Estimation of CNC Machining Parameter Levels for Brass Union Using an Adaptive Constrained Response Surface Optimization Model

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***Abstract*—The selection of appropriate levels of machining parameters is an important consideration that determines machinability or other quality measures. In this study, the CNC machining process was designed to optimize the effects of machining parameters such as feed rate, spindle speed, and tool life in the production of brass unions, which are commonly used in air conditioners. The numerical design was carried out using a proposed adaptive constrained response surface optimization model (ACRSOM). The ACRSOM's evolutionary operations began with the conventional factorial design, which was used to identify the influential effects of the main and some selected parameter interactions on transformed proportion responses. The first phase was used to move quickly toward the optimum with adequate design points, whereas the second phase was used to minimize the standard deviation of transformed responses under the desired mean target. The ACRSOM was generated in linear or nonlinear forms, based on either unreplicated or replicated designed plans, which were then combined to generate the new operating condition. With the optimal setting of 0.08 feed rate; 2,300 spindle speed and 10,000 tool life obtained from the proposed model, the percentage of defects is reduced from 0.3371 to 0.0610. Furthermore, process variation is greatly reduced from the previous operating condition.**

***Keywords*—brass union, carbide half-round drill, constrained response surface model, drilling process, designed experimental plan, proportion response**

I. Introduction

The production of brass air conditioner parts is currently in high demand. As a result, there must be competition in terms of product quality and timely delivery. To dominate this type of industry market, industrial factories must control their production for maximum efficiency and differentiate themselves from other production bases. All brass unions will be manufactured in collaboration with human workers using machinery with a camshaft to control the blade operations on CNC machines. However, these machines continue to cause production defects [1–2]. The effects of influential parameters on these CNC machines with camshaft operation will be the focus of this research.

Response surface methodology (RSM) is widely used to optimize analytical procedures and monitor the impact of process parameters on experimental response [3–4]. RSM is a collection of mathematical and statistical strategies based on experimental data and a fitted equation [5]. It must describe the structure of a data set in order to make statistical predictions. When several process parameters influence an interest response or set of responses, it is useful [6]. The goal is to optimize all of these parameters at once to achieve the highest level of system reliability [7–8].

It is critical to first select an experimental design that specifies which experiments should be carried out in the experimental domain under consideration. There are some experimental materials available for this purpose. When the data set lacks curvature, first-order experimental designs such as simplex or factorial designs can be used. Furthermore, the desired process response is frequently a proportion between 0 and 1. One of the simplest methods for applying specific statistical procedures to non-normally distributed data is to transform it. Nonparametric statistics lack the statistical power provided by

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transformations. The main disadvantage is that the transformation can be difficult to grasp at times.

The main purpose of this research was to determine the best levels of process parameters for CNC machining of brass unions. To optimize the process parameters, an analytical model was created using a two-level factorial designed plan. The process parameters investigated in this study were feed, spindle speed, and tool life. Data transformation was performed using the standard rule of thumb to overcome the statistical assumptions associated with the proportion response. It should be used when the proportions are close to 0 and/or close to 1. Proportions close to 0 and 1 will be stretched, while those close to 0.5 will be compressed.

The optimal parameter levels for CNC machining of brass unions were determined in this work. The innovations in this paper are summarized below.

1. In this paper, an adaptive constrained response surface optimization model (ACRSOM) of linear or nonlinear nature is proposed.

2. First, the model based on the mean is used to determine the optimum using an unreplicated designed plan.

3. The transformation is introduced to the model to take into account the categorical nature of the response data.

4. Finally, the model to reduce the standard deviation is then incorporated within the desired response restrictions utilizing a replicated designed plan.

The CNC machining process (CNCMP) is briefly described in the second section. The basic experimental design with transformed data is covered in the section “Related Methods.” The section “Numerical Results and Analysis” presents the results of the related methods. Finally, the section “Discussions and Conclusions” contains the research’s conclusions and discussions, as well as suggestions for future research.

