

AI-based Instability Monitoring and Process Optimization for Electrical Discharge Machining

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AI-based Instability Monitoring and Process Optimization for Electrical Discharge Machining

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Dedication

To my colleagues, friends, and family.

Abstract

Electrical discharge machining (EDM) is a non-contact manufacturing process that enables the fabrication of complex geometries in electrically conductive materials independent of their mechanical hardness. This makes EDM particularly suitable for machining hard and brittle materials such as cobalt-bonded tungsten carbide (WC-Co), which are widely used in micro-parts, precision molds, and high-performance tooling. However, EDM performance, especially in micro-scale and deep-hole machining, is strongly constrained by discharge instability caused by debris accumulation within the inter-electrode gap. Inadequate debris removal leads to frequent tool retraction, unstable discharge conditions, reduced material removal rate, and increased surface defects. Addressing these challenges requires an understanding of discharge dynamics that cannot be fully captured through conventional static optimization alone.

Chapter 1 presents the motivation and objectives of this research.

Chapter 2 reviews EDM fundamentals, the machining characteristics of WC-Co, powder-mixed and rotary EDM, and recent advancements in sensing and machine learning assisted manufacturing.

Chapter 3 experimentally investigates the effects of adding conductive, semiconductive, and insulating powders to the dielectric during micro-EDM of WC-Co. Although powder addition enhances short-hole machining performance, severe debris accumulation and instability occur during deep micro-hole machining. The roles of tool rotation and statistical optimization are also examined, but these approaches are insufficient to capture the dynamic evolution of instability.

Chapter 4 analyzes electrical discharge waveforms using artificial intelligence (AI)-based methods to identify discharge characteristics associated with instability. Heuristic detection and classification, together with Random Forest and XGBoost models, are employed to extract key features. Subsequently, a low-latency one-dimensional convolutional neural network (1D-CNN) is developed for direct waveform-based discharge classification.

Chapter 5 investigates the dynamic nature of instability through phase-segmented and tem-

poral analysis to evaluate the influence of tool rotation rate. A temporal convolutional network (TCN) is developed for early instability forecasting, and machine-learning-based models are proposed to predict the evolution of machined profiles from waveform features. A control system framework is proposed, and its offline validation is performed.

Chapter 6 presents the overall conclusions of this research. This study demonstrates that integrating waveform-level monitoring with an auxiliary, adaptive tool-rotation strategy enables a robust, generalizable framework for improving machining stability.

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Thank You
Gattu Sai Dutta

List of Achievements

Journal Publications:

- Gattu, S.D., and Yan, J., “Micro Electrical Discharge Machining of Ultrafine Particle Type Tungsten Carbide Using Dielectrics Mixed with Various Powders”, *Micromachines* Vol. 13, No. 7, 998, 20 pages, (2022). <https://doi.org/10.3390/mi13070998>
- Gattu, S.D., Bernardi, L.P., and Yan, J.; “Investigation of the Effect of Tool Rotation Rate in EDM Drilling of Ultrafine Grain Tungsten Carbide Using Predictive Machine Learning”, *Journal of Manufacturing and Materials Processing* Vol. 9, No. 6, 187, 26 pages, (2025). <https://doi.org/10.3390/jmmp9060187>

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Chapter 1

Introduction

1.1. Motivation

Cemented carbides are composite materials produced by powder metallurgy, consisting of hard carbide particles, such as tungsten carbide (WC) or titanium carbide (TiC), embedded in a metallic binder, typically cobalt (Co) or nickel (Ni). The development of cemented carbides originated from the need to replace expensive diamond wire-drawing dies with tungsten-based alternatives. After their successful use in drawing dies, these materials rapidly gained prominence in cutting tools and wear-resistant components [1]. Over time, particularly for tungsten carbide, applications have broadened to include aerospace engineering [2], [3], die manufacturing [4], and the oil and gas industries [5]. More recently, advances in microfabrication techniques have enabled the use of tungsten carbide in precision fields such as surgical instruments [6], biomedical devices [7], and fine jewelry [8].

The widespread industrial use of tungsten carbide can be attributed to its exceptional mechanical and thermal properties, including high hardness, fracture toughness, and Young's modulus [9], as well as a high melting point, excellent thermal conductivity [10], and strong resistance to chemical wear [11]. As industries increasingly demand microscale features, functional surfaces, and high-accuracy micro-mold structures, the limitations of traditional machining become more pronounced.

Electrical discharge machining (EDM), a non-contact thermoelectric material removal process, has therefore become one of the leading manufacturing methods for shaping and microstructuring. Its ability to machine hard, brittle materials with complex geometries makes it suitable for dies, micro-tools, and precision mold fabrication. Despite these advantages, EDM remains constrained by low material removal rate, high tool wear, unstable discharge behavior, and significant dielectric consumption. These challenges are magnified when machining ultrafine-grain WC-Co, where thermal and microstructural characteristics intensify issues such

as micro-cracking, debris accumulation, and recast formation.

Over the past decade, the emergence of Industry 4.0 has brought increasing emphasis on data-driven, connected, and adaptive manufacturing systems. In the context of EDM, this shift highlights the need for real-time sensing and intelligent decision-making that can interpret discharge behavior as machining conditions evolve. At the same time, longstanding challenges in EDM, such as unstable discharges, inefficient debris evacuation, and the need for post-processing, demand a deeper understanding of discharge mechanisms and the use of methods such as dielectric mixed with powder and surfactant, or tool vibration and rotation. Addressing these challenges ultimately requires integrating insights from process physics with signal-based models that can monitor and predict process states during machining.

This thesis is motivated by the need to understand the underlying causes of instability in EDM by linking process physics and the effects of operating parameters to micro-scale discharge behavior through data-driven modeling.

1.2. Objective and Significance of this Research

A fundamental distinction between EDM and conventional machining processes lies in the way tool motion is governed. Instead of following explicitly commanded trajectories, the tool position in EDM is regulated by a servo system that continuously adjusts the inter-electrode gap to maintain suitable discharge conditions. This gap-dependent actuation is essential for preventing arcing and short-circuiting and tightly links tool motion to the evolving discharge environment. As a consequence, machining outcomes such as material removal rate, tool wear, and surface quality exhibit significant variability, driven by the stochastic nature of plasma formation, debris transport, bubble dynamics, and transient gap evolution.

Traditional parameter-optimization approaches (e.g., Taguchi or ANOVA) provide valuable insights under fixed conditions but cannot capture the dynamic behavior of the discharge environment as machining progresses. A more advanced strategy requires real-time interpretation of waveform characteristics, early detection of instability, and predictive modeling that supports adaptive control.

The objective of this research is to develop a multi-level framework that links fundamental

process investigation, parameter studies, and data-driven modeling to support instability monitoring in EDM. The study aims to:

- Investigate micro-EDM configurations, including powder-mixed EDM to clarify their influence on discharge stability, gap behavior, and crater formation, and to identify the strengths and limitations in deep hole machining.
- Examine rotary-EDM at the macro scale and perform statistical parameter analysis using Taguchi-Grey methods to identify influential variables governing machining performance and stability.
- Develop supervised machine-learning models capable of learning the composition, evolution, and distinguishing characteristics of unstable machining zones in rotational EDM.
- Build predictive models that can anticipate the onset of instability with short-window waveform input and interpret how changes in rotation rate influence the development and recovery of unstable regimes.
- Integrate these insights into a high-level conceptual framework for adaptive, waveform-guided control of EDM, outlining how predictive information can be used to support real-time decision-making as well as evaluation for other configurations.

The significance of this research lies in advancing EDM from a predominantly empirical process to a predictive, intelligent machining system. By combining mechanistic insight, statistical modeling, and temporal machine-learning approaches, the framework aims to improve machining stability, reduce post-processing requirements, and support better energy and resource efficiency, key goals for sustainable and next-generation manufacturing.

1.3. Structure of this Thesis

The remainder of this thesis is organized as follows:

- **Chapter 2** provides a literature review of EDM fundamentals, machinability of tungsten carbide, process challenges, and optimization methods. It also surveys in-process sensing and machine-learning approaches, and identifies research gaps that motivate this thesis.

- **Chapter 3** examines machining behavior, including powder-mixed EDM and parameter-optimization techniques. The chapter clarifies why shallow-hole improvements do not extend to deep-hole machining and highlights the limitations of traditional optimization for capturing dynamic behavior.
- **Chapter 4** develops intelligent process-modelling methods using waveform-derived features. It introduces rule-based discharge classification, Random Forest/XGBoost instability prediction, and a robust 1D-CNN waveform classifier that generalizes across rotation and replaces manual detection.
- **Chapter 5** expands the analysis into dynamic modelling. Phase segmentation is used to interpret rotation-dependent behavior, and a Temporal Convolutional Network (TCN) is used to predict early instability. Models for tool-position estimation and machined-profile prediction are introduced, forming the basis of an adaptive rotation-control framework.
- **Chapter 6** summarizes the overall findings and discusses future directions toward real-time adaptive EDM control.

The flowchart of this thesis is shown in Figure 1-1.

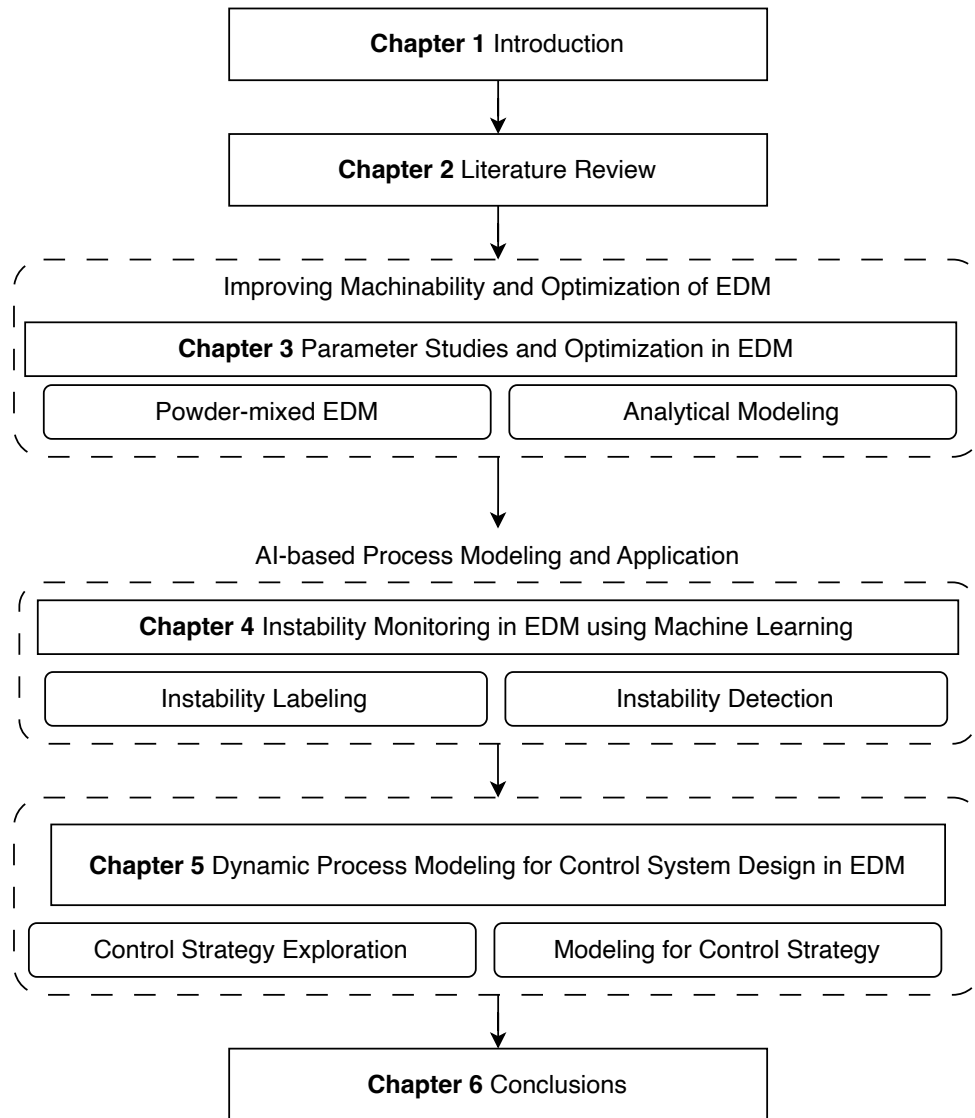


Figure 1-1: Thesis flowchart

Chapter 2

Literature Review and EDM Instability

This chapter outlines the fundamental phenomena and key technological developments in electrical discharge machining (EDM). It reviews the causes of discharge instability and explains why instability is particularly critical in the EDM of ultrafine tungsten carbide (WC-Co). The chapter then summarizes common optimization and process-modeling approaches. Finally, it discusses why data-driven methods are increasingly required to capture the dynamic nature of instability.

2.1. Mechanism of EDM

Electric discharge machining (EDM) is a non-contact, subtractive manufacturing process in which material is removed through localized thermoelectric erosion caused by a series of high-frequency electrical discharges. The method operates on the principle of dielectric breakdown between two conductive electrodes: the tool (typically made of copper or graphite) and the workpiece (commonly composed of hard alloys, carbides, or steels). Both electrodes are submerged in a dielectric fluid, such as mineral oil or deionized water, which serves as an electrical insulator, coolant, and flushing medium for debris removal [12].

Microscopically, all surfaces exhibit asperities; microscopic peaks and valleys arising from surface roughness (Figure 2-1(a)). When a voltage is applied across the two electrodes, namely, the anode and the cathode, charge localization occurs on their surfaces (Figure 2-1(b)). As the electrodes approach each other, the local electric field intensifies at these asperities. When the inter-electrode gap is reduced to a critical distance (d_{br}), the field strength within the dielectric exceeds its breakdown limit. At the point of minimum separation, ionization of the dielectric begins, forming a transient, low-resistance plasma channel between the tool and the workpiece (Figure 2-1(c)). The rapid flow of high-energy electrons and ions within this channel converts electrical energy into heat, raising the localized temperature to approximately 8,000-20,000 K [13], depending on the applied conditions. This intense heat melts and partially va-

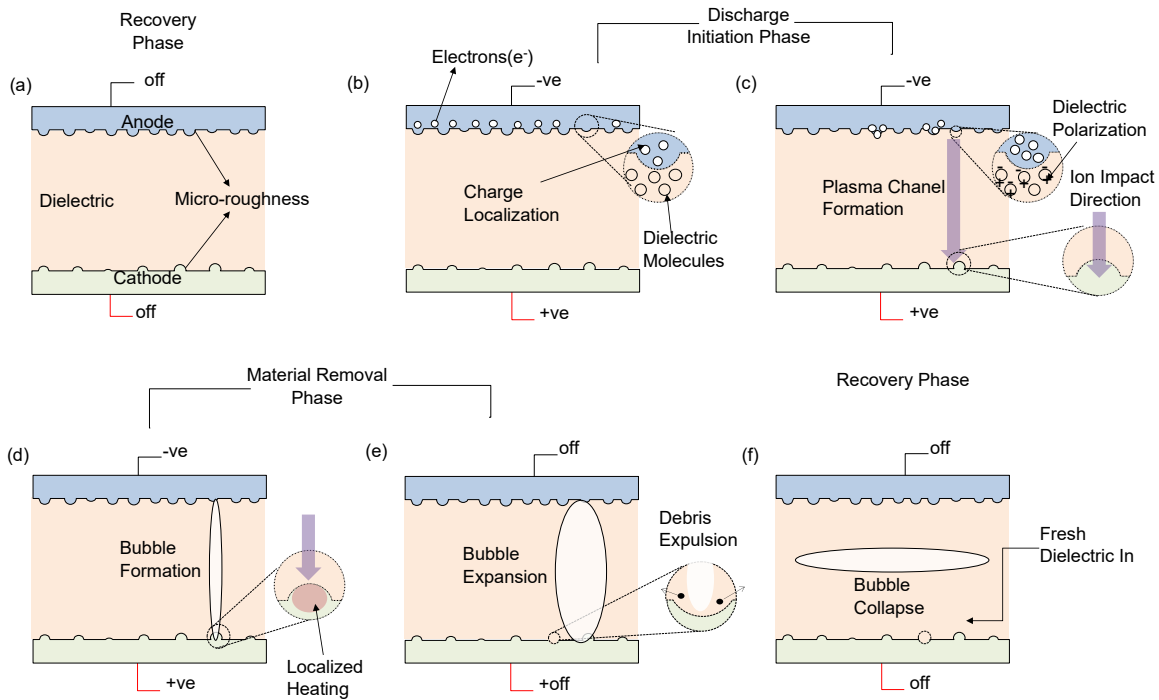


Figure 2-1: Mechanism of EDM.

porizes a minute volume of material from both the tool and the workpiece, as well as a small portion of the dielectric, resulting in the formation of a gaseous bubble (Figure 2-1(d)).

When the discharge terminates, the plasma channel collapses, and the surrounding dielectric rapidly quenches the molten region, causing the ejected material to solidify into fine, spherical debris particles suspended in the fluid (Figure 2-1(e)). As the vapor bubble cools and collapses, fresh dielectric flows into the gap, restoring the insulation strength and preparing the system for the subsequent discharge (Figure 2-1(f)). Repeating these discrete discharge cycles produces a series of overlapping craters on the workpiece surface, gradually forming the desired geometry.

The spark generation, material melting, and debris evacuation occur on a microsecond timescale (1-100 μ s), with discharge gaps typically in the range of 10-100 μ m. Consequently, EDM is a highly complex multiphysics process governed by the coupled interactions of electrical, thermal, and fluid dynamic phenomena [14]. Each discharge event involves rapid phase transitions among solid, liquid, and gaseous states within a confined region, followed by equally rapid cooling and solidification. The resulting transient behaviour makes accurate modeling and control of the process challenging. As a result, extensive experimental and numerical studies

continue to investigate these interdependent mechanisms to better understand plasma evolution, bubble dynamics, and material removal in EDM.

For sustained, stable machining, maintaining the appropriate dielectric gap is essential. The dielectric fluid not only insulates the electrodes but also helps remove debris from the discharge zone. If debris is not effectively flushed out, localized discharges may occur repeatedly in the same region, leading to uneven erosion, surface damage, and potential short-circuiting. Conversely, if the gap becomes too large, the electric field strength may be insufficient to initiate discharges, thereby reducing the machining rate. Therefore, achieving an optimal balance between dielectric breakdown and gap recovery is crucial for stable and efficient EDM operation.

2.2. Advances in EDM Technology

Efficient EDM operation requires discharge frequencies in the range of 10^3 - 10^6 Hz to maintain a high material removal rate. Since its invention during the Second World War by B. R. Lazarenko and colleagues [15], EDM technology has advanced significantly, driven by improvements in power supply design, servo control, and signal processing. Modern EDM systems enable precise control of voltage, current, and pulse durations, as well as automated adjustment of the electrode gap [16], [17]. These developments have allowed researchers to predict discharge behaviour, debris motion, and material removal more accurately, facilitating the modeling of machined profiles and surfaces, and the optimization of process parameters.

EDM machines are broadly categorized into two configurations: wire-EDM (WEDM) and die-sinking EDM. In WEDM, a tensioned, continuously fed wire, typically made of brass or copper, acts as the electrode to cut two-dimensional contours or three-dimensional profiles. Because wires as fine as 0.01 mm can be employed, this technique offers exceptional precision and is widely used for intricate component geometries.

In contrast, die-sinking EDM is primarily used to produce molds and dies with complex cavities, particularly for glass and plastic molding [18], [19]. In this process, a pre-fabricated electrode is immersed together with the workpiece in a dielectric medium, usually mineral oil. Material removal occurs as the electrode discharges replicate its geometry onto the workpiece

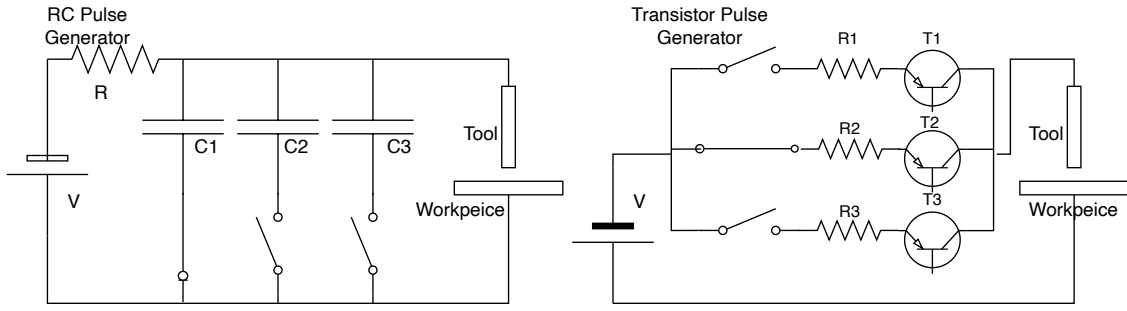


Figure 2-2: Schematic of electrical connections in RC circuit and transistor circuit EDM.

surface, making die-sinking EDM an economical method for batch fabrication and replication of detailed shapes. Both configurations rely on precise servo mechanisms to maintain a consistent inter-electrode gap and stable discharges, ensuring dimensional accuracy and repeatability.

Most EDM machines use one of two electrical systems to generate discharge pulses: resistor-capacitor (RC) or transistor (pulse-controlled) circuits. RC systems use a capacitor in parallel with the electrode circuit, whose discharge characteristics are determined by the capacitor's charge-discharge cycle. The voltage across an RC circuit varies exponentially with time, described by Equation 2.1,

$$Q(t) = CV(1 - e^{-t/RC}) \quad (2.1)$$

where Q is the instantaneous charge, C is the capacitance, V is the open-circuit voltage, and R is the circuit resistance. This behaviour allows the generation of very short discharge pulses suitable for micro-scale machining.

Transistor-based systems, on the other hand, use a combination of power transistors arranged in series to the electrode circuit. These systems provide robust control over pulse characteristics by adjusting pulse shape and pulse on and pulse off durations. Although extremely short pulse durations are difficult to achieve due to transistor switching limitations, multiple transistors can be combined to deliver high discharge currents. The general schematic of electrical connections in typical RC and transistor EDM systems is shown in Figure 2-2.

Because of these characteristics, RC circuits are typically employed in micro-EDM to produce burr-free micro-holes. In contrast, transistor circuits are preferred for high-volume machining where tool wear must be minimized [20]. The discharge energy of an RC circuit is

given by

$$E_{RC} = \frac{1}{2} C V^2 \quad (2.2)$$

, and for a transistor circuit by

$$E_T = VI \frac{T_{on}}{T_{on} + T_{off}} \quad (2.3)$$

where I is the discharge current and T_{on} and T_{off} represent the pulse-on and pulse-off times, respectively.

A summary of keywords and key research areas in EDM over the past decade (2015-2025) is presented in Figure 2-3. Because EDM is a well-established manufacturing process, a substantial portion of published work has focused on process optimization, particularly using design of experiments (DoE) using Taguchi designs along with statistical methods such as response surface methodology (RSM) and analysis of variance (ANOVA), with emphasis on improving surface roughness and material removal rate. With the expansion of EDM into biomedical applications [21], [22] and advanced materials, recent studies have increasingly examined new workpiece materials, including composites [23] and specialty alloys [24], [25], [26], beyond traditional hard steels and ceramics. A distinct trend toward miniaturization can also be observed, with growing attention to micro-EDM and, more recently, nano-EDM [27]. In parallel, various enhancement strategies, such as dielectric and tool modifications, and the emerging application of machine learning for process monitoring and control, have been reported.

2.3. Instability in EDM

Most modern EDM systems are equipped with advanced gap-control mechanisms. These systems use real-time feedback to maintain the average discharge voltage close to a reference value, thereby stabilizing the machining process and improving overall accuracy [28]. These systems employ complex combinations of electrical and mechanical feedback to determine thresholds that maintain servo stability. It has been widely reported that the majority of the power consumed by the EDM system is used to maintain the servo system's position within 1 μm accuracy, when the system can oscillate up to 1 mm range in 0.1 sec intervals [12]. Therefore, it becomes paramount to reduce servo overloads by reducing instabilities.

Keywords used in research article in EDM

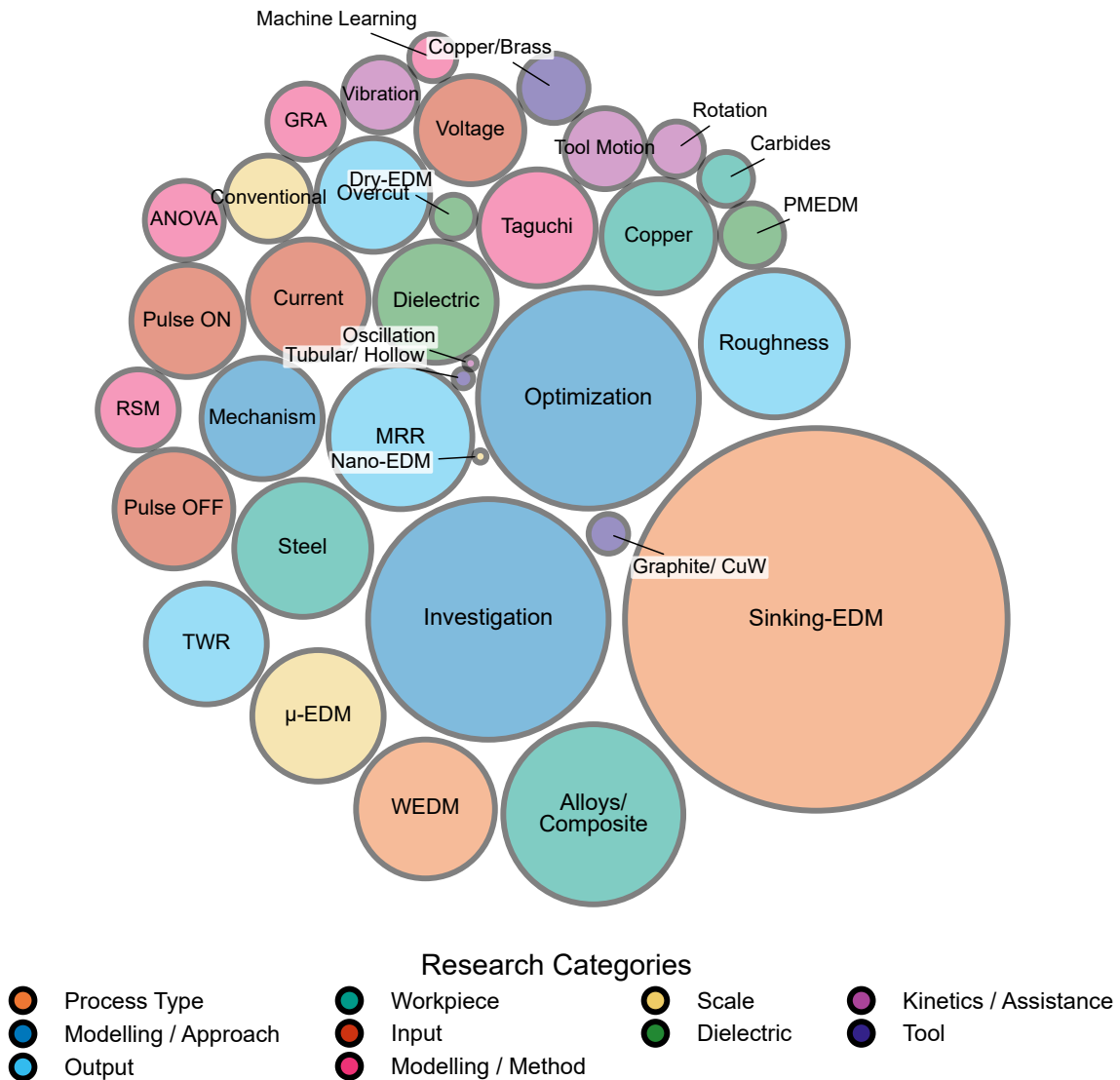


Figure 2-3: Review of research areas in EDM in the last 10 years

EDM instability is characterized by a transition in discharge behavior from well-dispersed, self-recovering sparking to abnormal discharge modes, including sustained arcing, frequent short circuiting, and extended open-circuit intervals. These abnormal conditions reduce machining efficiency, accelerate tool wear, and degrade surface integrity. They become more severe in micro-scale and deep-hole machining, where debris evacuation and dielectric renewal are restricted. An example of comparison of machined surfaces is shown in Figure 2-4(a),(b). In addition to increased surface roughness, macroscopic crack formation and surface distortions can be observed.

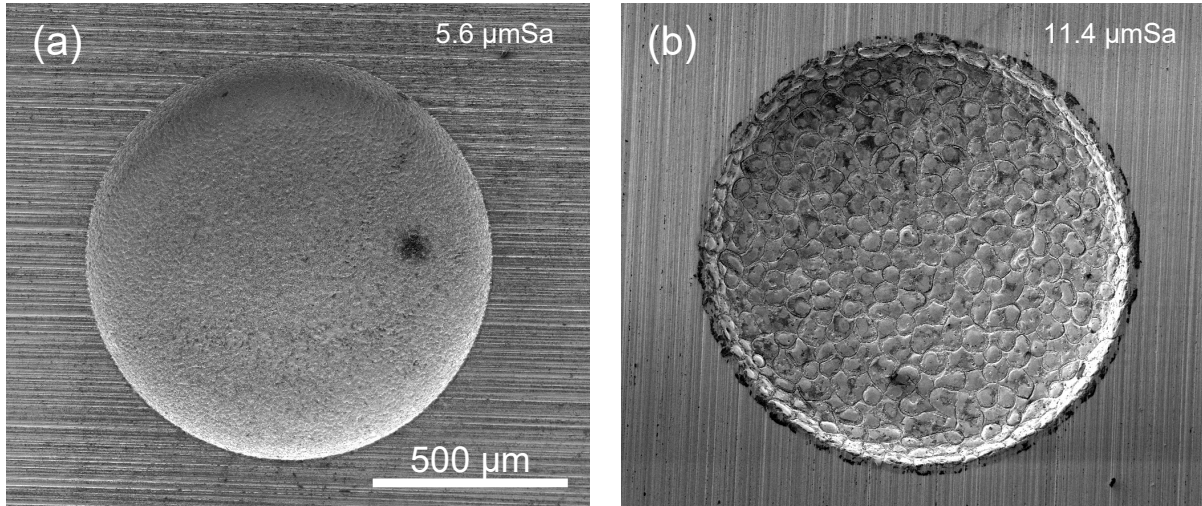


Figure 2-4: Comparison of machined surface after EDM using (a) stable, (b) unstable conditions.

A practical approach to describing instability is to treat the gap as a set of discrete electrical states inferred from gap voltage and current waveforms. Furutani et al. [29] classified the machining gap into six states: open-circuit, charge, normal discharge, continuous arc, abnormal discharge, and short-circuit, and further described plausible transition paths among these states. Their results show that machining performance is closely tied to the fraction of time spent in normal discharge rather than in non-productive or damaging states. This state-based view provides a clear bridge between micro-scale discharge phenomena and macro-scale outcomes such as machining time and removal efficiency.

Beyond monitoring, instability must be understood as a dynamic phenomenon whose characteristics change over time and as machining progresses. Wu et al. [30] quantified the ongoing machining condition using a scalar gap-state metric derived from the ratio of undesirable pulses (stable arc(τ_{arc}) and short pulses(τ_{sd})) to total pulses(τ_{total}), and demonstrated that uncontrolled variation in gap states can drive oscillatory control actions that further promote arcing. They emphasized that EDM conditions vary throughout a process due to time-varying gap contamination and changing chip concentration, motivating adaptive control strategies that explicitly account for stability while pursuing fast machining.

These studies collectively suggest two key insights: (i) instability can be meaningfully represented using discharge-state composition and its temporal evolution, and (ii) because gap conditions evolve, effective mitigation requires dynamic adaptation rather than purely offline

parameter optimization.

2.4. Ultrafine-type Tungsten Carbide

Recent advances in powder metallurgy have enabled the production of ultrafine-grained (micro-nano-sized) cemented carbides, where the average tungsten carbide particle size is typically below 1 μm [31]. Such ultrafine WC-Co materials exhibit markedly improved mechanical properties compared with conventional grades [32]. The reduction in grain size increases the grain-boundary area, thereby restricting dislocation motion and enhancing hardness according to the Hall-Petch relationship [33]. As a result, materials produced from nanosized powders can achieve hardness values over 2000-2500 HV while maintaining excellent dimensional stability [34]. These characteristics make ultrafine WC-Co particularly attractive for applications that demand superior wear resistance and surface precision, such as micro-dies and forming molds.

In this study, a WC-Co grade containing approximately 6 wt.% cobalt binder was employed. A lower binder content increases hardness and wear resistance at the expense of fracture toughness, a trade-off acceptable for die and mold applications that experience primarily compressive loading with minimal impact stresses [35]. The cobalt binder also enhances oxidation resistance [36] and high-temperature stability, extending the service life of molds subjected to repeated thermal cycles. Furthermore, cobalt exhibits excellent wettability with tungsten carbide particles, producing a uniform microstructure and strong interfacial bonding that contribute to long-term mechanical reliability [37]. For these reasons, WC-6% Co is widely used in precision dies, punches, and wear-resistant inserts where dimensional accuracy and surface finish are critical.

However, the ultrafine microstructure that imparts these desirable properties also increases machining difficulty. The combination of extremely high hardness and reduced toughness makes WC-Co prone to microcracking under mechanical stress [38], rendering conventional machining processes inefficient or impractical. Consequently, non-contact techniques such as electrical discharge machining (EDM), electrochemical machining (ECM) [39], [40], and laser-based processing have been adopted for its fabrication. Owing to its chemical inertness and the

formation of passive polytungstate films on the surface, ECM exhibits poor material removal efficiency when applied to WC-Co. Although laser-assisted turning [41] and laser microstructuring [42] have shown promise for post-processing of micro-molds, EDM remains one of the most widely used methods for preliminary shaping and surface generation due to its versatility, geometric accuracy, and ability to machine complex features.

2.5. EDM of Tungsten Carbide

As discussed in the previous section, electrical discharge machining (EDM) of tungsten carbide is a highly effective method because it allows machining without direct contact between the tool and the workpiece. Consequently, physical properties such as hardness and toughness, which typically hinder conventional machining of ceramic materials, have little influence on the EDM process. Furthermore, several studies have reported that the mechanical forces involved in EDM are incredibly low, enabling the precise fabrication of micro-rods and micro-dies with minimal or negligible tool deflection.

Since EDM is a thermal machining process, machining two-phase materials such as WC-Co is a complex phenomenon. The significant difference in melting points between tungsten carbide grains (above 3000 K) and cobalt binder (around 1420 K) [43] leads to preferential removal of cobalt, which in turn causes the formation of microcracks along the grain boundaries. In ultrafine-grained tungsten carbide, removal of the surrounding cobalt can also result in grain pull-out, similar to that observed during polishing [44], [45], leading to the formation of surface voids and pits. In addition, the high density and thermal conductivity of WC-Co promote the redeposition of molten material on the surface, forming a recast layer with significant residual stress [46]. As a result of these mechanisms, many studies have reported poor surface quality in the EDM of tungsten carbide [47].

Moreover, the high melting point and low thermal diffusivity [48] of tungsten carbide increase the discharge energy requirement for effective melting. In contrast, its high density hinders the removal of molten material from the discharge gap. The accumulation of debris in the inter-electrode gap enhances local conductivity, which promotes arcing and sustained discharges in localized regions. This leads to thermal damage, secondary discharges, and ac-

Keywords used in research article in EDM of Tungsten Carbide

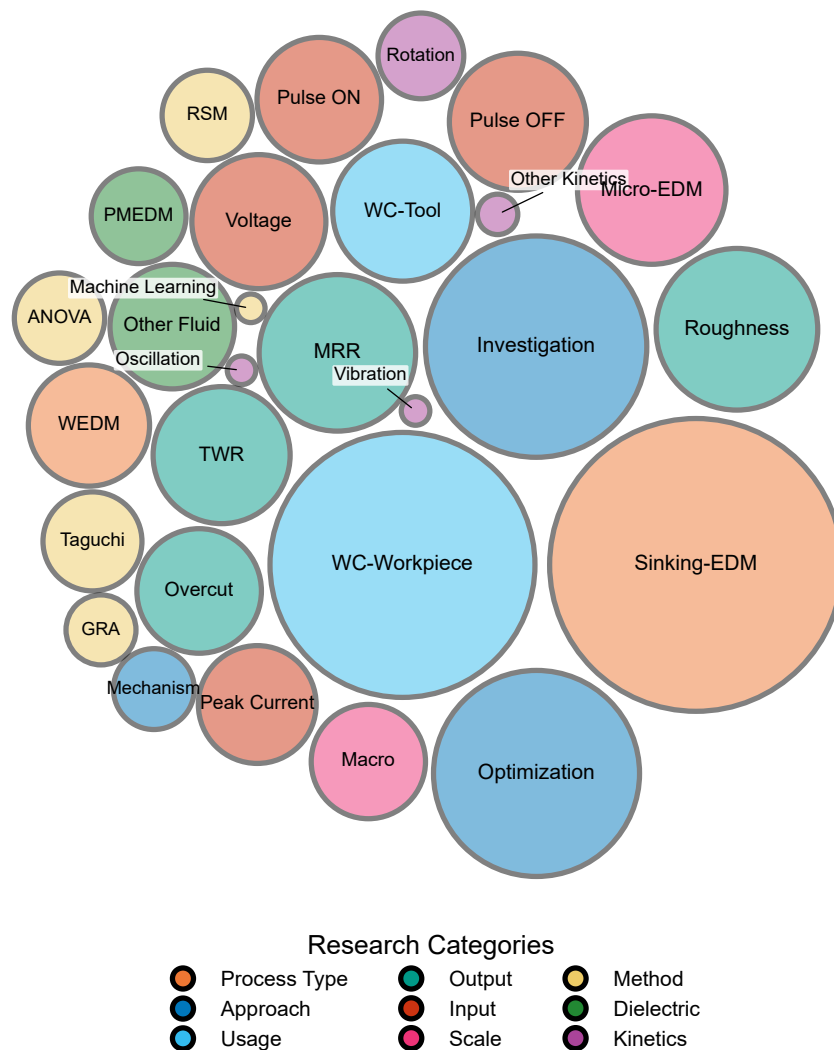


Figure 2-5: Review of research areas in EDM of tungsten carbide

celerated tool wear. Persistent debris accumulation can also cause short circuits, forcing the system to retract the tool to allow fresh dielectric and restore gap conditions. Together, these effects contribute to reduced material removal rate (MRR) and surface quality.

However, the same material properties that challenge machinability can also be advantageous. The combination of low MRR, high hardness, and superior bending strength makes tungsten carbide an ideal material as a micro-tool used in machining other difficult-to-cut materials [49]. This duality is reflected in recent research trends (Figure 2-5), which show a growing interest in using tungsten carbide not only as a workpiece but also as a tool electrode in micro-EDM applications.

Therefore, careful selection of machining parameters is essential for sustainable and high-precision processing of tungsten carbide with acceptable surface quality. Studies generally recommend using low-voltage, high-frequency short pulses to achieve stable discharges and minimize thermal damage. Nonetheless, simultaneously maximizing MRR while minimizing tool wear and surface roughness remains challenging. Consequently, extensive research has been devoted to developing optimization techniques and non-electrical process modifications to address these trade-offs. The use of these optimization strategies in EDM of tungsten carbide, as well as other materials, is discussed in the following section.

2.6. Optimization and Process Modeling in EDM

The primary goal of any manufacturing process is to produce components sustainably, maximizing material processing efficiency while minimizing waste. For parts fabricated using electrical discharge machining (EDM), especially those intended for applications such as glass molding or biomedical devices, post-processing is often required to remove surface defects or to impart specific functional characteristics. By achieving geometrical accuracy and surface quality as close as possible to the desired specifications during the EDM stage, the need for subsequent finishing operations can be significantly reduced. This not only reduces production time and costs but also minimizes errors caused by tool wear and machine calibration. To accomplish these objectives, researchers have proposed several enhancement approaches for EDM:

- Statistical optimization of process parameters to identify their influence on machining responses and determine optimal operating conditions;
- Process enhancement through external assistance, such as modifying tool motion, dielectric composition, or discharge characteristics; and
- Fundamental investigation of discharge phenomena at the micro-scale to better understand the mechanisms governing energy distribution, debris removal, and machining stability.

2.6.1. Statistical and Analytical Modeling

The key performance metrics in electrical discharge machining (EDM) include material removal rate (MRR), tool wear rate (TWR), surface roughness (Sa), and dimensional accuracy indicators such as overcut (OC). For application-specific requirements such as glass molding or medical implants, additional surface integrity measures are also critical, including surface composition [50], microhardness [51], and recast layer thickness [52]. Modern EDM systems provide control over primary process variables: discharge current, gap voltage, polarity, pulse-on and pulse-off durations, duty ratio, and servo feed. Secondary variables such as dielectric type and flow rate, electrode material, and flushing configuration are also commonly adjusted. A brief description of the main parameters follows:

- **Gap voltage (V):** Also known as open-circuit voltage, it is the average inter-electrode voltage that sets the electric-field intensity and, via servo control, the nominal gap distance.
- **Capacitance (C):** In RC micro-EDM, the storage capacitance sets the per-pulse energy $E = \frac{1}{2}CV^2$; increasing C enlarges crater size and MRR but raises tool wear and arcing risk. In transistor systems, added or stray capacitance influences pulse rise time and the effective energy delivered to the gap.
- **Peak current (I_p):** The maximum discharge current during a pulse; strongly influences crater size and MRR.
- **Pulse-on duration (T_{on}):** Time for which the pulse is applied; together with current, it governs discharge energy and removal rate.
- **Pulse-off duration (T_{off}):** Interval between pulses; allows dielectric recovery and debris evacuation, reducing arcing and short-circuits.
- **Duty ratio ($D = \frac{T_{on}}{T_{on}+T_{off}}$):** Fraction of time the pulse is on; controls average power and thermal load.
- **Feed rate:** Servo feed of the tool/workpiece to maintain the gap; retraction during short-circuits restores insulating conditions and stability.

- **Dielectric flow rate:** Volumetric flow through the gap; enhances debris removal and helps stabilize discharges (availability depends on machine configuration).

Most of these variables are highly interdependent, exhibiting complex, nonlinear relationships that make analytical or predictive modeling difficult. Therefore, systematic methods are required to study the influence of individual parameters and their interactions to achieve the desired process outcomes. Over the years, numerous statistical and design of experiments (DoE) approaches have been developed to optimize EDM performance.

Among these, the Taguchi method is one of the most widely adopted techniques. This approach uses a predefined set of experimental conditions based on orthogonal arrays, enabling efficient exploration of parameter combinations, minimizing the total number of experiments. Experimental results are typically analyzed using signal-to-noise ratios (SNRs) to identify conditions that maximize process stability and performance [53]. Because EDM often involves multiple, sometimes conflicting objectives, such as maximizing MRR and dimensional accuracy while minimizing Ra and TWR, researchers have employed multi-objective optimization techniques such as Grey Relational Analysis (GRA) [54], [55] and TOPSIS (Technique for Order of Preference by Similarity to Ideal Solution) [56], [57]. These approaches convert multiple responses into a single measurement value, allowing simultaneous evaluation.

To determine the relative contribution of each parameter, Analysis of Variance (ANOVA) is frequently used. ANOVA quantifies the statistical significance of individual and interactive effects on measured responses such as SNR or Grey Relational Grade (GRG) [58]. Luis et al. [59] and Maniyar et al. [60] have shown that peak current, pulse-on time, and gap voltage are often the dominant factors in increasing MRR of silicon carbide and tungsten carbide, respectively, whereas in micro-EDM, reducing gap voltage and increasing capacitance have the most significant effect on MRR [61]. Additionally, it has been found that tool wear rate can be reduced by using lower peak current and a longer pulse-off duration [62], [63]. Another common statistical method used in EDM research is Response Surface Methodology (RSM) [64], [65], which develops empirical relationships between process variables and output responses using polynomial regression models. Studies have been performed to predict material removal rate and surface roughness with high R^2 values [66], [67].

Although these statistical techniques have greatly enhanced process understanding and efficiency, their applicability to tungsten carbide, particularly for micro-EDM or the generation of micro-parts, remains limited. To address this limitation, subsequent research has focused on improving the discharge formation and progression mechanisms intrinsically, either through tool motion assistance, dielectric modification, or advanced monitoring and control strategies.

2.6.2. Dielectric Modification

A common method of introducing external changes to the EDM process is by altering the properties of the dielectric medium. Since the dielectric serves multiple essential functions, such as maintaining electrical insulation, ensuring uniform discharge distribution, and transporting debris, modifying its physical or chemical characteristics can significantly influence machining performance [68].

The most commonly used EDM dielectrics are deionized water and hydrocarbon-based oils. Deionized water is a cost-effective and environmentally sustainable fluid; however, studies have shown that oxide layers formed on the workpiece surface reduce the material removal rate (MRR), especially in carbides such as WC-Co. Although the resulting surface roughness is often reduced, proper flushing is still required to prevent ionisation. Consequently, water-based EDM systems are primarily limited to wire-EDM, where continuous flushing is possible.

Historically, kerosene has been widely used as a dielectric in die-sinking EDM due to its high MRR, but its low flash point presents a significant industrial safety hazard. In contemporary die-sinking EDM, long-chain mineral oils are more commonly used. Despite their higher viscosity, which hinders flushing, these oils can decompose during discharge, forming a thin pyrolytic carbon layer on the tool surface. Kunieda et al. [12] have shown that this layer can substantially reduce tool wear while maintaining acceptable MRR and surface quality. However, prolonged exposure to additives and decomposition products such as sulfides and nitrates can pose health risks to operators [69], [70].

Recent studies have therefore focused on advanced filtration systems and the development of biodegradable, plant-based dielectric oils as sustainable alternatives [71], [72]. More recently, dry EDM, which uses pressurized gases such as air [73], oxygen [74], or nitrogen [75] as the dielectric medium, has been investigated. Although this approach offers environmen-

tal and economic advantages, its low MRR, often resulting from limited flushing efficiency, currently restricts its use to micro-EDM and finishing applications.

2.6.2.1. Powder-mixed EDM

Another approach is to incorporate micro-nano-sized conductive or semi-conductive powders into the dielectric material. The presence of suspended particles within the discharge gap intensifies the electric field, with its vicinity leading to reduced spark ignition delay and breakdown voltage. These particles often form chains and bridges, resulting in discharges that are well distributed over wider surfaces, often with multiple shallow and narrow craters. These contribute to the effective removal of material with high surface quality. However, careful selection of powder concentration is required. In contrast, a higher particle concentration facilitates discharge formation and increases the formation of unstable arcs or short circuits, which are detrimental to surface quality.

Furthermore, a few studies have focused on optimizing the powder-mixed EDM (PMEDM) of WC-Co using analytical models [76], [77]. Jahan et al. [78] developed a mathematical model of powder behaviour in PMEDM, showing that the presence of conductive additives decreases the dielectric breakdown strength and thereby increases the nominal discharge gap. Numerous experimental investigations have confirmed that powder addition generally widens the discharge gap, which in turn tends to produce a wider yet weaker plasma formed, resulting in wide yet shallow craters (Figure 2-6(a,b)). However, the magnitude of this effect depends strongly on the powder's type, conductivity, concentration, and the dielectric conditions.

Approximate ranges of spark gaps reported across various studies for different powder types in micro-EDM are summarized in Table 2-1 [79]. These values should be considered indicative rather than universal, as they vary with machine configuration, discharge energy, and dielectric composition.

The most commonly used powders in EDM are aluminum (Al) and graphite (Gr). Their high electrical conductivity, low density, availability of particles at the nanoscale, and low hazardous nature make them widely used [80]. However, in recent years, the effects of many other particles, such as silicon (Si) [81], graphene [82], silicon carbide (SiC) [83], molybdenum sulfide (MoS₂) [84], and alumina (Al₂O₃), titanium dioxide (TiO₂)) [85] have also been studied.

