Optimizing a Milling Operation with a Nominal Target Response

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***Abstract*— Among a manufacturer's most important abilities is to produce new designs quickly and with minimal changeover time. This investigation involves optimizing a quality characteristic with parallel consideration of productivity, through the use of Taguchi Parameter Design. Specifically, this involves the optimization of surface finish in a milling operation toward the goal of an actual nominal target value as a specified surface roughness. A variation is utilized of the Taguchi signal-to-noise ratio equation based on the nominal-the-best formula and the mean squared difference. The result is that variation about a specified value is explored and minimized. Surface roughness is recorded, and a confirmation sample created at the indicated parameter levels. It is demonstrated here that Taguchi Parameter Design can be used meet a quality target, with parameters that make sense for productivity. This represents not only an efficient method of process optimization, but also upholds quality without sacrificing productivity.**

***Index Terms*—Milling, Optimization, Surface Roughness, Taguchi Parameter Deign.**

I. INTRODUCTION

A manufacturing system that makes use of formal quality methods such as Six Sigma must include this throughout the engineering process, from concept to production realization. The process engineering phase, for example, must include a selected design of experiments (DOE) methodology that makes sense for the company and its processes [1]. A robust method of process design will therefore consider as many quality characteristics as possible. This could obviously be to include in a DOE more than one response parameter. Another method, as studied here, is to select response parameters that affect more than one key performance area of the process, ideally with the goal of variance reduction.

One such example is the Taguchi Parameter Design Experiment (PDE) methodology, which has been devised to address one or more response parameters with the goal of reducing variance in a system [2]. Through the use of orthogonal arrays and signal-to-noise (S/N) ratios, a PDE utilizes non-linearity of a system to decrease its sensitivity to variability [3]. A PDE is therefore a powerful tool for robust process design and optimization through reduction of variation, which is a basic function of Six Sigma [4].

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Taguchi Parameter Design utilizes three S/N ratios:

1) *Smaller-the-better* (lowest possible response value),
2) *Nominal-the-best* (nominal response value), and
3) *Larger-the-better,* (highest possible response value).

The second formula, the nominal-the-best S/N ratio, has been selected for this study. When a quality characteristic is specified as a nominal value, it makes sense for both the capabilities of the process and productivity to set up parameters to this nominal value. Even if quality control can logically consider a specified characteristic to be simply maximized or minimized, productivity can be overlooked in such a situation.

II. REVIEW OF LITERATURE

The first step of a PDE is to understand both the experimental process and the manufacturing process being studies, such as by reviewing relevant literature [5]. Recent literature on PDE studies by researchers and professionals are helpful in gaining insights into the manufacturing process, and determining what aspects of PDE are best for given situations.

2.1 Machining Parameters

It has been widely established, and still widely explored, that the cutting speed and feed rate affect surface finish most profoundly in a milling operation under normal conditions [6] [7]. Even when varying the cooling method, these parameters have been found to be the primary factors for this response [8]. This indicates that these control parameters should play an important role in optimizing surface roughness.

2.2 Noise Factors

A robust PDE should make use of a noise factor in the experiment to introduce variation that the process will encounter in practice. The challenge is to select significant noise factors that one can effectively re-create in the laboratory setting.

A major issue in milling that contributes to both surface roughness and dimensional inaccuracies is tool wear. This is in fact a well-accepted noise factor in a milling operation, and it is specifically the flank wear that is considered when measuring tool life [9].

Another inherently difficult-to-control noise factor in milling is the ambient temperature. Air temperature changes due to weather, seasonal changes, and heat sources in the shop environment are all contributors to an unstable ambient temperature in the shop environment. Models of heat generation and flow in chip formation, particularly with

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respect to heat travel away from the cut with the chips, take into account the ambient temperature. [10].

2.3 Concepts of Taguchi Parameter Design

Once can find a number of published studies on using Taguchi Parameter design to control surface finish in milling, many of which incorporate multiple response factors. Typical studies include spindle speed, feed rate, and depth of cut as input parameters, and seek achieve a minimum surface roughness as the response factor – which utilizes a smaller-the-better S/N ratio [11] [12]. Other studies have been published that incorporate multiple response factors, such as a 2009 PDE study which had the goal of minimizing both surface roughness and flank wear [13]. A similar study was published more recently that included minimization of a third response factor – cutting force [14]. These studies both made use of grey relational analysis to combine the response factors. This certainly makes possible the inclusion of a productivity-based response factor along with surface roughness. One such study has been published, which uses "grey-based Taguchi method" to simultaneously maximize material removal rate (MRR) and minimize surface roughness, while making the claim that "traditional Taguchi method cannot solve a multi-objective optimization problem" [15].