II. CNC MACHINING PROCESS (CNCMP)

The basic structure of a CNC machine (Cincom A20) is made up of five functions: a driving system, a clamping system, a measuring system, an electrical system, and a control system. A transmission system controlled by a servo motor system and a control axis driving system controlled by a stepping motor comprise the driving system. The basic operation of servo motors and stepping motors is the rotation of the permanent magnet rotor caused by blowing the coil against the stator and energizing the magnetic field.

The workflow of a CNC machine is a program-controlled operation. The program is fed into the panel, and the knife turret is moved in accordance with the program to control the operation of each type of blade. The main spindle and sub spindle of the knife turret will be on opposite sides (Fig. 1). Each piece of work begins on the main spindle and is then moved to the end to be turned and drilled on the sub spindle.

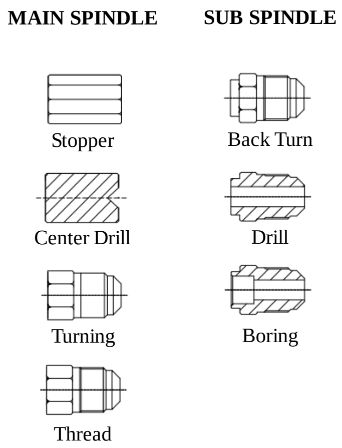

Figure 1. CNCMP for brass unions

Errors in the manufacture of brass unions can occur, resulting in additional flaws. These errors manifest themselves in various ways, resulting in a wide range of defective work that cannot be repaired or fixed. For this study, four defective brass unions are being considered (Fig. 2). The first flaw (No Hole) is a brass union in which the hole did not reach the opposite side of the workpiece, resulting in a blind hole that could be visually inspected.

The second defect (Hole No-Go) of brass unions is that the holes are either too small or too large for the targeted inner diameter of 7 mm. The workpieces do not meet the requirements that can be read from various devices when measuring the hole dimensions. Brass unions, which have an uneven and streaked inner hole surface as well as burrs inside the hole and can be visually inspected, are the third defect (Striped Inner Hole). Finally, this defect type (Hole Deform) can be visually inspected if the brass unions with drilled holes are not round or have a different appearance than the sphere.

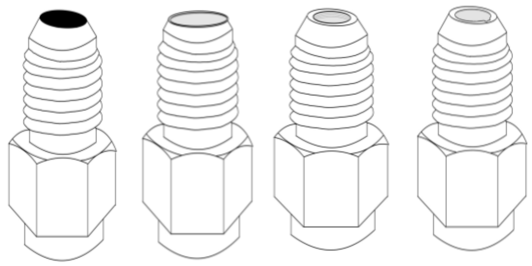

Figure 2. Brass unions with four types of defects of No Hole, Hole No-Go, Striped Inner Hole and Hole Deform

According to the production report, the amount of defect due to No Hole was found to be the highest in the third quarter of 2022. Other defects included Hole No-Go, Striped Inner Hole, and Hole Deform. All of these defects, according to experts, are caused by the carbide half-round drill, so its various parameters must be considered. Square-shaped defects, which are primarily caused by human error in that the workpiece is not removed from the workpiece container until the impact between the workpieces causes damage to the product's edges. This will not be considered in this study.

In this study, a CNC machine was used to drill a hole in the workpiece with a half-round drill blade. The procedure starts with a rotating workpiece holder that causes the workpiece to rotate at a predetermined rotational speed. The workpiece is then moved at a constant feed rate towards the blade along the horizontal axis. To achieve the required dimensions, the clamping system tightly clamps the cutting tool while only moving the vertical and depth axes. In the production of workpieces, ongoing half-round drill blades are used, and the blade will wear out after a certain number of workpieces, resulting in poor work [9].

When there is a lot of bad work, the blade is replaced. Feed (x_1), spindle speed (x_2), and tool life (x_3) are thus drilling process parameters that can be influenced. The proportion of defects will be calculated by counting the number of defects that occur on a daily basis and comparing them to the total number of pieces produced during the time required to study. Four types of defects discovered during CNCMP must be eliminated in order to continue improving the defect proportion of brass unions. The skilled worker should also be considered an uncontrollable variable or noise (Fig. 3) and the details of the Cincom A20 CNC machine is given in Table I.