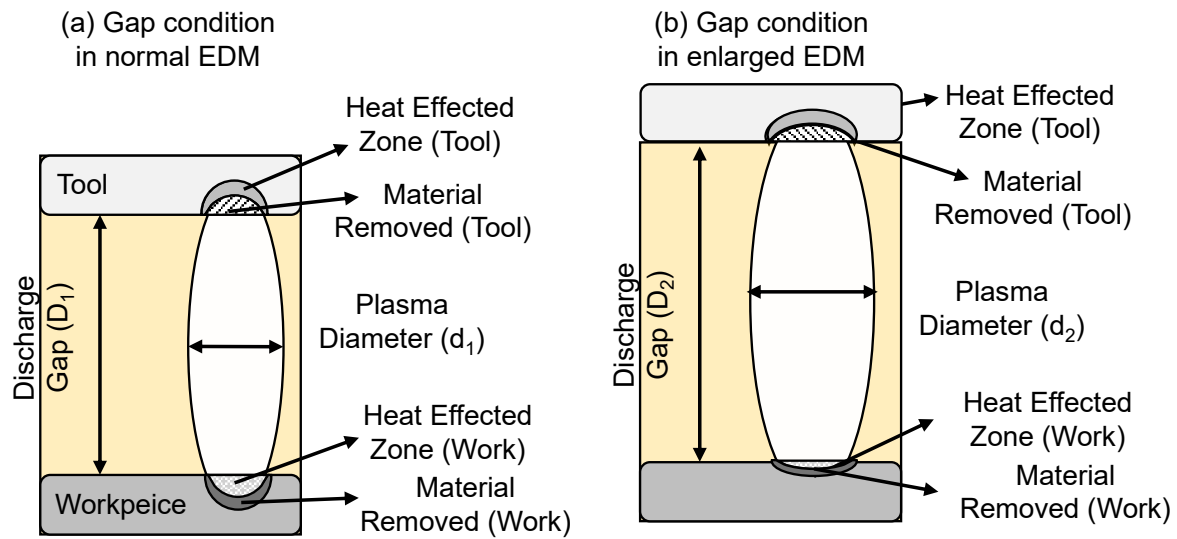


Figure 2-6: Effect of enlarged gap in crater geometry in EDM.

Table 2-1: Spark gaps for different powder-mixed EDM [79]

Powder Type	Spark gap (μm)
No powder	10-15
Graphite	45-50
Silicon	27-33
Aluminum	120-160
Crushed glass	10-15
Silicon Carbide	80-90
Molybdenum Sulphide	44-48

Pecas et al. [86] have shown that under a few conditions (powder concentration of 2 g/L for a 1 mm² electrode), silicon powder addition can generate a mirror surface finish on AISI H13 steel. Liew et al. [87] have used carbon nanofiber-assisted EDM of reaction-bonded silicon carbide (SiC) and have significantly improved material removal and electrode wear rates. Sahu et al. [88], and Jahan et al. [78] have used nano-alumina powder in the EDM of Inconel and tungsten carbide, respectively. They have shown an increase in the material removal rate and a decrease in the surface roughness for specific parametric values.

Although PMEDM has been widely studied, there remains a limited understanding of how recently explored powders influence the machinability of ultrafine-particle WC-Co under micro-EDM conditions. Recent investigations have begun examining environmentally considerate additives such as carbon nanofibers, alumina abrasives, and silicon recovered from wafer-polishing waste. These materials offer distinct physical properties and sustainability benefits,

but their effects on plasma dispersion, gap stability, and crater morphology remain insufficiently characterized.

2.6.2.2. Surfactant-mixed EDM

A key issue in powder-mixed EDM, particularly with nano-sized powders, is the tendency for particles to agglomerate due to their high surface energy, or to settle on the workpiece surface with heavy powders such as tungsten or MoS₂. These problems can be mitigated by employing external ultrasonic homogenizers or mechanical stirrers to maintain a uniform suspension. However, in addition to being expensive, such systems may be ineffective in specific applications, particularly in micro-EDM or when machining deep cavities, where flow circulation is restricted. To overcome these challenges, several studies have recommended adding surfactants to the dielectric fluid. Surfactants reduce surface tension, prevent particle agglomeration, and enhance debris removal from the discharge gap.

The most commonly used surfactants in EDM are lipophilic sorbitan monooleate compounds, commercially known as the SPAN series. Wu et al. [31] reported that, in the EDM of SKD61 steel, mixing SPAN 20 with kerosene increased both the material removal rate (MRR) and machining depth. Although the surface roughness did not increase significantly, a thinner recast layer was observed. This improvement was attributed to enhanced dielectric conductivity and more effective removal of pyrolytic carbon produced during discharges.

More recently, sustainable, biodegradable, hydrophilic polysorbate surfactants, commercially known as the Tween series, have gained attention as environmentally friendly alternatives. Asif et al. studied the effect of Tween series surfactants in the EDM of biomedical titanium alloys and reported significant improvements in MRR and tool wear rate (TWR). However, in most of these applications, the concentration of surfactant required is relatively high, typically in the range of 15-30 g/L.

A more common approach is to use surfactants in combination with powder-mixed EDM. Studies have shown that adding surfactants together with low-density powders such as graphite [89], B₄C [90], or carbon nanofibers [87], as well as with dense powders such as chromium [91] and TC₄ alloy [92], improves both machining efficiency and surface quality. However, there have been no significant studies on surfactant-assisted powder-mixed EDM for tungsten carbide,

leaving an opportunity for further research in this area.

2.6.3. Tool Motion Modification

Rotary EDM, in which the tool rotates during machining, has emerged as an effective strategy to enhance debris flushing, stabilize discharge, and improve machining performance. Studies have reported improvements in material removal rates [93], [94], surface finish [95], and tool life [96] with tool rotation assistance. However, while a moderate increase in rotation rate can enhance performance, at a higher rate the benefits plateau or even diminish [97]. This is due to excessive turbulence or arc formation [98], [99]. However, most rotation rates are in the range of 100-1000 rpm, which complicates selecting the optimal tool rotation rate, especially because differences in machining behavior across rotation rates are often subtle and nonlinear.

2.7. Technology Integrated Machining

Manufacturing is one of the primary contributors to the economy and livelihood of most societies; therefore, there is a continuous drive to improve both productivity and capability. Since the introduction of the term Industry 4.0, there has been a concentrated global effort to enhance the efficiency of manufacturing systems through digitalization and technological integration.

The key driver of this new industrial revolution is the pursuit of sustainable manufacturing systems capable of producing high-quality products and services with fewer or more environmentally sustainable resources. Sustainability encompasses multiple dimensions:

- Social aspects: Operator safety, ergonomics, and skill development.
- Environmental aspects: Energy efficiency, emission reduction, and recycling.
- Economic aspects: Maximizing productivity and maintaining competitiveness.

Technology can support these goals in numerous ways: by optimizing supply chains through blockchain technologies, by employing advanced sensors for real-time process monitoring, by improving training and scheduling systems to enhance operator performance, and by applying data analytics and machine-learning algorithms to analyze processes at both macro- and micro-scales.

2.7.1. In-process Monitoring

One of the key outcomes of Industry 4.0 has been the development and integration of advanced sensor systems in manufacturing processes. With significant advancements in micro-electro-mechanical systems (MEMS) technology, sensors have evolved from purely mechanical components into precise electromechanical systems capable of measuring physical phenomena at micro- and nano-scales [100]. Modern precision sensors can capture variations in force, voltage, temperature, and vibration at timescales below one microsecond, allowing real-time observation of process behavior and more accurate decision-making.

Commonly used sensing technologies in manufacturing include mechanical sensors for measuring cutting forces, torque, or vibration in turning and polishing; thermal sensors for monitoring tool temperatures in cutting or laser machining; acoustic sensors for detecting emissions and chatter; and optical sensors, such as high-speed cameras, for visualizing chip formation or laser plume motion. In electrical processes such as EDM, electrical sensors are predominant because they directly measure current and voltage signals associated with discharge events.

The most widely used form of in-process monitoring in EDM is current- and voltage-waveform analysis. By decomposing these waveforms, it is possible to detect sustained arcing or short-circuiting [101], [102], thereby preventing wire breakage in wire-EDM [103], [104], or severe tool damage in die-sinking EDM. More recently, Kitamura et al. [105] used high-speed cameras with transparent single-crystal SiC plates to study the role and dynamics of gas bubbles in EDM. Similarly, Shitara et al. [106] and Esser et al. [107] have directly observed debris particle motion and discharge locations in vibration-assisted micro-EDM. In contrast, Akematsu et al. [108] investigated the influence of capacitance and plasma shape in high-temperature EDM using thermal imaging.

Several EDM system developers and researchers have also analyzed discharge pulse waveforms to detect patterns and make control decisions, such as tool retraction or parameter adjustment. For EDM processes where electrical event frequencies exceed 10^5 Hz, this vast stream of waveform data offers an exciting opportunity for advanced data analytics and machine-learning-based modeling.

2.7.2. Artificial Intelligence for EDM

In technology-assisted EDM, the focus has shifted from data acquisition to data interpretation and intelligent decision-making. Conventional EDM systems often rely on explicit rule-based or fuzzy control logic to analyze discharge pulse trains and make critical decisions, such as initiating tool retraction or detecting wire breakage. However, these systems depend on pre-defined rules and lack adaptability to the stochastic nature of EDM discharges [109], [110].

In recent years, machine learning (ML) techniques have been increasingly applied to process monitoring and control. Machine learning, a subset of artificial intelligence (AI), enables the identification of underlying patterns in data without explicit human programming. In EDM, ML has been applied in three main areas: (a) identifying relationships between input parameters (e.g., current, voltage, feed rate) and output responses (e.g., MRR, surface roughness); (b) detecting early warning patterns, such as the onset of wire breakage or tool-workpiece contact; and (c) classifying and analyzing discharge waveforms for faster and more accurate identification of normal and abnormal discharges.

Two major categories of machine learning algorithms are commonly used: decision-tree-based models and neural-network-based models. Decision-tree approaches, such as Random Forest and Extreme Gradient Boosting (XGBoost), determine hierarchical decision paths that can classify outcomes (e.g., “stable” vs. “unstable” discharge conditions) or predict performance metrics. In contrast, neural networks, computational systems inspired by the human brain, consist of interconnected layers of nodes that can learn complex, nonlinear relationships from data. These models are particularly effective for processing high-frequency waveform signals and recognizing subtle temporal features associated with EDM process stability.

2.8. Summary

Most prior studies address EDM instability by identifying optimal parameter sets (e.g., voltage, current, and pulse timing) or by modifying controller architectures to maintain an acceptable average gap condition. In parallel, data-driven methods in EDM have often been used for post-process prediction of machining responses, such as material removal rate, surface roughness, and tool wear, using process parameters and limited monitoring signals. Few stud-

ies have explicitly targeted dynamic instability that emerges from time-evolving gap conditions, particularly in micro-scale and deep-hole machining.

The main contribution of this dissertation is a unified framework that links (i) physics-based understanding of gap deterioration and discharge-state behavior, (ii) waveform-derived characterization of micro-scale discharge dynamics through short-duration pattern recognition models, and (iii) an auxiliary mitigation strategy based on adaptive tool-rotation control. This approach complements conventional parameter optimization by operating as an external supervisory layer that interprets discharge behavior and adjusts rotation to improve stability, without requiring proprietary access to the machine controller.

Chapter 3

Parameter Studies and Optimization in EDM

3.1. Introduction

This chapter examines parameter-level optimization approaches for improving EDM of tungsten carbide, focusing on dielectric modification, electrical and servo parameter-level optimization, and the role of tool kinematics. The behavior of particles in powder-mixed EDM is investigated through single-discharge analysis and hole machining under both short-depth and deep-machining conditions. A multi-objective multi-parameter optimization is then performed to identify favourable electrical and servo settings for short-depth machining, followed by an evaluation of how tool rotation rate influences machining performance during deep-hole drilling. Together, these studies outline the strengths and limitations of traditional offline optimization approaches.

3.2. Powder-mixed EDM of Tungsten Carbide

3.2.1. Process Mechanisms of Powder-mixed EDM

During EDM, debris expulsion from the discharge gap is critical to process stability. Debris is generally removed via bubble expansion and dielectric flow [12], [106]. However, debris accumulation from inadequate flushing can lead to secondary discharges, arcing, or short-circuiting. These abnormal discharge conditions necessitate frequent tool backtracking, increasing both machining time and cost. Increasing the discharge gap width facilitates easier dielectric flow and debris removal, thereby promoting process stability.

Before dielectric breakdown, the electrode-workpiece system can be approximated as a parallel-plate capacitor (Figure 3-1(a)). The introduction of a particle transforms the homogeneous dielectric into a multiphase mixture with an effective relative permittivity, ϵ_{eff} . For dilute

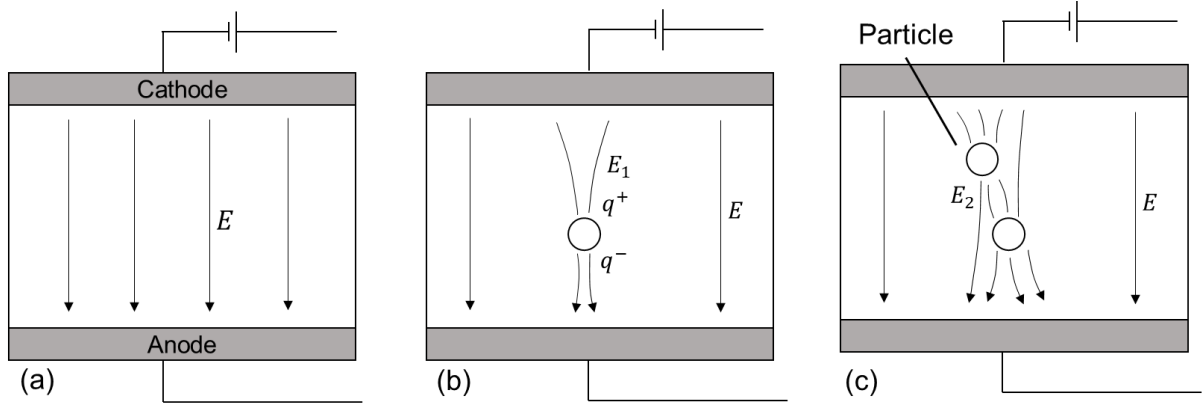


Figure 3-1: Schematic of (a) electric field between electrodes, (b) field distortion due to a single particle, and (c) bridge formation with multiple particles.

suspensions, this is approximated by the Maxwell–Garnett formulation [111]:

$$\varepsilon_{\text{eff}} = \varepsilon_m \frac{2\varepsilon_m + \varepsilon_p - \phi(\varepsilon_p - \varepsilon_m)}{2\varepsilon_m + \varepsilon_p + 2\phi(\varepsilon_p - \varepsilon_m)} \quad (3.1)$$

where ε_m and ε_p are the permittivities of the medium and particles, respectively, and ϕ is the particle volume fraction. Because $\varepsilon_p \gg \varepsilon_m$, the effective permittivity of the gap increases, acting as the primary driver for discharge initiation. At the microscopic level, the permittivity difference in the surrounding induces polarization and charge accumulation (q^+ , q^-) at the particle-dielectric interface. As shown in Figure 3-1(b), this intensifies the local electric flux (E_1), creating highly non-uniform field gradients even at a constant applied voltage [112], [113]. When multiple particles are present, these permittivity-driven gradients promote particle alignment along field lines, creating transient chains or bridges (Figure 3-1(c)). These structures, whether comprised of conductive particles or high-permittivity insulators, further amplify the local field (E_2) and effectively reduce the breakdown path length. Consequently, the dielectric fluid reaches its breakdown strength at a larger nominal interelectrode separation (d), providing a physical explanation for the observed widening of the discharge gap in powder-mixed EDM [78], [87].

The behavior of these particles is governed by the balance of forces within the gap (Figure 3-2(a)), including electromotive (F_e), surface tension (F_γ), and hydrodynamic forces (F_B). As reported by Furutania et al. [114], particles generally exhibit four characteristic behaviors (Figure 3-2b): (a) reciprocation, (b) sedimentation, (c) aggregation, and (d) chain formation.

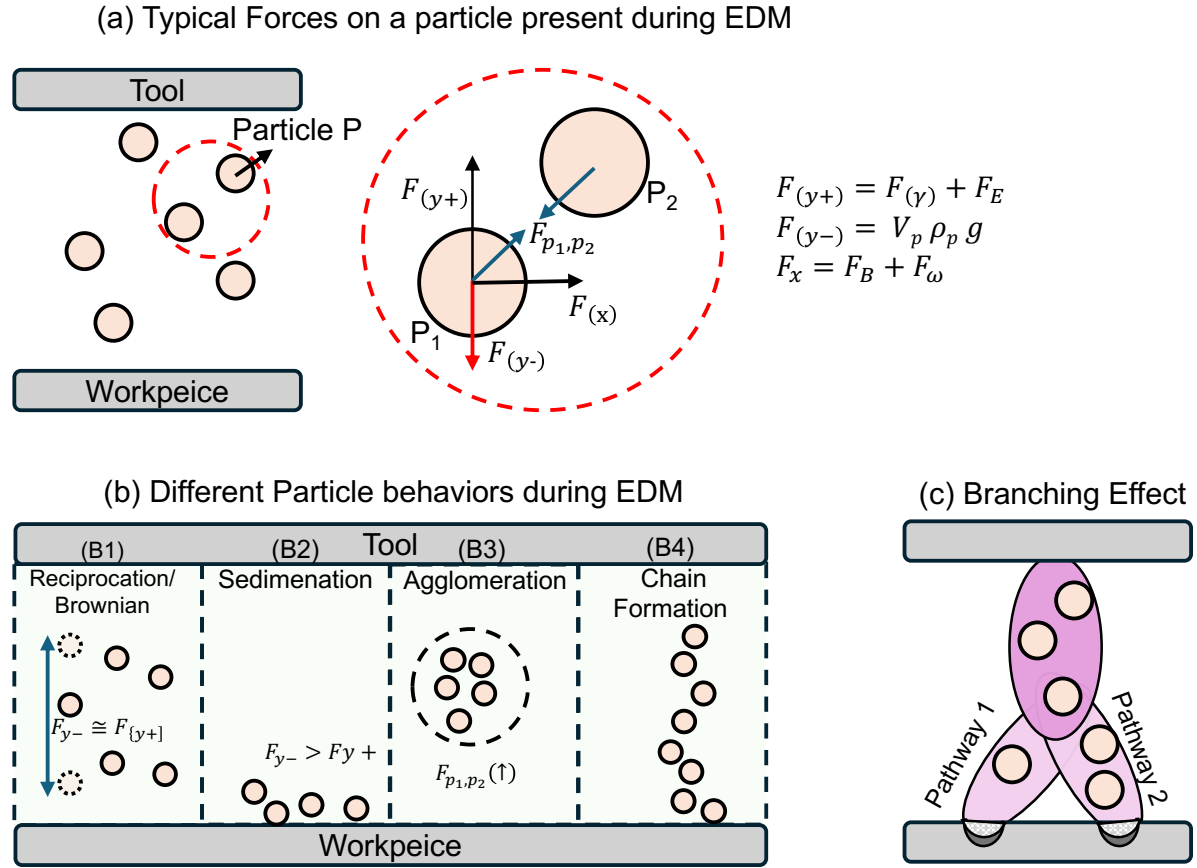


Figure 3-2: Schematic illustration of (a) forces acting on a particle, (b) representative particle behaviors within the discharge gap, (c) branching effect (adapted from [87], [114], [115]).

While reciprocation and chain formation promote discharge initiation at wider gaps, their efficiency depends on the specific electrical properties of the powder. For instance, carbon nanofibers (CNF) leverage high conductivity to rapidly form bridges [87], whereas alumina (Al_2O_3) primarily influences the process through permittivity-driven field distortion rather than direct charge transport. Semiconductors like silicon (Si) exhibit a hybrid behavior that is highly sensitive to the instantaneous temperature of the gap. The influence of these specific material properties on material removal rate and surface quality is discussed in detail in the following sections.

3.2.2. Experiment Methods

3.2.2.1. EDM Setup

In this study, a micro-EDM machine, Panasonic MG-ED72, was used. The device has a resolution of $0.1 \mu\text{m}$ in the x, y, and z axes. The machining is performed using a resistor-

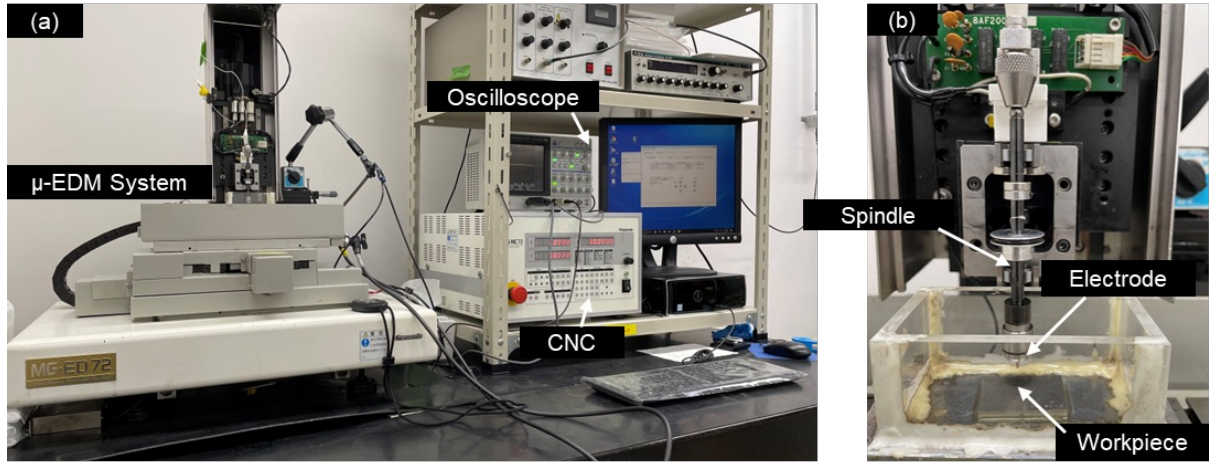


Figure 3-3: Photograph of (a) μ -EDM system, (b) electrode and workpiece arrangement.

capacitor (RC) circuit, which is suitable for micromachining [116]. The control parameters are a voltage range of ± 50 to ± 110 V and capacitances of 3300, 1100, 200, and 100 pF. The discharge gap, pulse duration, and peak current are not controllable. A spindle is attached to the micro-EDM machine, rotating at 3000 RPM. A custom acrylic tank was fabricated to contain the dielectric. Discharge progress was monitored using an oscilloscope. The photograph of the machining setup is shown in Figure 3-3. During experimentation, no external stirring or dielectric circulation was applied.

3.2.2.2. *Electrode and Workpiece*

Ultrafine grade cemented tungsten carbide (WC-Co) KM-10, produced by Toyo Tool, Japan, was used as the workpiece material. The average grain size was around $0.7\ \mu\text{m}$, and the cobalt binder concentration was about 6%. The mechanical properties of the workpiece are shown in Table 3-1. The workpiece surface was mirror-polished to a surface roughness of $0.01\ \mu\text{mSa}$ using a diamond powder slurry. A copper (Cu) electrode of a diameter of 1 mm from Nilaco Corporation, Japan, was used as a tool material. The electrodes were deburred and dressed using reverse-polarity EDM before each machining test. The scanning electron micrograph (SEM) of the surface of the workpiece is shown in Figure 3-4(a).

3.2.2.3. *Powder Materials*

Three different powders of varying shapes, densities, and electrical properties were used in this experiment. Commercially available polishing-grade alumina powder, BaikaloX 1CR,

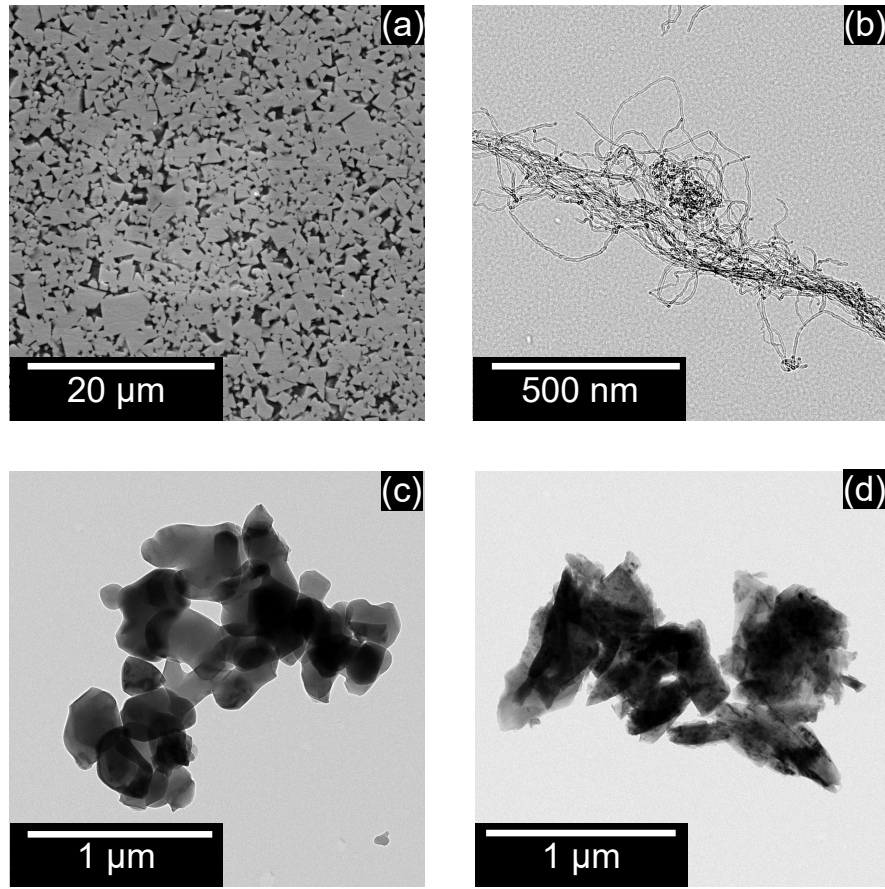


Figure 3-4: SEM of (a) tungsten carbide, TEM of (b) carbon nanofiber, (c) alumina, (d) silicon particles.

Table 3-1: Mechanical properties of the workpiece

Property	Value
Material type	Ultrafine particletype WC-Co (KM-10)
Grain size [μm]	0.69
Binder type and content ratio	Co (6%)
Density [g/cm ³]	14
Melting point [K]	3140
Hardness (HRA)	91.5
Tensile strength [GPa]	3.4
Toughness [MPam ^{1/2}]	11.2
Thermal conductivity [W/mK]	110

manufactured by Baikowski International Co. Ltd., was used as the insulator powder. Semiconductive silicon powder, manufactured by Kyocera, Japan, was used. Lastly, carbon nanofibers with diameters of 10-20 nm and heights of 0.1-10 μm, produced by Mitsubishi Chemicals, Japan, were used as a conductive powder in this experiment. The transmission electron micrographs [TEM] of carbon nanofiber, alumina, and silicon are shown in Figures 3-4(b)-(d),

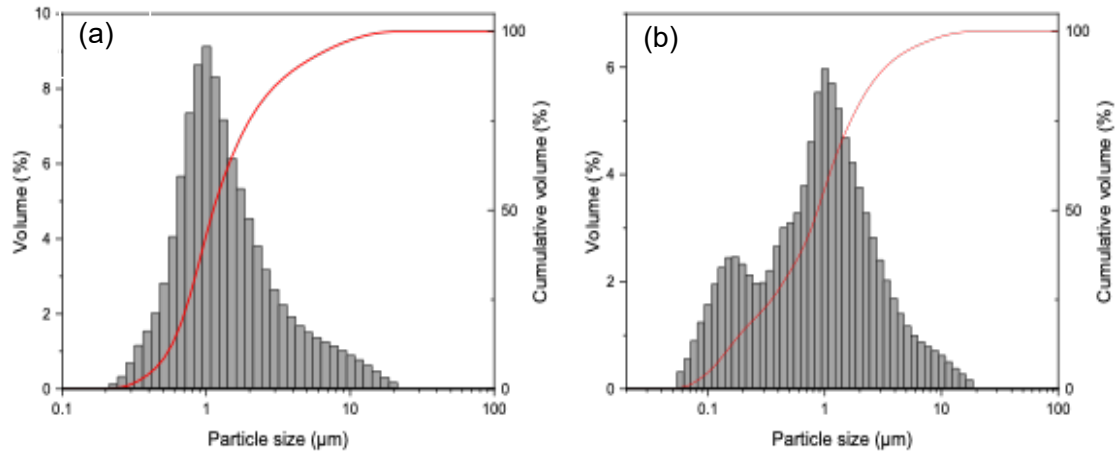


Figure 3-5: Particle size distribution of (a) silicon and (b) alumina used in this study.

respectively. A laser particle analyzer from Horiba Semiconductors, LA-960, was used to measure the particle size. Figures 3-5(a)-(b) show the size distribution of the silicon and alumina powders, respectively. The representative thermal and electric properties of the powder materials are listed in Table 3-2.

Table 3-2: Representative thermal and electrical properties of powders reported in the literature [117], [118], [119].

Property	Carbon nanofiber (CNF)*	Silicon	Alumina
Density [g/cm^3]	1.3–2.0	2.329	3.965
Effective relative permittivity (ϵ_r)	~5–15	11.7	9.8
Electrical conductivity [S/m]	$\sim 10^4$ - 10^5	10^{-4} - 10^2	10^{-12} - 10^{-14}
Thermal conductivity [$\text{W}/\text{m}\cdot\text{K}$]	~400	~150	~30
Melting point [K]	~3823	1687	2345

*Effective permittivity of carbon nanofiber powders depends on frequency, dispersion, and packing density; a single intrinsic value is not well defined. The values listed in this table are reference values.

3.2.2.4. Machining Conditions

Two different EDM tests were performed to determine the effect of powder addition on EDM: fundamental characteristics tests and hole-machining tests. The micro-EDM machine used in this study uses an in-built contact detection program. An edge is detected if a threshold number of discharges occurs within a resistance-capacitance (RC) cycle. This method was

used to obtain isolated single craters. Next, machining tests on the evaluation of powder-mixed EDM (PMEDM) were performed by drilling holes of a depth $[h]$ of 50 μm under different conditions, as shown in Table 3-3. The discharge energies used in this experiment are used for rough-phase micromachining. Full factorial experiments were performed with two repetitions for each condition. A hydrocarbon-based dielectric, Casty Lube EDS, was used.

As seen in Figure 3-6(a)-(b), the nanopowders used in this study exhibit a strong tendency to agglomerate into larger clusters due to interparticle forces. Such agglomeration can inhibit the formation of stable discharge and the evacuation of debris during EDM. To ensure a reproducible and homogeneous initial dispersion, the dielectric-powder mixture was therefore subjected to ultrasonic agitation for 15 min before each machining experiment. It is noted that this procedure improves initial dispersion but does not prevent reagglomeration or sedimentation during prolonged machining as seen in Figure 3-6(c)-(d), where carbon nanofiber aggregation as sedimentation is observed.

Table 3-3: Machining conditions

Property	Value
Tool	Copper (1 mm $\varnothing$)
Workpiece	WC-Co
Polarity	Tool (-ve)
Voltage [V]	90, 100, 110
Capacitance [pF]	3300
Feed rate [$\mu\text{m s}^{-1}$]	0.5
Powders	CNF, Al_2O_3 , Si
Concentration [g/L]	0, 0.25, 0.5, 0.75, 1.0

3.2.2.5. Evaluation Conditions

The machining output of EDM with various powders was evaluated with three parameters: material removal rate, electrode wear rate, and surface roughness. Material removal rate (MRR) is defined as the ratio of the volume of the material removed (Vol_m) to the machining time (M_t) (Equation 3.2). A laser microscope from Olympus, Japan, was used to map the three-dimensional topography of the machined hole. The analysis software TallyMap, Amtek Corp., was used to determine the mean depth plane $[d]$, and the diameter $[D]$ at ($z = \frac{1}{2}d$) of

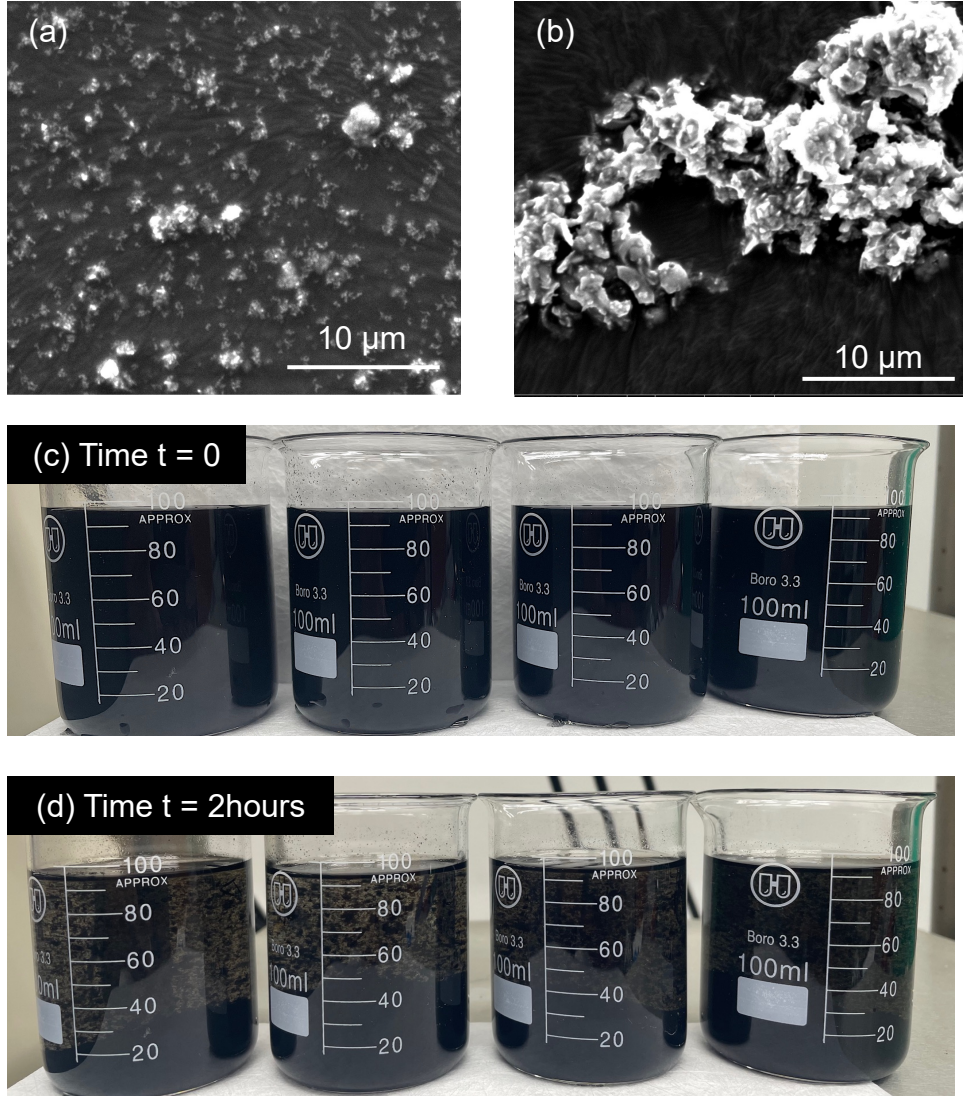


Figure 3-6: (a) Alumina and (b) silicon powders before dispersion, showing agglomerated particle clusters. Carbon nanofiber suspensions in a hydrocarbon-based dielectric at concentrations of 0.5–2.0 g/L, (c) immediately after homogenization and (d) after 2 h under static conditions, showing sedimentation and reagglomeration.

the hole machined.

$$\text{MRR} = \frac{\pi D^2 d}{4M_t} \quad (3.2)$$

Electrode wear rate is defined as the ratio of the volume of electrode worn (Vol_e) to machining time (M_t). Electrode wear is an essential factor in determining the economic feasibility of the machining process. Since the micro-EDM machine used in this study does not use any wear compensation mechanism, the difference between set depth [h] and actual machined depth [d] is the electrode wear. Since machining time varies with machining conditions, this research considers the electrode's relative wear compared to the workpiece. The equation to determine

relative electrode wear rate (REWR) is shown in Equation 3.3. The machined region's average surface roughness (Sa) was measured over an area of $256 \times 256 \mu\text{m}$ at intervals of $0.25 \mu\text{m}$. The ISO 25178 standard of measurement, with no filters, was measured over three locations on each machined surface.

$$\text{REWR} = \frac{D_e^2[h - d]}{D^2d} \quad (3.3)$$

3.2.3. Results and Discussion

3.2.3.1. Single Discharge Experiments

Figure 3-7(a)-(c) shows the single discharge craters obtained using EDM oil without powder addition for 90, 100, and 110 V, respectively. Unlike the craters in the EDM of other materials, such as silicon carbide [87], [106], [120], which show clear circular boundaries, craters in WC-Co were irregular. Furthermore, enlarged images of the crater surface, as shown in Figure 3-7(d), (e), indicate that the machining has not completely progressed to the crater's edge since the polishing marks from the original sample are retained after EDM (A1 and B1). These marks indicate that, at these discharge energies, the heat generated is insufficient to melt the material at the edges; instead, the grains are pushed outwards. Additionally, as seen in A2-B2, redeposited materials are also observed. Since tungsten carbide is a highly dense material, it is difficult to fully eject molten material from the discharge gap, leading to redeposition on the surface. Microcracks were also observed, as shown in B3. Crack formation results from the preferential removal of the cobalt binder, which has a lower melting point than tungsten carbide, leaving voids that develop into cracks.

Figures 3-8(a)-(i) show the SEM of single discharge craters observed at various PMEDM conditions. The average diameter of these craters is summarized in Figure 3-9. In the case of carbon nanofiber and alumina-mixed EDM, the average crater diameter was reduced, whereas it increased in the case of silicon. In addition, the crater diameter increased with voltage for all conditions.

According to previous research, the discharge gap increases significantly when carbon nanofibers (CNF) are added to the dielectric [87]. Owing to their high aspect ratio and electrical conductivity, CNF can rapidly form transient conductive chains across the interelectrode gap. In

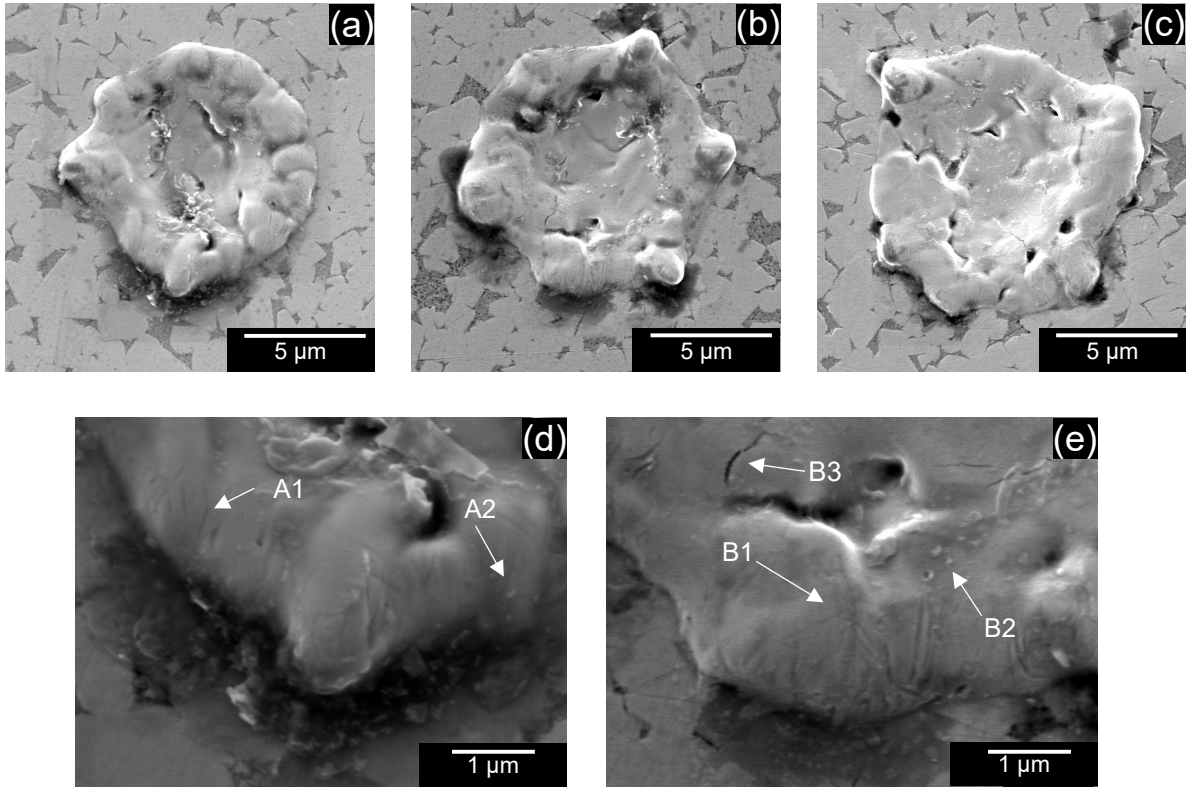


Figure 3-7: Single discharge craters for (a) 90 V, (b) 100 V, (c) 110 V using EDM oil without powder addition. Crater edge at (d) 90 V, (e) 100 V.

addition, strong interfacial polarization of dispersed fibers in the applied field promotes particle alignment along the field lines, increasing the likelihood of bridge formation. These conductive bridges allow discharge initiation at larger nominal separations d . Under such conditions, the plasma channel tends to branch into multiple paths, Figure 3-2(c), as reflected in the finer, fragmented crater features shown in Figure 3-8(a). Because the discharge energy is distributed over a wider effective area and across a larger gap, the energy density at the workpiece surface is reduced, resulting in the narrower craters observed in Figure 3-9.

In alumina-mixed EDM, the craters are also smaller than in the oil-only condition, but for a fundamentally different physical reason. Although alumina is electrically insulating, its relative permittivity ($\epsilon_r \approx 9.8$) is substantially higher than that of the base dielectric. This permittivity contrast induces localized intensification of the electric field around dispersed particles through polarization, promoting more uniform discharge initiation without the formation of fully conductive bridges. As a result, the discharge gap does not expand as significantly as in the CNF case; however, the spatial distribution of discharge triggering becomes more homogeneous. In

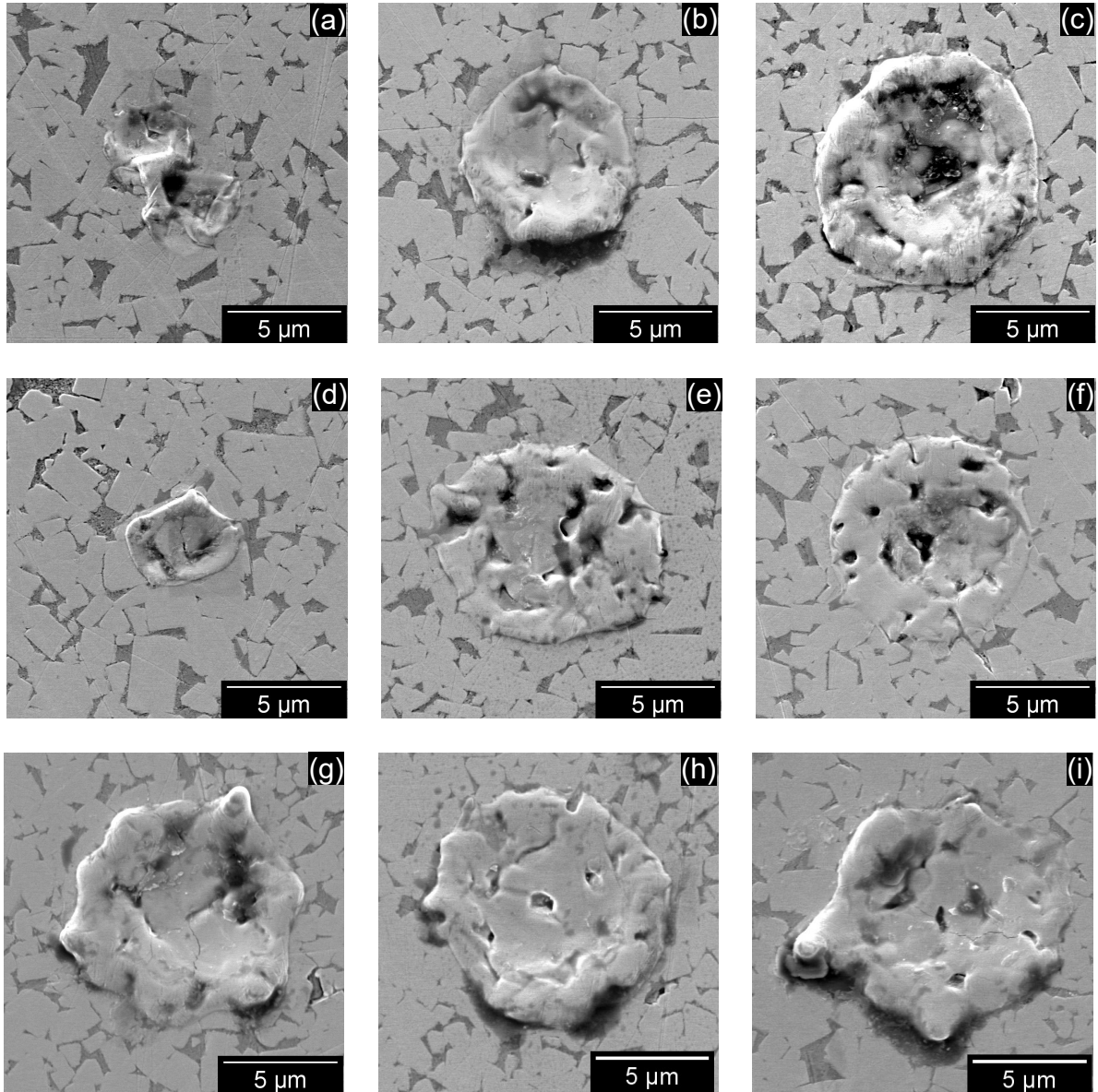


Figure 3-8: Single discharge craters for (a) 90 V, (b) 100 V, (c) 110 V using EDM oil with carbon nanofiber powder, (d) 90 V, (e) 100 V, (f) 110 V with alumina powder and (g) 90 V, (h) 100 V, (i) 110 V with silicon powder.

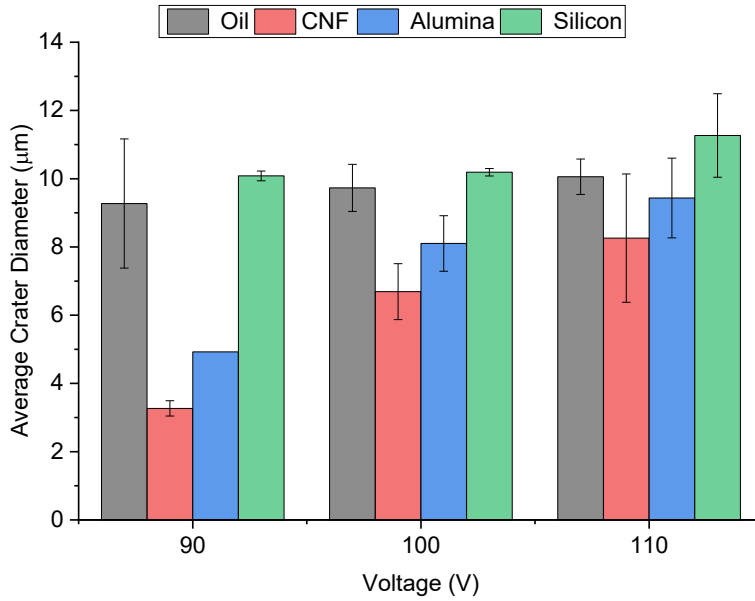


Figure 3-9: Average single discharge crater diameter under different conditions.

addition, alumina's relatively high thermal conductivity facilitates heat dissipation away from the discharge site, reducing localized overheating. The combined effect of permittivity-driven field homogenization and enhanced thermal diffusion results in reduced crater size and a more controlled material-removal process.

