A PARAMETER DESIGN STUDY IN A TURNING OPERATION USING THE TAGUCHI METHOD

by

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Abstract: *Modern manufacturers, seeking to remain competitive in the market, rely on their manufacturing engineers and production personnel to quickly and effectively set up manufacturing processes for new products. Taguchi Parameter Design is a powerful and efficient method for optimizing quality and performance output of manufacturing processes, thus a powerful tool for meeting this challenge. This paper discusses an investigation into the use of Taguchi Parameter Design for optimizing surface roughness generated by a CNC turning operation. This study utilizes a standard orthogonal array for determining the optimum turning parameters, with an applied noise factor. Controlled factors include spindle speed, feed rate, and depth of cut; and the noise factor is slightly damaged jaws. The noise factor is included to increase the robustness and applicability of this study. After experimentally turning sample workpieces using the selected orthogonal array and parameters, this study produced a verified combination of controlled factors and a predictive equation for determining surface roughness with a given set of parameters.*

I. Introduction

Achieving a desired level of surface quality for CNC-turned parts requires practical knowledge and skill to properly set up this type of operation with the given specifications and conditions. A manufacturing engineer or CNC machine setup technician is often expected to utilize experience and published shop guidelines for determining the proper machining parameters to achieve a specified level of surface roughness. This must be done in a timely manner to avoid production delays, effectively to avoid defects, and the produced parts monitored for quality. Therefore, in this situation, it is prudent for the engineer or technician to use past experience to select parameters which will likely yield a surface roughness below that of the specified level, and perhaps make some parameter adjustments as time allows or quality control requires.

Engineers and technicians establishing such an operation would ideally consider other implications of setup parameters such as production schedules, processing time, and noise factors. A more methodical, or experimental, approach to setting parameters should be used to ensure that the operation meets the desired level of quality with given noise conditions and without sacrificing production time. Rather than just setting a very low feed rate to assure a low surface roughness, for example, an experimental method might determine that a faster feed rate, in combination with other parameter settings, would produce the desired surface roughness.

Unfortunately, in most scenarios, time is limited and design of experiments (DOE) methods tend to be lengthy and cumbersome when considering the complex factors and noise that affect such an operation [1]. In order to optimize such an operation with such restrictions, a more efficient experimental method is needed.

An excellent solution to this issue is an approach known as Taguchi Parameter Design. As a type of fractional factorial design, Taguchi Parameter Design is similar to traditional DOE methods in that multiple input parameters can be considered for a given response. There are, however, some key differences, outlined in Table 1, for which Taguchi Parameter Design lends itself well to optimizing a production process [2]. As indicated in Table 1, using the Taguchi Parameter Design method would be ideal for this case, as it would allow for optimization of the turning process with a relatively small number of experimental runs. A key idea is the contention that Taguchi Parameter Design uses the non-linearity of a response parameter to decrease the sensitivity of the quality characteristic to variability [3]. Variability in a manufacturing process can be significant, often uncontrollable, and have varying effects on quality characteristics. Fortunately, according to Roy [4], the very intention of Taguchi Parameter Design is to maximize the performance of a naturally variable production process by modifying the controlled factors. Furthermore, since it can be done at the design stage, Taguchi Parameter Design allows quality engineers to reduce the need for quality control later [5].

Table 1. Comparing DOE and Taguchi methods

Aspect	DOE method	Taguchi method
Knowledge of the process being studied	Not required	In-depth knowledge required
Number of test runs	Relatively large; all combinations of inputs	Much smaller number of combinations
Noise factors	Usually not included	Included in the basic design
Variability of system being studied	Ignored; only used to look for most effective combination of inputs	Looks at both level and variability of output to select input combinations
Confirmation runs	Not required, as all combinations of inputs tested	Advisable; selected combination of inputs may not have been tested

