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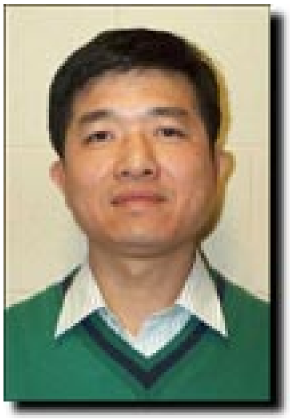

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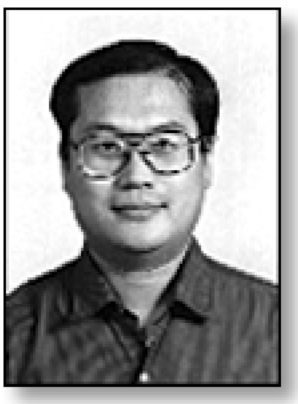

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Introduction

The increase of consumer needs for quality metal cutting related products (more precise tolerances and better product surface roughness) has driven the metal cutting industry to continuously improve quality control of metal cutting processes. Within these metal cutting processes, the end-milling process is one of the most fundamental metal removal operations used in the manufacturing industry (Lou & Chen, 1999). Surface roughness, which is used to determine and evaluate the quality of a product, is one of the major quality attributes of an end-milled product.

In order to obtain better surface roughness, the proper setting of cutting parameters is crucial before the process takes place. As a starting point for determining cutting parameters, technologists could use the hands on data tables that are furnished in machining data handbooks. Lin (1994) suggested that a trail-and-error approach could be followed in order to obtain the optimal machining conditions for a particular operation. Consequently, it is a very time consuming process of identifying the optimum cutting condition for a particular operation. Recently, a Design of Experiment (DOE) has been implemented to select manufacturing process parameters that could result in a better quality product.

The DOE is an effective approach to optimize the throughput in various manufacturing-related processes (Fidan, Kraft, Ruff, & Derby, 1998). In their study, three independent variables, each with three levels, had total of (3^3) = 27 experimental runs. Oftentimes, the optimum metal cutting process required studying more than three factors for the cutting parameters. For example, if a DOE setup considered four or five independent variables, each with at least three levels, then (3^4) = 81 runs or (3^5) = 243 runs were required in the experiments. Imagining the total cost of these experimental runs, one could conclude that it was very costly for the industry (Yang & Tarng, 1998). In addition, the time of these runs could delay any quality resolving actions for the industry.

More Industrial Technology (IT) graduates are facing challenges to improve the quality of products and processes with minimum cost and time constraints in their careers. The Taguchi parameter design techniques have been proved to be successful in meeting this challenge over the past 15 years (Antony & Kaye, 1999). Therefore, there is a need to not only introduce our IT graduates to DOE but also Taguchi parameter design. This paper attempts to introduce how Taguchi parameter design could be used in identifying the significant processing parameters and optimizing the surface roughness of end-milling operations. This systematic approach of implementing Taguchi parameter design could be sought out for IT curriculum (Foster, 2000).

Purpose of Study

There were two purposes of this research. The first was to demonstrate a systematic procedure of using Taguchi parameter design in process control of individual milling machines. The second was to demonstrate a use of the Taguchi parameter design in order to identify the optimum surface roughness performance with a particular combination of cutting parameters in an end-milling operation.

Surface Roughness Measurement Techniques

Surface roughness of a machined product could affect several of the product's functional attributes, such as contact causing surface friction, wearing, light reflection, heat transmission, ability of distributing and holding a lubricant, coating, and resisting fatigue (Lou & Chen, 1997). Therefore, surface roughness becomes one of the important quality aspects in end-milling products.