There are two points to be made regarding these studies that demonstrate how both current research and shop practice present a challenge to real-world application of Taguchi Parameter Design. First is the concept within most studies of minimizing the surface roughness response factor. Most studies certainly demonstrate that a Taguchi PDE can effectively minimize surface roughness, which would be suited for a situation where a very low surface roughness has been specified. If a mid-range surface roughness value was specified, and production was not an issue, the machinist could simply strive to set their feed rate to the lowest value, and thus a PDE would not then even be necessary. However, experts in production know that keeping machining time as low as possible while targeting the specified surface roughness is economically advantageous [16]. Furthermore, as it is common knowledge among machining experts that the lower the feed rate, the lower the resulting surface roughness (to a limit based upon tool geometry and other setup factors). Most experimental work in controlling or predicting surface roughness therefore utilize feed rate, which in itself is a directly related to cutting time and therefore productivity. With this in mind, it seems more relevant to utilize a PDE to target a specified surface roughness value through a nominal-the-best S/N ratio function. The high correlation between surface roughness and feed rate found in the studies cited herein as well others means that the lowest surface roughness yields the lowest feed rate, therefore lowering productivity. Should the actual specified surface roughness be targeted, the process would then be optimized with an acceptable response parameter without sacrificing productivity. This study encompasses this idea, seeking a more applicable use of a PDE in real-world production.

III. . PURPOSE OF STUDY

The purpose of this study is to use an efficient formal method for optimizing surface roughness to meet a specified target value, while at the same time considering productivity. This will involve using the Taguchi PDE methodology to create an optimization scheme that allows the system to meet the quality requirement while demonstrating the ability to control cutting time as well. Specifically, the goal of this study is to optimize the milling process such that:

1) The measured surface roughness meets a specified target value.
2) The cutting time shall be at the minimum possible while meeting the first goal.

In other words, this study will attempt to optimize the surface roughness response factor, without sacrificing productivity.

IV. EXPERIMENTAL DESIGN AND SETUP

This study will attempt to meet these goals while exploring and utilizing the various functions of a PDE. This includes experimental design and selection of parameters, running an experiment, analyzing data, determining the optimal combination, and confirmation.

4.1 Experimental Design

As suggested by the literature review, feed rate and depth of cut have a strong correlation to surface roughness, but these effects are generally nonlinear and can have significant interactions with spindle speed [17] [18]. Therefore, while slowing the feed rate will usually cause surface roughness to decrease, this will sacrifice productivity and may in the end not achieve the desired result with the given spindle speed and depth of cut. Furthermore, while lighter depths of cut usually ensure best possible surface roughness, this also decreases productivity through additional passes, and may not achieve the desired result.

Therefore, all three parameters should be included in the PDE to ensure the best possible combination of control parameters. This study will explore the most appropriate levels of the control parameters for a nominal surface roughness response parameter, which will keep cutting time at a reasonable value for this response parameter.

Table 1 indicates the control, response, and noise factors for this design. The response factor for this study is a nominal surface roughness specification, or target (T), of 1.6 μm R_a. This was select as a typical milling surface roughness value near the lower end of the capability spectrum of a typical milling process [19].

As suggested in the review of literature, the three control parameters include spindle speed, feed rate, and depth of cut. The ranges for the control parameters are based upon past experience with the process with the given setup, with additional tolerance provided to account for noise factors. The range of the control parameters were selected to encompass the given target response factor, based on what past work with this particular mill setup. Additionally, the levels for these factors were verified as being within the

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Table 1: Experimental Design Factors

Parameter	ID	Level 1	Level 2	Level 3
Spindle Speed (rev/min)	*v*	1500	2500	3500
Feed Rate (mm/min)	*f*	510	760	1010
Depth of Cut (mm)	*d*	1.50	2.00	2.50
Tool Condition	Y	New	Light Wear	
Ambient Temp. (ºC)	Z	20 ±15	40 ±15	
Target R_a (µm)	T	1.6		
Measured R_a (µm)	y_m			
Deviation from Target (µm)	Δ			

capability of the machining process with the given tool and workpiece material [20].

