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MULTI-OBJECTIVE ELECTRIC DISCHARGE MACHINING PROCESS PARAMETERS OPTIMIZATION OF INCONEL 718 USING FULL FACTORIAL EXPERIMENTS DESIGN.

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Abstract

This study investigates the optimization of Electrical Discharge Machining (EDM) parameters for Inconel 718 using a copper electrode, focusing on improving material removal rate (MRR) and minimizing surface roughness (Ra). A full factorial design of experiments (DOE) was employed with three key input parameters: pulse on time, pulse off time, and peak current. Regression models and machine learning algorithms were applied to predict response outcomes, with statistical validation through ANOVA and multi-objective optimization using desirability functions. The optimal parameters achieved an MRR of 54.12 mm³/min and Ra of 3.38 µm. The findings demonstrate the effectiveness of the experiments' full factorial design in enhancing EDM performance, supporting its adoption for precision machining of nickel-based superalloys.

Key Words: *Inconel 718, EDM, MRR, Ra, Machine Learning predictive model, full factorial, pulse on and off, peak current*

1. Introduction

Electrical Discharge Machining (EDM) has become an essential non-conventional machining technique for hard-to-cut materials, especially in aerospace, automotive, and biomedical industries [1]. Among these materials, Inconel 718 is a known nickel-based superalloy due to its excellent mechanical strength, corrosion resistance, and thermal stability [2]. However, its superior properties also make it extremely difficult to machine using conventional techniques, often leading to excessive tool wear and poor surface integrity [3].

EDM addresses these challenges by removing material in a dielectric fluid through electrical discharges between a tool electrode and the workpiece. Despite its effectiveness, the EDM process is highly sensitive to input parameters such as pulse-on time, pulse-off time, and peak current. These factors significantly influence critical response variables like Material Removal Rate (MRR) and Surface Roughness (Ra), which in turn affect productivity and component quality [4].

Recent advances in modelling and computational optimisation have enabled the application of machine learning (ML) to manufacturing processes. ML techniques offer powerful tools for predictive modelling, pattern recognition, and multi-objective optimisation, particularly when traditional analytical methods fall short due to process complexity and nonlinear interactions [5]. This shift is especially relevant in EDM, where empirical relationships are often difficult to generalise across material and process conditions [6-10].

This study integrates a full factorial design of experiments (DOE) with regression analysis and ML-based predictive modelling to optimise EDM parameters for Inconel 718. A desirability function approach is employed to minimise Ra and maximise MRR simultaneously. The novelty of this work lies in combining conventional experimental design with modern data-driven optimisation techniques, offering a more accurate and adaptable framework for EDM parameter tuning.

2. Materials and Methods

This study was designed to optimise the Electrical Discharge Machining (EDM) process parameters specifically for Inconel 718, aiming to achieve a high material removal rate (MRR) alongside minimal surface roughness (Ra). The experimental methodology combined a full factorial design of experiments (DOE) with regression analysis and machine learning techniques to ensure robust process optimisation and accurate predictive modelling. Key process parameters, namely, pulse-on time, pulse-off time, and peak current, were systematically varied and analysed using statistical and data-driven approaches. The carefully structured methodology facilitated reliable data

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collection, ensured repeatability across experiments, and provided a sound basis for evaluating the optimal machining conditions tailored to Inconel 718.

2.1 Experimental Setup

All machining experiments were conducted using the EDMN450CNC machine, guaranteeing precise control and repeatability over the selected process variables. The workpiece used was Inconel 718, a nickel-based superalloy renowned for its strength and thermal stability but recognized for its difficult machinability with conventional methods. For the electrode, high-purity copper was chosen due to its excellent electrical conductivity and low wear characteristics, both crucial for maintaining consistent and efficient EDM performance. Deionised water served as the dielectric fluid throughout the machining, effectively removing debris from the gap and creating stable conditions for electrical discharges during the EDM process.

