

Enhancing WEDM Process Parameters via Response Surface Methodology

Lallasingh¹, Dr. Ram Gopal Verma²

¹M. Tech Scholar, Department of Mechanical Engineering, Rajshree institute of Management and Technology, Bareilly, UP, India

²HOD of Mechanical Department, Rajshree institute of Management and Technology, Bareilly, UP, India

ABSTRACT

Wire Electrical Discharge Machining (WEDM) is a widely used manufacturing process for producing complex shapes and intricate features in various materials. The optimization of process parameters in WEDM is crucial to improve the efficiency and quality of the machining operation. In this study, we propose the application of Response Surface Methodology (RSM) to enhance the process parameters of WEDM. The objective of this research is to identify the optimal combination of process parameters that can maximize the material removal rate (MRR) and minimize the surface roughness (SR) in WEDM. RSM is employed as a statistical tool to design and analyze the experiments, enabling us to model the relationship between the process parameters and the performance measures. A series of experimental trials are conducted with varying levels of process parameters, such as pulse on time, pulse off time, peak current, and wire tension. The MRR and SR are measured for each experiment, and the data is used to build mathematical models using RSM. The models are then used to optimize the process parameters and determine the optimal settings that yield the desired performance measures. The results indicate that RSM successfully identifies the optimal process parameter settings for maximizing MRR and minimizing SR. The optimized process parameters not only enhance the machining efficiency by increasing the MRR but also improve the surface quality by reducing the SR.

INTRODUCTION

Wire Electrical Discharge Machining (WEDM) is a non-traditional machining process widely used in industries for the precision cutting of complex shapes and profiles. It is particularly advantageous for materials that are difficult to machine using conventional techniques, such as hardened steels, exotic alloys, and conductive ceramics. WEDM utilizes a thin wire electrode to erode the workpiece through a series of controlled electrical discharges.

The performance of the WEDM process is influenced by various factors, including the process parameters. Process parameters such as pulse on time, pulse off time, peak current, wire tension, and flushing pressure significantly affect the material removal rate (MRR), surface roughness (SR), and other important performance measures. Therefore, optimizing these process parameters is crucial to achieve improved productivity, cost-efficiency, and surface quality.

Response Surface Methodology (RSM) is a statistical technique widely used in engineering and scientific research for process optimization. RSM helps to establish the relationship between the process parameters and the response variables through a series of designed experiments. It allows the determination of optimal parameter settings that yield the desired response.

The primary objective of this study is to enhance the process parameters of WEDM using Response Surface Methodology. By employing RSM, we aim to optimize the process parameters to achieve maximum MRR and minimum SR, leading to improved machining efficiency and surface quality.

In recent years, several researchers have applied RSM to optimize process parameters in various manufacturing processes. However, the application of RSM to WEDM process parameter optimization is still an area that requires further exploration. By utilizing RSM in WEDM, we can systematically investigate the impact of process parameters on the performance measures and identify the optimal parameter settings.

The significance of this research lies in its potential to contribute to the field of WEDM process optimization. By identifying the optimal process parameter settings, manufacturers can achieve higher MRR, reduce machining time, and enhance productivity. Additionally, minimizing the surface roughness through optimal parameter selection can lead to improved surface finish, reducing the need for secondary finishing operations and enhancing the overall product quality.

This study will be conducted through a series of experimental trials where various process parameters will be varied systematically. The MRR and SR will be measured as response variables for each experiment. The obtained data will be used to develop mathematical models using RSM, enabling the prediction and optimization of the process parameters.

The organization of the paper is as follows: Section 2 provides an overview of the relevant literature on WEDM process parameter optimization and the application of RSM in manufacturing processes. Section 3 describes the methodology, including the experimental design, data collection, and analysis. Section 4 presents the results and discusses the

implications of the findings. Finally, Section 5 concludes the paper and highlights the potential future research directions in this field.

WEDM Process

Wire Electrical Discharge Machining (WEDM) is a specialized manufacturing process used for precision cutting and shaping of conductive materials. It involves the use of a thin, electrically charged wire electrode to erode the workpiece material through a series of controlled electrical discharges. WEDM is particularly suitable for materials that are difficult to machine using conventional methods, such as hardened steels, titanium alloys, and tungsten carbide. The WEDM process begins with the setup of the workpiece and the wire electrode. The workpiece, typically made of metal, is mounted on the machine's worktable, while the wire electrode is positioned above it. The gap between the wire electrode and the workpiece is controlled to ensure proper machining conditions. During the machining operation, a high-frequency voltage is applied between the wire electrode and the workpiece. This voltage generates a spark discharge or electrical arc, which rapidly heats and melts the workpiece material. The molten material is then flushed away by a dielectric fluid, typically deionized water, which also cools the wire electrode and prevents it from overheating.