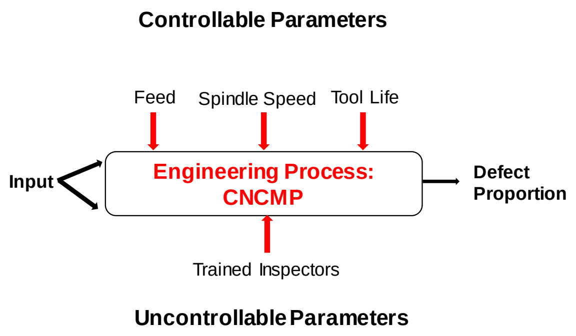

Figure 3. Design and noise parameters of the CNCMP

TABLE I. CINCOM A20 AND ITS MAIN SPECIFICATIONS

Items	Details
Maximal level of machining diameter	20mm
Maximal level of machining length on guide-bushing	200 mm
Maximal level of drilling diameter of the main spindle	10 mm
Maximal spindle speed	10,000 min^{-1}
Maximal level of drilling diameter in back machining process	8 mm
Maximal back spindle speed	8,000 min^{-1}
Spindle drive motors	2.2/3.7 kW
Tool spindle drive motors	0.75 kW

III. RELATED METHODS

A. Response Transformation

Residuals are experimental error estimates computed by subtracting the observed response from the estimated response. After estimating all unknown model parameters from the experimental data, it is calculated using the chosen model. The underlying assumption of an analysis of variance (ANOVA) and regression analysis is that residues are normally distributed and independent, with a mean of zero and a constant variance.

Working in industrial plants also necessitates considering response data characteristics as categorical data, such as good work/bad work, pass/fail in proportional form. As a result, when using statistical methods to analyze data with the aforementioned characteristics, the probability distribution characteristics of the data between the theoretical model and the actual study approach are critical issues for an ANOVA-based statistical inference principle.

Transforming data is one of the easiest techniques to use specific quantitative approach with data that is not normally distributed or in the form of a proportion or percentage. Transformations have the advantage of providing more statistical power than nonparametric statistics. The arcsine and logit transformations are the two most common methods for converting percent, proportions, and probabilities. Both transformations should be used when a number of proportions are close to 0 and/or close to 1. Proportions near 0 and 1 will be stretched, while those near 0.5 will be compressed.

The arcsine transform is also known as the angular transformation. The arcsine transform equals the inverse sine of the proportion's square root as shown in Eq. (1).

$$Y = arcsine\sqrt{p} \tag{1}$$

where p is the proportion or natural response, and Y is the transformed or coded response. The outcome can be expressed in either degrees or radians.

B. Adaptive Constrained Response Surface Optimization Model (ACRSOM)

Response surface methods (RSM) employ multiple factors at once, each with two or more levels [10]. In factorial experiments, several factors are involved the distinguishing feature under investigation simultaneously, and the investigator is engaged in both the main effects and the interaction effects among various factors [11–12].

Aside from deciding which factors to use, deciding what levels to use is one of the most difficult decisions for RSM. A general rule of thumb is to space levels as far apart as possible in order to see and effect while not exceeding the operating boundaries [13]. For this study, however, the standard two-level factorial design was used. This technically implies that the variables have no relationship.

In practice, a first-order or linear polynomial model will be used to generate the steepest ascent (or descent) path. When the lack of fit test shows that there is no significant effect on pure quadratic curvature, the new design points will be located using a preset step length from the current operating condition until no further development in response is observed. In complex problems, however, there are numerous associated responses. The most important response will be designated as the primary response, and the others as secondary responses [14]. Then, to determine preferable levels of the system's k parameters, a constrained response surface optimization model (CRSOM) is generated.

