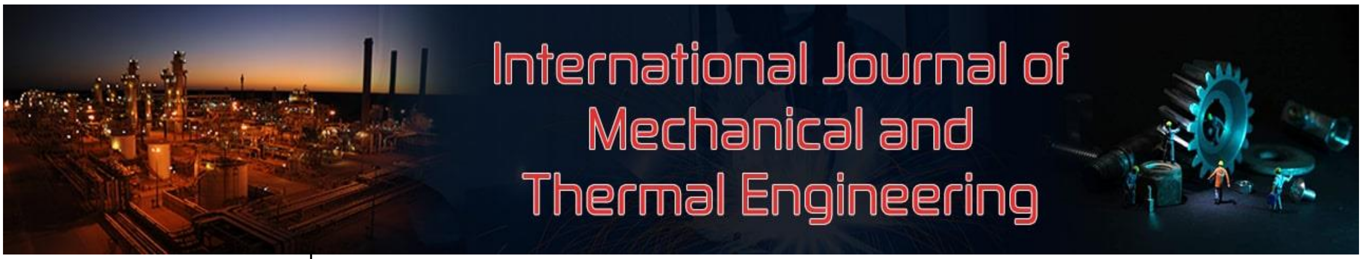

E-ISSN: 2707-8051
P-ISSN: 2707-8043
Impact Factor (RJIF): 5.89
IJMTE 2026; 7(1): 76-80
www.mechanicaljournals.com/ijmte
Received: 09-11-2025
Accepted: 15-12-2025

Mohammad Zahid Ahmad
Regional Development Lead, Europe, Middle East and Asia Pacific, BASF, Saudi Arabia - 34326, Kingdom of Saudi Arabia

Mohammad Shahnawaz
Manager, Process Engineering (DS), Maaden Waad Al Shamal Phosphate Company, Saudi Arabia - 11537

A Equbal
Faculty of Engineering and Technology, Department of Mechanical Engineering, Jamia Millia Islamia, New Delhi, India

Corresponding Author:
A Equbal
Faculty of Engineering and Technology, Department of Mechanical Engineering, Jamia Millia Islamia, New Delhi, India

A critical review on artificial intelligence in EDM: Advancements in process optimization, monitoring, and predictive control

Mohammad Zahid Ahmad, Mohammad Shahnawaz and A Equbal

DOI: https://www.doi.org/10.22271/27078043.2026.v7.i1b.114

Abstract
Electrical Discharge Machining (EDM) is a widely used non-traditional machining process that removes material from a workpiece by series of repetitive discharges. EDM is widely used in machining of hard, brittle, and heat-resistant materials, often achieving high precision. EDM process is influenced by various factors, including discharge energy, pulse duration, and electrode wear. These factors can be challenging to optimize due to their interdependencies and the highly nonlinear behaviour of the process. Traditionally, the optimization process has been conducted through trial and error or operator expertise, both of which are time-consuming and costly. Artificial Intelligence (AI), including machine learning (ML), neural networks (NN), fuzzy logic, and real-time process monitoring, offers powerful tools to automate and optimize these processes. This paper explores how AI is applied in EDM for process optimization, quality enhancement, predictive modeling, and real-time adjustments, with a focus on practical applications, methodologies, and challenges.

Keywords: Electrical discharge machining, artificial intelligence, machine learning, neural networks, fuzzy logic, parameter optimization

1. Introduction

Electrical Discharge Machining (EDM) is one of the most precise non-traditional machining techniques, widely used for producing intricate and complex shapes in conductive materials. Unlike traditional machining processes, EDM does not rely on mechanical cutting forces, but instead utilizes electrical discharges to erode material from the workpiece. The schematic diagram of EDM is shown in Fig. 1. The detail of the process can be found elsewhere in the literature [1-2]. This distinctive process allows for the machining of materials that are typically difficult or impossible to work with using traditional methods, such as hardened tool steels, aerospace alloys, and titanium [3-4]. These materials, which exhibit high hardness and resistance to wear, are particularly challenging for conventional cutting tools. In EDM, electrical discharges generate localized, extremely high temperatures, which are capable of melting and vaporizing the material, leading to the removal of tiny amounts of material with high precision [5]. Despite the remarkable capabilities of EDM, several inherent challenges hinder its efficiency and effectiveness. One of the primary obstacles lies in the complex interrelationships between the multiple process parameters that influence the outcome. Key parameters such as discharge energy, pulse duration, current, voltage, and dielectric fluid properties all interact in nonlinear ways, making the process difficult to optimize [1, 3]. For instance, while increasing the discharge energy can improve material removal rates (*MRR*), it may simultaneously degrade the surface finish quality or accelerate electrode wear. This delicate balance between various parameters must be carefully managed to achieve the desired results. Moreover, the issue of electrode wear significantly impacts the accuracy and consistency of EDM. As the electrode material erodes during the machining process, its shape and size change, which can lead to a deviation in the intended geometry of the workpiece.

