Journal of
INDUSTRIAL TECHNOLOGY

Volume 26, Number 1 - January 2010 through March 2010

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Peer-Refereed Applied Papers

KEYWORD SEARCH

Lean / Six Sigma
Machine Tools
Manufacturing
Materials & Processes
Quality
Research Methods
Statistical Methods

The Official Electronic Publication of The Association of Technology, Management, and Applied Engineering • www.atmae.org

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Optimizing the Turning Process Toward an Ideal Surface Roughness Target

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Abstract

Today's manufacturers hope to quickly and effectively set up and optimize processes associated with new and existing processes to remain competitive. Engineers and production personnel may utilize various methods and industrial technologies to achieve the optimization of a process to meet the company's needs. Ideally, this takes into consideration productivity, quality, and safety. This paper discusses an investigation into optimizing a quality characteristic, while considering productivity, through the use of Taguchi Parameter Design. A turning operation is the subject of this study, and the output parameter selected is surface roughness. Previously published studies show the tendency to seek the *lowest* surface roughness, which usually requires the lowest possible feed rate and therefore a long cutting time. This study seeks an *actual* target surface roughness value, which may allow for a higher feed rate depending upon that specified target. In using the variation of the *nominal-the-best* signal to noise formula that utilizes MSD, variation about a specified (ideal) value is explored and sought to be minimized. It is demonstrated here that Taguchi Parameter Design can be used to determine the optimal levels of controlled parameters to meet a quality target without sacrificing productivity.

Introduction

A typical manufacturing process has several quantitative and qualitative output and performance characteristics that are indicative of its contribution to the success of a manufacturing company. Such characteristics will generally fit into the broader areas of quality and productivity, with subcategories that include product requirements, throughput, flexibility, labor hours, downtime, safety, and reliability. Furthermore, these and other characteristics can be interdependent – a mismanaged increase in throughput can affect quality, for example. A robust system should therefore include a robust engineering process that seeks a balance among the output and performance aspects of a manufacturing process.

In any manufacturing company that puts its highest priorities in quality, this process will include selection of a design of experiments (DOE) that makes sense for the company and its processes (Peterka, 2005). There are various ways of seeking optimization of a process for more than one output characteristic. Perhaps the most obvious would 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. With either method, this usually involves the goal of variance reduction.

A Taguchi Parameter Design Experiment (PDE) is a method that is well-suited to address one or more response parameters with the goal of reducing variance in a system (Fowlkes & Creveling, 1996). A PDE makes use of orthogonal arrays that allow for efficient experimentation, and signal-to-noise (S/N) ratios that utilize both mean and variance in selecting optimal input levels. These optimal levels are selected based upon the specific S/N ratio formula, of which there are three types:

1. *Smaller-the-better*, for creating the lowest possible response value
2. *Nominal-the-best*, for targeting a nominal specified value
3. *Larger-the-better*, for creating the highest possible response value

A critical feature of a PDE is that it actually utilizes non-linearity of a system to decrease its sensitivity to variability (National Research Council, 2002). Manufacturing processes can have significant, often uncontrollable, variability, which can affect quality and productivity in many ways. A PDE is a logical method for such processes, as was designed specifically to maximize the performance of a naturally variable process (Roy, 2001).

Review of Literature

Conducting an effective PDE requires review of literature regarding turning parameters and similar studies as it is important to understand the process in this type of study (Cesarone, 2001). Additionally, recent reviews of PDE studies by researchers and professionals are helpful in determining what aspects of this method work best.

The controlled parameters in a turning operation that under normal conditions affect surface finish most profoundly are feed rate and cutting speed (Lascoe, Nelson, & Porter, 1973). Recent studies that explore the effect of setup and input parameters on surface finish all find that there is a direct effect in feed rate, that spindle speed's effect is generally nonlinear and often interactive with other parameters, and that depth of cut can have some effect due to heat generation or chatter (Feng & Wang, 2003; Gökkayaa & Nalbant, 2007; Lalwani, 2008; Özel, Hsu, & Zeren, 2005). This would seem to indicate that these controlled parameters would play an important role in optimizing surface roughness.

