0.372
2	1194	0.75	1100	0.367
3	1194	0.75	1100	0.453

Taguchi parameter design can provide a systematic procedure that can effectively and efficiently identify the optimum surface roughness in the process control of individual end milling machines. It also allows industry to reduce process or product variability and minimize product defects by using a relatively small number of experimental runs and costs to achieve superior-quality products. This research only demonstrates how to use Taguchi parameter design for optimizing machining performance for minimum surface roughness. This approach can be recommended for continuous quality improvement and off-line quality of any production process.

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