Predicting and compensating for this wear is crucial to ensure the longevity of the electrode and the precision of the machined part. Additionally, the surface integrity of the workpiece such as surface roughness, recast layers, and micro-cracking remains a persistent challenge in EDM operations. Achieving a smooth surface finish without compromising material removal rates is a delicate task that requires careful process control [6]. Traditionally, EDM optimization has been approached through manual parameter tuning, trial-and-error experimentation, or relying on the expertise of machine operators. While these methods can produce satisfactory results over time, they are time-consuming, inefficient, and prone to human error. Furthermore, EDM operations are highly susceptible to variations in material properties, tool wear, machine conditions, and environmental factors, which complicate the process further. As a result, the need for precise control over the EDM process is greater than ever, and the quest for more efficient, adaptable, and reliable machining techniques has led to the integration of cutting-edge technologies such as Artificial Intelligence (AI) [6].

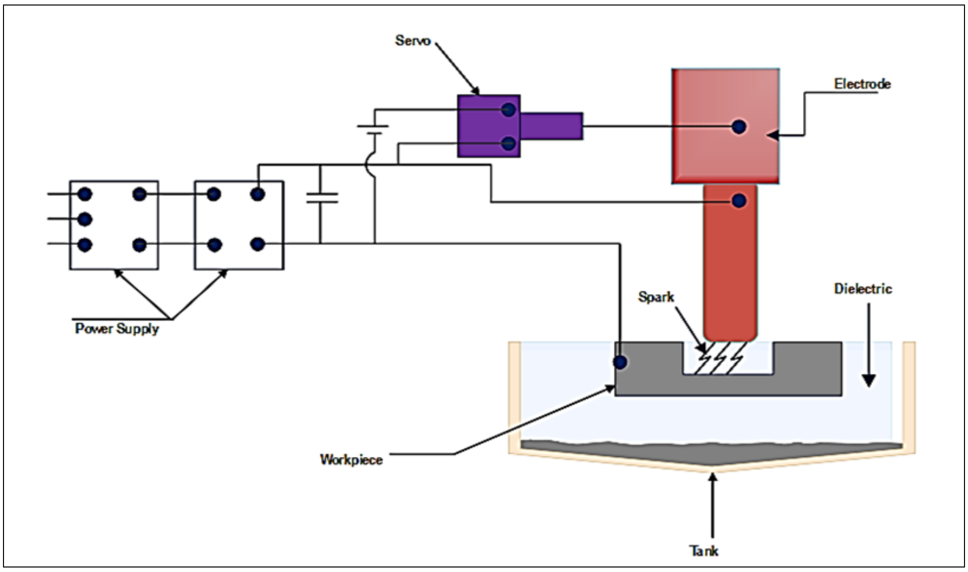

Fig 1: Schematic diagram of EDM

AI technologies have emerged as a revolution to various industries, and their application in EDM holds immense potential to address the challenges faced by traditional optimization methods. AI techniques such as machine learning (ML), artificial neural networks (ANN), fuzzy logic, and real-time process monitoring can drastically enhance the EDM process. By employing vast datasets, AI systems can identify patterns, predict outcomes, and optimize machining parameters with a level of precision and efficiency that surpasses conventional methods [7-8]. For instance, a machine learning models can predict key performance indicators such as material removal rate, surface roughness, and electrode wear, allowing operators to adjust parameters in real-time for optimal results. Neural networks can be used for process modeling, capturing complex relationships between inputs and outputs that are difficult to define mathematically [9]. Additionally, fuzzy logic controllers enable adaptive and flexible decision-making, which is particularly useful for dealing with the inherent uncertainty in the EDM process.

