Analysis and Optimization of Electrode Wear Rate in EDM Using Graphite Electrodes: A Statistical and GPR-Based Approach

THU-QUY LE[1], VAN-THANH DINH[2], NGOC-PI VU[3], TAT-LOI MAI[4,*]
[1]National Research Institute of Mechanical Engineering,
04 Pham Van Dong, Ha Noi City 11309,
VIETNAM

[2]East Asia University of Technology,
Trinh Van Bo Street, Hanoi City 12000,
VIETNAM

[3]Thai Nguyen University of Technology,
3/2 street, Tich Luong ward, Thai Nguyen City 251750,
VIETNAM

[4]Vinh University of Technology Education
3/2 Street, Vinh City 43109
VIETNAM

Corresponding Author

Abstract: - This study investigates the effects of key process parameters and graphite electrode types on the axial electrode wear rate (HWR) in electrical discharge machining (EDM). A series of controlled experiments was conducted to evaluate the statistical significance of input variables using analysis of variance (ANOVA). A second-order regression model was developed to quantify the relationship between the machining parameters and HWR. To enhance predictive accuracy and enable efficient optimization, a Gaussian Process Regression (GPR) model was constructed based on the experimental data. The GPR model demonstrated superior prediction capability compared to traditional regression models. Optimal process conditions for minimizing electrode wear were identified using the trained surrogate model. The proposed methodology provides a robust framework for predicting and reducing electrode wear in EDM applications involving graphite electrodes.

Key-Words: - EDM, Electrode wear, Graphite electrode, Axial wear rate (HWR), Regression modeling, Gaussian Process Regression (GPR), Process optimization.

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1 Introduction

Electrical Discharge Machining (EDM) has become a vital non-traditional manufacturing process for shaping hard and electrically conductive materials. Among its advanced configurations, ultrasonic vibration-assisted EDM (UV-EDM) has emerged as a powerful enhancement technique, significantly improving debris removal, machining stability, and surface quality, especially in micro and deep-hole machining scenarios, [1], [2]. By integrating ultrasonic vibrations, either in the tool, workpiece, or dielectric fluid, this hybrid approach mitigates adverse effects such as arcing, unstable discharges, and excessive tool wear, which often limit the effectiveness of conventional EDM, [3], [4].

Numerous studies have investigated the physical mechanisms and technological advantages of UV-EDM. For example, in [1] applied longitudinal/torsional ultrasonic vibrations in deep-hole EDM, achieving better debris expulsion and minimizing taper. Similarly, the authors in [2] analyzed debris trajectories under ultrasonic excitation, revealing improved flushing efficiency. The authors in [4] developed a novel electrode vibrating in longitudinal-torsional mode, which significantly enhanced micro-hole accuracy and material removal rate. These works consistently demonstrate that ultrasonic vibrations contribute to more efficient and controlled discharge behaviour.

The performance of UV-EDM is also influenced by cavitation, bubble dynamics, and particle motion in the spark gap. The author in [5] observed dynamic bubble behavior during ultrasonic-assisted discharges, while in [6] proposed a two-dimensional ultrasonic vibration system to improve surface finish and reduce recast layers in micro-EDM. In addition, the results of a study in [7] introduced a three-dimensional ultrasonic vibration system (RTDUV) that significantly improved debris removal, especially in narrow and enclosed features.

Tool wear, particularly the *Electrode Wear Rate* (EWR) or *Height Wear Ratio* (HWR), remains a critical challenge in EDM, directly affecting tool life, accuracy, and economic viability. While many studies have emphasized enhancing MRR and surface integrity, relatively few have focused specifically on modelling and optimizing electrode wear. Notable exceptions include the authors in [8], who combined experimental and numerical analysis to investigate tool vibration effects on wear, and in [9], who developed FEM models for ultrasonic-assisted workpiece dynamics. The surface formation mechanism in ultrasonic vibration-assisted EDM is significantly influenced by cavitation effects, as reported in [10].

