Multi-objective Optimization of Process Parameters in Electric Discharge Machining of Inconel 718 Using Machine Learning Techniques.

KEBEBEW ALEMU TUFA

A Thesis Submitted to

Department of Mechanical Engineering

School Of Mechanical, Chemical and Material Engineering

Present in Partial Fulfillment of the Requirements for Degree of Master's in Mechanical Engineering (Specialization in Manufacturing Engineering)

Office of Graduate Studies

Adama Science and Technology University

August, 2023

Adama, Ethiopia

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Declaration

I hereby declare that this Master Thesis entitled "Multi-objective Optimization of Process Parameters in Electric Discharge Machining of Inconel 718 Using Machine Learning Techniques" is my original work. It was not been submitted for the award of any academic degree, diploma, or certificate in this university and any other universities. All sources of materials that were used for this thesis have been accordinglyacknowledged through citation.

Kebebew Alemu Tufa		
Student Name	Signature	Date

Recommendation of Advisors

I, the advisor of this thesis work, hereby certify that I have read the revised version of this thesis entitled "Multi-objective Optimization of Process Parameters in Electric Discharge Machining of Inconel 718 Using Machine Learning Techniques" prepared under my guidance by Kebebew Alemu Tufa submitted in partial fulfillment of requirements for the degree of masters of science in Manufacturing Engineering.

Therefore, I recommend the submission of revised version of the thesis to the department following the applicable procedures.

Dr. G.M.SAYEED AHMED		24-08-2023
Major Advisor/supervisor	Signature	Date

Approval Sheet by Advisor

I, the advisor of the thesis entitled "Multi-objective Optimization of Process Parameters in Electric Discharge Machining of Inconel 718 Using Machine Learning Techniques" and developed by Kebebew Alemu Tufa; hereby certify that the recommendation and suggestions made by examiners are appropriately incorporated into final version of the thesis.

Dr. G.M.SAYEED AHMED		24-08-2023
Major Advisor/supervisor	Signature	Date

Approval of Board of Examiners

We, the undersigned, members of the Board of examiners of the thesis by Kebebew Alemu Tufa have read and evaluated the thesis entitled "Multi-objective Optimization of Process Parameters in Electric Discharge Machining of Inconel 718 Using Machine Learning Techniques" and examined the candidate during open defense. This is therefore to certify that the thesis is accepted for partial fulfillment of the requirement of the degree of Master of Science in Manufacturing Engineering.

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Getasew A. TADDESE (PhD)		25/08/2023
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Finally, approval and acceptance of the thesis is contingent upon submission of its final copy to the Office of Postgraduate Studies (OPGS) through the Department Graduate Council (DGC) and School Graduate Committee (SGC).

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Office of Postgraduate studies dean	Signature	Date

Abstract

Nickel-based alloys such as Inconel 718 are increasingly used in the automotive and aerospace industries due to their high strength, corrosion resistance, light weight and low wear rate. The process parameters were pulse on, pulse off, voltage and current. The response variables consisted of the material removal rate (MRR) and the surface roughness (SR) of the workpiece can be significantly improved by choosing the optimal machining parameters. The main objective of this research was to develop a model using machine learning techniques to predict the process parameter value for the optimum value of material removal rate and surface roughness, and also to develop a mathematical model based on the regression derived for the response. Regression models were created to predict how the in- process parameters affects output process parameters variables such as surface roughness, material removal rate. Regression models were performed using a full factorial design of experiments. The validity of the developed model was assessed using analysis of variance. Tests were performed on an EDMN450CNC compression EDM machine with Inconel 718 workpiece with a copper electrode used in the molding industry. The results showed that the pulse on time had a 47.76% as the most important parameter affecting the surface roughness, followed by the percentage of peak current at 26.7% and the interaction of the input parameters peak current against pulse on time and pulse on time vs pulse on time significantly affects surface roughness to roughness in ratios of 3.18% and 6.19%. Peak flow had a significant effect on material removal rate (78.13%), followed by pulses in time with 21.344%. The multi-objective optimization problem was solved using a supervised machine learning technique (Multiple Regression Predictive models) and a full factorial design of experiments with the help of a design expert software version 13. From the full factorial design of experiments, the optimal value of multiple responses of the process optimizer was Ra 3.80. µm and MRR were 52.0 mm^3/min for I, T-on and T-off 15A, 100 µs and T-off 15A, I 100 µs and T-off 20 µs, respectively. 80 µs and Ra was 3.01 µm I, T-in and T-out at 6A, 100 µs and 20 µs, respectively. Result obtained from multi-objective optimization by using desirability function Ra = 4.339µm and MRR= 55.440 mm^3/min at I, T-on and T-off was 15A, 100µs and 20µs where obtained.

Keywords: *Inconel 718, EDM, MRR, Ra, Machine Learning predictive model, full factorial, peak current, pulse-on and Pulse-off time*

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List of Acronyms and Abbreviations

ABC- Artificial Bee Colony Algorithms

ACO- Ant Colony Optimization

AI- Artificial Intelligence

EDM – Electrical Discharge Machining

ANN-Artificial Neural Network

FLA- Fuzzy Logic Algorithms

GA- Genetic Algorithms

HAS- Harmony Search Algorithms

MOD-Model

ML-Machine Learning

MRR- Material Removal Rate

OA-Orthogonal Array

OPM- Optimization Method

PSO- Particle Swarm Optimization Method

RSM- Response Surface Methodology

SA- Simulated Annealing Algorithms

SR- Surface Roughness

SST- Scatter Searching Technique

TAG- Taguchi Method

TWR- Tool Wear Rate

CHAPTER-1

1. INTRODUCTION

1.1 Background of the Study

Industrial demand for advanced materials with high hardness, temperature resistance and high strength-to-weight ratio for use in mold and die production, aerospace components, medical devices and automotive components continues. We focus on new manufacturing techniques that meet the productivity quality of the machined surface and reduce the cost of processing such materials. Electrical Discharge Machining (EDM) is an unconventional machining process typically used to produce components with complex profiles that are difficult to achieve with conventional manufacturing processes. S. Kumar et al. (2020). The process uses the thermal energy of the spark to process electrically conductive parts, regardless of the hardness of the work material. As with all other EDM processes, the selection of process variables and setting the appropriate parameter range for machining each product determines product quality and, in turn, design requirements. It is important to understand process complexity, process variables and factors affecting output parameters. Considerable research has been found on various approaches to optimize the EDM input process parameters and obtain the desired output. Material Removal Rate (MRR), Electrode Wear Rate (EWR), Wear Ratio (WR) and Surface Roughness (Ra). Input variables such as peak current, pulse on time, pulse off time, electrode material, electrode size and its bottom profile are tailored for each work-piece material and optimized to achieve the desired output, Naveen Babu et al. (2019).

In EDM, material is removed by applying a high frequency pulsating current (ON/OFF) to the work piece through an electrode. It removes very small pieces of material from the work piece in a controlled way. Both the electrode and the work piece are immersed in a liquid called a dielectric liquid. The work piece is usually the anode and the tool is cathode. The servo system maintains a thin gap of approximately 0.025 mm between the tool and the work piece. To obtain the correct shape and size of the work, a tool of suitable shape is used with the feed mechanism. The insulation used in the system is constantly recycled and filtered. No grinding or finishing is required after the EDM operation.

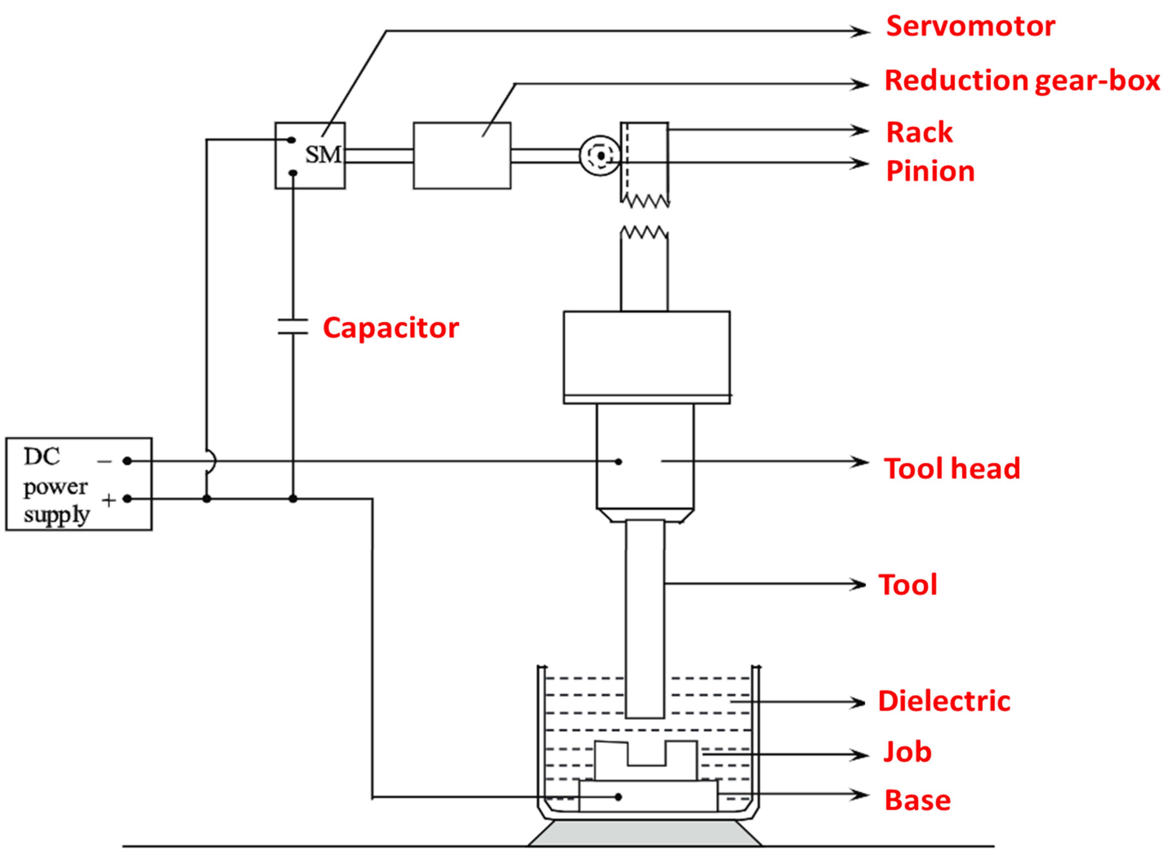


Figure 1-1 Schematic of an electric discharge machine

According to K. Palanikumar, J. Paulo Davim, Koneistus and öystökonein, (2013), there are basically three types of EDM according to the electrode used, ie. static EDM, wire cut EDM and micro EDM mill. Immersion EDM consists of an electrode and workpiece immersed in an insulating liquid. The electrode and the workpiece are connected to a power source, where the electrode is made according to the desired shape. The diameter of the wire is usually between 0.05 and 3.0 mm. The electrode is used only once and thrown away after use. The wire is controlled by a digitally controlled computer that programs the path of the wire. This form of EDM is the most accurate and can be used for rough and finish machining. A third recently developed type of EDM is the micro-EDM mill, with electrode diameters ranging from 50 µm to 10 mm. The complex electrode is replaced by moving standardized electrodes. The process is similar to traditional immersion EDM. Micro EDM complements wire EDM by offering the ability to drill pilot holes through heat treated materials and carbide. It can be used to machine cavities with nearly vertical 1.5° conical walls up to 10 mm deep, as well as very thin (andlt; 0.1 mm) ribs. This technique has an important application in micromachining.

In the manufacturing process industry, the modeling of a certain process is essential to understand the influence of influencing factors and the role of process parameters in the process responses (output), which allows the researcher to further optimize the process. Processing processes are usually complex to develop appropriate analytical models, and in the process of developing such analytical models, researchers make many assumptions that often conflict with reality. Sometimes it is difficult to adjust the parameters of the models according to the actual situation of the machining process. Due to the complexity of the processing process, process optimization and optimal control are difficult to achieve, and many analytical approaches are developed to achieve them. Each analytical approach developed so far has its strengths and weaknesses for specific problems, and neural networks are also developed and deployed in practice for specific problems. Neural networks, which can map input and output relationships and have large parallel computing capabilities, serve in the field of processing research, predict responses, understand the role of input variables and their interactive effects, and finally reach the level of system optimization process S. Kumar et al. (2020)

Along with the popularity of machine learning research and the increase in available data, the developed methods have found their way into various industries. Especially in this context, the use of data to optimize existing production lines is very important Mahesh et al. (2021). Optimization can be done in two different ways: on the one hand, improving the quality of the product itself; on the other hand, the production process can be improved. The use of machine learning is motivated by its additional features to save resources, processing time and energy and increase productivity where traditional methods such as six sigma strategies have reached their limits. In the eyes of the author, the term "machine learning" describes algorithms to identify and extract valuable patterns from data: data transformation methods (such as PCA), data discovery methods (such as k-means clustering), and traditional data methods guided regression and/or classification (eg decision trees) to newer methods (eg convolutional neural networks). They cover a wide range of algorithm complexity, origin and regency, and all share the Wang et al. acquisition and use of useful information for quality improvement. (2018).

Interest in integrating machine learning and optimization algorithms into manufacturing processes has been steadily increasing since 2009, and has been at a consistently high level since 2014. Thus, it remains a hot topic in recent research, starting with the development of scientific methods for sensors. an arrangement that traverses data storage and processing architectures and ends with machine learning and optimization algorithms Aggarwal et al. (2015). Electrical Discharge Machining Parida and Maity (2018) studied parameter optimization in Electrical Discharge Machining (EDM) and wire EDM Anurag (2017). All of them used ANN to predict quality criteria except Das et al. (2014) who applied a quadratic regression model. The process parameters were optimized with different algorithms: the added Lagrange multiplier algorithm of Gouda et al. (2021), GA, PSO and SA algorithm, leader strategy based wolf pack algorithm (LWPA) and artificial bee colony (ABC) algorithm, Wang et al. (2018). Specialized electrophoretic processes use applications such as wire EDM turning, micro-EDM Natarajan et al. (2022), i.e. optimizations of laser processing parameters using micro cleaning electrolysis, optimizations based on machine-learned predictive models were also performed. All used more or less the already mentioned combinations of ANN and NSGA-II in Weichert et al. (2019) SVM and GA and ANN and improved ant colony algorithm. Zhang et al. (2018) predicted processing time and electrode wear using a support vector machine as a regression model. In the second step, they performed multi-objective optimization using GA. The results show a Pareto optimal solution between minimum processing time and minimum electrode wear. In this study, multi-objective optimization of material removal rate and surface roughness was performed using machine learning techniques.

1.2 Problem of Statements

Nickel-based alloys such as Inconel are increasingly used in the automotive and aerospace industry due to their high strength, corrosion resistance, light weight and low wear. However, the use of nickel-based alloys is limited due to the extreme difficulty of working with conventional methods Pervaiz et al., (2014). Therefore, non-conventional methods have been used to process such nickel-based alloys. Electrical Discharge Machining (EDM) is one of the unusual methods that can machine any electrically conductive material, regardless of its hardness. There is extensive literature on micro- and macro-EDM to improve product responses through input parameter optimization Klocke et al., (2014). Because materials used in the automotive and aerospace industries must be precisely machined to meet the demanding applications.The optimum parameters in EDM vary by the expected responses in different materials based on the manufacturer priorities as well as the final product applications. Understanding the relationship between the EDM process parameters and the response variables in terms of a specific model, equation, or technique is crucial for defining the optimal values for different applications Naveen Babu et al., (2019).

These computer techniques are known as intelligent techniques, but they are complex and advanced in nature as they require computer programming knowledge. As a solution, we need a robust and efficient analytical method to solve the multi-objective optimization problem of a stochastic manufacturing process such as EDM. Due to the robust nature of machine learning, it is popular for its uncertainty tolerance; these approaches can provide solutions to such problems. The problem raised in this study based on the literature review was to determine Optimal Combination of EDM Process Parameters and Response Variables in Inconel 718 Machining with Copper Electrode Using Machine Learning Techniques. Process parameters included pulse on, pulse off, and current. The response variables consisted of the material removal rate (MRR) and the surface roughness (SR) of the workpiece can be significantly improved by choosing the optimal machining parameters.

1.3 Objective of the Study

1.3.1 General Objective

The main objective of this study was the multi-objective optimization of process parameters for EDM of Inconel 718 using machine learning techniques to predict the process parameter value for the optimal value of material removal rate and surface roughness.

1.3.2 Specific Objective

A. To investigate the experimental effect of selected process parameters (pulse on, pulse off and peak current) on MRR and SR in EDM machining of Inconel 718.

B. Develop a mathematical model to predict and analyze the optimal reaction parameter (MRR and SR) for Inconel 718 machining by EDM.

C. Developing a machine learning-based predictive model and analyzing process parameters using multi-objective optimization: Maximum Material Removal Rate (MRR) and Minimum surface roughness (SR)

1.4 Significances of the Study

This research will greatly contribute to the manufacturing industry in the machining of Inconel 718 by EDM process. A predictive model based on machine learning can lead to cost savings, time savings, better quality and less waste. At the same time, it makes it possible to design systems to control human behavior.

1.5 Scope of the research

This study was limited in scope. Levels of three parameters selected based on preliminary studies, viz. pulse on time (Ton), pulse off time (Toff) and peak current (Ip) were considered. Other process variables such as dielectric fluid wash pressure and applied voltage were kept constant in all experiments. In addition, only material removal rate and surface roughness were investigated.

1.6 Definition of Operational words

Optimization: This can be considered part of the discipline of operations research. Action research translates a real decision problem quantitatively, finds a solution in a model, and validates it in a real-world context. According to this point of view, optimization, according to the model of reality of Serafin (2000), involves a phase of finding a solution; Hillier and Lieberman (2009).

Multi-Objective Optimization: When an optimization problem involves more than one objective function, finding one or more optimal solutions is called multi-objective optimization.

Machine Learning: Is a subset of Artificial Intelligence (AI). It focuses on teaching computers to learn from data and improve with experience - rather than being specially programmed. In machine learning, algorithms are trained to find patterns and correlations in large data sets and make the best decisions and predictions based on this analysis. Machine learning applications improve with use and become more accurate the more data they have. How machine learning works. Machine learning ultimately works with algorithms. These algorithms are constantly looking for patterns, looking for information that can be understood and grouped. It uses this data and algorithms to help learn from the past and then make assumptions or predictions about the future.

Three main types of machine learning algorithms control how machine learning works. They are supervised learning, unsupervised learning and reinforcement learning. At the end of the day, these three different options produce similar results, but the journey to how they reach the end result is different.

Supervised learning in machine learning is quite practical. In it, the human provides both input and output to the machine. The machine uses algorithms to figure out how to get from point A to point B. By giving the machine an expected result, you help it find that result in the future. It uses algorithms to find relationships between point A and point B and is able to learn from its observations of both input and output variables.

Unsupervised learning

Unsupervised learning means that you simply give the machine input and let it find output based on patterns. This type of machine learning algorithm has more errors because you don't tell the program what the answer is. But unsupervised learning helps machines learn and evolve based on their observations. Unsupervised learning algorithms are less complex because human intervention is less important. Machines get information science work in unsupervised learning.

Reinforcement learning

Reinforcement learning is an algorithm that helps a program understand what it does well. Reinforcement learning, often classified as semi-supervised learning, is when you tell a machine what it is doing right so that it continues doing the same job. This semi-supervised learning helps neural networks and machine learning algorithms recognize when they have a puzzle right and encourages them to try the same pattern or sequence again. Sometimes reinforcement learning works, sometimes it doesn't. The real purpose of reinforcement learning is to help a machine or program understand the correct path so that it can repeat it later. These algorithms often use specific conventions to help identify patterns and organize data for the machine. Common practices include classification, regression, clustering, predictive analysis and decision trees. The most popular ways algorithms group data are: Classification.

Machine learning classification is the way networks segment and separate data based on rules you provide. Classification is used in supervised training of learning algorithms. They classify the data for you and separate it according to your specifications so that you can present results according to different categories. For example, classification machine learning models can help marketers discern customer demographics so you can show them personalized advertising based on their classification.

Clustering. Clustering is similar to classification in that it separates similar elements, but it is used in unsupervised training, so groups are not separated according to your needs. Clustering is often used in machine learning models when researchers are trying to find differences in data sets and learn more about them. In data analysis or data science, when a researcher is trying to figure out what makes some groups different, they might try grouping to see if the computer can show any subtle differences.

Predictive analysis

Predictive analytics is used in machine learning models to decide the future. Based on the information the network receives, it can help make predictions about what will happen in the future. Amazon is a great example of predictive analytics; Based on your past shopping experiences, Amazon shows you similar products you might like based on predictive analytics. It learns about your behavior and helps give you things that seem to interest you.

Regression

In machine learning, regression algorithms are used to plan and model the probability of a certain variable. Machines can look at different variables and predict their relationship, helping drivers understand what to expect in the future. Regression helps identify connections between data points.

Mathematical Modeling: In engineering and engineering, it provides an analytical basis for planning and management where predictions can be made with confidence without spending valuable resources of money and effort.

Pulse on: Pulse on time or pulse duration: The time during which, when the insulation breakdown voltage is reached, a spark (electron discharge) occurs between the electrode (wire) and the workpiece and causes it to ionize. As a result, the spark causes erosion of the workpiece material.

Pulse Off: Pulse Off Time or Pulse Interval: The time between successive sparks during which no current is applied to the electrodes and dielectric ionization occurs. During this time, the dielectric also flows the processing residues of the IEG (processing gap).

Material Removal Rate: Material removal rate is defined as the amount of material removed from the workpiece per unit of time. The material removal rate can be calculated from the difference in material removal volume or weight before and after treatment.