Silicon exhibits a hybrid discharge behavior. As a semiconductor with a relative permittivity ($\epsilon_r \approx 11.7$) slightly higher than that of alumina and an electrical conductivity that increases with local gap temperature, silicon particles promote a moderate expansion of the discharge gap. Unlike the extensive conductive bridging and plasma branching observed with CNF, or the predominantly permittivity-driven field homogenization in alumina-mixed EDM, silicon supports the formation of a relatively stable, high-energy plasma channel. This intermediate gap expansion produces an extended plasma column that sustains a higher energy density at the workpiece surface than in the CNF case, resulting in the widest craters observed among the three powder types.

3.2.3.2. Hole Machining by Carbon Nanofiber-mixed EDM

The machined profiles and the material removal rate with oil and carbon nanofiber-mixed EDM are summarized in Figure 3-10 and Figure 3-11, respectively. In the only EDM oil condition, the maximum MRR was $0.0026 \text{ mm}^3/\text{min}$ at 110 V, decreasing with decreasing voltage.

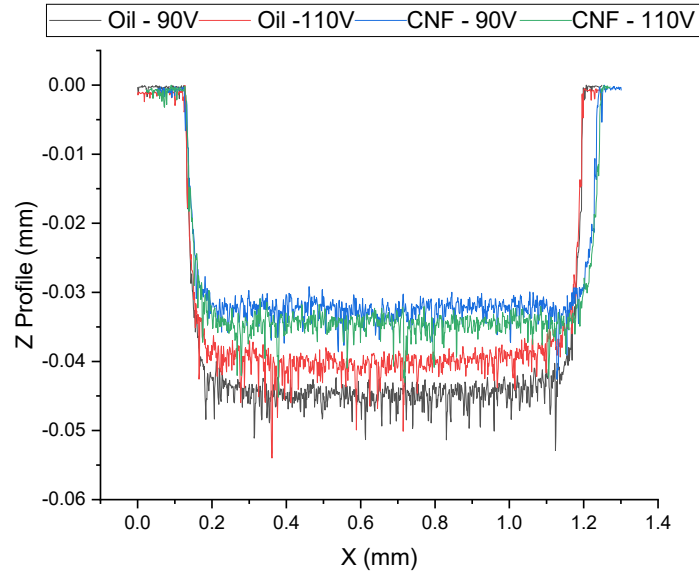


Figure 3-10: Profiles of machined holes at 90 V and 110 V using oil and 0.5 g/L carbon nanofiber-mixed EDM.

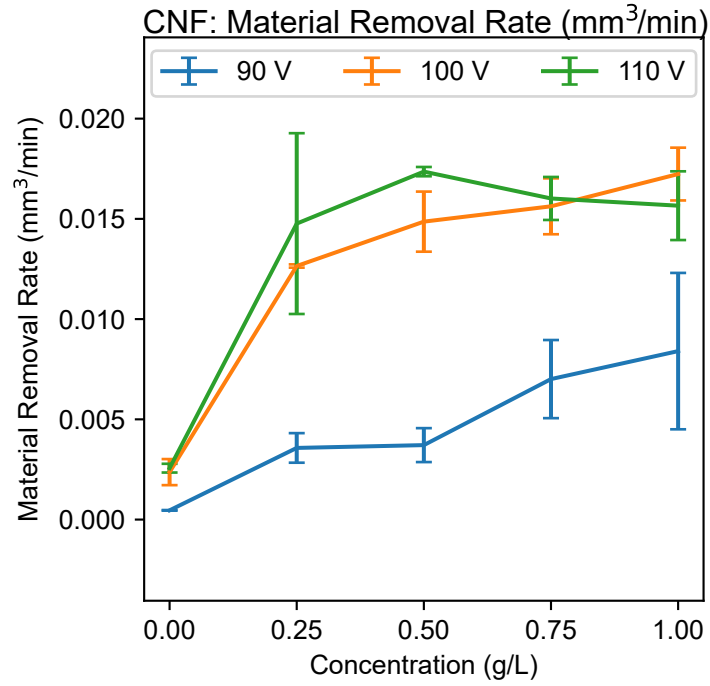


Figure 3-11: Material removal rate using carbon nanofiber-mixed EDM.

With an increase in voltage (V), the maximum discharge energy per spark (W) increases, and as a result, the material removed per discharge also increases, Equation 3.2. This can be seen evidently in Figure 3-9, where the crater diameter increased with an increase in voltage.

It can be seen from the machined profiles in Figure 3-10 that the machined holes were

shallower and wider with the addition of the carbon nanofiber. The increase in the machined hole diameter, called diametric overcut, is caused by a wider discharge gap resulting from the addition of nanofibers.

It was observed that, even though the machined hole in the oil-only condition was deep, the MRR increased across all CNF concentrations and voltages. At a higher discharge energy of 110 V, the maximum MRR was 0.017 mm³/min at a concentration of 0.5 g/L, which was over 6.5 times that of the oil-only condition. This tremendous improvement in MMR can be attributed to the ease of initiating discharge and the wider discharge gap. It was also observed that at 110 V, the machining speed was equal to the set feed speed (0.5 μm/s) at all concentrations. This indicates that there is no ineffective discharge period in this condition, where the tool is forced to retract to prevent short-circuiting, indicating that machining stability was maintained throughout. This can also be monitored by observing the snapshots of waveforms on the oscilloscope, as seen in Figure 3-12(a). During EDM with oil, significant secondary discharges with waveform M1 were observed, in contrast to normal EDM (M2). It was also observed that arcing led to the formation of complex waveforms [121], as seen between M2–M3, followed by short-circuiting and tool retraction. In contrast, as seen in Figure 3-12(b), the addition of carbon nanofiber increased the number of sparks, and complex waveforms were not observed.

It can be seen from Figure 3-11 that the MRR increases with an increase in concentration and then decreases after a peak at 0.5 g/L for 110 V. In EDM with oil, without process alteration, it has been reported that the spark tends to accumulate in a single region [106], [122]. As debris concentration increases, spark formation in the vicinity is likely, as shown in Figure 3-1(b). Whereas, in powder-EDM, sparks are not localized since particles are dispersed throughout the surface. In carbon nanofiber-mixed EDM, initially, as the particle concentration increases, the number of discharge pathways increases, dispersing EDM and improving process stability, thereby increasing MRR. However, as the particle concentration increased, many nanofibers began to accumulate or adhere to the electrodes, inhibiting discharge.

Similarly, an improved material removal rate was observed when the voltage was reduced to 90 V. A machining rate of 0.008 mm³/min was achieved, over 18 times that with only oil. Generally, the discharge gap decreases considerably at low voltages, increasing the possibility

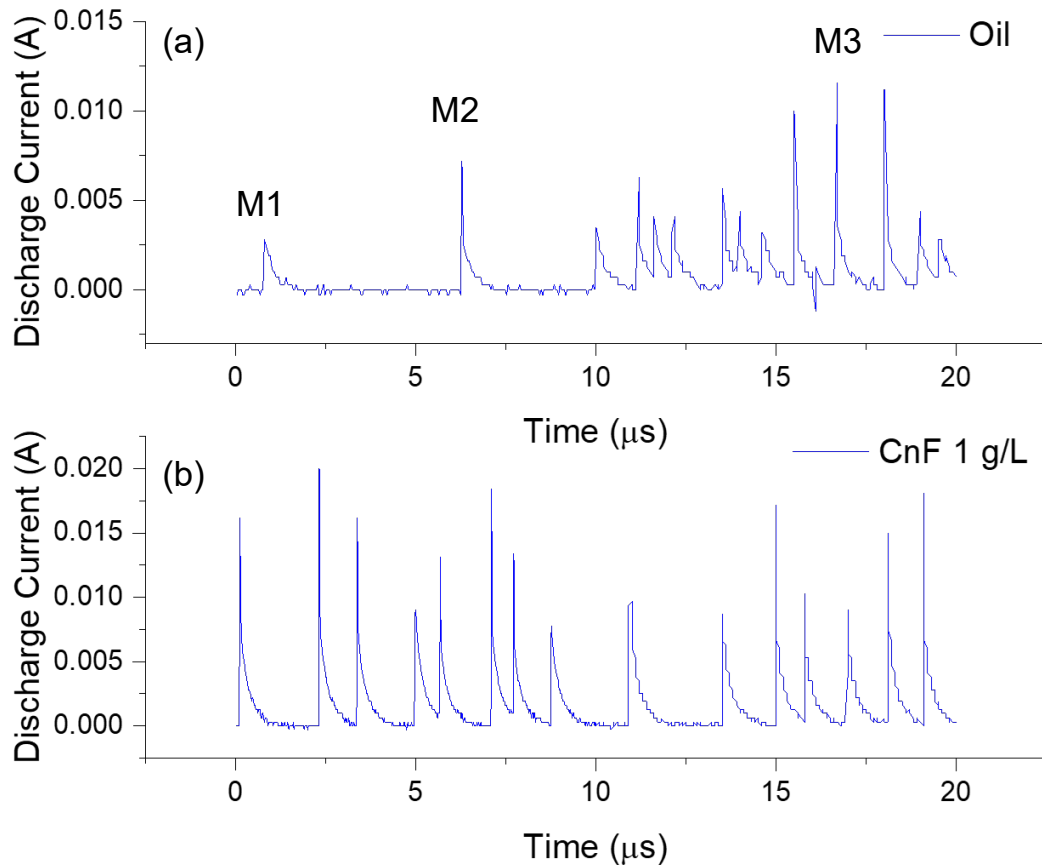


Figure 3-12: Snapshot of current waveforms during EDM using (a) oil and (b) carbon nanofiber-mixed EDM (1 g/L) at 110 V.

of debris accumulation within the working gap. This increases the frequency of ineffective discharges, such as short-circuiting due to debris accumulation and secondary discharges on the machined debris. Thus, flushing away debris becomes a prime concern. During carbon nanofiber-mixed EDM, the machined speed increased from 0.18 to 0.53 times the set machining speed ($0.5 \mu\text{m/s}$) when the concentration increased from 0.25 to 1.0 g/L. There was a significant no-discharge period, indicating sustained instability. However, during the tool backtracking period, the fresh dielectric with powder flows in, removing the debris. This period is essential at low voltage, where the discharge gap is lower, as it resets the dielectric. The proportion of powder entering the gap increases with concentration, allowing machining to be restarted quickly. Although machining efficiency increased, it can be concluded that, at a feed rate of $0.5 \mu\text{m/s}$ and 90 V using carbon nanofibers, uninterrupted stable machining cannot be achieved.

An improvement of over 7.7 times in the MRR without powder addition was observed at 100 V. Similar to 110 V, the machining was almost continuous, the machining speed increasing

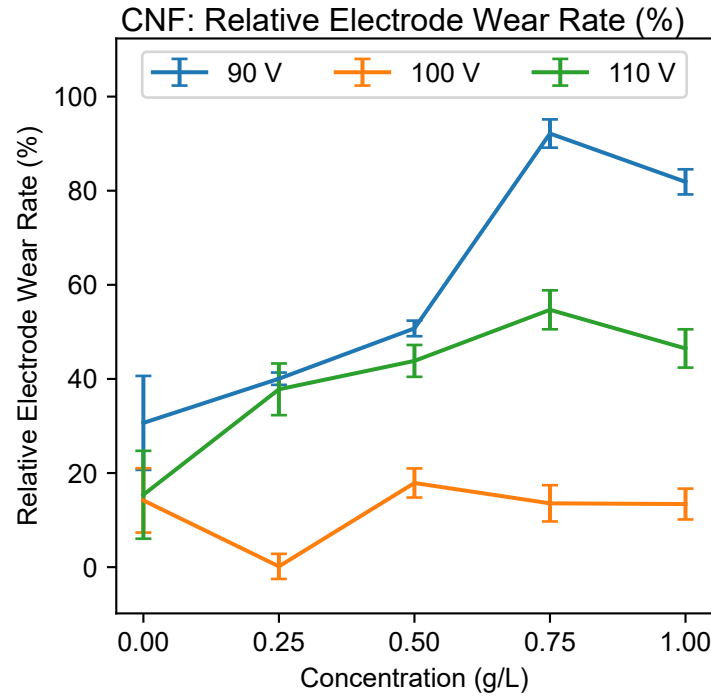


Figure 3-13: Relative electrode wear rate using carbon nanofiber-mixed EDM.

from 0.68 to 0.92 times the feed speed. Furthermore, the MRR increased with concentration. At 1.0 g/L, the MRR was even higher than 110 V. The brief intermissions during EDM at 100 V allowed new dielectrics to flow in, which is considered to improve the machining rate compared with 110 V.

Figure 3-13 compares electrode wear for different machining conditions in carbon nanofiber-mixed EDM. Unlike in previous studies, the electrode wear rate increased with the addition of CNF to the dielectric, and this increase was further pronounced with increasing powder concentration. During the EDM process, plasma travels from the cathode to the anode, where it bombards the anode, removing material through heat transfer and abrasive action. However, some electrons also travel in the opposite direction, causing material to be removed from the anode. Since the kinetic energy of ions is higher than that of electrons, the amount of material removed from the anode is much higher. In addition, the temperature in the discharge gap can exceed 3000 K [123], removing material from both electrodes. Thus, the tool wear depends on the electrodes' electrical and thermal properties. The melting point of copper is much lower than that of tungsten carbide [1631 K], and its thermal conductivity is higher; thus, the melting rate of copper will be higher at high temperatures. At high voltage or discharge energy, the elec-

tron fraction is high, and the temperature in the working gap is very high. Hence, a higher wear rate is observed. The dielectric flow into the discharge gap, which acts as a coolant, reduces heat transfer to the electrodes and helps prevent electrode wear.

As mentioned above, the machining at higher voltages [100 and 110 V] was almost continuous. Since no external flushing was used, if no electrode backtracking occurs, the flow of the new dielectric is limited. The debris removed is due only to bubble expansion, not debris flow, and as a result, the temperatures within the gap will continue to rise. The electrode wear will increase correspondingly with an increasing machining rate, as seen in Figure 3-13. Since the discharge energy at 100 V is lower than at 110 V, the gap temperature is expected to be lower, resulting in a lower tool wear rate.

In contrast, very high electrode wear was observed at 90 V. This result is similar to previous studies, in which the electrode wear rate decreased with the discharge energy and then increased. Due to improper flushing at lower energies, arcing will occur, resulting in more material being removed from the electrode than from the workpiece. A considerable variation in the relative electrode wear rate was also observed due to this instability, with the effect more pronounced at 90 V. In addition to arcing, as concentration increased, the tool wear rate also increased during continued machining, similar to higher energies. A decrease in wear rate was observed at 1 g/L at all voltages. It is believed that at very high concentrations, particle adhesion to the electrode surface increases. This adherence may have prevented heat transfer from the dielectric to the electrode.

Figure 3-14 shows the SEM of the surface of the machined holes at different voltages using EDM oil. The craters are narrow and shallow at lower voltages (Figure 3-14(a, b)). Many surface defects, such as microcracks (C1), micropores (C2), and redeposited materials (C3), were observed. The number of redeposited materials increased at higher voltages, as seen in Figure 3-14(c). At high voltages, the gap temperature was higher, and molten debris could not cool quickly, so it redeposited onto the surface. Similar surface defects could also be seen in carbon nanofiber-mixed EDM as seen in Figure 3-15(a)-(d). However, the redeposited materials were more extensive (D1) and could also be seen at lower voltages (Figure 3-15(a, b)).

Previous results have shown that adding powder increases discharge dispersion, resulting

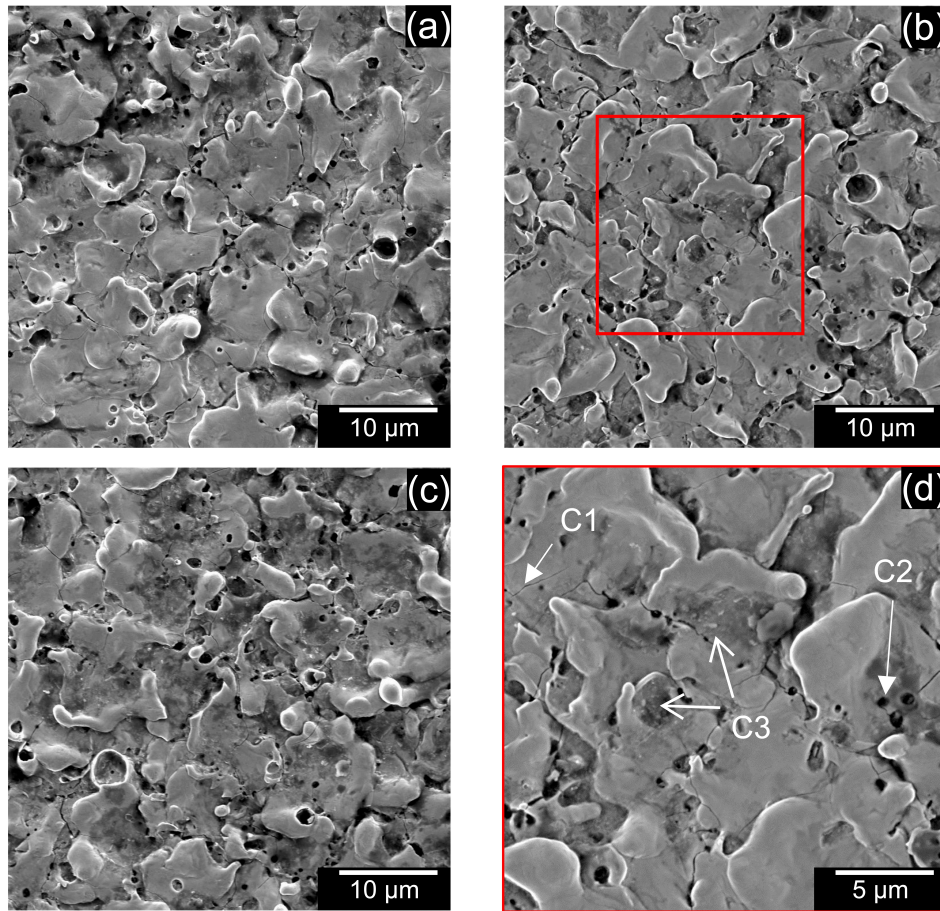


Figure 3-14: SEM of the machined surface using oil-only at (a) 90 V, (b) 100 V, (c) 110 V, and (d) enlarged region of 100 V.

in a more uniform surface. In addition, it has also been reported that using powder-mixed EDM produces wide yet shallow craters [47]. These two factors are considered to result in lower surface roughness. Figure 3-16 shows the result of surface roughness. At 110 V, adding powder decreased surface roughness across all concentrations, whereas at lower voltages, it showed various trends. At higher discharge energy, the material removed per discharge is increased. This results in a deep crater, as seen in section 3.2.3.1. As the discharge energy decreases, the crater size decreases, resulting in a smoother surface finish. This phenomenon is also observed in this study when the voltage is reduced from 110 to 100 V. However, the surface roughness increases when the voltage is further reduced. At the 90 V condition, redeposited materials could have increased surface roughness when compared to only the EDM oil condition, as seen in Figure 3-15(a). In summary, using carbon nanofiber powder-mixed EDM of tungsten carbide significantly improved the machining rate across all machining conditions. However,

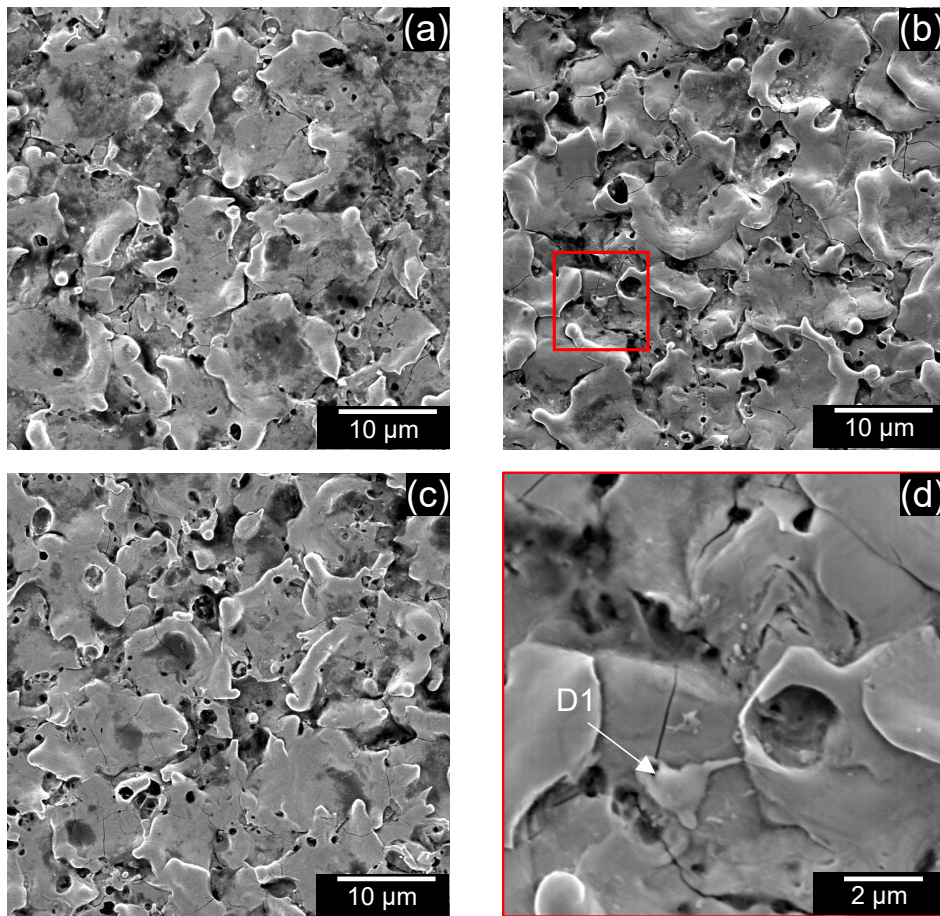


Figure 3-15: SEM of machined surface using 0.5 g/L carbon nanofibers at (a) 90 V, (b) 100 V, (c) 110 V, (d) enlarged region of 100 V.

an increased tool wear rate was observed. Under certain machining conditions, a fine surface was observed. Among the machining conditions, at 100 V, a high material removal, low tool wear, and a smoother finish can be simultaneously achieved at concentrations of 0.5–0.75 g/L. These results also agree with a previous study [87], which showed improvements in MRR using carbon nanofibers on reaction-bonded silicon carbide.

3.2.3.3. Hole Machining by Alumina-mixed EDM

Figure 3-17 shows the MRR obtained at various machining conditions using alumina. At high discharge energy, MRR was higher than in the oil-only condition, similar to CNF. The highest MRR obtained was 0.00971 mm³/min at 0.5 g/L, about 3.8 times that of the oil-only condition. It was also observed that MRR initially increases and then decreases with increasing concentration. As mentioned in Section 4.2, theoretical and experimental evidence show that particle addition increases the discharge gap regardless of particle properties. However, unlike

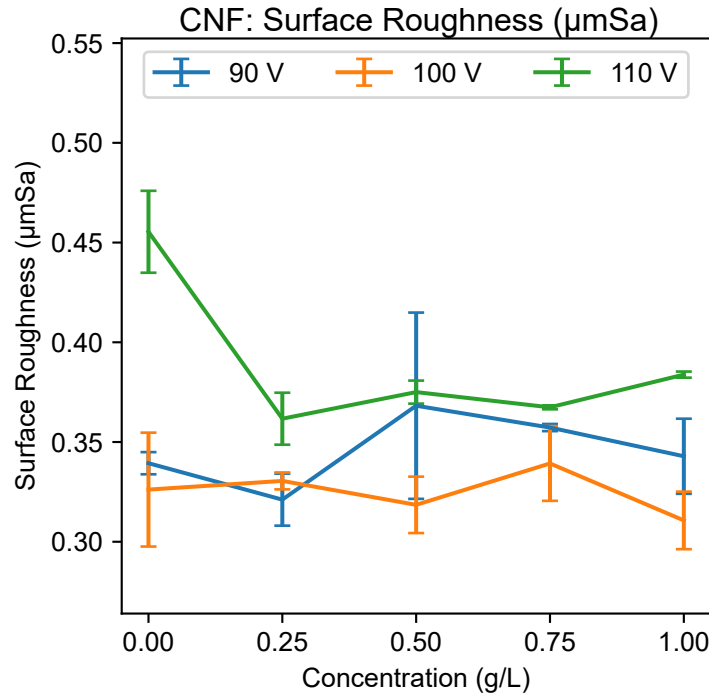


Figure 3-16: Surface roughness using carbon nanofiber-mixed EDM.

CNF, alumina particles, due to their insulating nature, do not polarize easily in an electric field because they lack free electrons and do not form dipoles. The formation of 'bridges' is inhibited. However, under strong electric fields, even insulating materials become polarized. This indicates that the alumina particles can participate in spark formation at high voltages. This effect decreases as the voltage decreases. These results agree with previous studies showing that alumina improves MRR in transistor circuits at high peak voltages [88], [124]. These results show that although MRR improved at 110 V compared to oil, machining still did not occur for a significant period. At the low discharge energy of 90 V, adding alumina increased the MRR at all concentrations. However, the improvement was not substantial. The highest MRR was $0.00055 \text{ mm}^3/\text{min}$, 1.19 times the only oil condition. It can be seen from Figure 3-9 that the average crater size of alumina-mixed EDM was much lower than that of oil-only conditions at all conditions, indicating that the material being removed per spark is very low. Thus, the improvement in machining rate is due to the shorter no-discharge period. The machined feed speed was also similar to the oil-only added condition. It was observed that, due to the higher density of alumina than the dielectric, the powder settling was a significant phenomenon. Since no external stirring or circulation was used, the powder sedimentation cannot be overcome.

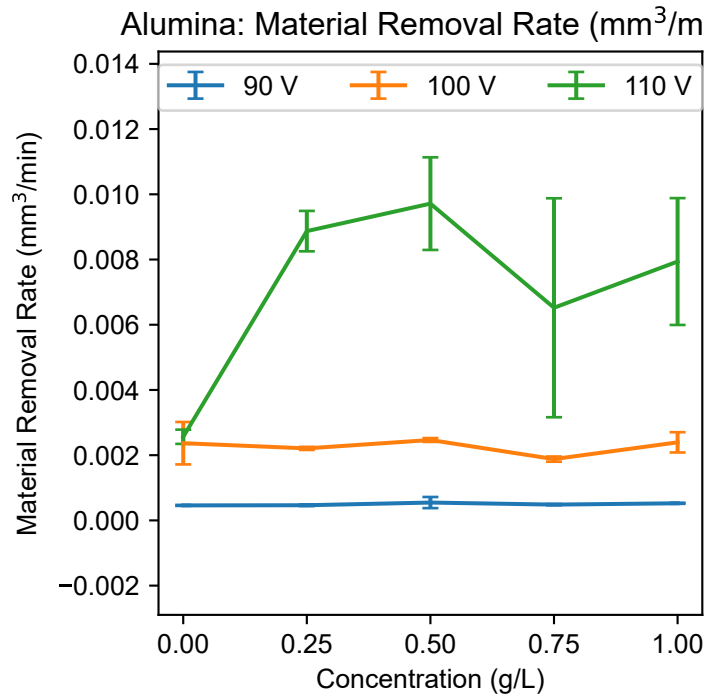


Figure 3-17: Material removal rate using alumina-mixed EDM.

Furthermore, as the machining time increased, the fraction of powder suspended in the dielectric decreased. During electrode backtracking, the fresh dielectric contained a limited amount of alumina. As a result, when machining time is extended, the MRR approaches that of oil-only machining. In addition, as mentioned earlier, the alumina addition does not directly improve spark formation. An increase in particle concentration will only inhibit the EDM process. Additionally, as at 90 V, no significant improvement in MRR was observed at 100 V.

Figure 3-18 shows the relative electrode wear of alumina-mixed-EDM. Similar to CNF, the tool wear rate generally increased with the addition of powder and was more significant at 90 V. Unlike CNF addition, where tool wear is attributed to high gap temperature during continuous machining, the tool wear in alumina is expected to be due to frequent arcing and short-circuiting. As a result, significant variation in electrode wear was observed. This is evident in that electrode wear increases with decreasing voltage and concentration in most conditions.

Figure 3-19(a)-(c) shows the SEM of the machined surfaces with alumina-mixing. The surface roughness of the machined holes using alumina is shown in Figure 3-20. The addition of alumina decreased the surface roughness at 110 and 100 V for all concentrations. Small, shallow craters, as seen in Figure 3-9(d)-(f), and a uniform discharge distribution helped

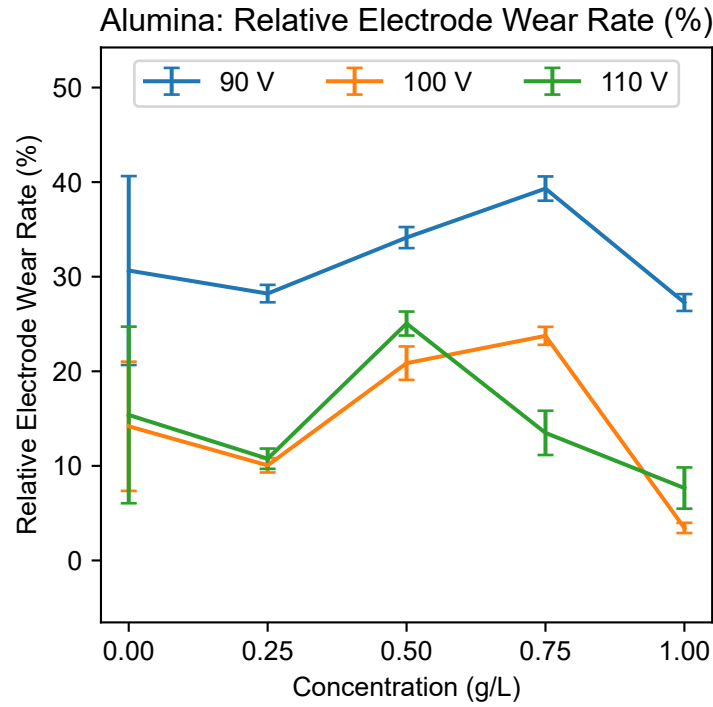


Figure 3-18: Relative electrode wear rate using alumina-mixed EDM.

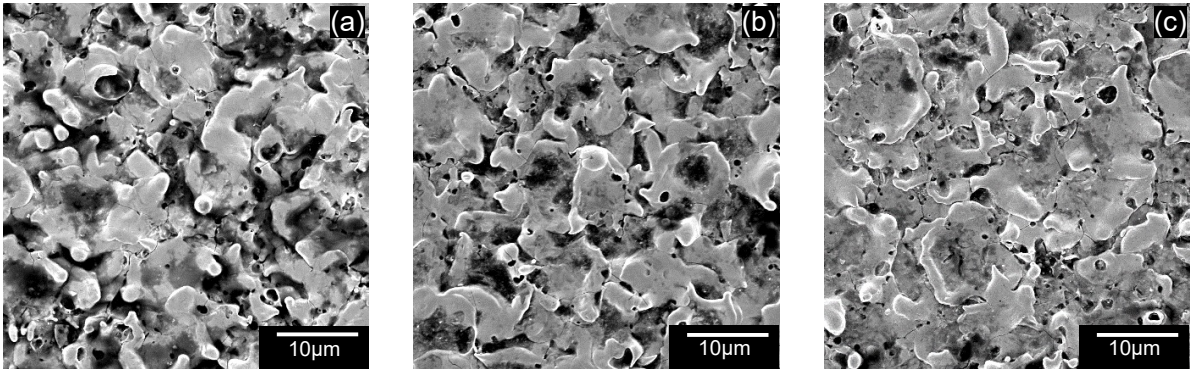


Figure 3-19: SEM of machined surface using 0.5 g/L alumina at (a) 90 V, (b) 100 V, (c) 110 V.

achieve a smoother surface. Moreover, as the voltage decreases to 90 V, frequent arcing and short-circuiting make the surface rough. It has also been observed that concentration does not significantly affect surface roughness. As mentioned above, as machining time increases, the suspended powder concentration within the dielectric decreases due to sedimentation, resulting in similar surfaces.

Effective machining with alumina can be achieved using 110 V for rough machining and 100 V for fine finishing. The effect of concentration is not significant. In their study on the use of nano-alumina powders in finish-phase machining [120], the authors reported no significant increase in MRR but an improvement in surface roughness. In our study using micro-alumina

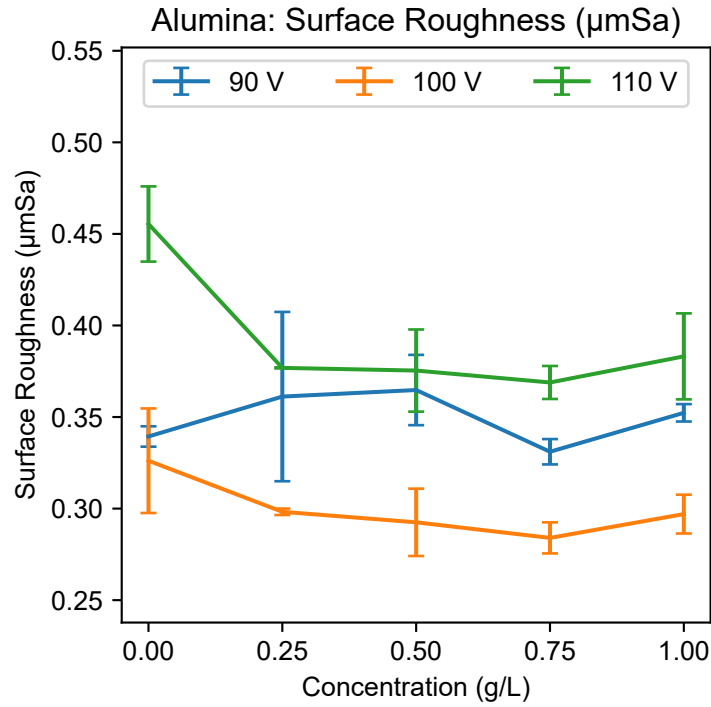


Figure 3-20: Surface roughness using alumina-mixed EDM.

under rough-machining conditions, we observed a similar improvement in roughness. However, we have found that alumina can improve the material removal process at higher machining energies.

3.2.3.4. Hole Machining by Silicon-mixed EDM

The material removal rate obtained during the machining using silicon is shown in Figure 3-21. It was observed that the MRR increased for all conditions in the presence of silicon. The highest MRR of 0.0197 mm³/min was obtained at 1 g/L at 110 V. It was also observed that the MRR increases with an increase in particle concentration at higher voltages. As with CNF, silicon particles within the discharge gap cause electric-field aberrations. However, silicon's aberration is expected to be lower than that of nanofibers with very high electrical conductivity. Furthermore, silicon particles are much smaller than nanofibers that are 0.1-10 μm in length. Due to Van der Waals forces, particle agglomeration is also higher at smaller sizes.

As seen in Figure 3-9(g)-(i), the crater diameter of silicon, unlike CNF and alumina, is higher than that of oil. Additionally, the crater diameter did not vary significantly with voltage, as observed in oil-only conditions. The material removed per discharge is thus higher than that of oil-only conditions. Moreover, because of the permittivity of silicon, its dipoles align

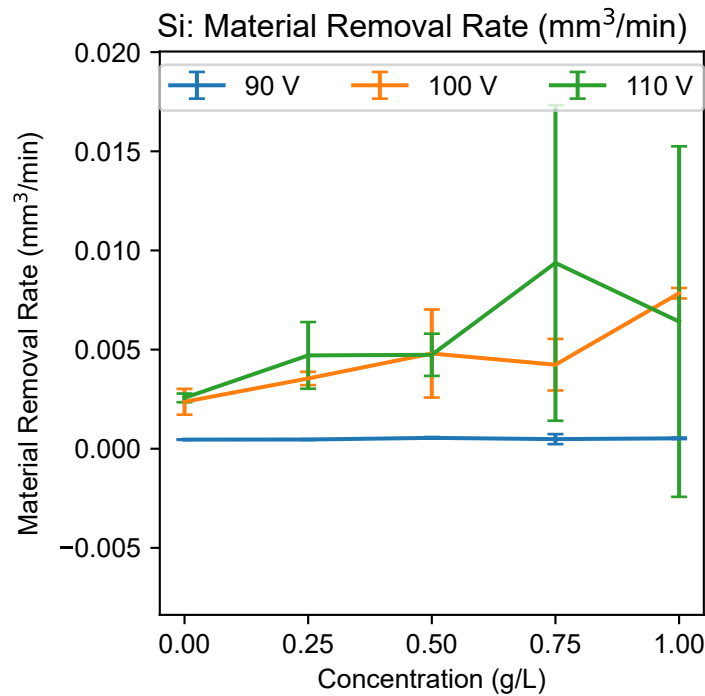


Figure 3-21: Material removal rate using silicon-mixed EDM.

themselves with the electric field. This, in turn, also improves discharge distribution. These two factors are expected to increase MRR. Furthermore, semiconductors exhibit a decrease in resistivity with increasing temperature. Thus, if machining is continuous and the working gap's temperature rises, silicon's conductivity would increase sharply. A highly conductive powder would further enhance discharge energy transfer in subsequent discharges, enabling rapid machining. The temperature in the working gap is generally higher at high discharge energies. Furthermore, an increase in concentration can enhance this effect. This is evident in the MRR results shown in Figure 3-21. Increasing the voltage increased the material removal rate. Furthermore, the increase in concentration improved it further. However, at 90 V, the increase in concentration did not improve the MRR considerably and was found to be reduced at very high concentrations. At low voltage, the gap size is significantly smaller. The size of the agglomerated Si particles becomes similar to that of the gap itself. This inhibits the machining process, and the effect is further reduced as the powder concentration increases. The relative electrode wear for different machining conditions is shown in Figure 3-22. As with CNF and alumina, high tool wear was observed at 90 V, which decreased with increasing voltage. It was due to increased arcing at low voltages. This instability in machining also led to significant

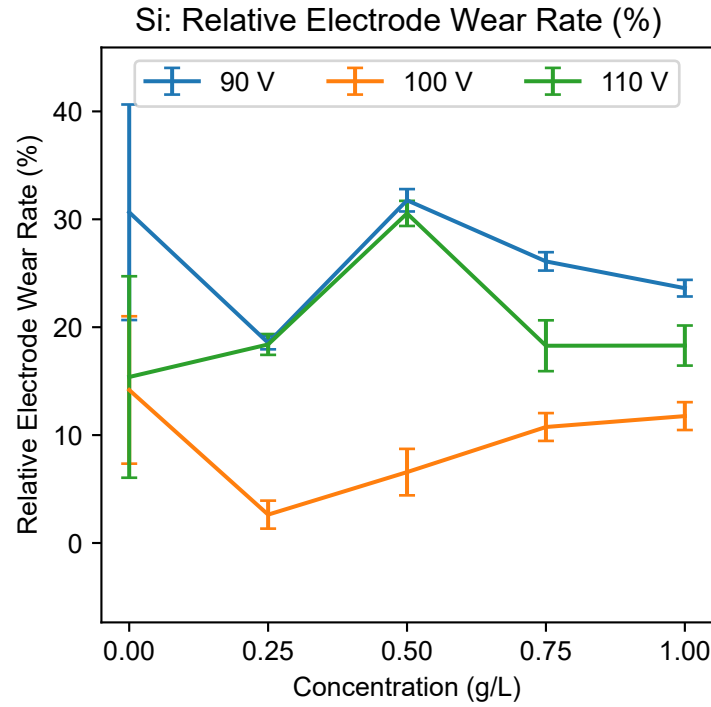


Figure 3-22: Relative electrode wear rate using silicon-mixed EDM.

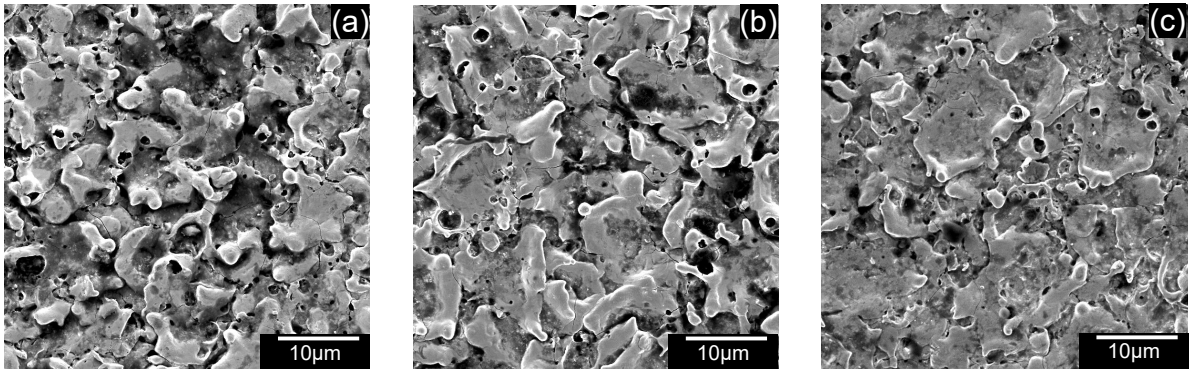


Figure 3-23: SEM of machined surface using 0.5 g/L silicon at (a) 90 V, (b) 100 V, (c) 110 V.

fluctuations in electrode wear at lower voltages.

Figure 3-23(a-c) shows the SEM of the machined surfaces with silicon-mixing. Surface roughness is shown in Figure 3-24. It was observed that the surface roughness decreased for most conditions during PMEDM with Si powder. The roughness value decreases initially with voltage and then increases. Like CNF and Al_2O_3 , the initial decrease in surface roughness was due to the reduction in crater size, as seen in Figure 3-9. However, unlike other powders, the difference in crater size between 90 V and 100 V is insignificant. The roughness increases due to a higher proportion of short circuits and arcing, resulting in unevenness across the surface.

Furthermore, the roughness decreased with increasing concentration. Initially, as concen-

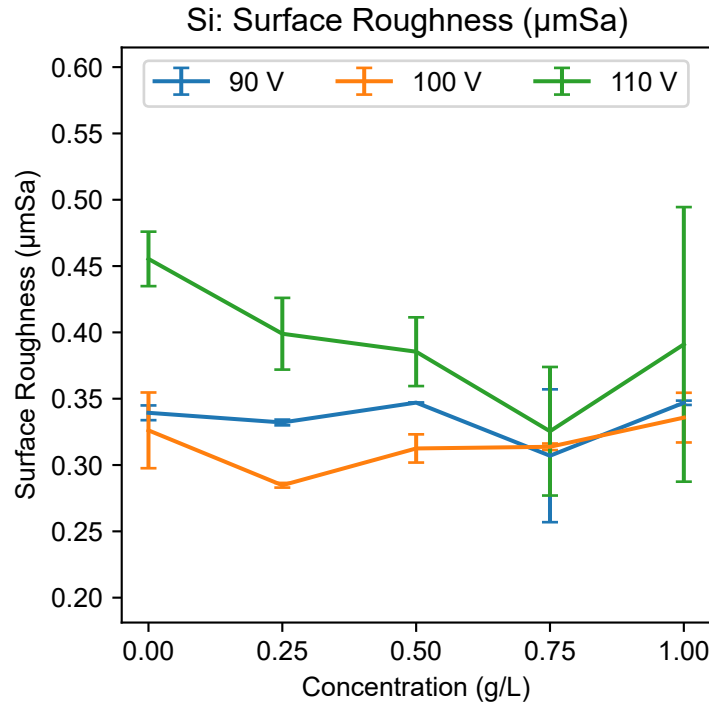


Figure 3-24: Surface roughness using silicon-mixed EDM.

tration increases, discharges become uniformly distributed due to a larger number of possible discharge pathways. However, at very high concentrations, many particles begin to agglomerate, resulting in discharge concentrations near the agglomerates and an uneven surface.

Silicon-mixed EDM of tungsten carbide can be an effective alternative to conductive powders. However, they can yield high material removal rates only at high discharge energy and powder concentrations. The electrode wear rate is also lower than CNF for most conditions. In their study, Pecas et al. [86] used silicon powder (10 μm) in the EDM of AISI H13. They indicated that adding silicon improved the roughness values. We have also found that silicon addition can improve the roughness in micromachining conditions.

3.2.3.5. Evaluation of Deep Micro-hole Machining

To test the effectiveness of the results derived above, a high-aspect-ratio deep-hole machining operation was performed. Since carbon nanofiber-mixed EDM was capable of producing an acceptable surface finish with a high material removal rate at most concentrations and voltages, it was used for the evaluation. A tubular electrode with a 0.5 mm diameter and a 0.1 mm hole was used. The hole was with the parameter shown in Table 3-4.

The results of deep-hole machining using EDM are shown in Figure 3-25. At very low

Table 3-4: Machining parameters for deep-hole machining

Parameter	Value
Voltage (V)	100
Capacitance (pF)	220
Feed rate ($\mu\text{m/s}$)	0.5
Depth (mm)	To termination
Powder concentration (g/L)	0,0.5

discharge energies, the initial machining stage (Figure 3-25(a)) shows that the progression of powder-mixed EDM and oil-only EDM is nearly identical. As machining proceeds into the mid stage (Figure 3-25(b)), the oil-only condition terminates prematurely due to instability caused by persistent arcing and inadequate debris flushing, whereas carbon nanofiber-mixed EDM continues to advance, as shown in Figure 3-25(c). The carbon nanofiber-mixed EDM produces a visibly smoother surface without coking or significant surface defects, as observed in Figure 3-26(b,d), in contrast to the oil-only condition shown in Figure 3-26(a,c).

However, during the later stages of deep-hole machining, even powder-mixed EDM struggles to maintain continuous cutting, requiring repeated tool retraction that can persist for over 20 min. As machining depth increases, debris evacuation becomes increasingly difficult due to restricted flow paths. In addition, at greater machining depths, the high aspect ratio of carbon nanofibers may promote entanglement and clustering within the confined side gap, leading to partially debris-like structures that are more difficult to evacuate and increasing the likelihood of secondary discharges along the sidewalls.

These observations suggest that dielectric modification alone is insufficient for sustaining high-aspect-ratio machining. We therefore propose that dynamically adjusting the rotation rate during machining may reduce instability and enable deeper, more stable drilling. The following section evaluates the influence of rotation rate on deep-hole machining behavior.

Overall, powder-mixed EDM improves material removal and surface quality at shallow depths, but these advantages diminish in high-aspect-ratio drilling due to debris accumulation and unstable discharge cycles. This motivates the exploration of tool rotation as an additional mechanism for stabilising deep machining.