Despite this progress, current literature presents several gaps. First, most prior studies on UV-EDM have concentrated on qualitative or empirical assessments of electrode wear rather than systematic statistical analysis of contributing process parameters. Second, while regression models such as RSM have been sporadically applied, the use of advanced predictive modelling tools like Gaussian Process Regression (GPR) for HWR estimation and optimization is still underexplored. Lastly, multi-level validation of wear prediction combining statistical inference, regression modelling, and machine learning remains rare.

To address these gaps, the present study aims to: (1) conduct a comprehensive statistical analysis of the influence of key EDM parameters, including ultrasonic amplitude, pulse-on time, pulse-off time, and peak current-on HWR when machining with graphite electrodes; (2) establish a second-order polynomial regression model (RSM) for HWR; and (3) develop and validate a GPR-based surrogate model to predict and optimize electrode wear performance. The combination of these methods offers both interpretability and precision, contributing to more reliable process planning in UV-EDM applications.

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2 Experimental Work

An experimental investigation was carried out to evaluate the effects of five input process parameters—vibration amplitude (A), pulse-on time (Ton), pulse-off time (Toff), peak current (IP), and servo voltage (SV)—on the electrode wear rate (HWR) during ultrasonic vibration-assisted electrical discharge machining (UVEDM). The experimental setup is illustrated in Figure 1 (Appendix).

Machining operations were conducted using a Sodick A30 CNC EDM machine, integrated with an ultrasonic vibration system to enhance machining performance. Ultra-sonic vibrations were supplied by an MPI WG-3000 ultrasonic generator (MPI Ultrasonics, Switzerland) with a power rating of 3000 W. The vibration was transmitted via an RPS-5020-4Z ultrasonic transducer, operating at a frequency of 20 kHz and a nominal power of 2000 W. A custom-designed horn was fabricated specifically for this study to ensure efficient delivery of ultrasonic energy to the tool–workpiece inter-face.

Graphite HK2 was selected as the tool electrode material due to its favorable electrical and thermal properties, while Diel MS 7000 (Total, France) was used as the dielectric fluid. The workpiece material was 90CrSi tool steel, known for its high hardness and wear resistance.

After each machining trial, the electrode was sectioned along its longitudinal axis to facilitate accurate evaluation of axial wear. The electrode wear rate (HWR) was then determined based on the change in length along the axial direction, using a

PS-530G digital microscope (manufactured in Taiwan) for precise measurement.

The experimental design matrix, along with the corresponding measured HWR values, is summarized in Table 1 (Appendix).

3 Results and Discussion

This section presents and discusses the modeling and optimization results of the electrode wear rate (HWR) in ultrasonic vibration-assisted electrical discharge machining (UVEDM), using both response surface methodology (RSM) and Gaussian Process Regression (GPR) approaches. The accuracy of each model was evaluated in terms of the coefficient of determination (R^2), and the optimal process parameters for minimizing HWR were identified.

3.1 Quadratic Regression Model for HWR (RSM)

A second-order polynomial regression model was developed using Response Surface Methodology (RSM) to describe the relationship between the input process parameters—vibration amplitude (A), pulse-on time (Ton), pulse-off time (Toff), peak current (IP), and servo voltage (SV)—and the electrode wear rate (HWR). The model achieved a coefficient of determination $R^2 = 0.8166$, with an adjusted R^2 of 0.6699, indicating that while the model fits the data moderately well, aconsiderable ortion of the variation in HWR remains unexplained.

The estimated regression equation is expressed as follows:

$$HWR\ (mm/h) = 8{,}5578 + 0{,}1298A - 0{,}3594Ton - 0{,}5212\ Toff + 0{,}1681IP - 1{,}4459SV + 0{,}0094(A\ .\ Ton) - 0{,}0196(A\ .\ Toff) - 0{,}0030(A\ .\ IP) - 0{,}0081(A\ .\ SV) - 0{,}0106(Ton\ .\ Toff) - 0{,}0084(Ton\ .\ IP) + 0{,}0033(Ton\ .\ SV) - 0{,}0025(Toff.\ IP) + 0{,}0768(Toff\ .\ SV) + 0{,}0003(IP\ .\ SV) + 0{,}0103A^2 + 0{,}0179Ton^2 + 0{,}0135Toff^2 + 0{,}0013IP^2 + 0{,}0550SV^2 \quad (1)$$

Although a few terms such as Toff, Toff × SV, Ton^2, and $Toff^2$ were statistically significant ($p < 0.05$), the majority of linear and interaction terms exhibited high p-values, implying weak or inconsistent influence on HWR. This weak statistical robustness is also reflected in the adjusted R^2, which drops substantially to 0.6699 after accounting for model complexity (Table 2, Appendix).