$MRR=(wb-wa)/t$

Where Wb and Wa are the weight of the workpiece before and after processing. Time, t = processing time in minutes. Surface roughness measures the fine micro-uniformity in surface texture, which consists of three components, namely roughness, waviness and shape.

1.7 Organization of the Thesis

This study, entitled "Multi-objective optimization of process parameters in electric discharge machining of Inconel 718 using machine learning techniques", was divided into five chapters. The first chapter of the thesis is an introduction, which contains an overview of the selected workpiece, the machine used and the optimization method, the thesis problem, its meaning and objectives, and finally its scope and limitations. The second chapter provides an overview of previous research related to this study and describes a summary of the literature with research gaps. The third chapter discusses the materials and methodologies used in this thesis. It contains detailed information about the workpiece and cutter, the machinery and equipment used and the testing procedure followed. The fourth chapter presents the main results and predictions of the experimental studies with a detailed discussion. This chapter examines the effect of process parameters (pulse in, pulse out, and peak flow) on surface roughness and material removal rate. The last chapter five the conclusion, recommendations and further research directions of the entire study were given.

CHAPTER TWO

2. LITERATURE REVIEW

Introduction

A literature review is a very important milestone in the research journey. It reveals what has been done in a certain area and what still needs to be done in a selected area. Therefore, it was decided to review the existing literature to avoid duplication and continue the research direction. An extensive literature review was conducted from various sources such as books, national and international journals and the Internet. In order to study the results of the input process parameters of Inconel superalloy on the machining quality of the EDM process, it is necessary to fully understand all aspects of the EDM process and the analysis tools that various researchers have already tried in this field.

Recently, research work on the optimization of processing parameters has been developed on the subjects of various processing operations to increase the quality and efficiency in the production of parts. Recently, several approaches have been developed for the process of optimizing machine parameters. Various research topics are classified in this section to provide an overview of their research achievements.

2.1 Machining of Inconel 718 by Using Electrical Discharge Machining

Early research focused on fatigue life studies. Investigated the fatigue of Inconel 718 and concluded that although the microhardness and roughness of machined surfaces increased slightly, a hard tempered layer was formed; the fatigue life of electrophoresis-produced samples was slightly less than that of machined surfaces, Primary material Chen et al. (2016). Kang and Kim (2017) studied Hastelloy-X under different EDM conditions and evaluated the surface integrity. The parameter that was varied in the study was the pulse time and the results showed that the MRR and EWR behaved non-linearly with respect to the pulse duration, while the morphological and metallurgical characteristics showed more of a continuous tremor (Talla et al., (2016)) .L9 orthogonal arrays were also used in the experiments and the results showed that a caustic made of phosphoric acid and hydrochloric acid at an appropriate temperature can significantly improve the removal of the folded layer of Inconel 718 alloy.

The microhardness test of the recast layer and the base material showed that phosphoric acid and hydrochloric acid corrosion can only damage the structure of the recast layer, and the hardness of the base material would not be damaged at all.

The Grey-Taguchi method is ideal and suitable for parametric optimization of the Wire-Cut EDM process using several performance parameters such as MRR, SR and groove width. The oxygen resistance of the alloyed sample with positive electrode polarity is better than that of the unalloyed superalloy, and the effective temperature of the alloy resistance of the alloy layer has been reached to 1100 oC. However, the oxidation resistance of the alloy layer was not improved by the electric discharge doping (EDA) process of the Al-Mo composite electrode (Li et al., 2016). The alloying effects of different EDA conditions were also determined and compared in their previous work introducing the Haynes 230 superalloy EDA process with aluminum and molybdenum. Appropriate experimental conditions can help form an aluminum-rich layer on the surface of the superalloy (Li et al., 2016). They reported that the physical properties of the powder additives play an important role in modifying the composition and morphology of the remade layer. They investigated the effect of powder suspension insulators on the folded layer of Inconel 718 EDMed surface (Klocke et al., 2014). found that the addition of graphite powder significantly improves the machining rate of 12 g/L fine graphite at the best parameter setting after the potential of graphite powder as an additive to improve the machining properties of Inconel 718 doped EDM (Kumar et al. , 2021b).). Atomic force microscope (AFM) analysis of carbon nanotube (CNT) improves surface properties such as surface morphology, surface roughness, and microcracks from micro to nanoscale (Prabhu and Vinayagam, 2016).

2.2 EDM Process Parameters

Material removal rate, electrode wear rate, taper angle, total circularity, and total expansion were investigated during machining of Inconel 825 superalloys using the input parameters input current, pulse on time, and electrode diameter. According to the results, the proposed approach significantly improved the processing in the EDD process (Natarajan et al., 2022). Input parameters of pulse on time, pulse of time, peak current, service voltage and wire speed and output parameters of surface roughness values in machining Inconel 718, artificial neural network (ANN), support vector machine (SVM) and genetic algorithm (GA) were used. SVM predictions were the most accurate of all studied models, as shown by an R value of 0.99998 with experimental results and the lowest mean absolute percentage error (MAPE) of 0.0347% (A. Kumar and Pradhan, 2022). investigated the surface roughness during processing of Inconel 718 with the input parameters ANN and GEP current, decoupling, time and voltage. The study established a model to estimate probable surface roughness using process parameters and surface roughness values and resulted in a 61.31% improvement in surface roughness (Mahesh et al., 2021).

This work deals with one optimization to minimize the surface roughness of Inconel-825 alloy in WEDM process using the teaching-learning based optimization (TLBO) algorithm. Three input process parameters (i.e. pulse on time, pulse off time and peak current) of Wire EDM were used (Singh et al., 2020). A higher value of Vm resulted in higher wire wear and poorer part quality as indicated by surface finish and flatness defects of machined parts, according to wire breakage studies performed with wire breakage input parameters pulse time, pulse off time, service voltage and wire pitch clue with adaptive neuro-fuzzy - with the inference system and#40;ANFISand#41; (Sinha and Chakradhar, 2020). During machining of Inconel 718, a model was developed to predict failures in the actual machining process using artificial neural network methodology and input parameters such as pulse on time, pulse on time, servo voltage and wire feed speed. Validation tests were then conducted to evaluate the performance of the model in real-world processing scenarios, and the model showed 95% predictive accuracy (Dewangan et al., 2020). Machine quantity (MR), tool wear rate (TWR), undercut (OC) and narrow undercut (TOC) were investigated with input parameters current (I), V, pulse time ([t.sub.on]).) and [t.sub.off] gray-Taguchi and TOPSIS processing with Inconel 718. In addition, the best parameter setting (I = 10 A, V = 30 V, [t.sub.on] = 100 [micro] s , (Weichert et al., 2019)

2.3 Effect of Process Parameters on Material Removal Rate

Electrode and three input factors such as duty cycle , pulse duration (tons) and Peak current (Ip) were predicted and optimized using the central composite for machining MRR AISI d2 tool steel for EDM process as copper material. -based experimental design (Dewangan et al., 2014). Discharge current and pulse duration were found to be important parameters affecting the rate of material removal. Tosun, Cogun and Tosun explained the optimization and experimental investigation of the EDM process parameters, viz. dielectric flow pressure, wire speed, open circuit voltage, pu (Y. Chen and Mahdivian, 2000). They found that dielectric flow rate and discharge current and their interactions played an important role in cutting operations to maximize MRR. They did this by developing a non-linear regression analysis of the relationship between control factors and MRR, which resulted in a valid mathematical model (Baskaran et al., 2014). presented the statistical design of a fauna-based study on the effect of machining parameters on material removal rate (MRR) in a cylindrical wire electrical discharge turning (cwedt) process using AISI d3 (din x210cr12) tool steel (Haddad and Tehrani). , 2008). The effect of EDM parameters such as pulse time, voltage, spindle speed and power on MRR was analyzed using analysis of variance (anova). A model was developed for MRR using response surface methodology.

Taguchi l8 oa investigated the material removal rate (MRR), surface roughness (sr), cutting width and dimensional deviation during machining of Inconel 718 and found that pulse time was the most important factor in MRR. 95% confidence level (Dabade and Karidkar, 2016). The effects of peak current, pulse exit time, and wire voltage on the material removal rate were investigated, and then the best operating parameters for good machining properties of titanium alloy (ti-6al-4v) were proposed using a complete experimental setup (Saedon) .). . et al., 2014). Using appropriate methods such as taguchi quality loss design technique and desirable gray Taguchi technique, they optimized the process parameters such as wire walking speed, on pulse, service voltage, wire voltage and off pulse time to achieve maximum MRR during production. finely divided copper gear. They analyzed that as the wire feed speed, pulse time and wire voltage increase, the loss function decreases because larger sparks are produced (Mohapatra et al., 2020).

2.4 Effect of Process Parameters on Surface Roughness

In order to achieve good surface roughness, it is necessary to adjust some factors including electrical parameters, dielectric fluid, workpiece material, etc. The researchers suggest that as the discharge energy increases, the roughness of the EDMed surfaces also increases. A higher eruption energy produces a larger crater and thus a higher surface roughness value. To achieve the desired surface roughness, 1040 steel with a thickness of 30, 60 and 80 mm and 2379 and 2738 steel with a thickness of 30 and 60 mm were processed (Gökler and Ozanözgü, 2000). In the developed mathematical models, it was observed that the surface roughness increased as the peak current increased and decreased as the wire voltage and duty factor increased. Inconel 601 material (Hewidy et al., 2005b). Using ANOVA techniques, it was found that the wire EDM process pulse time and peak current and wire voltage and peak current and pulse duration had a significant effect on the surface roughness of the newly developed DC 53. steel (Kanlayasiri and Boonmung, 2007).

Developed artificial neural network (ANN) models and multi-response optimization technique to predict and select the best process parameters for EDM process using Inconel 718 material for experiments and 0.25 mm diameter brass wire as tool electrode. They used the Taguchi L9 OA experimental method to conduct experiments with various process parameters such as delay, switching current, on pulse and wire step speed. They found a pulse of 0.25 mm to be temporally optimal (Ramakrishnan and Karunamoorthy, 2005c). Multi-response optimization of material removal rate and surface roughness with controlled process parameters such as duty cycle, gap voltage, wire feed speed and slot flow was presented with a proposed experimental design as a Taguchi L9 orthogonal matrix (Mohanty et al., 2018).

Experiments were performed with six process parameters: dielectric flow rate, wire voltage, wire speed, pulse frequency, pulse duration, and discharge current varied at three levels. Information related to process responses, e.g. MRR, SF and spacing were calculated for each experiment (Datta and Mahapatra, 2010). The surface roughness characteristics investigated during rough cutting were optimized in EDM using the Taguchi method combined with gray correlation analysis. Process parameters (peak current, wire voltage, pulse on, pulse off, and wire speed) were investigated using a mixed L18 orthogonal array (Jangra et al., 2012). They also concluded that spark gap voltage and wire voltage were important parameters to achieve better surface finish. This was due to an increase in the tension of the wire, which reduces its vibration and improves the surface quality of Titanium Ti-6Al-4V (Aliaset al., 2012b). ANOVA was used to determine the significance of machining parameters on surface roughness (SR) performance characteristics while investigating the behavior of three control parameters during machining of titanium alloy (Ti6Al4V). They found that peak current was the most influential factor on surface roughness, followed by temporal pulse (Prasad et al., 2014). They used the Taguchi technique to experimentally determine the effect of four input parameters on the surface roughness of EN 19 and AISI 420 (SS420) steels during the EDM process. They found that the pulse parameter had the greatest effect on the surface roughness of both materials (Reddy et al., 2015). (Rajyalakshmi and Ramaiah, 2013) The effect of electromagnetic wire processing parameters on the surface properties of Inconel 825 such as surface roughness was investigated and an excellent linear multiple regression model was developed that integrates process parameters, processing efficiency and shows suitability. proposed model for predicting surface roughness. Pulse timing was the most important parameter among others affects the surface quality.

2.6 Mathematical Modeling of EDM Process Parameters

2.6.1 Regression Analysis

Regression analysis includes any technique for modeling and analyzing multiple variables the focus is on the relationship between the dependent variable and one or more independent variables. Specifically, regression analysis helps us understand how a typical value the dependent variable changes when one of the independent variables is changed, whereas other independent variables are held fixed. Mostly regression analysis estimates independent variable conditional expectation with independent variables. In all cases the objective of assessment is a function of the independent variables called a regression function.

Regression analysis is an empirical modeling method to determine the relationship between different process parameters and responses with different searches and desired criteria of the importance of these process parameters in the related responses. It is consecutive experimental strategy for empirical model optimization and construction. Purpose The purpose of regression analysis is to develop a mathematical relationship between responses and processing parameters. In many experimental situations, it is possible to represent independent factors quantitative form. Then these factors can be considered as a functional relationship Yu = f (X1, X2, X3, .Xk) ± er, Between the responses Yu and k there is an independent quantitative factor X1, X2, X3, .Xk as shown in fig. equation 1. The function is called a response surface or response function. Experimental the error is measured by the residual error er. A characteristic surface corresponds to a certain set of independent variables. If the mathematical form is unknown, it can be approximated satisfactorily in the test range using a polynomial.

The higher the grade polynomial, the better the correlation. The method can be applied to development mathematical models in the form of multiple regression equations that correlate the dependent parameters such as metal removal rate, tool wear rate, surface roughness, etc., more than two independent parameters, independent parameters in the electric discharge processing are peak current, pulse on time, pulse off time and tool lift time. When applying regression in the analysis, the dependent parameter is seen as a fitted mathematical model.

2.6.2 Formulation of Mathematical model

Regression analysis combines mathematical and statistical techniques with an empirical model a building a response model for certain independent input variables can be obtained using conducting experiments and applying regression analysis. Mathematical models in general used represents,

$$Y = \Phi\ (Ip,\ T\text{-}on,\ T\text{-}off) \pm er$$

Where Y is the processing response, Φ is the response function, and I, T-on, and T-off are machining of independent variables and er is an error. General quadratic polynomial mostly the response equation is used. It also confirms that this model offers excellent results examining the relationship between independent factors and responses. Secondly the ordinal response surface representing MRR, TWR, and SR can be expressed as a function processing parameters Ip, T-on and T-off.

2. 7 Machine Learning Paradigm in Machining Application

In recent decades, ML has attracted great attention among academic researchers and industrial engineers in many research fields. To assess practical applications in industrial machining, this review divides six macro-categories of problems addressed by ML: vibration, roughness, quality, modeling, machine condition monitoring, and tool condition monitoring.

2.7.1 Chatter

A traditional structured approach is the application of a Stability Lobe Diagram (SLD), which defines process parameters to prevent unwanted vibrations. SLD is used to label data; however, the system is learned from analytical models and therefore requires effective initial modeling. Process parameters were used to train and compare several models: ANN, Support

Vector Machine (SVM) and a new approach based on kernel interpolation (KI) to predict SLD. All models achieved more than 88 percent accuracy. In particular, the KI model achieved the highest accuracy (94%). A new method based on deep neural networks and transfer learning has been proposed, as DNN models are pre-trained with simulated data obtained from analytical stability models (İnaç et al., 2022). In the study, the accuracy of the test set was 83.6% using spindle speed, depth of cut and tool holding length and entry and exit angle as inputs. The final results showed that EEMD outperformed wavelet packet transform (WPT) in extracting transfer learning features. They introduced topological data analysis - specifically, Carlsson coordinates and model functions - which achieved high accuracy with several algorithms; the most accurate were SVM and Gradient Boosting. In addition to accelerometers, audio sensors are sometimes considered for speech recognition, such as when binary classification has been obtained using SVM, short-time Fourier transforms (STFT), and automatic measurement devices.

2.7.2 Roughness

The classification models allow the range of regression values to be discretized, as shown when the roughness between 0 and 300 nm was discretized into 150 clusters of 2 nm each. Despite limiting the actual maximum accuracy in the final raw value, the discretization allowed increased classification accuracy and predictability (Wright et al., 2015). The classification method can provide a similar regression prediction with a large number of classes, but other applications require high accuracy in their predictions, so the laser micrometer measured vibration signals were implemented in t-Distributed stochastic neighbor embedding (t-SNE). Yu et al used the vibration signal and process parameters with a DL method—namely, a knowledge-based deep belief network (KBDBN)—to classify the roughness value into three levels with a detection rate of 97.67%. In contrast, other studies based on tree algorithms used a model to classify roughness into four levels. adopted Deep Forest, a DL method based on WPT and Fast Fourier Transform (FFT) of force and load signals to predict the roughness class, and achieved a test accuracy of 90.91%. used binomial modeling (BP-ANN) to predict cutting force and final roughness. used ANOVA as a feature selection method to predict wire electrical discharge machining (WEDM) roughness. [63] proposed a roughness prediction model based on discrete wavelet transform (DWT) and RMS peak value of acoustic emission with an accuracy of more than 97% for grinding parameters. investigated acoustic emission, force and current measurements using PCA feature reduction to obtain correct tool change time based on roughness prediction using ANN with a mean absolute percentage error (MAPE) of 4.2%.

2.7.3 Quality

Several ML applications have been presented in the literature to improve overall machine tool (MT) efficiency and quality. presented the application of ANN (Multi-Layer Perceptron-MLP) to model MT thermomechanical deformations of Carbon Fiber Reinforced Polymer (CFRP) structures based on global temperature changes, the temperature gradient between the front and back of the ram. used DL applications to model thermal deformation using RST-based data mining and reduced thermal error by ~99%. focused on thermal displacement prediction, applying DNN with Bayesian Dropout, and considering sensor failures to test model reliability. In reference, the aim of the study was to predict thermal flow based on four different operating conditions; the authors used prepared coefficients to initialize the CNN, resulting in the so-called CNN-FT (fine tuning). used a CNN approach and a domain adaptation module to predict the thermal error, achieving a model accuracy of more than 94.87% and an MSE of less than 6.1 × 10-6. The CNN scheme is also applied to detect workpiece surface defects using laser beam scattering data as input and simulated training data to reduce the required time. The evaluation of the quality error of the machined part has been evaluated in several studies with analyzes performed using tree-based algorithms. applied RF Ensemble with Synthetic Minority Oversampling Technique (SMOTE) to predict flat deviation based on tool life, average working force and flank wear with test accuracy of 86.44%. RF was also applied to diameter, roundness and other quality parameters using torque values and statistical time domain characteristics of speed or axial force and torque along with process parameters. investigated acoustic emission, force and current measurements using PCA feature reduction to obtain correct tool change time based on roughness prediction using ANN with a mean absolute percentage error (MAPE) of 4.2%.

2.7.4 Modeling

Interesting applications are related to the prediction of the process forces acting on the workpiece and the calculation of coefficients to define the stability of the machining.

developed an ANN model for modeling the cutting force in end grinding. The authors examined the process parameters and rotation angle to generate the data needed to train the ML model, obtaining an RSME of 1.0058 and an R2 of 99.98%. The network structure was realized with ResNet configuration, taking responsive lighting and process data as input, so that the two-way LSTM model could predict partial deformation with 10.61% error [29]. Predicting dynamic heat generation to monitor robotic belt sanding. presented a Bayesian Adaptive Direct Research-Least Squares Support Vector Machine (BADS-LSSVM) with an RBF kernel, considering audio signal and process forces (e.g., normal and tangential). In this case, force characteristics were obtained using the motion smoothing filter method and dynamic friction coefficient extraction. SVM can also be used to model and control the trajectory and several MT parameters such as tool speed, roughness (with 90% accuracy) and part properties such as diameter prediction (with 97% accuracy) as shown.

2.8 Research Gap

In order to understand the relationships between various process parameters and performance characteristics, the EDM process has been studied by several researchers with different fields and machine configurations. Choosing the combination/levels of EDM process parameters is a difficult task due to the complexity of the EDM process. To solve this problem, a multi-objective optimization of the EDM process was performed, generally considering a higher MRR with a low SR. For this purpose, many researchers have proposed various statistical multi-objective optimization techniques. Some have optimized the abrasive mixed EDM process using OA and gray relationship analysis (GRA). They added silicon powder (2 g/L) to the dielectric fluid to study the effect of the powder on the MRR and SR. They concluded that using an optimization technique improves performance. Similarly, others have implemented a principal component analysis (PCA)-based utility for multi-response optimization of the EDM process. This approach considers the relationships between responses. They concluded that a PCA-based tool leads to better optimization. An experimental study on mild steel using the reverse EDM process was also presented. Response surface methodology was used to design the experiments, resulting in a Pareto optimal solution for Inconel 718 EDM. They modeled the EDM process with an ANN and then used a supervised elitist non-dominated sorting genetic algorithm to find the optimal solution parameter. These computer techniques are known as intelligent techniques, but they are complex and advanced in nature as they require computer programming knowledge. As a solution, we need a robust and efficient analytical method to solve the multi-objective optimization problem of a stochastic manufacturing process such as EDM. Due to the robust nature of machine learning, it is popular for its uncertainty tolerance; these approaches can provide solutions to such problems.

CHAPTER THREE

3. Materials and Methodology

3.1 Introduction

A study was conducted to optimize the EDM process parameters to obtain the best values for surface roughness and higher material removal rates when drilling an Inconel 718 conformal hole with a copper electrode. This chapter presents the details of the experimental methods and the properties of the material used in the study.

3.2 Experimental Procedure

In this research, an experimental study was conducted according to the research plan that was prepared using a full factorial design of experiments. The general procedure of the experimental study is shown in Figure 3.1. The input process parameters are the workpiece material, the processing parameters defined in the specific machine tool and the cutter, which are placed and fixed in the corresponding tool holder.