An important feature of a PDE is the use of a noise factor in the experiment to introduce variation that one will see in the processes application. It is important to select noise factors that one can simulate or actually control at more than one level, and one that is applicable to the problem at hand. Variation in edge radius from tool-to-tool in a batch of inserts of the same specifications has been found to be as high as 0.001 in, and has been shown to have an effect on cutting forces (Schimmel, Manjunathaiah, & Endres, 2000). Furthermore, costs and availability often create the need to select inserts from various manufacturers, leading to an even greater source of variation (Lynch, 2003). As cutter inserts are changed occasionally due to wear or failure, this would appear to be a possibly significant noise factor that is easily incorporated into an experiment.

There are a number of excellent studies regarding optimization of surface roughness in a turning operation using PDE methods. A survey of journal articles published between 2004 and 2009 yields studies that vary in scope and level of analysis, yet with consistently good results. Table 1 lists some of these reviewed studies, along with the key experimental design features of each. Note that the studies listed here represent the features of all studies reviewed, and illustrate the large number of studies utilizing the three basic turning parameters (speed, feed, depth of cut) to minimize surface roughness.

Table 1. Key Features of Reviewed Studies

Reference Citation	Controlled Parameters	Response Factors	S/N Ratio for each Response Factor
Gaitonde, Karnik, & Davim, 2008	Cutting Speed Depth of Cut Feed Rate	Surface Roughness MRR1	STD[2] LTD[3]
Hascalik & Caydas, 2007	Cutting Speed Depth of Cut Feed Rate	Surface Roughness Tool Life	STD[2] LTD[3]
Jayant & Kumar, 2008	Cutting Speed Depth of Cut Feed Rate	Cutting Force Surface Roughness	STD[2] STD[2]
Kandananond, 2009	Depth of Cut Feed Rate Spindle Speed	Surface Roughness	STD[2]
Lan & Wang, 2009	Cutting Speed Depth of Cut Feed Rate Tool Nose Runoff[4]	Surface Roughness	STD[2]
Lin, 2004	Cutting Speed Depth of Cut Feed Rate	Cutting Force Surface Roughness Tool Life	STD[2] STD[2] LTD[3]
Manna & Bhattacharyya, 2004	Cutting Speed Depth of Cut Feed Rate	Surface Roughness	(not used)[5]
Prasad, Janardhana, & Rao, 2009	Cutting Speed Depth of Cut Feed Rate	Surface Roughness	STD[2]

[1] Material Removal Rate (cm^3/min or in^3/min)
[2] Smaller-the-better type equation
[3] Larger-the-better type equation
[4] Verticle position of the tool nose with respect to turning axis center
[5] Considered lowest response mean to be ideal

The studies listed in Table 1 each utilized different combinations and levels of turning parameters, with the goal of minimizing surface roughness, usually utilizing the lower-the-better S/N ratio. Some more advanced studies utilized cutting force, material removal rate, or tool life as response factors simultaneously with surface roughness. The authors also demonstrate clear and useful correlations between at least some of their control parameters and the response. None indicated the use of experimental noise factors, relying on prevailing experimental noise to drive variability. All of these studies did well to efficiently determine the parameters' treatment combinations necessary to minimize surface roughness of the turned surface. However, a minimum target is not always ideal, as often a nominal surface roughness value is specified for the design, and experts in production know that keeping machining time as low as possible while maintaining the specified surface roughness is economically advantageous (Tabenkin, 1999). 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). 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, in contrast with the studies reviewed here. This study encompasses this idea, seeking a more applicable use of a PDE in real-world production.

Purpose of Study

This study makes use of the Taguchi PDE method for optimizing selected parameters of a turning operation in such a way that it meets a specified surface roughness target and addresses productivity. The purpose is 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 a turning operation such that the following requirements are met:

1. The measured surface roughness shall meet a specified target value.
2. The cutting time shall be at the minimum possible while still allowing for Item 1.

In other words, this study will attempt to optimize the process toward a nominal surface roughness value, without sacrificing productivity with unnecessarily high cutting times.