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Furthermore, the predicted vs. actual plot in Figure 2 reveals visible deviations from the ideal line, indicating that the quadratic regression model may be insufficient to capture the inherent nonlinearities and stochastic nature of the UVEDM process.

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These limitations underscore the need for a more flexible and robust modeling technique. In this study, Gaussian Process Regression (GPR) is proposed as an alternative, data-driven approach capable of capturing complex nonlinear interactions with higher prediction accuracy, as will be discussed in the next section.

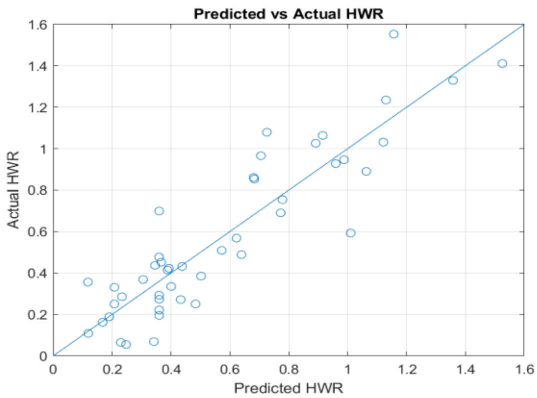

Fig. 1: Actual versus predicted HWR values from the RSM model

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3.2 GPR-Based Modeling and Model Performance Comparison

To overcome the limitations of the quadratic RSM model in capturing the nonlinear discharge–vibration interactions of UV-EDM, a comprehensive Gaussian Process Regression (GPR) analysis was performed. Twelve combinations of kernel and basis functions were evaluated, including Squared Exponential, Rational Quadratic, Matern 3/2, and Matern 5/2 kernels with constant, linear, and quadratic basis functions. The full comparison of R^2 and adjusted R^2 values for allkernel–basis pairs is presented in Table 3 (Appendix).

3.3 Optimization of HWR using the GPR Surrogate Model with Sensitivity and Uncertainty Analysis

The predicted versus actual HWR plot for the best GPR model (Matern 3/2 kernel with linear basis) is shown in Figure 3. The data points align closely with the 45° reference line, suggesting excellent predictive accuracy and very low residual error.

The optimal GPR model was subsequently used to identify the optimal process parameter set that minimizes the electrode wear rate (HWR) while maintaining physical feasibility with the constraint HWR ≥ 0.05 mm/h. The optimal parameter set is provided in Table 4.

To assess robustness, uncertainty quantification and sensitivity analysis were also performed. The uncertainty analysis yields a 95% confidence interval at the optimum based on the predictive standard deviation. Figure 4 illustrates the distribution of HWR obtained from the Monte Carlo simulation.

A local sensitivity analysis (±10%) for each input parameter further reveals the effect of parameter variability on predicted HWR, as summarized in Table 5 (Appendix).

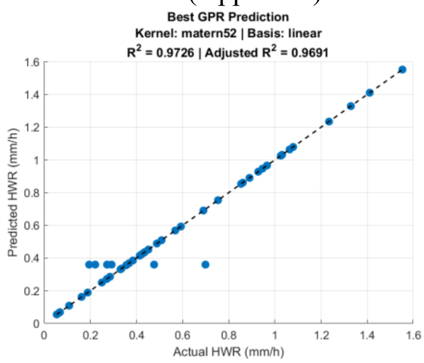

Fig. 2: Predicted vs. actual electrode wear rate (HWR) using the best GPR model (Matern 3/2 kernel with linear basis)