There are various simple surface roughness amplitude parameters used in industry, such as roughness average (R_a), root-mean-square (rms) roughness (R_q), and maximum peak-to-valley roughness (R_y or R_{max}), etc. (PDI Webmaster, 2000). The parameter R_a is used in this study. The average roughness (R_a) is the area between the roughness profile and its mean line, or the integral of the absolute value of the roughness profile height over the evaluation length (Figure 1). Therefore, the R_a is specified by the following equation:

$$R_a = \frac{1}{L}\int_0^L |Y(x)|dx, \qquad (1)$$

where

R_a = the arithmetic average deviation from the mean line
L= the sampling length
Y= the ordinate of the profile curve

There are many methods of measuring surface roughness, such as using specimen blocks by eye or fingertip, microscopes, stylus type instruments, profile tracing instruments, etc. A Pocket Surf stylus type instrument (produced by Federal Products Co.) was used in this study due to its easy setup and minimum cost (approximately $1,600).

Taguchi Parameter Design

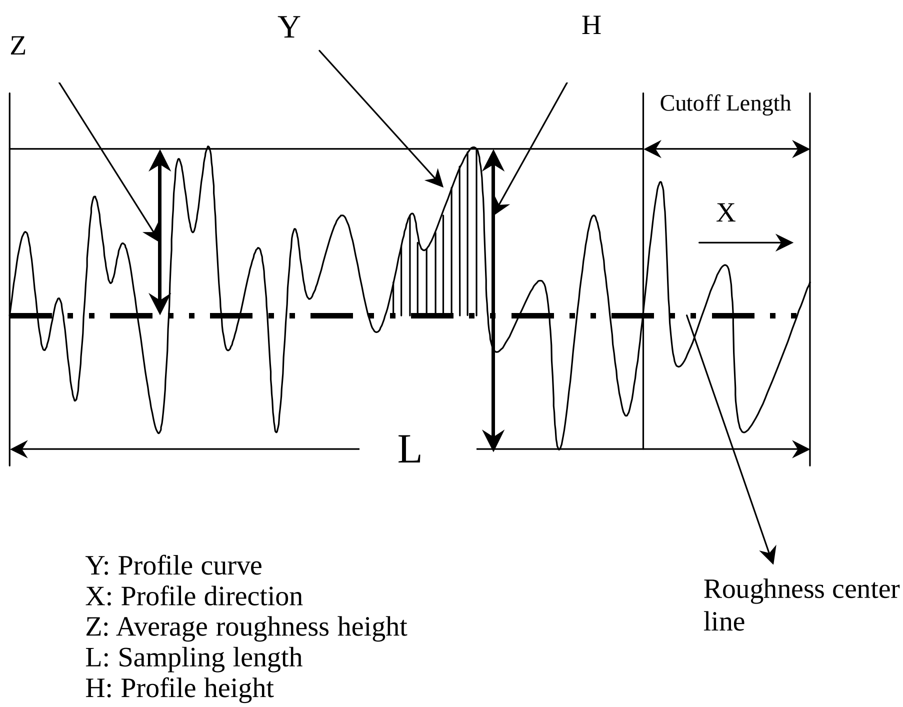
In the early 1950s, Dr. Genichi Taguchi, "the father of Quality Engineering," introduced the concept of off-line quality control techniques known as Taguchi parameter design (Antony & Kaye, 1999). Off-line quality control techniques are those activities performed during the product (or process) design and development phases. Taguchi parameter design is based on the concept of fractional factorial design (Montgomery, 1997). The two major goals of parameter design are (1) to minimize the process or product variation and (2) to design robust and flexible processes or products that are adaptable to environmental conditions. "Robust" means that the process or product performs consistently and is relatively insensitive to factors that are difficult to control (Torng, Chou, & Liu, 1998).

Two important tools used in parameter design are orthogonal arrays and signal-to-noise (S/N) ratios (Phadke, 1989). Orthogonal arrays have a balanced property in which every factor setting occurs the same number of times for every setting of all other factors in the experiment. Orthogonal arrays allow researchers or designers to study many design parameters simultaneously and can be used to estimate the effects of each factor independent of the other factors. Therefore, the information about the design parameters can be obtained with minimum time and resources (Antony & Kaye, 1999). The signal-to-noise ratio is simply a quality indicator by which the experimenters and designers can evaluate the effect of changing a particular design parameter on the performance of the process or product. Figure 2 demonstrates the procedure and steps of Taguchi parameter design (Fowlkes & Creveling, 1997).

