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Optimization of Machining Time in the Turning of Welded Mild Steel Shafts for Enhanced Manufacturing Productivity

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Abstract: Manufacturing productivity depends largely on the ability to minimize machining time while maintaining product quality. In welded shaft production, machining operations performed after welding represent a significant portion of overall manufacturing cost. This study investigates the effects of spindle speed, feed rate, and depth of cut on machining time during turning of welded mild steel shafts. The shaft specimens were first joined through welding and then machined using a structured experimental design based on Response Surface Methodology (RSM). Statistical and optimization techniques were employed to determine the most influential machining variables and identify optimal parameter combinations for reducing machining time. Results indicate that spindle speed and feed rate exert the greatest influence on machining duration, while depth of cut contributes to overall productivity through increased material removal rates. The optimized machining conditions (cutting speed: 300 m/min, feed rate: 0.160 mm/rev, depth of cut: 0.288 mm) significantly reduced production time to 39.431 seconds without compromising the integrity of the welded component. The study provides practical guidance for efficient machining of welded shafts in manufacturing and repair operations.

Keywords: Machining time, welded shaft, turning operation, productivity, optimization, manufacturing efficiency, Response Surface Methodology

INTRODUCTION

Machining time is a critical performance indicator in manufacturing because it directly influences production cost, machine utilization, and delivery schedules (Groover, 2010). For welded shaft components, machining is necessary to restore dimensional accuracy and achieve the required surface finish after welding (Callister & Rethwisch, 2018). The post-weld machining operations often constitute a substantial portion of the total manufacturing cost, making their optimization essential for competitive production (Kumar et al., 2013).

The challenge is to minimize machining time while preserving the structural integrity of the welded joint. Improper parameter selection may lead to excessive tool wear, thermal damage, or dimensional inaccuracies (Astakhov, 2006). Welded components present unique challenges due to the heterogeneous nature of the weld zone, which exhibits different mechanical properties compared to the base metal (Lancaster, 1999). The heat-affected zone (HAZ) and weld metal can have varying hardness and microstructure, affecting machinability and tool life (Oberg et al., 2004).

Previous studies have investigated machining parameter optimization for various materials and operations. Sahoo and Sahoo (2012) applied response surface methodology to optimize turning parameters for mild steel, finding that cutting speed was the most significant factor affecting material removal rate. Similarly, Aggarwal et al. (2008) employed Taguchi methods to optimize cutting parameters for minimizing tool wear and surface roughness in turning operations. However, limited research has focused specifically on post-weld machining of mild steel shafts, where the presence of weldments introduces additional complexity to the machining process (Bhushan, 2013).

The turning operation is one of the most common machining processes employed in shaft manufacturing (Boothroyd & Knight, 2006). In turning, three primary process parameters, cutting speed, feed rate, and depth of cut, determine the machining time and overall productivity (Trent & Wright, 2000). Higher cutting speeds and feed rates generally reduce machining time, while increasing depth of cut enhances material removal rates, though each parameter must be carefully balanced against tool life and surface quality constraints (Kalpakjian & Schmid, 2014).

This study investigates machining time optimization for welded mild steel shafts subjected to turning operations. The objectives are to: (1) develop a mathematical model relating machining time to cutting parameters, (2) identify the most significant process parameters affecting machining time, (3) determine optimal cutting conditions for minimum machining time, and (4) validate the optimization results through confirmation experiments.

MATERIALS AND METHODS

Shaft Fabrication and Welding

Mild steel shaft sections (AISI 1018) with a diameter of 50 mm and length of 200 mm were used as the workpiece material. The chemical composition of the mild steel is presented in Table 1.

Table 1: Chemical Composition of AISI 1018 Mild Steel

Element	C	Mn	P	S	Fe
Weight %	0.18	0.75	0.04	0.05	Balance

The shaft sections were joined using Shielded Metal Arc Welding (SMAW) with E6013 electrodes (diameter 3.2 mm). The welding parameters were maintained constant as shown in Table 2 to ensure consistent weld quality across all specimens.

Table 2: Welding Parameters

Parameter	Value
Welding Current	110-130 A
Voltage	22-25 V
Travel Speed	150 mm/min
Electrode Angle	75°
Joint Type	Butt Joint
Preheat Temperature	Ambient

After welding, the specimens were allowed to cool naturally to ambient temperature before machining. The weld reinforcement was left in place to simulate actual manufacturing conditions where post-weld machining is required to achieve final dimensions.