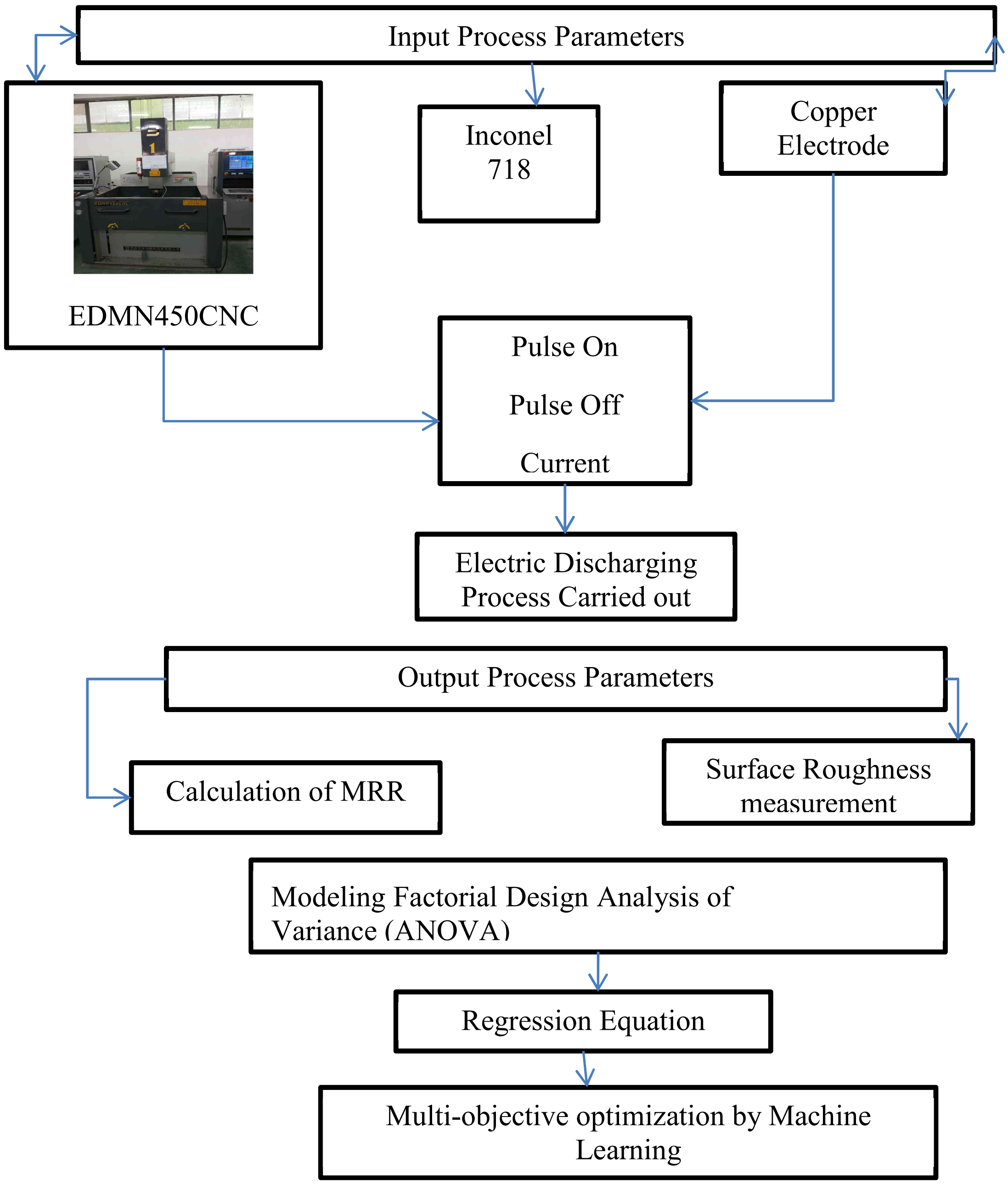


Figure 3-1 Schematic diagrams of experimental procedure

3.3 Machine and Equipment Used

This subtopic describes the materials and machine tools used in an experimental study of drilling a 6 mm and 10 mm diameter whole with a copper cutter and Inconel 718 us workpiece on an EDMN450CNC machine.

3.3.1 Work Piece Material

Inconel 718 was used as the raw material in this study because it has many applications in the aerospace, oil and gas, and cryogenic industries. The material is known to retain its excellent mechanical properties at high temperatures. The nickel-based superalloy has excellent fatigue and sliding properties at high temperatures. However, superalloys such as Inconel are considered difficult to cut due to low thermal conductivity, excessive heat in the machining zone, work hardening, chemical affinity of the tool material at high temperatures, and edge formation. These interactions result in excessive tool wear and surface damage (Parida and Maity, 2018). EDM, a non-contact material removal process, involves almost zero cutting force and residual stress. Thus, the process is an ideal alternative to machined superalloys. Also, industrial requirements for machining very complex Inconel profiles such as spruce grooves, spruce grain roots, etc. favors plunge EDM because of its flexibility and ability to trace complex shapes. The process has been proven to meet the strict geometric and dimensional tolerances of the gas turbine industry (Klocke et al., 2012; Klocke et al., 2014; Anurag, 2018). The chemical and mechanical properties of the material are given in tables 3.1 and 3.2

Table 3-1 Chemical composition of Inconel 718

Alloying element	Ni	Cr	Mo	Fe	Al	Nb(+Ta)
Weight by mass %	42-46	19.5-22.5	2.5-3.5	22	0.1-0.5	0.08-0.5
Alloying element	Cu	Mn	Si	Ti	C	-
Weight by mass %	1.5-3	1	0.5	1.9-2.4	0.025	-

Table 3-2 Mechanical and Physical properties of Inconel 718

Ultimate Tensile Strength (N/mm^2)	965
Hardness	38 HRC
Modulus of Elasticity (N/mm^2)	199
Electrical Resistivity (Ω.m)	1.17
Density (Kg/m^3)	8080
Specific Heat (J/g.^{0}K)	435
Thermal Conductivity at 100°C(W/m. ^{0}K)	12
Melting Range(^{0}C)	1311-1366
Electrical conductivity(mΩ/mm^2)	0.25

Figure 3-2 Spectrometry used to identify Chemical Composition

3.3.2 Cutting Tool Material

In EDM, the selection of the right electrode materials is an important factor to ensure machining quality and improve productivity. Therefore, a researcher should consider the following properties of electrode materials to make the right choice: Copper electrode was chosen for this study because it is the most suitable electrode in electrical discharge machining (EDM).

Figure 3-3 Copper electrode

3.3.3 Machine Used (EDMN450CNC)

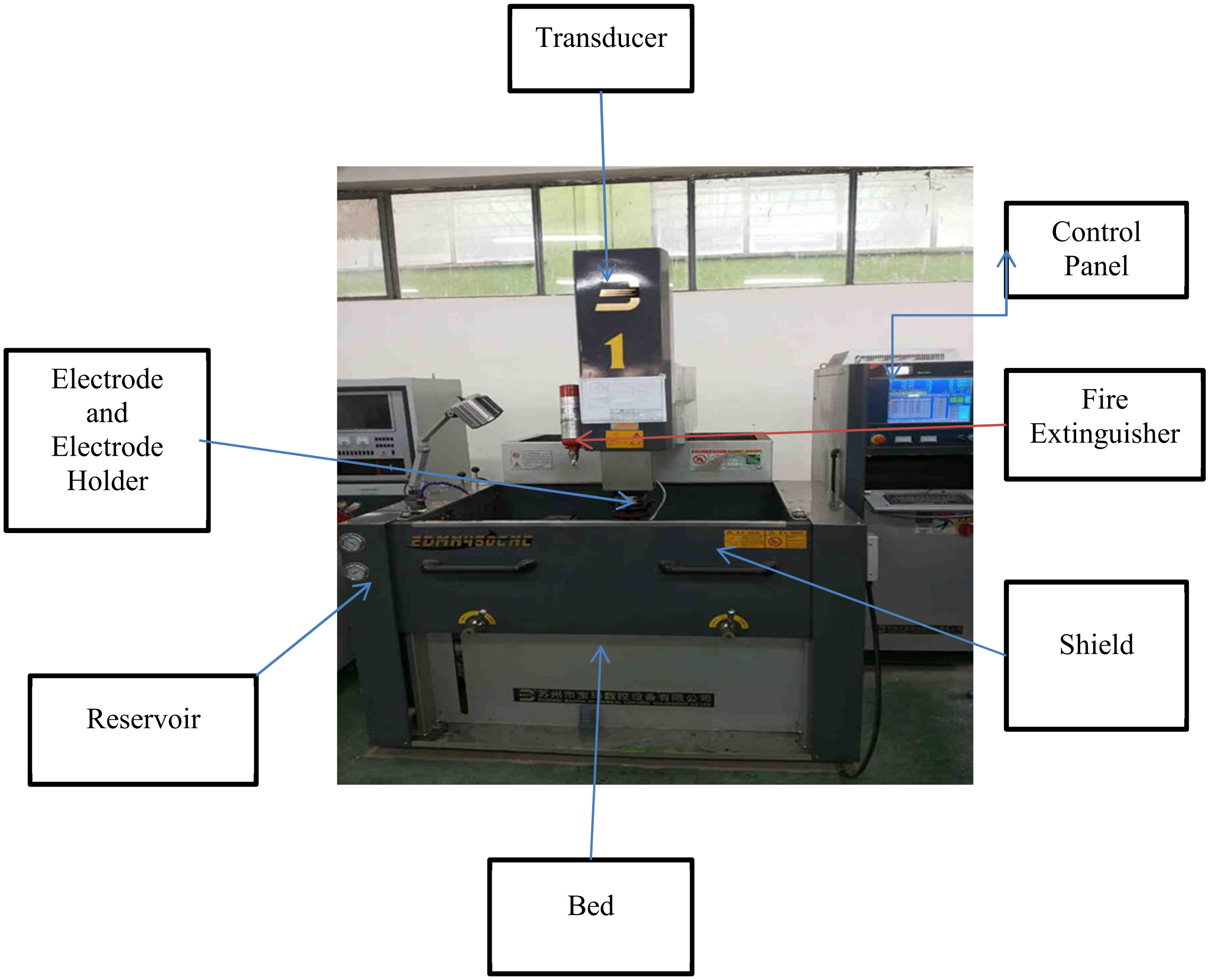


Figure 3-4 EDMN450CNC

3.3.4 Dielectric Fluid Selection

In electrical discharge processing, material removal occurs primarily as a result of thermal vaporization and melting. Heat treatment must be carried out without oxygen, as this leads to a poor surface. Therefore, a dielectric fluid must be used to create an oxygen-free working environment. The main requirements of EDM dielectric fluid are sufficient viscosity, high flammability, minimal odor, good oxidation resistance, good electrical discharge efficiency and low cost. The chosen dielectric fluid is deionized water with a conductivity of ~ 20 µS/cm.

3.4 Measurement of Performance Characteristics

3.4.1 Material Removal Rate

The material removal rate is defined as the amount of material removed from the workpiece per unit of time. The material removal rate can be calculated from the difference in material removal volume or weight before and after processing. The material removal rate is defined as the amount of material removed from the workpiece per unit of time. The material removal rate can be calculated from the difference in material removal volume or weight before and after processing. MRR=(wb-wa)/t where Wb and Wa are the weight of the workpiece before and after processing. Time, t = processing time in minutes. Surface roughness measures the fine micro uniformity in surface texture, which consists of three components, namely roughness, waviness, and shape. MRR=(wb-wa)/t Where Wb and Wa are the weight of the workpiece before and after processing, respectively. Time, t = processing time in minutes.

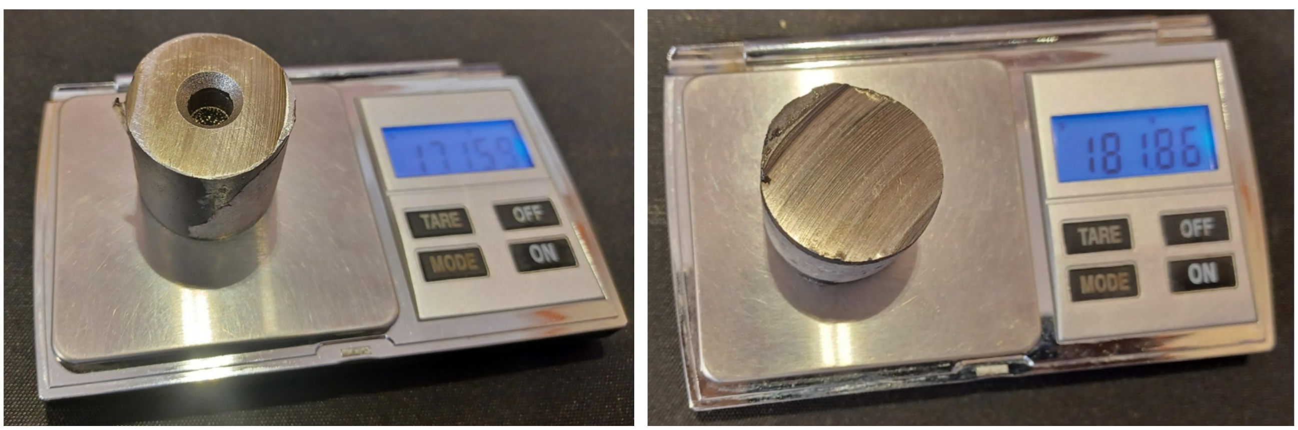


Figure 3-5 weight balance

3.4.2 Surface Roughness

The researcher chose surface roughness test KR220 (found by Ethiopian Conformity Assessment Enterprise) to measure the surface roughness. The Surface Roughness Tester KR220 (14 parameters of roughness) works together with the control platform KA 620 (rotating, different measuring angles available) with LCD touch screen display and built-in printer. KR220 surface roughness tester uses electromechanical integration, small volume, light weight, easy to use; Using DSP chip for control and data processing, high speed, low consumption; 128 x 64 OLED dot matrix display, digital / graphic display; emphasize the lack of perspective; Intuitive and rich display information, can display all parameters and graphics; Conforms to national standards ISO, DIN, ANSI, JIS; A balance icon prompting the user to load; Continuous working time: more than 20 hours. Display of measurement information, menu information, incorrect information and machine change and other advice about this information; Can be connected to computer and printer.

Figure 3-6 Surface Roughness Tester KR220

3.5 Selection of Process Parameter

In the EDM process, an important task is to select the process parameters to achieve high material removal. For experimental purposes, the process parameters for this Inconel 718 were selected based on information found in the literature, tool manufacturers' recommendations, the test material manufacturer's instruction manual, current industry practice and experience. The following table shows the process parameters and material hardness used by different researchers.

Table 3-3 Process parameters selected by various researchers

Researchers	Material	Tool	Process parameters		
			Pulse- on (µs)	Pulse-off (µs)	Current (A)
Natarajan et al. (2022).	Inconel 825 super alloys	Brass	80 150 220	40 60 80	5 8 12
A. Kumar & Pradhan, (2022).	Inconel 718	Copper	100 150 200	20 30 50	15 18 22
Sinha & Chakradhar, (2020).	Inconel 718	Copper	80 95 115	10 15 20	6 10 15
Dewangan et al., (2020	Inconel 600	Copper	100 120 150	35 45 55	15 20 25
Weichert et al., (2019)	Inconel 625	Wire	100 200 300	30 50 60	8 10 15
Klocke et al., (2014).	Inconel 718	Copper	30 50 90	15 20 25	20 30 35
Ramakrishnan & Karunamoorthy, (2005).	Incoloy 800	Brass	50 100 150	40 50 80	20 30 40
Chen et al. (2016).	Inconel 718	Wire	150 250 350	40 60 80	8 9 10

Considering all above-mentioned factors, the following cutting parameters were employed for an experiment. The selected cutting parameters were shown in Table 3.4.

Table 3-4 Levels of parameters and their range used for an experiment

Variables	Levels		
	Level I	Level II	Level III
Pulse-on (μs)	100	150	200
Pulse- off (μs)	20	40	80
Current (A)	6	10	15

3.6 Research Methodology

Designed experiments in a general and complete DOE design are powerful statistical tools for process understanding and outcome optimization. In fully factorial DOE, the researcher identifies the appropriate output that the researcher wants to improve and the factors or variables that are likely to affect the output. Once the researcher has identified the factors, determine the levels or settings the researcher wants to study and the number of combinations of individual factors and levels. After the experiment is over, the researcher uses statistical software to analyze the results. From there, the researcher could statistically determine main effects of factors, interactions between factors, and optimal levels or settings. A full factorial design of experiments was used to construct the design matrix and regression models. The steps involved in FFDE techniques are as follows: Design a series of experiments to adequately and reliably measure the true mean response of interest. Statistical approach ie. Regression modeling was developed for the results obtained after the experimental studies. After obtaining the regression equations, transformation and reduction were performed to obtain models with a high coefficient of determination to predict the measured responses (process parameters obtained), material removal rate (MRR) and surface roughness (Ra). Analysis of variance (ANOVA) was performed, as well as diagnostic and regression model fit checks.

3.6.1 Design of the Experiments

In this study, the researcher chooses full factorial design of experiments over other experimental design methods because: we can determine main effects, we can determine the effect of interactions on the response variable with independent optimal settings. Variables can be set for evaluation. This design consists of three factors, each on three levels. So the number of runs is 33 = 27 attempts were made. This means that k factors are considered, each at three levels. These are (usually) called low, medium and high levels. The reason for proposing three-level models is to model the possible curvature of the response function and to handle the case of nominal factors on three levels. The third level of the continuous factor facilitates an examination of the quadratic relationship between the response and each factor. The model for such experiments is Yijk=μ Ai Bj ABij Ck ACik BCjk ABCijk ϵijk Note that if there is no replication, the fit is exact and there is no error term (epsilon term) in the model.

Table 3-5 Design variables of the experiment

Control parameters	**Response Parameters**	**Constant Parameters**
Pulse Current(I)	Material Removal Rate (MRR)	Capacities
Pulse-On Time(T_{on})	Surface Roughness (SR)	Polarities
Pulse-Off Time (T_{off})		Electrode materials

Table 3-6 Experimental Design Matrix

	Factor 1	Factor 2	Factor 3
Run	A:current	B:Pulse-on	C:Pulse- off
	A	μs	μs
1	6	100	20
2	6	100	40
3	6	100	80
4	6	150	20
5	6	150	40
6	6	150	80
7	6	200	20
8	6	200	40

9	6	200	80
10	10	100	20
11	10	100	40
12	10	100	80
13	10	150	20
14	10	150	40
15	10	150	80
16	10	200	20
17	10	200	40
18	10	200	80
19	15	100	20
20	15	100	40
21	15	100	80
22	15	150	20
23	15	150	40
24	15	150	80
25	15	200	20
26	15	200	40
27	15	200	80

3.6.2 Analysis of Variance (ANOVA)

The purpose of the analysis of variance (ANOVA) was to find out which parameters significantly influence the quality characteristic. ANOVA is a statistical method used to find out the effect of all control parameters. Analysis of variance used the percentage of each control factor to measure the respective effects on performance characteristics. This analysis considered a 5% significance level, ie 95% confidence level. ANOVA results indicate whether or not differences in outcome measures are statistically significant. ANOVA analysis is included when p-values below 0.05 are significant and above 0.05 are not significant. The percentage measures the percentage of each model member of the total sum of squares. A percentage is often a rough but effective guide to the relative importance of each model term. The percentage of each influencing parameter was calculated based on analysis of variance.

Each term used in the ANOVA table has been explained here Block: The block row shows how many response variations are assigned to the blocks. The block variation is removed from the analysis. Blocks are not tested (no F- or p-value) because they are considered an reproducible and difficult to modify factor. Model: The model line shows how much variation in the response is explained by the model, along with the overall model significance test. Terms: The model is divided into individual terms and tested independently. Residual: The residual row shows how much variation in the response is still unexplained. Cor Total: This row shows the amount of variation around the mean of the observations.

Sum of Squares: the sum of the squared differences between the overall mean and the amount of variation explained by its line source. df: degrees of freedom: the number of estimated parameters used to calculate the original sum of squares. Root Mean Square: Sum of squares divided by degrees of freedom also called dispersion.

F-value: A test to compare the baseline mean square with the residual mean square. Probability > F: (p-value) The probability of seeing an observed F-value if the null hypothesis is true (no factor effects). Small probability values require rejection of the null hypothesis. The probability is equal to the integral under the curve of the F-distribution beyond the observed F-value. ie, if the Prob>F value is very small (by default below 0.05), the source tested significant results. Significant model terms are likely to affect the answer. A significant lack of fit indicates that the model does not fit the observed replication data. Mean: sum of squares for average effect. The "df" column gives the degrees of freedom for each source. In response surface methodology, the total number of degrees of freedom is equal to the number of model coefficients added row by row. Mixture model: Let q be the number of components in the mixture. The degrees of freedom for the linear terms in the mixed model are (q-1), not q, because the sums of squares are mean-corrected.

CHAPTER FOUR

4. Result and Discussion

4.1 Introduction

The effects of EDM process parameters (pulse on, pulse off and peak current) on surface roughness and material removal rate were experimentally evaluated using copper as the cutter. The experiment was performed on an electric discharge machine EDMN450CNC using a copper electrode as a cutter. 27 experiments were conducted to determine the optimal condition. During and after processing, measurements were made for each final response, statistical analysis was performed to obtain optimal parameters as needed, and main effects were identified. The values of these responses, which were made in a full factorial design of experiments, were analyzed by ANOVA. Statistical work was performed using Design Expert version 13. General (multiple optimizations) were performed using Minitab 21's machine learning based predictive model. The results of each experiment were discussed in this chapter. To minimize errors, the experiment was conducted in a controlled environment. An experimental design was used to identify the optimal cutting parameters and the most influential parameters. Data analysis and regression model developed in analysis of variance were performed with Design Expert version 13, and multi-objective optimization was performed using Design Expert and Minitab software. This section introduced the details of the result used in the study and the discussion. In addition, predictive and optimization models are discussed with supporting photos and diagrams.