II. Review of Literature

Conducting an effective Taguchi Parameter Design study requires review of literature regarding turning parameters and similar studies. Of course, the most readily controlled factors in a turning operation are feed rate, cutting speed, and depth of cut; each of which may have an effect on surface finish [6]. Several studies exist which explore the effect of feed rate, spindle speed, and depth of cut on surface finish [7, 8, 9, 10]. These studies all supported the idea that feed rate has a strong influence on surface finish. Spindle speed and depth of cut were found to have differing levels of effect in each study, often playing a stronger role as part of an interaction. This would seem to indicate that these controlled parameters would play an important role in optimizing surface roughness. Vibration as an uncontrolled noise factor can also affect surface finish. Lin and Chang [11] studied the effect of radial vibrations on surface finish, and found that the amplitude and frequency due to spindle speed both had strong effects on the surface topography. Spindle vibrations due to damaged or unbalanced jaws, for example, would therefore have an effect on surface finish depending on the degree of out-of-balance condition and the speed of the spindle.

Some very informative studies were found that were conducted using the Taguchi Parameter Design method for the purpose of optimizing turning parameters [10, 12, 13, 14, 15, 16]. These studies made use of various workpiece materials and controlled parameters to optimize surface roughness, dimensional accuracy, or tool wear. Each utilized different combinations and levels of cutting speed, feed rate, depth of cut, cutting time, workpiece length, cutting tool material, cutting tool geometry, coolant, and other machining parameters. These studies all discovered clear and useful correlations between their control and response parameters. This would indicate that there are a number of different parameters that can be included in this type of study, and unique combination of parameters can be tailored to suit a given situation.

The purpose of this study is to efficiently determine the optimum turning operation parameters for achieving the lowest surface roughness in that range of parameters, while considering a noise factor. This study will include the following features in order to meet this purpose and distinguish it from the reviewed literature:

- The use of an array with the fewest experimental runs possible.
- Relationships between the control parameters and the response parameter.
- The use of damaged chuck jaws as a noise factor.
- Effects of the noise parameter on the response parameter.
- Optimum turning operation parameters for surface roughness, given this noise factor.

III. Experimental Design and Setup

In order to meet this purpose in terms of both efficiency and effectiveness, this study will utilize the Taguchi Parameter Design methodology. This includes selection of parameters, utilizing an orthogonal array, conducting experimental runs, data analysis, determining the optimum combination, and verification.

As suggested in the introduction, spindle speed (v), feed rate (f), and depth of cut (d) are included as controlled parameters in this study. Considering that the literature suggested that feed rate has a much higher effect on surface roughness than the other two parameters, it was determined that a robust but efficient experiment would include feed rate with more levels than the other factors. The feed rate factor in this experiment therefore has four levels: 0.002, 0.003, 0.004, and 0.005 inches per revolution (ipr). Spindle speed and depth of cut were then given two levels (v = 2500, 3500 rpm; d = 0.010, 0.020 in.). These ranges of feed rate would be expected to produce a good finish on the parts [17], and the spindle speed and depth of cut were selected to meet the hardware setup specifications while providing reasonable variability in the experiment. It was also intended that this would allow the selection of an orthogonal array with as few runs as possible, while still allowing for a robust experiment.

The array selected to meet these criteria is a modified L8 array, which allows for one factor at four levels and up to four factors at two levels (Table 2). Note that this is based on the basic L8 (2^7) array, with the first three columns combined to allow for a four-level factor.

Table 2. Modified L8 orthogonal array

	Control Factors				
Run	1,2,3	4	5	6	7
1	1	1	1	1	1
2	1	2	2	2	2
3	2	1	1	2	2
4	2	2	2	1	1
5	3	1	2	1	2
6	3	2	1	2	1
7	4	1	2	2	1
8	4	2	1	1	2

Also suggested in the introduction, a source of noise for this experiment would be the condition of the jaws on the chuck. Therefore, two sets of jaws were selected – one set with some damage from extensive use, and one set which had never previously been used. The damage on the jaws was slight enough to allow safe use in the lathe, but significant enough to cause vibration due to an out-of-balance condition. The N1 noise condition is designated for the damaged jaws, and the N2 noise condition is designated for the new jaws. This is included as a separate outer array, which requires a replication of each run in the orthogonal array for each noise condition. A customized array, with all factors and noise conditions included, is shown in Table 3.