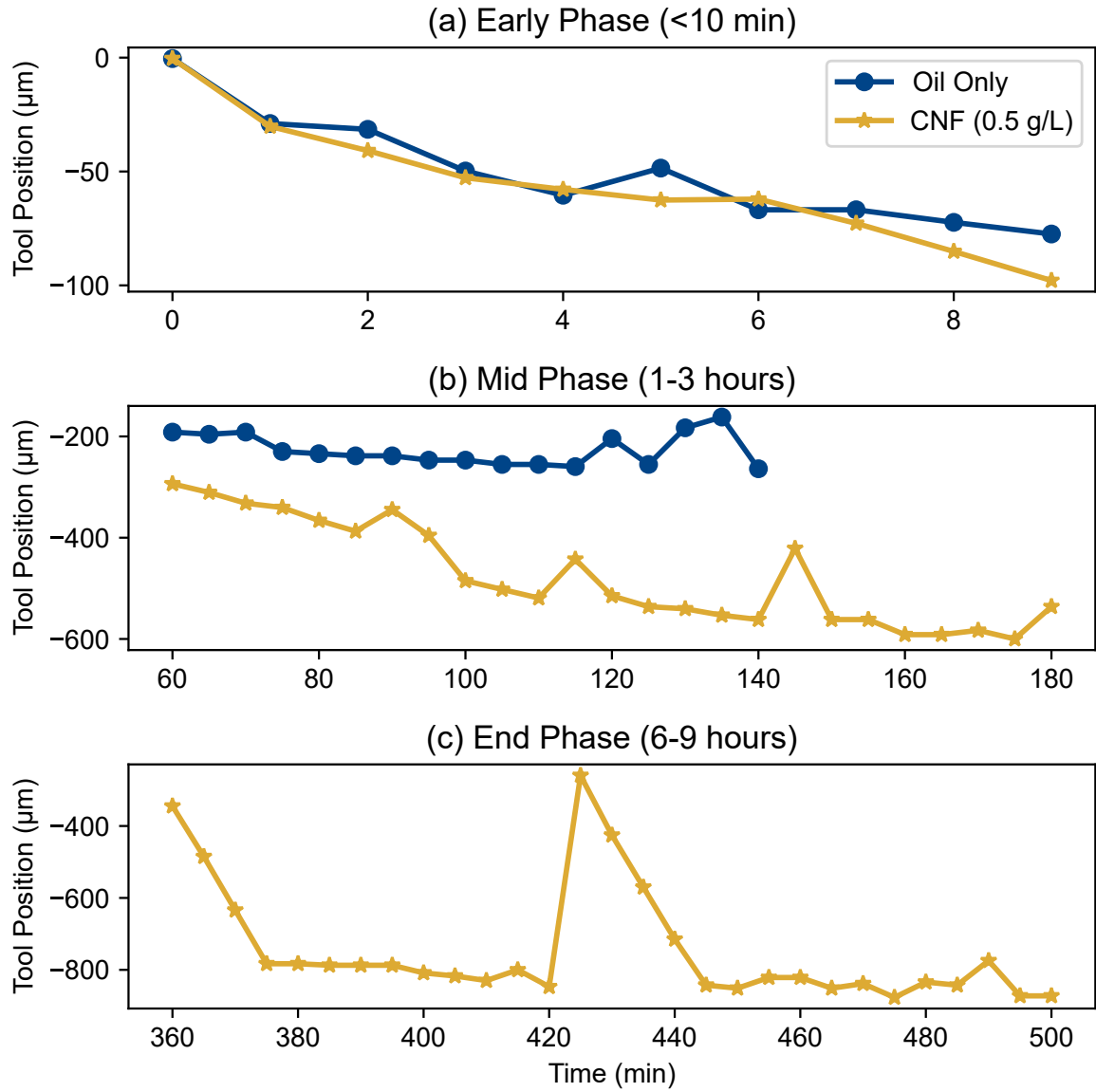


Figure 3-25: Tool position evolution for different machining conditions at (a) early, (b) middle, and (c) late machining.

3.3. Offline Parameter Optimization and Baseline Rotational Behavior

This section evaluates machining behavior under fixed electrical and kinematic settings. First, a Taguchi-Grey analysis is used to identify influential electrical parameters and establish a non-rotary baseline. Then, rotation-rate experiments are used to investigate how fixed-tool kinematics influence machining performance.

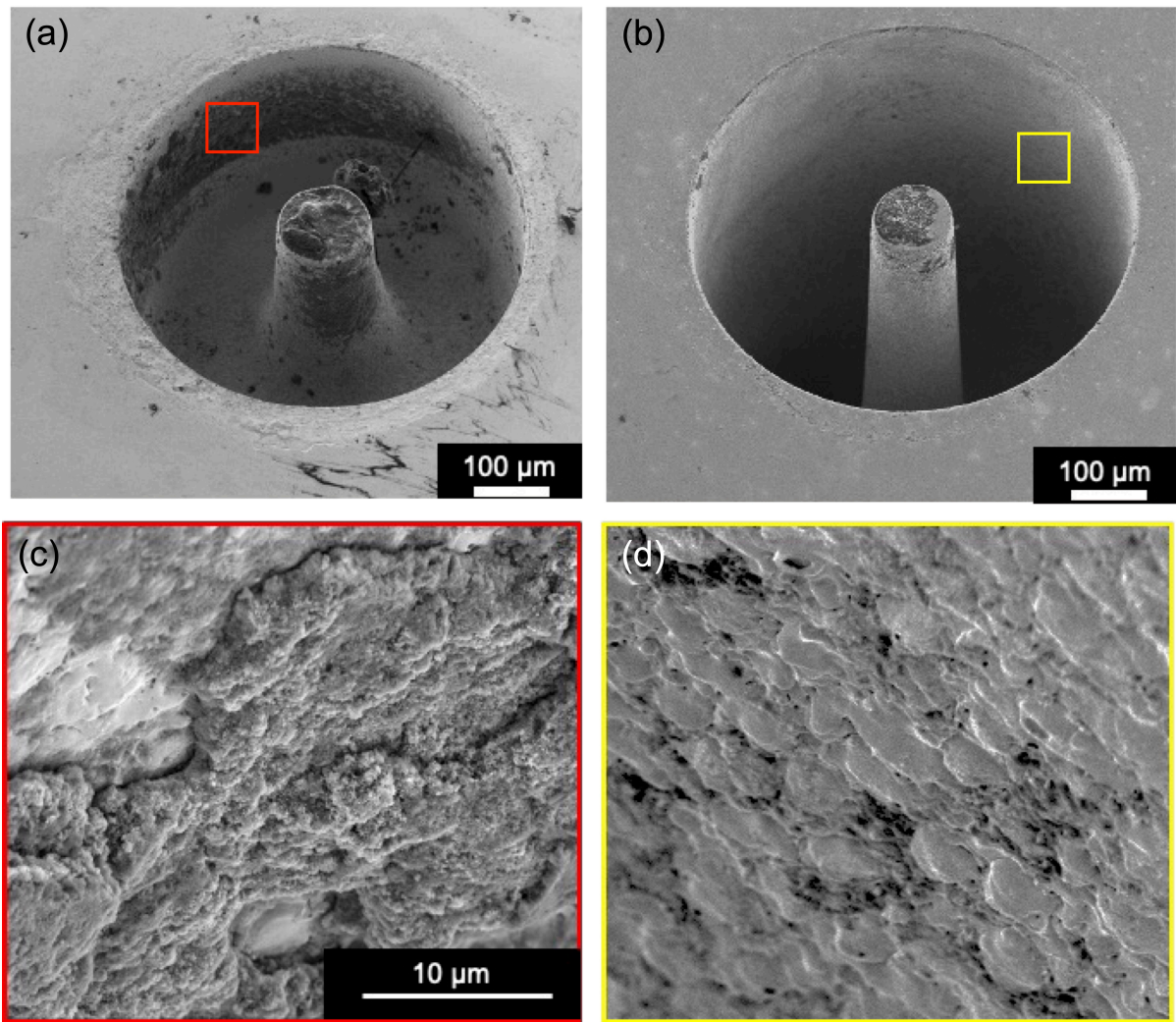


Figure 3-26: SEM of machined micro-pillars and zoomed surfaces for (a), (c) oil-only and (b), (d) and carbon nanofiber-mixed conditions.

3.3.1. Experimental Setup

To evaluate the effect of tool rotation rate in deep hole machining, experiments were performed on the Mitsubishi EA8PV die-sinking EDM machine. Tool rotation was controlled using a Nakanishi E2280 pneumatic air spindle, with rotational rate regulated via an Arduino Uno and ADC-based system. The dielectric fluid used was Shell Paraol 250, equipped with a custom two-stage filtration system comprising 10 μm and 0.5 μm filters. The machining setup is shown in Figure 3-27.

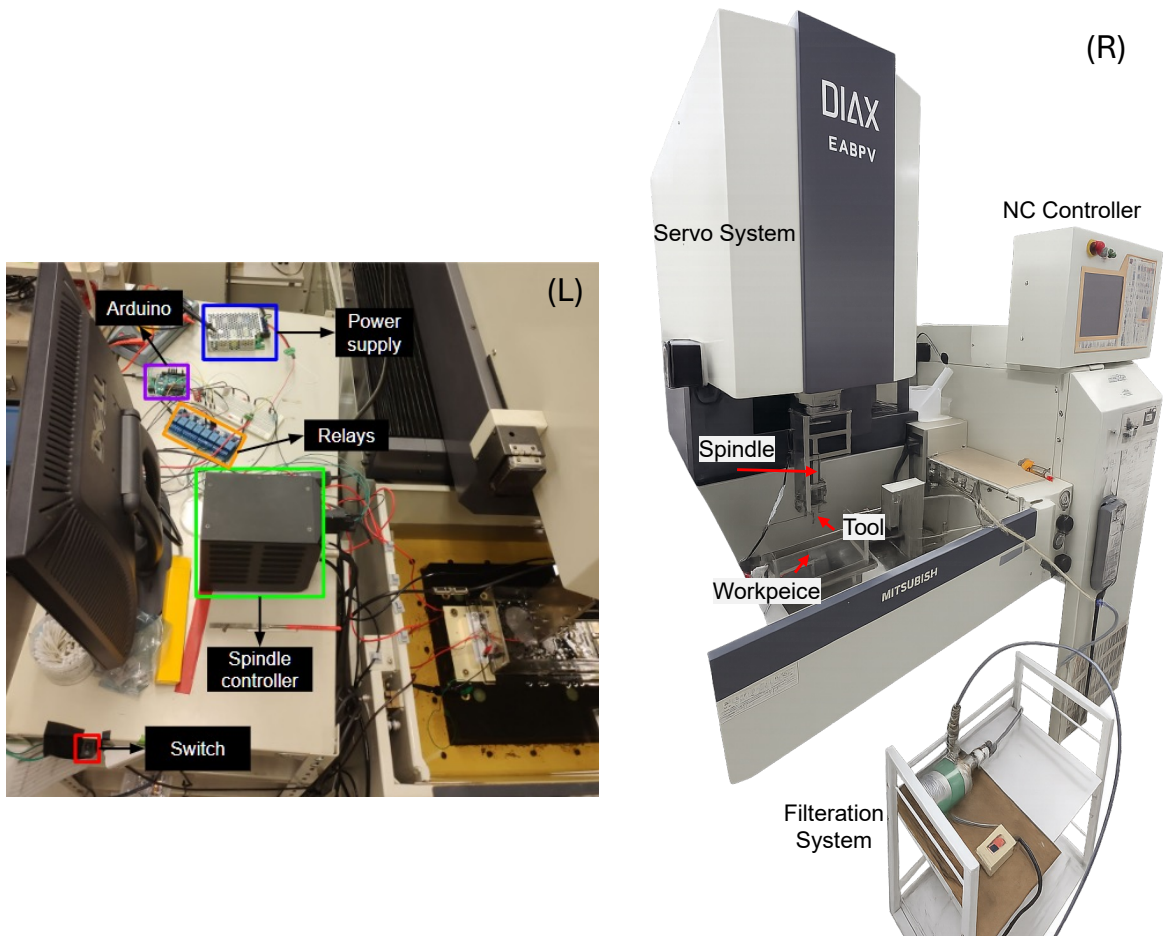


Figure 3-27: Photograph of the machining setup (R) and rotation control system (L).

3.3.2. Design of Experiments

Two sets of experiments were conducted to evaluate the effect of tool rotation in EDM. The first was a parameter-optimization experiment to establish baseline machining performance, followed by micro-through-hole drilling of tungsten carbide to investigate the influence of different rotation rates. The optimization experiments were conducted at lower settings of the transistor-resistor circuit, representing the semi-finish machining region with discharge energy [1-10 mJ]. Informed by prior literature [115] and manufacturer recommendations to reduce tool wear, short and frequent pulses with a gradual power rise were applied. To ensure adequate resolution in waveform acquisition, a minimum pulse duration of 4 μs (8 samples) was maintained. Subsequently, rotation evaluation experiments were conducted by machining a 1 mm thick tungsten carbide plate at rotation rates ranging from 1,000 to 10,000 RPM.

The Taguchi method was employed to determine optimal machining parameters within

defined experimental constraints. Five parameters: open circuit voltage (V_o), peak discharge current (I_p), feed rate (f), pulse-on duration (T_{on}), and duty ratio (DR), were each evaluated at four levels using an L16 orthogonal array, as shown in Table 3-5. 200 μm blind holes were machined at a rotation rate of 2000 RPM.

Table 3-5: Orthogonal array for Taguchi-Grey optimization

E.ID	Voltage [V]	Feed Rate [$\mu\text{m}/\text{min}$]	Peak Current [A]	Pulse On [μs]	Duty Ratio
1	80	60	1	4	0.2
2	80	120	1.5	8	0.3
3	80	180	2	16	0.4
4	80	240	2.5	32	0.5
5	110	60	1.5	16	0.5
6	110	120	1	32	0.4
7	110	180	2.5	4	0.3
8	110	240	2	8	0.2
9	150	60	2	32	0.3
10	150	120	2.5	16	0.2
11	150	180	1	8	0.5
12	150	240	1.5	4	0.4
13	220	60	2.5	8	0.4
14	220	120	2	4	0.5
15	220	180	1.5	32	0.2
16	220	240	1	16	0.3

Performance evaluation was categorized into three domains: material removal rate (MRR), surface roughness (S_a and S_z), and profile accuracy, specifically, machining depth (d) and diametric overcut (DOC). Each output metric had a distinct optimization goal: maximizing MRR, minimizing surface roughness, and achieving dimensional accuracy in profile features. To address the multi-objective nature of the problem, the Grey relational analysis (GRA) method was adopted. The procedure includes: (1) normalization of data, (2) computation of Grey relational coefficients (GRC), and (3) ranking based on Grey relational grade (GRG). Based on the optimization objective, one of three normalization formulas was used: smaller-the-better, larger-the-better, or nominal-the-best Equations 3.4, 3.5, and 3.6. The GRC was calculated using Equation 3.7, and the GRG using Equation 3.8. Notation was simplified for clarity but

remains consistent with standard GRA formulations [125], [126].

$$n_i(k) = \frac{\max x_i(k) - x_i(k)}{\max x_i(k) - \min x_i(k)} \quad (3.4)$$

$$n_i(k) = \frac{x_i(k) - \min x_i(k)}{\max x_i(k) - \min x_i(k)} \quad (3.5)$$

$$n_i(k) = 1 - \frac{x_i(k) - obj(k)}{\max |x_i(k) - obj(k)|} \quad (3.6)$$

Where $x_i(k)$ are the values of output k for experiment ID i , and $obj(k)$ is the goal value of output k .

$$GRC_i(k) = \frac{\Delta_{min} + \zeta \cdot \Delta_{max}}{\Delta_i(k) + \zeta \cdot \Delta_{max}} \quad (3.7)$$

Where $\Delta_i(k) = |x_i(k) - n_i(k)|$ is the deviation of the sequence. The distinguishing coefficient ζ was set to 0.5, a commonly used value in the literature, to ensure moderate sensitivity in the GRC calculation.

$$GRG_i = \sum_{k=1}^n \beta_k GRC_i(k) \quad (3.8)$$

To balance machining objectives, the five responses were grouped into three categories: machining efficiency (MRR), surface quality (Sa, Sz), and profile accuracy (d, DOC). Equal weight was applied to each category when calculating the GRG, in accordance with the study's goal of balanced optimization.

3.3.3. Results

The summary of performance metrics and the corresponding Grey relational grades (GRG) for each experimental condition is shown in Table 3-6. Experiments 7 and 8 achieved the highest GRG values. Subsequent SEM-based inspections (Figure 3-28) revealed minimal surface defects, such as micro-cracks, supporting the selection of these conditions. Experiment 7 was selected as the baseline setting for the subsequent rotation-rate evaluation. The intermediate steps of data normalization and the Grey relational coefficients are provided in Table A-1.

To evaluate machining performance across different rotation rates, a study was conducted, summarized in Table 3-7. Since the material removal rate for through-holes is directly influenced by both top and bottom diameters, machining time (Mach.Time) was considered as an

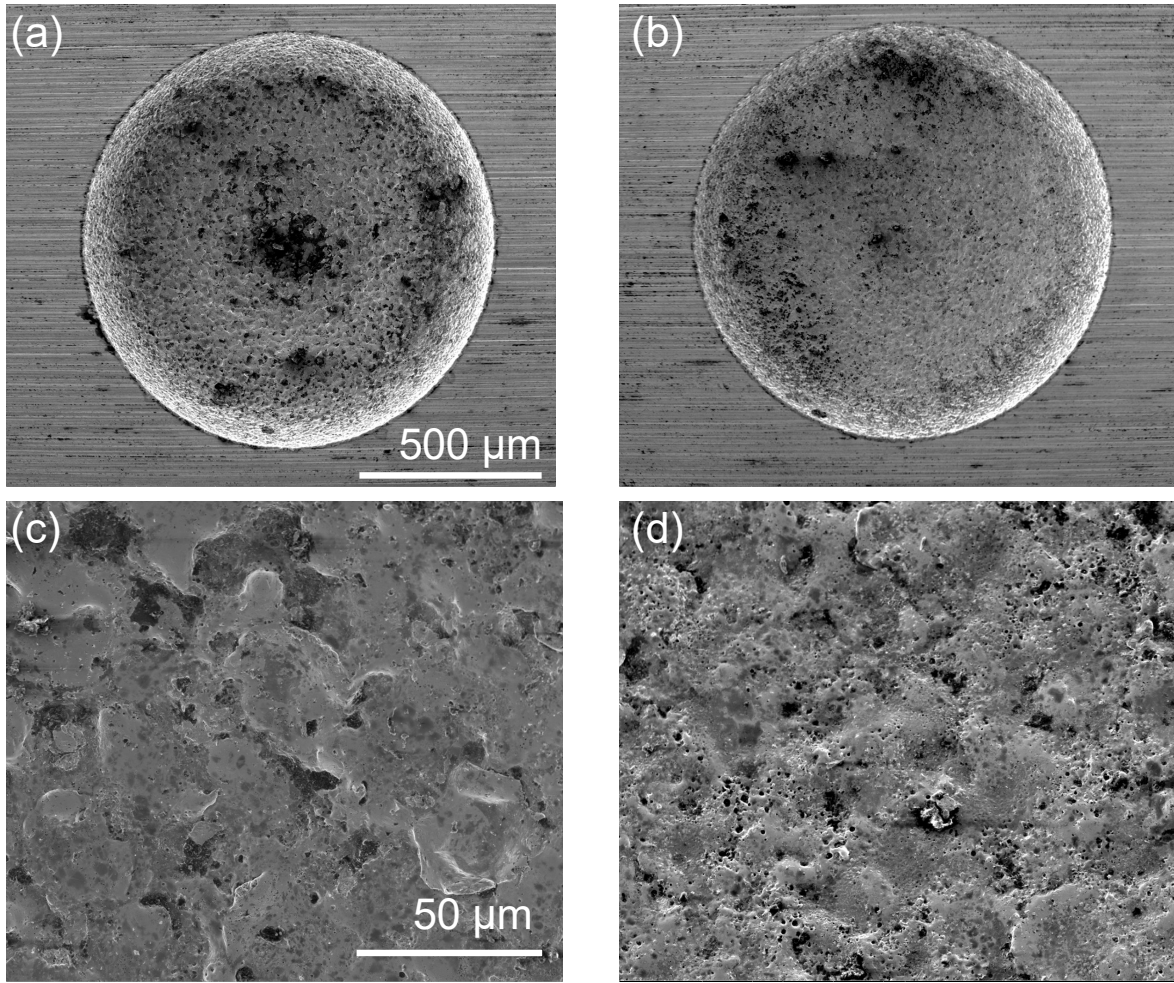


Figure 3-28: SEM of machined hole for experiments 7 (a), (c) and 8 (b), (d) respectively.

independent metric. Additionally, as illustrated in Figure 3-29(d)-(e), inlet chipping was observed for some conditions, prompting the inclusion of roundness metrics (Top Rou, Bot Rou). Three distinct temporal surfaces (B1, B2, B3) were observed in the hole cross-sections (Figure 3-29(b),(e)), and were therefore excluded from quantitative analysis. Equal weights were assigned to machining time, diameter, and roundness in the Grey relational grade (GRG) computation.

From the results, the best performance was observed at 1000 and 9000 RPM, which emerged as potential optimums. Normalized data and Grey relation coefficients for these conditions are shown in Table A-2.

While the fixed-rotation rate analysis provides useful baselines, it remains an offline evaluation based on post-machining measurements and does not explicitly capture when and where, within the hole, these distortions develop. In the following, prior fluid-dynamic findings and

Table 3-6: Summary of results and Grey relational grades (GRG) for each parameter evaluation experiment

E.ID	Results					GRG	Rank
	MRR [$\times 10^{-3}$ mm ³ /min]	Sa [μ m]	Sz [μ m]	DOC [μ m]	d [μ m]		
1	18.74	0.88	15.14	23.59	184.43	0.47	13
2	32.23	1.21	22.35	26.49	197.49	0.62	6
3	66.56	1.82	23.73	30.68	225.31	0.62	5
4	71.84	3.25	39.30	38.17	269.97	0.54	9
5	49.23	1.94	24.89	33.83	276.93	0.47	12
6	24.25	3.07	32.78	33.41	235.20	0.43	15
7	79.90	1.34	20.25	21.37	221.17	0.84	1
8	35.86	0.75	12.78	19.32	192.09	0.74	2
9	26.76	4.42	37.70	40.34	184.15	0.44	14
10	24.00	2.46	30.28	25.98	192.25	0.54	10
11	48.99	1.61	21.95	28.62	189.27	0.60	7
12	63.41	1.45	21.82	25.58	214.76	0.67	3
13	37.43	1.86	26.58	25.83	220.97	0.54	8
14	58.89	1.57	24.94	22.55	227.19	0.64	4
15	16.07	3.38	36.51	27.53	209.60	0.49	11
16	17.21	2.41	26.08	31.76	154.30	0.43	16

Table 3-7: Summary of machining metrics

Rotation Rate [RPM]	Mach. Time [min]	Top Dia. [μ m]	Bot Dia. [μ m]	Top Rou. [μ m]	Bot Rou. [μ m]	GRG	Rank
1000	17.18	1075.38	946.09	23.57	3.92	0.76	1
2000	17.62	1106.06	945.98	26.26	5.81	0.63	5
3000	18.70	1107.25	939.29	22.17	5.92	0.55	7
4000	18.42	1112.93	968.52	23.93	18.84	0.53	8
5000	18.37	1071.83	950.82	3.37	10.88	0.68	3
6000	17.97	1123.92	953.23	22.82	3.71	0.64	4
7000	19.32	1116.01	960.14	25.97	11.72	0.50	10
8000	18.98	1120.61	971.63	26.59	14.28	0.52	9
9000	16.93	1126.05	978.17	19.34	17.17	0.75	2
10000	19.10	1098.28	953.79	21.81	3.46	0.60	6

SEM observations are used to connect the observed profile changes to plausible mechanisms of debris transport, thereby motivating time-varying rotation strategies.

However, these results do not capture the temporal effects of tool rotation rate during EDM. Previous studies by Cetin et al. [127] have shown that when periodic tool motion, such as tool jumping, is applied, concavity or cylindrical distortion can develop along the side surface of

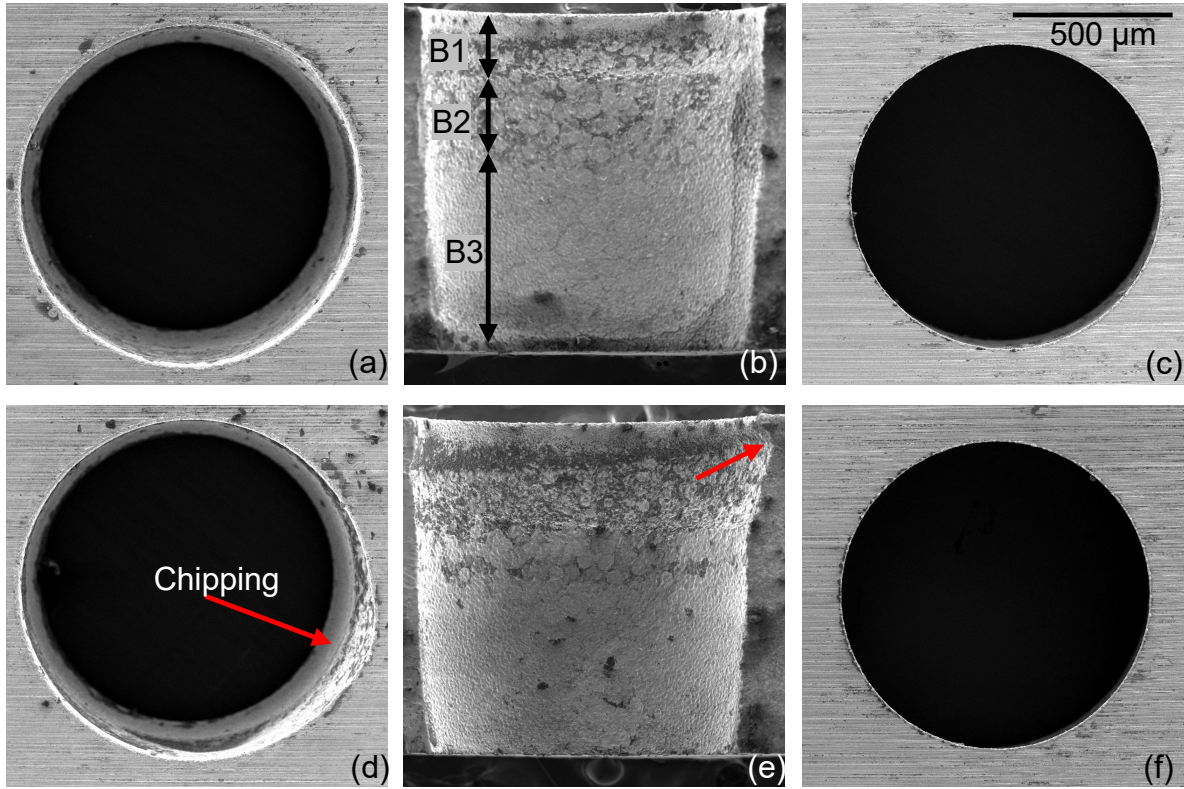


Figure 3-29: SEM of the top, cross-section, and bottom surface of the machined hole for 3000 (a)-(c) and 8000 RPM (d)-(f), respectively. (All micrographs are at the same scale.)

machined holes. Fluid dynamic simulations further attribute this behavior to the formation of localized vortical flow structures near the tool corner and within an annular region above the tool bottom [127], [128].

From the present experimental results, it can be observed that lower tool rotation rates generally produce smaller hole diameters. This indicates that increasing the rotation rate tends to increase the diametric overcut. While reduced overcut is beneficial near the top surface, excessive radial tool wear at lower rotation rates results in a significantly smaller outlet diameter. This behavior suggests that global geometric metrics alone are insufficient to describe the evolving machining conditions.

Based on prior simulation studies by Boban et al. [128], it is hypothesized that three dominant debris recirculation zones are formed within the machining gap: (i) near the tool corner, (ii) near the workpiece corner, and (iii) within an annular region above the bottom of the tool. At low rotation rates, the centrifugal forces acting on debris particles are insufficient to evacuate debris from zones effectively (i) and (ii). As a result, frequent tool retraction is required to

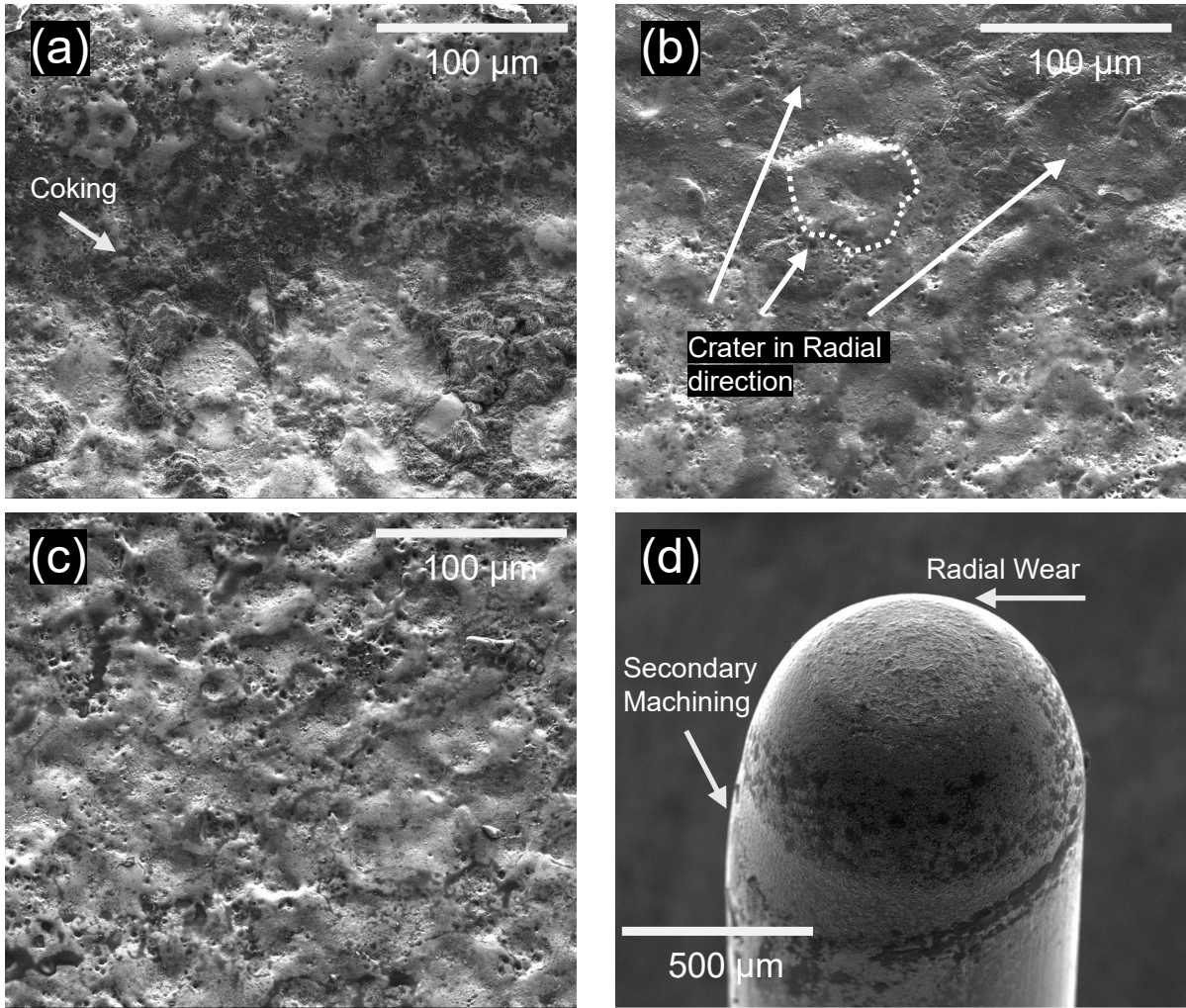


Figure 3-30: SEM of the machined zones at (a) top, (b) middle, and (c) bottom surfaces of a hole machined at 3000 RPM, and (d) the tool after machining.

restore stable discharge conditions.

Inadequate debris removal promotes arcing, which leads to thermal degradation of the dielectric and carbon deposition on both the tool and workpiece surfaces, commonly referred to as coking. This behavior is evident in Figure 3-30(a),(d). In addition, debris accumulation in the side gap triggers secondary discharges, leading to preferential radial erosion of the tool. This effect is clearly visible in Figure 3-30(b), where discharge craters are oriented radially. Additionally, SEM of the machined tool indicates that this annular zone is away from the tool bottom, where radial and axial wear are dominant. At higher rotation rates, strong centrifugal forces increase the tangential velocity of debris within this annular region. Consequently, debris removal becomes increasingly difficult, necessitating prolonged tool retraction and contributing to non-uniform sidewall erosion.

These observations indicate that the influence of tool rotation rate on machining stability is inherently time and depth-dependent. Fixed rotation conditions are therefore unable to simultaneously suppress debris accumulation across all recirculation zones throughout the machining process.

To evaluate whether time-varying rotation profiles can mitigate these effects, three dynamic tool rotation strategies were investigated: (i) linearly increasing rotation rate from 1000 to 10000 RPM, (ii) linearly increasing rotation rate from 4000 to 10000 RPM, and (iii) linearly decreasing rotation rate from 10000 to 1000 RPM. The corresponding rotation profiles are defined in Equations 3.9-3.11, and the resulting machining performance is summarized in Table 3-8. The results are indicative that dynamic rotation profiles can effectively achieve targeted machined profiles. Tests 1 and 3 show that a smaller rotation rate at the top indeed produces a smaller hole diameter, and a large rotation rate at the bottom can produce a larger hole. Test 2, with a moderately increased rotation rate, showed results closer to the target diameter profiles.

$$Test\ 1 = \lfloor 1000 + 6 \times Time\ (s) \rfloor\ RPM \quad (3.9)$$

$$Test\ 2 = \lfloor 4000 + 4.45 \times Time\ (s) \rfloor\ RPM \quad (3.10)$$

$$Test\ 3 = \lfloor 10000 - 6 \times Time\ (s) \rfloor\ RPM \quad (3.11)$$

Table 3-8: Results for dynamic test rotation rate experiments

Test Case	Mach. Time [min]	Top Dia. [μm]	Bot Dia. [μm]	Top Rou. [μm]	Bot Rou. [μm]
Test 1	18.25	1062.98	956.03	3.22	11.48
Test 2	19.45	1122.70	997.89	26.01	24.61
Test 3	18.63	1114.94	966.17	21.03	1.61

However, despite the optimized settings, deep-hole machining performance remained substantially lower than the short-depth baseline: while short-depth machining reached $79 \times 10^{-3} \text{ mm}^3/\text{min}$, deep-hole machining under the optimized offline conditions decreased to $47\text{-}51 \times 10^{-3} \text{ mm}^3/\text{min}$ (approximately 60% of the short-depth value). Moreover, global metrics such as top and bottom diameters do not capture the cylindrical distortions and temporal surface features that develop during drilling; these are only revealed through destructive cross-sectional microscopy.

This limitation highlights why traditional offline optimization, which relies on offline measurements, is insufficient for a process governed by evolving gap conditions. Therefore, the following chapters focus on identifying time-resolved indicators from discharge waveforms and tool motion to infer the machining state and determine when to adjust process parameters, such as rotation rate.

3.4. Summary

This chapter examined the influence of powder addition, short- and deep-hole machining behavior, and offline parameter optimization on the EDM of tungsten carbide. The summary of findings is as follows:

1. Powder-mixed EDM fundamentally modifies pre-breakdown discharge behavior through powder-dependent electrical properties. Conductive CNF and insulating Al_2O_3 reduced crater size by promoting discharge dispersion via conductive bridging and permittivity-driven field homogenization, respectively. In contrast, semiconductive Si enabled a more stable, high-energy plasma channel, producing wider craters with limited voltage dependence.
2. Material removal rate increased for all powders due to improved discharge initiation and reduced ineffective discharge periods. CNF yielded the largest improvement owing to its high electrical conductivity. At the same time, Si and Al_2O_3 exhibited MRR improvements primarily at higher voltages, where permittivity-driven polarization and temperature-activated conductivity effects became dominant. In all cases, MRR increased with powder concentration up to an optimum, then decreased due to particle agglomeration or adhesion.
3. Powder addition generally increased electrode wear, particularly for CNF, as a consequence of sustained high-temperature plasma and reduced dielectric cooling during continuous machining. Surface roughness improved most consistently at 100–110 V for all powders due to reduced crater size and enhanced discharge dispersion. However, at lower voltages, increased instability, debris redeposition, and intermittent arcing led to unreliable roughness improvements.

4. Although CNF-mixed EDM significantly enhanced short-depth machining performance, these benefits did not persist during deep-hole drilling. As machining depth increased, debris accumulation, powder sedimentation, and restricted dielectric flow led to persistent arcing, frequent tool retraction, and unstable discharge cycles, demonstrating that dielectric modification alone is insufficient to sustain high-aspect-ratio machining.
5. Taguchi–Grey optimization identified favourable fixed electrical settings, and tool rotation rate evaluation revealed local optima at 1000 and 9000 RPM. Increasing the rotation rate increased the proportion of discharges occurring in the side gap, leading to greater diametric overcut. However, improved debris evacuation in the bottom gap reduced radial tool wear, indicating a trade-off between dimensional accuracy and local machining stability under fixed-rotation conditions.
6. Nevertheless, even under optimized electrical and kinematic conditions, deep-hole machining achieved only approximately 60% of the material removal rate obtained in short-depth conditions. Furthermore, cylindrical distortions were observed under all fixed rotation-rate conditions due to evolving instability along the machining depth. These limitations demonstrate the inadequacy of offline optimization for a process governed by time-varying gap conditions and motivate the need for dynamic, waveform-based modelling and control strategies explored in the subsequent chapters.

Chapter 4

Instability Monitoring in EDM using Machine Learning

4.1. Introduction

This chapter develops an intelligent process modeling framework for EDM of tungsten carbide using electrical waveforms and discharge statistics. Building on the parameter-level analysis from the previous chapter, this chapter shifts the focus from fixed input-output relationships to data-driven interpretations of discharge behavior and machining stability. The chapter first details the waveform-acquisition and event-detection pipeline, then introduces a rule-based discharge classification that distinguishes sparks, arcs, short circuits, and secondary events. These labeled discharges are then used to define rotation rate-normalized indicators of unstable machining, such as end-of-machining (EOM) detection and batch-level under- and over-machining.

Using these physically motivated labels, supervised machine-learning models are trained to detect instability from both raw waveform features and grouped discharge categories. Random Forest and XGBoost classifiers are evaluated alongside SHAP-based feature importance interpretation. Finally, a 1D convolutional neural network (1D-CNN) is introduced to learn discharge classes directly from waveform segments, reducing dependence on hand-crafted thresholds while remaining compatible with the timing constraints of adaptive rotation control. Together, these methods form the first block of the intelligent modeling layer, linking discharge-level dynamics to machining stability.

4.2. Methodology

4.2.1. Data Acquisition

Waveform data were acquired using an Iwatsu SS-0130R voltage probe and an Iwatsu SS-240A current probe, connected to a Picoscope 3403D MSO oscilloscope. A sampling interval of 504 ns was used to capture the waveforms, with pulse-on and pulse-off durations of 4 μ s and

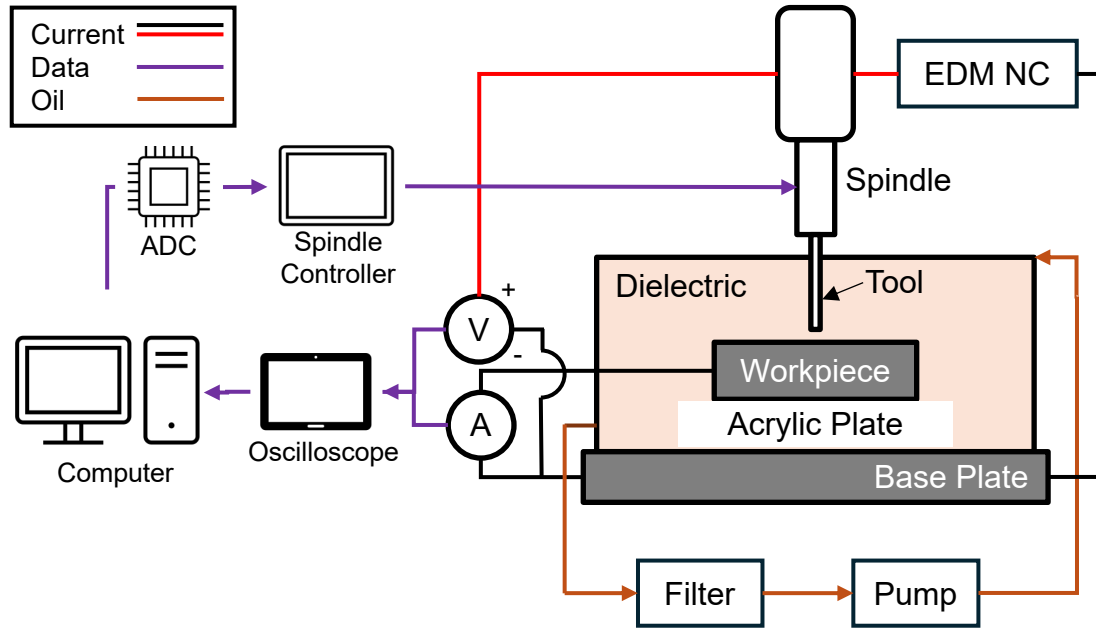


Figure 4-1: Experimental setup

9.6 μ s, respectively. The data were recorded in binary format using Python wrappers from the PicoSDK library. A schematic of the complete machining setup is shown in Figure 4-1.

4.2.1.1. Waveform Capture and Discharge Classification

To reduce the impact of electrical noise, both inductive and capacitive, a weighted moving average filter was applied to voltage and current signals. The kernel used was (0.05, 0.15, 0.6, 0.15, 0.05), which effectively smoothed high-frequency fluctuations while preserving the underlying discharge shape. This filtering stage ensures reliable event detection in the next processing phase.

The EDM system employed in this study features an always-on voltage and a pulsed current profile. A switched-capacitor (SC) circuit was used, in which the current rises gradually during each discharge. The discharge pulse duration was defined empirically as the interval during which the current exceeded 60% of its local peak, capturing the effective energy-delivery window.

Discharge events were flagged whenever this 60% threshold was crossed. For each event, the start time, average voltage, maximum current, discharge duration, and inter-discharge delay were computed. The event-detection methodology is illustrated in Figure 4-2, while the classification criteria are detailed in Table 4-1.

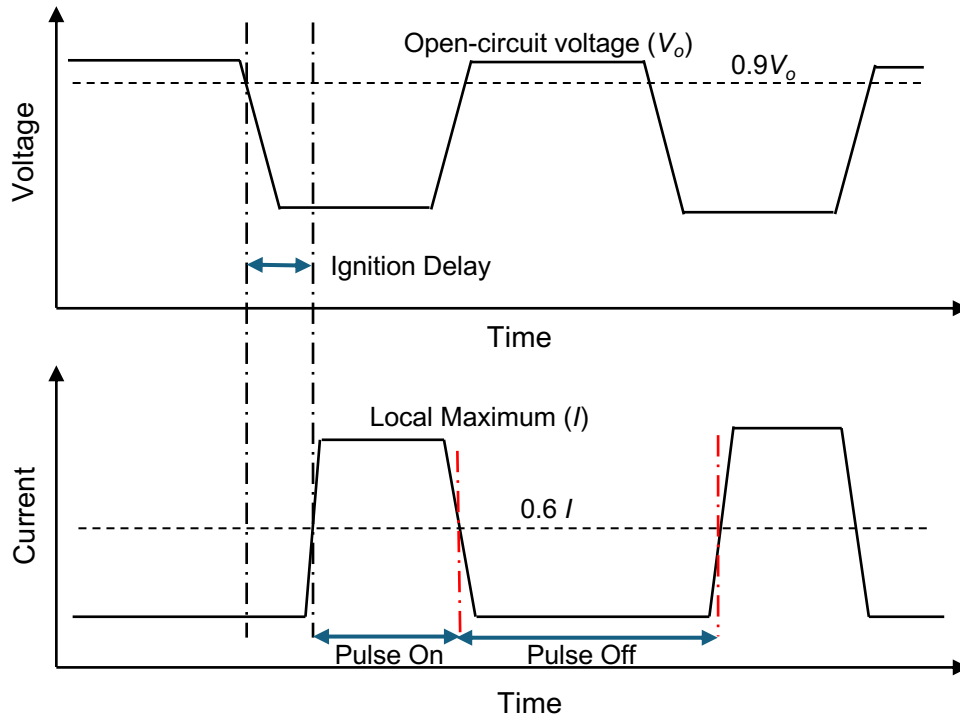


Figure 4-2: Discharge detection schematic.

In addition to standard discharge categories from previous studies [101], [129], two new classes are introduced: Unstable Sparks (US) and Partial Sparks (PS). These capture events with pulse-off durations shorter than nominal off-time, typical in circuits with continuous voltage and pulsed current. This categorization was needed because many discharges occurred under these conditions, as shown in Figure A-1.

Table 4-1: Key conditions for classification of detected discharges.

Class	Symbol	Key conditions
Short circuit	SC	$V < 0.01V_o$
Clean sparks	SP	$V > 0.01V_o$; $I > 0.75I_p$; $0.9T_{on} \leq T \leq 1.1T_{on}$; Delay $\geq T_{off}$
Transient arcs	TA	$V > 0.01V_o$; $1.1T_{on} < T \leq 1.4T_{on}$
Arcs	AR	$V > 0.01V_o$; $T > 1.4T_{on}$
Unstable sparks	US	Same as SP but Delay $< T_{off}$
Partial sparks	PS	Same as SP but $I < 0.75I_p$
Secondary discharges	SD	All other discharges not matching the above categories

Where V_o , I_p , T_{on} , T_{off} refer to open circuit voltage, peak current, pulse on duration, and pulse off duration, respectively.

4.2.1.2. Regression-based Parameter Analysis

The empirical relationships between the input parameter (X) and the output metrics (Y) were further explored through regression modeling. Both linear regression (LR) and non-linear machine learning-based ensemble models: Random Forest (RF) and Extreme Gradient Boosting (XGB), were implemented using the scikit-learn Python library.

For linear regression, which is sensitive to multicollinearity, features with variance inflation factors (VIFs) above 5 were removed iteratively. To improve model performance, backward sequential selection identified the most relevant variables. The objective was to retain as many features as possible while still achieving high performance, defined as $R^2 > 0.8$ and $MAPE < 20\%$.

For the non-linear RF and XGB models (as described in [130]), which are inherently robust to multicollinearity, no VIF filtering was applied. An 80:20 train-test split was used unless a predefined test set was available.

These regression models were not intended solely for high-accuracy prediction but were used to evaluate the nature of relationships, linear or non-linear, between input parameters and output metrics, and to identify key influencing variables.