Experimental Design, Setup, and Results

The study was carried out using a Fadal VMC-40 vertical milling machine with multiple tool-change capabilities (max number of tools = 21) and with 15 HP spindle horsepower (Figure 3). The machine is capable of a three-axis movement (along the x, y,

Figure 1. Surface roughness profile.



and z planes). CNC programs can be developed in the VMC CPU or downloaded from a 3 $^{1}/_{2}$" diskette or data link. In this study, the CNC program was downloaded from a 3 $^{1}/_{2}$" diskette.

The experimental design, setup, and results are presented as follows:

Step 1. Selection of the quality characteristic

There are three types of quality characteristics in the Taguchi methodology, such as smaller-the-better, larger-the-better, and nominal-the-best. For example, smaller-the-better is considered when measuring fuel consumption of an automobile or shrinkage of a plastic component (Antony & Kaye, 1999). The goal of this research was to produce minimum surface roughness (R_a) in an end-milling operation. Smaller R_a values represent better or improved surface roughness. Therefore, a smaller-the-better quality characteristic was implemented and introduced in this study.

Step 2. Selection of noise factors and control factors

In the previous studies, Savage (1998) and Chen & Lou (2000) indicated that depth of cut, cutting speed, and feed rate had significant effects on surface roughness in the end milling operations. In this study, the controllable factors are depth of cut (A), cutting speed (B), feed rate (C), and tool diameter (D), which were selected because they can potentially affect surface roughness performance in end-milling operations. Since these factors are controllable in the machining process, they are considered as controllable factors in the study.

One of the important attributes of Taguchi parameter design is it could also consider uncontrollable (Noise) factors in the analysis. One of the noise factors used in this study is the measurement location of the work piece. It is very difficult to control the surface roughness measurement because it is different at separate locations. In this study, the measurement location of the finished surface was considered as a noise factor and was measured at three different locations. Table 1 listed all the Taguchi design parameters and levels.

Step 3. Selection of Orthogonal Array

There are 18 basic types of standard Orthogonal Arrays (OA) in the Taguchi parameter design (Torng, Chou, & Liu, 1997). Since four factors were studied in this research, three levels of each factor were considered. Therefore, an L_{18} Orthogonal Array (L_{18} (2^1 x 3^7)) was selected for this study. The layout of this L_{18} OA is shown in Table 2. Each run will have three data collected. Therefore, a total of (18*3) = 54 data values were collected, which were conducted for analysis in this study.

Step 4. Conducting the experiments

Figure 3 illustrates the experimental settings in this study for work piece and end-milling operations (Lou, Chen & Li, 1998). The tool used in this experiment was a four-flute, high-speed steel end mill. The material used for the experiment were one-inch-cubic blocks of 6061 aluminum.

The 18 experiments, shown in Table 2, were randomly run by the CNC Fadal vertical milling machine.