Assumptions or approximations based on linear or nonlinear programming may also result in appropriate problem representations across a range of process parameters [15–16]. The objective and constraint functions in the CRSOM can be linear (Eq. (2)) or nonlinear (Eq. (3)), which is important for properly representing an application as a mathematical program at times. These parameter levels yield the best primary transformed response while meeting all secondary transformed response constraints. In addition, the proposed model includes plausible regions of influential parameters ($x_i, i = 1,2,3$). The terms β_0 and β_i are the parameters of the model and ε_{ij} represents the discrepancy between true and observed achievement.

$$Y_{SD} \text{ or } Y_M = \beta_0 + \sum_{i=1}^{3} \beta_i x_i + \varepsilon_{ij} \tag{2}$$

$$Y_{SD} \text{ or } Y_M = \beta_0 + \sum_{i=1}^{3} \beta_i x_i + \beta_4 x_1 x_2 + \beta_5 x_1 x_3 + \beta_6 x_2 x_3 + \beta_7 x_1^2 + \beta_8 x_2^2 + \beta_9 x_3^2 + \varepsilon_{ij} \tag{3}$$

For a replicated designed plan, the CRSOM's goal is to generate appropriate design points without overestimation. A regression analysis is used to determine the CRSOM's standard deviation ($\widehat{Y_{SD}}$) and the mean ($\widehat{Y_M}$) of transformed responses. Linear (LCRSOM) and nonlinear (NLCRSOM) programming models are developed in response to the lower (LB) and upper (UB) bounds of secondary responses and influential parameters (X), which are as follows:

$$\begin{aligned} &\text{Minimize } \widehat{Y_{SD}} \\ &\text{Subject to} \\ &(\text{T-}\Delta) \le \widehat{Y_M} \le (\text{T+}\Delta) \\ &\text{LB} \le X \le \text{UB} \end{aligned} \tag{4}$$

where Δ is the maximum deviation calculated from the mean of the transformed responses that is close to the specified target value (T).

When there is an unreplicated designed plan, the CRSOM's objective ($\widehat{Y_M}$) will be applied without regard for the specified target value, as follows:

$$\begin{aligned} &\text{Optimize } \widehat{Y_M} \\ &\text{Subject to} \\ &\text{LB} \le X \le \text{UB} \end{aligned} \tag{5}$$

This adaptive method iteratively provides a process for learning by experimenting and investigating. A search analysis is the first stage of the methodology. As a result, the research begins with a survey of a large decision space with numerous parameters. As needed, later iterations of the methodology may be more focused. The following steps provide a systematic overview of the general framework of the proposed method, which can be modified to meet the needs of the industrial application.

Finding the parameters (X) and their achievable lower (LB) and upper bound (UB) ranges is the first step (UB). The second step is to transform the natural response to the transformed or coded response by using experimental design to identify parameters that meaningfully affect the natural response (p). Third, it is an improved and developed model for estimating the mean ($\widehat{Y_S}$) and standard deviation ($\widehat{Y_P}$) of transformed response variables. Finally, using Eq. (4), determine the optimal value of the controllable variable (X) and adjust the mean and variance.

IV. Numerical Results and Analysis

The level of a half-round drill blade's pertinent factors has been established by the manufacturing of brass unions. Recent production data indicate the following level of pertinent parameters for a half-round drill blade: The feed rate can be changed from 0.03–0.12 mm/rev in steps of 0.01 mm/rev; the rotational speed can be changed from 750–3000 rev/sec in steps of 50 rev/sec; and the tool life of the blade depends on the assessment of each machine engineer and has various level configurations.

For the case study, the amount of defects produced during the manufacturing process is investigated using the binomial distribution. In order to interpret and infer the values, each practice uses a statistical method that is based on the theory and concept of the binomial distribution. By using the Central Limit Theorem and a larger sample size, the normal distribution can be used to approximate the binomial distribution. As a result, it is now used as a benchmark when determining whether to infer the ratio statistically. To get the most accurate factor analysis results, additional considerations for this study were made by converting the ratio.