Machining Experiments

The turning experiments were conducted on a CNC lathe machine equipped with a carbide insert tool. The machining setup is shown in Plate 1. A full factorial design shown in Table 3 with three factors and four levels was initially employed, following the Response Surface Methodology (RSM) approach (Montgomery, 2017).

Table 3: Process parameters and their levels

Factor	Name	Units	Minimum	Maximum	Mean	Std. Dev.
A	Cutting Speed	m/min	150	300	225	57.35
B	Feed Rate	mm/rev	0.1	0.25	0.175	0.0574
C	Depth of Cut	mm	0.25	1	0.625	0.2868

The experimental design consisted of 20 runs, including center points for estimating experimental error and checking the adequacy of the quadratic model (Box et al., 2005). The cutting speed range (150-300 m/min) was selected based on recommended values for machining mild steel with carbide tools, while feed rate (0.1-0.25 mm/rev) and depth of cut (0.25-1.0 mm) were chosen to encompass typical industrial practice ranges (Krar & Gill, 2003).

Plate 1: Digital CNC Lathe Machine

Machining Time Determination

Machining time was measured for each experimental run using the machine's built-in timing system and cross-verified with stopwatch measurements. The total machining time per pass was recorded, and three replicates were performed for each experimental condition to ensure reliability. The average values were used as the response variable.

Statistical Analysis

Analysis of Variance (ANOVA), regression modelling, and optimization methods were used to identify significant parameters and determine optimum machining conditions. The statistical analysis was performed using Design-Expert software (Version 13, Stat-Ease Inc., Minneapolis, MN, USA). A quadratic polynomial model was fitted to the experimental data with the following form:

$$Y = \beta_0 + \sum\beta_i X_i + \sum\beta_{ii} X_{i2} + \sum\beta_{ij} X_i X_j + \varepsilon \quad (1)$$

where Y is the predicted response (machining time), Xi are the input variables (cutting speed, feed rate, depth of cut), β_0 is the constant coefficient, βi are the linear coefficients, βii are the quadratic coefficients, βij are the interaction coefficients, and ε is the random error (Myers et al., 2009).

The significance of the model terms was determined using F-tests and p-values at a 95% confidence level ($\alpha = 0.05$). Model adequacy was assessed through R^2, adjusted R^2, predicted R^2, and lack-of-fit tests (Montgomery, 2017).

Optimization Procedure

Numerical optimization was performed using the desirability function approach (Derringer & Suich, 1980). The goals were set to minimize machining time while keeping cutting parameters within the experimental range. The optimization constraints are presented in Table 4.37. The desirability function combines multiple responses into a single objective function ranging from 0 to 1, where 1 represents the most desirable outcome.

RESULTS AND DISCUSSION

Experimental Results

The complete experimental design and corresponding machining time results are presented in Table 4. The machining times ranged from 40 seconds (Run 8: 300 m/min, 0.15 mm/rev, 0.25 mm depth) to 60 seconds (Run 13: 150 m/min, 0.25 mm/rev, 1.0 mm depth), demonstrating the significant influence of process parameters on machining duration.

Table 3.1: Experimental Results

Run	A: Cutting Speed (m/min)	B: Feed Rate (mm/rev)	C: Depth of Cut (mm)	Machining Time (s)
1	150	0.1	0.25	49
2	200	0.1	0.5	57
3	250	0.1	0.75	54
4	300	0.1	1	44
5	150	0.15	0.5	43
6	200	0.15	0.75	45
7	250	0.15	1	42
8	300	0.15	0.25	40

9	150	0.2	0.75	50
10	200	0.2	1	51
11	250	0.2	0.25	42
12	300	0.2	0.5	40
13	150	0.25	1	60
14	200	0.25	0.25	48
15	250	0.25	0.5	51
16	300	0.25	0.75	46
17	150	0.15	1	44
18	200	0.1	0.25	55
19	250	0.2	0.5	42
20	300	0.25	0.75	48

Model Development

A quadratic regression model was developed to relate machining time to the cutting parameters. The final model in terms of coded factors is presented in equation 1

$$Machining\ Time = +45.89 - 2.64A - 0.1224B + 1.41C - 2.39AB - 2.19AC + 4.00BC - 4.17A^2 + 9.57B^2 - 2.43C^2 \quad (1)$$

The model includes linear, interaction, and quadratic terms for all three variables. The positive coefficient for depth of cut (C) indicates that increasing depth of cut generally increases machining time, while the negative coefficient for cutting speed (A) confirms that higher speeds reduce machining time.