Figure 2. Procedure and steps of Taguchi parameter design

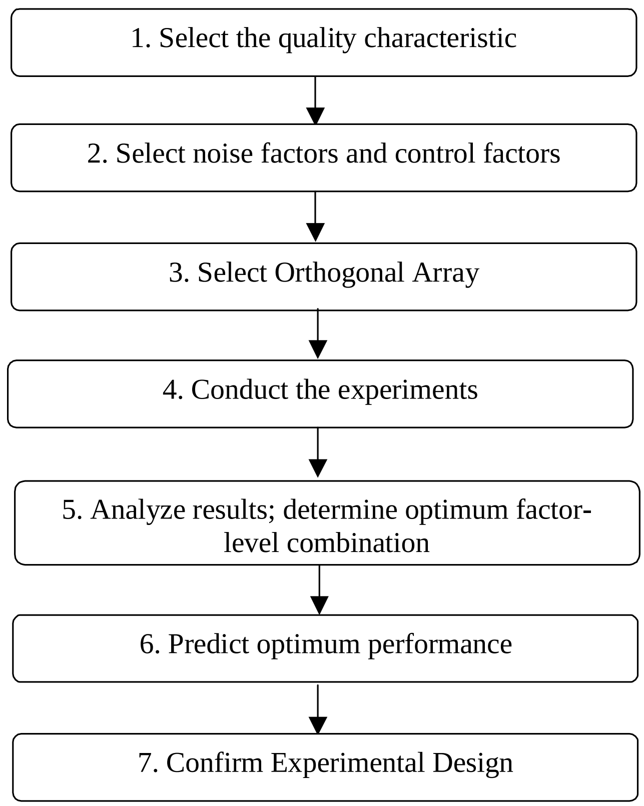


Table 1. Variable factor levels

Controllable Factors	Level 1	Level 2	Level 3
A: Depth of cut	0.01 (in)	0.02	0.03
B: Cutting speed	1500 (rpm)	3000	5000
C: Feed rate	10 (ipm)	20	30
D: Tool diameter	0.5 (in)	0.75	1.0

Also, three measured surface roughness data values were collected using the manual stylus type instrument to measure the finished workpieces after end milling was completed. After the data were collected and recorded in Table 3, signal-to-noise ratios of each experimental run were calculated based on the following equation, which are listed in Table 3 with the data.

$$S/N(\eta) = -10 \times \log\left(\frac{1}{n}\sum_{i=1}^{n} y_i^2\right), \quad (3)$$

where n = number of measurements in a trial/row, in this case, n=3 and y_i is the *i*th measured value in a run/row. The average response values were also calculated and recorded in Table 3.

Step 5. Analyzing the results and determining the optimum cutting conditions

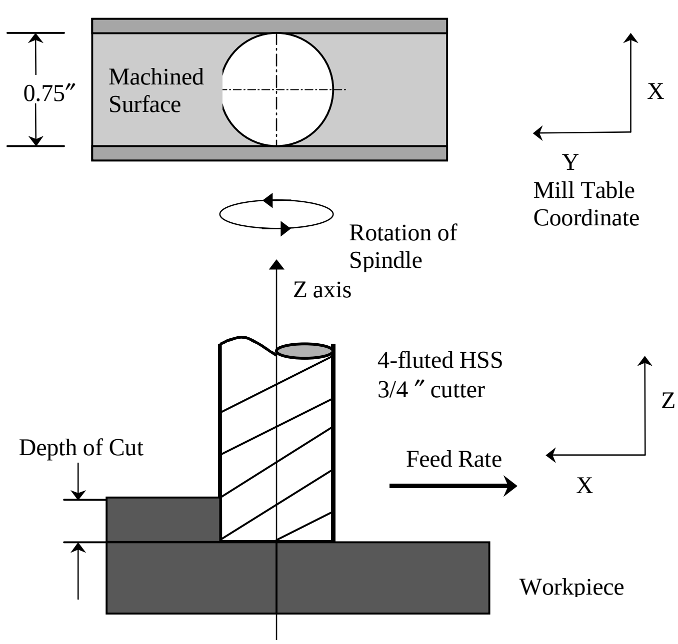
a) Analysis of Raw Data and S/N Ratios

After raw data were collected (Table 3), average effect response values (Table 4) and S/N response ratios (Table 5), respectively, were calculated based on Table 3. The calculation of average effect response values and S/N ratios were based on the following procedure. For example, the average effect for level one of depth of cut was computed using data from experimental numbers 1-3 and 10-12 of Table 3. The average effect for level two of depth of cut was computed using experimental numbers 4-6 and 13-15 of Table 3. The average effect for level three of depth of cut was computed using experimental numbers 7-9 and 16-18 of Table 3. Similarly, the average effect of cutting speed and feed rate was computed for all other cutting levels. The S/N ratio is calculated in the same way. The average effects and S/N ratios for each level of cutting parameters are summarized and referred to in the average effects response table and S/N ratios response table for surface roughness (Ra), as shown in Tables 4 and 5.