Table 3. Modified L8 orthogonal array, customized for this study

Inner Control Factor Array				Outer Noise Array	
Run	*f*	v	d	N1	N2
1	0.002	2500	0.010		
2	0.002	3500	0.020		
3	0.003	2500	0.020		
4	0.003	3500	0.010		
5	0.004	3500	0.010		
6	0.004	2500	0.020		
7	0.005	3500	0.020		
8	0.005	2500	0.010		

The experimental setup includes all hardware and software needed to generate turned surfaces, measure their surface roughness, collect all necessary data, and analyze this data. The lathe, shown in Figure 1, is a modern CNC slant bed lathe with a Fanuc controller. The work pieces selected for this experiment were cut from 1-inch diameter 6061-T6511 Aluminum Alloy rod, per ASTM B221. These workpieces would be machined with a straight turning operation, with just enough surface area to allow for cutting stabilization and subsequent surface roughness measurement. The major hardware used is listed in Table 4, along with specifications applicable to this study. Software used for this study includes Microsoft *Excel* spreadsheet and SAS Institute Inc. *JMP* statistical package.

Figure 1. CNC lathe

Table 4. List of hardware

Item	Specifications
CNC Lathe	Clausing/Colchester Storm A50 Slant Bed Lathe Spindle speed range: 1000-4000 rpm Feed rate range: 0.000001 – 4.000000 inch per revolution (ipr) Least input movement increment: X 0.00005 inch, Z 0.0001 inch
Lathe Chuck Jaws (3-Jaw Chuck)	(1) Used jaws with slight damage (operable but with some nicks) (2) New jaws, never used and matched to chuck for correct balance
Cutting Tool Insert	VNE Versa Turn CCGT 432-AF (0.032 inch nose radius)
Surface Roughness Measurement Device	Federal Pocketsurf Stylus Profilometer; Measures R_a in μinch; Stylus travel 0.1 inch; Resolution 1 μin. Ra; Accuracy of ±4 μin. Ra

IV. Data Collection

A total of sixteen workpieces were turned in accordance with the experimental design, and each measured for surface roughness four times at approximately 90º intervals around the part. Surface roughness was measured with the workpiece fixtured to the profilometer such that measurements were taken across the lay. While the setup is a three-jaw chuck as noted in Table 4, the surface roughness measurements were taken at random points around each workpiece. This helped avoid possibly biased measurements should the damaged jaws create a directional vibration or wobble strong enough to cause a variance in surface roughness around the turned surface. Future studies may include measurement points with respect to each jaw as a possible source of noise.

Note that a full factorial design with the same number of factors and levels would require thirty-two workpieces (4 levels of f × 2 levels of v × 2 levels of d × 2 levels of N). This study therefore cuts the number of workpieces and experimental runs in half.

Replication was therefore provided given the two noise conditions as well four surface roughness measurements, which can also be a significant source of variability [18]. The tabulation of the collected data is found in Table 5, which is the orthogonal array with an expanded inner array for replications. The individual surface roughness measurements (indicated by y_i), are in this inner array, and the mean for each run ($\overline{R}_a$) is in the next column to the right.