Table 2. Parameters and Levels for Experimental Design

Controlled Parameters	ID	Level 1	Level 2	Level 3	Level 4
Feed Rate, f (in/rev)	A	0.002	0.003	0.004	0.005
Spindle Speed, N (rev/min)	B	2500	3500		
Depth of Cut, d (in)	C	0.010	0.020		
Noise Factor	**ID**	**Level 1**	**Level 2**		
Tool Insert #	X	T1	T2		
Tool Manufacturer	Z	M1	M2		
Response Factor	**ID**	**Value**			
Target Surface Roughness, R_a (µin)	T	32			
Measured Response, R_a (µin)	y_m				

Experimental Design and Setup

This study will attempt to meet these goals while utilizing the various procedures and features of the Taguchi PDE method. This includes experimental design and selection of parameters, conducting an experiment, data analysis, determining the optimal combination, and verification. As suggested by the literature review, the control of feed rate and depth of cut for productivity and surface roughness requires a balance between the two. Slowing feed rate will cause surface roughness to approach the minimum possible with the given tool and workpiece setup, but this will sacrifice productivity in cutting time for a tool path. Smaller depths of cut usually ensure best possible surface roughness, but this may require additional passes. Spindle speed is the only possible parameter that usually has a positive effect on both response parameters. As feed rate in turning is usually measured in linear distance per revolution, increasing spindle speed will increase linear travel in a given *time* unit. This usually has a maximum value, which is based upon the maximum cutting speed for a given workpiece/tool materials combination. Additionally, vibrations can further limit the positive effect of spindle speed on surface roughness (Lin & Chang, 1998). Therefore, this study will need to explore the most appropriate levels of the controlled parameters for the *nominal* surface roughness and thus avoid sacrificing productivity by strictly minimizing surface roughness.

Table 2 indicates the controlled, response, and noise factors for this design. The response factor for this study is a nominal surface roughness specification, or target (T), of 32 µin R_a. This was selected as a typical turning surface roughness value near the lower end of the capability spectrum of a typical turning process (Davis, 1989). This provides a target value that is meaningful as a preferred surface roughness specification (Oberg et al, 2008) that experience in this lab has shown to require very low feed rates (< 0.006 in/rev).

As suggested in the review of literature, the three controlled parameters include spindle speed, feed rate, and depth of cut. The ranges for the controlled parameters are based upon past experience with the process with the given setup, with additional tolerance provided to account for noise factors. For example, past experience for this setup has shown that a feed rate of 0.003 – 0.004 in/rev should provide a surface roughness that meets the response value in Table 2. An additional 0.001 in/rev has been added to both limits of this range, to arrive at the range used here. The range for depth of cut was arrived at similarly; it has been found in this laboratory that the lathe used provides the best control of surface finish with a depth of cut of less than 0.025 in.

The two levels selected provide a light (0.010 in) and moderate (0.020 in) cut relative to this amount. Finally, the spindle speed range is based upon the recommended cutting speed for this material (Oberg et al., 2008), which exceeds the lathe's upper limit of 4000 rev/min. Normally, the spindle speed in this laboratory is set at 3000 rev/min for aluminum, and the two levels for this experiment were set at 500 rev/min below and above this speed. This was done so both in consideration of the need for a range that is not too low as to cause built-up edge and not too high as to push the limits of the machine tool.

The noise factors were generated as a selection of two turning inserts (T1 and T2) from each of two manufacturers (M1 and M2). As mentioned earlier, this was done so as to introduce noise in the form of variation between inserts due to typical variation in selection. These inserts are both ANSI style CCGT432AF inserts, an uncoated grade with a 0.032 in nose radius geometry ideal for turning aluminum. The two brands used were Vardex Versa-Turn (M1) and Valenite ValTURN (M2), both of which utilized the same SCLCR tool holder.

The selected design of controlled and noise factors were fitted to an orthogonal array prescribed for Taguchi Parameter Design. The array selected to meet these criteria is a modified L8 array, which allows for one factor at up to four levels and up to four factors at two levels (Table 3). Each column in the array corresponds to a controlled parameter, and the inner array contains the prescribed levels of these parameters for each run. For example, in Run 1, each controlled parameter is set at Level 1; in Run 2, the first controlled parameter is set at Level 1 while the rest are set at Level 2; and so on. Note that this is based on the basic L_8 (2^7) array, with the first three columns combined to allow for a four-level factor (Fowlkes & Creveling, 1996).

Table 4 shows the orthogonal array further tailored to fit this study. This includes the codes for the controlled parameters (A, B and C) as well as the outer array for the noise factors (X and Z). It is in this array that the experimental data is later entered and analyzed.