4.1.1 Result Values Obtained from Electrical Discharging Experiment

Data collection plays an important role in statistical analysis in any field, because it determines the progress of the analysis in the best or worst direction. Correct and targeted data collection yields better results than analysis. With such a focus, it is very important to choose an appropriate data collection technique for analysis. In this work, Electric Discharge of Inconel 718 process was chosen to process the electrical discharge to continue the full factorial design of the experiments. The resulting values for each test when drilling Inconel 718 with a copper electrode are shown in Table 4-1.

Table 4-1 Experimental Results

No	I	T-on	T-off	Power	vhp	sv	% co	single gap	MRR (mm^3/min)	Ra
1	6	100	20	7	1	60	5.5	0.09	23	3.20
2	6	100	40	6	1	60	4	0.095	26	3.50
3	6	100	80	4	1	60	1	0.12	30	4.50
4	6	150	20	2	1	60	0.8	0.26	27	5.50
5	6	150	40	4	1	60	0.5	0.16	18	5.50
6	6	150	80	4	1	60	0.6	0.17	22	5.70
7	6	200	20	4	1	60	0.63	0.19	32	5.20
8	6	200	40	4	1	60	2	0.18	22	6.00
9	6	200	80	4	1	60	0.8	0.185	18	5.85
10	10	100	20	10	1	60	10	0.11	38	3.50
11	10	100	40	9	1	60	6	0.13	42	4.20
12	10	100	80	9	1	60	4.5	0.14	45	4.60
13	10	150	20	6	1	60	1.5	0.19	40	6.30
14	10	150	40	6	1	60	1	0.21	37	6.50
15	10	150	80	6	1	60	0.9	0.22	35	6.30
16	10	200	20	6	1	60	0.9	0.23	37	6.80
17	10	200	40	6	1	60	3.5	0.23	35	6.90
18	10	200	80	6	1	60	0.5	0.24	32	6.80
19	15	100	20	13	1	60	12	0.12	51.5	4.2
20	15	100	40	12	1	60	8	0.13	58	4.50
21	15	100	80	10	1	60	1	0.2	59	5.50
22	15	150	20	10	1	60	1	0.2	51	5.80
23	15	150	40	10	1	60	1	0.2	58	5.70
24	15	150	80	6	1	60	0.9	0.22	35	5.00

25	15	200	20	10	1	60	0.7	0.26	42	5.89
26	15	200	40	10	1	60	0.5	0.23	57	4.85
27	15	200	80	10	1	60	0.5	0.22	50	4.74

4.2 Surface roughness analysis and discussion

4.2.1 Statistical Analysis

4.2.1.1 Fit Summary

Fit Summary is a software tool that helped run the regression calculation to fit all polynomial models to the selected response. The program calculated the effects of all model terms and produced statistics such as p-values, predicted and adjusted R-squared values to compare the models. This tool collected important statistical information that was used to fit the final model and select the correct starting point for the proposed model. Design-Expert uses Fit Summary tables to calculate the Whitcomb score (a heuristic scoring system) to select a default model.

The Whitcomb score consists of two

Parts: Score1 = M × L × Pred R-squared

• score 2 = M × W × Modified R-squared Where: M is the sum of squares of the sequential model: • M = 1 if the p-value is less than or equal to 0.05 • M = 0.05/p-value if p-value is greater than 0.05 • M = 0 if the model has an alias L is the lack of fit (LOF) score: • L = 1 if the LOF p-value is greater than or equal to 0.10 • L = p-value/0.10 if the LOF p-value is less than 0.1

Table 4-2 Whitcomb Score

Model type	M	L	Pred R^2	Adj R^2	Score 1 M*L*Pre R	Score 2 L*M* Adj R^2	Rank
Linear	1	0.01	0.9644	0.9739	0.0009644	0.0009739	
2FI	1	0.164	0.9264	0.9717	0.1519	0.1593	Selected
Quadratic	1	0.1587	0.8734	0.9688	0.1386	0.1537	
Cubic	0	-		0.9982	0	0	Aliased

For Cubic Model both score value 1 and score value 2 were 0 because M value was 0 for aliased case. From table 4.2 below the researcher concluded that model **(2FI)** having highest value of whitcomb score value of (score1=0.1519 and score2=0.1593) was selected as a suggested model for further analysis of surface roughness in terms of the linear model of input parameters and interaction effect of each process parameters.

Table 4-3 Fit summary

Source	Sequential p-value	Adjusted R^2	Predicted R^2	
Linear	< 0.0001	0.9439	0.9244	
2FI	**0.0164**	**0.9717**	**0.9664**	**Suggested**
Quadratic	0.3150	0.9688	0.8734	
Cubic	0.0516	0.9982		**Aliased**

Tables 4-3 and 4-4 showed that the proposed 2FI vs. The linear model, while the cubic and quadratic models were an alias, that is, it is the highest-order model that explains significantly more response variability (p-value small), non-significant lack of fit (p-value > 0.10) and matched Reasonable agreement between R-squared and predicted R-squared (within 0.2 of each other). The predicted R-squared for the selected case, which (0.9664) was higher than the other models, shows how well the regression model predicts responses to new observations. This statistic helps us determine when a model fits the original data but fails to make valid predictions for a new observation.

Table 4-4 Sequential Model Sum of Squares

Source	Sum of Squares	df	Mean Square	F-value	p-value	
Mean vs Total	947.56	1	947.56			
2FI vs Linear	**79.37**	**3**	**21.79**	**189.98**	**< 0.0001**	**Suggested**
Linear vs Mean	6.28	3	2.09	4.35	0.6401	
Quadratic vs 2FI	1.77	3	0.5891	1.27	0.7150	
Cubic vs Quadratic	5.38	7	0.7689	3.10	0.5136	Aliased
Residual	2.48	10	0.2480			
Total	1042.84	27	38.63			

Table 4-5 Model summary statistics

Source	Std. Dev.	R^2	Adjusted R^2	Predicted R^2	PRESS	
Linear	0.8317	0.9734	0.9639	0.9544	23.57	
2FI	**0.6939**	**0.9629**	**0.9717**	**0.9664**	**23.43**	**Suggested**
Quadratic	0.6800	0.9880	0.8288	0.9034	27.85	
Cubic	0.4980	0.9947	0.9082	0.9256	30.50	Aliased

4.2.1.2 Analysis of Variance for Surface Roughness

ANOVA is where descriptive statistics and statistical tests are presented. In general, look for low p-values to identify significant terms in the model. From the analysis of variance of the surface roughness presented in Table 4-5, the F-value of the model of 20.97 shows that the model is significant. There is only a 0.01% chance that such a large F-value could occur due to noise. P-values below 0.0500 indicate that the model terms are significant. In this case, A, B, AB, BC are important model terms. Values above 0.1000 indicate that the model terms are not significant. Table 4.6 shows that pulse time has a significant effect on surface roughness of 47.76%, followed by peak current of 26.7% significant effect on surface roughness, but pulse exit time had no significant effect on surface roughness. Of the interaction effects, current versus pulse time and pulse time versus pulse time significantly affect the surface roughness by 3.18% and 6.19%, respectively. If the model has many irrelevant terms (disregarding the terms needed to support the hierarchy), model reduction can improve your model. And sufficient accuracy in Table 4-6 the predicted R^2 of 0.9717 is reasonably consistent with the adjusted R^2 of 0.9812; i.e. the difference is less than 0.2. Adeq Precision measures the signal-to-noise ratio. A ratio greater than 4 is desirable. The model ratio was 39.7318, indicating sufficient signal. This template can be used to navigate in design mode.

Table 4-6 Analysis of Variance for Surface Roughness

Source	Sum of Squares	Df	Mean Square	F-value	p-value		Percentage of contribution
Model	**60.59**	**6**	**10.10**	**20.97**	**< 0.0001**	**Significant**	
A-Current	17.80	1	17.80	36.98	< 0.0001		26.7%
B-Pulse-on	31.84	1	31.84	66.14	< 0.0001		47.76%
C-Pulse-off	1.11	1	1.11	2.30	0.1447		1.66%
AB	2.12	1	2.12	4.41	0.0487		3.18%
AC	0.0304	1	0.0304	0.0632	0.8041		0.045%
BC	4.13	1	4.13	8.57	0.0083		6.19%
Residual	9.63	20	0.4815				
Cor Total	70.22	26					

Table 4-7 Fit statistics

Std. Dev.	0.3039	**R^2**	0.9845
Mean	3.32	**Adjusted R^2**	0.9812
C.V. %	9.71	**Predicted R^2**	0.9717
		Adeq Precision	39.7318

4.2.1.3 Regression Model for Surface Roughness

This model used to determine the statistical relationship between EDM process parameters and surface roughness. The change process parameters associated with the change in the surface roughness was ascertained by using this model.

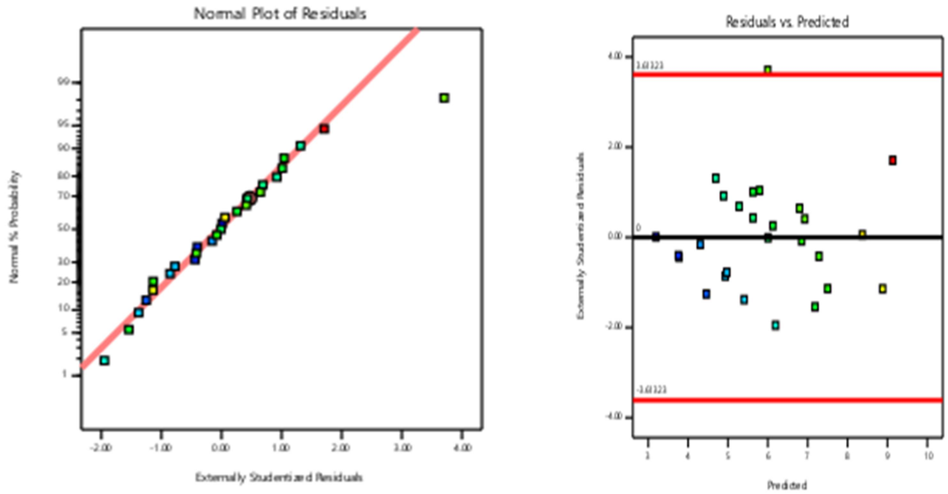
Regression Equation

$$Ra = +5.99 + 1.00\,A + 1.34\,B + 0.4196\,AB - 0.5759\,BC$$

The equation in terms of actual factors can be used to make predictions about the response for given levels of each factor. Here, the levels should be specified in the original units for each factor. This equation should not be used to determine the relative impact of each factor because the coefficients are scaled to accommodate the units of each factor and the intercept is not at the center of the design space.

4.2.2 Parametric influence on surface roughness

The plot of normal probability versus intrinsic residual in Figure a below showed that the residuals follow a normal distribution, ie. follows a straight line. Both the diagram of residuals and predictions in Figure 4.2 b, which is a diagram of residuals and increasing predicted response values, which was used to test the assumption of constant variance, and the plot showed random variance or a constant range of residuals in the plot, indicating that no changes are necessary. Thus, the model is suitable for analyzing the influence of individual parameters on surface roughness.

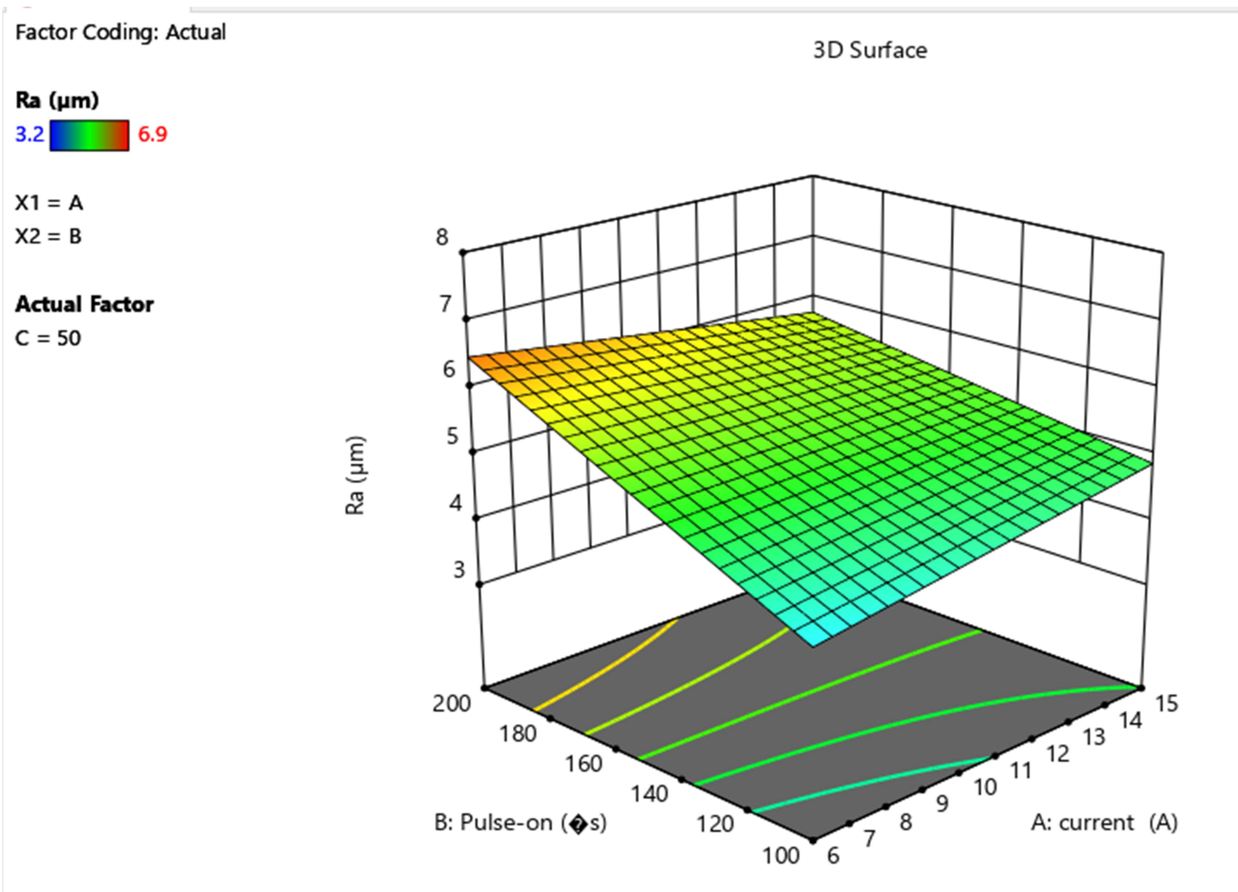


(a) (b)

Figure 4-1 (a) Normal plot of residuals and (b) Residuals vs. Predicted

4.2.2.1 Effect of Current and Pulse on Time on Surface Roughness

Effect of Peak current onsurface roughness is shown on Figure 4.3, it is observed that as Peak current have a significant effect on surface roughness with the increase the pulse on time values .It is observed from study and from ANOVA peak current is significant factor affecting surface roughness. Similar observation was reported by Ghodsiyeh, Lahiji, et al (2021) Studied the behavior of three control parameters during machining of titanium alloy (Ti6Al4V). ANOVA was employed to recognize the level of significance of the machining parameters on the performance characteristics of surface roughness (SR). They found that peak current was the most affecting parameter on surface roughness followed by pulse on time. Figure 4-3shows 3D Surface projection of the contour plot graph for Interaction effects of Current and Pulse on Time on surface roughness. From figure 4.3 A and B there cleary seen as pulse on time and current increases the amount of surface roughness were increased. They found that the pulse parameter had the greatest effect on the surface roughness of both materials Reddy et al., (2018). Longer pulse-on times result in more craters and material erosion since the discharge energy is directly related to the pulse-on time Lin & Lee, (2021). A longer pulse-on time thus produces a rougher surface. Low pulse-on time is necessary to produce the low surface roughness of the EDM-machined surface. Annamalai et al, (2019) found that the peak current must be kept optimum for minimum surface roughness. During increase of the pulse on duration, the roughness average values also increases and thus the pulse on time must be optimum. shows the effect of peak current and pulse durations on surface roughness of Inconel 718. Ra increases with the increase in discharge current and pulse duration. Figure 4.3 B shows the differences in Surface burn size for the lowest and highest Ra. When the discharge current is high, then the spark intensity are more, as a result, a larger crater depth on the surface of the work piece are produced, hence Ra is high. Pulse duration also strongly influences the Ra. An increase in pulse duration results in proportional increase in spark energy and consequently melting boundary becomes deeper and wider, and hence increases the roughness value Kumar., (2018). The lowest Ra with value of 8.53µm is achieved at a peak current of 20A and pulse duration of 200µs.



(A)

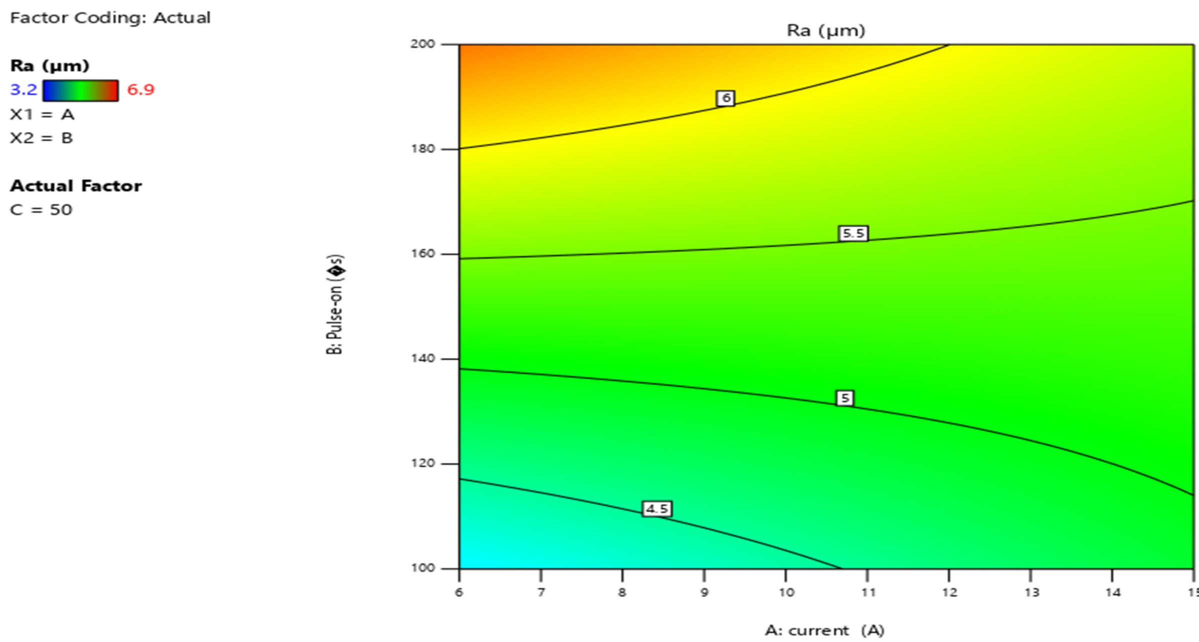


Figure 4-2 Interaction Effects of Current and Pulse on Time on Ra

4.3 Material Removal Rate analysis and discussion

4.3.1 Statistical Analysis

4.3.1.1 Fit Summary

Fit Summary is program tool that calculated the effects, for all model terms and produced statistics such as p-values, lack of fit and R-squared values for comparing the models. This tool collected the important statistics used to select the correct starting point for the final model fitting and suggested model.

Design-Expert uses the Fit Summary tables to calculate the Whitcomb Score (a heuristic scoring system) to select a default model. The Whitcomb Score has two components:

- Score1 = M ✕ L ✕ Pred R-squared
- Score2 = M ✕ L ✕ Adjusted R-squared

Where: **M** is the Sequential Model Sum of Squares score:

- M = 1 if the p-value is less than or equal to 0.05

- M = 0.05/p-value if the p-value is greater than 0.05
- M = 0 if model is aliased

L is the Lack of Fit (LOF) score:

- L = 1 if the LOF p-value is greater than or equal to 0.10
- L = p-value/0.10 if the LOF p-value value is less than 0.1

From table 4.8 the selected model for expressing the output response variables of MRR were linear in type by having a sequential P-value of < 0.0001 which adjusted R square and Predicted R square value of 0.9587 and 0.9870 respectively which having a reasonable variation between them.

Table 4-8 Fit summary for MRR

Source	Sequential p-value	Adjusted R^2	Predicted R^2	
Linear	**< 0.0001**	**0.9587**	**0.9870**	**Suggested**
2FI	0.6477	0.9440	0.9553	
Quadratic	0.1226	0.9837	0.9525	
Cubic	0.9348	0.9782		**Aliased**

Table 4-9 Sequential Model Sum of Squares

Source	Sum of Squares	Df	Mean Square	F-Value	p-value	
Mean vs Total	66107.26	1	66107.26			
Linear vs Mean	**19033.56**	**3**	**6344.52**	**28.25**	**< 0.0001**	**Suggested**
2FI vs Linear	400.15	3	133.38	0.5598	0.6477	

Quadratic vs 2FI	1342.66	3	447.55	2.22	0.1226	
Cubic vs Quadratic	1544.31	7	220.62	1.17	0.3948	Aliased
Residual	1878.06	10	187.81			
Total	90306.00	27	3344.67			

Table 4-10 Model Summary Statistics

Source	Std. Dev.	R^2	Adjusted R^2	Predicted R^2	PRESS	
Linear	**14.99**	**0.7866**	**0.7587**	**0.6970**	**7333.00**	**Suggested**
2FI	15.44	0.8031	0.7440	0.5553	10760.78	
Quadratic	14.19	0.8586	0.7837	0.5925	9862.09	
Cubic	13.70	0.9224	0.7982	-0.0712	25921.38	Aliased

4.3.2 Analysis of Variance for Material Removal Rate

Descriptive statistics and statistical tests were presented in this section. In which low p- values identified important terms in the model. From Analysis of Variance for Material Removal Rate on Table 4-10

The Model F-value of 28.25 implies the model is significant. There is only a 0.01% chance that an F-value this large could occur due to noise.