Table 5. Array complete with experimental data

Inner Control Factor Array				Outer Noise Array									
				N1				N2					
Run	f	v	d	y_1	y_2	y_3	y_4	y_1	y_2	y_3	y_4	$\overline{R}_a$	η
1	0.002	2500	0.010	20	21	19	19	16	18	16	17	18.25	-25.26
2	0.002	3500	0.020	17	22	18	19	17	16	18	15	17.75	-25.04
3	0.003	2500	0.020	34	42	30	30	24	20	20	22	27.75	-29.15
4	0.003	3500	0.010	32	30	25	26	25	21	22	26	25.88	-28.33
5	0.004	3500	0.010	42	46	41	38	31	26	30	33	35.88	-31.23
6	0.004	2500	0.020	38	41	40	40	31	32	32	34	36.00	-31.18
7	0.005	3500	0.020	49	52	54	49	43	45	52	41	48.13	-33.68
8	0.005	2500	0.010	55	51	52	54	54	57	38	55	52.00	-34.37
								Overall Means				32.70	-29.78

V. Data Analysis

In addition to $\overline{R}_a$, the filled array in Table 5 includes the Signal-to Noise (S/N) ratio of the individual runs, which is calculated as:

1) $$\eta = -10\log\left[\frac{1}{n}\left(\sum y_i^2\right)\right]$$

where η = the S/N ratio; y_i = the individual surface roughness measurements in a run for both noise conditions; and n = the number of replications (in this case, n = 8). The S/N ratio is a summary statistic which indicates the value and dispersion of the response variable with the given noise factors [19]. In this case, the S/N ratio equation is based on the Taguchi smaller-the-better loss function, as the idea is to minimize the response.

The data in Table 5 can then be analyzed using informal and statistical methods. This begins with determining the effects of each treatment level on the response and S/N ratio. The effects are merely the means of the response and S/N ratio at each level for each factor, which are shown in Table 6. These values can then be graphically analyzed (Figures 2 through 4), to look for relative effects on the response. A steeper slope in the graphed response and S/N ratio effects indicates a greater effect of the parameter on the response. Figures 2 through 4 indicate a much stronger effect on R_a for feed rate than the other two parameters, as was expected by the literature review. This can also be statistically tested, using analysis of variance (ANOVA), to analyze the effects of parameters on the response. Fowlkes and Creveling [20] suggest looking at the F-ratios calculated in the ANOVA for each parameter to determine this, with the following criteria:

- $F < 1$: Control factor effect is insignificant (experimental error outweighs the control factor effect).
- $F \approx 2$: Control factor has only a moderate effect compared with experimental error.
- $F > 4$: Control factor has a strong (clearly significant) effect.

Table 6. Response and S/N ratio main effects

$\overline{R}_a$ Effects

level	f	v	d
level 1	18.00	33.50	33.00
level 2	26.81	31.91	32.41
level 3	35.94	-	-
level 4	50.06	-	-

η Effects

level	f	v	d
level 1	-25.15	-29.99	-29.80
level 2	-28.74	-29.57	-29.76
level 3	-31.21	-	-
level 4	-34.03	-	-