The numerical results of the Adaptive Constrained Response Surface Optimization Model (ACRSOM) are presented in detail in this study. The CNCMP only has one response for the number of defects per manufactured workpiece. Explicit constraints keep the parameter levels within their feasible ranges. The levels of the three influential parameters ($x_i, i = 1,2,3$) were optimized by CRSOM. As shown in Fig. 3, these parameters are feed (x_1), spindle speed (x_2), and tool life (x_3). The completely randomized design is most frequently used in an ANOVA to monitor all process parameters from all existing design observations.

The variance among designed experiments must be constant across all levels of treatment for an ANOVA, and especially for the mean comparisons. The F test's primary presumption, and if it is violated, no results from the ANOVA should be drawn. This assumption strongly affects the F test because the mean square error (MSE), the denominator, is the average within-treatment variance. Assuming, on average, that the real values of all within-treatment variances are equal. The average variance is not enough to compare means if the deviations of different treatment levels diverge.

There are two options if the data indicates that the assumptions for an ANOVA cannot be valid. The first choice is to conduct a different test, like a non-parametric test, which does not require the rejected premises. The second option is to ensure the transformed response complies with the analysis' generalizations by appropriately transforming the response. But this study went with option two.

As advised by the literature, the pilot experiment in this study used the arcsine transformation on the percentage of defect proportion data. By expanding both tails and contracting the middle, it sought to break the relationship between variance and the mean. In experiments with a single replicate, there aren't enough observations to calculate the error sum of squares. The ANOVA table needed two more runs because there were ten design points with two levels of three parameters.

One way to determine the normality assumption on both natural and transformed responses is to look at the normal probability plot of effects based on the current operating condition or the first scenario (S1) of 0.06 feed rate; 2,650 spindle speed and 20,000 tool life. The transformed data meet the assumptions better than the natural data, leading to a much stronger P-value of 0.667, despite the fact that the data do not contradict any of the assumptions. The improvement in the data is demonstrated by the plots of percentage versus percentage (Fig. 4(a)) and transformed percentage (Fig. 4(b)) of defect proportions.

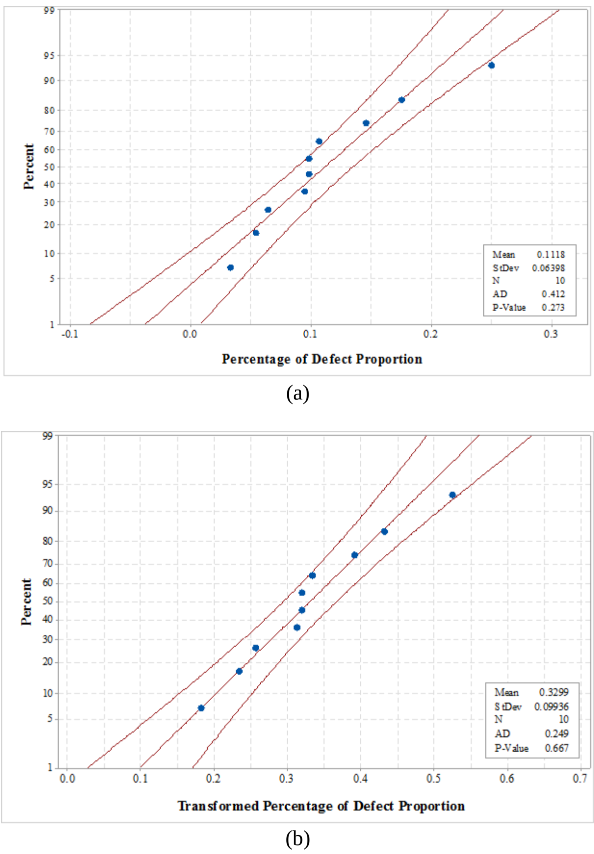

Figure 4. Normal probability plot of the percentage of defect proportion (a) and the transformed percentage of defect proportion (b)

At the 25% level of significance, the arcsine transformation used to analyze this data revealed significant main effects of spindle speed and tool life as well as the interaction effect of feed and spindle speed (Table II). The ANOVA results of arcsine-transformed data are not necessarily different from those of natural data, though, at the level of the overall ANOVA F test.