The movement of the wire electrode is controlled by computer numerical control (CNC) to precisely shape the workpiece according to the desired design. The wire electrode is continuously fed from a spool to maintain a consistent cutting path. As the wire electrode advances, it erodes the workpiece material, creating a cut with a narrow kerf width.

The success of the WEDM process depends on several critical process parameters. These parameters include pulse on time, pulse off time, peak current, wire tension, flushing pressure, and wire feed rate. Each parameter influences specific aspects of the machining operation, such as material removal rate, surface roughness, and accuracy.

Optimizing these process parameters is essential to achieve desired machining outcomes. The objective is to maximize the material removal rate while minimizing surface roughness and maintaining dimensional accuracy. By finding the optimal combination of process parameters, manufacturers can improve productivity, reduce machining time, and enhance the quality of the machined components. The optimization of WEDM process parameters can be challenging due to their complex interactions. Response Surface Methodology (RSM) provides a statistical approach to systematically explore and optimize these parameters. By designing a series of experiments and analyzing the response variables, such as material removal rate and surface roughness, RSM enables the

development of mathematical models that describe the relationship between the process parameters and the performance measures. WEDM is a sophisticated machining process that utilizes electrical discharges to shape conductive materials with precision. By optimizing the process parameters using techniques like Response Surface Methodology, manufacturers can enhance the efficiency and quality of WEDM operations, enabling the production of intricate and high-quality components for various industries.

METHODOLOGY

Experimental Design: A systematic experimental design is employed to gather data on the machining performance and response variables. The design should consider a range of process parameters, including pulse-on time, pulse-off time, peak current, wire tension, and wire feed rate. The design can be based on techniques such as the central composite design or Box-Behnken design, which allow for the exploration of parameter settings within a defined range.

The experiments are performed based on the designed experimental matrix, and the response variables are measured and recorded. The response variables may include material removal rate (MRR), surface roughness (Ra), and any other relevant performance indicators.

Response surface methodology is applied to develop mathematical models that describe the relationship between the process parameters and the response variables. The models can be developed using regression analysis techniques, such as multiple linear regression or quadratic regression, to capture the main effects and interactions of the process parameters.

The developed models are analyzed using statistical techniques such as analysis of variance (ANOVA) to determine the significance of the process parameters and their interactions. The analysis helps identify the key process parameters that have a significant impact on the response variables.

The mathematical models are then utilized for process optimization. The desirability function approach can be employed to find the optimal combination of process parameters that simultaneously maximize MRR and minimize Ra. The desirability function assigns a desirability value to each combination of parameter settings, and the optimization algorithm seeks to maximize the overall desirability.

RESULTS AND DISCUSSION

Experimental Setup

Table 1 Machining parameters and their levels

| Symbol | Parameters | Units | Range | Levels | | |
|------------------|-------------------|-------|---------|--------|-----|-----|
| | | | | -1 | 0 | +1 |
| T _{on} | Pulse on Time | μs | 115-125 | 115 | 120 | 125 |
| T _{off} | Pulse off Time | μs | 40-60 | 40 | 50 | 60 |
| WF | Wire Feed | m/min | 5-7 | 5 | 6 | 7 |
| SV | Spark Gap Voltage | V | 70-80 | 70 | 75 | 80 |

Utilizing a Box-Behnken Design (BBD) in predicting responses allows for the advantageous exploration of intermediate levels of input parameters, thereby enabling the optimization of system performance at a micro level. To achieve optimal results, all components must be simultaneously adjusted to their highest or lowest levels within the BBD framework. This design approach avoids the need for stringent testing conditions by incorporating a center point, interlocking designs, and factorial designs of trial. The BBD experimental design requires three levels for each component, providing a balanced and efficient methodology for estimating component interactions with the desired responses. In contrast, Central Composite Designs (CCD) necessitate five levels for each parameter, thereby enabling even more precise estimation of component interactions while minimizing the number of required tests.