The selected noise factors include ambient air temperature in the mill enclosure, and the wear condition of the tool. The two levels for ambient air temperature here are standard room temperature (20 ±15ºC) and an elevated temperature of 40 ±15ºC.

It can be seen at this point that the experiment will require nine treatment combinations with four replications each, for a total of thirty-six runs, or milled workpieces. By comparison, a full factorial design with the same number of factors and levels would require 108 workpieces (33 = 27 runs x 4 replications each).

Table 2: $L_9(3^4)$ Orthogonal Array.

					Outer Noise Factor Array			
	Inner Control Factor Array				Y1		Y2	
Run	1	2	3	4	Z1	Z2	Z1	Z2
1	1	1	1	1	(y_i)	(y_i)	(y_i)	(y_i)
2	1	2	2	2	(y_i)	(y_i)	(y_i)	(y_i)
3	1	3	3	3	(y_i)	(y_i)	(y_i)	(y_i)
4	2	1	2	3	(y_i)	(y_i)	(y_i)	(y_i)
5	2	2	3	1	(y_i)	(y_i)	(y_i)	(y_i)
6	2	3	1	2	(y_i)	(y_i)	(y_i)	(y_i)
7	3	1	3	2	(y_i)	(y_i)	(y_i)	(y_i)
8	3	2	1	3	(y_i)	(y_i)	(y_i)	(y_i)
9	3	3	2	1	(y_i)	(y_i)	(y_i)	(y_i)

4.2 Experimental Setup

After the orthogonal array has been selected, the second step in Taguchi parameter design is running the experiment. The experimental setup includes all hardware and software needed to generate milled surfaces, measure their surface roughness, collect all necessary data, and analyze this data. This setup includes the following list of hardware:

- CNC Mill: Bridgeport VMC (vertical machining center).
- Surface Roughness Measurement Device: Stylus profilometer (measures Ra in µm; stylus travel 2.54 mm.; tolerance ±0.1 µm; min. resolution 0.025 µm).
- Space Heater: 1500W compact forced air space heater with thermostat and safety devices to prevent operation when overheated or tipped over.
- Thermometer: Digital thermometer with probe, range includes 10–50ºC, resolution 1ºC.
- End Mill: 31.75 mm (1.25 in) diameter, three-tooth tool holder for carbide inserts.
- Tin coated carbide inserts – three new and three with induced flank wear (induced by grinding and subjecting to a preliminary milling process).
- Surface table: polished granite surface for more stable and accurate surface roughness measurements.
- Microsoft *Excel*, SAS Institute *JMP*, and Nutek *Qualitek* software packages for DOE, charting data, and statistical analysis.

This process was performed as a dry cutting condition to allow the ambient air temperature to directly interact with the cutting process. The workpieces selected for this experiment were cut from 38.1 mm x 25.4 mm (1.5 in x 1.0 in) 6061-T6511 aluminum alloy bar that meet the specifications of ASTM B221. These workpieces were cut into 76.2 mm (3 in) lengths, and set up with the mill to create a slot down the middle of the part.

Surface roughness measurements were taken in the university's Metrology Laboratory, using a stylus profilometer. This device was set up on a granite surface table and to measure down the center of the cut, perpendicular to the lay. Each specimen was measured three times, once in the center and once on each end of the slot (see Fig. 1).

Software used for this study includes Microsoft *Excel* spreadsheet, which provided data collection, analysis, and charting functions; and SAS Institute *JMP*, which provides more capable statistical analysis of the data. Nutek *Qualitek* software was used to aid in the DOE and selection of an appropriate S/N ratio formula.

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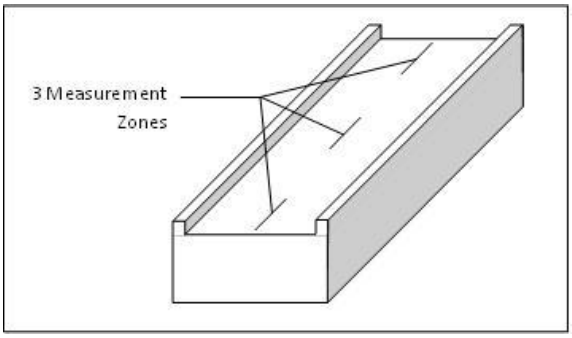

Fig. 1: Milled specimen, and three measurement zones.