TABLE II. ANOVA TABLE FOR DETERMINING THE SIGNIFICANT PARAMETERS INCLUDING THEIR INTERACTIONS ON THE SECOND SCENARIO

Source of Variation	Degree of Freedom (DF)	Sum Squares (SS)	Mean Squares (MS)	F-Value	P-Value
Model	7	0.08224	0.011749	3.56	0.237
Linear	3	0.074808	0.024936	7.55	0.119
x_1	**1**	0.049331	0.049331	14.94	0.061
x_2	1	0.004722	0.004722	1.43	0.354
x_3	1	0.015177	0.015177	4.6	0.165
2-Way Interactions	3	0.01738	0.005793	1.75	0.383
x_1*x_2	1	0.014708	0.014708	4.45	0.169
x_1*x_3	**1**	0.000041	0.000041	0.01	0.921
x_2*x_3	1	0.002485	0.002485	0.75	0.477
3-Way Interactions	1	0.001592	0.001592	0.48	0.559
$x_1*x_2*x_3$	**1**	0.001592	0.001592	0.48	0.559
Error	2	0.006605	0.003303		
Total	9	0.088845			

Due to the suggested methods for using the model separately, the analysis is resistant to the selection of the importance values for the parameter values. The analyst can also develop the adaptive model and execute subsequent iterations of the methodology, if desired. The analyst could then assess how sensitive the suggested strategy is to the choice of the adaptive constrained response surface optimization model. The regression coefficients for forming the ACRSOM (Eq. (5)) at this stage are shown in Table III at a 90% confidence interval, and the objective function is given below:

$$\widehat{Y_M} = 7.69\text{-}88.9x_1\text{-}0.00338x_2 + 0.000007x_3 + 0.0401x_1 \times x_2$$

where the feasible ranges of all parameters are $0.03 \leq x_1 \leq 0.12$; $750 \leq x_2 \leq 3{,}000$ and $5{,}000 \leq x_3 \leq 20{,}000$.

TABLE III. ESTIMATED REGRESSION COEFFICIENTS AND THEIR PARTIAL STATISTICAL TEST FOR THE SECOND SCENARIO

Term	Coefficient	T-Value	P-Value
Constant	7.69	2.25	0.074
x_1	−88.9	−2.32	0.068
x_2	−0.00338	−2.36	0.065
x_3	0.000007	2.24	0.076
x_1*x_2	0.0401	2.49	0.055

The above model can be used to establish the preferred level for the process, as shown in Table IV, based on the results of the pilot experiment in the second scenario (S2). To assess the relationships between the three process parameters and the transformed response of the defect proportion percentage, ACRSOM was used. Sixteen experiments were run in a random order. For each design point, Table IV displays the outcomes of the two level factorial experimental plans.

TABLE IV. PARAMETERS AND FEASIBLE PROCESS PARAMETERS LEVELS INCLUDING THE SECOND SCENARIO

Process Parameter	S2	Level		Unit
		1	2	
Feed	0.08	0.08	0.1	mm/rev
Spindle Speed	2,500	2,300	2,500	rev/sec
Tool Life	20,000	10,000	20,000	pieces

Minitab was used to approximate and evaluate the full regression coefficients, as well as their statistical significance. The two types of numerical results are the mean and standard deviation of transformed responses. Both sets of data were subjected to analysis of variance (ANOVA) in order to fit a constrained response surface optimization model using the least squares method and assess the fit's quality.

On the mean response, at the 95% confidence level, F-Statistic = 5.84, the P-value less than 0.05 explicitly stated that the fitted model with main and interaction effects has a high significance and is reliable in predicting the mean of transformed responses (Fig. 5). Furthermore, according to the computed lower the transformed target of the percentage of the defect proportion and the maximum deviation (Δ) calculated from the mean of the transformed responses are both set at 0.2255 and 0.1228. F-Statistic level, the parameter of tool life was found to be significant at the 85% confidence level (Table V).