Table 3. Modified L8 Orthogonal Array

	Inner Controlled Factor Array				
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

Table 4. Modified L8 Orthogonal Array, Customized to this Study

				Outer Array			
	Inner Array			X1		X2	
Run	A	B	C	Z1	Z2	Z1	Z2
1	1	1	1				
2	1	2	2				
3	2	1	1				
4	2	2	2				
5	3	1	2		(y_i)		
6	3	2	1				
7	4	1	2				
8	4	2	1				

It can be seen at this point that the experiment will require eight treatment combinations with four replications each, for a total of thirty-two runs, or turned workpieces. By comparison, a full factorial design with the same number of factors and levels would require sixty-four workpieces (4 levels of f × 2 levels of v × 2 levels of d × 4 noise replications).

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 used is a single Hardinge CNC slant bed lathe that provides significant dampening of vibrations that have been found to be a source of noise when controlling surface roughness (Kirby, Zhang, & Chen, 2004). This process was performed as a dry cutting condition, as coolant is rarely used in turning processes at this laboratory. The work pieces selected for this experiment were cut from 1.0 in diameter 6061-T6511 aluminum alloy rod that meet the specifications of ASTM B221. These workpieces would be machined with a straight turning operation, to a turned length of 1.0 in – just enough surface area to allow for cutting stabilization and subsequent surface roughness measurement. This represents a limitation in the application of this study to this particular turning process; it should be noted that other lathe processes (e.g., tapers, facing, arcs) or longer cuts would likely change the results of this experiment. Therefore, the experimental process should match the application of the study.

Surface roughness measurements were taken in the university's Metrology Laboratory, using a Mitituyo SJ-201P stylus profilometer. This device was set up on a granite surface table and aligned with a v-block setup to allow measurements that are taken on a stable surface and perpendicular with the lay of each sample.

Software used for this study includes Sun Microsystems' *OpenOffice.org* spreadsheet, which provided data collection, analysis, and charting functions. The bulk of the analysis for this study was performed using Nutek Inc.'s *Qualitek-4*. This software provides design, analysis, and interpretation of Taguchi methods in a way that allows easy yet effective usage by all potential practitioners (Knight, 1999).

Data Collection Procedures

The experimental setup was used to create turned samples in a randomized sequence of treatment combinations prescribed by the orthogonal array seen in Table 4. The turning 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 turned work pieces was measured and recorded. Each work piece was measured four times, in approximately 90º increments around the circumference. The average of these measurements was then entered into the *Qualitek* software as the measured response (y_m), and was then ready for analysis.

Results and Analysis

The collected data can be found in Table 5, which is the customized orthogonal array with this data included. Two additional columns included here – the measured surface roughness data for each run ($\overline{R}_a$), and the S/N ratio (η). The S/N ratio utilized for this *nominal-the-best* study is calculated as follows:

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

where

η = the S/N ratio
n = the number of replications (4 in this case)
ym,i = the individual measured response (y_m) for the given run (i = 1 to n)
T = target (32 in this case)

The S/N ratio is a summary statistic which is an indication of the magnitude and dispersion of the response variable with the given noise factors (Chinnam, 2001). 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 (Nutek, 2006).

An initial look at the data in Table 5 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 more formal analyses, such as Analysis of Means (ANOM), S/N Ratio Analysis, and Analysis of Variance (ANOVA).

ANOM and S/N Ratio Analysis can both be used to ascertain both the relative effects of the controlled parameters as well as the levels that provide the optimal response. This starts with determining the effects of each treatment level on the mean response and S/N ratio. The mean response effects (MREs) are calculated as the means of the difference between the response value and target value:

$$MRE = \frac{1}{n} \left[\Sigma \left(y_{m,i} - T \right) \right] \quad (2)$$

where

MRE = the mean response effect (see terms of Eq. 1)

Therefore, this becomes an analysis of the response values in relation to the target. The values for MRE in Table 6 therefore should be as close as possible to zero, with large positive numbers indicating quality defects and large negative numbers indicating possible waste in productivity.

The S/N ratios effects are calculated as the mean of the S/N ratios at each level for each factor, which are shown in Table 6. These values can then be graphically analyzed (Figures 1 through 3), 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 1 through 3 indicate a much stronger effect on R_a for feed rate than the other two parameters, as was expected by the literature review.