V. DATA COLLECTION PROCEDURE

The experimental setup was used to create specimens as pictured in Fig. 1, in a randomized sequence of treatment combinations prescribed by the orthogonal array seen in Table 2. The milling process was closely supervised to ensure that there were no anomalous issues such as built up edge or tool failure. After all runs were completed, the surface roughness of the specimens was measured and recorded. Each work piece was measured three times as indicated in Fig. 1, and the average of these measurements recorded for each treatment combination. This value is then rounded off to the nearest whole value, since the resolution of the meter is by whole number values of 1.

VI. RESULTS AND ANALYSIS

The tabulation of the collected data is found in Table 3, which is the customized orthogonal array with the included data. Three additional columns are seen here (the response columns), the first of which being the average of the response data for each run ($\overline{y_m}$). The second column contains the difference between the recorded average response and the target response (Δ), or:

$$\Delta = \overline{(y_m)} - (T - \chi), \qquad (1)$$

Where T = the target surface roughness specification (1.6 µm), and χ is the tolerance of the profilometer.

Based upon the tolerance and resolution of the profilometer, the value of χ was set at 0.125 µm. This would help ensure that any variance in measurement due to the accuracy of the device, along with round off of values to the resolution, will not create a possibility of the surface roughness being more than the target value.

The S/N ratio, designated as η in the table, is utilized for this *nominal-the-best* study and calculated as follows:

$$\eta = -10Log\left\{\frac{1}{n}\left[\Sigma\left(y_{m,i} - (T-\chi)\right)^2\right]\right\}, \qquad (2)$$

Where η = the S/N ratio; n = the number of replications (4 in this case); $y_{m,i}$ = the individual measurements for the given run (i = 1 to n); and T = target (1.6 in this case).

Table 3: Data and Calculations

Run	y_i				Response Factors		
	Y1		Y2		$\overline{y_m}$	**Δ**	**η**
	Z1	**Z2**	**Z1**	**Z2**			
1	1.02	1.19	1.91	1.65	1.44	-0.03	8.98
2	1.63	1.60	1.55	1.78	1.64	0.16	14.69
3	1.73	1.65	2.57	3.38	2.33	0.86	-0.89
4	0.79	0.81	2.18	1.96	1.44	-0.04	3.86
5	0.89	1.12	1.50	1.27	1.19	-0.28	8.91
6	1.24	1.14	1.60	1.65	1.41	-0.07	12.80
7	0.69	0.76	1.22	0.89	0.89	-0.59	4.15
8	0.69	0.71	1.35	1.52	1.07	-0.41	5.14
9	0.89	1.07	1.50	1.32	1.19	-0.28	8.74

The S/N ratio is a summary statistic which indicates the value and dispersion of the response variable with the given noise factors [22]. In this case, the S/N ratio equation is based on the Taguchi nominal-the-best and the mean squared difference (MSD), which is one of four equations available in the Qualitek software. The MSD nominal-the-best equation is recommended as it combines mean and variability and identifies the optimal condition in the most straight forward way through the use of the actual target value [23].

An initial look at the data in Table 3 reveals two characteristics important to the study – variability in the responses between the runs and variability within the noise factor replications. Whether this variability is statistically significant requires additional analyses.

6.1 Analysis of Means and S/N Ratios

Analysis of Means (ANOM) and S/N Ratio Analysis each provide both indications of the relative effects of the control parameters as well as the levels that provide the optimal response. This starts with determining the effects of each treatment level on the means of the responses and S/N ratios. The mean response effect (MRE) for a treatment level of a factor is calculated as the means of the difference between the response value and target value:

$$\overline{\Delta} = \frac{1}{n}\left[\sum\left(y_{m,i} - (T-\chi)\right)\right], \qquad (3)$$

Where $\overline{\Delta}$ = the MRE; n = the number of replicationssm/; $y_{m,i}$ = the measured response for the given level of a factor (i = 1 to n); and $(T - \chi)$ = the target value minus the tolerance, or 1.47 µm. Additionally, the mean S/N ratio for each level of each factor is calculated. MRE and mean S/N ratio values for each parameter's level are shown in Table 4.