The fitted regression model used to predict the mean of transformed responses is depicted below along with the statistics in Table VI. The residuals appear to fit the assumptions of normality, independence, and variance stability (Fig. 6). The transformed target of the percentage of the defect proportion and the maximum deviation (Δ) calculated from the mean of transformed responses are both set at 0.2255 and 0.1228.

$$\widehat{Y_M} = 8.42 - 100.3\, x_1 - 0.00365\, x_2 + 0.000004 x_3 + 0.0446 x_1 \times x_2$$

TABLE V. ANOVA TABLE FOR DETERMINING THE SIGNIFICANT PARAMETERS INCLUDING THEIR INTERACTIONS ON MEAN FOR THE THIRD SCENARIO

Source of Variation	DF	SS	MS	F-Value	P-Value
Model	7	0.10816	0.015451	5.84	0.016
Linear	3	0.081483	0.027161	10.26	0.006
x_1	1	0.066338	0.066338	25.07	0.002
x_2	1	0.020137	0.020137	7.61	0.028
x_3	1	0.007362	0.007362	2.78	0.139
2-Way Interactions	3	0.031623	0.010541	3.98	0.06
$x_1 * x_2$	1	0.028797	0.028797	10.88	0.013
$x_1 * x_3$	1	0.000348	0.000348	0.13	0.727
$x_2 * x_3$	1	0.002715	0.002715	1.03	0.345
3-Way Interactions	1	0.000348	0.000348	0.13	0.727
$x_1 * x_2 * x_3$	1	0.000348	0.000348	0.13	0.727
Error	7	0.018525	0.002646		
Total	14	0.126685			

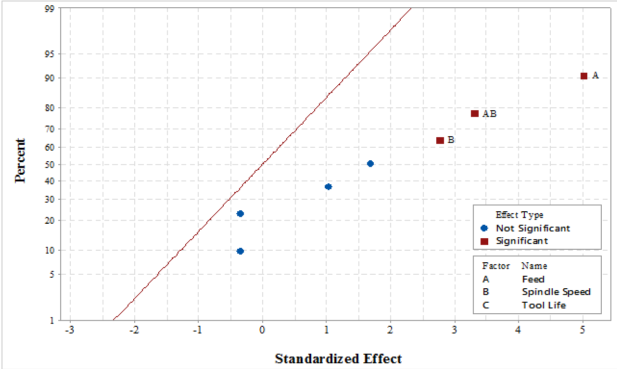

Figure 5. Normal probability plot of effects on the mean response of transformed defect proportion percentage

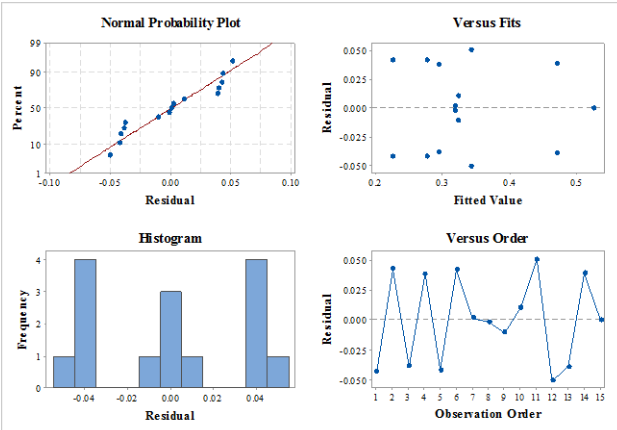

Figure 6. Residual analysis based on the mean response of transformed defect proportion percentage

TABLE VI. ESTIMATED REGRESSION COEFFICIENTS ON MEAN AND THEIR PARTIAL STATISTICAL TEST FOR THE THIRD SCENARIO

Term	Coefficient	T-Value	P-Value
Constant	8.42	3.18	0.0099
x_1	−100.3	−3.4	0.0068
x_2	−0.00365	−3.29	0.0081
x_3	0.000004	1.81	0.0996
$x_1 * x_2$	0.0446	3.62	0.0047

With the additional experiments, the fitted model with main and interaction effects has high significance and is reliable in predicting the standard deviation of transformed responses at the 75% confidence level, F-Statistic = 4.21, with a P-value less than 0.25. The regression model that was fitted to predict the mean of transformed responses is shown below.