When the regression models failed to meet the performance thresholds, a correlation analysis was conducted. The Pearson correlation coefficient between two variables x and y is given by Equation 4.1:

$$Corr(x, y) = \frac{Cov(x, y)}{\sigma_x \sigma_y} \quad (4.1)$$

4.2.2. Labeling and Predictive Modeling

4.2.2.1. End-of-Machining (EOM) Detection

After data preparation, we first developed a model to detect the End-of-Machining (EOM) phase. This was essential to isolate the effective machining period from the chaotic breakthrough or termination phases, which often introduce labeling noise. The EOM phase is characterized by decaying discharge signals: highly oscillatory waveforms with gradually diminishing amplitude, as illustrated in Figure 4-3(a). To detect this transition, a Fast Fourier Transform (FFT) was applied to the total discharge signal, leveraging the observation that the EOM re-

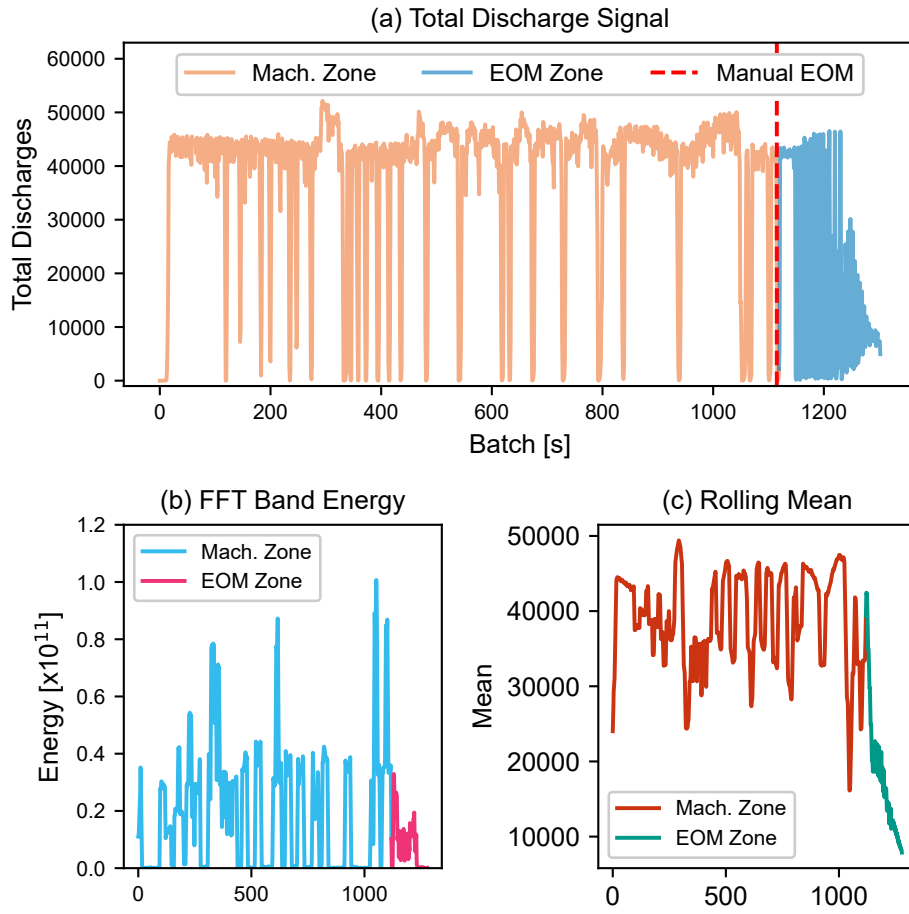


Figure 4-3: (a) Total discharges signal in the stable and EOM phases, (b) FFT energy in frequency bands [0.08-0.12 Hz], (c) rolling mean of discharge count over a 25-second window.

gion exhibits a clear reduction in band energy within the [0.08-0.12 Hz] frequency range. This band was selected empirically because it consistently highlighted the dominant low-frequency oscillation (approximately 8-12 s period) observed near EOM and provided separable energy levels compared with stable machining. A preliminary manual annotation of the EOM onset was made via visual inspection. This initial label was then used to train a Random Forest classifier on features such as FFT band energy, Figure 4-3(b), and the rolling mean of discharge count over a 25-second window, Figure 4-3(c). The trained model enabled automatic detection and segmentation of machining and EOM phases, ensuring that subsequent analysis focused only on the machining regime.

4.2.2.2. Instability Labeling Strategy

Within the machining phase, the term *instability* may refer to undesirable conditions such as frequent tool oscillations, extended tool retraction, inefficient material removal, short circuits, or erratic discharge behavior. For effective machine learning-based classification, it is essential to establish a consistent and physically meaningful definition of instability that remains valid across varying rotation rates.

Based on exploratory analysis, two categories of instability were identified: (1) Quantitative instability, characterized by a significant deviation in the total number of discharges from typical machining behavior, and (2) Qualitative instability, involving compositional shifts in discharge events, such as increased arcing or secondary discharges.

In this chapter, the instability label is based on quantitative thresholds (total discharge events per second). In contrast, qualitative discharge composition features are used as predictive inputs to explain and detect these quantitatively defined unstable zones. To construct a rotation rate-normalized definition of instability, the distribution of total discharge event counts was examined within each rotation condition using 1-second machining batches. This quantile-based approach reduces sensitivity to noise while preserving the dominant under- and over-machining signatures. As illustrated in Figure 4-4(a), tool retraction predominantly occurs when machining enters the over-machining unstable zone. To capture these extremes consistently across experiments, the 10th and 85th percentiles of the discharge-count distribution were computed for each rotation rate and used as instability thresholds. These values, refined through iterative testing, provided a practical balance between adequate class representation and clear separability for supervised learning. Batches with discharge counts below the 10th percentile or above the 85th percentile were therefore labelled as *unstable*, while all others were labelled as *stable*. These binary labels form the ground truth for the classification models developed in this and the next chapter.

To classify stable and unstable machining batches based on the defined labels, we used two commonly applied tree-based ensemble learning algorithms: Random Forest (RF) [131], [132], and Extreme Gradient Boosting (XGBoost or XGB) [133]. RF builds multiple decision trees using randomly sampled data and features, thereby improving robustness and reducing

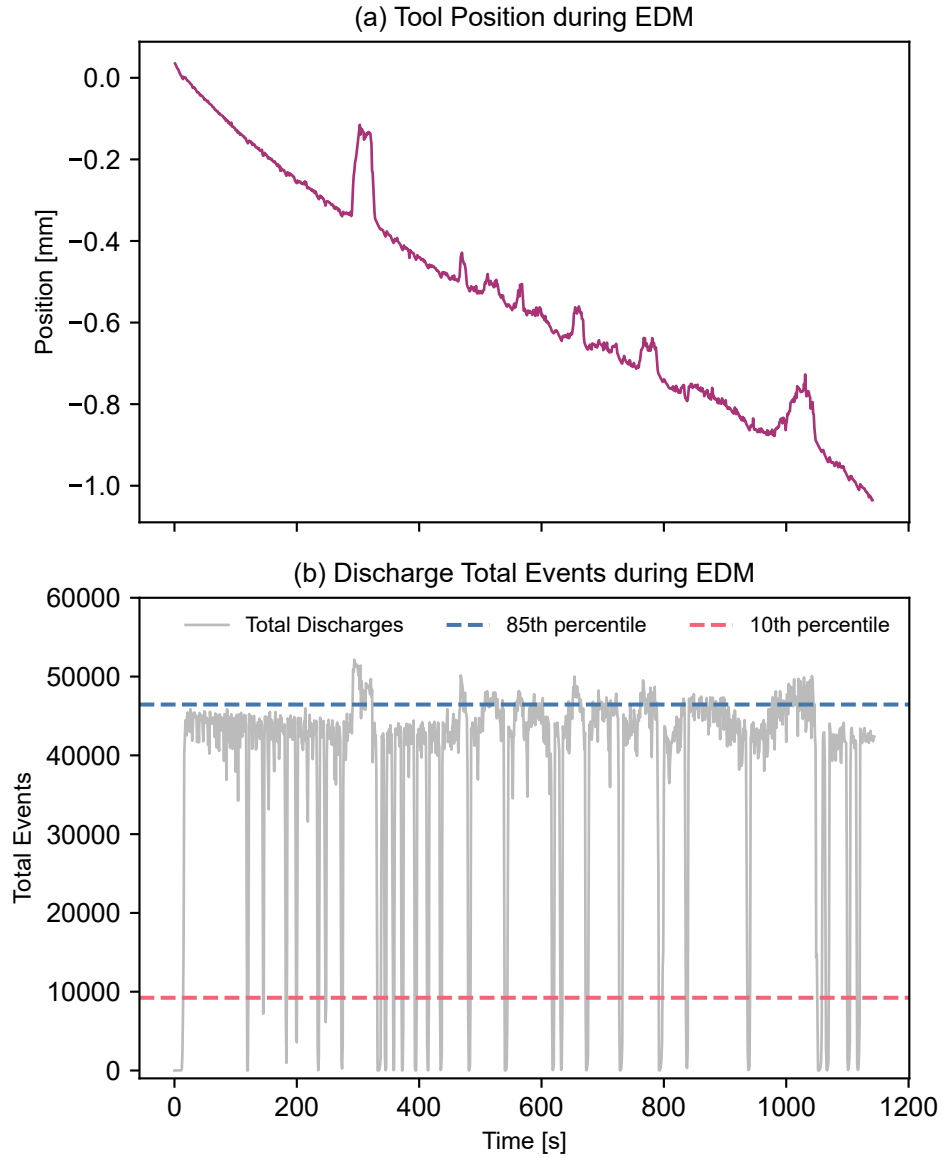


Figure 4-4: (a) Tool position and (b) discharge event counts for 1 s batches with labelled instability zones.

overfitting. XGBoost, on the other hand, builds trees sequentially, with each tree aiming to correct errors introduced by previous trees. These models are often used for structured data classification tasks and are known for their performance in practical applications, such as defect detection [134], [135] and process monitoring in manufacturing [136].

In this study, we applied both models to predict machining stability at the batch level, using features engineered from event statistics and signal-based indicators.

4.2.2.3. Supervised Classification

Two types of features were extracted for model training. The first set comprises raw waveform-derived features, including the mean, standard deviation, maximum, and minimum values of voltage, current, discharge duration, ignition delay, and the duration between successive discharge starts (inter-discharge delay), calculated over 1-second batches.

The second set includes classified discharge features, such as the count of each discharge type, 10-second rolling averages, and temporal derivatives. While percentage-based features were initially explored, they were excluded to avoid data leakage, as they directly depend on the total discharge count used for labeling.

In total, over 20 features were considered. To address the potential high dimensionality and multicollinearity, an initial Random Forest model was used to evaluate feature importance. Features with low SHAP (SHapley Additive Explanations) scores and high variance inflation (VIF > 10) were removed, and the top 15 features were selected. Additionally, to address class imbalance (unstable batches comprising 25%), the Synthetic Minority Oversampling Technique (SMOTE) was applied to batch-level features during training. The fixed-rotation-rate experiments were used for training, while the dynamic rotation-rate experiment was held out as an unseen test set.

This split evaluates whether a classifier can generalise from fixed rotation rate conditions to dynamic rotation rates, without using rotation rate as an explicit input feature.

The two classifiers, RF and XGBoost, were evaluated. Hyperparameter tuning was performed using grid search. A conservative decision threshold of 0.5 was adopted to prioritize recall over precision, given the application's focus on detecting potentially unstable conditions where false negatives are more critical than false positives. The complete machine learning workflow is outlined in Figure 4-5.

4.3. Results and Discussion

4.3.1. Exploratory Modeling and Feature Selection for Instability Labelling

Based on the methodologies described in Section 4.2.1.2, linear regression models were evaluated using R^2 and MAPE as shown in Table 4-2. Only MRR and Sa achieved the target

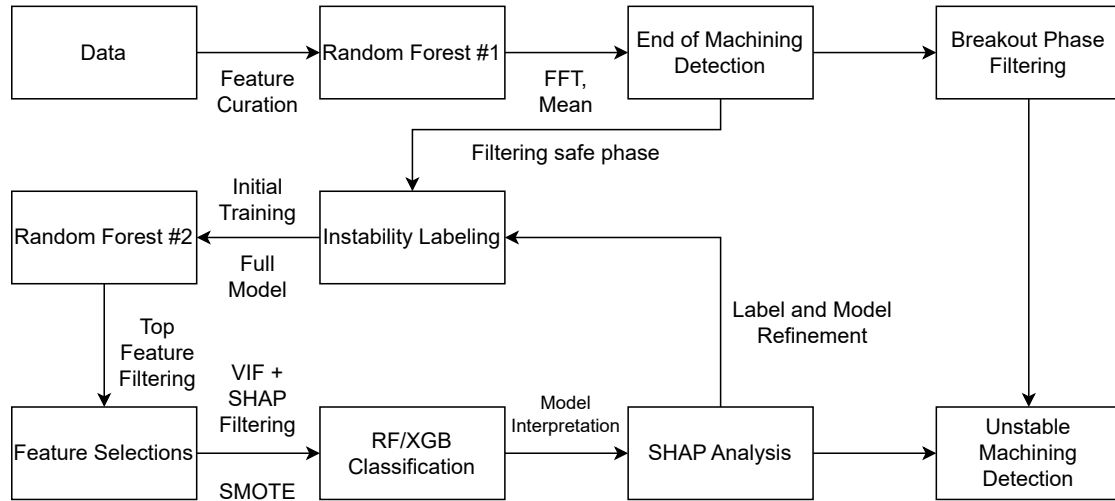


Figure 4-5: Workflow for instability detection and supervised classification.

thresholds of $R^2 > 0.8$ and $MAPE < 20\%$ and were considered suitable for interpretation. The MRR showed strong dependence on peak current and pulse-on duration (Equation 4.2). For Sa, as seen in Equation 4.3, lower voltage, shorter pulse durations, and higher feed rates were found to be favorable for achieving better surface quality. These findings align with prior studies on semi-finish EDM of hard materials [137], [138], [139].

Table 4-2: Linear regression performance for each target output.

Target	R^2	MAPE (%)
MRR	0.861	15.970
Sa	0.948	12.355
Sz	0.496	18.384
Depth	0.172	11.635
Overcut	0.771	8.988

$$MRR = 6.471 + 1.717 I_p + 0.065 T_{on} + 0.062 DR \quad (4.2)$$

$$Sa = -0.017 + 0.008 T_{on} + 0.011 V_p - 0.002 f \quad (4.3)$$

To explore empirical modeling, linear and non-linear regression models were applied, with rotation rate as the sole input variable, as shown in Table 4-3. However, most models yielded negative R^2 scores, indicating they performed worse than simple mean-based prediction. This suggests either insufficient data points or a non-monotonic relationship between rotation rate

and output metrics (i.e., one that alternates between increasing and decreasing).

We then explored whether including on-machine measurements could improve model performance by incorporating two feature sets: Z1 (raw electrical signals) and Z2 (discharge classifications), as described in section 4.2.1.1.

Despite these enhancements, regression models (especially linear ones) still performed poorly. For example, the linear model trained on raw signal features produced an implausibly negative R^2 (e.g., -748 for bottom roundness), indicating poor model generalization and potential issues with input scaling or multicollinearity. While ensemble models (e.g., Random Forests) achieved marginal improvements (e.g., $R^2 = 0.69$ for machining time), overall predictions remained weak.

Table 4-3: Model R^2 scores for different feature sets

Output	Rotation Features			Signal Features			Classified Features		
	LinReg	RF	XGB	LinReg	RF	XGB	LinReg	RF	XGB
Mach. Time	-20.20	-18.27	-17.99	-58.28	0.69	-0.67	-4.08	0.10	-0.22
Top Dia.	-0.63	-1.81	-3.86	-9.00	0.28	-0.14	-713.80	-0.22	0.00
Bottom Dia.	0.46	0.72	0.92	-177.40	-0.62	-0.15	-3141.73	-0.74	-0.78
Top Rou.	-0.83	-0.99	-1.50	-35.22	0.01	-0.43	-1080.21	-0.46	-1.77
Bottom Rou.	-0.08	0.47	0.82	-748.46	-0.46	-0.83	-17641.0	-1.33	-2.25

Due to these limitations, the focus shifted from regression modeling to correlation-based analysis. Pearson correlation coefficients were computed both between input features and output metrics ($Z - Y$), and among input features themselves ($Z - Z$), along with rotation rate [RR] for classified data, as visualized in Figure 4-6. A correlation threshold of $|r| \geq 0.6$ was used to denote strong associations.

The findings revealed several key relationships between discharge types and machining outcomes. An increase in weak partial sparks and transient arcs was significantly correlated with longer machining times, suggesting inefficiencies in energy transfer. A higher count of secondary discharges, resulting from poor flushing, was associated with enlarged top and bottom diameters, leading to pronounced overcuts. In contrast, clean sparks resulted in reduced top and bottom diameters, thereby reducing overcuts, reaffirming their role as desirable discharges. Interestingly, short circuits also showed a negative correlation with overcut (top and bottom diameters). This counterintuitive trend is interpreted as a secondary effect arising from increased

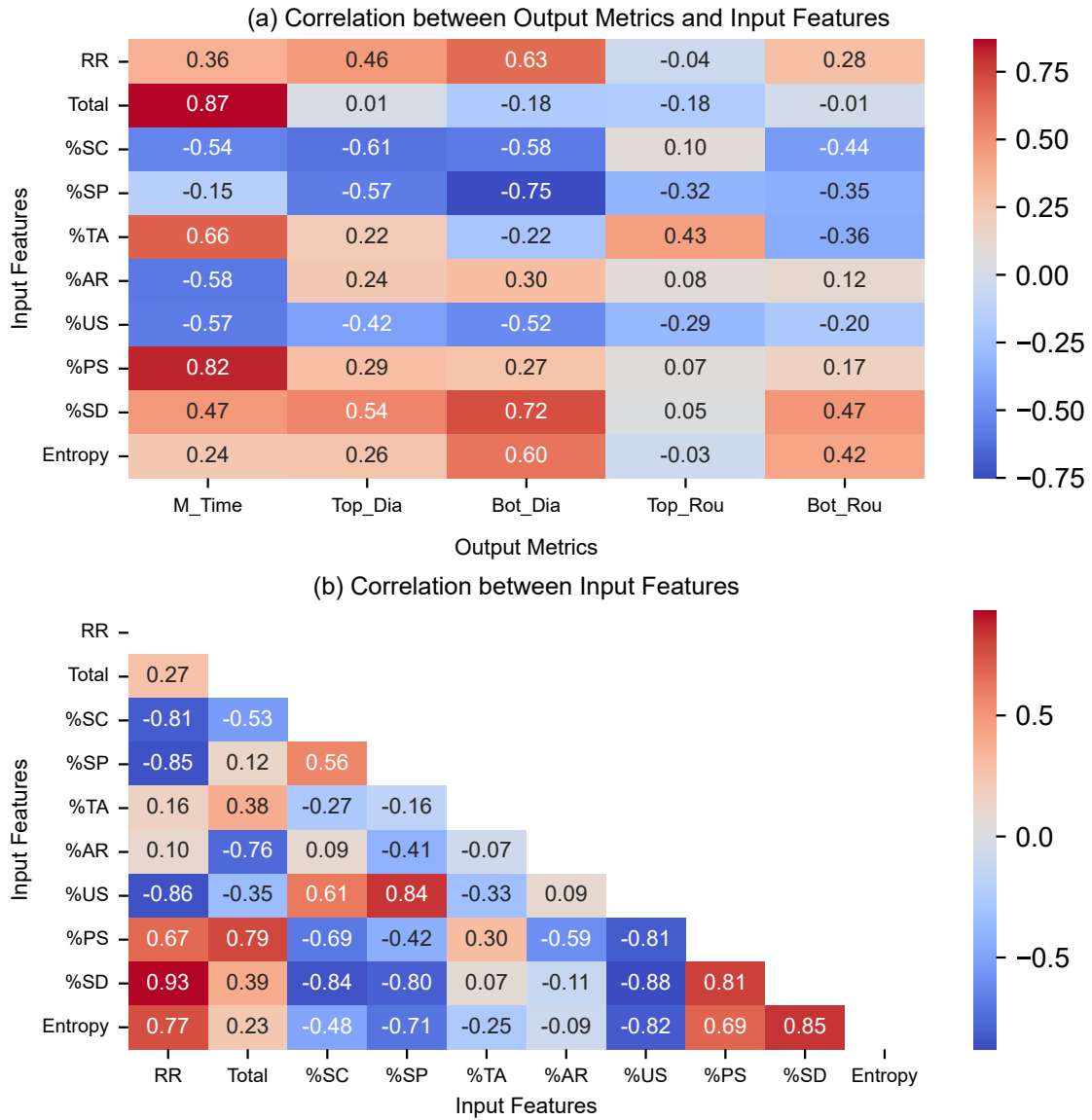


Figure 4-6: Pearson correlation coefficient heatmap for (a) input features vs. output metrics and (b) within input features for classified features.

clean-spark frequency and the suppression of secondary discharges.

Despite these insights, extensive multicollinearity among the features substantially weakened the explanatory power of regression-based models.

An important physical insight emerged: increasing the rotation rate tends to increase the frequency of partial sparks and secondary discharges, likely because increased fluid shear disrupts discharge channels. While increasing tool rotation helps break down short circuits more rapidly, it comes at the cost of a reduced clean-spark frequency. In summary, increased rotation rate increases chaos or entropy within the discharge gap as seen in Figure 4-6(b). These

inferences were further supported by correlations derived from raw signal features, as shown in Figure A-2.

These results underscore the value of time-resolved discharge pattern analysis over aggregate statistics when evaluating the influence of rotation. To reduce feature dimensionality and address multicollinearity among discharge categories, we propose condensing discharge types into two interpretable classification schemes: one based on the discharge timing (henceforth on discharge timing) derived features (Table 4-4) and the other based on the impact of the discharge event (Table 4-5).

Table 4-4: Class 1: based on discharge timing derived features.

Category	Constituents	Description
D1	SC	Non-machining discharges with variable duration
D2	AR, TA	Long-duration discharges; indicates overcut or high energy
D3	US, SD	Discharges with minimal inter-discharge delay
D4	SP, PS	Sparks with optimal duration and delay, vary in energy

Table 4-5: Class 2: based on impact of the discharge event.

Category	Constituents	Description
E1	SC	Dominant failure mode; produces minimal or no material removal
E2	AR, SD	High energy or erratic discharges; increase tool wear or cause tool retraction
E3	TA, PS, US	Spark-like discharges with sub-optimal energy, duration or delay characteristics
E4	SP	Clean sparks; primary contributors to efficient and stable material removal

This categorization is used in the next stage of our machine learning framework to reduce feature complexity while preserving physical interpretability.

4.3.2. Supervised Classification using Machine Learning

The End-of-Machining (EOM) detection model achieved an overall accuracy of 98%, with a precision of 0.85 and a recall of 0.89 for the EOM class. The confusion matrix in Table 4-6 shows that only 22 batches were misclassified as EOM before the actual onset, while the majority of false positives occurred after the true EOM point, as seen in Figure 4-7(Predicted EOM Phase), indicating the model's conservative behavior.

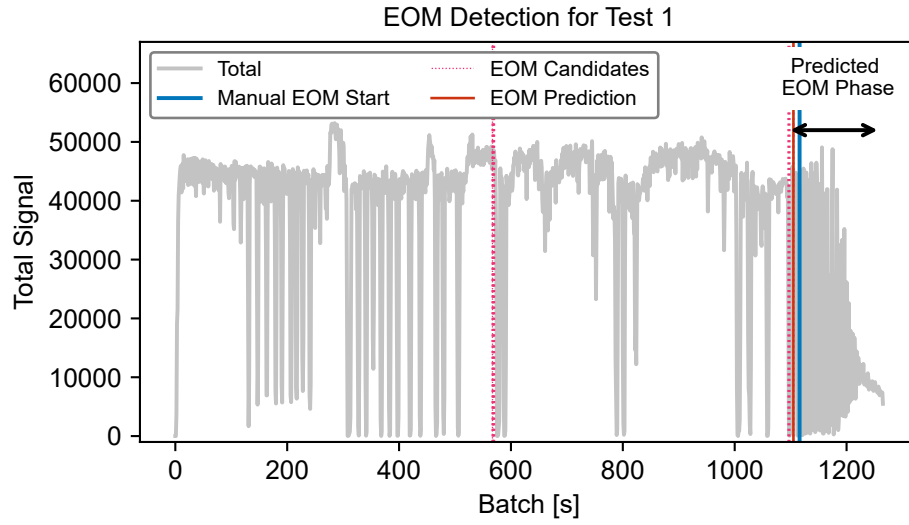


Figure 4-7: Candidates and predicted true end-of-machining batches.

To avoid premature deactivation in a proposed dynamic control system, a post-EOM misclassification tolerance of 10 batches was adopted. While early false positives could impact control decisions, post-EOM misclassifications are acceptable since control would already be disengaged after detection. This conservative buffer ensures safe and robust labeling in anticipation of future deployment.

Table 4-6: Confusion matrix results for EOM detection.

	Predicted: Not EOM	Predicted: EOM
Actual: Not EOM	2254	32
Actual: EOM	22	176

The model metrics and global temporal characteristics for the machine learning models in the segmented machining zone (trained on fixed rotation rate data and evaluated on the dynamic rotation rate test experiment) are summarised in Table 4-7 and Figure 4-8, respectively.

Table 4-7: Performance metrics for different feature types and classifiers.

Metric	Raw Features		Class 1 Features		Class 2 Features	
	RF	XGB	RF	XGB	RF	XGB
Precision	0.694	0.729	0.816	0.760	0.710	0.696
Recall	0.907	0.858	0.448	0.544	0.885	0.907
F1-score	0.787	0.788	0.578	0.634	0.788	0.788
Accuracy	0.877	0.885	0.836	0.843	0.881	0.878

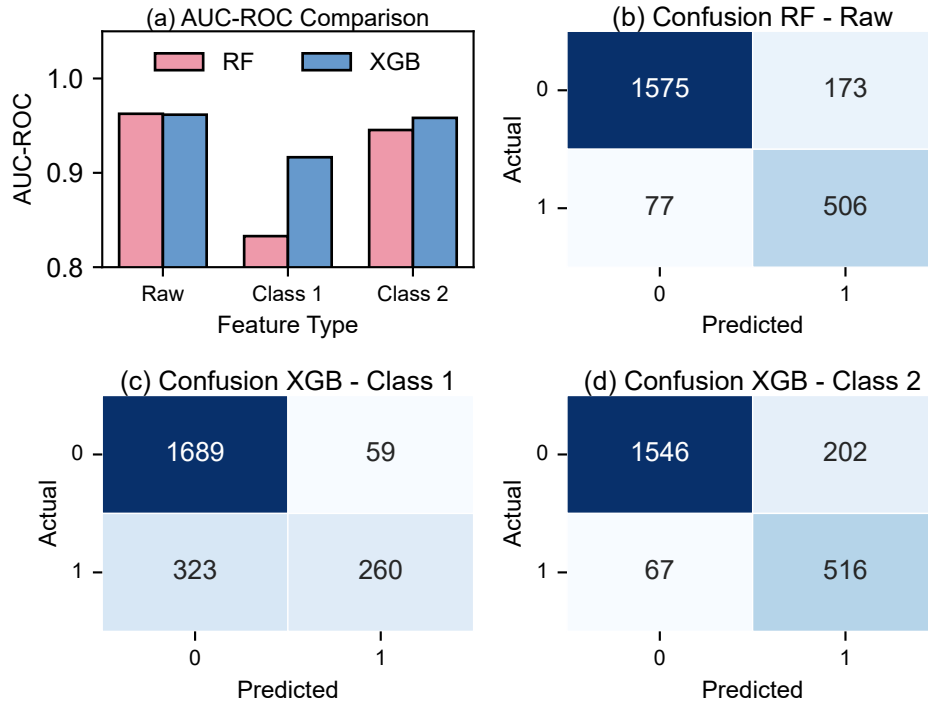


Figure 4-8: (a) AUC-ROC for different feature types and classifiers at probability threshold = 0.5. (b)-(d) Confusion matrix for different feature types and classification models.

In general, the Extreme Gradient Boosting (XGB) classifier outperformed the Random Forest (RF) classifier in terms of accuracy, the proportion of correctly predicted batches, and F1-score, which balances precision and recall, making it particularly useful under class imbalance. As shown in Figure 4-8(a), most models achieved high confidence levels (ROC-AUC > 0.9), indicating that small changes in the probability threshold are unlikely to affect classification outcomes significantly.

Additional insights are drawn from the confusion matrices in Figure 4-8(b)-(d) and the batch-level prediction overlays in Figure 4-9(a)-(c). The model trained on raw electrical signal features exhibits more sensitive predictions, flagging a larger number of unstable batches, including those with subtle variations in discharge characteristics. This is particularly evident during the early machining periods (Figure 4-9(a)). In contrast, models based on discharge timing (Class 1) produce more conservative predictions, mainly identifying the most severe instances of instability, but fail to capture sustained over-machining. Meanwhile, the model using discharge impact-based features (Class 2) offers a more balanced prediction across different instability patterns.

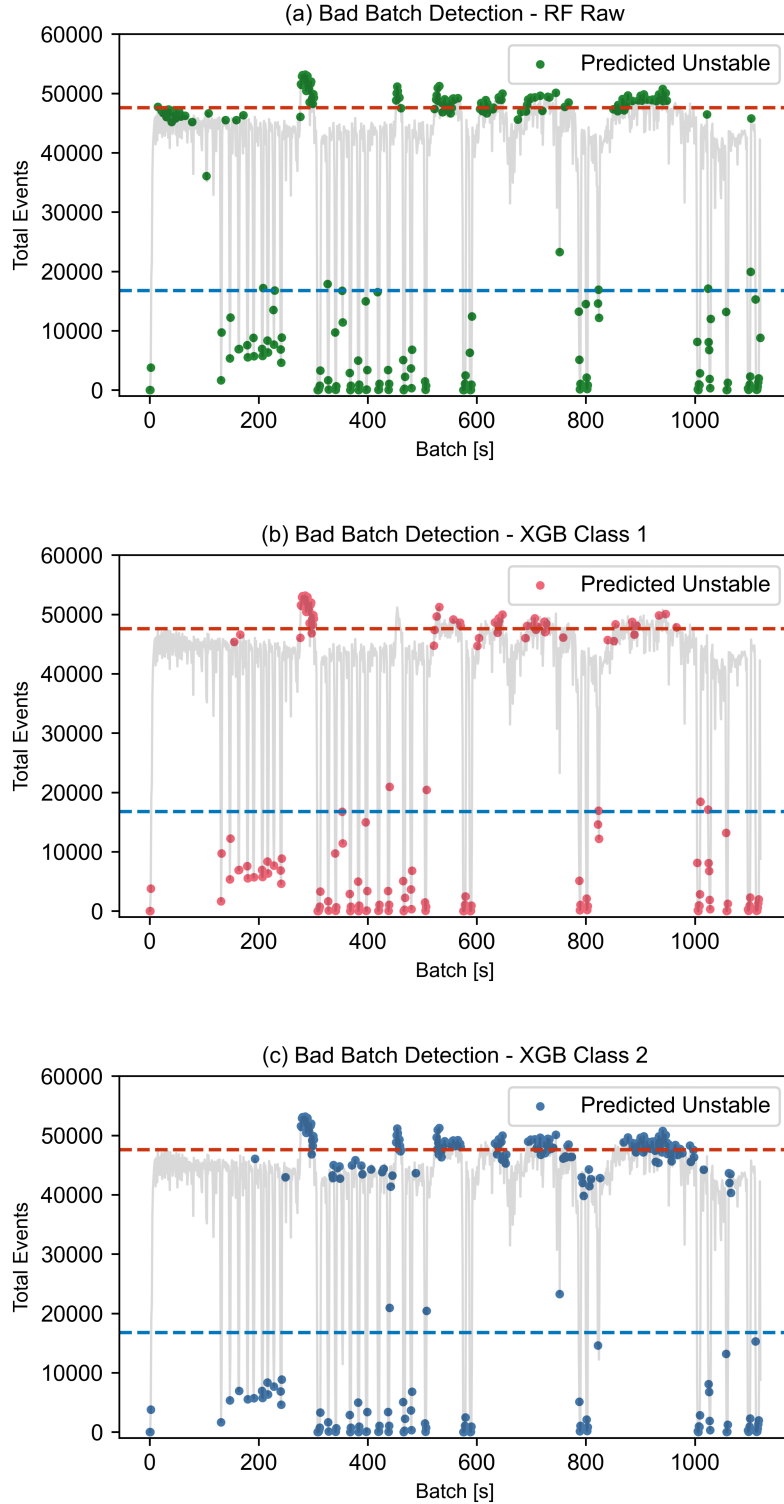


Figure 4-9: Predicted unstable batches from the best-performing models using (a) raw signal, (b) discharge timing, and (c) discharge impact features. Horizontal lines indicate predefined unstable zones, blue for under-machining (<10th percentile) and red for over-machining (>85th percentile) based on total event count, used to compare model performance.

This comparison highlights a key trade-off. Raw signal-based models are highly sensitive and computationally efficient due to minimal preprocessing, but are also more prone to noise and false positives. Classification-based models, built on features such as discharge timing or impact, offer greater physical interpretability and targeted detection, albeit at the cost of increased computational effort. For real-time monitoring, the RF model with raw features may be better suited for early anomaly detection. However, for corrective interventions, the discharge classification-based models provide more robust and interpretable predictions.

Given that this study aims to enable adaptive control of tool rotation, the model based on discharge-impact features (Class 2) is recommended. While it achieves only moderate precision, its consistently high recall ensures dependable detection of potentially unstable conditions, critical for preventive control, even if it occasionally sacrifices precision.

Additionally, we analyzed the model's prediction methodology by examining the SHAP values of the five most important features, as shown in Figure 4-10. In the plot, dot color represents the actual feature value, while the SHAP value indicates the (unitless) magnitude and direction of that feature's contribution toward predicting instability. In this study, both under-machining and over-machining conditions were collectively labeled as unstable machining. This broad classification can introduce non-monotonic behavior in the relationships between features and predicted outcomes. Such non-monotonicity was evident in the top raw-signal feature (mean inter-discharge delay, i.e., discharge gap) (Figure 4-10(a)), where both low values could correspond to either stable or unstable conditions depending on contextual factors. In contrast, stable machining zones were generally associated with higher current levels. The short delay pulses (D3), despite exhibiting the high feature importance, likely due to their dominance in discharge counts (Figure A-1), did not show a strong association with stable machining, as seen in Figure 4-10, also demonstrated a non-monotonic trend. Meanwhile, category E3, comprising 'almost spark' discharges such as Transient Arcs (TA), Partial Sparks (PS), and Unstable Sparks (US), showed a consistently strong association with stable machining, as seen in Figure 4-10(b),(c). These observations underscore the importance of discharge type grouping for determining model interpretability and efficiency, and highlight the potential multicollinearity among discharge categories.

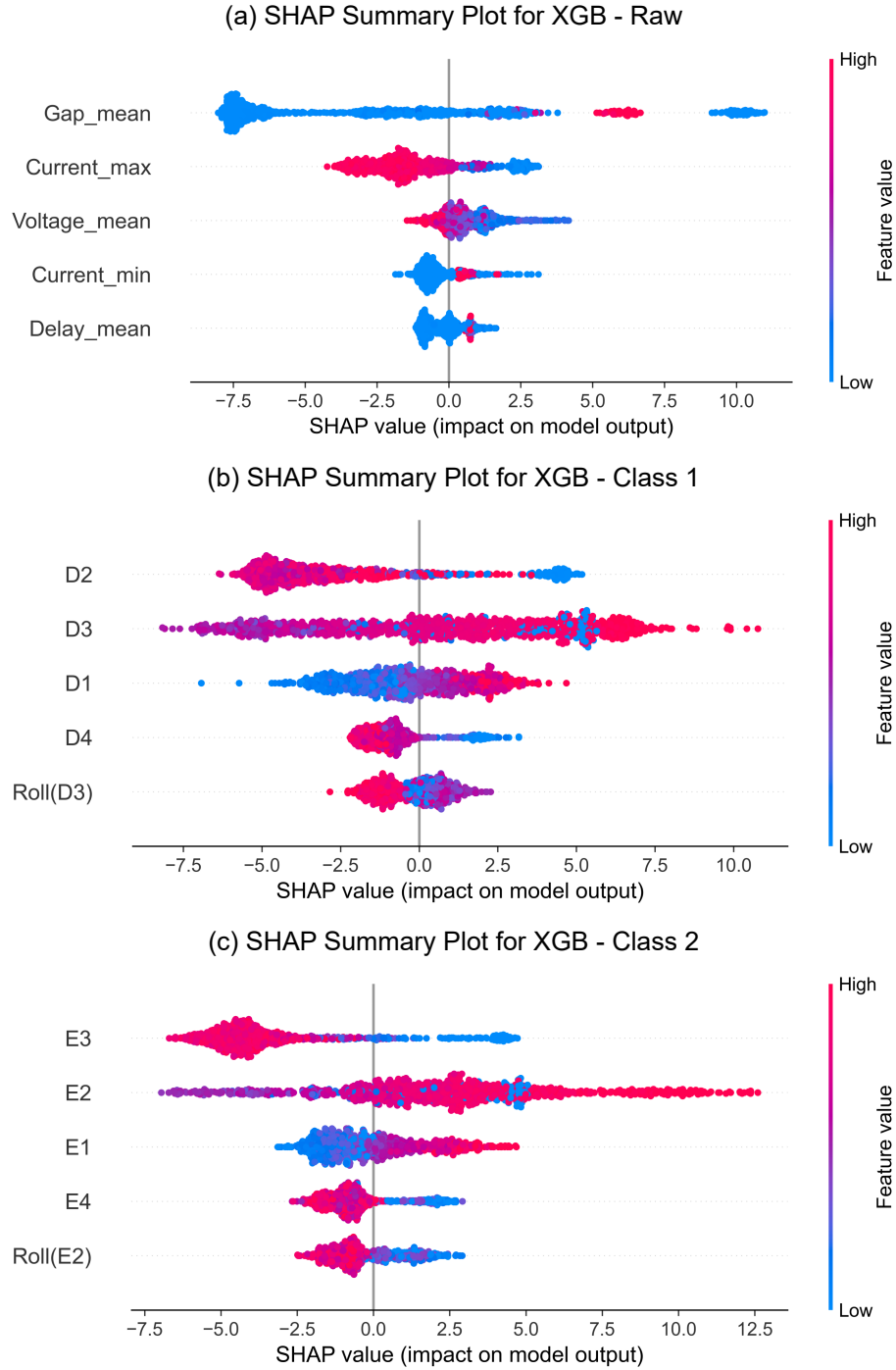


Figure 4-10: SHAP summary plot for 5 most important features for XGB models on (a) raw signal features, (b) discharge timing features, and (c) discharge impact features.

Moreover, while the correlation analysis showed only a weak positive relationship between short circuits and sparks, in Figure 4-6(b), the SHAP summary from the classification model revealed a strong opposing effect; stable machining was associated with a higher occurrence of sparks and a lower presence of short circuits (D1, E1 and D4, E4).

Overall, although clear monotonic trends were not consistently observed, the SHAP analysis provided valuable insights into the model's internal decision-making and the relative importance of individual features in identifying machining instability.

4.4. Robust Modeling of EDM Discharges using 1D-CNN

While the heuristic classifier and tree-based machine learning models provide useful discharge labels and instability indicators, they rely on manually defined thresholds and on features aggregated over fixed windows. To obtain a more flexible discharge model that can generalise across different waveform acquisition and machining configurations and rotation rates, as well as be capable of identifying time-varying waveform signals, a one-dimensional convolutional neural network (1D-CNN) was developed to classify discharges directly from voltage-current waveforms. For waveform classification, which varies at high frequency, the local pulse morphology was captured using a 1D-CNN implemented as a temporal convolutional network (TCN).

This section describes the data preparation workflow and network architecture, followed by an evaluation of classification performance and inference latency against real-time monitoring requirements.

4.4.1. Methods

The TCN model was developed in conjunction with the rule-based pipeline discussed in Table 4-1. First, the offline detector-classifier was applied to all fixed-rotation experiments to obtain pulse-level labels. The key methodological difference is as follows: the heuristic classifier converts voltage-current samples into discrete events and then assigns event-level classes, whereas the TCN operates directly on fixed-length windows of waveform samples, predicts a class for each sample, and subsequently aggregates these predictions to event-level interpretations. All accuracies and performance metrics reported in this section are therefore

evaluated at the sample level with respect to the rule-based pipeline. The aim is to replace the heuristic classifier with a more flexible, data-driven approach that can adapt to different waveform acquisition and machining configurations and rotation rates.

For implementation, the rule-based pipeline assigns integer class IDs $c \in \{0, \dots, 7\}$ to the discharge categories listed in Table 4-1, corresponding to no-discharge (0), short-circuit (1), spark (2), transient arc (3), arc (4), unstable spark (5), partial spark (6), and secondary arc (7). As grouping based on discharge impact (E1-E4) was shown to be effective for instability analysis, the TCN was trained and evaluated using both the original class labels and their grouped counterparts.

For efficient training and streaming I/O, waveform and label sequences were stored as NumPy shards. Each shard contains contiguous waveform segments of shape $(N, L, 2)$ (voltage and current channels) and corresponding target labels of shape (N, L) , where L denotes the segment length in samples and N the number of segments within the shard. Each shard corresponds to approximately 1.25 s of recorded data.

The TCN operates on fixed-length waveform segments. During training, random crops of length $L = 8192$ samples were drawn from the shards, corresponding to approximately 4.1 ms per crop at a sampling interval of 504 ns, and arranged into mini-batches of size 16. Each channel was normalised using the global mean and standard deviation computed from the training set only. The network architecture consists of an initial causal Conv1D layer, followed by a stack of residual dilated convolutional blocks with exponentially increasing dilation factors, and a final 1×1 convolution projecting to the output discharge classes. This design provides a receptive field spanning multiple discharge pulses and their short-term temporal context while maintaining a modest parameter count.

Because the discharge data are highly imbalanced, class weights were computed from empirical class frequencies and incorporated into a weighted sparse categorical cross-entropy loss. The model was trained using the Adam optimiser with an initial learning rate of 5×10^{-4} for up to 50 epochs, with 400 steps per epoch. Approximately 10% of the static training shards were reserved for validation. Early stopping and learning-rate reduction at a plateau, monitored by the validation loss, were applied to stabilise convergence and prevent overfitting. Multiple runs

of five randomly selected shards from the dynamic rotation-rate experiment were used for final evaluation, corresponding to approximately 6.25 s of unseen data.

To assess suitability for real-time deployment, inference latency was benchmarked by measuring forward-pass time for batches of size $N = 1, 8$, and 32 , each with a fixed segment length of $L = 8192$ samples. These timings were compared with the oscilloscope data rate (approximately 2.0 MSamples/s per channel) and a representative decision-update interval. Throughput, reported in MSamples/s, refers to the number of processed time samples ($N \times L$), where each time sample comprises both voltage and current inputs. Based on these results, a lightweight variant with reduced depth and channel width (TCN-Lite) was developed. To further evaluate generalisability across computational platforms, a reference latency map was constructed by systematically varying N and L .

Table 4-8: TCN and TCN-Lite architectures.

Parameter	TCN	TCN-Lite
Block structure	Double convolution	Single convolution
Residual connection	Yes (two-layer)	Yes (single-layer)
Initial layer filters	32	8
Filters per block	64	16
Number of blocks	6	4
Dilation rates	1, 2, 4, 8, 16, 32	1, 2, 4, 8
Sequence length L (samples)	8192	512–16384
Batch size N (windows)	1, 8, 32	1–32

4.4.2. Results

Figure 4-11 shows the confusion matrix for the grouped discharge classes (E1-E4) predicted by the TCN model. Table 4-9 summarises the corresponding grouped-class performance. The model achieves high F1-scores (0.83-0.87) for the instability-relevant classes E1-E3 on the dynamic rotation-rate test set. Misclassifications predominantly occur between the nearly-spark (E3) and clean-spark (E4) classes, while short circuits and arc/secondary events (E1-E2), which are primary indicators of unstable machining, are rarely confused with clean sparks.

For the discharge duration used in this experimental setup (4 μ s) and a sampling interval of 504 ns, the temporal resolution at the spark-to-nearly-spark boundary is limited to approx-

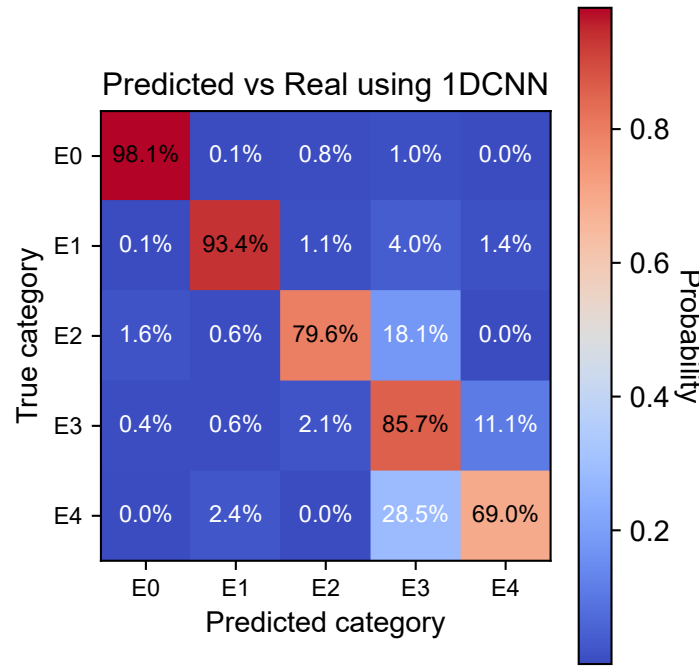


Figure 4-11: Confusion matrix of the grouped discharge classes (E1-E4) for the TCN classifier.

Table 4-9: Grouped-class performance (E1-E4) for the TCN model.

Class	Precision	Recall	F1-score	Support
E1 (Short)	0.81	0.93	0.87	778,158
E2 (Arc/Secondary)	0.86	0.80	0.83	5,884,706
E3 (Nearly Sparks)	0.88	0.86	0.87	14,540,047
E4 (Clean Spark)	0.21	0.69	0.32	658,698

imately one sample. While increasing the oscilloscope sampling rate could further improve class separability, doing so would substantially increase data volume and potentially reduce end-to-end throughput. Within the current system constraints, the achieved resolution is sufficient, as the model reliably detects harmful discharge modes and their persistence, with residual ambiguity largely confined to the stable spark regime.

Figure 4-12(a) shows the training and validation loss curves for the TCN, indicating stable convergence without overfitting. However, as illustrated in Figure 4-12(b), the inference throughput of the full TCN is approximately 0.8 MSamples/s, which is below the oscilloscope streaming rate of approximately 2.0 MSamples/s. Consequently, the full model cannot keep pace with real-time acquisition in its original configuration. Figures 4-12(c)-(d) further show that the total processing time of the full TCN is approximately 5-9 times longer than that of the rule-based detector-classifier, primarily due to the deeper stack of dilated convolutional blocks.

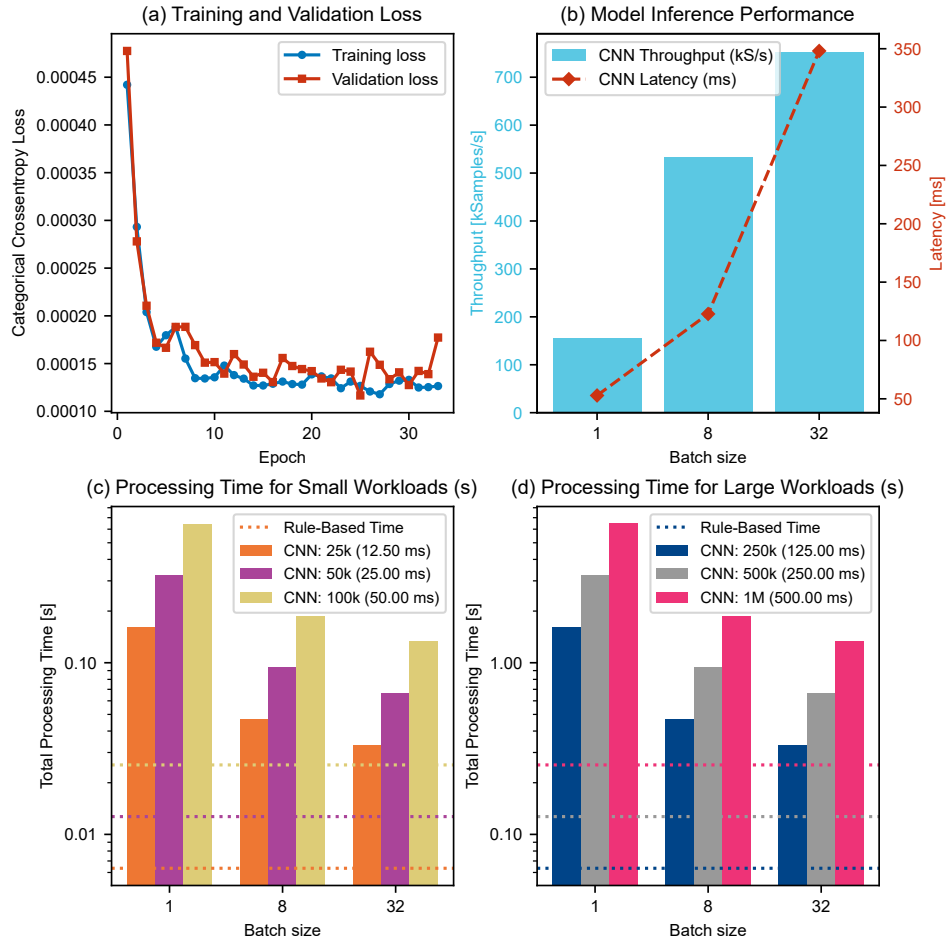


Figure 4-12: Training history and latency analysis of the TCN classifier. (a) Training and validation loss curves. (b)-(d) Inference throughput and total processing time for different batch sizes and workload lengths, compared with the rule-based detection-classification pipeline.