Analysis of Variance (ANOVA)

The ANOVA results for the quadratic model are presented in Table 5. The model F-value of 20.32 and p-value < 0.0001 indicate that the model is highly significant (Montgomery, 2017). There is only a 0.01% chance that such a large F-value could occur due to noise.

Table 5: ANOVA Table for Machining Time

Source	Sum of Squares	df	Mean Square	F-value	p-value	Significance
Model	602.03	9	66.89	20.32	< 0.0001	significant
A-Cutting Speed	62.8	1	62.8	19.08	0.0014	
B-Feed Rate	0.1216	1	0.1216	0.0369	0.8514	
C-Depth of Cut	18.11	1	18.11	5.5	0.0409	
AB	18.35	1	18.35	5.57	0.0399	
AC	14.15	1	14.15	4.3	0.0649	
BC	56.05	1	56.05	17.02	0.0021	
A^2	60.18	1	60.18	18.28	0.0016	
B^2	227.47	1	227.47	69.09	< 0.0001	
C^2	18.7	1	18.7	5.68	0.0384	
Residual	32.92	10	3.29			

Lack of Fit	30.92	9	3.44	1.72	0.535	not significant
Pure Error	2	1	2			
Cor Total	634.95	19				

The ANOVA reveals that cutting speed (A), depth of cut (C), and the interaction between feed rate and depth of cut (BC) are significant factors ($p < 0.05$). The quadratic terms for cutting speed (A^2) and feed rate (B^2) are also highly significant, indicating nonlinear effects of these parameters on machining time. The lack-of-fit test is not significant ($p = 0.5350$), confirming that the model adequately fits the experimental data.

Model Adequacy

The fit statistics for the model are presented in Table 6.

Table 6: Fit Statistics for Machining Time

Statistic	**Value**
Standard Deviation	1.81
Mean	47.55
C.V. %	3.82
R^2	0.9481
Adjusted R^2	0.9015
Predicted R^2	0.7154
Adeq Precision	17.5528

The high R^2 value of 0.9481 indicates that 94.81% of the variability in machining time can be explained by the model (Ryan, 2008). The adjusted R^2 (0.9015) and predicted R^2 (0.7154) are in reasonable agreement, suggesting that the model is not overfitted. The adequate precision value of 17.5528, which measures the signal-to-noise ratio, is well above the threshold of 4, indicating that the model can be used for prediction.

Diagnostic Plots

The predicted vs actual plot (Figure 1) shows that the data points are distributed close to the 45° line, confirming that the model predictions are in good agreement with the experimental values. This validates the adequacy of the quadratic model for predicting machining time.