Real-time process monitoring systems, powered by AI, can continuously assess machining conditions, detect deviations, and automatically adjust parameters to maintain optimal performance [7]. These systems can help mitigate the impact of machine variability, material inconsistency, and tool wear, ensuring that the machining process remains stable and predictable throughout the operation. The ability to reduce human intervention, predict failures before they occur, and make data-driven decisions in real-time can significantly improve the overall efficiency, precision, and cost-effectiveness of EDM operations.

Incorporating AI into the EDM process is not merely about automating traditional tasks but represents a fundamental shift in how machining is approached. AI can lead to more precise, consistent, and adaptive EDM processes, which will ultimately result in higher-quality parts, reduced machining time, and lower operational costs [10]. This paper explores the various ways in which AI is being applied to EDM, focusing on process optimization, predictive maintenance, real-time control, and adaptive systems. Through the exploration of AI-driven methodologies, this paper aims to demonstrate how AI can unlock new levels of performance in EDM, setting the stage for the next generation of smart manufacturing.

2. EDM Process Overview and Its Challenges

EDM operates by applying a series of rapid electrical discharges between an electrode (commonly made of copper or graphite) and a workpiece, made of electrically conductive material. The discharges occur in a dielectric fluid, which acts to cool the workpiece, flush debris, and insulate the discharge gap. The energy of each discharge creates high temperatures that melt or vaporize the material at the point of contact, causing the material to erode.

2.1 Key Parameters Influencing EDM Performance

The various parameters affecting EDM performances are:

1. **Pulse Duration:** The length of time that the discharge occurs. Longer pulses can increase material removal rate (*MRR*), but they can also degrade surface finish and increase electrode wear [2].
2. **Discharge Energy:** The energy generated by each electrical discharge is directly related to material removal rate and surface roughness. High discharge energy typically leads to faster material removal but can result in poor surface finish [2, 5].
3. **Electrode Wear:** As the electrode erodes during the process, its shape and size change, which can alter the

precision of machining. Managing electrode wear is crucial for maintaining accuracy over the course of machining operations [2].

4. **Dielectric Fluid:** The dielectric fluid plays an essential role in the EDM process by cooling the workpiece and flushing away debris. Variations in the fluid's properties can impact machining accuracy.

2.2 Challenges in EDM
The various challenges encountered by an EDM process are listed as under:

- **Optimization of Process Parameters:** The relationship between the various input parameters (such as pulse duration, discharge energy, and current) and the resulting output parameters (such as MRR and surface finish) is highly nonlinear and complicated [1, 2].
- **Tool Wear:** The wear of the electrode leads to geometric changes and affects machining precision over time. Predicting tool wear and compensating for it during the process is crucial for maintaining quality [4].
- **Surface Integrity:** EDM often leaves recast layers, micro-cracks, and surface roughness. Achieving a smooth surface with minimal defects while maximizing material removal rate remains a challenge [2, 4].
- **Material-Specific Optimization:** Each material requires specific EDM parameters, and the correct parameters are not always intuitive. Ensuring that the optimal parameters are selected based on the material is a key challenge.

These challenges underscore the need for advanced control systems to monitor and adjust parameters in real-time, which is where AI comes into play.

3. AI Applications in EDM
Artificial Intelligence has the potential to transform the EDM process in a number of ways. In particular, AI can assist in process optimization, predictive modeling, real-time control, and parameter selection. The most prominent AI techniques used in EDM are machine learning (ML), artificial neural networks (ANNs), fuzzy logic, and real-time process monitoring.

3.1. Machine Learning for Parameter Prediction
Machine learning (ML) allows systems to learn from historical data, making it possible to predict the outcomes of specific machining conditions without requiring extensive trial-and-error experimentation [11]. In EDM, ML can be employed to predict critical performance indicators such as *MRR*, surface roughness, and tool wear.

- **Supervised Learning:** Supervised learning techniques, such as linear regression, support vector machines (SVM), and decision trees, have been used to model the relationships between input parameters (like pulse duration, discharge energy, and voltage) and output responses (such as *MRR* and surface roughness). These models are trained on historical data to make predictions about future EDM operations.
- **Unsupervised Learning:** Unsupervised learning approaches, such as clustering algorithms, can identify hidden patterns or clusters within data, such as grouping specific types of workpiece materials and selecting optimal parameters for each group.