P-values less than 0.0500 indicate model terms are significant. In this case A and B is a significant model terms. Values greater than 0.1000 indicate the model terms are not significant. If there are many insignificant model terms (not counting those required to support hierarchy), model reduction may improve your model. From table 4.8 the recommended model for expressing MRR in terms of EDM process Parameters was Linear Model. Here interaction effect between parameters was not considered here. From the three parameters peak current have a significant Effect on Material removal rate with 78.13% contribution followed by Pulse on time with 21.344%.

Table 4-11 Analysis of Variance for Material Removal Rate

Source	Sum of Squares	df	Mean Square	F-value	p-value		% contribution
Model	19033.56	3	6344.52	28.25	< 0.0001	Significant	
A-Current	18908.22	1	18908.22	84.20	< 0.0001		78.13%
B-Pulse-on	5165.18	1	10.89	73.52	<0.0001		21.34%
C-Pulse-off	10.89	1	114.46	0.5097	0.4825		0.045%
Residual	114.46	23	224.57				
Cor Total	24198.74	26					

The Predicted R^2 of 0.9869 is in reasonable agreement with the Adjusted R^2 of 0.9973; i.e. the difference is less than 0.2. Adeq Precision measures the signal to noise ratio. A ratio greater than 4 is desirable. The ratio of 90.0593 indicates an adequate signal. This model can be used to navigate the design space.

Table 4-12 Fit Statistics

Std. Dev.	65.39	**R^2**	0.9973
Mean	1933.04	**Adjusted R^2**	0.9958
C.V. %	3.38	**Predicted R^2**	0.9868
		Adeq Precision	90.0593

4.3.3 Regression for Material Removal Rate

Regression technique was employed for figuring out the statistical relationship between EDM process parameters and Material removal Rate and to make predictions about the response for given levels of each factor. The equation in terms of coded factors can be used to make predictions about the response for given levels of each factor. By default, the high levels of the factors are coded as +1 and the low levels are coded as -1. The coded equation is useful for identifying the relative impact of the factors by comparing the factor coefficients.

Regression Equation

MRR (mm3/min) = 49.48 - 26.04 I_6 - 11.59 I_10 + 37.63 I_15 + 2.52 Ton_100 - 3.48 Ton_150
+ 0.96 Ton_200 + 1.19 Toff_20 + 2.07 Toff_40 - 3.26 Toff_80

4.3.4 Parametric Influence on Material Removal Rate.

The graph of Normal Probability plot versus internally student zed residual on Figure 4.4 a showed that the residuals follow a normal distribution, thus follow straight line. which is a plot of the residuals versus the ascending predicted response values used to tests assumption of constant variance and the plot showed a random scatter or constant range of residuals across the graph that indicates that the model is valid to conduct effect of individual factors on Material Removal Rate.

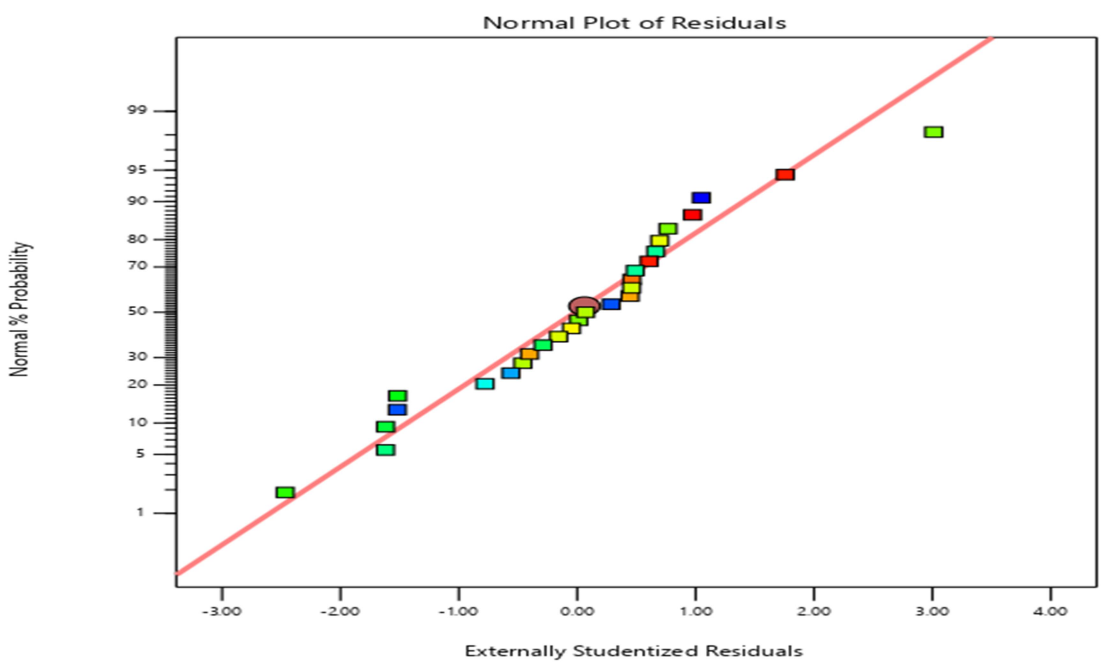
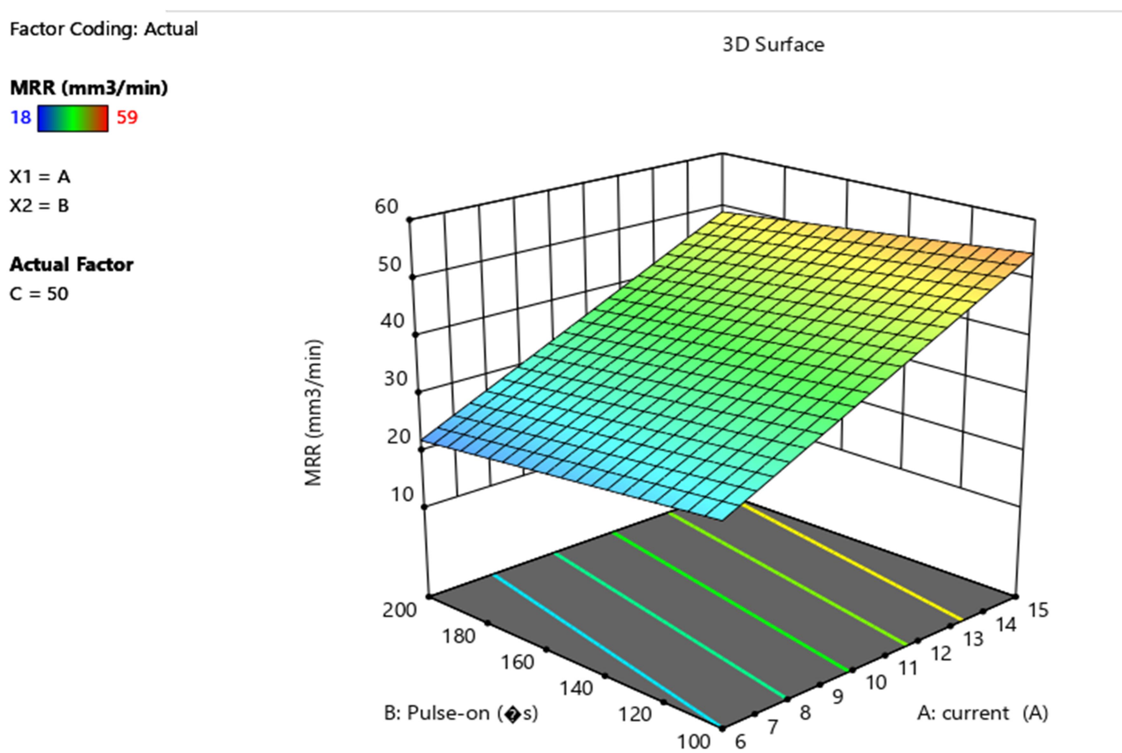
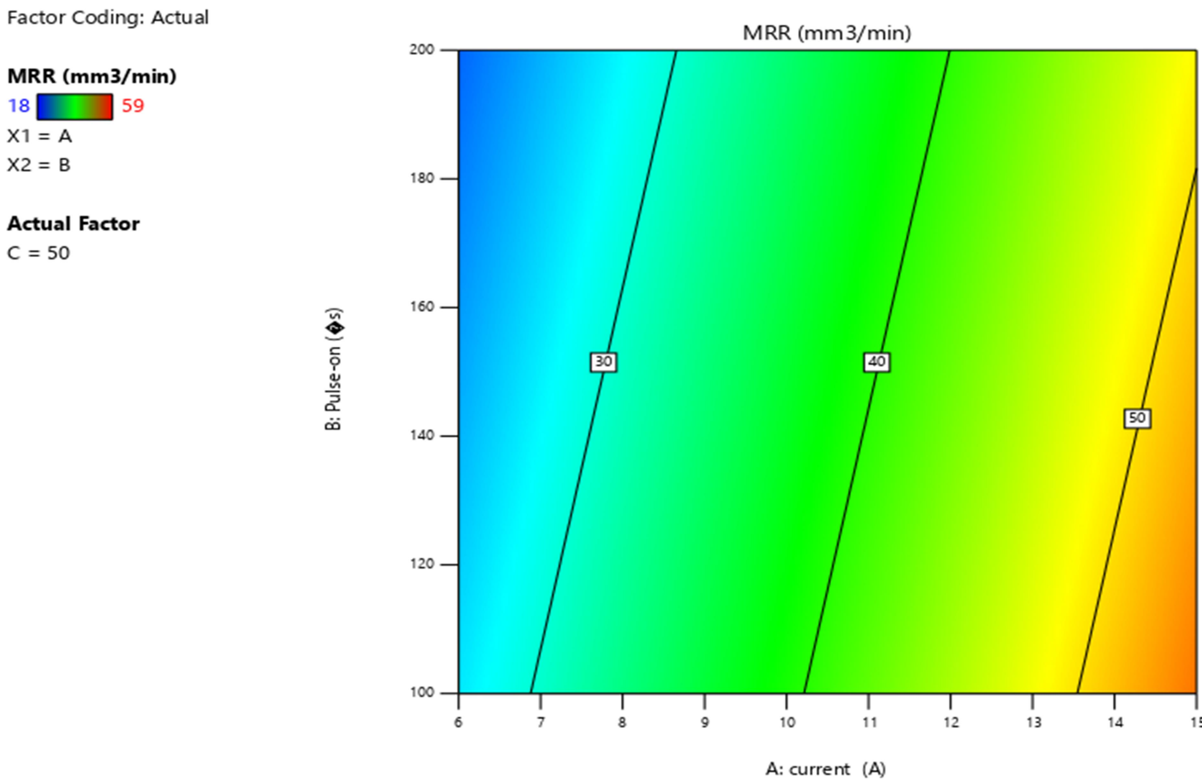


Figure 4-3 (a) Normal plot of residuals

Figure 4-5 clearly showed that the material removal rate was greatly affected by time peak current and pulse. The figure shows that increasing heart rate over time increases MRR. The rate of increase in MRR is greater for shorter pulse time than for higher pulse on time combinations. This is because the higher the pulse over time, the higher the discharge energy and spark intensity, which increases material removal. Shows the relationship between current and MRR in TONs (100 µs), where increasing current increases MRR. As can be seen from the results obtained with the flow (6A), it does not affect the material removal of the index when the values were close and the absence of thermal activity and electric spark and, as previously mentioned, the pulse on the right time (100 µs). The effect of peak current and pulse durations on the MRR is shown in figure 4-5. It is shown that the peak current affects the MRR significantly. An increased in peak current MRR increase for all setting of pulse duration. MRR increases with the increase in peak current due to the increases of the energy per pulse causes temperature raises sharply that leads to rapid melting of work piece material at sparking area. However, higher pulse duration decreased MRR for all peak current used. With a pulse duration longer than 200µs, the MRR start decreases because of the exceeding value of pulse interval. High ignition delay due to high pulse interval in each cycle reduces the machining rate at a constant machining efficiency. The highest MRR is achieved at 15A of peak current and 200µs of pulse on withvalue approximately 54.1227 mm3/min.



(A)



(B)

Figure 4-4 Interaction Effect between Pulse-on time vs Current on MRR

4.4 Development of Mathematical Model for Effect of EDM Process Parameters on MRR and Ra

Regression analysis combines mathematical and statistical techniques for empirical model building. A model of the response to certain independent input variables can be obtained by conducting experiments and applying regression analysis, The mathematical models commonly used are represented by,

$Y = \Phi\ (Ip, Ton, Tof) \pm er$,

Where Y is the machining response, Φ is the response function and Ip, Ton, and Tof are machining independent variables and er is the error. The general second-order polynomial response equation is mostly used. It also confirms that this model provides an excellent explanation of the relationship between the Independent factors and the responses. The second order response surface representing the MRR and SR can be expressed as a function of machining parameters Ip, Ton and Tof The relationship between the response and machining parameters has been expressed as follows

Ra = 5.924 - 0.930 I_6 - 0.146 I_10 + 1.076 I_15 -1.569 Ton_100 + 0.354 Ton_150 + 1.215 Ton_200

0.202 Toff_20 - 0.080 Toff_40 + 0.281 Toff_80

Coefficients in Terms of Coded Factors for Ra

Factor	**Coefficient Estimate**	**df**	**Standard Error**	**95% CI Low**	**95% CI High**	**VIF**
Intercept	5.99	1	0.1349	5.71	6.27	
A-Current	1.00	1	0.1647	0.6578	1.34	1.02
B-Pulse-on	1.34	1	0.1652	0.9987	1.69	1.02
C-Pulse-off	0.2440	1	0.1608	-0.0913	0.5794	1.00
AB	0.4196	1	0.1999	0.0026	0.8365	1.00
AC	-0.0493	1	0.1963	-0.4588	0.3601	1.02
BC	-0.5759	1	0.1967	-0.9862	-0.1656	1.02

The coefficient estimate represents the expected change in response per unit change in factor value when all remaining factors are held constant. The intercept in an orthogonal design is the overall average response of all the runs. The coefficients are adjustments around that average based on the factor settings. When the factors are orthogonal the VIFs are 1; VIFs greater than 1 indicate multi-colinearity, the higher the VIF the more severe the correlation of factors. As a rough rule, VIFs less than 10 are tolerable.

Final Equation in Terms of Coded Factors for Ra

Ra = +5.99 +1.00 A + 1.34 B + 0.2440 C + 0.4196 AB - 0.0493 AC – 0.5759 BC

The equation in terms of coded factors can be used to make predictions about the response for given levels of each factor. By default, the high levels of the factors are coded as +1 and the low levels are coded as -1. The coded equation is useful for identifying the relative impact of the factors by comparing the factor coefficients.

Final Equation in Terms of Actual Factors For Ra

Ra = -0.918511 – 0.038934 Current + 0.026481 Pulse on + 0.069560 Pulse-off + 0.001865 Current * Pulse-on – 0.000365 Current * pulse-off – 0.000384 Pulse-on * Pulse-off

The equation in terms of actual factors can be used to make predictions about the response for given levels of each factor. Here, the levels should be specified in the original units for each factor. This equation should not be used to determine the relative impact of each factor because the coefficients are scaled to accommodate the units of each factor and the intercept is not at the center of the design space.

MRR (mm^3/min) = 49.48 - 26.04 I_6 - 11.59 I_10 + 37.63 I_15 + 2.52 Ton_100 - 3.48 Ton_150 + 0.96 Ton_200 + 1.19 Toff_20 + 2.07 Toff_40 - 3.26 Toff_80

Coefficients in Terms of Coded Factors for MRR

Factor	Coefficient Estimate	df	Standard Error	95% CI Low	95% CI High	VIF
Intercept	50.40	1	2.91	44.38	56.43	
A-Current	32.34	1	3.52	25.05	39.64	1.0000
B-Pulse-on	-0.7778	1	3.53	-8.08	6.53	1.0000
C-Pulse-off	-2.48	1	3.47	-9.65	4.70	1.0000

The coefficient estimate represents the expected change in response per unit change in factor value when all remaining factors are held constant. The intercept in an orthogonal design is the overall average response of all the runs. The coefficients are adjustments around that average based on the factor settings. When the factors are orthogonal the VIFs are 1; VIFs greater than

1 indicate multi-colinearity, the higher the VIF the more severe the correlation of factors. As a rough rule, VIFs less than 10 are tolerable.

Final Equation in Terms of Coded Factors for MRR

MRR = +50.40 + 32.34A – 0.7778B -2.48C

The equation in terms of coded factors can be used to make predictions about the response for given levels of each factor. By default, the high levels of the factors are coded as +1 and the low levels are coded as -1. The coded equation is useful for identifying the relative impact of the factors by comparing the factor coefficients.

Final Equation in Terms of Actual Factors for MRR

MRR = -18.60534 + 7.18761 Current – 0.015556 Pulse-on – 0.082540 Pulse-off

The equation in terms of actual factors can be used to make predictions about the response for given levels of each factor. Here, the levels should be specified in the original units for each factor. This equation should not be used to determine the relative impact of each factor because the coefficients are scaled to accommodate the units of each factor and the intercept is not at the center of the design space.

4.5 Multi-Objective Optimization of EDM Process Parameters by using Machine Learning Predictive Methods

I. Numerical and Graphical Optimization by Using Full factorial design of Experiments

Optimization process was carried on the Design expert version 13. After the machining of Inconel 718 by using Electric discharge machine, optimization of input parameters were carried out in order to get optimum combined value of surface roughness and material removal rate. Here in this study surface roughness was minimized and material removal rate were maximization problem.

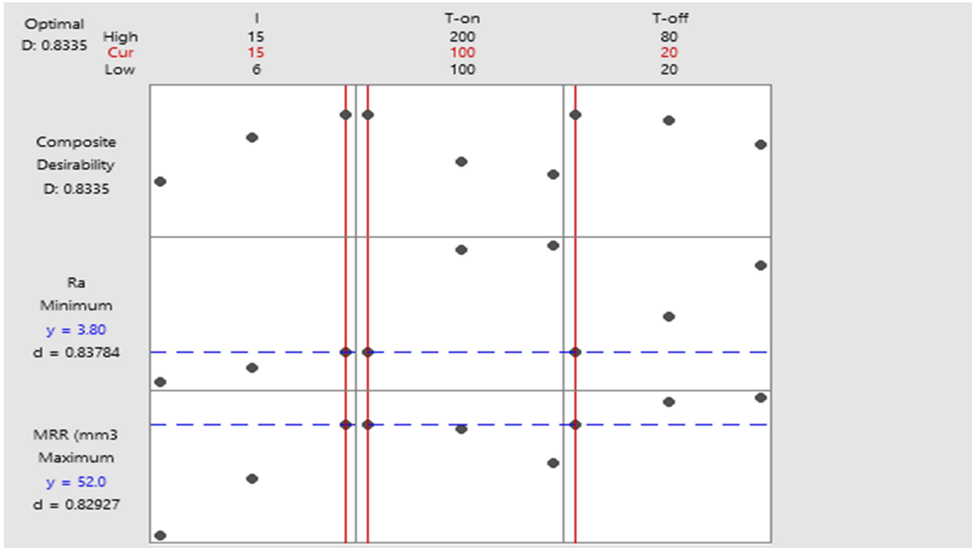


Figure 4-5 Multi-objective optimizations of Ra and MRR by using FFDOE

In figure 4-6 above both surface roughness and material removal rate were minimized and maximized respectively. The minimized value of surface roughness for better result were 3.80µm at the level value of input parameters of I,T-on and T-off 15A,100µs and 20µs respectively. Since the optimization were multi-objective Inconel were machined at this value in order to get better value of 52mm^3/min.