This ANOM is therefore essentially an analysis of the response values in relation to the target, in addition to the mean S/N ratios. The ideal MRE values in Table 4 are those that are as close as possible to zero, with large positive

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Table 4: MREs for Response and S/N Ratio

	Level 1		Level 2		Level 3	
	$\overline{\Delta}$	$\overline{\eta}$	$\overline{\Delta}$	$\overline{\eta}$	$\overline{\Delta}$	$\overline{\eta}$
v	0.33	7.60	*-0.13*	*8.52*	-0.43	6.01
f	-0.22	5.66	*-0.18*	*9.58*	0.17	6.89
d	-0.17	8.97	-0.05	*9.10*	*0.00*	4.06

numbers indicating quality defects and large negative numbers indicating possible waste in productivity. As indicated in Table 4, Level 2 for spindle speed and feed rate, and Level 3 for depth of cut appear to yield the best response in the experimental runs. The S/N ratios, however, indicate that Level 2 for all factors will yield the most robust process.

These values can be graphically analyzed (Charts 1-3) to find relative effects on the response. A steeper slope effects indicates a greater effect of the parameter on the S/N ratio and the response. Charts 1-3 indicate a much stronger effect on R_a for feed rate than the other two parameters, as was expected

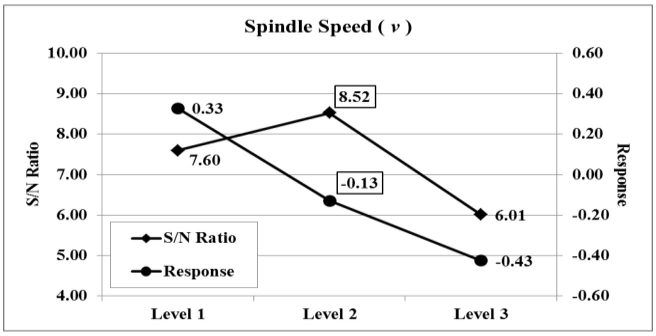

Chart 1: MREs and mean S/N ratios for feed rate

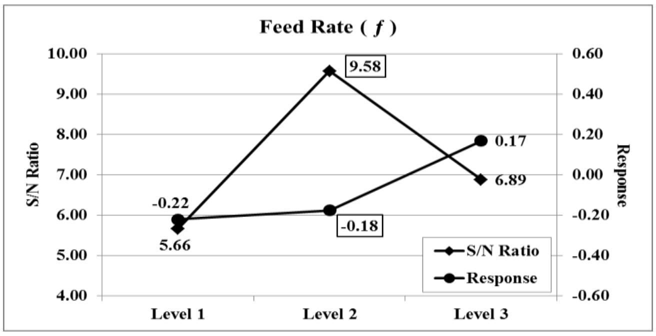

Chart 2: MREs and mean S/N ratios for spindle speed

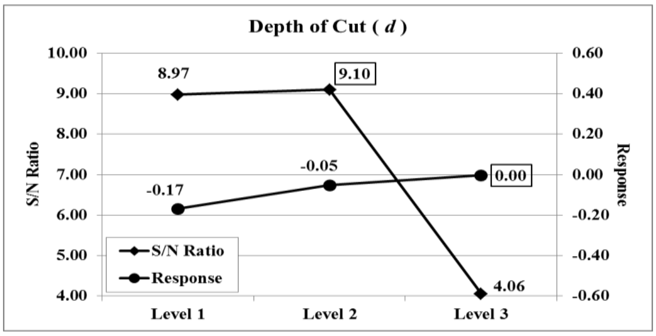

Chart 3: MREs and mean S/N ratios for depth of cut

by the literature review. Finally, as seen in Table 4 and Chart 3, there is a conflict in the optimal level of depth of cut, as indicated by the response and S/N ratio. As this difference is insignificant with respect to the tolerance and resolution of the profilometer, the response for Levels 2 and 3 for depth of cut (d) can be considered linear, and the optimal level can be selected based on S/N ratio alone. Additionally, selecting the level based on the S/N ratio is ideal, since the S/N ratio effect can be considered as resulting in the best response given the noise in the system [21].

6.2 Analysis of the Optimal Combination

Plotting the MREs for the response and S/N ratio on the graphs in Charts 1 through 3 also indicate the optimal level for each parameter in this study. Both the response and S/N ratio can be used to derive the optimal condition, which is basically the optimal treatment combination of control parameters for the given response and noise conditions. The quality characteristic, MRE, is a nominal-the-best characteristic in which the response closest to zero is the ideal level for a parameter. The S/N ratio, however, will always be highest at the optimal condition, since it is ideal to have the signal be as high as possible relative to the noise.