A study by Jatti *et al.* [12] applied machine learning models to predict the *MRR* and surface roughness in EDM operations. Their model was able to predict machining outcomes with high accuracy, providing operators with useful insights into how to optimize process parameters for better performance.

3.2. Neural Networks for Process Modeling
Neural networks (NN), especially artificial neural networks (ANN), are powerful tools in AI for modeling complex and nonlinear systems like EDM. ANNs are particularly useful for process modeling in EDM, where the relationships between input parameters and output quality are difficult to express mathematically.

- **Feedforward Neural Networks (FNNs):** These are typically used for predicting outcomes such as material removal rate, surface roughness, and tool wear. FNNs consist of multiple layers of nodes (neurons) where each layer processes input information and passes it to subsequent layers.
- **Recurrent Neural Networks (RNNs):** These types of networks are used for real-time process adaptation, as they are capable of maintaining a memory of previous states in the machining process. This is important for monitoring tool wear and adapting parameters dynamically.

Pradhan *et al.* [13] used an ANN to predict MRR and surface roughness in EDM, with highly accurate results. Their model used input parameters such as pulse duration, discharge energy, and voltage to predict performance outcomes and could be employed for real-time adjustments.

3.3. Fuzzy Logic for Adaptive Control
Fuzzy logic systems (FLS) are especially useful in situations where the relationship between input and output is uncertain or vague. Unlike traditional binary logic systems, fuzzy logic can handle multiple states or degrees of truth, such as "high," "medium," and "low," which makes it highly suited for the complex and unpredictable nature of EDM.

- **Fuzzy Control Systems:** In EDM, fuzzy controllers can adjust machining parameters dynamically based on sensor feedback in real-time. For instance, a fuzzy logic controller might adjust the pulse duration or discharge energy based on surface finish quality or the rate of electrode wear. The system would learn from past observations and make decisions based on linguistic variables.
- The primary advantage of fuzzy logic in EDM is its ability to handle uncertainty and imprecision in input data. Since EDM involves highly variable parameters that cannot always be precisely defined, fuzzy logic allows the system to make intelligent decisions based on approximate information.

Application can be seen, where a fuzzy logic controller was implemented to optimize EDM parameters in real-time, balancing material removal rate with surface finish quality [14]. The fuzzy logic system continuously adjusted the pulse on-time and off-time, resulting in improved performance and reduced electrode wear.

3.4. Real-time Process Monitoring and Predictive Maintenance: AI-based systems can also be used for real-time monitoring of EDM parameters, helping operators detect and respond to issues as they occur during machining. Sensors can measure parameters such as voltage, current, temperature, and gap size in real-time, and AI algorithms can analyze this data to predict potential issues.

- **Predictive Maintenance:** AI can be used to predict tool wear and failure before they occur. For example, by continuously monitoring the electrode wear and machining conditions, AI algorithms can forecast when the electrode needs to be replaced, helping to avoid unexpected downtime.
- **Process Control:** AI can enable adaptive process control by dynamically adjusting machining parameters in response to real-time feedback. This ensures that the EDM process remains stable even under varying conditions, such as changes in material hardness or wear of the electrode.

A notable implementation was developed by Singh *et al.* [15] where real-time monitoring using AI systems predicted tool wear and made continuous adjustments to maintain optimal machining conditions. The study showed improved performance and reduced tool replacement costs as a result of these AI interventions.

4. Benefits and Limitations of AI in EDM

Various benefits offered by application of AI in EDM are:

1. **Efficiency Gains:** AI models can optimize EDM parameters, improving material removal rates and surface quality while reducing machining time and costs.
2. **Enhanced Quality:** AI-based adjustments ensure that surface roughness and dimensional accuracy are maintained, even when operating conditions change.
3. **Adaptability:** AI systems can adapt in real-time to variations in materials, workpiece geometry, and electrode wear, ensuring consistent machining results.
4. **Automation:** AI reduces the reliance on expert knowledge and manual adjustments, automating decision-making and leading to more efficient and reliable operations.
5. **Cost Reduction:** With better optimization and predictive maintenance, AI reduces tool wear and failure, leading to cost savings in maintenance and replacement.