2.2 Design of Experiments

A full factorial design was utilised in this study, providing comprehensive insight into the effects and interactions of the process variables. Each of the three control parameters—pulse-on time (Ton), pulse-off time (Toff), and peak current (Ip)—was set at three distinct levels, resulting in a total of 27 experimental runs. Specifically, pulse-on time was varied at 100, 150, and 200 microseconds to assess its impact on machining energy and outcome. Meanwhile, pulse-off time was adjusted among 20, 40, and 80 microseconds to evaluate its influence on the cooling period and debris removal. The peak current varied at 6, 10, and 15 amperes, considering its direct effect on material removal and surface finish. MRR and Ra, the primary response parameters, were systematically measured in each run, providing a clear assessment of machining efficiency and surface quality for this challenging superalloy.

2.3 Measurement Tools

The material removal efficiency was quantified using the weight loss method, where the workpiece was weighed before and after machining, and the difference in mass over the machining time was used to calculate the MRR. For surface roughness determination, a Surface Roughness Tester model KR220 was employed, offering precise measurement of ‘Ra’ to characterize the final quality of the machined surface. These measurement approaches ensured a reliable, repeatable, and accurate assessment of machining performance throughout the study.

Table 1 Process Parameter Levels

Parameter	Level I	Level II	Level III
Pulse-on (Ton, μs)	100	150	200
Pulse-off (Toff, μs)	20	40	80
Current (Ip, A)	6	10	15

3. Results and Discussion

3.1 ANOVA and Regression Modelling

The experimental data were analyzed using ANOVA and regression modelling to identify the significance and strength of each process parameter on the two main responses: surface roughness (Ra) and material removal rate (MRR).

The effects of input variables and their interactions were quantitatively described using regression equations, developed from experimental data:

$$Ra = -0.9185 - 0.0389(Current) + 0.0265(Pulse\text{-}on) + 0.0696(Pulse\text{-}off) + 0.0019(Current*Pulse\text{-}on) - 0.0004(Current*Pulse\text{-}off) - 0.0004(Pulse\text{-}on*Pulse\text{-}off)$$

$$MRR = -18.6053 + 7.1876(Current) - 0.0156(Pulse\text{-}on) - 0.0825(Pulse\text{-}off)$$