Table 2. Orthogonal array ($L_{18}(2^1 \times 3^7)$)

Experiment No.	1	2 (A) Depth of cut (in)	3 (B) cutting speed (rpm)	4 (C) Feed Rate (ipm)	5 (D) Tool Dia (in)	6	7	8	(Noise factor) Measurement location 1 2 3
1	1	0.01	1500	10	0.5	1	1	1	
2	1	0.01	3000	20	0.75	2	2	2	
3	1	0.01	5000	30	1.0	3	3	3	
4	1	0.02	1500	10	0.75	2	3	3	
5	1	0.02	3000	20	1.0	3	1	1	
6	1	0.02	5000	30	0.5	1	2	2	
7	1	0.03	1500	20	0.5	3	2	3	
8	1	0.03	3000	30	0.75	1	3	1	
9	1	0.03	5000	10	1.0	2	1	2	
10	2	0.01	1500	30	1.0	2	2	1	
11	2	0.01	3000	10	0.5	3	3	2	
12	2	0.01	5000	20	0.75	1	1	3	
13	2	0.02	15000	20	1.0	1	3	2	
14	2	0.02	3000	30	0.5	2	1	3	
15	2	0.02	5000	10	0.75	3	2	1	
16	2	0.03	1500	30	0.75	3	1	2	
17	2	0.03	3000	10	1.0	1	2	3	
18	2	0.03	5000	20	0.5	2	3	1	

Figure 3. Experimental setting of the work piece and the end mill process



b) <u>Analysis of Variance</u>

The purpose of the analysis of variance (ANOVA) is to determine which cutting parameters significantly affect the quality characteristic (Ra). Table 6 shows the results of ANOVA analysis of raw data for surface roughness. From Table 6, it is apparent that the F values of factor A (depth of cut), factor B (cutting speed), and factor C (feed rate) were all greater than $F_{0.05, 2, 45} = 3.2$. Factor D (tool diameter) was not a significant cutting factor affecting surface roughness. Its F value =1.03 is less than $F_{0.05, 2, 45}=3.2$.

c) <u>Determination of the Optimum Factor-Level Combination</u>

Figure 4 shows three graphs, each of which contains a curve representing the mean and a curve representing the S/N ratio. The values of the graphs are from Table 4 and 5. The objective of using the S/N ratio as a performance measurement is to develop products and processes insensitive to noise factors. The S/N ratio indicates the degree of the predictable performance of a product or process in the presence of noise factors. Process parameter settings with the highest S/N ratio always yield the optimum quality with minimum variance (Antony & Kaye, 1999). Consequently, the level that has a higher value determines the optimum level of each factor. For example, in Figure 4, level two for depth of cut (A_2= 0.02 in) has the highest S/N ratio value, which indicated that the machining performance at such level produced minimum variation of the surface roughness. In addition, the lower surface roughness value had a better machining performance. Furthermore, level two of depth of cut (A_2 = 0.02 in) has indicated the optimum situation in terms of mean value.

Similarly, the level three of cutting speed (B_3=5000 rpm) and the level one of feed rate (C_1=10 ipm) have also indicated the optimum situation in terms of S/N ratio and mean value. While the level of tool diameter (D) can be selected from any one of the three levels (D_1=0.5in, D_2=0.75in, and D_3=1.0in), the tool diameter did not have a significant effect on surface

Table 3. Results of the $L_{18}(2^1 \times 3^7)$ experiment

Experiment No. (i)	(R_{aij}) j = 1,2,3 Response Value 1	2	3	(R_{ai}) Average Response Value	(dBi) S/N Value
1	116	100	75	97.0	-39.9
2	136	147	121	134.7	-42.6
3	80	105	90	91.7	-39.3
4	46	50	47	47.7	-33.6
5	73	71	77	73.7	-37.4
6	80	88	69	79.0	-38.0
7	72	81	103	85.0	-38.7
8	118	115	106	113.0	-41.1
9	27	28	27	27.3	-28.7
10	195	145	159	166.3	-44.5
11	47	45	61	51.0	-34.2
12	65	83	62	70.0	-37.0
13	89	78	61	76.0	-37.7
14	77	98	86	87.0	-38.8
15	48	29	36	37.7	-31.7
16	124	93	103	106.7	-40.6
17	47	55	44	48.7	-33.8
18	58	71	46	58.3	-35.5