$$\widehat{Y_{SD}} = -0.831 - 3.04 x_1 + 0.000485 x_2 + 0.000075 x_3$$
$$+ 0.000180 x_1 \times x_3 - 0.0000004\, x_2 \times x_3$$

ACRSOM numerical optimization was used to predict optimal CNCMP conditions. The optimal conditions for obtaining the lowest value of transformed response of the percentage of defect proportion are as follows: 0.08 feed rat; 2,300 spindle speed and 10,000 tool life. Experiments were also carried out to validate the predicted model's accuracy, and the experiment was carried out with three replicates at the optimal conditions chosen.

The difference (D) between predicted and observed error values was less than 1% transformed response of defect proportion, indicating that the regression model was adequate. According to these statistical tests of actual data (Fig. 7), the third scenario (S3) is suitable for implementing its new operating condition, with a P-value of 0.036. The Fisher's mean comparison test, on the other hand, revealed that neither scenario 2 nor 3 were statistically significant.

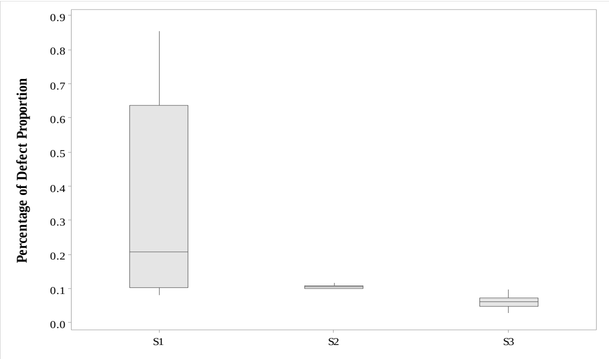

Figure 7. Box-Whisker Plot for the percentage of actual defect proportion for three scenarios

V. Discussions and Conclusions

In this paper, the parameters of a half-round drill blade for the CNC machining process that can minimize the defect proportion of brass unions were investigated. The feed rate, speed, and tool life input parameters, as well as their experimental settings, were chosen using the literature and the CNC machine operator's expertise. The most commonly used experiment via the two level factorial designed plans was employed in the development of an adaptive constrained response surface optimization model (ACRSOM). The arcsine transformation was also used in this model, which is useful for stabilizing variances and normalizing proportional data.

The ACRSOM was divided into two phases. When there was an unreplicated designed plan, the CRSOM's goal was to move quickly toward the optimum. When the replicated designed plan was obtained, the model searched for the operating condition with the lowest standard deviation level of proportion responses. The best percentage of defects value was 0.0610 at 0.08 feed rate; 2,300 spindle speed and 10,000 tool life. This result was better than the percentage of defects obtained from the conventional and previous phases of the ACRSOM, which were 0.3371 and 0.1057, respectively. In comparison to the conventional method, it thus increased the viability of the proposed method as a powerful technique for robust design.

More research could be conducted to compare different response transformations for reducing variance and normalizing proportional or percentage data. By comparing the results of other transformation methods to the results of linear regression on untransformed data, changes in residual plots, changes in the P-value, and changes in the significance determination can be used to determine how well the residuals adhere to the assumptions of normality, homogeneity, and independence. Future research on the economics of turning, milling, and other machining operations will almost certainly concentrate on metaheuristics and evolutionary operations to determine process parameters [17–20].

Conflict of Interest

The authors declare no potential conflicts of interest with respect to research, authorship, and/or publication of this article.

Author Contributions

P. Luangpaiboon contributed to the design, conceptualization, methodology, software, validation, visualization of the research, to the analysis of the results and to the writing - review & editing of the manuscript. N. KANTAPUTRA and N. Chongsawad contributed to an implementation, formal analysis, investigation, data curation of the research, and to the writing-review & editing of the manuscript. P. Aungkulanon, L. RUEKKASAEM and W. ATTHIRAWONG contributed to data curation of the research, and to the writing - review & editing of the manuscript.

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