II. Optimization by Using Predictive Regression Models

Most supervised-learning problems can be categorized as either "classification" problems or "regression" problems. Classification problems involve predicting a discrete valued output, such as a number or a certain species. By contrast, regression problems involve predicting a continuous valued output, such as stock market movement or the price of goods. The present study considered a regression-type problem, in which the aim was to predict the optimum values of EDM responses, given knowledge of the settings assigned to the three machining parameters. The data required to train the ML model were obtained from the full factorial design of experiments described in the previous section, where the level settings for the three machining parameters. The assessment of the machine learning algorithm is carried out by testing its accuracy against a set of data. Alternatively, for a statistical model, confidence intervals, significance tests, and other tests can be used to appraise the model's validity by analyzing the parameters of the regression. Machine learning is all about results, which is similar to working for a company where you are measured solely by the quality of your performance, as opposed to statistical modeling, which is primarily concerned with finding correlations between variables and then assessing their significance and making predictions

Terminologies Related to the Regression Analysis:

- Dependent Variable**:** The main factor in Regression analysis which we want to predict or understand is called the dependent variable. It is also called target variable**.**
- Independent Variable**:** The factors which affect the dependent variables or which are used to predict the values of the dependent variables are called independent variable, also called as a predictor**.**
- Outliers: Outlier is an observation which contains either very low value or very high value in comparison to other observed values. An outlier may hamper the result, so it should be avoided.
- Multi-collinearity: If the independent variables are highly correlated with each other than other variables, then such condition is called Multi-collinearity. It should not be present in the dataset, because it creates problem while ranking the most affecting variable.
- Under-fitting and Over-fitting**:** If our algorithm works well with the training dataset but not well with test dataset, then such problem is called Over-fitting. And if our algorithm does not perform well even with training dataset, then such problem is called under-fitting**.**

- **Regression: Ra versus I, T-on, T-off**

Optimal Tree Diagram

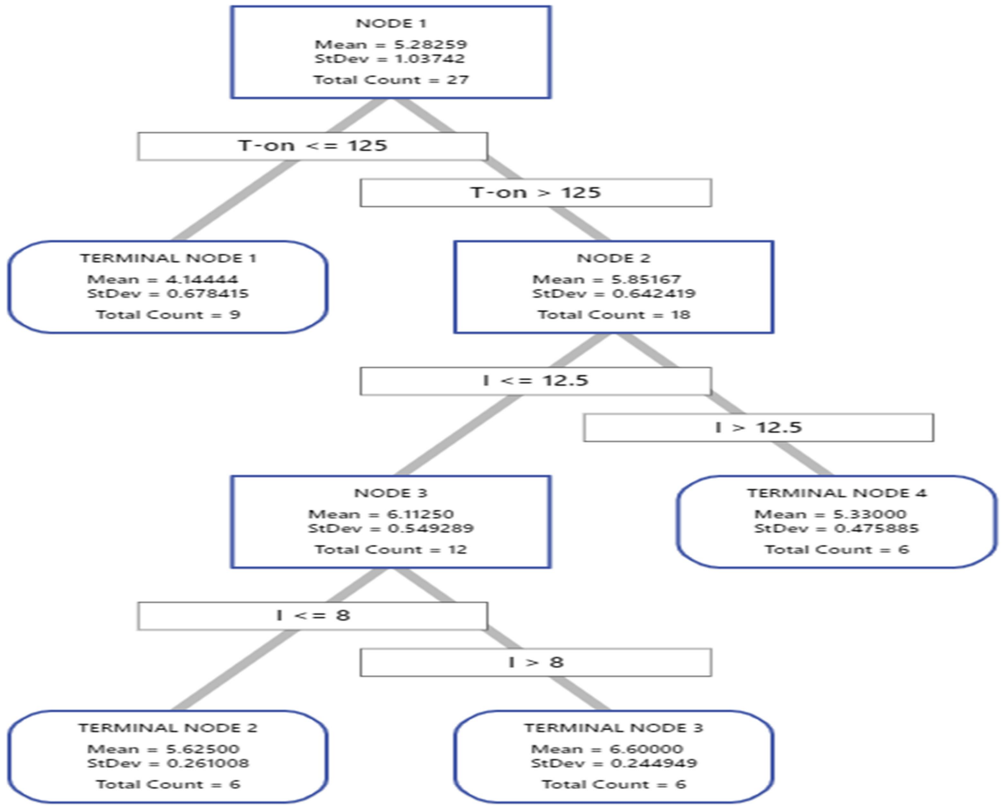


Figure 4-6 Optimal Tree Diagram for Ra

Table 4-13 Predictive Model Summary for Ra

Total predictors		3
Important predictors		2
Number of terminal nodes		4
Minimum terminal node size		6
Statistics	**Training**	**Test**
R-squared	78.42%	70.71%
Root mean squared error (RMSE)	0.4819	0.5615
Mean squared error (MSE)	0.2322	0.3153
Mean absolute deviation (MAD)	0.3965	0.4681
Mean absolute percent error (MAPE)	0.0835	0.0981

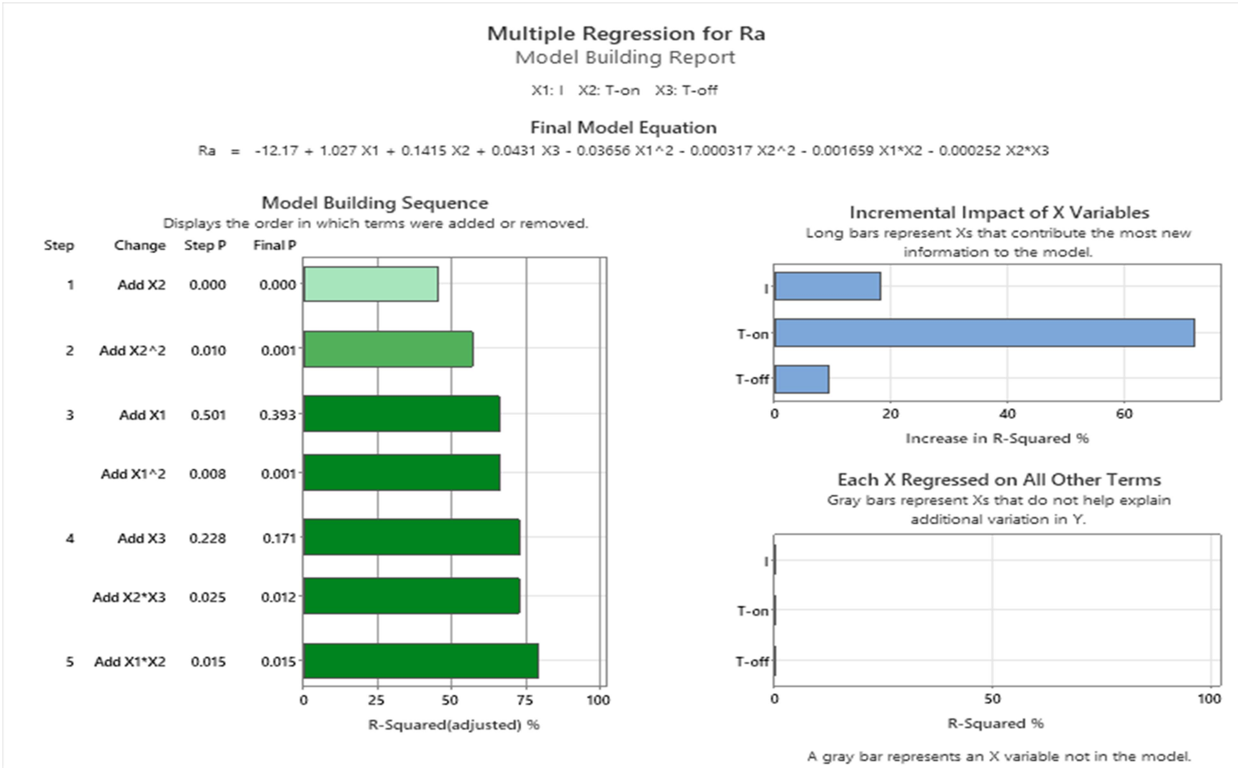


Figure 4-7 Multiple Regression for Ra Model Building

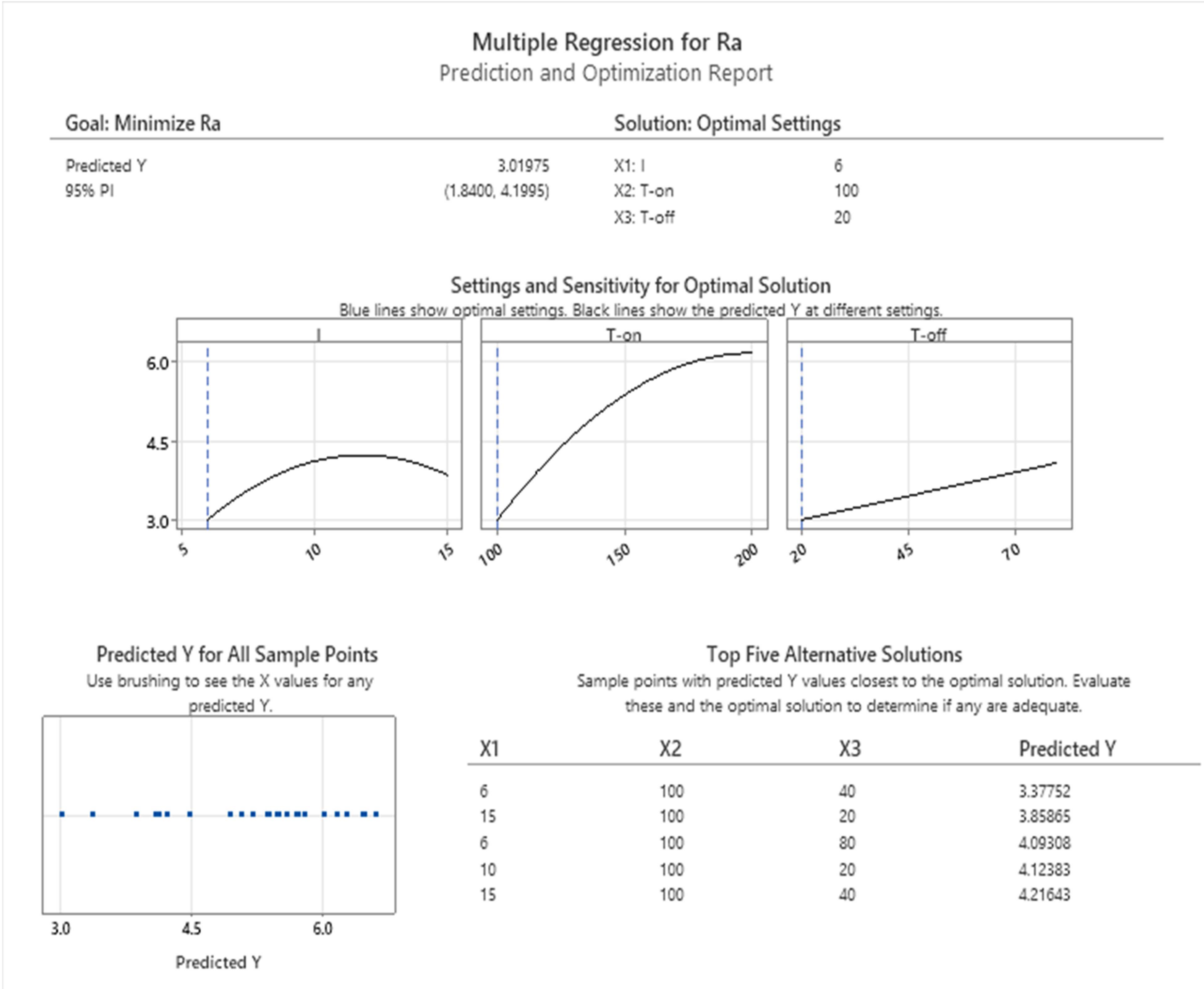


Figure 4-8 Prediction and Optimization Report for Ra

From table 4.14 the optimum surface roughness were 3.37752μm at combination of current 6A, Pulse-on time 100μs and Pulse-off time were 40μs. this combination results better than the result obtained by using full factorial design of experiments.

Table 4-14 Top Five Alternative Solutions

Current (A)	Pulse-on time (μs)	Pulse-off time (μs)	Predicted Y (μm)
6	**100**	**40**	**3.37752**
15	100	20	3.85865
6	100	80	4.09308
10	100	20	4.12383
15	100	40	4.2643

- **Regression: MRR versus I, T-on, T-off**

Optimal Tree Diagram

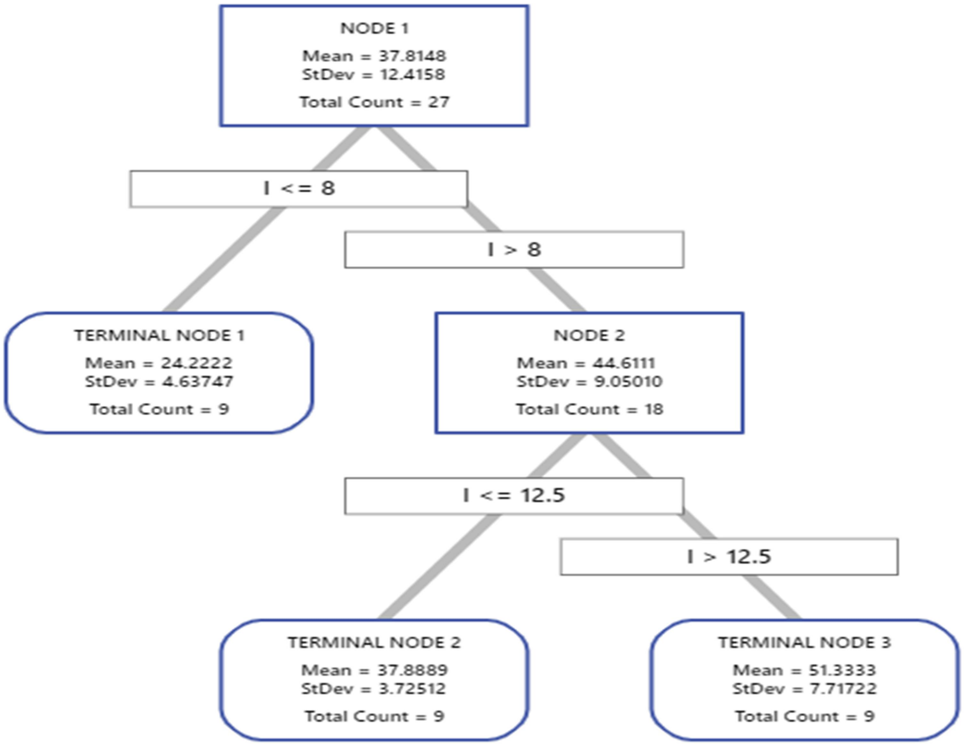


Figure 4-9 Optimal Tree Diagram for MRR

Table 4-15 Predictive Model Summary for MRR

Total predictors		3
Important predictors		1
Number of terminal nodes		3
Minimum terminal node size		9
Statistics	**Training**	**Test**
R-squared	89.47%	85.87%
Root mean squared error (RMSE)	5.6255	6.0987
Mean squared error (MSE)	31.6461	37.1940
Mean absolute deviation (MAD)	4.3621	4.7145
Mean absolute percent error (MAPE)	0.1280	0.1397

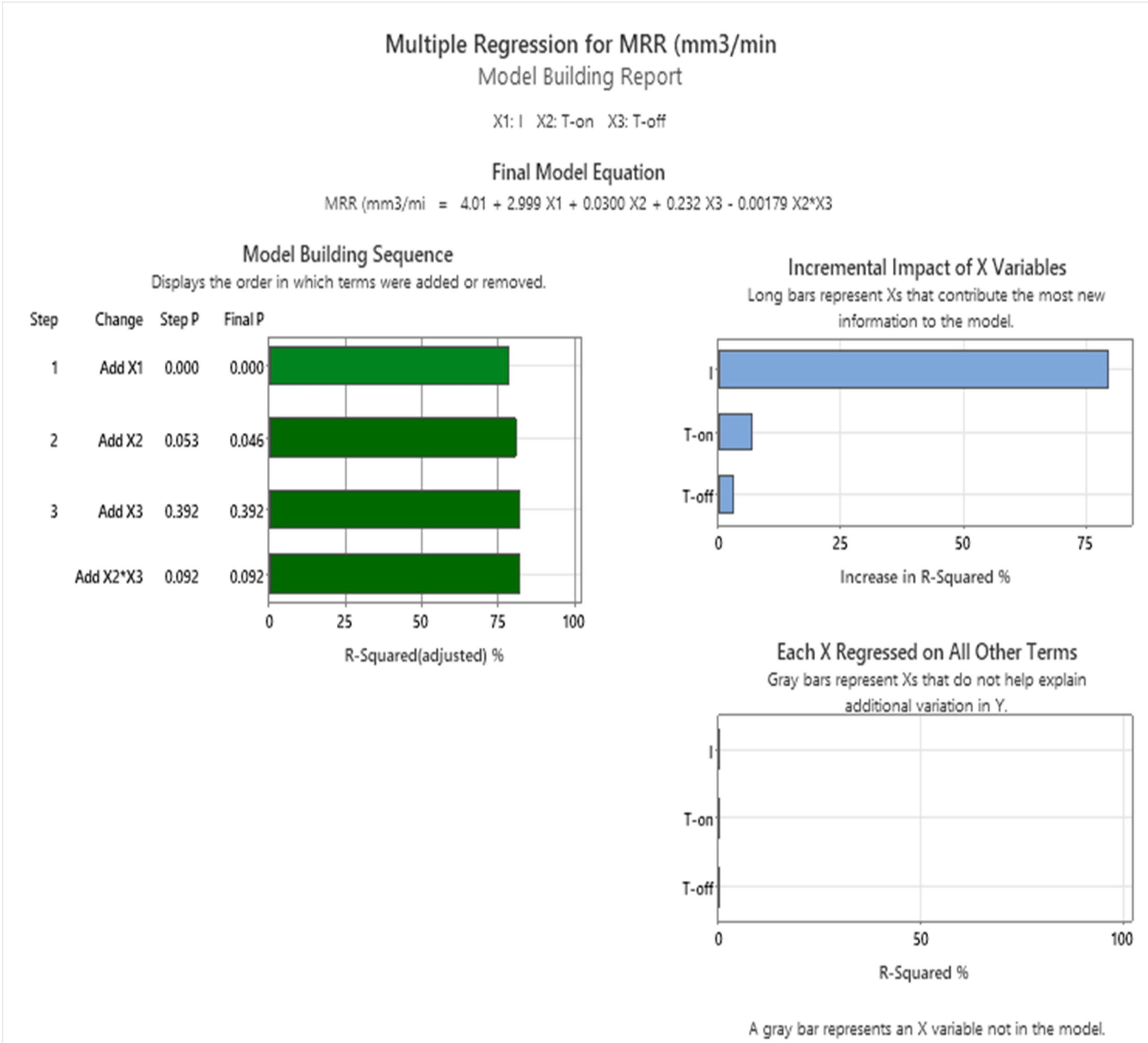


Figure 4-10 Predictive model building for MRR

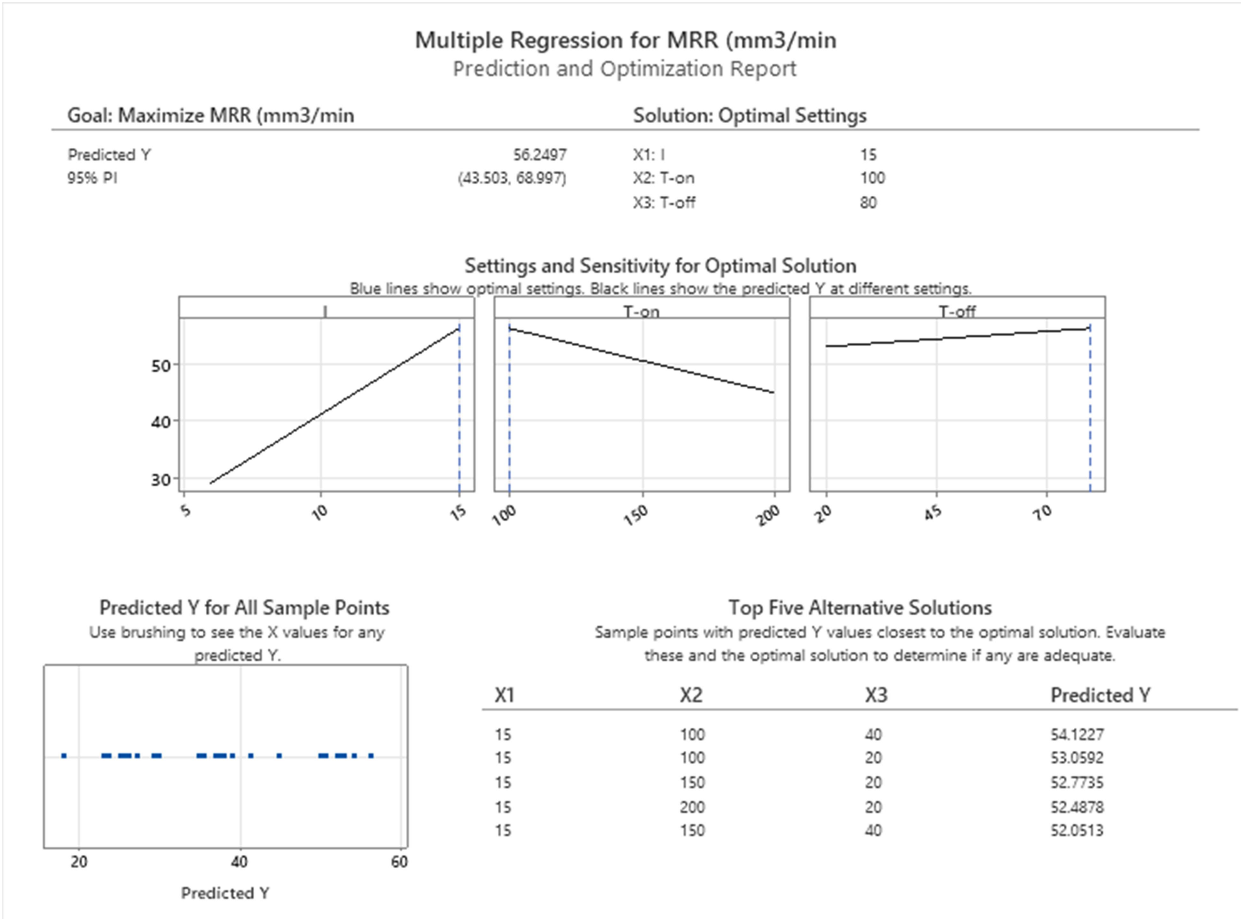


Figure 4-11 Prediction and Optimization Report for MRR

From table 4.14 the optimum Material removal rate were 54.1227 mm^3/min at combination of current 15A, Pulse-on time 100µs and Pulse-off time were 40µs. this combination results better than the result obtained by using full factorial design of experiments.

Table 4-16 Top Five Alternative Solutions

Current (A)	Pulse-on time (µs)	Pulse-off time (µs)	Predicted Y (mm^3/min)
15	**100**	**40**	**54.1227**
15	100	20	53.0592
15	150	20	52.7735
15	200	20	52.4878
15	150	40	52.0513

III. Multi objective optimization by using desirability function

In order to reduce surface roughness and increase material removal rate discover the optimum EDM parameters for multi-responses, the desirability function approach was used. The multi-objective optimization report comprised in table 4.17, the optimal solutions table 4.18 for the process, and the desirability bar graph. Table 4-17 presents the constraints on multi-objective optimization. Moreover, Table 4-18 summarizes all the criteria applied to find the optimum settings. The optimum setting for input factors was in range. Desirability analysis was performed material removal rate value with the-larger- the-better and, surface roughness values with the-smaller-the-better desirability function. Figure 4-13 shows the desirability bar graph for each optimum solution. The factor settings are shown in the first three bars and the optimal expected response values are shown in the two remaining bars. The desirability bar graph provided a graphical view of desirable individual response for surface roughness (49.5405%) and material removal rate (91.3175%). The desirability of combined responses was 67.26%. A total of 10 desirable results were obtained, and the solutions with desirability values close to 1 are the best options. In this case, any of solutions 1, 2 or 3 can be selected. Moreover, this selection predicted the lowest possible combined values of surface roughness and highest possible material removal rate. The best possible cutting parameter combination was at 15A for Peak current, 100µs and 20µs for Pulse on time and Pulse off time, respectively.