To address this limitation, the lightweight TCN-Lite architecture was introduced, trading a modest reduction in classification accuracy for a substantial increase in throughput. To systematically characterise latency behaviour, the TCN-Lite model was evaluated across a range of batch sizes N and sequence lengths L . Figure 4-13 presents heatmaps of (a) inference latency and (b) classification accuracy for a fixed workload of approximately 500 kSamples (250 ms). Accuracy values correspond to weighted averages over the grouped classes E1-E4, excluding no-discharge periods (E0).

For a sampling interval of 504 ns and an oscilloscope I/O buffer duration of 250 ms, achieving predictions within half the buffer duration (125 ms) requires a sequence length greater than 4096 samples. Additional speedups can be achieved through parallel processing; however, for large batch sizes, Python-level overhead increasingly dominates TensorFlow execution time.

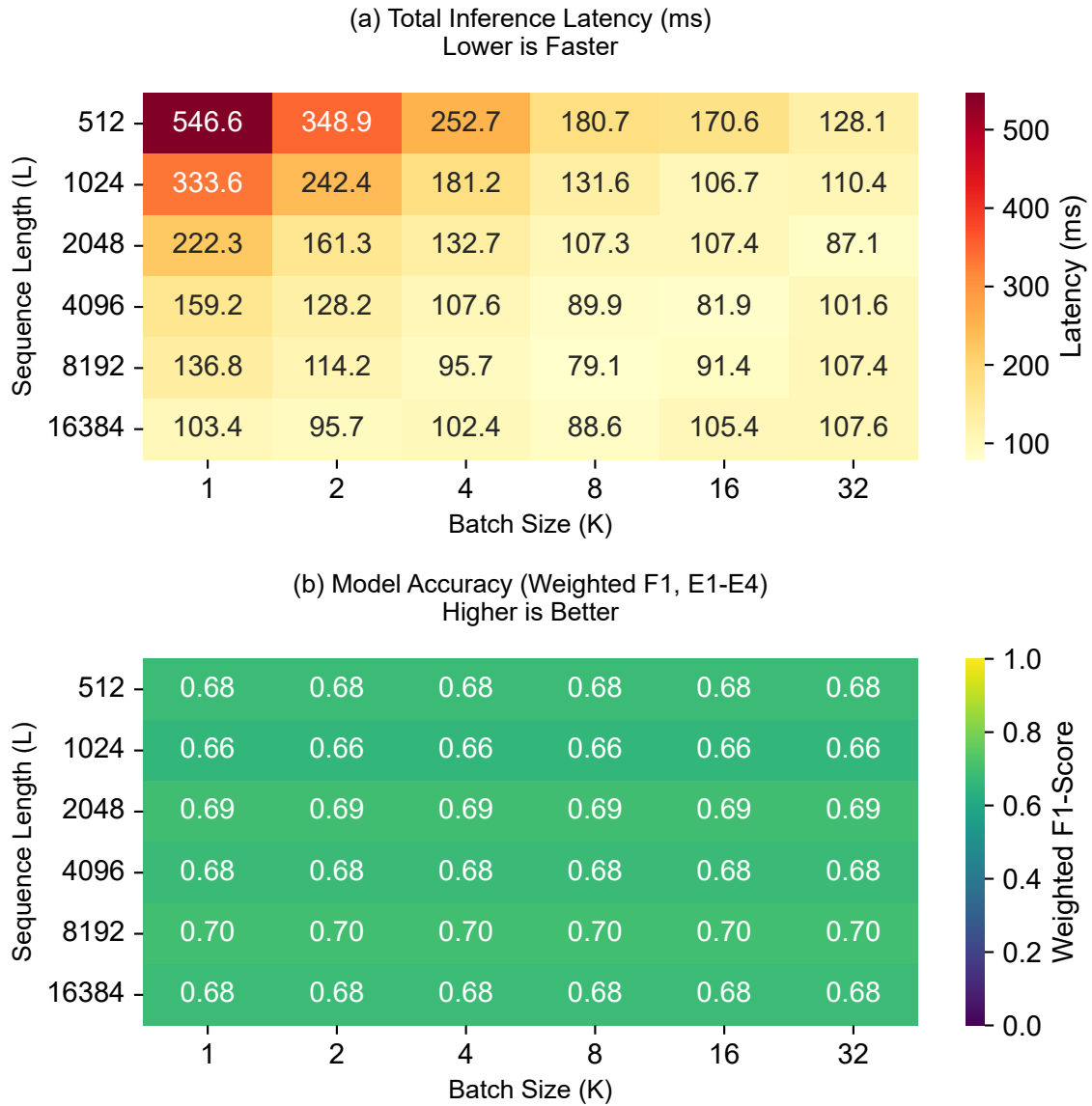


Figure 4-13: (a) Total inference latency and (b) accuracies for different batch sizes and sequence lengths for 500 kSamples.

Across all tested configurations, classification accuracy remained largely insensitive to variations in N and L . On the benchmarking platform used in this study (Apple MacBook Pro M1), the lowest latency was achieved with a batch size of $N = 8$ and a sequence length of $L = 8192$. The resulting latency maps are intended as reference guides for selecting suitable (N, L) combinations; actual deployment performance will depend on the specific CPU/GPU architecture and I/O capabilities of the target system.

Figure 4-14 further illustrates the effect of decreasing waveform buffer duration when processing one batch per forward pass. While classification accuracy remains stable, longer buffer

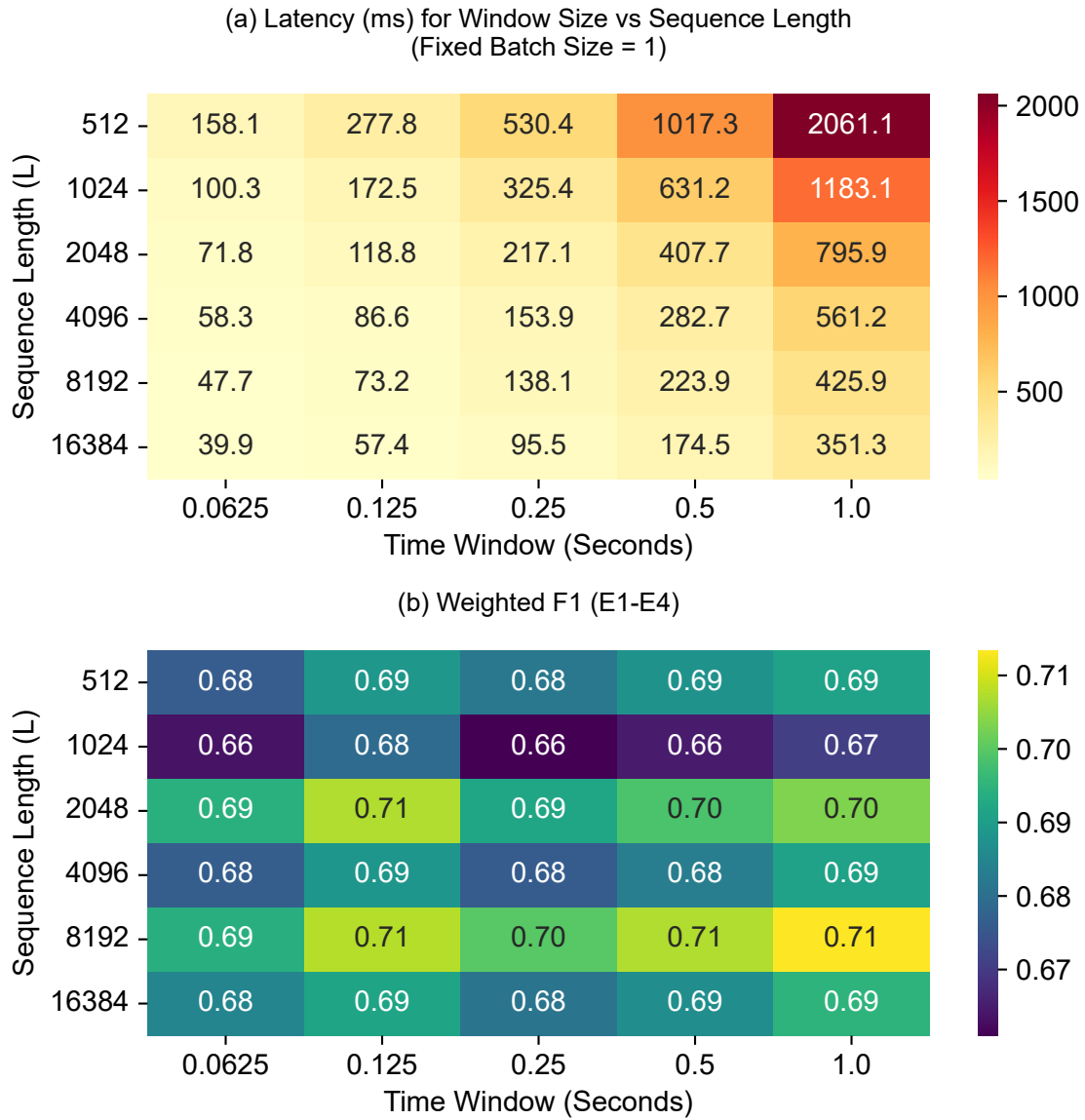


Figure 4-14: (a) Latencies and (b) accuracies for different batch sequence lengths and time windows, processed at 1 batch per forward pass.

durations increase end-to-end latency approximately linearly. In practice, the achievable performance of the proposed system is ultimately constrained by the oscilloscope's and processing hardware's data-acquisition and I/O bandwidth.

4.5. Summary

This chapter developed an intelligent process modeling framework for instability monitoring in EDM of tungsten carbide based on waveform-derived features, discharge classifications, and supervised learning. The summary of findings is as follows:

1. A complete waveform-acquisition and event-detection pipeline was established, enabling the reliable identification of individual discharges and their categorisation into physically meaningful types, such as clean sparks, arcs, short circuits, unstable sparks, and secondary discharges. This provided the foundation for feature engineering and subsequent machine-learning models.
2. End-of-Machining (EOM) detection and rotation rate-normalized instability labelling were implemented using a combination of FFT band energy and discharge-count statistics. The EOM classifier achieved an accuracy of 98%, while batch-level instability labels, defined via under- and over-machined discharge-count thresholds, enabled supervised learning of stable and unstable machining conditions across different rotation rates.
3. Random Forest and XGBoost classifiers trained on raw waveform features and grouped discharge features (Class 1 and Class 2) achieved high performance for instability detection, with F1-scores around 0.79 and ROC-AUC values above 0.9 for the best models. Raw-feature models offered high sensitivity, whereas grouping discharges into impact-based categories (E1-E4) improved physical interpretability and provided clearer links between discharge compositions and machining stability.
4. SHAP analysis revealed that instability arises from complex, often non-monotonic interactions between discharge types and signal features. Clean sparks were consistently associated with stable machining, while combinations of short circuits, arc/secondary discharges, and almost-spark events (E1-E3) dominated unstable regimes. These results highlighted the limitations of purely correlation-based analysis and demonstrated that feature grouping and explainable ML are effective tools for interpreting EDM behavior.
5. A 1D-CNN classifier implemented as a temporal convolutional network (TCN) was developed to model discharge classes directly from voltage-current waveforms. The model achieved high F1-scores (0.83-0.87) for instability-related classes (E1-E3).
6. For real-time waveform classification, a TCN-Lite model was evaluated across a range of batch sizes and sequence lengths. The lowest latency was achieved with a batch size of $N = 8$ and a sequence length of $L = 8192$, resulting in a latency of 79.1 ms.

Overall, the intelligent modeling approaches presented in this chapter demonstrate that waveform-level information, combined with supervised learning and explainable feature analysis, can robustly characterise machining stability beyond traditional offline optimisation. These results form the basis for the dynamic, time-dependent prediction and adaptive control strategies developed in the next chapter.

Chapter 5

Dynamic Process Modeling for Control System Design in EDM

5.1. Introduction

In the previous chapter, intelligent process modeling showed that grouping individual discharge types into discharge impact classes (E1-E4) enabled reliable prediction of machining stability from waveform statistics. A 1D-CNN discharge classifier was also introduced to learn these classes directly from voltage–current waveforms, but this came at the cost of increased latency compared with the simple rule-based scheme.

In this chapter, building upon the findings from fixed-rotation modeling, the focus shifts to dynamic process modeling and control-oriented interpretation. The central questions addressed are: (i) how waveform information can reduce the duration and severity of unstable machining, (ii) whether instability can be predicted early enough to allow corrective action within practical latency constraints, and (iii) to what extent the final machining outcome, including radius profile and cylindrical distortion, can be inferred from electrical features.

To address these questions, three complementary components are developed:

- **Phase-aware correction strategy:** using phase statistics derived from discharge-based labelling to analyse how stable and unstable periods evolve under different rotation rates.
- **Dynamic instability prediction:** developing sequence-based models that can issue early warnings of instability while remaining compatible with real-time monitoring constraints.
- **Geometric outcome modeling:** linking waveform-derived features and inferred tool position to the machined radius profile to assess how well cylindrical distortions and over-machined regions can be predicted from electrical data.

Together, these elements demonstrate how electrical waveforms can be transformed into instability indicators, early-warning signals, and approximate geometric predictions, providing transferable building blocks for the design of an adaptive rotation-control framework for EDM

of tungsten carbide.

5.1.1. Correction Strategy Exploration

Based on the prediction model derived in section 4.3.2, unstable machining zones were repredicted for different tool rotation rates, using the E-class XGB model. Figure 5-1(a) shows the aggregate count of discharges for each spark type in stable and unstable machining phases. During instability, a significant drop in the total number of discharges was observed. However, there was a noticeable increase in secondary discharges, which are likely responsible for over-machining.

To better understand the role of rotation, the counts of different spark types at each rotation rate were normalized relative to the 1000 RPM baseline. As shown in Figure 5-1(c),(d), transient arcs and arcs remained relatively constant (within 10% variation) across all rotation rates, indicating that the occurrence of long-duration discharges is not significantly influenced by rotation. Two key observations emerged: First, increasing the rotation rate reduced short circuits by up to 40% during stable machining, but had no effect during unstable machining. In contrast, while clean and unstable spark counts decreased significantly during instability at higher rotation rates (by more than 45%), they remained unaffected during stable phases. Furthermore, secondary discharges increased at higher rotation rates under both stable and unstable conditions, likely due to fluid shear that disrupted the discharge channels.

These contrasting behaviors help reconcile the earlier discrepancy between correlation and SHAP-based analysis. While short circuits and sparks showed a weak positive correlation overall, their opposing trends across stable and unstable phases at different rotation rates led to compensating effects in the aggregate data. This behavior is also reflected in Figure 4-6(b).

From these findings, we infer that increasing the rotation rate suppresses short circuits during stable machining but does not affect them during instability; in unstable machining, higher rotation rates instead tend to increase secondary discharges, as clean sparks shift into this category.

This insight forms the basis for an adaptive rotation control strategy: increase rotation rate during stable phases to improve flushing efficiency, and decrease it upon detecting instability to preserve spark effectiveness. Moreover, Figure 5-1(b) reveals that the temporal evolution

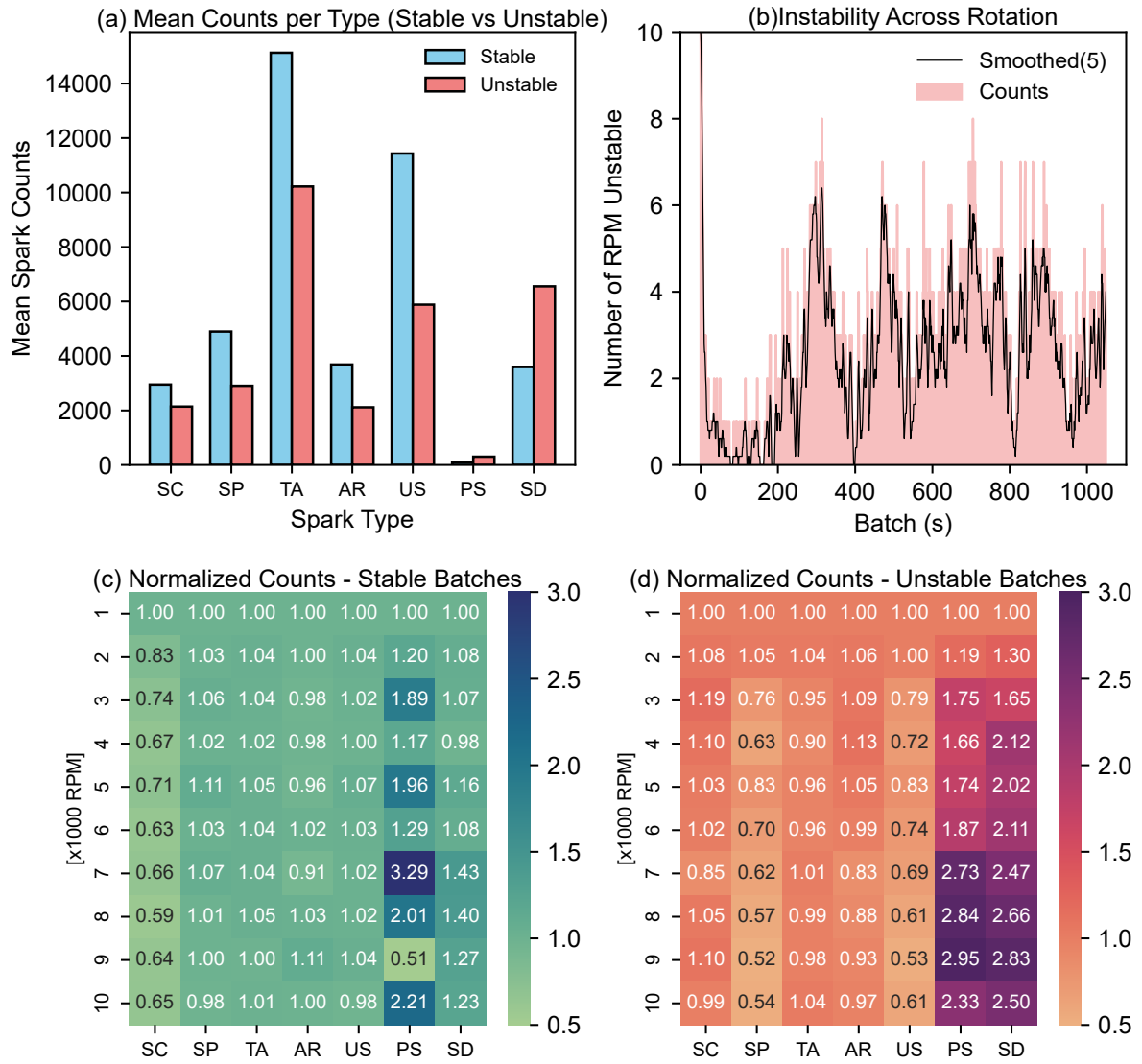


Figure 5-1: (a) Count of discharges for each spark type in stable and unstable machining phases. (b) Cumulative number of rotation rates exhibiting unstable machining as a function of time. (c)-(d) normalized count of discharges for each spark type in stable and unstable machining phases at different rotation rates.

of instability occurs across all rotation rates, suggesting time-dependent patterns in machining behavior. Such trends are difficult to capture with static tree-based models such as Random Forests and XGBoost. Sequence-based models, such as recurrent neural networks (RNNs) and temporal convolutional networks (TCNs), are needed to learn and predict these evolving patterns, potentially enabling earlier and more adaptive control.

Violin plots of the continuous stable and unstable machining batches and their frequency counts are shown in Figure 5-2. The plots show that higher rotation rates are associated with longer-tailed distributions in both stable and unstable phase durations. This suggests that once

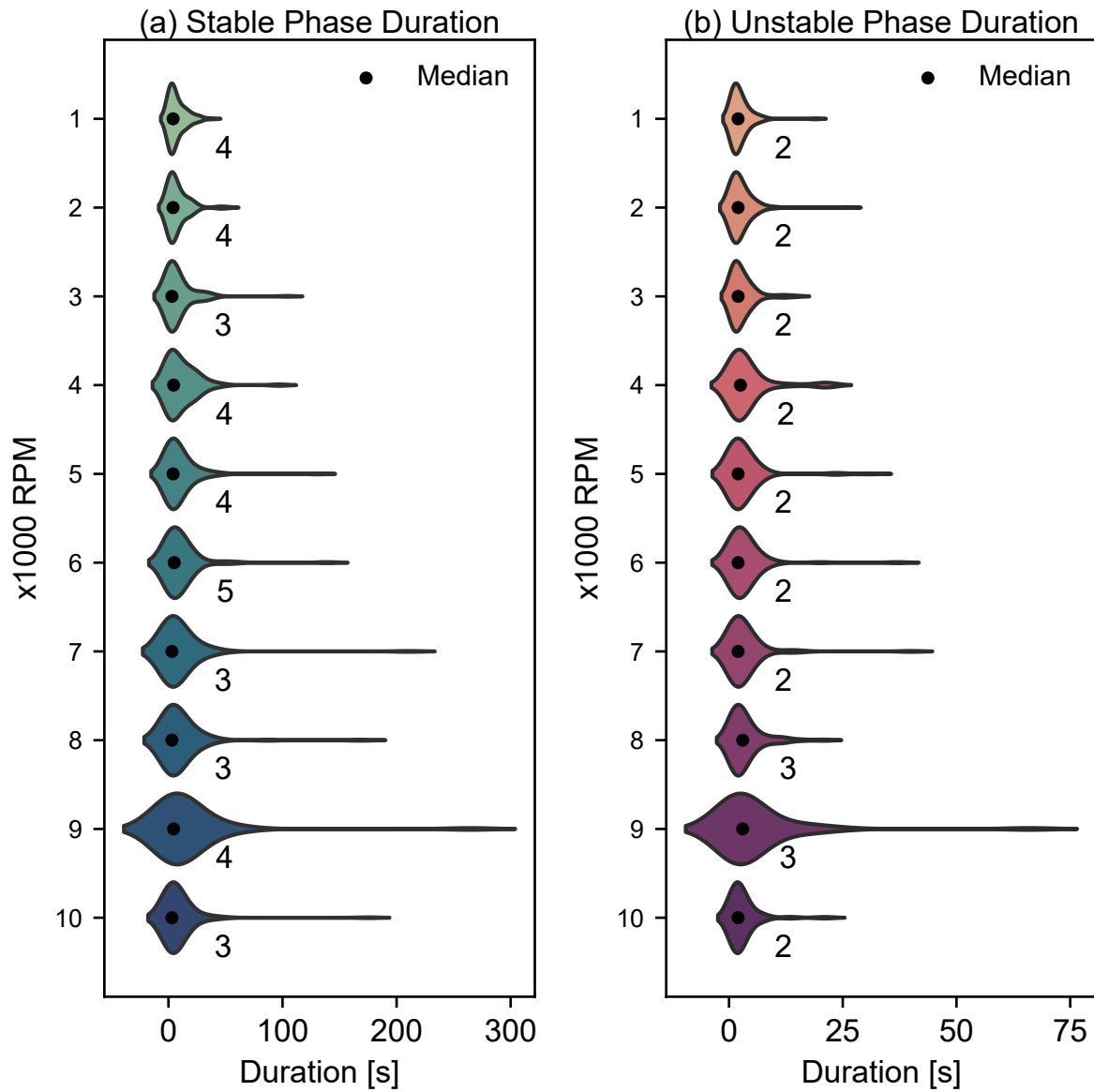


Figure 5-2: Violin plots of (a) stable and (b) unstable consecutive phase durations at different rotation rates.

a particular phase is established at a higher rotation rate, it tends to persist longer. In contrast, lower rotation rates exhibit more compact distributions, indicative of shorter-lived phases. The cause of this phenomenon can be hypothesized as follows: a low tool rotation rate is unable to clear debris from the bottom discharge gap, so the tool must oscillate to facilitate further progression. However, due to high tangential forces, debris caught in the side gap becomes difficult to remove, leading to tool retraction. This observation validates the potential of rotation rate to modulate machining phase stability.

Based on these two analyses, we propose a simple framework for control-oriented deci-

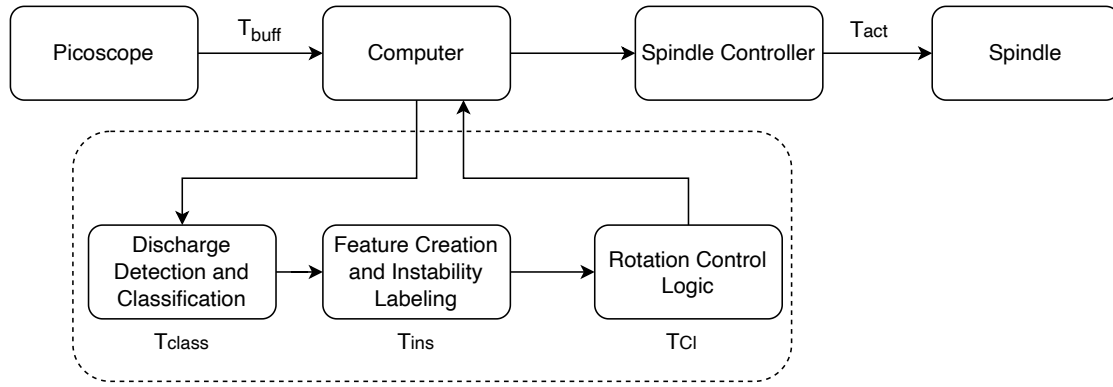


Figure 5-3: Time delays involved in the end-to-end loop from waveform acquisition to spindle actuation.

sion logic. During machining, if stable conditions persist, increase the rotation incrementally every 4 seconds (the median duration of stable phases). If instability persists for more than 2 seconds, decrease the rotation rate to achieve a more stable machining condition. However, this analysis also has several limitations. The proposed control strategy is based on a limited number of observed rotation transitions and should be regarded as preliminary. Moreover, the predictive modeling employed here operates at a 1 s batch size, which is comparable to the proposed 2 s control-adjustment timescale; this temporal proximity may limit the current model's responsiveness in capturing finer-grained transitions. Finally, since the experiments focused exclusively on ultrafine-grained tungsten carbide, the applicability of the proposed models and control strategy to other electrode or workpiece materials remains to be validated.

5.2. Early Instability Monitoring and Forecasting

From the preceding analysis, we established that during rotary EDM of tungsten carbide, the mean duration of unstable machining phases is approximately 2 s (denoted T_{cl}). In contrast, stable phases persist for about 4 s on average. Any effective monitoring and control-oriented framework must therefore be able to detect and react to impending instability within this critical time scale. Figure 5-3 illustrates the time delays involved in the end-to-end loop from waveform acquisition to spindle actuation. The delays involved are as follows:

- T_{buff} : buffering time needed to stream waveform data from the oscilloscope,
- T_{class} : time required to process the buffered waveform, detect individual discharges, and

classify them,

- T_{ins} : time required for feature construction and instability prediction through XGBoost models,
- T_{act} : actuator delay associated with Arduino microcontroller, spindle controller, motor driver.

The total latency for a control-oriented decision is the sum of these delays:

$$T_{\text{total}} = T_{\text{buff}} + T_{\text{class}} + T_{\text{ins}} + T_{\text{act}}. \quad (5.1)$$

For the monitoring or adjustment system to prevent machining instability before it fully develops, the total latency must satisfy the following critical condition:

In practice, waveform buffering and processing can be partially overlapped in a streaming implementation, reducing the effective decision delay.

$$T_{\text{total}} < T_{\text{cl}}, \quad \text{where } T_{\text{cl}} = 2 \text{ s}. \quad (5.2)$$

In practice, T_{buff} is dictated by the oscilloscope streaming rate and memory constraints: extremely small buffer sizes increase I/O overhead and noise, whereas excessively large buffers increase latency and memory usage, as discussed in Chapter 4. T_{act} depends on the Arduino controller and spindle drivers, and is largely non-controllable. T_{ins} is extremely small (typically microseconds to a few milliseconds). Although the heuristic rule-based detector and the TCN-Lite (discussed in the previous chapter) offer improved computational efficiency and robustness, they still introduce a mandatory processing time T_{class} due to their nature as per-batch, reactive classifiers.

A fundamental limitation of this reactive discharge-classification pipeline is that instability is only detected after it has already emerged in the waveform statistics. While reducing T_{class} can lower latency, it cannot eliminate the time spent waiting for the unstable state to manifest. For dynamic rotation adjustment, the decision logic must respond before the machining state becomes fully unstable.

This motivates the development of an early warning or forecasting model capable of issuing an early warning based on a short history of electrical information, effectively saving time in the processing loop by streamlining the decision logic.

To address this requirement, a Temporal Convolutional Network (TCN) was implemented to predict the probability of instability one to two steps ahead. Unlike in previous studies that used neural networks such as RNNs, ANNs, and LSTMs [103], [104], we propose using TCNs for this task. TCNs use dilated causal convolutions, allowing them to model long temporal dependencies while maintaining stable gradients and relatively low computational overhead. These properties make the TCN architecture well-suited for low-latency EDM monitoring, where computational efficiency and reliability are critical for approaching the condition $T_{\text{total}} < 2$ s.

5.2.1. Methods

If X_t denotes the vector of waveform-derived features computed for the t^{th} 1 s batch, and L is the history window length, the TCN model predicts the probability of instability at the next step as

$$\hat{Y}_{t+1} = f_{TCN}(X_{t-L+1}, \dots, X_t) \quad (5.3)$$

Before training, each feature sequence is normalised using the mean and standard deviation computed from the fixed-rotation-rate training experiments. The TCN is built as a stack of causal 1D convolution blocks with residual connections and increasing dilation factors. This design allows the model to see both short-term and longer-term patterns within the history window of length L without using any information from the future.

At the output of the convolutional stack, a global average pooling layer is applied along the time axis to compress the sequence into a single feature vector. This vector is passed to a fully connected layer with softmax activation, which outputs the class probabilities for the machining state (stable [10], under-machining [11], over-machining [12]). Because stable periods dominate the data and severe instability events are relatively rare ($< 25\%$), a class-weighted loss function was used during training so that the model pays sufficient attention to unstable and over-machining (disaster) cases. To make the probabilistic outputs usable for decision-making,

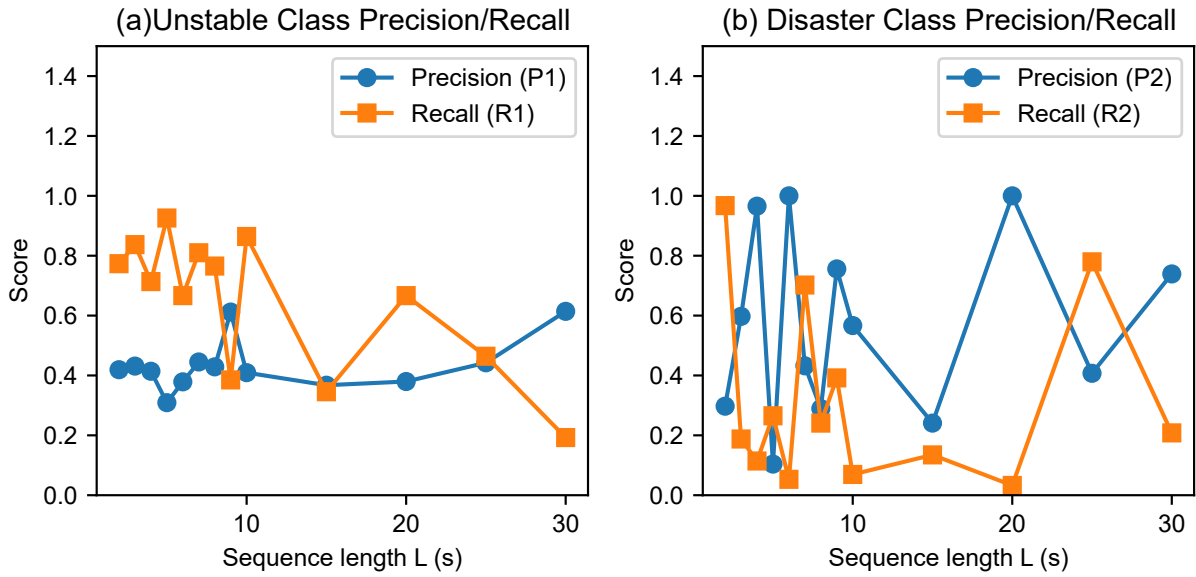


Figure 5-4: Precision and recall for unstable class (11+12) and disaster class (12) for all sequence lengths.

a probability threshold was selected on a held-out validation subset so that the predicted probability $\hat{p}_{t+1}$ serves as a practical indicator of instability risk.

An instability warning is triggered when the calibrated probability exceeds a sequence-specific threshold τ . This threshold is selected on the validation data to control false alarms, preventing frequent and false fluctuations from triggering unnecessary corrective actions.

5.2.2. Results

When the decision threshold is selected on held-out validation data to control false alarms, the TCN achieves a consistent level of early warning performance across a broad range of sequence lengths. Table 5-1 and Figure 5-4 summarise the calibrated precision and recall for the combined unstable class (11+12) and the disaster class (12) for all tested window lengths with $k_{\text{consec}} = 1$. For the primary unstable class, precision remains in the range 0.31–0.61, while recall lies between 0.35–0.93 depending on the window length. In the practically relevant regime of $L = 5$ –10 s, the unstable-class recall is typically 0.75–0.88 with moderate precision around 0.36–0.45, yielding macro-F1 scores in the mid 0.6 range. This behaviour is well suited to early-warning decision-making: the detector is deliberately tuned to favour high sensitivity to the onset of instability, while maintaining a controlled false-alarm rate through calibrated thresholds.

Table 5-1: Precision and recall for unstable and disaster classes at different TCN window lengths for prediction of Y_{t+1} and Y_{t+2}

Window Length k (s)	Prediction of Y_{t+1}				Prediction of Y_{t+2}			
	P_1	R_1	P_2	R_2	P_1	R_1	P_2	R_2
2	0.419	0.773	0.297	0.967	0.397	0.672	0.260	0.355
3	0.431	0.837	0.597	0.188	0.384	0.689	0.708	0.069
4	0.414	0.714	0.966	0.114	0.376	0.684	1.000	0.016
5	0.309	0.926	0.104	0.265	0.382	0.679	0.258	0.033
6	0.379	0.667	1.000	0.053	0.386	0.677	0.483	0.057
7	0.445	0.810	0.432	0.702	0.372	0.681	0.311	0.057
8	0.429	0.765	0.289	0.241	0.401	0.679	0.478	0.135
9	0.612	0.385	0.756	0.392	0.353	0.694	0.824	0.057
10	0.409	0.864	0.567	0.069	0.370	0.691	0.084	0.057
15	0.367	0.346	0.241	0.135	0.251	1.000	0.161	0.164
20	0.380	0.667	1.000	0.033	0.397	0.671	0.731	0.078
25	0.442	0.464	0.407	0.780	0.472	0.446	0.359	0.721
30	0.614	0.193	0.739	0.208	0.420	0.594	0.698	0.180

The stable class (10) also exhibits good reliability (not shown explicitly in the table), with overall three-class accuracies in the range of approximately 0.65–0.80 for most window lengths. In other words, the TCN can distinguish extended stable periods from genuinely unstable regions while still issuing timely warnings when the machining state begins to deteriorate.

The dependence on sequence length L follows a clear physical trend. Very short windows ($L \leq 4$) lack sufficient temporal context and therefore show more variable precision-recall behaviour. In contrast, very long windows ($L \geq 20$) tend to over-smooth the temporal dynamics and attenuate the earliest instability signatures. Between these extremes, a broad optimum emerges for $L \approx 5$ –10 s, where the model consistently achieves the best trade-off between unstable-class recall and precision. This is consistent with the empirical observation from Chapter 4 that instability typically develops over approximately 2–4 s; the TCN benefits from a short history that slightly exceeds this intrinsic time scale but degrades when the context window becomes much longer.

Hierarchical decoding into the unstable (11+12) and disaster (12) subclasses reveals a complementary pattern. Across all sequence lengths, the disaster class is predicted with relatively high precision (often above 0.4 and occasionally approaching 1.0) but comparatively low recall, reflecting both the rarity of such events and the conservative thresholding used to meet

the global precision constraint. Short-to-intermediate windows ($L \approx 5\text{--}10\text{ s}$) and mid-range windows ($L \approx 7$ and $L \approx 25\text{ s}$) provide a reasonable compromise, where disaster recall reaches values of 0.4–0.7 while preserving usable precision. From an early-warning decision-making perspective, this behaviour is acceptable: the primary requirement is to detect the onset of the generic unstable regime (class 1), while class 2 acts as an escalation signal indicating that over-machining has already begun.

Taken together, these results demonstrate that a TCN trained on grouped discharge features provides a robust early-warning module for EDM machining of tungsten carbide. With a window length of only 5–10 s and a calibrated threshold enforcing moderate precision, the model reliably captures the onset of instability with high sensitivity, low latency, and adequate differentiation between normal and disaster-type behaviour. This forecasting capability provides a critical building block for a future adaptive rotation-control framework, enabling corrective actions to be considered before harmful instability fully develops.

5.3. Machined Profile Modeling

Beyond material removal rate and tool wear rate, the other primary indicator of machining quality in rotary EDM of tungsten carbide, particularly for micro-injection molds and micro-tools, is the geometric accuracy and surface quality of the machined hole. Post-process measurement metrics such as top and bottom radii (Chapter 3) provide only a coarse assessment and fail to capture localized distortions along the hole wall. In all experiments, pronounced cylindrical distortions were observed (Figure 3-29), with both their axial extent and magnitude increasing with rotation rate.

As revealed by SHAP analysis, phase-specific discharge statistics, and instability segmentation, the results from the previous sections have established that tool rotation rate influences machining stability. In particular, abnormal discharge modes such as arcs and secondary discharges (E2) were identified as dominant contributors to excessive side erosion. These modes are closely linked to insufficient debris evacuation. At the same time, higher rotation rates modify debris trajectories through centrifugal effects; their net impact on flushing efficiency depends on complex flow interactions within the discharge gap.

Because such distortions directly degrade dimensional accuracy and surface integrity, it is of practical importance to determine whether the final machined profile can be inferred from in-process electrical information. Accordingly, this section investigates the extent to which the depth-wise radius profile of the machined hole can be modeled using features derived solely from electrical waveform data.

5.3.1. Methods

A critical piece of information required for accurately modeling the machined surface, in addition to the electrical waveform, is the tool position during machining. While most modern EDM machines can output tool positions in real time, older systems or proprietary equipment, such as the Mitsubishi EA8PV, pose challenges for direct data transfer due to low sampling rates. Furthermore, transferring tool position data from an external device can introduce an undesirable time lag and synchronization issues into the proposed control system framework. Consequently, the ability to predict the tool's position based solely on electrical signals offers two major benefits: it reduces potential time lag and significantly simplifies system integration.

To gain valuable insights and understand the process outcome to a high degree of precision, dense measurement data of the machined profile is necessary. Although 3D optical microscopy is a common measurement method, it was not suitable for this experiment due to the requirement for precise measurement over a $1 \times 1 \text{ mm}^2$ region.

Instead, we used a 3D laser profiler, the Mitaka NHK3P. To maintain high-density points while balancing measurement time, continuous Y-direction measurement was sacrificed. Measurements were taken at a $10 \text{ }\mu\text{m}$ spacing (Y-axis) with a $1 \text{ }\mu\text{m}$ resolution (X-axis). This produced approximately 100 discrete profiles, enabling precise estimation of local radius and roughness. Building on this measurement approach, the next step was to automate the segmentation of geometric features in these profiles.

To segment circular arcs from the raw profiles, a 1D-CNN pattern-recognition model was trained on labelled data (Figure 5-5(b)) to automatically extract curvature segments.

Following segmentation, a custom Python program for circle fitting was used to identify and quantify the cylindrical distortions correctly. As depicted in Figure 5-6, distortions can lead to multiple possible circular fits. The program addresses this by: (i) filtering, defining

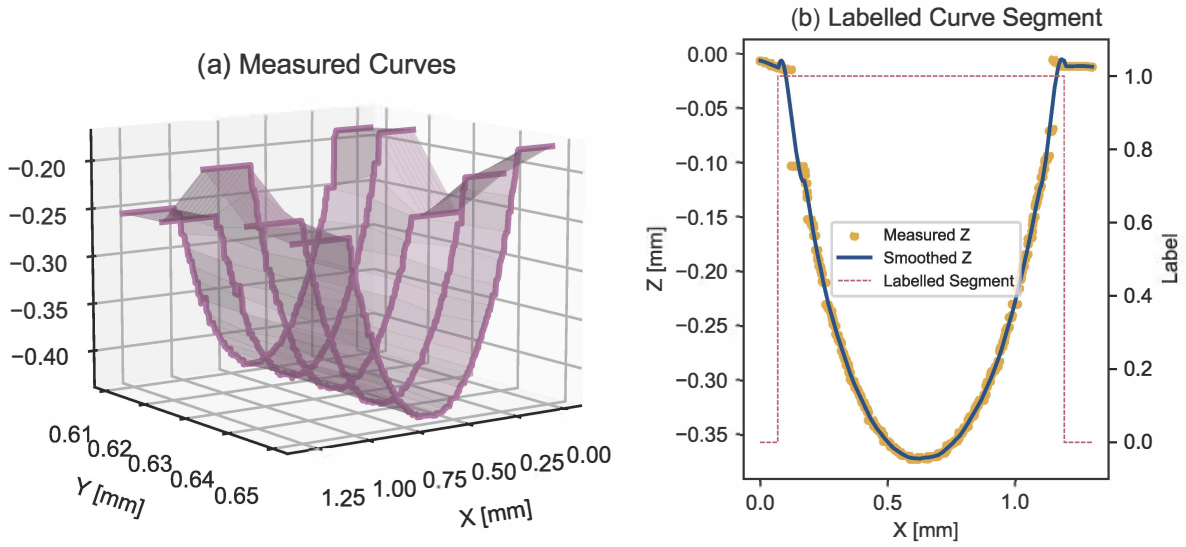


Figure 5-5: (a) Example of measured machined surface profile at different depths, (b) output from the 1D-CNN curvature segmentation, highlighting circular arc regions.

a custom range of acceptable values, followed by (ii) optimization, selecting the circle that achieves the maximum number of fit points within the tolerance. This process was used to obtain the profile radius and roughness. The summary of radius and roughness measurements for different rotation rates and depths is shown in Figure 5-7.

5.3.1.1. Data Acquisition and Preprocessing

In this setup, we used an optical camera operating at 25 frames per second (fps) as the primary source of actual tool position data, since the native output from the EDM device was low frequency (1 Hz). The captured position data was extracted using OpenCV and Tesseract packages and subsequently cleaned and synchronized. Given the high-frequency movement of the EDM servo system, and to align with the batch size used for instability prediction models, the position data were averaged over a 1-second interval to yield a mean tool position.

5.3.1.2. Machine Learning Modeling

The extracted position data were used to train a two-step predictive model consisting of a Random Forest (RF) regressor followed by an Isotonic Regressor. The goal is to predict the EDM system's control logic for tool retraction and oscillations. Additionally, two different types of feature sets were evaluated: (a) based on total discharge events, and (b) component total-based. Since this is a dynamic problem, we also included the current time as a feature. To

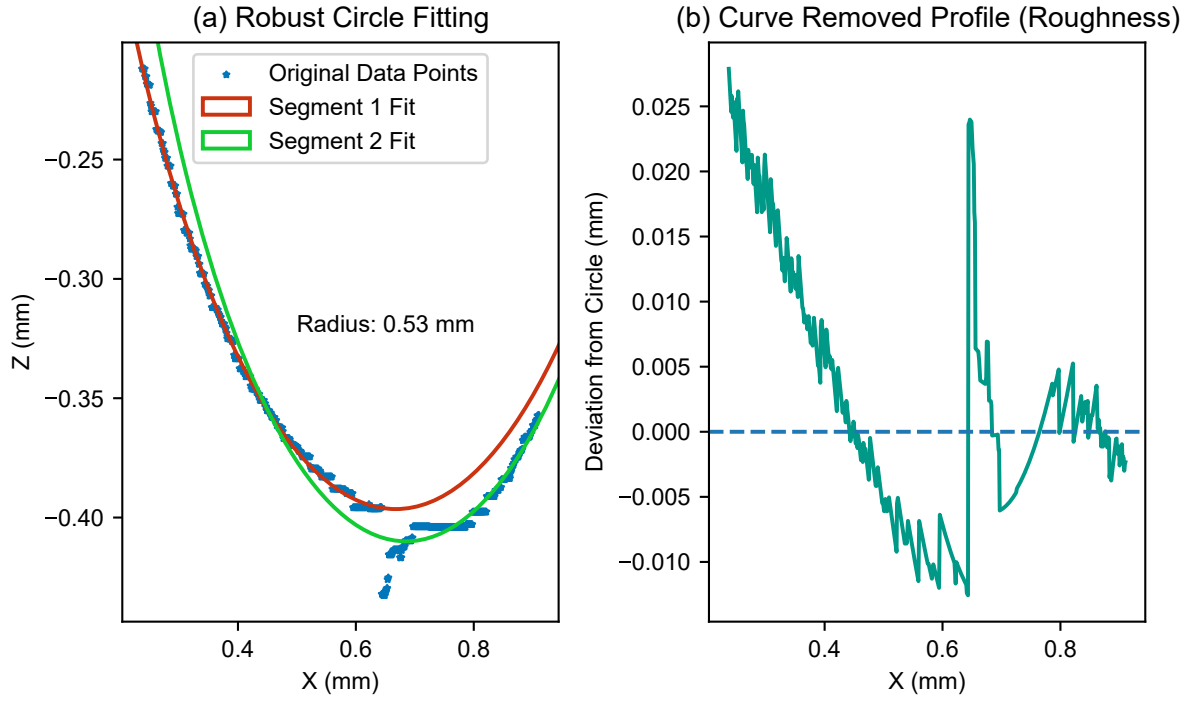


Figure 5-6: (a) Example fitted circular profiles illustrating cylindrical distortion along depth. (b) Corresponding roughness distribution extracted from the segmented curvature regions.