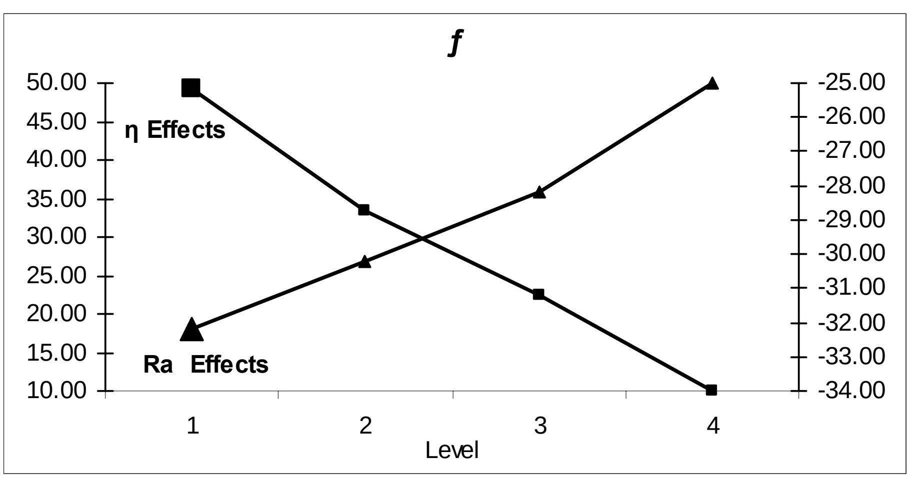

Figure 2. Response and S/N ratio effects for feed rate

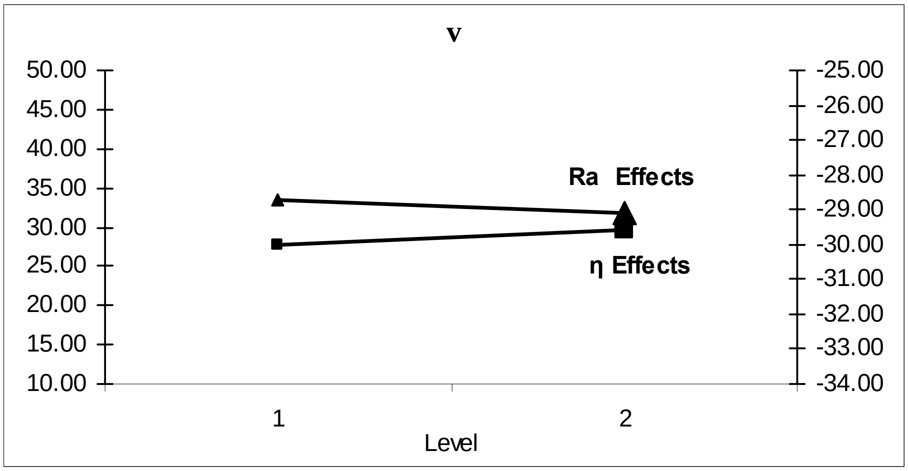

Figure 3. Response and S/N ratio effects for spindle speed

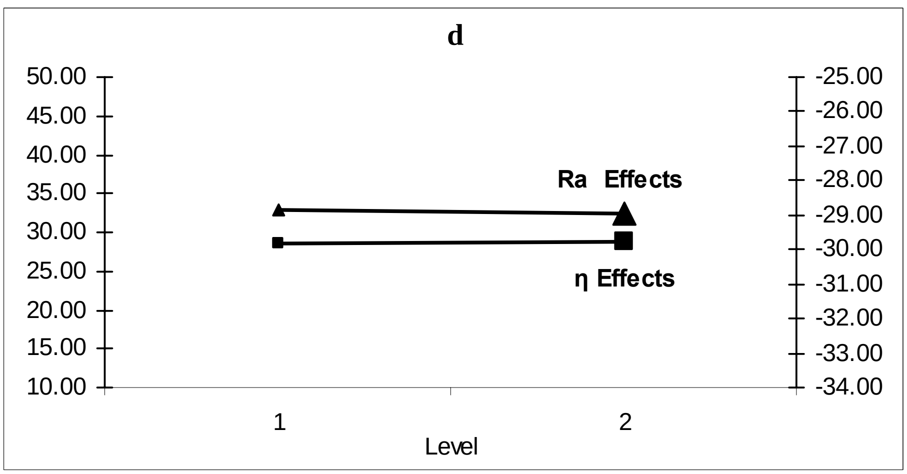

Figure 4. Response and S/N ratio effects for depth of cut

An ANOVA was run using the *whole model analysis* feature in JMP, in order to look at the combined effects of the parameters. As seen in the ANOVA in Table 7, feed rate has an F-ratio much greater than four, indicating that it is very significant. Spindle speed has an F-ratio which is just a little greater than two, indicating only a moderate effect in this setup. This is perhaps an indication that as the literature review found, spindle speed has various effects depending on feed rate and other factors. Depth of cut, however has an F-ratio smaller than one, and thus had no significant effect in this study.