Table 4-17 Constraints for optimization of cutting parameters and responses

Name	Goal	Lower Limit	Upper Limit	Lower Weight	Upper Weight	Importance
A:current	is in range	6	15	1	1	3
B:Pulse-on	is in range	100	200	1	1	3
C:Pulse-off	is in range	20	80	1	1	3
Ra	minimize	3.2	6.9	1	1	3
MRR	maximize	18	59	1	1	3

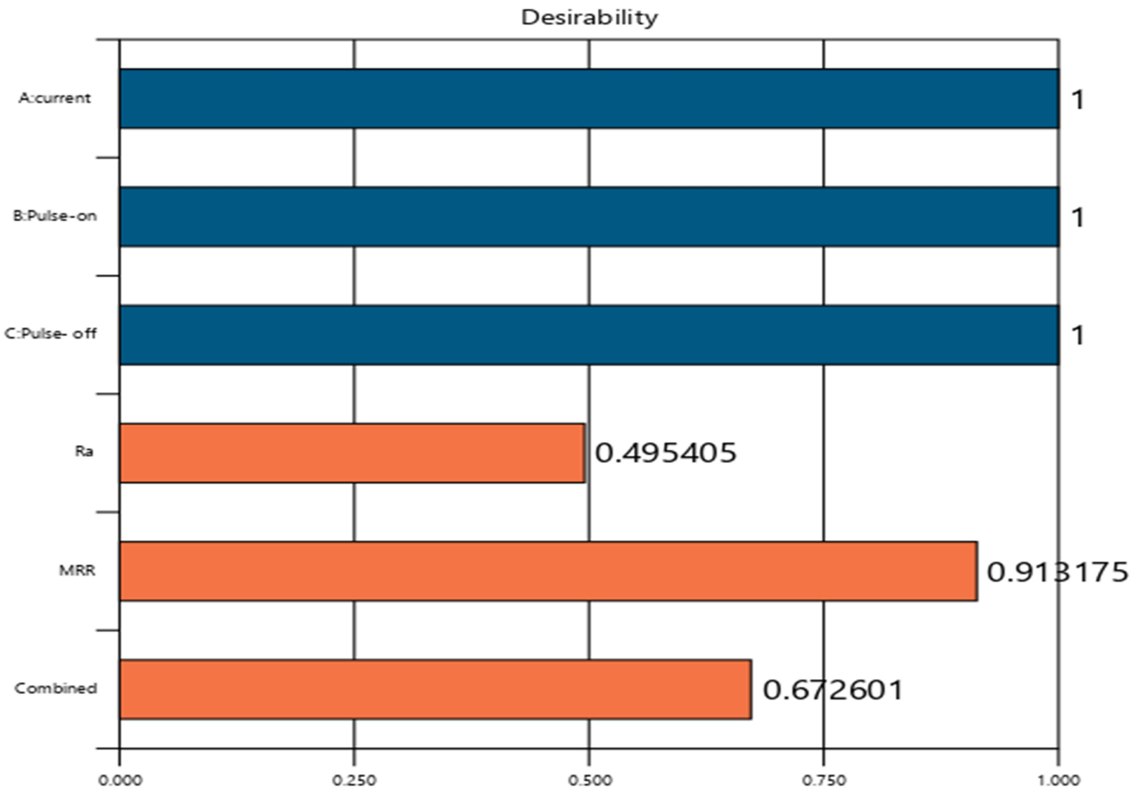


Figure 4-12 Desirability bar Graph

Solution of optimized cutting parameters for work material

Number	current	Pulse-on	Pulse-off	Ra	MRR	Desirability	Desirability (w/o Intervals)	
1	**15.000**	**100.000**	**20.000**	**4.339**	**55.440**	**0.673**	**0.795**	**Selected**
2	14.963	100.020	20.000	4.336	55.328	0.672	0.794	
3	15.000	100.371	20.012	4.345	55.420	0.672	0.794	
4	14.929	100.000	20.019	4.333	55.227	0.672	0.794	
5	15.000	100.001	20.511	4.348	55.422	0.671	0.793	
6	15.000	100.000	20.537	4.348	55.421	0.671	0.793	
7	14.891	100.000	20.000	4.329	55.113	0.671	0.793	
8	14.852	100.000	20.000	4.326	54.997	0.671	0.792	
9	15.000	100.847	20.000	4.353	55.395	0.671	0.792	
10	15.000	100.000	20.859	4.354	55.409	0.671	0.792	

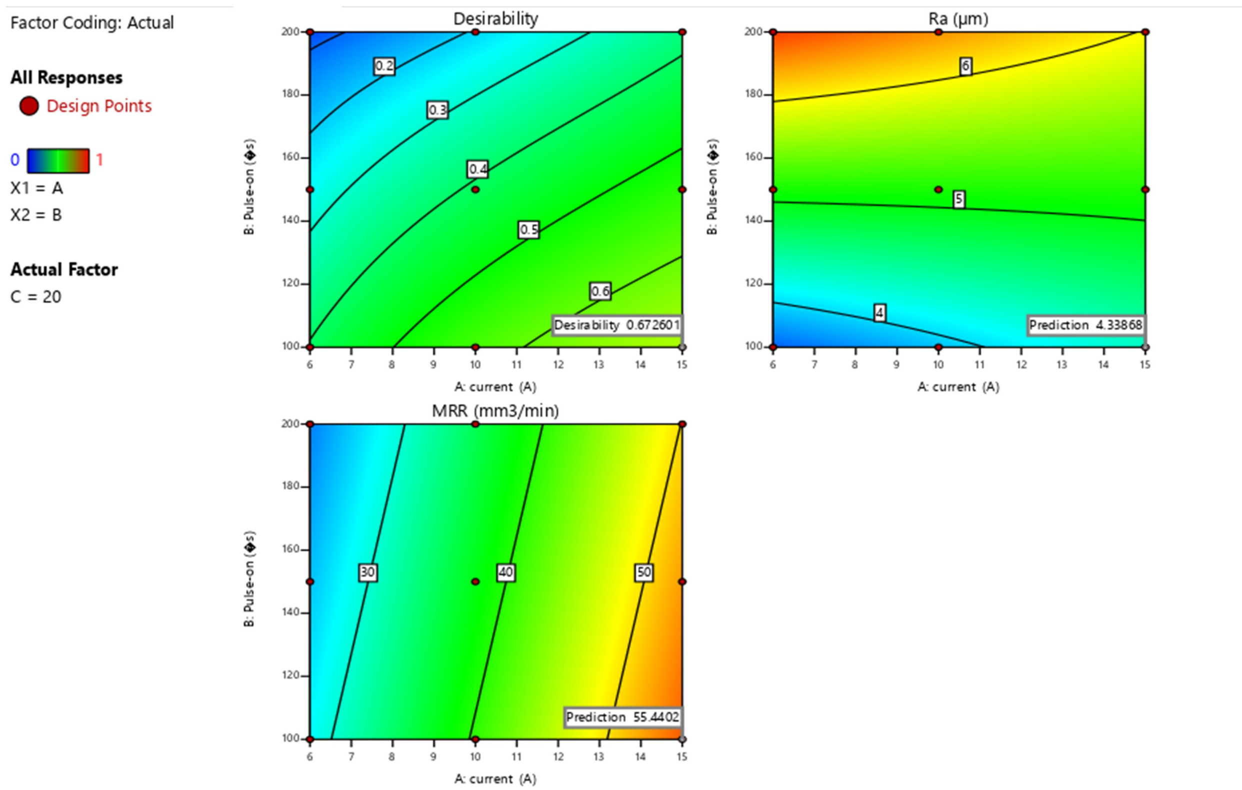


Figure 4-13 Contour Graph for multi-objective by using desirability function

4.6 Conformation Test

After determining the optimal combination of parameters, the last phase is to verify the MRR, surface roughness by conducting the confirmation experiment. The A3B1C1 (I=15A, T-on=100µs and T-off=20µs) is an optimal parameter combination of the machining process by predictive model. The confirmation test is carried out with the optimal parameter combination A3B1C1, and the results are tabulated in Table 4-17 and matches.

Table 4-18 Confirmation test results

Type	Initial	Optimal/Predicted	Experimental
Level combination	$A_3B_1C_1$	$A_3B_1C_1$	$A_3B_1C_1$
MRR (mm3/min)	52.0	52.0	51.85
Ra (µm)	3.80	3.80	3.83

5. Conclusion and Recommendation

5.1 Conclusion

This thesis entitled with multi-objective optimization of EDM process parameters of Inconel 718 by using Machine Learning Techniques. In this thesis, an experimental investigation was conducted on EDM of Inconel 718 super alloy. Then, the influence of process conditions was studied on MRR and surface roughness by intelligent methods. The material used was Inconel 718 which was difficult to machine through conventional method. This is the reason behind this since it's possible to machine through EDM process. The copper electrode was used for discharging purpose and EDMN450CNC machine were used for discharging purposes. Full factorial design of experiments was employed and three parameters (Current, Pulse on time and Pulse-off Time) and two output parameters are investigated Surface roughness and Material Removal Rate.

- The experimental results indicated that MRR is more affected by process conditions than surface roughness. Maximum MRR was found to be 55.44mm^3/min at a peak current of 15 (A), pulse-on time of 200 (μs), and pulse-off time of 20 (μs). In addition, the best surface quality obtained was 3.3772 (μm) at a peak current of 6 (A), pulse-on time of 150 (μs), and pulse-off time of 40(μs).
- The results indicated that the surface quality is impaired by the enhancement of peak current and pulse off time. It was changed from 3.80-3.37752 μm when pulse on time and current were changed from 100 μs -150 μs and 6Ato 15A respectively.
- The results on MRR indicated that while the current and pulse on time are effective for the enhancement of MRR. The MRR was increased from 52mm^3/min to 54.1227 mm^3/min by enhancement of peak current. It was also shown that pulse off time has fewer effect on MRR compared to other process parameters.
- By implementation of a multi objective optimization algorithm (Machine learning Predictive model), maximized MRR and surface quality obtained were better than experimental tests (55.44m^3/min and 4.33μm, respectively). In addition, different testing conditions that are satisfactory for both process outputs were suggested.
- Finally, it is concluded that implemented regression type of predictive model in this paper can be efficiently developed for optimizing the other process conditions of the

EDM process (microstructure changes, tool wear rate and residual stress) in future researches.

5.2 Recommendation

By adopting the analysis made in this thesis, this research can be extended with increased number of electrode materials with increased levels for obtaining comparatively better results.

- This research can be extended for increased numbers of experiments for better analysis and build a predictive model by using different algorithms of machine learning other than regression type predictive models and to increase accuracy of the model.
- This research can be extended for EDM with different proportion of electrode materials on INCONEL 718.

5.3 Scope for Future Work

- Future researches could be directed toward considering higher number of input process parameters. This will contribute to the optimization of the process considering a higher number of criteria.
- The impact of EDM process parameters such as pulse-on time, pulse-off time, and current was investigated in this study. Additional factors such as tool wear, material composition, and different electrode tool and so on could be considered in future research.
- In order to conduct a thorough investigation into the behavior of electrode wear, further research using XRD could be included.

6. References

Aggarwal, V., Singh, J., Sharma, S., Garg, H., Sharma, A., Singh, G., & Parshad, J. (2020). An experimental study of wire breakage frequency on different electrodes during WEDM of Inconel-722. IOP Conference Series, 954(1), 012013. https://doi.org/10.1088/1757-899x/954/1/012013

Aggogeri, F., Pellegrini, N., & Tagliani, F. L. (2021). Recent Advances on Machine Learning Applications in Machining Processes. Applied Sciences, 11(18), 8764. https://doi.org/10.3390/app11188764

Alam, N., Siddiquee, A. N., Fan, P., & Khan, N. M. (2022). A comprehensive review on wire EDM performance evaluation. Proceedings of the Institution of Mechanical Engineers, Part E: Journal of Process Mechanical Engineering, 236(4), 1724–1746. https://doi.org/10.1177/09544089221074843

Alias, A., Abdullah, B., & Abbas, N. M. (2012a). Influence of Machine Feed Rate in WEDM of Titanium Ti-6Al-4V with Constant Current (6A) Using Brass Wire. Procedia Engineering, 41, 1806–1811. https://doi.org/10.1016/j.proeng.2012.07.387

Alias, A., Abdullah, B., & Abbas, N. M. (2012b). Influence of Machine Feed Rate in WEDM of Titanium Ti-6Al-4V with Constant Current (6A) Using Brass Wire. Procedia Engineering, 41, 1806–1811. https://doi.org/10.1016/j.proeng.2012.07.387

Baskaran, S., Anandakrishnan, V., & Duraiselvam, M. (2014). Investigations on dry sliding wear behavior of in situ casted AA7075–TiC metal matrix composites by using

Taguchi technique. Materials in Engineering, 60, 184–192. https://doi.org/10.1016/j.matdes.2014.03.074

Brüning, J., Denkena, B., Dittrich, M., & Hocke, T. (2017). Machine Learning Approach for Optimization of Automated Fiber Placement Processes. Procedia CIRP, 66, 74–78. https://doi.org/10.1016/j.procir.2017.03.295

Chalisgaonkar, R., Kumar, J., & Pant, P. (2020). Prediction of machining characteristics of finish cut WEDM process for pure titanium using feed forward back propagation neural network. Materials Today: Proceedings, 25, 592–601. https://doi.org/10.1016/j.matpr.2019.07.260

Chen, Y., & Mahdivian, S. (2000). Analysis of electro-discharge machining process and its comparison with experiments. Journal of Materials Processing Technology. https://doi.org/10.1016/s0924-0136(00)00531-8

Chen, Z., Peng, R. L., & Johansson, S. (2016). Surface Integrity and Fatigue Performance of Inconel 718 in Wire Electrical Discharge Machining. Procedia CIRP, 45, 307–310. https://doi.org/10.1016/j.procir.2016.02.053

Dabade, U. A., & Karidkar, S. S. (2016). Analysis of Response Variables in WEDM of Inconel 718 Using Taguchi Technique. Procedia CIRP, 41, 886–891. https://doi.org/10.1016/j.procir.2016.01.026

Datta, S., & Mahapatra, S. S. (2010). Modeling, simulation and parametric optimization of wire EDM process using response surface methodology coupled with grey-Taguchi technique. International Journal of Engineering, Science and Technology &B. Lagos, 2(5). https://doi.org/10.4314/ijest.v2i5.60144

Dewangan, S., Biswas, C., & Gangopadhyay, S. (2014). Optimization of the Surface Integrity Characteristics of EDM Process Using PCA based Grey Relation Investigation. Procedia Materials Science, 6, 1091–1096. https://doi.org/10.1016/j.mspro.2014.07.180

Dewangan, S., Kumar, S., Jha, S., & Biswas, C. (2020). Optimization of Micro-EDM drilling parameters of Ti–6Al–4V alloy. Materials Today: Proceedings, 33, 5481–5485. https://doi.org/10.1016/j.matpr.2020.03.307

El-Taweel, T. A., & Hewidy. (2009). Enhancing the performance of electrical-discharge machining via various planetary modes. International Journal of Machining and Machinability of Materials, 5(2/3), 308. https://doi.org/10.1504/ijmmm.2009.023397

Gautam, N., Goyal, A., Sharma, S. S., Oza, A. D., & Kumar, R. (2022). Study of various optimization techniques for electric discharge machining and electrochemical machining processes. Materials Today: Proceedings, 57, 615–621. https://doi.org/10.1016/j.matpr.2022.02.005

Ghodsiyeh, D., Golshan, A., & Izman, S. (2013a). Multi-objective process optimization of wire electrical discharge machining based on response surface methodology. Journal of the Brazilian Society of Mechanical Sciences and Engineering, 36(2), 301–313. https://doi.org/10.1007/s40430-013-0079-x

Ghodsiyeh, D., Golshan, A., & Izman, S. (2013b). Multi-objective process optimization of wire electrical discharge machining based on response surface methodology. Journal of the Brazilian Society of Mechanical Sciences and Engineering, 36(2), 301–313. https://doi.org/10.1007/s40430-013-0079-x

Gökler, M. İ., & Ozanözgü, A. M. (2000). Experimental investigation of effects of cutting parameters on surface roughness in the WEDM process. International Journal of Machine Tools & Manufacture, 40(13), 1831–1848. https://doi.org/10.1016/s0890-6955(00)00035-

Guo, K., Yang, Z., Yu, W. C., & Buehler, M. J. (2021). Artificial intelligence and machine learning in design of mechanical materials. Materials Horizons, 8(4), 1153–1172. https://doi.org/10.1039/d0mh01451f

Haddad, M. J., & Tehrani, A. F. (2008). Material removal rate (MRR) study in the cylindrical wire electrical discharge turning (CWEDT) process. Journal of Materials Processing Technology, 199(1–3), 369–378. https://doi.org/10.1016/j.jmatprotec.2007.08.020

Hewidy, El-Taweel, T. A., & El-Safty, M. (2005a). Modelling the machining parameters of wire electrical discharge machining of Inconel 601 using RSM. Journal of Materials Processing Technology, 169(2), 328–336. https://doi.org/10.1016/j.jmatprotec.2005.04.078

Hewidy, El-Taweel, T. A., & El-Safty, M. (2005b). Modelling the machining parameters of wire electrical discharge machining of Inconel 601 using RSM. Journal of Materials Processing Technology, 169(2), 328–336. https://doi.org/10.1016/j.jmatprotec.2005.04.078

İnaç, H., Ayözen, Y., Atalan, A., & Dönmez, C. Ç. (2022). Estimation of Postal Service Delivery Time and Energy Cost with E-Scooter by Machine Learning Algorithms. Applied Sciences, 12(23), 12266. https://doi.org/10.3390/app122312266

Jangra, K. K., Grover, S., & Aggarwal, A. (2012). Optimization of multi machining characteristics in WEDM of WC-5.3%Co composite using integrated approach of Taguchi, GRA and entropy method. Frontiers of Mechanical Engineering, 7(3), 288–299. https://doi.org/10.1007/s11465-012-0333-4

Kanlayasiri, K., & Boonmung, S. (2007). Effects of wire-EDM machining variables on surface roughness of newly developed DC 53 die steel: Design of experiments and regression model. Journal of Materials Processing Technology, 192–193, 459–464. https://doi.org/10.1016/j.jmatprotec.2007.04.085

Klocke, F., Welling, D. R., Klink, A., Veselovac, D., Nöthe, T., & Perez, R. (2014). Evaluation of Advanced Wire-EDM Capabilities for the Manufacture of Fir Tree Slots in Inconel 718. Procedia CIRP, 14, 430–435. https://doi.org/10.1016/j.procir.2014.03.039

Kumar, A., & Pradhan, M. K. (2022). EDM Process Optimization of Machining Parameters for Through Hole Making on HCHCR AISI-D7 Steel Using RSM. In Springer eBooks (pp. 179–195). https://doi.org/10.1007/978-981-16-8341-1_15

Kumar, S., Varol, T., Canakci, A., Kumaran, S. T., & Uthayakumar, M. (2021a). A review on the performance of the materials by surface modification through EDM. International Journal of Lightweight Materials and Manufacture, 4(1), 127–144. https://doi.org/10.1016/j.ijlmm.2020.08.002

Kumar, S., Varol, T., Canakci, A., Kumaran, S. T., & Uthayakumar, M. (2021b). A review on the performance of the materials by surface modification through EDM. International Journal of Lightweight Materials and Manufacture, 4(1), 127–144. https://doi.org/10.1016/j.ijlmm.2020.08.002

Li, L., Zhao, L., Li, Z. B., Feng, L., & Bai, X. (2016). Surface characteristics of Ti-6Al-4V by SiC abrasive-mixed EDM with magnetic stirring. Materials and Manufacturing Processes, 32(1), 83–86. https://doi.org/10.1080/10426914.2016.1151043

Lodhi, B. K., & Agarwal, S. K. (2014). Optimization of Machining Parameters in WEDM of AISI D3 Steel Using Taguchi Technique. Procedia CIRP, 14, 194–199. https://doi.org/10.1016/j.procir.2014.03.080

Mahesh, K., Philip, J. T., Joshi, S. R., & Kuriachen, B. (2021). Machinability of Inconel 718: A critical review on the impact of cutting temperatures. Materials and Manufacturing Processes, 36(7), 753–791. https://doi.org/10.1080/10426914.2020.1843671

Ming, W., Zhang, Z., Wang, S., Zhang, Y., & Shen, F. (2019). Comparative study of energy efficiency and environmental impact in magnetic field assisted and conventional electrical discharge machining. Journal of Cleaner Production, 214, 12–28. https://doi.org/10.1016/j.jclepro.2018.12.231

Mohanty, S. R., Routara, B. C., Nanda, B., Das, D., & Sahoo, A. (2018). Study of machining characteristics of Al-SiCp12% composite in nano powder mixed dielectric electrical discharge machining using RSM. Materials Today: Proceedings, 5(11), 25581–25590. https://doi.org/10.1016/j.matpr.2018.10.365

Mohapatra, K. D., Satpathy, M. P., & Sahoo, S. K. (2020). Optimisation of WEDM parameters in a gear cutting process using MOORA-based GA. International Journal of Process Management and Benchmarking, 10(1), 99. https://doi.org/10.1504/ijpmb.2020.104234