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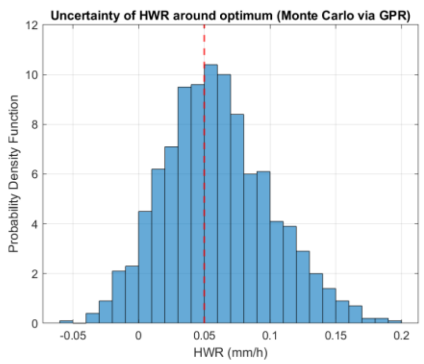

Fig. 4. Probability density function of HWR around the optimal solution obtained by Monte Carlo simulation (1000 samples)

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The combination of GPR-based optimization, uncertainty quantification, and sensitivity analysis provides a comprehensive robustness assessment of the optimized operating region for minimizing electrode wear in UV-EDM. Although the GPR-predicted confidence interval is wide—reflecting both model uncertainty and sparse data near the minimum—the Monte Carlo simulation confirms that the operating region consistently yields low HWR values. The sensitivity results further identify Ton and IP as the critical parameters governing robustness, offering practical guidance for process control and optimization.
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Table 4. Optimal input parameters for minimizing HWR using the GPR model

Parameter	Optimal Value
A (μm)	3.1214
Ton (μs)	15.7220
Toff (μs)	12.6802
IP (A)	8.0680
SV (V)	4.0000
Predicted minimum HWR	0.0500 mm/h

Source: created by the authors

4 Conclusions

This study investigated the modeling and optimization of electrode wear rate (HWR) in ultrasonic vibration-assisted EDM (UVEDM) using graphite electrodes and 90CrSi tool steel workpieces. Two modeling approaches—Response Surface Methodology (RSM) and Gaussian Process Regression (GPR)—were employed to analyze the influence of five process parameters: vibration amplitude (A), pulse-on time (Ton), pulse-off time (Toff), peak current (IP), and servo voltage (SV).

Key conclusions from this work are as follows:

1. The quadratic regression model obtained via RSM yielded an R^2 value of 0.8166, with only a few significant terms, indicating limited predictive capability and the presence of unexplained nonlinear effects.
2. In contrast, the GPR model using the Matern 3/2 kernel with a linear basis achieved a substantially higher R^2 of 0.9726, demonstrating superior accuracy in capturing the complex relationships between process parameters and HWR.
3. Using the best-performing GPR model, constrained optimization (HWR ≥ 0.05 mm/h) identified the optimal parameter set as A = 3.1214

μm, Ton = 15.7220 μs, Toff = 12.6802 μs, IP = 8.0680 A, and SV = 4.0 V, yielding a minimum predicted HWR of 0.0500 mm/h. Uncertainty quantification based on GPR predictive variance indicated a 95% confidence interval of [−0.4269, 0.5269] mm/h at the optimum, reflecting the intrinsic stochasticity of EDM discharges and data sparsity near the low-wear region. A Monte-Carlo simulation (1000 samples) further confirmed that most perturbations in the vicinity of the optimum still produce low HWR values, validating the robustness of the solution.

4. Local sensitivity analysis (±10%) demonstrated that Ton and IP are the two most influential factors governing the robustness of the optimized solution (Table 5, Appendix). Ton exhibited the highest sensitivity, indicating that small deviations in pulse-on time significantly affect wear behavior, whereas increases in IP consistently elevated wear due to higher discharge energy. In contrast, amplitude A and pulse-off time Toff showed modest sensitivity, suggesting stable low-wear performance in their local neighborhood. These findings offer practical guidance for parameter tuning in industrial UV-EDM operations.