The level in each graph that meets these conditions is indicated with a hollow marker (and in Table 4 with an underline). As derived from the ANOM and S/N ratio analysis, the optimal treatment combination for this study is therefore {A2 B2 C2}. This sets the optimal feed rate (*f*) at 760 mm/min, the spindle speed (*v*) at 2500 rev/min, and the depth of cut (d) at 2.0 mm. The optimal treatment combination for the control parameters is summarized in Table 5.

The control parameters can also be statistically tested using analysis of variance (ANOVA) to analyze the effects of these parameters on the response. A simple set of criteria based on the size of the F ratio can be applied to this study [20]:

- F ratio < 1: Control factor effect is insignificant (error effects outweigh control factor effect).
- F ratio ≈ 2: Control factor has only a moderate effect compared with experimental error.
- F ratio > 4: Control factor has a strong (clearly statistically significant) effect.

	Optimal Settings		
Control Parameters	Level	Value	Effect on Response
Feed Rate, *f* (mm/min)	2	760	Strong
Spindle Speed, *v* (rev/min)	2	2500	Weak
Depth of Cut, *d* (mm)	2	2.00	Insignificant
Noise Factors			
Tool Condition, Y	-	-	Not Found
Air Temperature, Z	-	-	Significant

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Table 5 : Summary of Results

Factor	DOF	SS	F-Ratio	Prob >F
f	2	1340.22	4.28	0.19
v	2	422.68	1.35	0.43
d	2	66.93	0.21	0.82
Noise/Error	2	313.43		
TOTAL	8	2143.26		

Table 6: ANOVA Results

Utilizing SAS JMP software, an ANOVA was performed to analyze the effects of the control parameters on the variability of the response. As seen in Table 6, the F ratio for feed rate indicates strong effects, thus a clearly statistically significant effect. The F ratio for spindle speed has a value close to two, indicating that its effect is close to that of the experimental error. Depth of cut has an insignificant effect, based upon the above criteria. This is also included in the summary in Table 5. These effects provide a couple of things to consider: first, the noise factors may have a significant effect, relative to all but one of the control parameters; and second, the range of spindle speed and depth of cut may not have been sufficient enough to produce significant variability. With this in mind, it may be valuable to explore the effects of the noise factors.

A t test for each noise factor was then performed on the responses for the noise factors, to determine if significant variability occurred here. The results of the t test are summarized in Table 7. The results of this includes p value for noise factor Y (tool condition) that is very small, indicating that there appears to be a significant difference between the mean response for a new and worn tool. This is also supported by significant values in the 95% confidence interval for difference in means. The resulting p value for Z (ambient air temperature), however, is larger, greater than the alpha value of 0.05, indicating that this test could not determine a significant difference between the means. Additionally, the 95% confidence interval for the difference in means for the Z factor includes zero, and thus it cannot be ruled out that there is no difference in means. This indicates that the tool condition did provide a significant effect on the response parameter, yet the ambient air temperature did not. This could be because this experiment did not provide sufficient data for the t test to find significant effects of this noise factor on the response, or that such effects are insignificant. Further investigation of this noise factor would be helpful for future studies. However, this is beyond the scope of this parameter design study, as noise factors are only included to provide variance in the experiment and find a treatment combination that is most immune to this variance [24].

6.3 Confirmation of the optimal combination

The optimal combination found with this analysis can then be verified with a predictive equation as well as experimentally through confirmation runs. The Taguchi predictive equation calculates a response value given the contributions of each factor at its level in the optimal combination. This equation is reported as [20]:

$$y_p = \bar{\bar{y}} + (\bar{y}_A - \bar{\bar{y}}) + (\bar{y}_B - \bar{\bar{y}}) + (\bar{y}_C - \bar{\bar{y}}) \qquad (4)$$

Where y^p = the predicted response effect (y_m - T) or S/N ratio effect; $\bar{\bar{y}}$ = the overall mean response effect (Equation 3) or S/N ratio of the experiment; and $\bar{y}_A$, $\bar{y}_B$, and $\bar{y}_C$ = the MRE or mean S/N ratio for the optimal levels of the control parameters (from Table 5).