Table 7. ANOVA for controlled factors

Source	DF	Sum of Squares	F Ratio	Prob > F
f	3	1125.3809	207.6378	0.0048
v	1	5.0801	2.8119	0.2356
d	1	0.7051	0.3903	0.5959
Error	2	3.6133		
C. Total	7	1134.7793		

The effects of the noise factors can also be determined using both informal and formal statistical means. One can see in Table 8 that the means for the N1 (damaged jaws) noise condition tended to be slightly higher than the N2 (new jaws) noise condition. However, for half of the runs, this difference is within the accuracy of the profilometer, warranting a t-test to more accurately determine the effect of the noise. As seen in Table 9, this t-test resulted in a confidence interval of differences between the means for N1 and N2 that includes zero, and p-value of 0.354. Assuming that statistically significant differences would yield a p-value of 0.050 or less, it appears that the difference between the means for N1 and N2 are not significantly different. Therefore, it cannot be determined from this experiment that this noise condition significantly affects surface roughness. This could be because the vibration dampening features of the lathe used was sufficient to overcome any imbalance in the jaws, or because the number of runs was insufficient to allow statistical detection of differences. This is beyond the scope of this study, however, as this type of experiment includes noise factors for the sole purpose of determining a combination of control factors that results in a response variable that is the most immune to noise factors [4].

Table 8. Mean responses for noise factor

Run	N1	N2
1	20	17
2	19	17
3	34	22
4	28	24
5	42	30
6	40	32
7	51	45
8	53	51

Table 9. Noise factor t-test

	t	df	p-value	Mean Difference	Std. Error Difference	95% C. L. Difference Lower	Upper
Equal Variance	0.959	14	0.354	6.125	6.39	-7.580	19.830
Unequal Variance	0.959	14	0.354	6.125	6.39	-7.581	19.831

VI. Determining the Optimum Condition

Both the response and S/N ratio can be used to derive the optimum condition, which is basically the optimum combination of treatment levels for the given response and noise conditions. Since the quality characteristic, R_a, is a smaller-the-better characteristic, the smallest response is the ideal level for a parameter. The S/N ratio, however, will always be highest at the optimum condition, since we always want the signal to be much higher than the noise. Since not all treatment combinations have been run in the experiment, this requires a separate analysis which considers all possible treatment combinations.

The graphs of Figures 2 through 4 can be used to determine the optimum treatment combination, which has been indicated by the enlarged points on these graphs. The optimum combination is therefore f1-N2-d3, or feed rate at 0.002 ipr, spindle speed at 3500 rpm, and depth of cut at 0.020 in. Since the ANOVA indicated that depth of cut is not a significant factor here, it can actually be run at either level. However, since the literature review suggests a possible effect, the depth of cut will be run at the higher level that is more likely to produce chatter [21]. This combination has actually been run in the experimental procedure (Run 2), and its value can be further analyzed and verified.

VII. Predictive Equation and Verification

The first step in verifying the optimum combination is to use a predictive equation to predict a response value given the contributions of each factor at its level in the optimum combination. A simple yet effective equation generally used for this type of study is given by Fowlkes and Creveling [20]:

2) $$y_{predicted} = \bar{y}_{\exp} + (\bar{y}_A - \bar{y}_{\exp}) + (\bar{y}_B - \bar{y}_{\exp}) + (\bar{y}_C - \bar{y}_{\exp})$$

where $y_{predicted}$ = the predicted response value (in this case R_a) or S/N ratio; $\bar{y}_{\exp}$ = the overall mean response of the experimental runs (in this case, $\overline{\overline{R_a}}$) or S/N ratio; and $\bar{y}_A, \bar{y}_B, \bar{y}_C$ = the response or S/N ratio effects for factors A, B, & C (in this case, f, v, & d) at a given level for each. Applying this formula to the data in Tables 5 and 6, a predicted response at the ideal condition is 16.91 μin., and a predicted S/N ratio is -24.92. One can do a quick inspection at this point to verify that this appears to be in line with the data in Table 5.