Table 5. Orthogonal Array with Data and Calculations

				Outer Array					
	Inner Array			X1		X2			
Run	A	B	C	Z1	Z2	Z1	Z2	$\overline{R}_a$	η
1	1	1	1	20	18	17	20	18.75	-22.49
2	1	2	2	21	17	20	16	18.5	-22.71
3	2	1	1	36	35	33	34	34.5	-8.75
4	2	2	2	31	29	30	26	29	-10.97
5	3	1	2	45	42	38	42	41.75	-20.05
6	3	2	1	38	39	36	35	37	-14.39
7	4	1	2	54	53	50	49	51.5	-25.85
8	4	2	1	50	53	49	49	50.25	-25.26

Determination and Analysis of Optimal Combination

The effects plotting on the graphs in Figures 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 controlled 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 optimum condition, since it is ideal to have the signal much higher than the noise. The level in each graph that meets these conditions is indicated with a star. This ANOM has indicated an optimal treatment combination of {A2 B2 C1}. This puts the optimal feed rate at 0.003 in/rev, the spindle speed at 3500 rev/min, and the depth of cut at 0.01 in, as summarized in Table 7.

The controlled parameters can also be statistically tested using Analysis of Variance (ANOVA) to analyze the effects of these parameters on the response. Fowlkes & Creveling (1996) suggest a simple set of criteria based on the size of the *F* ratio:

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.

Utilizing the *Qualitek* software, an ANOVA was performed to analyze the effects of the controlled parameters on the variability of the response. As seen in Table 8, the *F* ratios for feed rate and spindle speed indicate strong effects while the depth of cut has an insignificant effect, based upon the above criteria. This is also included in the summary in Table 7. However, it should be noted that the values of *P* in the ANOVA represent the relative influence of the controlled parameters

Table 6. Mean Response Effects and S/N Ratios

Mean Response Effects

Level	A	B	C
1	-13.375	4.625	3.125
2	-0.250	1.687	3.187
3	7.375		
4	18.875		

S/N Ratios

Level	A	B	C
1	-22.596	-19.285	-17.722
2	-9.860	-18.332	-19.895
3	-17.224		
4	-25.555		

Figure 1. MREs and S/N ratios for feed rate.

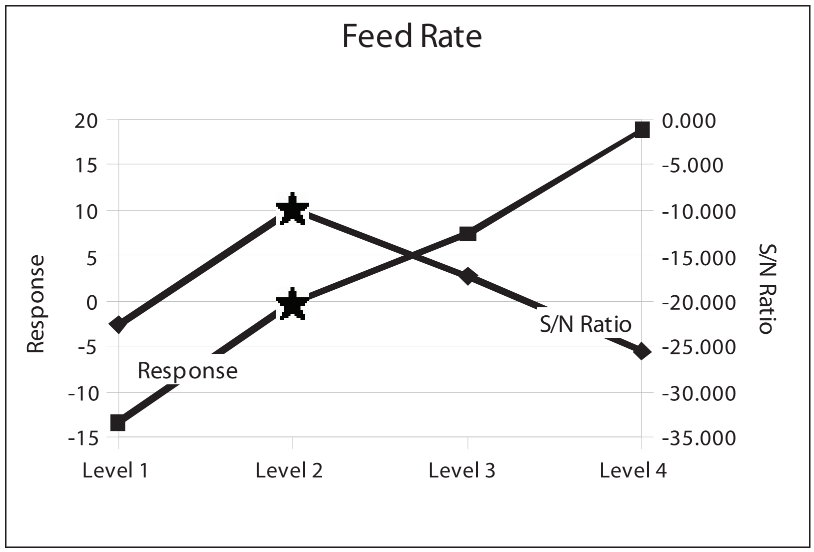
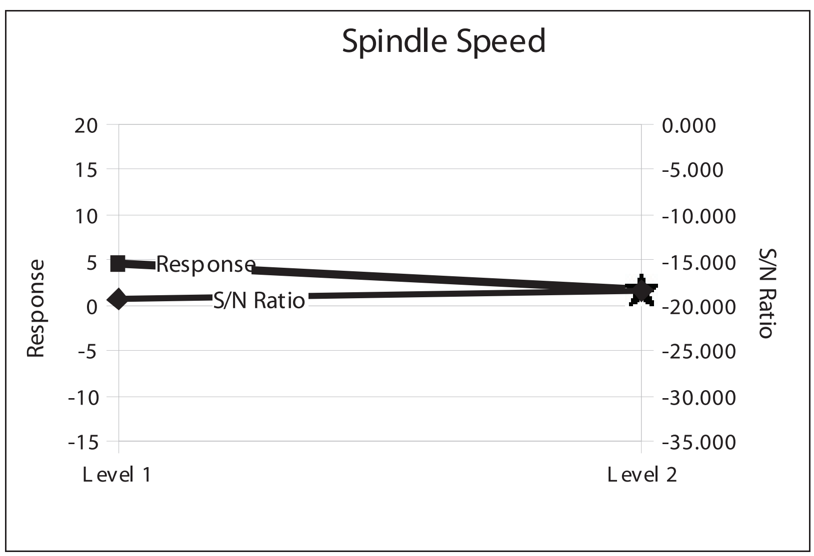