Table 2: Factorial Design Matrix and Results

| | | “Factor 1” | “Factor 2” | “Factor 3” | “Factor 4” | “Response 1” | “Response 2” |
|-------|-------|--------------------|---------------------|----------------|------------------------|-----------------|---------------------|
| “Std” | “Run” | “A: Pulse on Time” | “B: Pulse off Time” | “C: Wire Feed” | “D: Spark Gap Voltage” | “Cutting Speed” | “Surface Roughness” |
| | | Åµs | µs | m/min | V | m/min | Åµm |
| 24 | 1 | 120 | 60 | 6 | 80 | 0.52 | 2.29 |
| 7 | 2 | 120 | 50 | 5 | 80 | 0.56 | 2.32 |
| 11 | 3 | 115 | 50 | 6 | 80 | 0.41 | 2.49 |
| 15 | 4 | 120 | 40 | 7 | 75 | 0.86 | 3.45 |
| 22 | 5 | 120 | 60 | 6 | 70 | 0.65 | 2.39 |
| 10 | 6 | 125 | 50 | 6 | 70 | 0.81 | 3.55 |
| 25 | 7 | 120 | 50 | 6 | 75 | 0.62 | 2.25 |
| 6 | 8 | 120 | 50 | 7 | 70 | 0.71 | 2.32 |
| 21 | 9 | 120 | 40 | 6 | 70 | 0.98 | 3.62 |
| 20 | 10 | 125 | 50 | 7 | 75 | 0.78 | 2.42 |
| 2 | 11 | 125 | 40 | 6 | 75 | 0.91 | 3.38 |
| 18 | 12 | 125 | 50 | 5 | 75 | 0.72 | 2.32 |
| 4 | 13 | 125 | 60 | 6 | 75 | 0.59 | 2.15 |
| 26 | 14 | 120 | 50 | 6 | 75 | 0.65 | 2.41 |
| 3 | 15 | 115 | 60 | 6 | 75 | 0.45 | 2.19 |
| 16 | 16 | 120 | 60 | 7 | 75 | 0.55 | 2.27 |

Table 3: ANOVA analysis for Cutting Speed

| Sr. No. | Response | Suggested Model | Regression Model |
|---------|-------------------|-----------------|--|
| 1 | Surface Roughness | Quadratic Model | $SR = 4.3317 - 0.08 \times T_{on} + 0.046 - 0.2733 \times SV - 0.0011 \times T_{on} \times T_{off} - 0.0007 \times T_{on}^2 + 0.0017 \times SV^2$ |
| 2 | Cutting Speed | Quadratic Model | $CS = -127.40 + 1.58 \times T_{on} + 0.32 \times T_{off} + 1.057 \times WF + 0.624 \times SV + 0.003 \times T_{off}^2 + 0.010 \times SV^2 - 0.005 \times T_{on} \times T_{off} - 0.020 \times T_{off} \times WF - 0.020 \times T_{on} \times SV$ |

ANOVA analysis for Cutting Speed

ANOVA, or Analysis of Variance, is a statistical method used to compare means across multiple groups and determine if there are significant differences among them. It is often used in experimental designs to assess the impact of different factors on a dependent variable. In this case, we will focus on using ANOVA to analyze the effect of cutting speed on a particular outcome. Cutting speed refers to the velocity at which a cutting tool moves

relative to the workpiece in machining operations. To conduct an ANOVA analysis, we would start by collecting data on the dependent variable of interest (e.g., surface finish, tool wear, or cutting force) for different cutting speeds. The data should ideally include multiple observations for each cutting speed to account for variability. Next, we would organize the data into groups based on the different cutting speeds. The ANOVA analysis would then calculate the variation within each group (within-group sum of squares) and the variation between the groups (between-group sum of squares). The F-statistic is then calculated as the ratio of between-group sum of squares to within-group sum of squares. By comparing the calculated F-statistic to the critical value from an F-distribution table, we can determine whether the differences between the means of the groups (i.e., cutting speeds) are statistically significant. If the calculated F-statistic is greater than the critical value, we can conclude that there is a significant effect of cutting speed on the dependent variable.

Table 4: ANOVA of Cutting Speed

| “Source” | “Sum of” | “df” | “Mean” | “F-value” | “p-value” | |
|-----------------------|----------|------|------------|------------|-------------|-----------------|
| “Model | 0.54683 | 1 | 0.09113850 | 40.8359903 | 7.91853E-11 | significant |
| “A-Pulse on Time” | 0.19253 | 3 | 0.19253333 | 86.2674813 | 4.54762E-09 | |
| “B-Pulse off Time” | 0.19763 | 3 | 0.19763333 | 88.5526137 | 3.60558E-09 | |
| “D-Spark Gap Voltage” | 0.10083 | 3 | 0.10083333 | 45.1799049 | 9.34377E-07 | |
| “AB” | 0.0121 | 1 | 0.0121 | 5.42158859 | 0.029477765 | |
| “BĀ” | 0.03627 | 8 | 0.03627843 | 16.2551016 | 0.000558201 | |
| “DĀ” | 0.01246 | 7 | 0.01246666 | 5.58587915 | 0.027358139 | |
| “Residual” | 0.0491 | 22 | 0.00223181 | | | |
| “Lack of Fit” | 0.03642 | 18 | 0.00202333 | 0.63827549 | 0.774047097 | not significant |
| “Pure Error” | 0.01268 | 4 | 0.00317 | | | |
| “Cor Total” | 0.59593 | 1 | | | | |

The statistical significance of the model is supported by the high F-value of 40.84. This implies that the likelihood of obtaining such a result due to random variation is only 0.01%, indicating a strong relationship between the variables and the outcome.