Table 4. Average effect response table for the raw data

Levels	Depth of cut (A)	Cutting Speed (B)	Feed rate (C)	Tool diameter (D)
1	101.78	96.44	51.56	76.22
2	66.83	84.67	82.94	84.94
3	73.17	60.67	107.28	80.61
Max-Min	34.95	35.77	55.72	8.72
Rank	3	2	1	4

Table 5. Average effect response table for S/N ratio

Levels	Depth of cut (A)	Cutting Speed (B)	Feed rate (C)	Tool diameter (D)
1	-39.58	-39.16	-33.65	-37.51
2	-36.19	-37.98	-38.13	-37.76
3	-36.39	-35.03	-40.38	-36.90
Max-Min	3.39	4.13	6.73	0.86
Rank	3	2	1	4

roughness. In this study, the level two of tool diameter (D_2=0.75in) was selected to conduct the confirmation runs. Therefore, the optimum cutting condition will be (depth of cut=0.02in (A_2), cutting speed=5000rpm (B_3), and feed rate=10 in/min (C_1), and tool diameter (D_2)=0.75in) and was determined to be able to produce the optimum surface roughness within the specific cutting condition range.

<u>Step 6. Predicting Optimum Performance</u>

Using the aforementioned data, one could predict the optimum surface roughness performance using the cutting conditions as:

Predicted Mean =

$$\overline{A}_2+\overline{B}_3+\overline{C}_1+\overline{D_2}-3\times(\overline{y}_{..})$$

= 66.83+60.67+51.56+84.94-3(80.59)
= 22.26 μin.

Similarly, the S/N ratio could be predicted as:

Predicted S/N =

$$\overline{\eta}_{A2}+\overline{\eta}_{B3}+\overline{\eta}_{C1}+\overline{\eta_{D2}}-3\times(\overline{\eta})$$

= -36.19-35.03-33.65-37.76+3(37.4)
= -30.43 dB.

With this prediction, one could conclude that the machine creates the best surface roughness (R_a = 22.26 μin) within the range of specified cutting conditions (Table 1). A confirmation of the experimental design was necessary in order to verify the optimum cutting conditions.

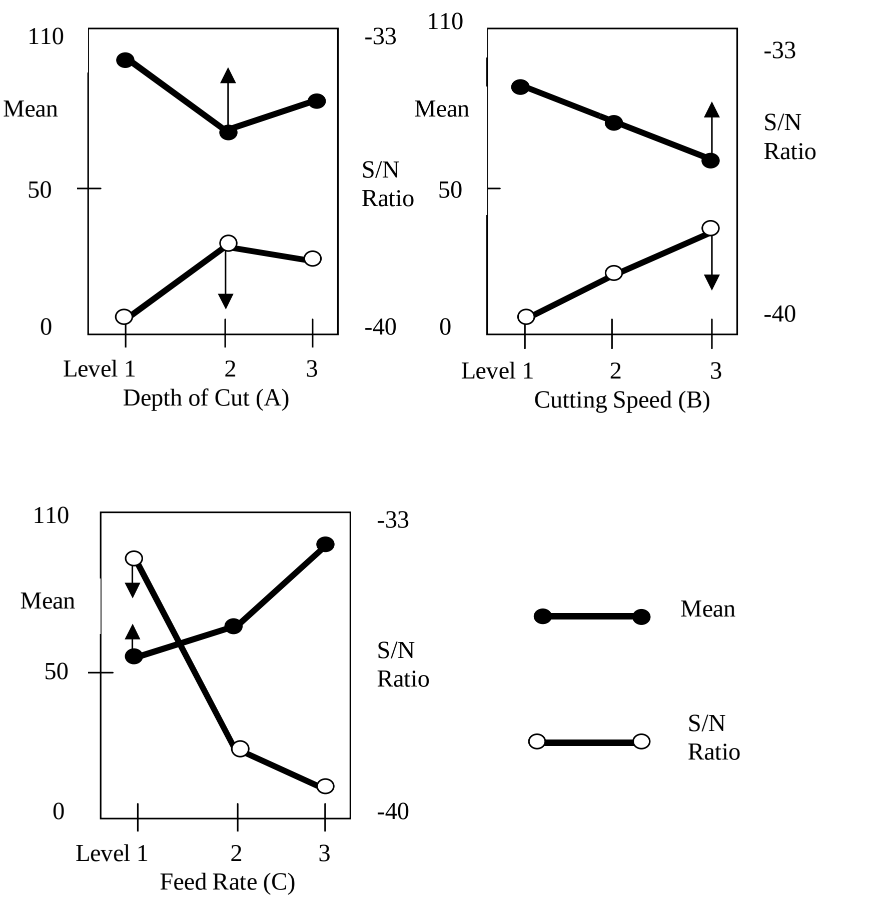
<u>Step 7. Establishing the design by using a confirmation experiment</u>