Figure 2. MREs and S/N ratios for spindle speed.



and interactions on the variability of the response (Nutek, 2006). This indicates that the feed rate has the most relative influence here, at 94.99%, and spindle speed only 1.38%. Error, which represents the noise factors and other uncontrolled parameters, has a relative effect of 3.63%. Therefore, while the ANOM found an optimal combination due to variations in the experiment, the ANOVA determined that the experiment did not provide statistical significance in the effects of spindle speed and depth of cut. This provides us with a couple of things to consider: first, the noise factors may have a significant effect, relative to all but one of the controlled parameters; and second, the range of spindle speed and depth of cut may not have been sufficient enough to produce significant variability. Unfortunately, with this type of experiment, it does not always make sense to select wider ranges of these parameters, and the small sample sizes here can make statistical analysis misleading. 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 9. The results of this show that resulting *p* values are greater than the alpha value of 0.05 for both noise factors, indicating that this test could not determine a significant difference between the means. Additionally, the 95% confidence intervals for the difference in means for both factors include zero, and thus it cannot be ruled out that there is no difference in means. This could mean that this experiment did not provide sufficient data for the t test to find significant effects of the noise factors on the response, or that such effects are insignificant. Further investigation of these noise factors 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 (Roy, 2001). Just as a machinist relying upon experience, one can rely here on the results on the ANOM, along with the studies described earlier that indicate the possible significance of the three control factors as well as the noise factors. Therefore, as a starting point, verification of the performance of the turning process with this optimal combination can be conducted.

Figure 3. MREs and S/N ratios for depth of cut.

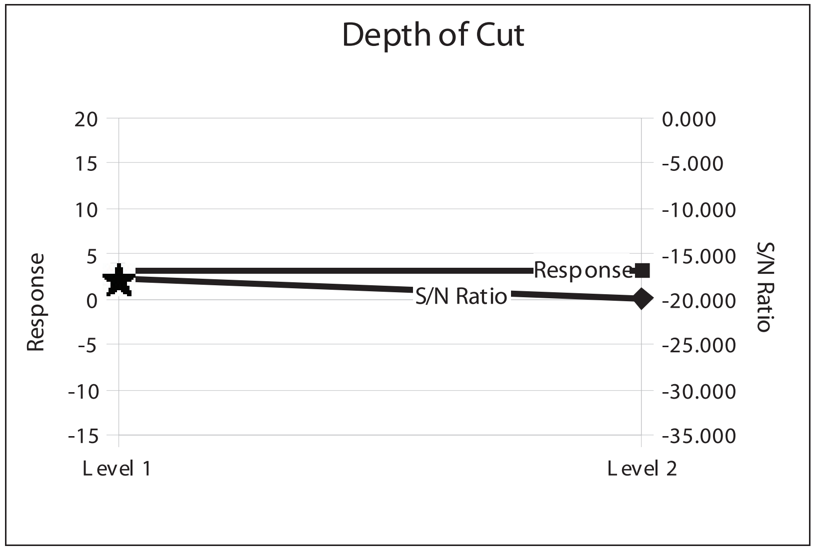


Table 7. Summary of Results of Study

Controlled Parameters	ID	Optimal Settings: Level	Optimal Settings: Value	Effect on Response
Feed Rate, *ƒ* (in/rev)	A	2	0.003	Strong
Spindle Speed, N (rev/min)	B	2	3500	Strong
Depth of Cut, d (in)	C	1	0.010	Insignificant
Noise Factors				
Tool Insert #	X			not found
Tool Manufacturer	Z			not found