Muthukumar, V., Rajesh, N., Venkatasamy, R., Sureshbabu, A., & Senthilkumar, N. (2014). Mathematical Modeling for Radial Overcut on Electrical Discharge Machining of Incoloy 800 by Response Surface Methodology. Procedia Materials Science, 6, 1674–1682. https://doi.org/10.1016/j.mspro.2014.07.153

Natarajan, K., Ramakrishnan, H., Gacem, A., Vijayan, V., Karthiga, K., Ali, H. E., Prakash, B., & Mekonnen, A. (2022). Study on Optimization of WEDM Process Parameters on Stainless Steel. Journal of Nanomaterials, 2022, 1–7. https://doi.org/10.1155/2022/6765721

Newton, T. H., Melkote, S. N., Watkins, T. R., Trejo, R. M., & Reister, L. (2009). Investigation of the effect of process parameters on the formation and characteristics of recast layer in wire-EDM of Inconel 718. Materials Science and Engineering A-structural Materials Properties Microstructure and Processing, 513–514, 208–215. https://doi.org/10.1016/j.msea.2009.01.061

Prabhu, S., & Vinayagam, B. K. (2016). Multiresponse Optimization of Edm Process with Nanofluids Using Topsis Method and Genetic Algorithm. Archive of Mechanical Engineering, 63(1), 45–71. https://doi.org/10.1515/meceng-2016-0003

Prasad, A. D., Ramji, K., & Datta, G. L. (2014). An Experimental Study of Wire EDM on Ti-6Al-4V Alloy. Procedia Materials Science, 5, 2567–2576. https://doi.org/10.1016/j.mspro.2014.07.517

Rahul, Datta, S., Biswal, B. B., & Mahapatra, S. S. (2017). Electrical discharge machining of Inconel 825 using cryogenically treated copper electrode: Emphasis on surface integrity and metallurgical characteristics. Journal of Manufacturing Processes, 26, 188–202. https://doi.org/10.1016/j.jmapro.2017.02.020

Rajyalakshmi, G., & Ramaiah, P. V. (2013). Multiple process parameter optimization of wire electrical discharge machining on Inconel 825 using Taguchi grey relational analysis. The International Journal of Advanced Manufacturing Technology, 69(5–8), 1249–1262. https://doi.org/10.1007/s00170-013-5081-z

Ramakrishnan, R., & Karunamoorthy, L. (2005a). Multi response optimization of wire EDM operations using robust design of experiments. The International Journal of Advanced Manufacturing Technology, 29(1–2), 105–112. https://doi.org/10.1007/s00170-004-2496-

Ramakrishnan, R., & Karunamoorthy, L. (2005b). Multi response optimization of wire EDM operations using robust design of experiments. The International Journal of Advanced Manufacturing Technology, 29(1–2), 105–112. https://doi.org/10.1007/s00170-004-2496-

Ramakrishnan, R., & Karunamoorthy, L. (2005c). Multi response optimization of wire EDM operations using robust design of experiments. The International Journal of Advanced

Manufacturing Technology, 29(1–2), 105–112. https://doi.org/10.1007/s00170-004-2496-

Reddy, V., Deepthi, N., & Jayakrishna, N. (2015). Multiple Response Optimization of Wire EDM on Aluminium HE30 by using Grey Relational Analysis. Materials Today: Proceedings, 2(4–5), 2548–2554. https://doi.org/10.1016/j.matpr.2015.07.201

Saedon, J., Jaafar, N., Yahaya, M. F., Saad, N. H., & Kasim, M. S. (2014). Multi-objective Optimization of Titanium Alloy through Orthogonal Array and Grey Relational Analysis in WEDM. Procedia Technology, 15, 832–840. https://doi.org/10.1016/j.protcy.2014.09.057

Shivade, A. S., & Shinde, V. D. (2014). Multi-objective optimization in WEDM of D3 tool steel using integrated approach of Taguchi method & Grey relational analysis. Manufacturing Engineering, 10(4), 149–162. https://doi.org/10.1007/s40092-014-0081-7

Singh, V., Bhandari, R. K., & Yadav, V. K. (2016). An experimental investigation on machining parameters of AISI D2 steel using WEDM. The International Journal of Advanced Manufacturing Technology, 93(1–4), 203–214. https://doi.org/10.1007/s00170-016-8681-

Singh, Y., Singh, Y., Kumar, S., & Sharma, A. (2020). Predictive analysis of surface roughness in EDM using semi-empirical, ANN and ANFIS techniques: A comparative study. Materials Today: Proceedings, 25, 735–741. https://doi.org/10.1016/j.matpr.2019.08.234

Sinha, S., & Chakradhar, D. (2020). Prediction and analysis of process failures by ANN classification during wire-EDM of Inconel 718. Advances in Manufacturing, 8(4), 519–536. https://doi.org/10.1007/s40436-020-00327-w

Srinivasan, V., & Palani, P. (2020). Surface integrity, fatigue performance and dry sliding wear behaviour of Si3N4–TiN after wire-electro discharge machining. Ceramics International, 46(8), 10734–10739. https://doi.org/10.1016/j.ceramint.2020.01.082

Srivastava, A. K., Yadav, S., & Singh, D. K. (2021). Modeling and Optimization of Electric Discharge Machining Process Parameters in machining of Al 6061/SiCp Metal Matrix Composite. Materials Today: Proceedings, 44, 1169–1174. https://doi.org/10.1016/j.matpr.2020.11.235

Swain, N., Venkatesh, V., Kumar, P., Srinivas, G., Ravishankar, S., & Barshilia, H. C. (2017). An experimental investigation on the machining characteristics of Nimonic 75 using uncoated and TiAlN coated tungsten carbide micro-end mills. Cirp Journal of Manufacturing Science and Technology, 16, 34–42. https://doi.org/10.1016/j.cirpj.2016.07.005

Talla, G., Gangopadhyay, S., & Biswas, C. K. (2016). Influence of graphite powder mixed EDM on the surface integrity characteristics of Inconel 625. Particulate Science and Technology, 35(2), 219–226. https://doi.org/10.1080/02726351.2016.1150371

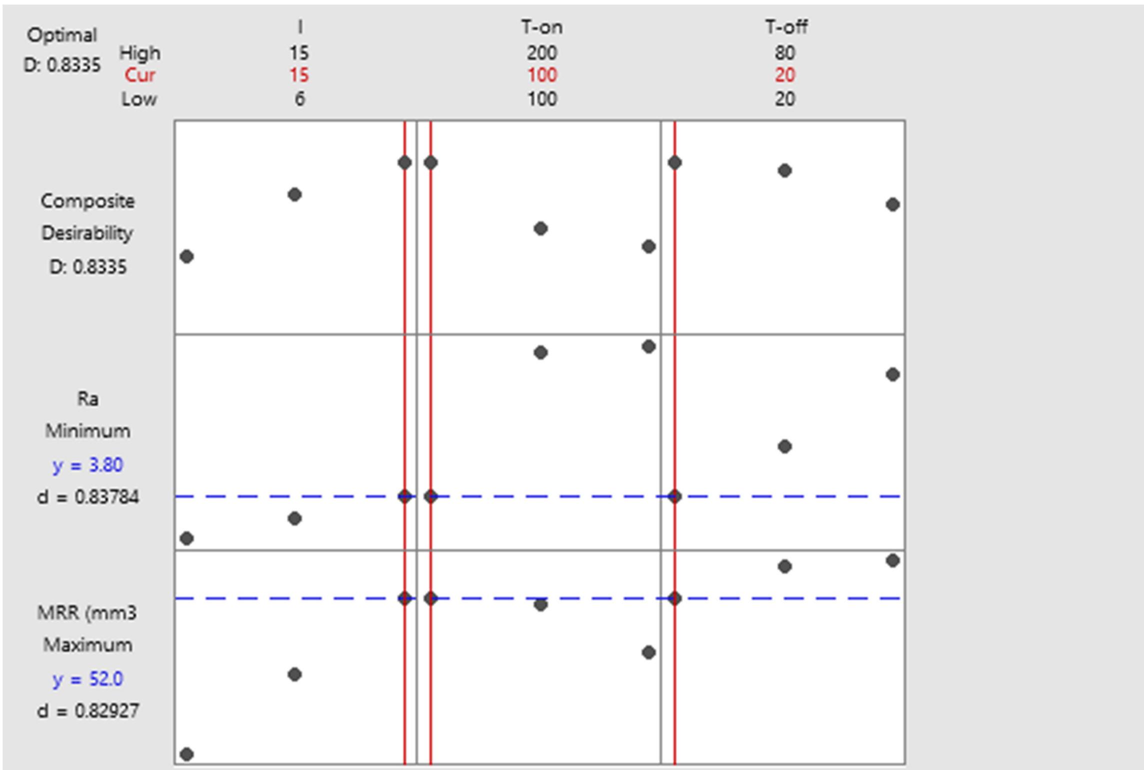
Weichert, D., Link, P., Stoll, A., Rüping, S., Ihlenfeldt, S., & Wrobel, S. (2019). A review of machine learning for the optimization of production processes. The International Journal of Advanced Manufacturing Technology, 104(5–8), 1889–1902. https://doi.org/10.1007/s00170-019-03988-5

Wright, D., Smartt, S. J., Smith, K. W., Miller, P. D., Kotak, R., Rest, A., Burgett, W. S., Chambers, K. C., Flewelling, H., Hodapp, K. W., Huber, M., Jedicke, R., Kaiser, N., Metcalfe, N., Price, P. B., Tonry, J. L., Wainscoat, R. J., & Waters, C. L. (2015). Machine learning for transient discovery in Pan-STARRS1 difference imaging. Monthly Notices of the Royal Astronomical Society, 449(1), 451–466. https://doi.org/10.1093/mnras/stv292

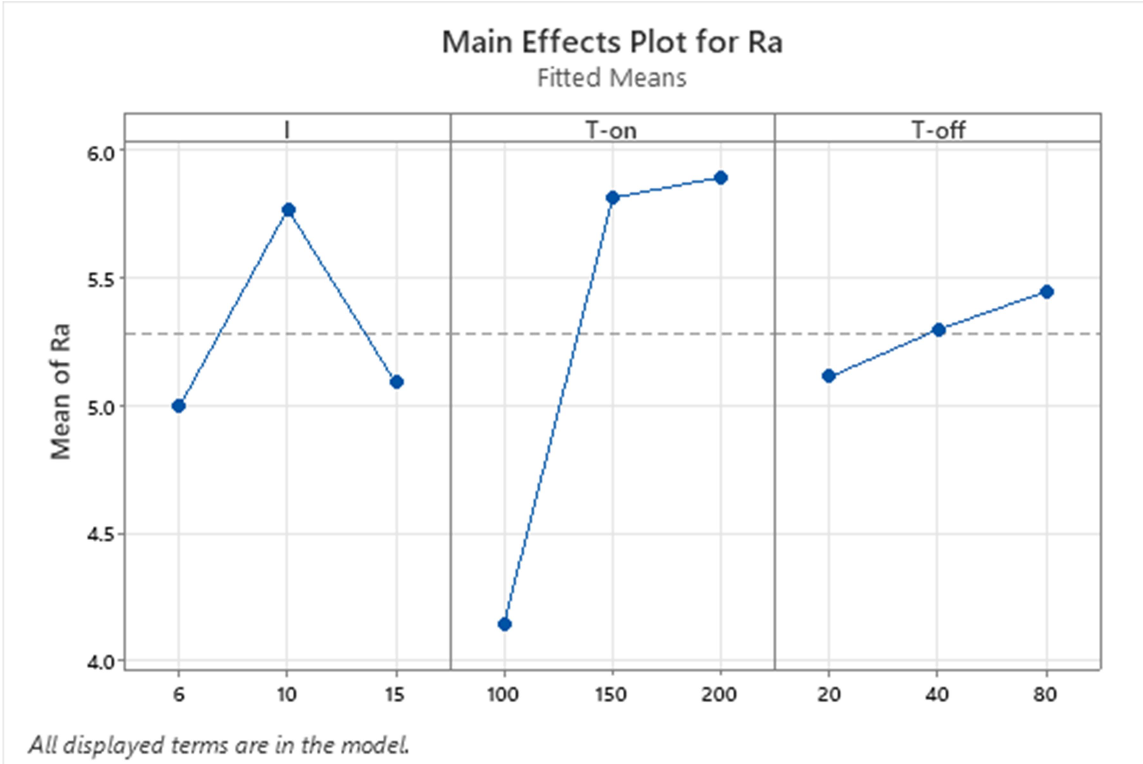
Zakaria, M., Abdullah, R. S. a. R., Kasim, M. S., & Ibrahim, M. N. M. (2019). Enhancing the Productivity of Wire Electrical Discharge Machining Toward Sustainable Production by using Artificial Neural Network Modelling. Emitter International Journal of Engineering Technology, 7(1), 261–274. https://doi.org/10.24003/emitter.v7i1.365

Appendix

A. Response Optimization: Ra, MRR (mm3/min)



B. Factorial Plots for Ra



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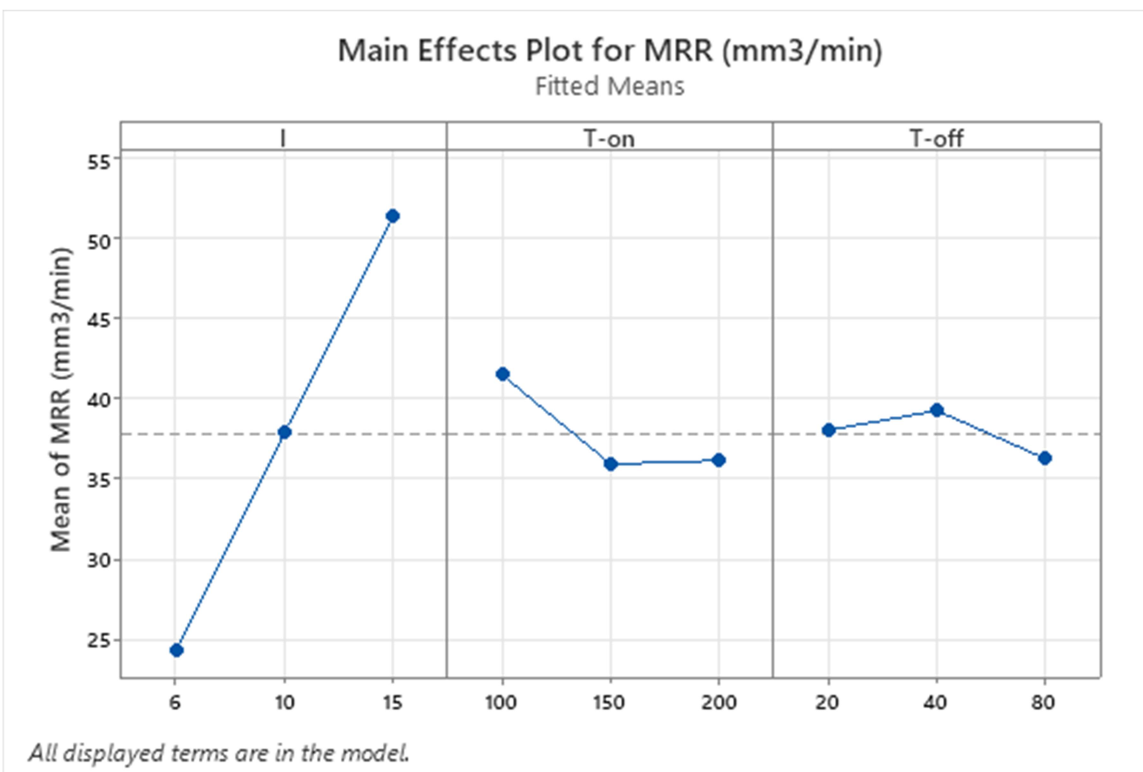
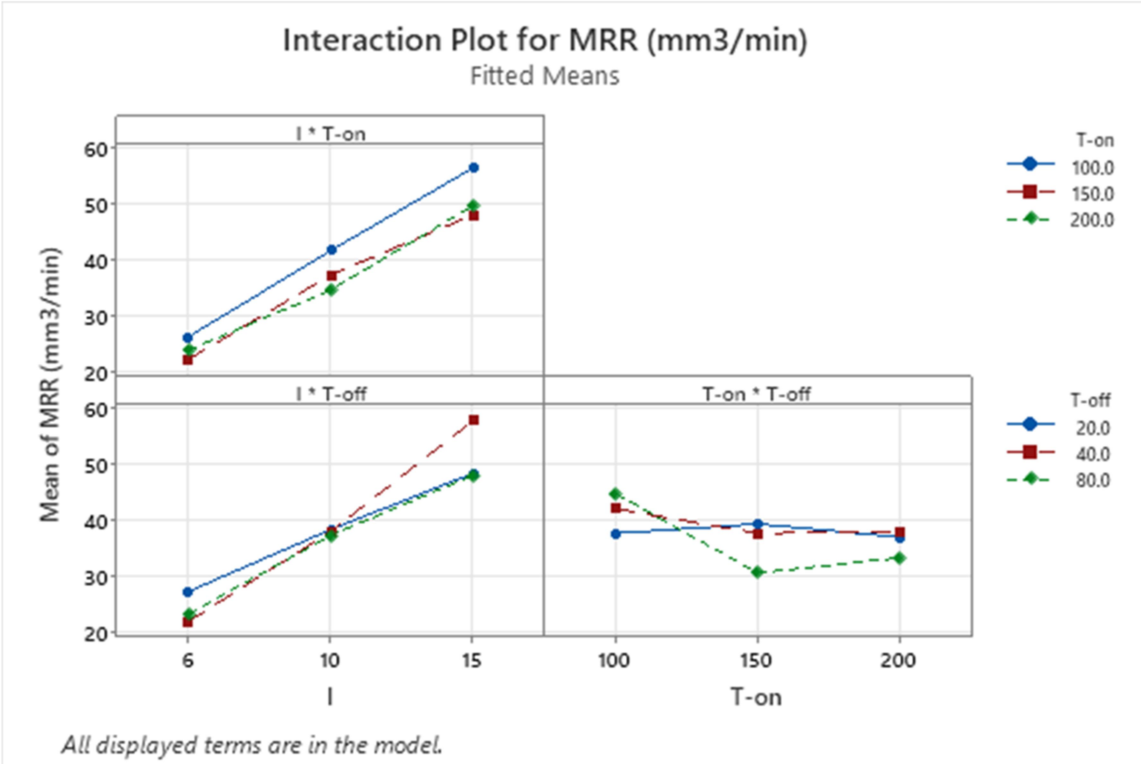
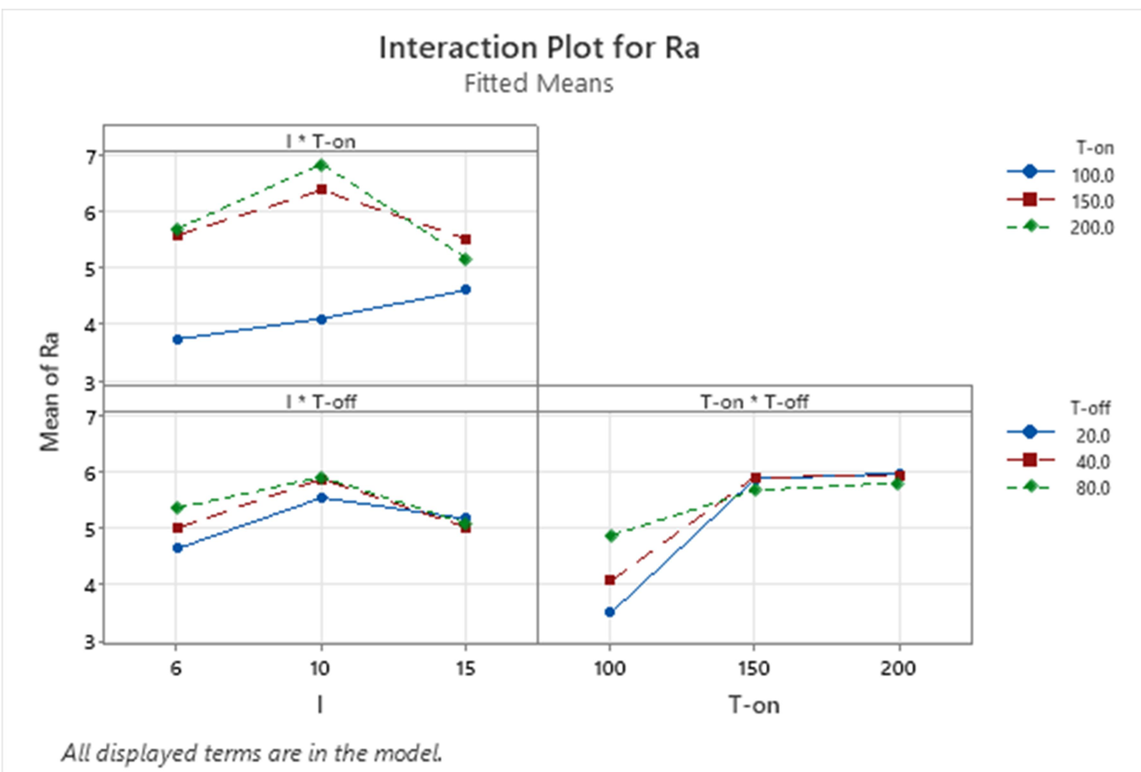
Factorial Plots for MRR (mm3/min)





Interaction Plot for MRR (mm3/min)
Fitted Means
I * T-on
I * T-off
T-on * T-off
T-on
100.0
150.0
200.0
T-off
20.0
40.0
80.0
Mean of MRR (mm3/min)
I
T-on
All displayed terms are in the model.



Interaction Plot for Ra
Fitted Means
I * T-on
I * T-off
T-on * T-off
T-on
100.0
150.0
200.0
T-off
20.0
40.0
80.0
Mean of Ra
I
T-on
All displayed terms are in the model.