Additionally, certain terms in the model have p-values less than 0.0500, which further confirms their importance. In this case, the important model terms are A, B, D, AB, B2, and D2. These terms have a significant impact on the outcome variable and should be considered when interpreting the results. Conversely, if a higher F-value (greater than 0.1000) were observed, the specific terminologies of the model would be less relevant. If the model contains numerous irrelevant terms, it is advisable to streamline the model by removing unnecessary variables, while still maintaining the necessary terms to preserve the model's hierarchy. By doing so, the model can be improved in terms of simplicity and interpretability, focusing only on the essential factors that significantly contribute to the outcome.

CONCLUSION

Wire Electrical Discharge Machining (WEDM) is a widely used manufacturing process for precision cutting and shaping of conductive materials. The optimization of process parameters in WEDM plays a crucial role in achieving improved productivity, efficiency, and surface quality. In this study, we applied Response Surface Methodology (RSM) as a statistical tool to enhance the process parameters of WEDM.

Through a series of experiments and data analysis, we successfully established mathematical models using RSM to predict the relationship between the process parameters and the performance measures, such as material removal rate (MRR) and surface roughness (SR). These models allowed us to identify the optimal combination of process parameters that maximize MRR and minimize SR.

The application of RSM in WEDM process optimization has demonstrated significant benefits. By optimizing the process parameters, we can achieve higher material removal rates, resulting in reduced machining time and improved productivity. Additionally, the optimization helps in minimizing surface roughness, leading to enhanced surface finish and reduced need for additional finishing operations.

The findings of this study highlight the effectiveness of RSM in enhancing the WEDM process parameters. Manufacturers can utilize the optimized parameter settings to improve their machining operations and achieve better quality components. This optimization approach can be applied in various industries where WEDM is employed, such as automotive, aerospace, and tool manufacturing.

It is important to note that the optimization process is specific to the material being machined and the desired outcomes. Therefore, further research and experimentation may be required for different materials and performance requirements. Additionally, other

process parameters not considered in this study, such as wire diameter and dielectric fluid properties, can also be investigated to further enhance the WEDM process.

In conclusion, the application of Response Surface Methodology in optimizing the process parameters of WEDM offers valuable insights and benefits to the manufacturing industry. By systematically analyzing the effects of process parameters on performance measures, manufacturers can achieve higher efficiency, improved surface quality, and overall enhanced productivity in the WEDM process.

REFERENCES

1. Kumar, A., & Kumar, D. (2011). A review on the state of the art in wire electric discharge machining (WEDM) process. *International Journal of Mechanical Engineering Research and Development (IJMERD)*, 1(1).
2. Özel, T., & Karpaz, Y. (2005). Predictive modeling of surface roughness and tool wear in hard turning using regression and neural networks. *International journal of machine tools and manufacture*, 45(4-5), 467-479.
3. Asiltürk, I., & Akkuş, H. (2011). Determining the effect of cutting parameters on surface roughness in hard turning using the Taguchi method. *Measurement*, 44(9), 1697-1704.
4. He, K., Gao, M., & Zhao, Z. (2019). Soft computing techniques for surface roughness prediction in hard turning: a literature review. *IEEE Access*, 1–1. doi:10.1109/access.2019.2926509
5. Asgar, M. E., & Singholi, A. K. S. (2018, August). Parameter study and optimization of WEDM process: A Review. In *Iop conference series: Materials science and engineering* (Vol. 404, No. 1, p. 012007). IOP Publishing.
6. Agrawal, A., Goel, S., Rashid, W. B., & Price, M. (2015). Prediction of surface roughness during hard turning of AISI 4340 steel (69 HRC). *Applied Soft Computing*, 30, 279-286.
7. Aslan, E., Camuşcu, N., & Birgören, B. (2007). Design optimization of cutting parameters when turning hardened AISI 4140 steel (63 HRC) with Al₂O₃+ TiCN mixed ceramic tool. *Materials & design*, 28(5), 1618-1622.
8. Balachandramurthi, A. R., Moverare, J., Dixit, N., & Pederson, R. (2018). Influence of defects and as-built surface roughness on fatigue properties of additively manufactured Alloy 718. *Materials Science and Engineering: A*, 735, 463–474. doi:10.1016/j.msea.2018.08.072

9. Beatrice, B. A., Kirubakaran, E., Thangaiah, P. R. J., & Wins, K. L. D. (2014). Surface roughness prediction using artificial neural network in hard turning of AISI H13 steel with minimal cutting fluid application. *Procedia Engineering*, 97, 205-211.
10. Gurau, L., Irlle, M. Surface Roughness Evaluation Methods for Wood Products: a Review. *Curr Forestry Rep* **3**, 119–131 (2017).
11. Muthuramalingam, T., & Mohan, B. (2015). A review on influence of electrical process parameters in EDM process. *Archives of civil and mechanical engineering*, 15(1), 87-94.