Applying the response and S/N ratio values for the optimal combination of factors yields a predicted response effect of -0.21 µm and a predicted S/N ratio of 12.45. This predicted response effect is added to the given target value of 1.47 µm, yielding a predicted measured surface roughness of 1.26 µm. Comparing this value with the experimental data in Table 3, it can be seen that the optimal combination is not among the experimental runs. Run 5, however, has the closest treatment combination and response values to that of the optimal. The optimal combination provides a measured response value that is very close to that of Run 5, and a S/N ratio that is larger (and therefore better). It must also be noted at this point the noise factor Y (tool condition) provides a significant difference in means. For the example Run 5, there is a mean response of 1.00 µm for the Y1 noise treatment and 1.38 µm for the Y2 noise condition. This is a difference of 0.38 µm, which is more than the standard deviation for these two runs (σ_{Run_5} = 0.26), and nearly equal to the average standard deviation of the entire table ($\bar{\sigma}$ = 0.39). Therefore, this noise treatment is significant and should be included in the confirmation runs. Since the ambient air temperature noise treatment (Z) was not found to be significant, this factor was not included in the confirmation runs. The confirmation runs were performed at normal room temperature for convenience.

The confirmation runs involve using the same experimental setup and the optimal combination of control parameters to create a sample for measurement and comparison to the predicted response. Additionally, each run will be randomly assigned one of the two treatments of noise factor Y, Tool Condition. A sample of ten workpieces were milled with the

Factor	*t*-ratio	DOF	*p* value	Mean Diff.	Std. Error Diff.	95% C.I. Lower	95% C.I. Upper
Y	0.14	17	<0.0001	0.62	0.11	0.39	0.85
Z	0.01	17	0.62	0.03	0.06	-0.10	0.16

Table 7 : T Test results

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Run	Noise Treatment	y_m	Δ	Mean	Standard Deviation
1	Y1	37	-21	-11.20	8.65
2	Y1	39	-19		
3	Y2	55	-3	99% C.I.	
4	Y2	56	-2	Upper	Lower
5	Y1	51	-7	-20.09	-2.31
6	Y2	38	-20		
7	Y1	40	-18		

Table 8: Results Confirmation Runs

selected parameters and measured with the same procedure as the experimental setup. The resulting values for these confirmation runs can be seen in Table 8.

Also indicated in Table 8 are the statistics of this confirmation sample, including the mean, standard deviation, and 99% confidence interval. These values indicate that the mean surface roughness of sample turned with the optimal combination is 3.14 µin below the predicted value of -8.06 µin. Both the 99% confidence interval and the confirmation runs themselves include values that are nearly all below the predicted R_a. This could be due to not including the air temperature noise factor, and could perhaps change if a larger sample size was utilized for the confirmation run, to help distribute the noise effects evenly. Additionally, one must consider that the treatment combinations for this experiment are finite and that Run 5 of the main experiment is the closest to this sample size in terms of treatment combination and response. Therefore, it can be said with reasonable certainty that the selected optimal treatment combination provides the best response in terms of proximity to the target value and S/N ratio.

VII. Conclusion

This study demonstrated an efficient method for determining the optimal milling operation parameters for a specified surface finish through the use of a Taguchi Parameter Design Experiment (PDE). The use of a modified L9 orthogonal array, with three control parameters and two noise factors, required only thirty-six workpieces to conduct the experimental portion, one-third the number required for a full factorial design. The experimental design used here is unique to most published studies in that it utilizes a nominal-the-best S/N ratio, thus seeking to approach a production-friendly target value rather than just the largest or smallest possible. A smaller-the-better S/N ratio, often used to minimize surface finish in machining operations, would likely have selected the slowest feed rate in this study, as this would provide the best surface roughness. This study found a reasonable treatment combination for the given target, and thus did not sacrifice productivity through an excessively low feed rate.

It was found that the feed rate and spindle speed had significant effects on surface roughness, while 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 ambient air temperature noise factors was not found to be statistically significant with the given sample size, although they could still be considered vital to provide necessary variance to make this experiment robust. The tool wear noise factor was statistically significant, and would be a recommended inclusion in future PDE studies.

This PDE yielded an optimal treatment combination well as a predictive equation that yielded realistic and production-friendly values. A verification procedure was then performed, which yielded a sample with a 99% confidence interval that includes the predicted value.

This area of research would benefit from future applications of this nominal-the-best PDE, especially as introduced in a real-world application, such as a manufacturing plant. Additionally, studies with wider varieties of materials, process variations, and cutting tools would demonstrate usefulness in more applications. Bringing more realistic and applicable examples of Taguchi Parameter Design to light should be a

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