Next, the robustness of this parameter optimization can be verified experimentally. This requires prediction and confirmation runs of both the optimum condition and one of the other experimental combinations. Each treatment combination was predicted, and then five workpieces were run at these combinations and measured using the same experimental setup. These confirmation runs were performed at both levels of noise, for a total of 20 runs. The results of these confirmation runs, including response and S/N ratio, are shown in Table 10.

Table 10. Confirmation runs

	Run	N1				N2				Ra	η
Optimum	1	19	19	18	18	16	16	16	13	16.88	-24.60
	2	17	16	18	15	16	16	16	13	15.88	-24.05
	3	21	19	18	18	15	18	16	17	17.75	-25.02
	4	18	20	18	18	16	14	18	17	17.38	-24.84
	5	19	18	17	19	16	17	17	17	17.50	-24.87
						Overall Means				17.08	-24.68
Non-optimum	1	55	51	52	54	45	46	43	41	48.38	-33.74
	2	58	55	55	59	54	57	38	55	53.88	-34.69
	3	51	50	52	50	42	42	43	44	46.75	-33.43
	4	59	55	60	49	42	38	46	46	49.38	-33.97
	5	59	59	54	56	41	40	42	43	49.25	-33.96
						Overall Means				49.53	-33.96

Table 11 shows the results of this process, which can be interpreted in terms of robustness of this experiment. The "non-optimum" condition was the treatment combination which yielded the highest response in the experimental runs. The difference between the two predictions and verifications is used to help interpret any uniform data shifts. As seen in Table 11, however, errors between predicted and confirmation run results were very low, and even within the measurement accuracy of the profilometer. This indicates a good confirmation that this study yielded a valid optimum control factor treatment combination.

Table 11. Verification

		Ra	η
(1) Optimum	Predicted	16.91	-24.92
	Verification	17.08	-24.68
	Error	0.17	0.25
(2) Non-optimum	Predicted	51.16	-34.25
	Verification	49.53	-33.96
	Error	-1.63	0.30
(1-2) Difference	Predicted	-34.25	9.33
	Verification	-32.45	9.28
	Error	1.80	-0.05

VIII. Conclusions and Recommendations

This study utilized an efficient method for determining the optimum turning operation parameters for surface finish under varying noise conditions, through the use of the Taguchi parameter design process. Conclusions can be summed up with the following:

- The use of a modified L8 orthogonal array, with three control parameters and one noise factor, required only sixteen workpieces to conduct the experimental portion, half the number required for a full factorial design.
- Feed rate had the highest effect on surface roughness, spindle speed had a moderate effect, and depth of cut had an insignificant effect. This would indicate that feed rate and spindle speed might be included alone in future studies, although the literature review would caution against ruling out depth of cut altogether.
- The noise factor, "damaged" and new chuck jaws, was not found to have a statistically significant effect here, although the inclusion of this noise could still help make this experiment robust.
- A parameter design yielded an optimum condition of the controlled parameters, as well as a predictive equation. A verification procedure was then performed, which indicated that the selected parameter and predictive equation were accurate to within the limits of the measurement instrument.

Most research to date in this area has taken place in controlled environments with limited or simulated noise. While this study (as well as others) has demonstrated that this method of machining parameter optimization can be accomplished with minimal down time, the practical application of this requires more research. This area of research would benefit from future studies taking place in an industrial environment, such as a manufacturing plant. Additionally, the addition of more representative conditions and materials, such as steel bar stock, coolant, and cutting tool variations would provide a more robust and applicable study. Addressing issues such as numerous uncontrolled noise factors and time constraints for experimentation and implementation would be important in demonstrating Taguchi Parameter Design as a valuable and manageable tool for off-line quality engineering and production optimization.

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