Apart from various benefits offered, the application of AI also has some limitations as listed under

1. **Data Dependency:** AI requires large datasets to function effectively. Inadequate or noisy data can degrade the accuracy of predictions and control actions.
2. **Complexity:** Developing and implementing AI systems in EDM requires expertise in both machining and AI, making it a complex and expensive endeavour.
3. **Interpretability:** Some AI models, especially deep learning systems, act as "black boxes," meaning it can be difficult to understand the rationale behind certain decisions. This lack of transparency could be problematic for quality control and troubleshooting.
4. **Initial Cost:** The upfront costs for implementing AI-based solutions whether for process optimization, real-time monitoring, or predictive maintenance can be high, making it inaccessible for smaller shops or businesses without sufficient resources.

5. Conclusion

Artificial Intelligence offers significant potential to improve the performance and efficiency of the Electrical Discharge Machining (EDM) process. The integration of machine learning, neural networks, fuzzy logic, and real-time monitoring provides tools to optimize EDM parameters, enhance machining precision, predict tool wear, and reduce reliance on human intervention. Despite its promise, challenges such as the need for large datasets, system complexity, and the interpretability of AI models must be addressed to fully capitalize on these technologies. As AI continues to advance, its applications in EDM will likely expand, driving further improvements in machining precision, productivity, and overall manufacturing quality.

References

1. Equbal A, Sood AK. Electrical discharge machining: an overview on various areas of research. Manuf Ind Eng. 2014;13:1-6.
2. Equbal A, Equbal MI, Sood AK. An investigation on the feasibility of fused deposition modelling process in EDM electrode manufacturing. CIRP J Manuf Sci Technol. 2019;26:10-25.
3. Gounder SP, Tamil S, Vartharajan S, Venkatesan R. Study of micro-EDM parameters of stainless steel 316L: material removal rate optimization using genetic algorithm. Int J Eng Technol. 2014;6(2):1065-1071.
4. Singh R, Dvivedi A, Kumar P. EDM of high aspect ratio micro-holes on Ti-6Al-4V alloy by synchronizing energy interactions. Mater Manuf Process. 2020;35:1188-1203.
5. Equbal A, Equbal A, Khan ZA, Badruddin IA, *et al.* Investigating the dimensional accuracy of the cavity produced by ABS P400 polymer-based novel EDM electrode. Polymers (Basel). 2021;13:4109.
6. Ming W, Jia H, Zhang H, Zhang Z, Liu K, Du J, Shen F, Zhang G. A comprehensive review of electric discharge machining of advanced ceramics. Ceram Int. 2020;46:21813-21838.
7. Ishfaq K, Sana M, Ashraf WM. Artificial intelligence-built analysis framework for the manufacturing sector: performance optimization of wire electric discharge machining system. Int J Adv Manuf Technol. 2023;128:5025-5039.
8. Paturi UMR, Cheruku S, Pasunuri VPK, *et al.* Machine learning and statistical approach in modeling and optimization of surface roughness in wire electrical discharge machining. Mach Learn Appl. 2021;6:100099.
9. Ubale SB, Deshmukh SD, Ghosh S. Artificial neural network-based modelling of wire electrical discharge machining on tungsten-copper composite. Mater Today Proc. 2018;5(2):5655-5663.
10. Bharti PS. Two-step optimization of electric discharge machining using neural network-based approach and TOPSIS. Interdiscip Appl Sustain. 2020;23:81-96.
11. Equbal A, Akhter S, Equbal MA, Sood AK. Application of machine learning in fused deposition modeling: a review. Fused Deposition Modeling Based 3D Printing. 2021;4(1):445-463.
12. Jatti VS, Dhabale RB, Mishra A, Khedkar NK, Jatti VS, Jatti AV. Machine learning-based predictive modeling of electrical discharge machining of cryo-treated NiTi,

NiCu and BeCu alloys. Appl Syst Innov. 2022;5(6):107.
13. Pradhan BB, Bhattacharyya B. Modelling of micro-electrodischarge machining during machining of titanium alloy Ti-6Al-4V using response surface methodology and artificial neural network algorithm. Proc Inst Mech Eng Part B J Eng Manuf. 2009;223(6):683-693.
14. Kao C, Shih A, Miller SF. Fuzzy logic control of microhole electrical discharge machining. J Manuf Sci Eng. 2008;130(6):064502.
15. Munaro R, Attanasio A, De Prete A. Tool wear monitoring with artificial intelligence methods: a review. J Manuf Mater Process. 2023;7(4):129.