Table 8. ANOVA for Controlled Parameters

Factor	DOF	SS	Variance	F-Ratio	Pure Sum	P (%)
f	3	4398.09	1466.03	262.76	4381.36	94.99
N	1	69.03	69.03	12.37	63.45	1.38
d	1	0.03	0.03	0.005	0.000	0.000
Noise/Error	26	145.06	5.58			3.63
Total	31	4612.21				100.00

Table 9. Results of T Tests for Noise Factors X and Z

Factor	t	Df	p value	Mean Diff.	Std. Error Diff.	95% C.I. Lower	95% C.I. Upper
X	0.530	30	0.600	2.313	4.363	-6.599	11.224
Z	0.157	30	0.876	0.688	4.382	-8.262	9.637

Verification

Verification of the optimal combination given in Table 7 can be done using a predictive equation, as well as experimentally using confirmation runs. A predictive equation is used to calculate 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 reported by Fowlkes & Creveling (1996):

$$y_p = \bar{\bar{y}} + (\bar{\bar{y}}_A - \bar{\bar{y}}) + (\bar{\bar{y}}_B - \bar{\bar{y}}) + (\bar{\bar{y}}_C - \bar{\bar{y}}) \quad (3)$$

where

y_p = the predicted response effect (y_m - T) or S/N ratio effect

$\bar{\bar{y}}$ = the overall mean response effect (Equation 2) or S/N ratio of the experiment

$\bar{\bar{y}}_A$, $\bar{\bar{y}}_B$ and $\bar{\bar{y}}_C$ = the MRE or S/N ratio effect for the optimal levels (from Table 6).

Applying this formula to the optimal combination yields a predicted response effect of -1.75 µin, and a predicted S/N ratio effect of -8.30. One can calculate the response value based on the response effect and the equation:

$$RE = y_m - T \quad (4)$$

where

RE = the response effect (µin)
y_m = the measured value (µin)
T = the target value (32 µin).

Solving for y_m with the given RE of -1.75, the predicted measured value for the response would be 30.25 µin. This can be visually compared with the experimental data in Table 5; while the optimal combination is not among the experimental runs; Run 4 has the closest values to this combination. The optimal combination provides a measured response value that is very close to that of Run 4, and a S/N ratio that is a bit larger (which is better).

Next, this predicted response can be verified through confirmation runs. This involves using the same experimental setup and the optimal combination of controlled parameters to create a sample for measurement and comparison to the predicted response. The selection of tools used in the main experiment was selected randomly for each workpiece. A sample of ten workpieces were turned and measured, the values of which can be seen in Table 10.

Table 10. Confirmation Sample Data and Statistics

Workpiece #	$\bar{R}_a$	Verification Sample Statistics			
1	30	$\bar{\bar{\mu}}$	$\sigma\sigma$	99% C.I.	
2	30	29.20	1.93	[27.54	30.86]
3	31				
4	27				
5	29				
6	32				
7	28				
8	28				
9	26				
10	31				

Also indicated in Table 10 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 about 1 µin below the predicted value of 30.25 µin. The 99% confidence interval of the confirmation sample includes the predicted value nearly at its maximum. This could perhaps change if a larger sample size was utilized for the confirmation run, which would help distribute the noise effects evenly. Additionally, one must consider that the treatment combinations for this experiment are finite and that Run 4 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.

Conclusions and Recommendations

This study demonstrated an efficient method for determining the optimal turning operation parameters for a specified surface finish through the use of Parameter Design Experiment (PDE) methods. The use of a modified L8 orthogonal array, with three control parameters and two noise factors, required only thirty-two workpieces to conduct the experimental portion, half 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 realistic 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 noise factors were 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.

This parameter design yielded an optimal treatment combination well as a predictive equation that yielded realistic 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. Additionally, the addition of multiple machine tools as a noise factor would utilize potential variance between machines in such a study. Bringing more realistic and applicable examples of Taguchi Parameter Design to light should be a goal of all researchers in this area.

Finally, it is also advantageous to perform studies similar to this in academia as class learning exercises. By practicing Taguchi Parameter Design projects, one can gain experience and knowledge in industrial DOE and statistics, as well as the in-depth study of manufacturing processes. Furthermore, just as is found in a production environment, this provides an efficient project in an academic environment as well.

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