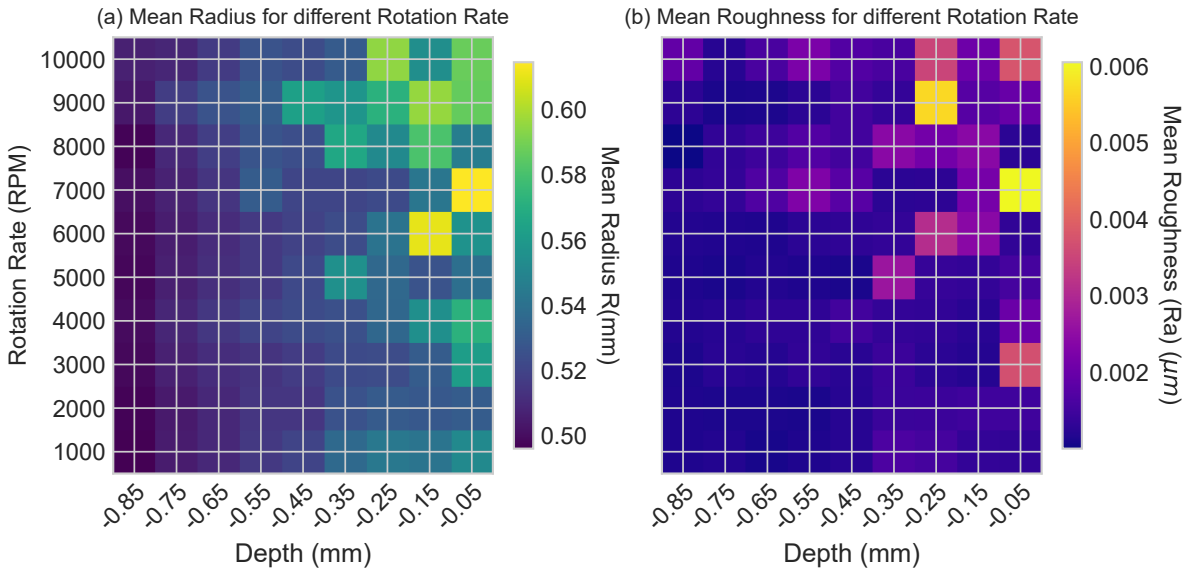


Figure 5-7: Heatmaps of radius and roughness measurement for different rotation rates and depths.

calibrate and refine the RF regression output, isotonic regression was applied as a monotonic post-processing step.

Feature Set 1: $\{t, E_{\text{total}}(t), E_{\text{total}}(t-1), E_{\text{total}}(t-2)\}$

Feature Set 2: $\{t, E_c(t), E_c(t-1), E_c(t-2) \mid c = 1, \dots, 7\}$

5.3.1.3. Modeling of Radius Based on Electrical Data

Predicting post-experimental measurements from in-process data is challenging because it requires equating continuous-time state data (e.g., electrical signals, tool position) with discrete measurement data (e.g., laser profilometer).

To bridge this gap, the machined surface was divided into position bins. These bins were centered on the measured depths (p), with a bin size equal to the measurement pitch (0.01 mm). If the mean tool position y_t at time t lies in the region of $p - 0.005 < y_t < p + 0.005$, the time-state data is then mapped to this position bin, effectively converting the time-state-space problem into a space-state problem. In this research, we propose two models to predict the radius at each depth from electrical waveform data.

1. Physics-based model: (Gaussian spread)

In this method, the radius is modelled based on the concept that electric-discharge erosion is not a single-point material-removal process but rather a spatially distributed process. Based on single crater SEM observation 3-7, we hypothesize that the machining progression follows a Gaussian model with a spread 2σ and an amplitude proportional to the intensity of discharge. The measured profile value (D) at position p and time t is modelled as:

$$D(p, t) = D(p, t - 1) + f(t) g(E_t) h(p - x_t; \sigma) \quad (5.4)$$

where $f(t)$ is the time-decay term accounting for radial tool wear, $g(E_t)$ represents the effect of discharge intensity (state), and $h(p - x, \sigma)$ is the spatial effect of EDM, with a Gaussian spread centered around the tool position as seen in Figure 5-8. The effect of axial tool wear was not considered in this approach. The schematic of the Gaussian spread model is shown in (Figure 5-8(a)-(b))

The method of the Gaussian exposure model is as follows: (1) First, the exposure matrix indicating the Gaussian spread is defined around the tool position at time t , $x(t)$, is given by:

$$A_{t,p} = \frac{1}{\sqrt{2\pi}\sigma^2} \exp \left[-\frac{(p - x_t)^2}{2\sigma^2} \right] \quad (5.5)$$

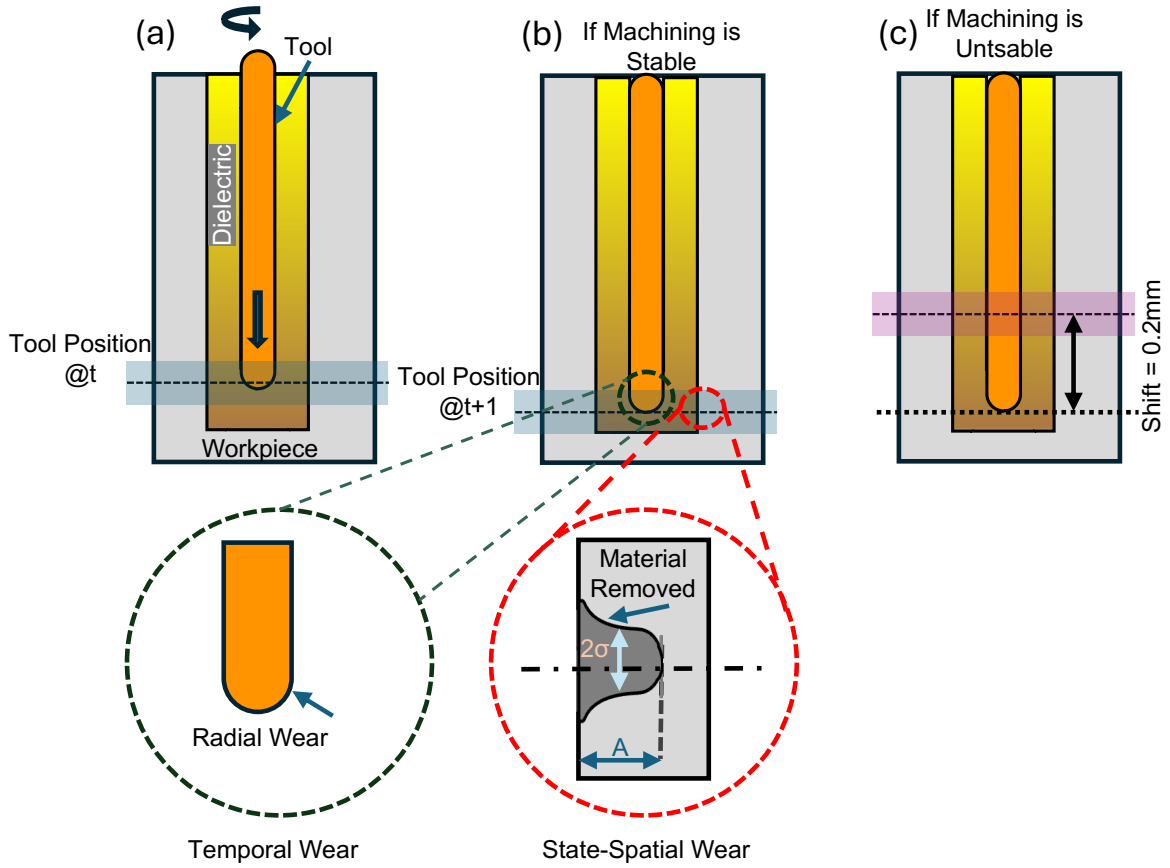


Figure 5-8: Schematic illustration of the Gaussian exposure model used for the machined radius prediction.

The contribution of each discharge type c is accumulated as:

$$B_{c,p} = \sum_t I_{c,t} A_{t,p} \quad (5.6)$$

where $I_{c,t}$ is the intensity of event type c at time t . To equate intensity and discharge counts, the model was evaluated with three scaling functions: (a) linear, (b) square root, and (c) cube root. To determine the effect of each discharge type (c), the removal efficiency coefficients β_c are determined by solving the following ordinary least squares (OLS) problem:

$$\min_{\beta} \left\| Y(p) - \sum_{c=1}^7 \beta_c B_{c,p} \right\|_2^2 \quad (5.7)$$

Where $Y(p)$ is the measured radius at position p .

(2) Machine learning model: In parallel with the physics-based Gaussian model, a machine learning model, Random Forest (RF) regressor, was also implemented to directly predict the

final radius at each depth bin from electrical waveform-derived features. Similar to the Gaussian spread model, the RF model was built on the same logic of mapping electrical waveform data to position bins. In addition, a two-phase feature preparation was followed: if the batch is classified as stable, the wear is applied at position bin p , and if the batch is classified as unstable, the wear is applied at position $p - \gamma$, where γ is the spatial shift. The stable labels are obtained from the XGB model discussed in Chapter 4. Because different depth bins can contain different numbers of time samples (due to tool oscillations, retractions, and non-uniform dwell time), raw event totals can bias the feature representation. To reduce this bias, each discharge-type count was converted into a per-bin density:

$$\rho_c(p) = \frac{\sum_{t \in \mathcal{B}(p)} E_{c,t}}{N_p}, \quad (5.8)$$

where $\mathcal{B}(p)$ is the set of time indices mapped to depth bin p , $E_{c,t}$ is the count of discharge type c at time t , and N_p is the number of samples assigned to bin p . In practice, a log-compression $\log(1 + \rho_c)$ was applied to soften the influence of bins with unusually high densities. Since the EDM system has a resolution of 1 μm and a feed rate of 3 $\mu\text{m/s}$ (180 $\mu\text{m/min}$), it is assumed that each tool will pass through each depth bin.

This density formulation is consistent with the time-to-space conversion, but, rather than smoothing erosion spatially as in the Gaussian baseline, the RF model receives a normalized representation of discharge activity per depth bin. The density features, therefore, reduce the dominance of high-dwell bins and provide a more comparable input scale across depth and across rotation rates.

Shift strategies for unstable erosion offset: As discussed in Section 5.1.1, unstable machining can produce sidewall erosion that is spatially offset (γ) from the bottom tool position. To account for this, two shift strategies were evaluated when mapping unstable batches into depth bins: (i) a fixed shift of 0.2 mm (200 μm) based on visual inspection of SEM and position data, and (ii) an optimized shift estimated from fixed rotation-rate experiments by selecting the shift value that best aligns predicted and measured radius profiles, in between 0.15-0.25 mm. These two settings are labelled as Shift 200 μm and Shift Autodetect.

The RF model was then trained on fixed rotation-rate experiments using all available po-

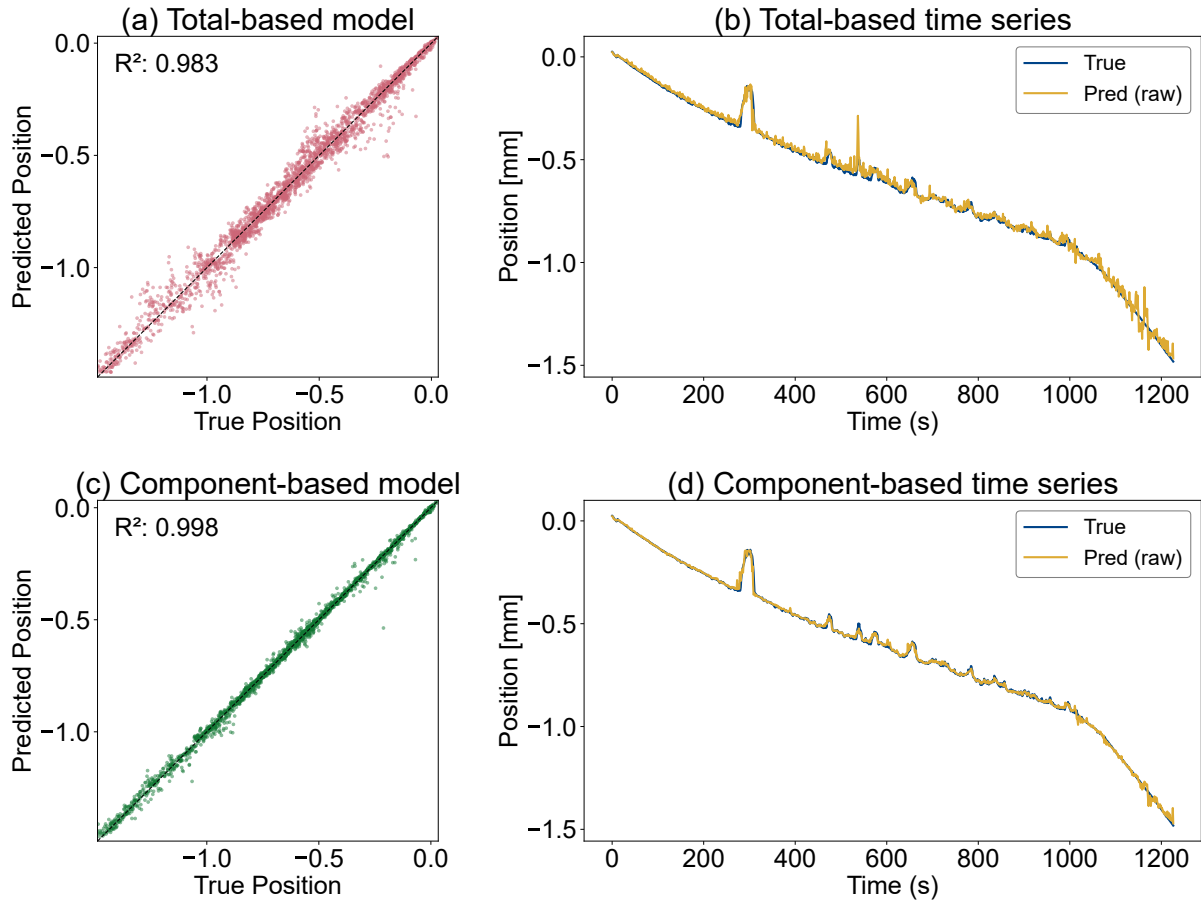


Figure 5-9: Comparison between measured and RF+isotonic predicted tool position for a representative fixed rotation-rate experiment.

sition bins with measured radii. It was evaluated on the two test cases. In these tests, the radius profile obtained from the laser profilometer was used as the training target y . At the same time, the input features were derived solely from the electrical waveform and the inferred tool-position signal. Model performance of the predicted radii $\hat{y}$ was assessed using mean absolute error (MAE), and root mean squared error (RMSE) over the whole depth range, alongside visual comparison of predicted and measured profiles.

5.3.2. Results

Figure 5-9 shows the results of tool position prediction using the Random Forest (RF) regressor with isotonic post-processing, based on (a), (b) total discharge event counts-based and (c), (d) component discharge count-based features. Both models show a high degree of agreement with the measured tool position, with the component-based feature set yielding consistently lower prediction error and improved tracking of rapid tool oscillations.

The strong correspondence between predicted and measured positions indicates that the tool position changes by the EDM servo system can be reliably inferred from electrical waveform-derived features alone. This is particularly important for control-oriented applications, as it removes the need for direct access to tool position signals, which are often limited in sampling rate, delayed, or unavailable on proprietary EDM platforms. In the proposed framework, the predicted position is therefore used as a surrogate state variable for subsequent geometric modeling, enabling radius prediction and spatial binning to be performed solely from electrical waveform data.

The performance of the Gaussian exposure model was first evaluated in fixed-rotation-rate experiments, where discharge statistics, tool motion, and erosion behaviour are comparatively stationary. As summarised in Table 5-2, the Gaussian exposure model reproduces the coarse trend of radius growth across fixed rotation-rate conditions when sublinear intensity mappings are used. Square-root and cube-root scaling yield RMSE values on the order of $1-3 \times 10^{-2}$, whereas the linear intensity formulation produces substantially larger errors (on the order of 10^{-1}) for dynamic rotation-rate cases and is therefore excluded from further consideration. These results indicate that a strictly linear superposition of Gaussian erosion footprints is insufficient to represent the non-linear erosion behaviour observed under changing rotation conditions.

Figures 5-10 and 5-11 further illustrate this behaviour. For training rotation rates, the Gaussian model successfully predicts the gradual widening of the hole with depth and reproduces the general envelope of the measured profile. Among the tested intensity mappings, square-root and cube-root scaling of discharge intensities yield slightly lower residual errors than linear scaling, suggesting a sublinear relationship between discharge count and effective material removal.

However, when applied to test experiments in which the rotation rate was dynamically varied, the limitations of the Gaussian exposure model become evident. Although the model continues to follow the global trend of radius variation, it fails to reproduce sharp local peaks, valleys, and asymmetric distortions observed in the measured profiles. In particular, the model struggles to adapt when the rotation rate changes rapidly, as it relies on a fixed spatial spread and a linear superposition of component-wise erosion effects (Test 2). As a result, the predicted

Table 5-2: Comparison of Gaussian-exposure models under different component intensity transforms (OLS fitting)

Metric	Linear	Square Root	Cube Root
Global σ	0.0300	0.0300	0.0300
Spatial shift (bins)	22	22	22
Global RSS	4.19e-01	4.12e-01	3.90e-01
RMSE (Training Rotation Rate)			
1000	1.72e-02	1.44e-02	1.41e-02
2000	1.01e-02	1.05e-02	1.09e-02
3000	1.39e-02	1.29e-02	1.31e-02
4000	1.23e-02	1.36e-02	1.48e-02
5000	1.88e-02	1.86e-02	1.73e-02
6000	2.73e-02	2.56e-02	2.50e-02
7000	3.36e-02	3.61e-02	3.67e-02
8000	2.55e-02	2.22e-02	2.20e-02
9000	1.73e-02	1.96e-02	1.88e-02
10000	2.91e-02	2.88e-02	2.56e-02
RMSE (Test Rotation Rate)			
Test 1	2.92e-01	2.78e-02	5.25e-02
Test 2	2.72e-01	3.56e-02	5.83e-02

profiles tend to appear overly smooth and lag behind sudden changes in machining conditions.

A physically consistent formulation would constrain the erosion coefficients to be non-negative, reflecting positive material removal. In practice, enforcing this non-negativity constraint across all rotation-rate conditions led to biased fits and poor reconstruction of the dynamically varying rotation-rate machined profiles, indicating that a simple linear, non-negative superposition of fixed Gaussian footprints is too restrictive for this process.

These observations indicate that while the Gaussian exposure formulation provides a physically interpretable baseline, it is inherently limited by its simplifying assumptions. The use of a single global spread parameter and linear ordinary least-squares fitting cannot fully represent the complex, non-linear interactions between discharge statistics, debris transport, flushing dynamics, and rotation history that govern sidewall erosion in rotary EDM. Consequently, the Gaussian exposure model is treated here as a physics-inspired baseline that can reproduce only the coarse trend of radius growth. At the same time, detailed local interactions must be captured by more flexible data-driven models.

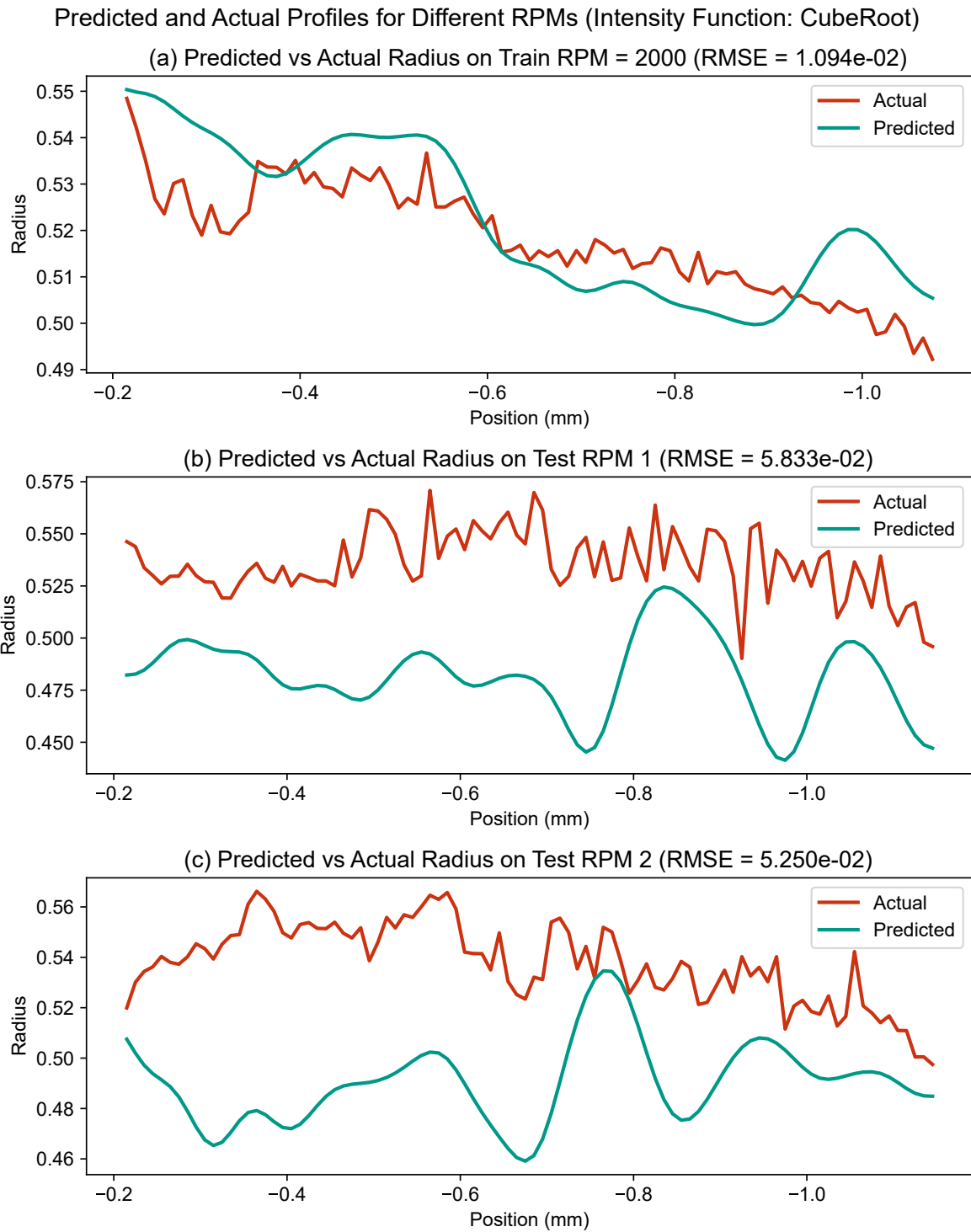


Figure 5-10: Measured versus Gaussian-model predicted radius profiles using cube-root intensity scaling for (a) training and (b), (c) test profiles.

This motivates the use of more flexible data-driven approaches, such as the machine learning-based radius model introduced in the following section, which can exploit non-linear relationships and adapt to changes in rotation rate and local machining state without imposing a fixed

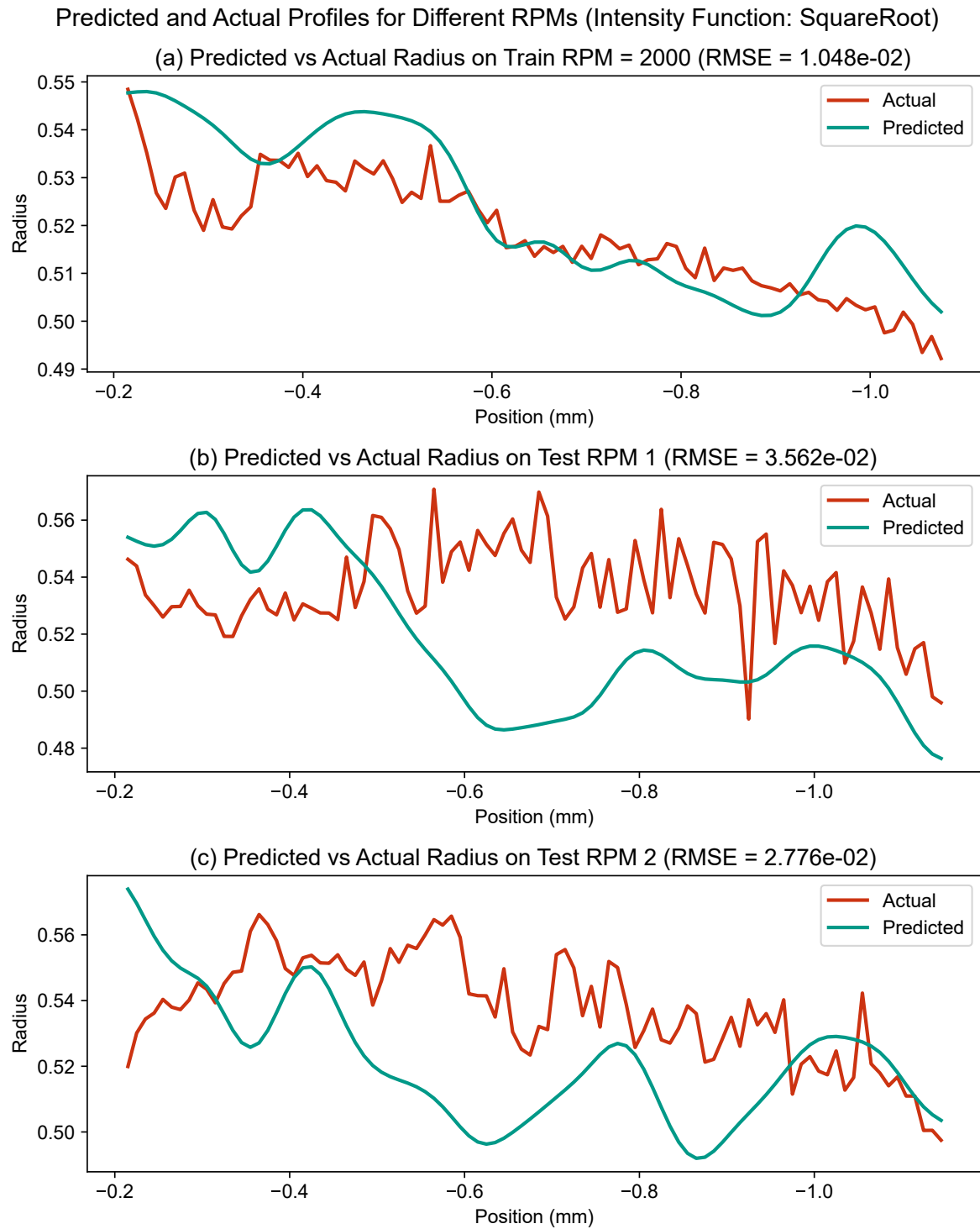


Figure 5-11: Measured versus Gaussian-model predicted radius profiles using square-root intensity scaling for (a) training and (b), (c) test profiles.

spatial footprint.

Table 5-3 summarises the effect of feature set design on the Random Forest radius prediction performance for test rotation-rate experiments. Results are reported for both a fixed spatial

shift (200 μm) and a shift automatically determined from fixed rotation-rate experiments.

Table 5-3: Effect of feature set design on random forest radius prediction performance (evaluated on test rotation-rate cases)

Feature Set	Shift 200 μm		Shift Autodetect	
	MAE	RMSE	MAE	RMSE
Electrical only	1.72e-02	2.13e-02	1.83e-02	2.26e-02
Electrical + Time	2.06e-02	2.69e-02	2.00e-02	2.36e-02
Electrical + Time + Rotation Rate	1.90e-02	2.44e-02	1.91e-02	2.48e-02

Across both shift strategies, using only electrical features yields the lowest numerical error (RMSE $\approx 2.13\text{e-}2$). However, visual inspection of the predicted profiles indicates that this configuration tends to smooth the radius response and fails to capture finer local variations associated with cylindrical distortion (Figure 5-10 and Figure 5-11). This suggests that minimizing global RMSE alone does not guarantee physically meaningful profile reconstruction.

Including temporal features, such as the mean time spent in each position bin, did not consistently improve numerical error once waveform data were mapped into depth bins, indicating that much of the temporal context is already embedded in the spatial aggregation process. In contrast, incorporating rotation rate as an additional feature reduced the error relative to the time-only case and improved qualitative agreement with the measured profiles. This supports the conclusion that radial wear is not solely governed by discharge activity, but is also influenced by rotation-dependent interactions such as flushing efficiency, debris transport, and sidewall erosion. The predicted versus measured radius profiles for the best-performing Random Forest models, for both training and test data under the two shift strategies, are shown in Figures 5-12 and 5-13.

To further examine how prediction accuracy varies with machining depth, the depth-wise distribution of radius-prediction errors was evaluated using root-mean-square error (RMSE). Figure 5-14(a) shows the cumulative RMSE at each depth bin for the training, test, and combined datasets. Prediction errors are consistently higher on the test data than on the training data. This difference arises primarily because the training data uses tool positions obtained directly from camera measurements. In contrast, in the blind test experiments, the tool position is inferred solely from electrical waveform data using the model described in Section 5.3.1.2.

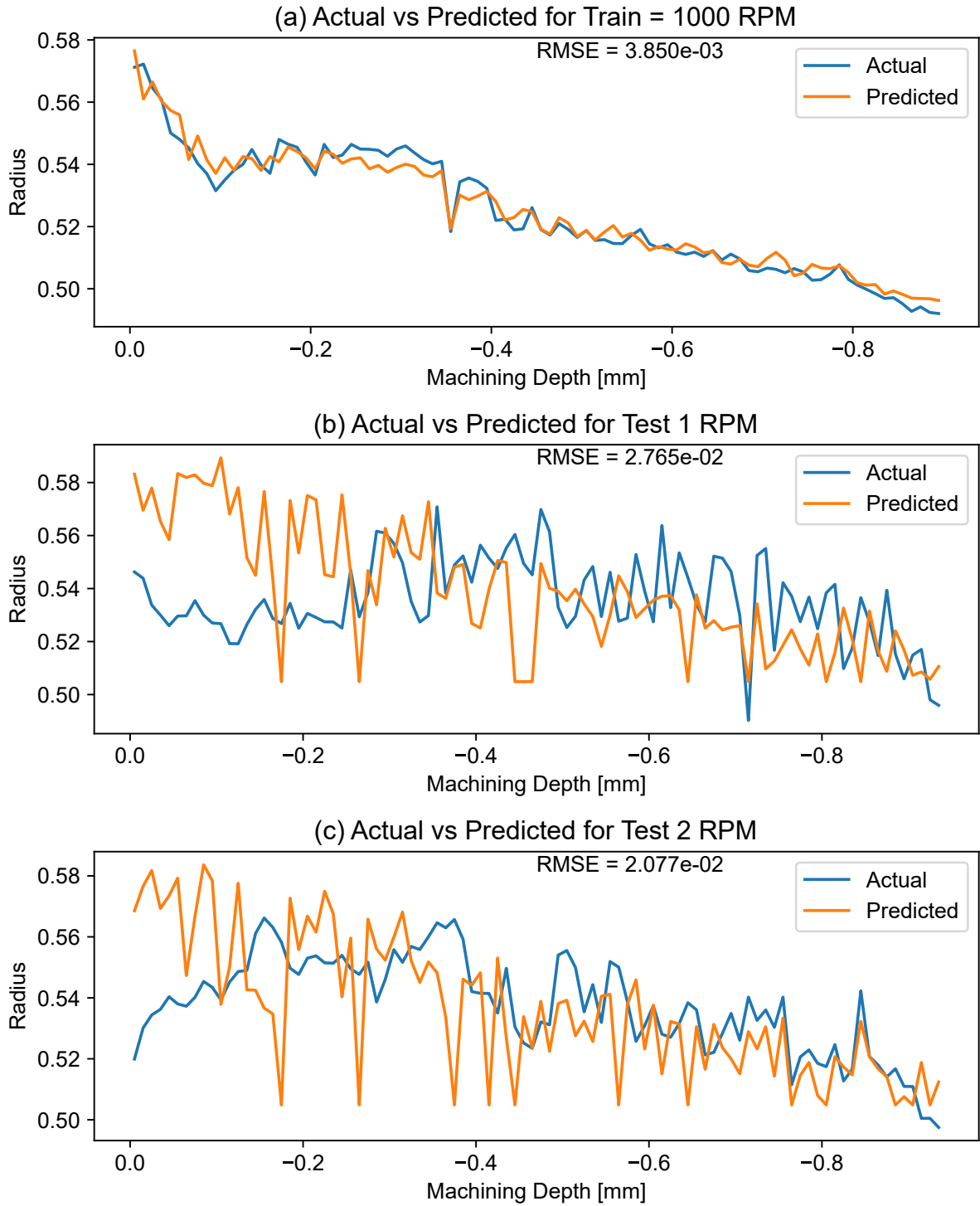


Figure 5-12: Comparison of actual and predicted radius profiles using random forest for (a) training and (b)-(c) test rotation rates using a fixed shift of 0.2 mm.

As a result, errors from tool-position prediction propagate into the radius estimation, leading to compounded uncertainty.

The depth-wise error profile shown in Figure 5-14(b) exhibits a clear trend: higher errors near the inlet region, reduced error in the mid-depth region, and a gradual increase toward the

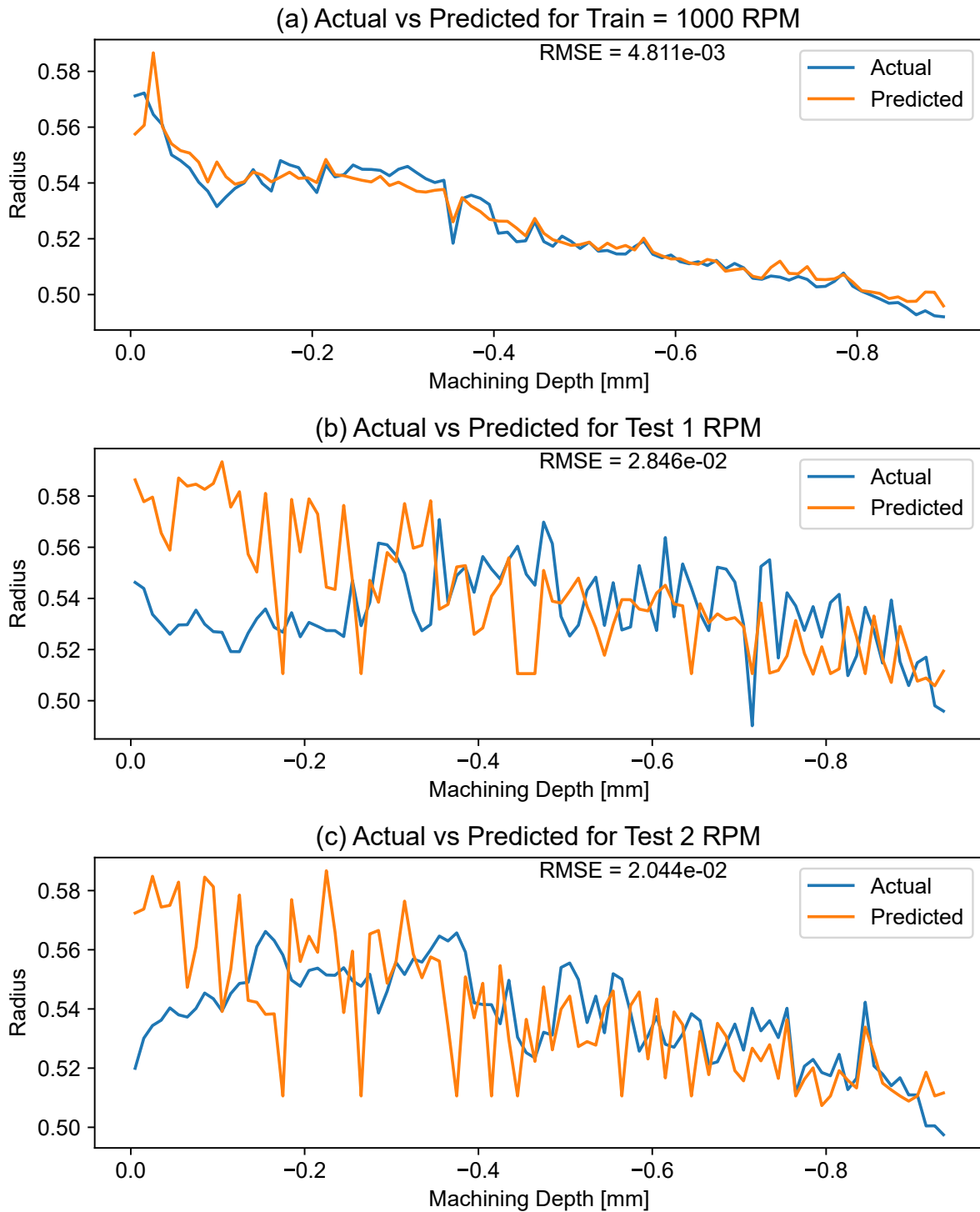


Figure 5-13: Comparison of actual and predicted radius profiles using random forest for (a) training and (b)-(c) test rotation rates using a fixed shift autodetect

end of machining. The elevated error near the inlet is attributed to continuous exposure of the upper sidewalls to debris accumulation, which increases the likelihood of stray discharges, particularly near the neck of the hole. Toward the final depth, the increase in error is associated with end-of-machining (EOM) effects, including increased process noise and breakout-related

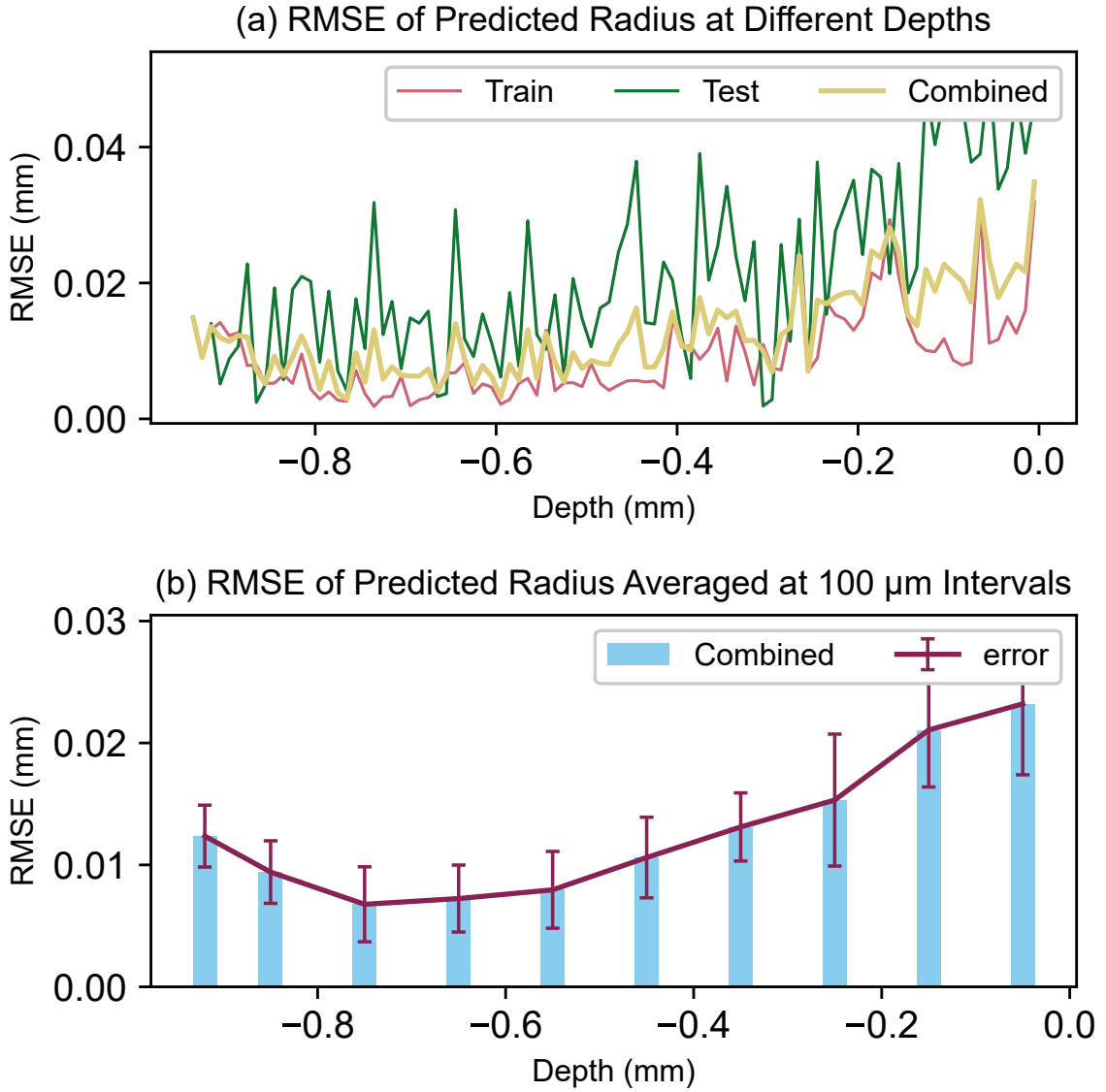


Figure 5-14: (a) Comparison of cumulative RMSE values for different datasets at each depth bin, and (b) RMSE values averaged over 100 μm depth intervals.

disturbances. The current model adopts a two-phase representation of machining (stable and unstable) and does not explicitly account for the EOM phase, which exhibits distinct erosion characteristics and therefore contributes additional modeling error.

It is noted that the physics-inspired Gaussian exposure model captures this depth-dependent behavior slightly better than the purely data-driven approach, as it incorporates a spatially distributed erosion mechanism. However, it remains limited in its ability to represent localized distortions. Future models should therefore integrate both spatial exposure mechanisms to capture global erosion trends and point-based exposure effects to better resolve local geometric

deviations.

Despite these improvements, the overall differences in error across feature sets remain modest. This reflects an inherent limitation of the available data: the ground-truth radius profiles are sparse and obtained from destructive cross-sectional measurements, limiting the ability of any model to resolve fine-scale geometric variations fully. Nevertheless, when combined with spatial binning and inferred tool position, the Random Forest model provides a practical compromise between numerical accuracy and physical interpretability for downstream control-oriented analysis.

It is also worth noting that, as shown in Chapter 3, conventional machine-learning regressors failed to predict global radii metrics when only static process parameters were used. In contrast, the present results demonstrate that incorporating temporal structure through waveform-derived features and depth-resolved binning enables substantially more accurate prediction of local geometric variations. This suggests that while electrical signals alone may not capture all erosion mechanisms, their temporal evolution contains valuable information that can be exploited when appropriately mapped into the spatial domain.

5.4. Offline Evaluation of the Control Strategy

5.4.1. Validation of Control Framework

The control strategy proposed in Section 5.1.1 is based on two empirical design rules: (i) when instability persists for roughly 2 s, the rotation rate should be decreased to avoid entering a strongly unstable regime, and (ii) rotation should only be increased after several seconds of consistently stable behaviour, so as to avoid rapid oscillations of the tool rotation rate. To verify that these rules are consistent with the process's dynamic behaviour, an offline analysis was conducted on the two test rotation rates, Test 1 and Test 2 RPM. In both experiments, the batch-level instability labels predicted by the XGB model ($XGB_Pred \in \{0, 1\}$) (Section 4.3.2) were treated as a binary state sequence, and the statistics of consecutive stable (0) and unstable (1) runs were analysed as a function of the actual rotation rate.

For each experiment, the time series were first grouped by the actual rotation rate and then decomposed phase-specifically. For each rotation rate, the mean and maximum run lengths

Table 5-4: Run-length statistics for stable (0) and unstable (1) states in the dynamic rotation rate tests

Experiment	RPM	Mean ₀ (s)	Mean ₁ (s)	Max ₀ (s)	Max ₁ (s)	Frac_time_in_1
Test 1 RPM	1000 (start)	65.00	2.00	128.0	3.0	0.03
	2000	10.92	3.00	27.0	16.0	0.22
	3000	5.09	2.35	17.0	10.0	0.33
	4000	7.18	2.50	42.0	6.0	0.27
	5000	3.66	1.61	39.0	5.0	0.30
	6000	5.00	3.55	42.0	20.0	0.43
	7000	7.06	2.94	30.0	7.0	0.28
	8000 (end)	1.60	1.50	3.0	2.0	0.43
Test 2 RPM	4000 (start)	20.88	2.50	64.0	5.0	0.11
	5000	6.39	3.32	20.0	27.0	0.33
	6000	5.76	3.04	34.0	10.0	0.35
	7000	5.05	4.95	38.0	28.0	0.50
	8000	5.95	4.76	32.0	25.0	0.46
	9000 (end)	3.20	4.16	22.0	24.0	0.57

of the stable and unstable states were computed. In addition, the fraction of time spent in the unstable state was evaluated. This yields, for each rotation rate, a compact summary of how often instability occurs, how long it tends to persist once it appears, and how long stable phases typically last. Table 5-4 summarises the run-length statistics of stable and unstable machining phases for the two dynamic rotation-rate experiments. Rather than focusing on individual numerical values, the table reveals clear qualitative trends that are consistent across both tests.

In the Test 1 experiment, where the rotation rate increases more aggressively, unstable phases typically persist for approximately 2–4 s, with occasional extended instability lasting up to 20 s at certain rotation rates. Stable phases are generally longer, particularly at low rotation rates, indicating that the process alternates between stable and unstable regimes rather than remaining permanently unstable.

In contrast, the Test 2 experiment, which follows a more gradual increase in rotation rate, shows a more systematic trend: higher rotation rates are associated with longer and more persistent unstable phases. At rotation rates above 7000 RPM, unstable runs frequently last 4–5 s and occasionally extend beyond 25 s. This behaviour is consistent with the phase-duration trends observed earlier in Figure 5-2, confirming that high rotation-rate regions correspond to genuinely unstable machining conditions in which instability, once triggered, tends to persist.

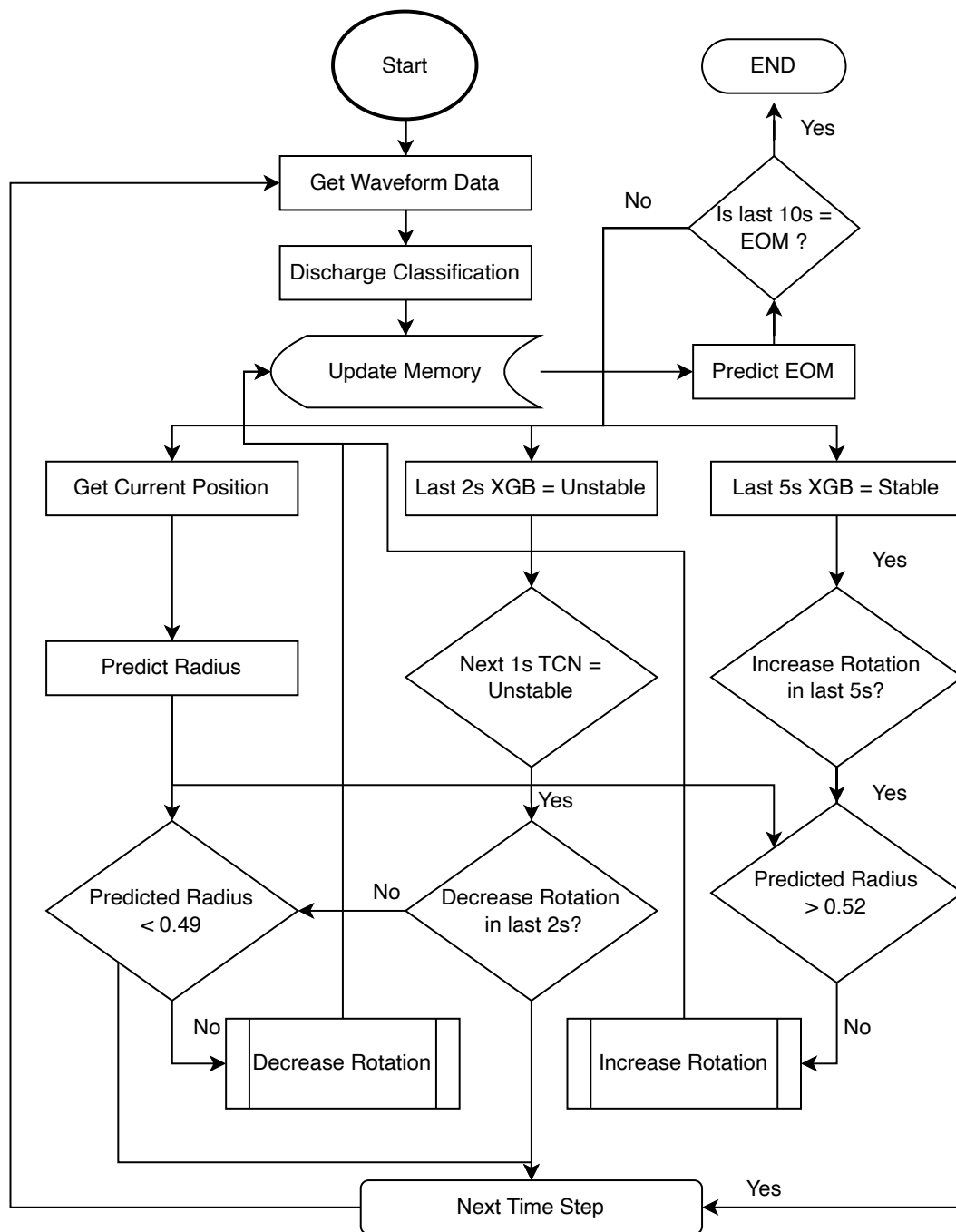


Figure 5-15: Flowchart of the proposed control strategy.