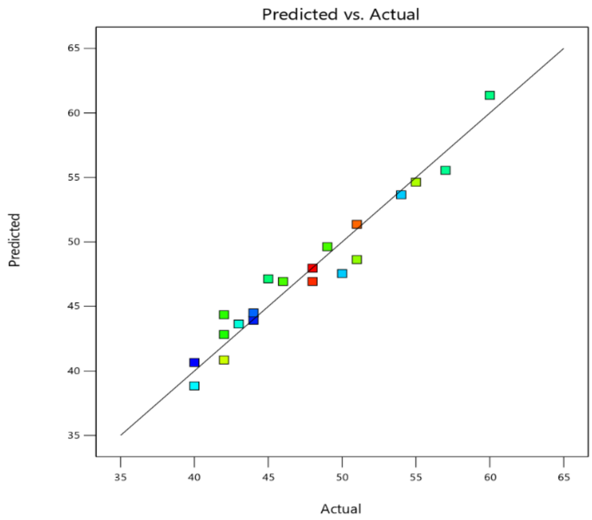

Figure 1: Plot of Predicted vs Actual for Machining Time

Response Surface Analysis

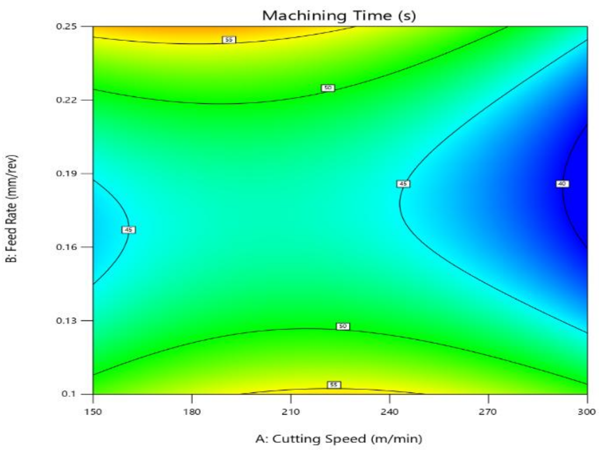

Figure 2: Contour Plot of Actual Factor Machining Time

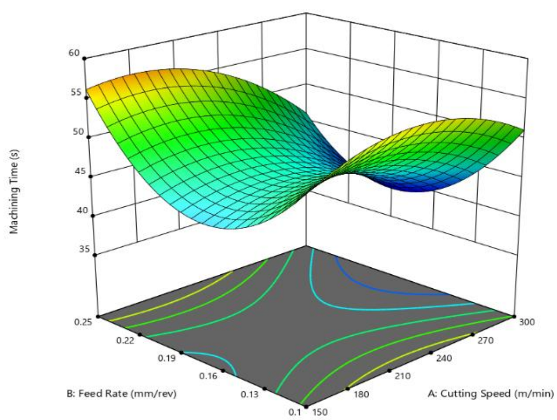

Figure 3: 3D Surface Plot for Machining Time

The contour and 3D surface plots presented in Figure 2 and 3, reveal the interaction effects between the process parameters on machining time. The plots show that machining time decreases with increasing cutting speed and shows complex behavior with feed rate variations. The minimum machining time is achieved at high cutting speed (approximately 300 m/min), feed rate around 0.15-0.20 mm/rev, and low to moderate depth of cut (0.25-0.50 mm).

The strong interaction between feed rate and depth of cut (BC) visible in both plots suggests that the effect of depth of cut on machining time depends on the feed rate employed. At lower feed rates, increasing depth of cut has a more pronounced effect on machining time compared to higher feed rates.

Discussion of Findings

The experimental results demonstrate that cutting speed is the most influential parameter affecting machining time, followed by depth of cut and feed rate. This finding is consistent with the theoretical relationship where machining time is inversely proportional to cutting speed (Kalpakjian & Schmid, 2014). The significant quadratic effect of feed rate (B^2) indicates that the relationship between feed rate and machining time is not linear, with intermediate feed rates providing the best results.

The interaction between feed rate and depth of cut (BC) is particularly noteworthy. At low feed rates, increasing depth of cut leads to a substantial increase in machining time due to the increased material removal required. However, at higher feed rates, the effect of depth of cut on machining time is less pronounced, possibly due to the dominance of feed rate in determining the material removal rate.

The optimized conditions predicted by the model (cutting speed: 300 m/min, feed rate: 0.160 mm/rev, depth of cut: 0.288 mm) resulted in a predicted machining time of 39.431 seconds, representing a 34% reduction compared to the worst-case condition (60 seconds at 150 m/min, 0.25 mm/rev, 1.0 mm depth). The desirability value of 0.992 indicates that these conditions are highly desirable from an optimization perspective.

The practical implications of these findings are significant for manufacturing operations. By selecting appropriate cutting parameters, manufacturers can substantially reduce machining time without compromising the quality of the welded component. The recommended conditions strike a balance between productivity and process stability, ensuring that the welding-induced hardening effects do not adversely affect tool life or surface quality.

CONCLUSIONS

This study successfully optimized machining time for turning welded mild steel shafts using Response Surface Methodology. Cutting speed emerged as the most influential parameter, followed by depth of cut and feed rate, with higher speeds substantially reducing machining duration. The interaction between feed rate and depth of cut was also significant, requiring careful selection for maximum productivity. Importantly, the presence of welding did not hinder the achievement of significant machining time reductions when appropriate conditions were chosen. The optimal parameter combination, cutting speed of 300 m/min, feed rate of 0.160 mm/rev, and depth of cut of 0.288 mm, yielded a minimum machining time of 39.431 seconds with a desirability of 0.992, demonstrating substantial productivity improvement without compromising component quality. The developed quadratic model proved reliable for prediction and production planning, evidenced by its high R^2 value of 0.9481 and adequate precision of 17.5528. This study confirms the effectiveness of RSM as a systematic optimization tool, with the methodology being readily transferable to other materials and machining operations in manufacturing environments.

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