The confirmation experiment is very important in parameter design, particularly when screening or small fractional factorial experiments are utilized. The purpose of the confirmation experiment in this study was to validate the optimum cutting conditions ($A_2B_3C_1D_2$) that were suggested by the experiment that corresponded with the predicted value. In this research, the confirmation runs with the optimum cutting condition $A_2B_3C_1D_2$ resulted in response values of 18, 20, 25, and 29 μin. Thus, the Mean (=23 μin) and the S/N ratio (= -27.38 dB) were calculated. The Mean prediction interval was (-3.78 μin, 39.54 μin), and the prediction interval of the S/N ratio was (-33.09 dB, ∞ dB). Since the Mean and S/N ratio of the four confirmation runs were all within the 95% confidence interval, the optimum cutting condition has been verified. Therefore, the optimum surface roughness (Ra = 23 μin) can be obtained under the above-mentioned cutting condition in the Fadal CNC vertical milling machine.

Table 6. ANOVA table for responded raw data

Source of Variation	Degree of Freedom	Sum of square	Mean of square	F Value	P Value
Depth of cut (A)	2	12474.91	6237.46	18.72	<0.0001
Cutting speed (B)	2	11974.21	5987.11	17.96	<0.0001
Feed rate (C)	2	28088.23	14044.12	42.14	<0.0001
Tool diameter (D)	2	689.09	344.55	1.03	0.365
Error	45	14997.12	333.27		
Total	53	68223.56			

Figure 4. Response graphs of three significant cutting factors (↑ indicates the optimal level of response mean; ↓ indicates the optimal level of S/N ratio)



Conclusion

In this study, the analysis of confirmation experiments has shown that Taguchi parameter design can successfully verify the optimum cutting parameters, which are $A_2B_3C_1D_2$ [depth of cut=0.02in (A_2), cutting speed=5000rpm (B_3), feed rate=10 in/min (C_1), and tool diameter=0.75in (D_2)]. The material used for the experiment was Al 6061. In order to set the cutting parameters, four confirmation runs were conducted. The average value of surface roughness [Mean (=23 μin) and S/N ratio (= -27.38 dB)] were calculated and were found to be within the 95% confidence interval. Therefore, the optimum surface roughness was verified in end-milling operations.

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 not only demonstrates how to use Taguchi parameter design for optimizing machining performance with minimum cost and time to industrial readers but also shows the Industrial Technology educator a project exercise in any Taguchi-related curricula.

Further study could consider more factors (e.g. materials, lubricant, etc.) in the research to see how the factors would affect surface roughness. Also, further study could consider the outcomes of Taguchi parameter design when it is implemented as a part of management decision-making processes.

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