Based on these observations, two control-oriented decisions are formulated. A control decision-logic flowchart was developed, as shown in Figure 5-15. First, changes in rotation rate are most effective when applied promptly after a phase transition. Accordingly, if the process remains in a stable phase for more than 4 s without any recent rotation change, the rotation rate is in-

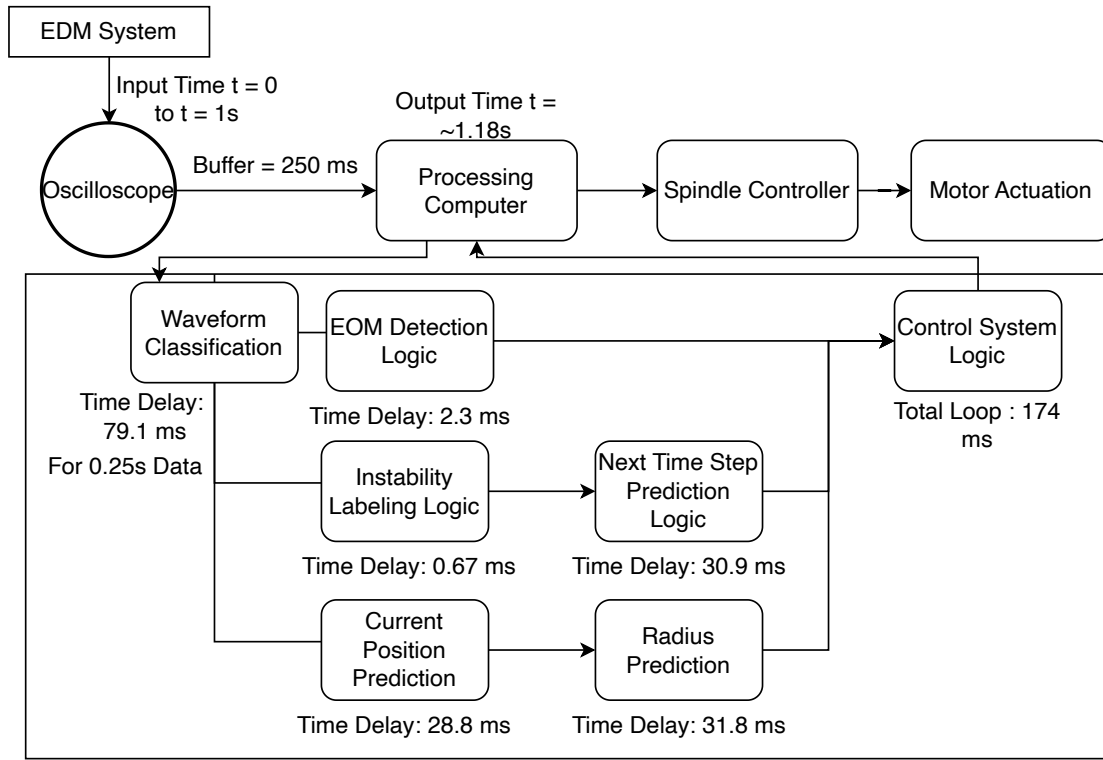


Figure 5-16: Time delays of different machine learning components in the proposed framework

creased. Conversely, if instability persists for more than 2 s without any recent adjustment, the rotation rate is decreased. A third decision rule is introduced based on the predicted machined radius. As shown earlier, increasing the rotation rate tends to increase the machined radius. To prevent excessive over-machining or under-machining, upper and lower radius limits are imposed (0.52 mm and 0.49 mm, respectively). These geometric constraints are applied in series with the stability-based rules. Using this control strategy, the proposed framework was simulated offline on recorded waveform data from the dynamic rotation-rate experiments. The corresponding workflow and approximate computational latencies are illustrated in Figure 5-16. The dominant source of latency is waveform buffering and classification, which is primarily governed by the oscilloscope's sampling and buffering configuration. For the current implementation, the overall control-loop delay is approximately 0.2 s, which is well within the 1 s batch resolution used for decision-making.

The simulated rotation-rate adjustments and their effect on the predicted machined radius, for Test 1 and Test 2, are shown in Figure 5-17, 5-18 and Figure A-3, A-4 respectively. These results demonstrate the feasibility of integrating instability detection, forecasting, and geometric

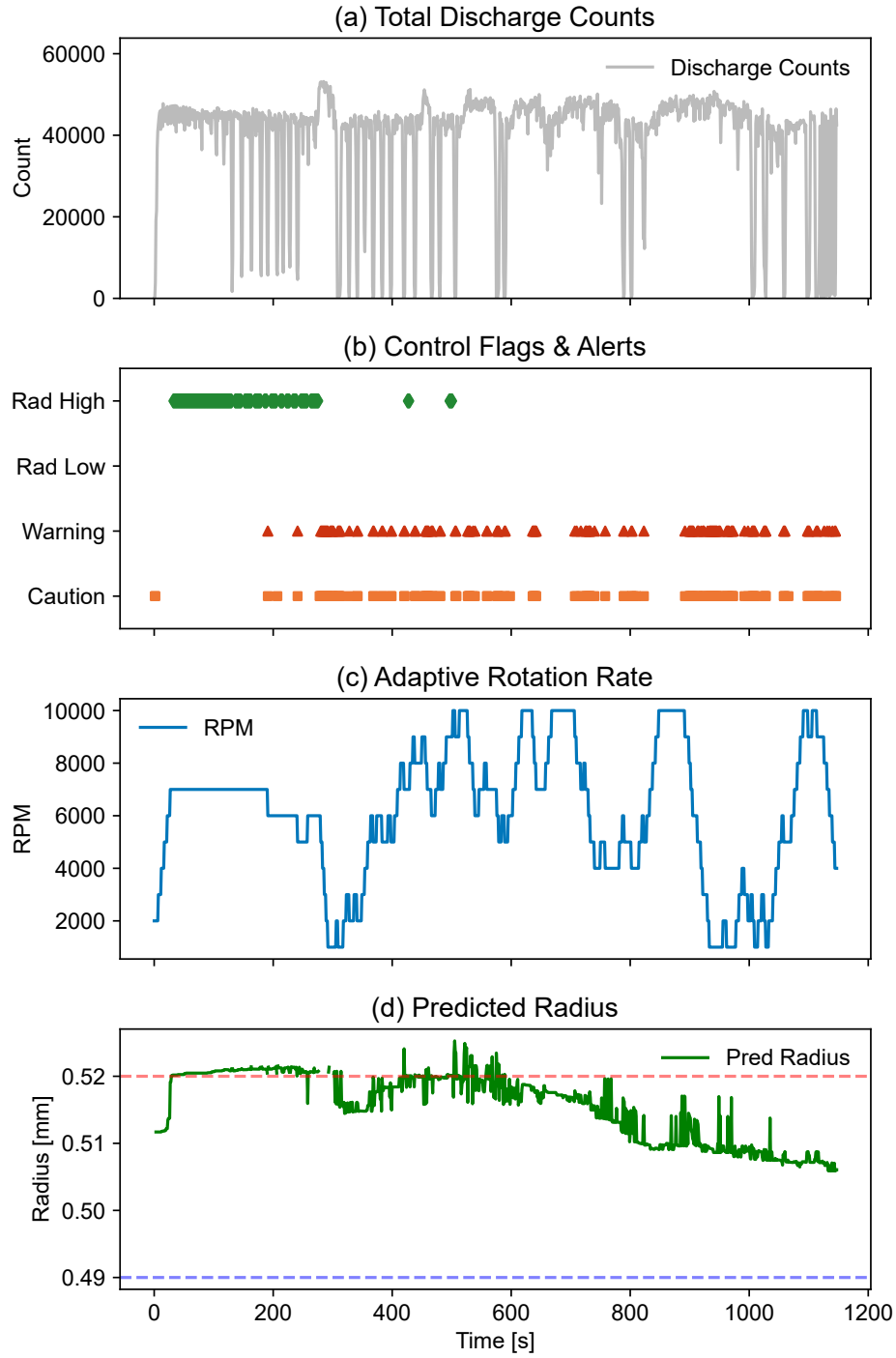


Figure 5-17: Simulation of the proposed framework for dynamic rotation rate with (a) total discharge events, with (b) cautions and warnings raised for rotation change, and (c) modeled rotation rate changes for rotation rate profile Test 1.

constraints into a unified supervisory decision framework.

Nevertheless, several limitations remain. The proposed control logic was developed for a fixed set of electrical and servo parameters, and for a specific tool-workpiece combination. While the TCN-based forecasting model is relatively robust to variations in signal amplitude,

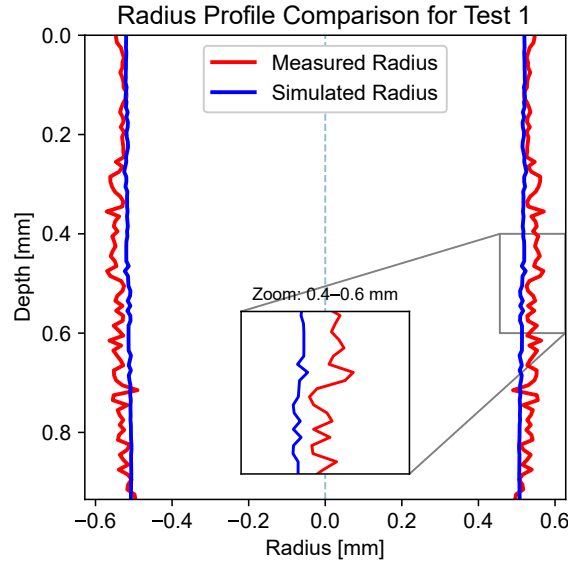


Figure 5-18: Simulated and actual machined radius profile for Test 1.

the instability labelling and control thresholds were derived empirically under fixed conditions. In addition, the magnitude and rate of rotation-rate changes were selected heuristically based on limited experimental observations. These aspects should be refined through online testing and closed-loop implementation in future work.

5.4.2. Applicability to Other Configurations

Following the offline validation of the proposed control system framework, the applicability of the control logic to other configurations is investigated. These configurations include variations in workpiece material, electrical-servo parameters, and tool-related conditions. Two types of validation experiments are conducted in this section: (i) material effects and (ii) electrical parameter effects.

For the investigation of electrical parameter effects, the experimental conditions follow the same design of experiments (DoE) listed in Table 3-5. The experimental conditions used to evaluate material effects are summarized in Table 5-5. In all cases, the electrical waveforms are acquired, discharge events are detected and classified, and the resulting data are grouped following the procedure described in Chapter 4.

The mean total number of discharge events per second, along with the percentage distribution of stable and unstable machining phases, is summarized in Table 5-6. It is observed that

Table 5-5: Experimental conditions for evaluating material effects

Parameter	Value
Workpiece	Tungsten Carbide
Voltage [V]	110
Current [A]	2.5
Pulse On [μ s]	4
Pulse Off [μ s]	9.6
Feed Rate [μ m/min]	180
Tool	Copper (Cu), Copper Tungsten (CuW)
Tool Rotation Rate [RPM]	2000, 8000

during stable machining phases, the mean discharge events per second are comparable for both electrode materials and at both rotation rates. Furthermore, when aggregated over all machining phases, the mean total discharge events per second exhibit less than 3% variation across materials and rotation rates.

This observation indicates that, for a given set of electrical parameters, the EDM system maintains a nearly constant average discharge activity. In contrast, auxiliary conditions such as electrode material and tool rotation rate primarily influence the composition of discharge events rather than the total event rate. The average composition of discharge classes E1-E4 for stable and unstable machining phases is therefore reported separately in Tables A-4 and A-5.

Table 5-6: Mean total discharge counts per second under stable and unstable machining conditions

Condition	Cu		CuW	
	2000 RPM	8000 RPM	2000 RPM	8000 RPM
Total (Stable)	40104	40381	41032	40194
Total (Unstable)	26621	25328	26834	33753
Total	42648	43148	43252	43908
Stable (%)	73.23	72.80	78.22	60.06
Unstable (%)	26.77	27.20	21.77	39.94

The differences in discharge composition between stable and unstable machining phases are visualized in Figure 5-19. Although the magnitude of compositional change differs between the two electrode materials, the direction of change associated with increased tool rotation rate is consistent. This observation validates the phase-specific rotation-rate effect modeling adopted in the preceding sections.

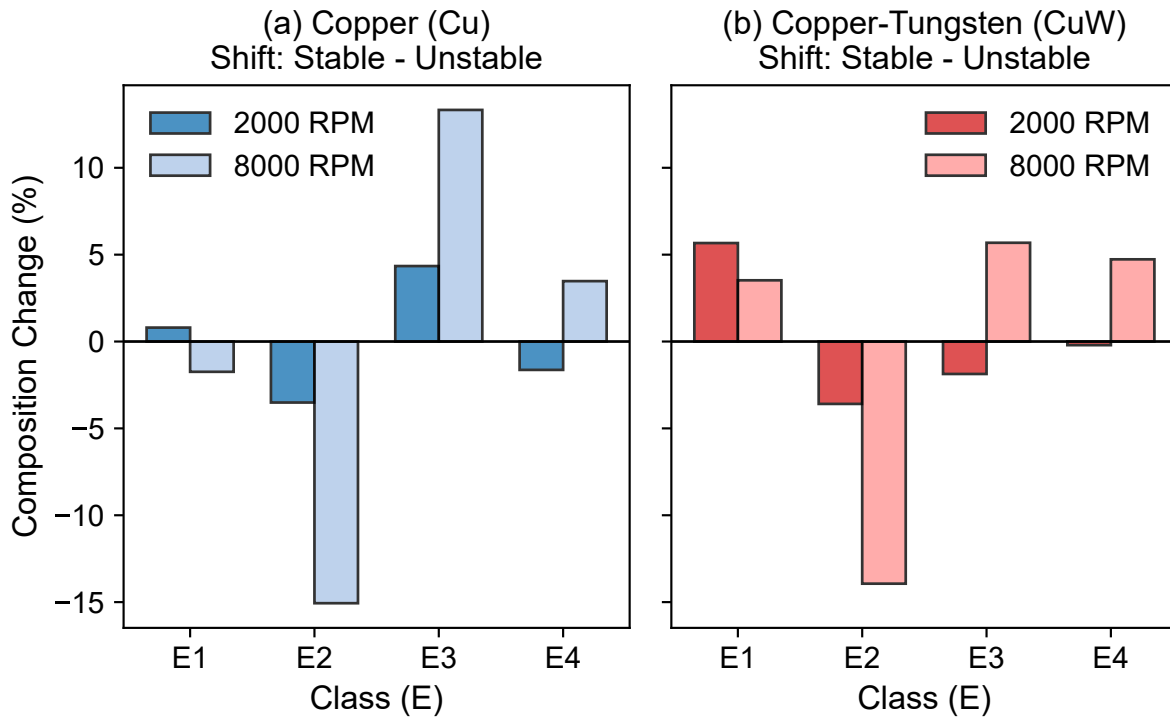


Figure 5-19: Change in discharge composition between stable and unstable phases for different electrode materials and rotation rates.

In addition, the consecutive duration statistics of stable and unstable machining phases are summarized in Table 5-7. For the copper–tungsten electrode, the results closely agree with the trends observed in earlier experiments. In the case of the copper electrode, although an anomalously long unstable phase is observed at one condition, the copper–tungsten results consistently indicate that higher rotation rates lead to longer and more persistent unstable phases. These findings further validate the control logic of reducing the tool rotation rate when instability persists beyond approximately 2 s.

Having established that the total discharge event rate is primarily a system-level parameter, while discharge composition is influenced by material and auxiliary conditions, the next step is to explore methods for improving discharge composition through electrical parameter optimization. As shown in Figure 5-19 and Table A-4–A-5, the material-induced compositional shift is mainly governed by changes in the E2 and E3 discharge classes. Therefore, a Taguchi-based design is employed to identify electrical parameter combinations that improve the weighted mean percentage of E2 and E3 events.

The Taguchi signal-to-noise (S/N) ratios and repeatability metrics for the key discharge

Table 5-7: Phase duration statistics under different materials, rotation rates, and stability conditions

Material	RPM	Condition	Runs	Mean	Median	Max
Cu	2000	Stable	137	6.57	3	52
		Unstable	138	2.38	2	26
	8000	Stable	106	8.63	3	168
		Unstable	107	3.20	2	21
CuW	2000	Stable	134	6.70	3	84
		Unstable	135	1.85	1	9
	8000	Stable	130	6.59	4	90
		Unstable	131	4.35	2	100

classes (%E2 and %E3) are listed in Table A-6. For a given set of electrical parameters, the total number of discharge events per second remains highly consistent, with coefficients of variation below 0.05, confirming good process repeatability. Based on the S/N analysis, optimal parameter levels can be identified. For example, from the Figure 5-20, when using a copper electrode, a voltage of 80 V, a pulse-on time of 4 μ s, and a feed rate of 240 μ m/min are favorable for reducing instability. Although the effects of duty ratio and peak current exhibit competing trends, prioritizing the E2 discharge class needs an optimal duty ratio of 0.3 and a peak current of 1 A. These trends are consistent with the findings reported in Chapter 3. In this way, electrical waveform information obtained from static optimization methods can be systematically integrated with dynamic process-state changes introduced through auxiliary rotation control, enabling the proposed machine learning-based instability monitoring framework to be extended to a broad range of EDM configurations.

Nevertheless, the proposed framework requires recalibration of machine learning models when applied to different materials, tools, or electrical-servo configurations, as material-dependent discharge interactions and debris dynamics can vary significantly. In addition, the present study evaluates the framework exclusively in an offline setting. Further experimental validation, including real-time closed-loop implementation and testing across a wider range of materials and process conditions, is necessary to fully assess robustness and practical applicability. Despite these limitations, the results indicate that the proposed approach provides a viable and extensible foundation for adaptive EDM control across diverse machining configurations.

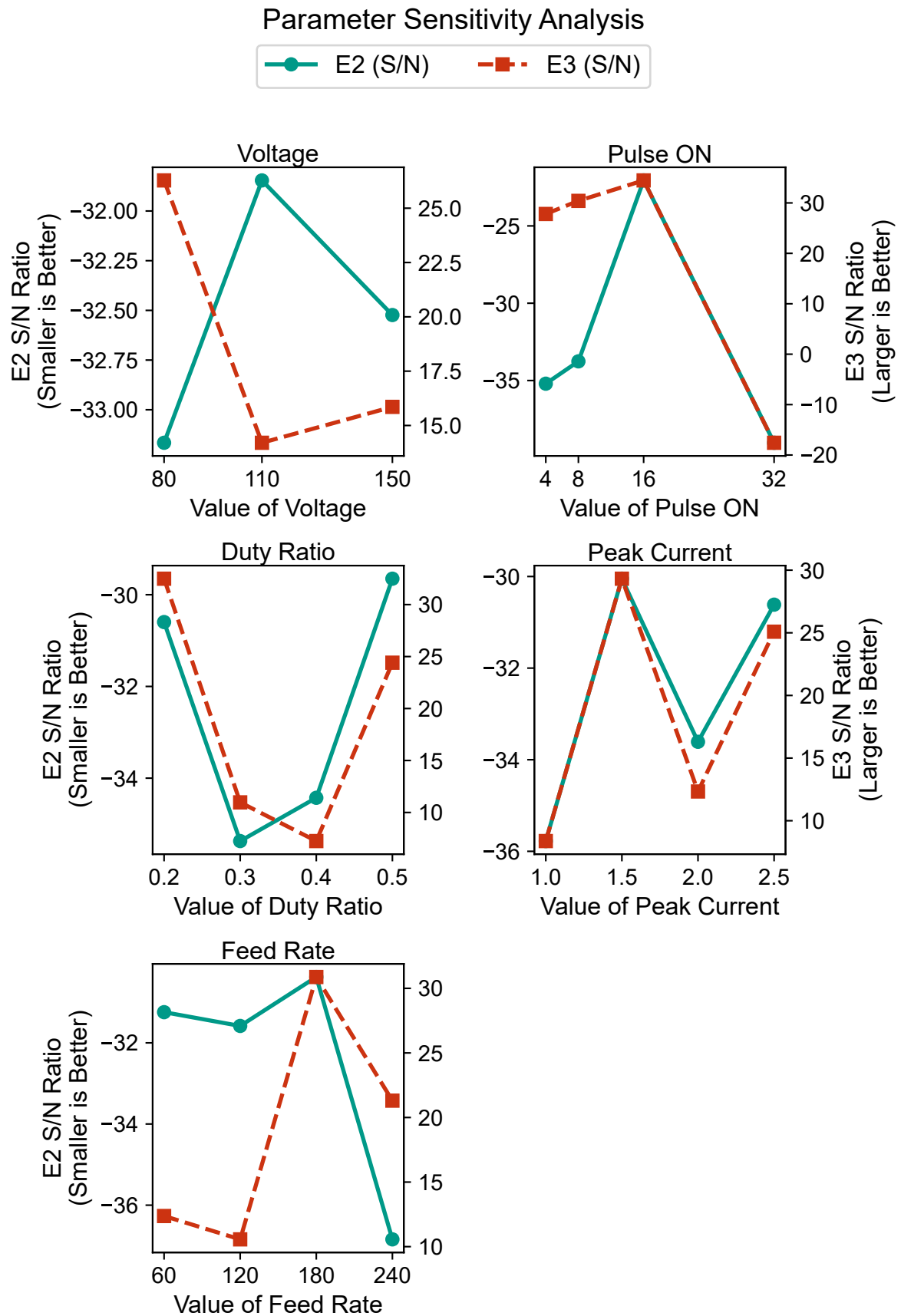


Figure 5-20: Parameter sensitivity analysis based on Taguchi signal-to-noise ratios.

5.5. Summary

In this chapter, a dynamic, waveform-driven modeling framework was developed to connect discharge behaviour, temporal instability, and machined hole geometry in rotary EDM of tungsten carbide. Building on the instability labels and phase statistics established in the previous chapter, the focus here was on understanding phase-specific rotation effects, developing early-warning models for instability, and investigating whether geometric outcomes can be inferred from electrical waveform data and their applicability to other systems. The summary of findings is as follows:

- Machining time can be meaningfully segmented into stable and unstable phases, and the influence of rotation rate differs markedly between these regimes. Increasing the rotation rate during stable machining suppresses short circuits and improves flushing. In contrast, high rotation during unstable phases reduces the number of effective sparks and increases secondary discharges, thereby promoting over-machining and sidewall erosion.
- The duration of both stable and unstable phases increases with rotation rate, with higher rotation rates producing longer-lived phases once a regime is established. Based on the observed median phase durations, a simple supervisory decision logic was formulated: incrementally increase the rotation rate when stability persists for approximately 4 s, and reduce the rotation rate when instability persists for approximately 2 s.
- A Temporal Convolutional Network (TCN) was employed to forecast instability one batch ahead using short histories of grouped discharge features. For history lengths of approximately 5-10 s, the model achieved unstable-class recall around 0.8 with moderate precision, providing an effective early-warning capability within the characteristic 2 s instability time scale. This demonstrates that sequence-based models can reduce effective decision latency compared with purely reactive classifiers.
- A measurement and modeling pipeline was established to relate electrical waveforms to the machined profile. Tool position was inferred from waveform-derived features using a Random Forest regressor with isotonic calibration. In contrast, a 1D-CNN-based curvature detector and circle-fitting procedure were used to extract radius and roughness from

high-density laser profiles. These analyses confirmed that higher rotation rates tend to produce broader and deeper cylindrical distortions along the hole wall.

- Two complementary approaches were explored for predicting radius from electrical data. A physics-inspired Gaussian exposure model reproduced the coarse trend of radius growth but was limited in its ability to capture local distortions. In contrast, a Random Forest-based model using waveform-derived features, inferred position, and rotation-rate context achieved radius prediction errors on the order of 2×10^{-2} for dynamic rotation-rate experiments and successfully recovered major peaks, valleys, and distorted regions of the profile, highlighting the importance of non-linear interactions between discharge statistics, depth, and rotation history.
- An offline simulation of the proposed machine learning-based adaptive rotation-control framework indicates that the overall computational latency is approximately 0.2 s, which is well below the 1 s batch resolution used for instability detection and decision-making. Because the total discharge event rate remains nearly constant across different materials and rotation rates for fixed electrical parameters, the proposed framework relies primarily on discharge composition and temporal evolution rather than absolute event counts. This suggests that the framework can be extended to other EDM system configurations by combining conventional parameter optimization methods with waveform-based instability monitoring after recalibration.

Overall, this chapter demonstrates that combining phase-specific rotation analysis, early-instability forecasting, and geometry modeling from electrical waveforms enables the formulation of a theoretical adaptive rotation-control framework for EDM. Although the proposed framework has been evaluated offline and requires further validation through real-time implementation and additional process observables, the results establish a framework for designing and implementing adaptive control strategies for rotary EDM.

Chapter 6

Conclusion

This chapter summarises the thesis’s overall findings and integrates contributions from parameter-level analysis, waveform-based process modelling, and dynamic instability prediction in EDM of tungsten carbide. The study progressed from analysing offline optimized machining behaviour, including powder-mixed EDM, to identifying signal-level indicators of instability, and finally to developing temporal models capable of forecasting instability and inferring geometric outcomes. Together, these contributions clarify the limitations of offline optimisation and outline a pathway toward stability-oriented, waveform-driven process adaptation.

6.1. Overall Contributions

1. Chapter 3 examined traditional optimisation methods, including powder-mixed EDM and parameter optimisation. Powder addition was shown to improve early-stage machining efficiency; however, deep-hole experiments revealed that debris accumulation and unstable gap conditions increasingly dominate process behaviour with depth. While statistical optimisation identified influential parameters under fixed conditions, these methods were unable to capture the inherently time-dependent nature of discharge behaviour. These observations highlighted that material- or dielectric-level modifications alone are insufficient to guarantee sustained stability, motivating the need for waveform-based monitoring and adaptive decision-making.
2. Chapter 4 introduced regression and machine-learning methods using waveform-derived features. A rule-based discharge classifier enabled the construction of grouped features, which were used to train Random Forest and XGBoost models for instability prediction. A 1D-CNN classifier was subsequently developed to replace manual discharge typing, providing a waveform-driven and rotation-invariant method for detecting instability. These results demonstrated that EDM behaviour can be interpreted reliably from signal-level information, independent of explicit gap or force measurements, thereby establish-

ing a robust foundation for subsequent temporal and control-oriented modelling.

3. Chapter 5 extended the modelling framework into the temporal domain. Phase segmentation clarified how rotation affects stable and unstable machining phases, establishing rotation rate as a viable control input. A Temporal Convolutional Network (TCN) provided early-instability prediction within the critical reaction window, while additional models estimated tool position and predicted machined profiles from waveform features. Together, these models demonstrate that instability evolution and geometric trends can be inferred from electrical waveforms, providing the modelling components required for a theoretical, supervisory adaptive rotation strategy rather than a fully implemented closed-loop controller.

Advances in sensing hardware and data-driven algorithms have enabled the extraction of increasingly rich information from existing manufacturing systems. In modern EDM machines, electrical waveforms are routinely available with high temporal resolution; however, effective utilisation of this information for stability control remains limited. In particular, maintaining stable machining conditions during the EDM of micro-scale and high-aspect-ratio components remains challenging, as instability often emerges dynamically and cannot be fully mitigated by offline parameter optimisation or enhanced sensing alone.

The key contribution of this dissertation lies in integrating physics-based understanding of discharge behavior with data-driven modeling to form an auxiliary, waveform-based framework for instability mitigation in EDM. Unlike conventional approaches that aim to control instability by directly adjusting electrical parameters, such as voltage or pulse conditions, the proposed framework operates as an external supervisory system that monitors discharge behavior and adapts tool rotation accordingly. This auxiliary strategy complements existing optimization methods and can be applied to legacy EDM systems without requiring access to proprietary controllers. By linking micro-scale discharge dynamics to macro-scale machining outcomes via waveform analysis and machine learning, this work offers an alternative, generalizable approach to addressing instability in EDM.

Overall, this dissertation concludes that instability in EDM is a dynamic, time-evolving phenomenon that cannot be adequately addressed solely through offline parameter optimisa-

tion, and that waveform-level monitoring combined with auxiliary, adaptive strategies offers a practical pathway toward improved machining stability.

6.2. Future Work

Future research should focus on extending the proposed modelling framework toward real-time operation and broader applicability. As the present study was designed and evaluated offline with the intention of future online deployment, the resolution of waveform data streaming was limited by practical buffering and processing constraints. Higher-resolution waveform acquisition may enable the identification of additional discharge patterns and transient behaviours, which could further improve the robustness and responsiveness of instability detection and prediction. Consequently, studies on optimising data buffering, memory management, and real-time processing architectures will be necessary to adapt the framework to systems with higher data density and varying hardware capabilities.

In addition, the present work focused on tungsten carbide as a workpiece material with different electrode configurations. Extending the analysis to different electrode and workpiece combinations, as well as varying dielectric conditions, would allow investigation of how material properties influence discharge behaviour and instability dynamics. Such studies could support the development of material-aware adaptations of the proposed models and improve their generality across a broader range of EDM applications.

Furthermore, although powder addition and dynamic tool rotation were each shown to improve machining stability, their combined influence has not yet been systematically investigated. Future studies should therefore focus on the coupled effects of dielectric modification and adaptive kinematic control on instability evolution, particularly under deep-hole machining conditions. In addition, further validation of the proposed auxiliary framework is required to evaluate its effectiveness in monitoring and mitigating instability across different powder types, concentrations, and machining regimes.

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Appendix

Table A-1: Summary of normalized values and Grey relational coefficients (GRC) for each parameter evaluation experiment

E.ID	Normalized Results					Grey Relational Coefficients				
	MRR	Sa	Sz	DOC	d	MRR	Sa	Sz	DOC	d
1	0.04	0.96	0.91	0.80	0.80	0.34	0.93	0.85	0.71	0.76
2	0.25	0.87	0.64	0.66	0.97	0.40	0.80	0.58	0.59	1.00
3	0.79	0.71	0.59	0.46	0.67	0.71	0.63	0.55	0.48	0.64
4	0.87	0.32	0.00	0.10	0.09	0.80	0.42	0.33	0.36	0.38
5	0.52	0.67	0.54	0.31	0.00	0.51	0.61	0.52	0.42	0.36
6	0.13	0.37	0.25	0.33	0.54	0.36	0.44	0.40	0.43	0.56
7	1.00	0.84	0.72	0.90	0.72	1.00	0.75	0.64	0.84	0.69
8	0.31	1.00	1.00	1.00	0.90	0.42	1.00	1.00	1.00	0.88
9	0.17	0.00	0.06	0.00	0.79	0.38	0.33	0.35	0.33	0.75
10	0.12	0.53	0.34	0.68	0.90	0.36	0.52	0.43	0.61	0.89
11	0.52	0.76	0.65	0.56	0.86	0.51	0.68	0.59	0.53	0.83
12	0.74	0.81	0.66	0.70	0.81	0.66	0.72	0.59	0.63	0.77
13	0.33	0.70	0.48	0.69	0.73	0.43	0.62	0.49	0.62	0.69
14	0.67	0.77	0.54	0.85	0.65	0.60	0.69	0.52	0.76	0.62
15	0.00	0.28	0.11	0.61	0.88	0.33	0.41	0.36	0.56	0.85
16	0.02	0.55	0.50	0.41	0.41	0.34	0.52	0.50	0.46	0.49

Table A-2: Summary of normalized values and Grey relational coefficients (GRC) for each parameter evaluation experiment

RPM	Normalized Results					GRG				
	Mach. Time	Top Dial	Bot Dia.	Top Rou.	Bot Rou.	Mach. Time	Top Dial	Bot Dia.	Top Rou.	Bot Rou.
1000	0.42	0.93	0.18	0.13	0.97	0.46	0.88	0.38	0.36	0.94
2000	0.45	0.37	0.17	0.01	0.85	0.48	0.44	0.38	0.34	0.77
3000	0.09	0.35	0.00	0.19	0.84	0.35	0.43	0.33	0.38	0.76
4000	0.36	0.24	0.75	0.11	0.00	0.44	0.40	0.67	0.36	0.33
5000	0.05	1.00	0.30	1.00	0.52	0.35	1.00	0.42	1.00	0.51
6000	0.48	0.04	0.36	0.16	0.98	0.49	0.34	0.44	0.37	0.97
7000	0.07	0.19	0.54	0.03	0.46	0.35	0.38	0.52	0.34	0.48
8000	0.25	0.10	0.83	0.00	0.30	0.40	0.36	0.75	0.33	0.42
9000	1.00	0.00	1.00	0.31	0.11	1.00	0.33	1.00	0.42	0.36
10000	0.00	0.51	0.37	0.21	1.00	0.33	0.51	0.44	0.39	1.00

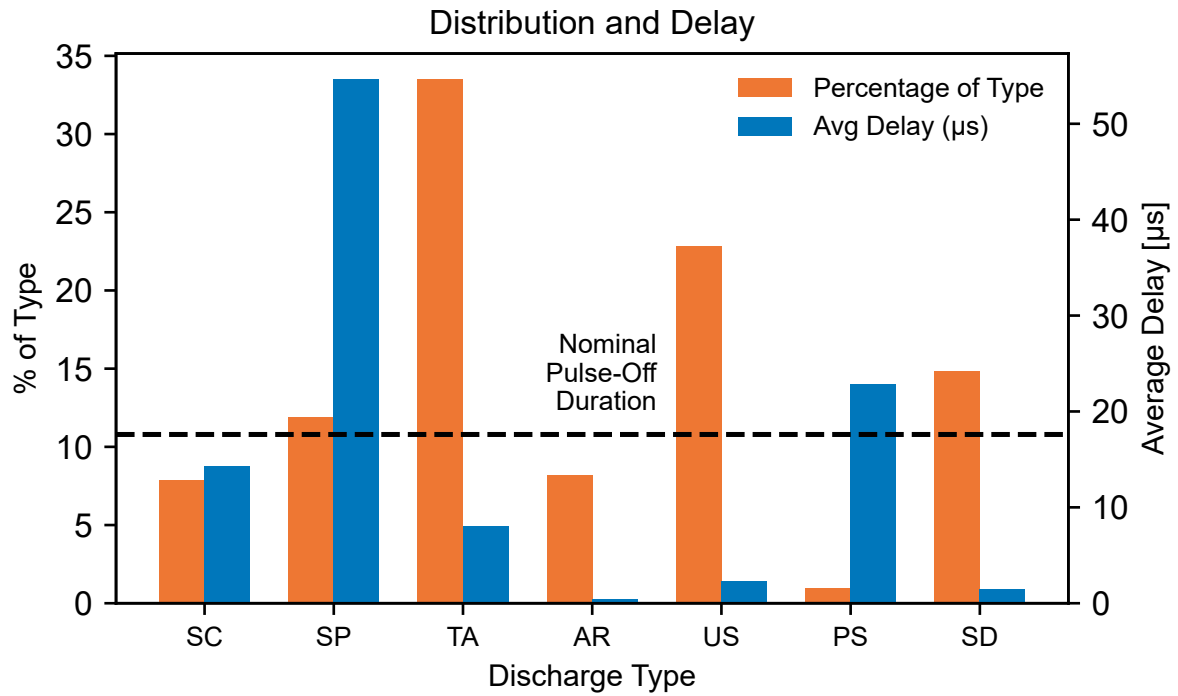


Figure A-1: Distribution and average inter-discharge delay for each discharge type.

Table A-3: Per-class precision and recall for fine-grained discharge classes (0–7) and grouped classes (E1–E4) for the TCN and TCN-Lite models (4096–32)

Class	TCN		TCN-Lite		Support
	Precision	Recall	Precision	Recall	
0	0.998	0.980	0.999	0.967	98 068 955
1	0.612	0.853	0.362	0.864	822 125
2	0.290	0.651	0.218	0.674	1 345 326
3	0.736	0.527	0.684	0.307	12 050 383
4	0.908	0.774	0.835	0.767	7 187 432
5	0.001	0.021	0.009	0.279	839
6	0.548	0.903	0.489	0.917	5 356 431
7	0.146	0.763	0.077	0.861	168 509
E1	0.612	0.853	0.362	0.864	822 125
E2	0.830	0.790	0.712	0.821	7 355 941
E3	0.833	0.837	0.817	0.727	17 407 653
E4	0.290	0.651	0.218	0.674	1 345 326

Table A-4: Stable-class discharge composition (%) for each condition

Feature	Cu 2000	Cu 8000	CuW 2000	CuW 8000
E1	8.43	6.15	12.52	12.28
E2	43.20	45.76	51.40	52.43
E3	36.20	36.29	22.64	22.79
E4	12.18	11.80	13.44	12.51

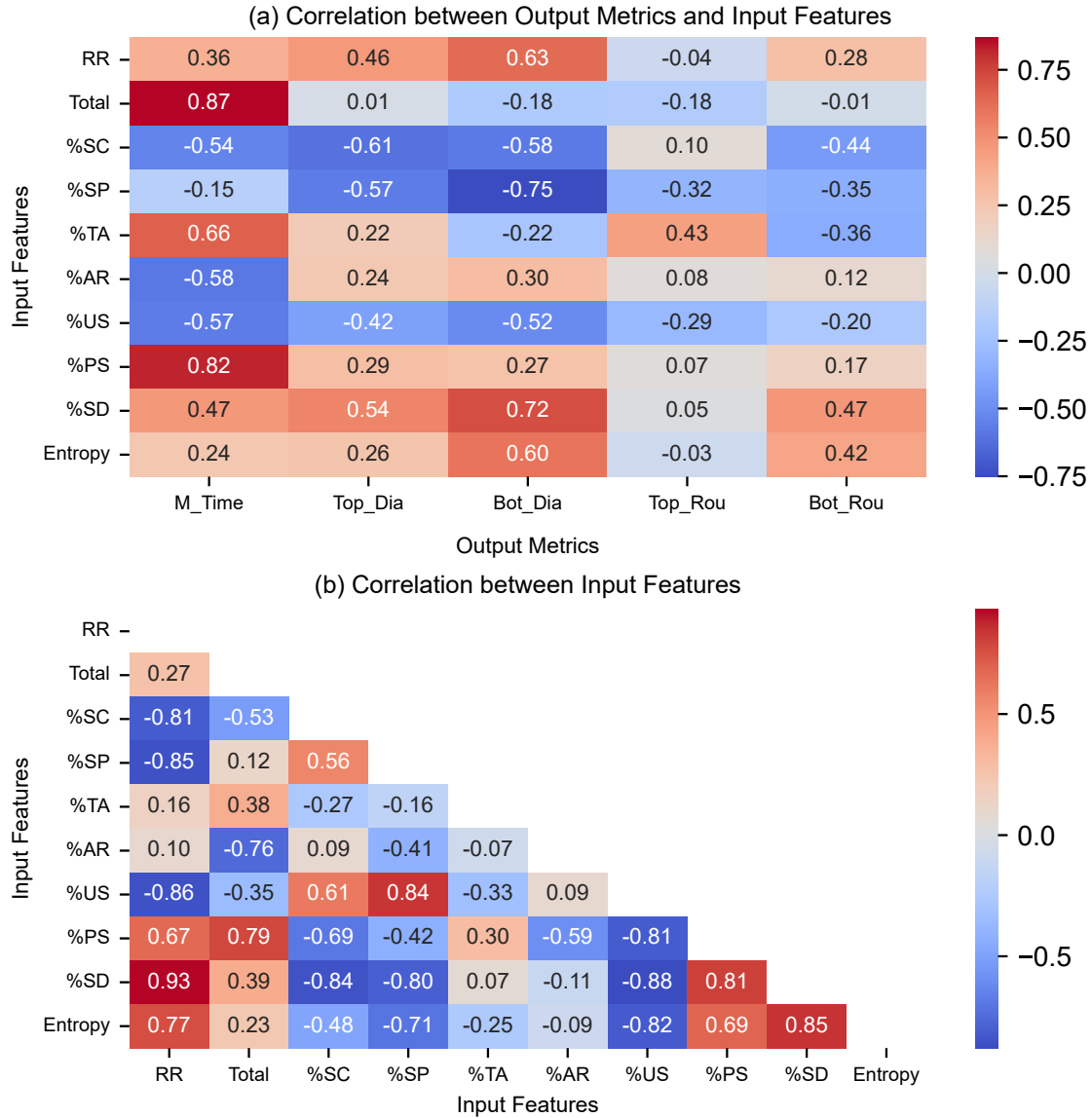


Figure A-2: Pearson correlation coefficient heatmap for (a) input features vs. output metrics and (b) within input features for raw signal features.

Table A-5: Unstable-class discharge composition (%) for each condition

Feature	Cu 2000	Cu 8000	CuW 2000	CuW 8000
E1	7.62	7.89	6.85	8.76
E2	46.71	60.83	54.99	66.36
E3	31.85	22.96	24.51	17.10
E4	13.81	8.33	13.65	7.78

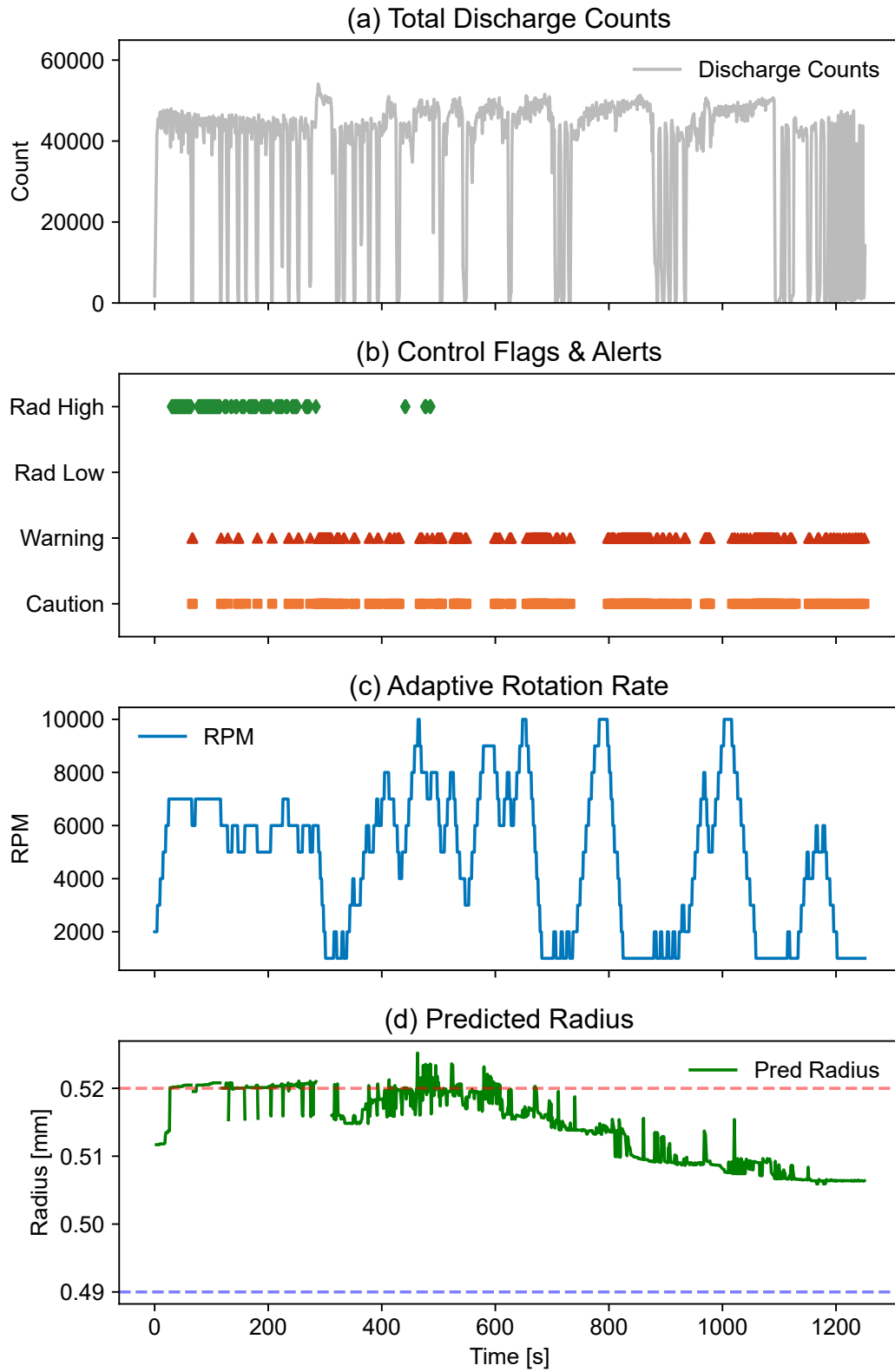


Figure A-3: Simulation of the proposed framework for dynamic rotation rate with (a) total discharge events, with (b) cautions and warnings raised for rotation change, and (c) modeled rotation rate changes for rotation rate profile Test 2.

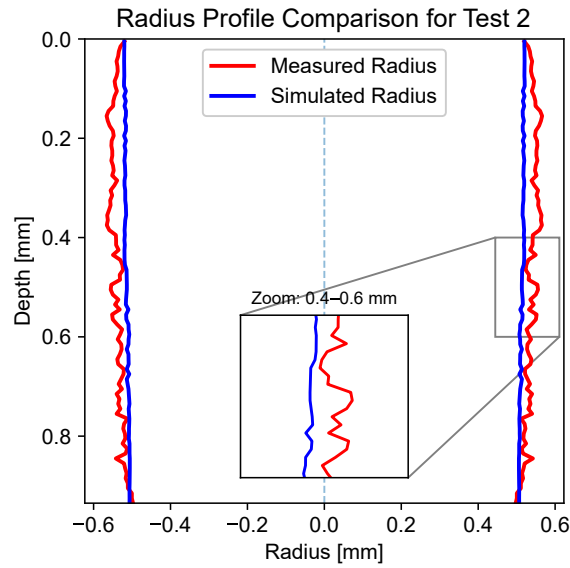


Figure A-4: Simulated and actual machined radius profile for Test 2.

Table A-6: Taguchi signal-to-noise (S/N) ratios and repeatability metrics calculated from repeated experiments ($n = 2$).

E.ID	Mean Total/sec	Std Total/sec	COV	SNR _{E2} (smaller-is-better)	SNR _{E3} (larger-is-better)
1	28249.75	2103.78	0.074	-35.246	30.726
2	20823.74	341.25	0.016	-33.703	30.887
3	12598.44	22.44	0.002	-25.984	33.636
4	3774.00	144.95	0.038	-37.731	9.865
5	10749.55	129.46	0.012	-19.060	33.292
6	7935.02	8.33	0.001	-39.921	-35.670
7	30272.44	428.69	0.014	-32.987	28.927
8	15830.19	16.74	0.001	-35.416	30.270
9	4483.77	54.50	0.012	-39.426	-26.903
10	7345.33	7.51	0.001	-21.126	36.475
11	28415.47	755.60	0.027	-32.161	30.074
12	37684.89	468.85	0.012	-37.381	23.779