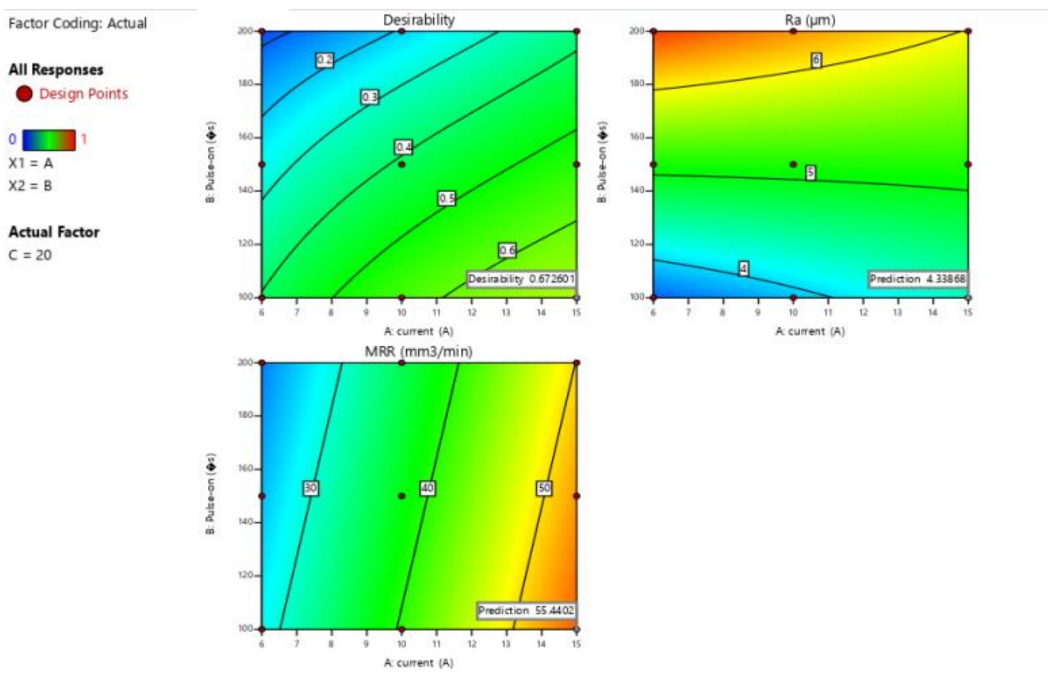

Fig. 1 Contour Graphs for Multi-Objective Optimisation Using Desirability Function

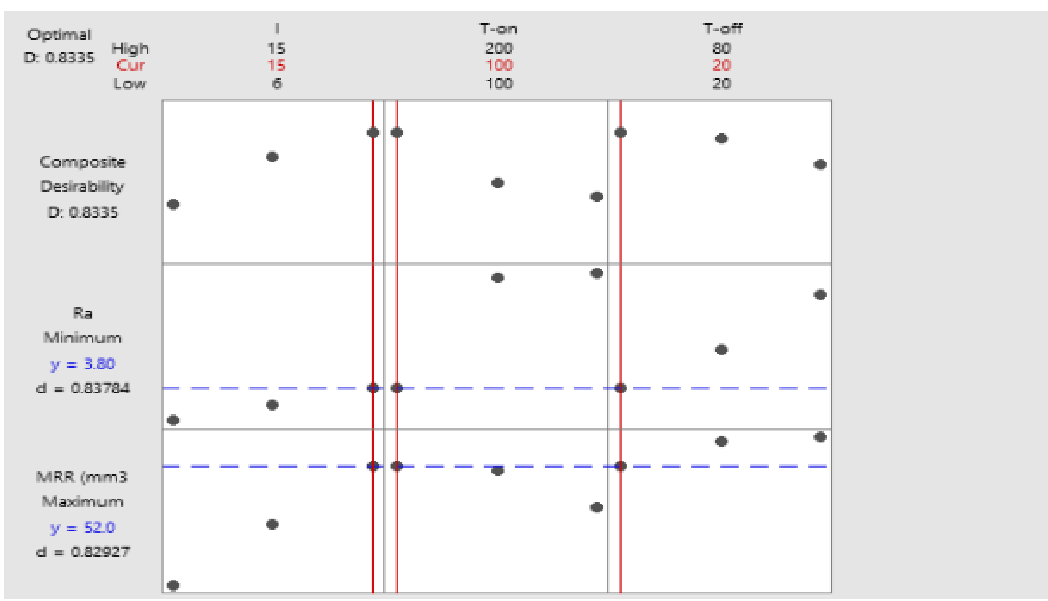

Fig. 2 Multi-Objective Optimisation via Full Factorial Design and Desirability Function

3.2 Optimization

A multi-objective optimization was conducted using the desirability function, concurrently targeting the minimization of Ra and maximization of MRR. Contour plots (Fig. 1) visually illustrate the trade-offs between these two objectives.

Comprehensive optimization through a full factorial design (Fig. 2) identified suitable parameter sets for each objective, as summarized in Table 2.

Table 2 Optimal Parameters for Ra and MRR

Parameter	Ra Optimization	MRR Optimization
Current (A)	6	15
Pulse-on (µs)	100	100
Pulse-off (µs)	40	40
Ra (µm)	3.38	4.34
MRR (mm^3/min)	29.6	54.1

4. Conclusions

This study validates the use of machine learning algorithms for optimising EDM process parameters in the machining of Inconel 718. Peak current and pulse-on time were key variables significantly affecting MRR and Ra. Multi-objective optimisation yielded ideal combinations for enhanced machining efficiency and surface quality. The methodology is practical for future innovative manufacturing systems, particularly high-performance alloys.

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