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APPENDIX

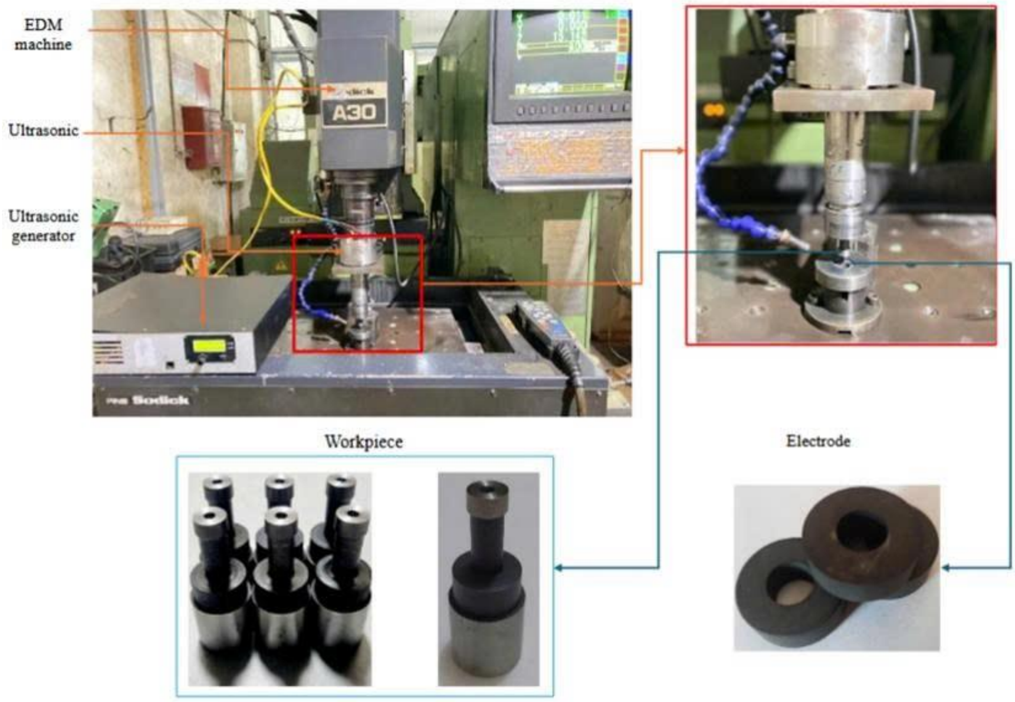

Fig. 3: Experimental setup
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Table 1. Experimental matrix and corresponding HWR values

No.	A (µm)	Ton (µs)	Toff (µs)	IP (A)	SV (V)	HWR (mm/h)
1	1.2	8	12	10	5	1.031
2	1.2	16	12	10	5	0.286
3	5.2	8	12	10	5	0.947
4	5.2	16	12	10	5	0.423
5	3.2	12	8	5	5	0.069
6	3.2	12	8	15	5	0.593
7	3.2	12	16	5	5	0.368
8	3.2	12	16	15	5	0.691
9	3.2	8	12	10	4	0.890
10	3.2	8	12	10	6	1.235
11	3.2	16	12	10	4	0.055
12	3.2	16	12	10	6	0.452
13	1.2	12	8	10	5	0.509
14	1.2	12	16	10	5	0.489
15	5.2	12	8	10	5	1.026
16	5.2	12	16	10	5	0.437
17	3.2	12	12	5	4	0.356
18	3.2	12	12	5	6	0.250
19	3.2	12	12	15	4	0.854
20	3.2	12	12	15	6	0.754
21	3.2	8	8	10	5	1.553
22	3.2	8	16	10	5	1.329
23	3.2	16	8	10	5	0.966
24	3.2	16	16	10	5	0.065
25	1.2	12	12	5	5	0.109
26	1.2	12	12	15	5	1.079
27	5.2	12	12	5	5	0.189
28	5.2	12	12	15	5	0.861
29	3.2	12	8	10	4	0.928

No.	A (µm)	Ton (µs)	Toff (µs)	IP (A)	SV (V)	HWR (mm/h)
30	3.2	12	8	10	6	0.432
31	3.2	12	16	10	4	0.331
32	3.2	12	16	10	6	1.064
33	1.2	12	12	10	4	0.415
34	1.2	12	12	10	6	0.385
35	5.2	12	12	10	4	0.272
36	5.2	12	12	10	6	0.251
37	3.2	8	12	5	5	0.568
38	3.2	8	12	15	5	1.411
39	3.2	16	12	5	5	0.163
40	3.2	16	12	15	5	0.335
41	3.2	12	12	10	5	0.195
42	3.2	12	12	10	5	0.699
43	3.2	12	12	10	5	0.293
44	3.2	12	12	10	5	0.273
45	3.2	12	12	10	5	0.222
46	3.2	12	12	10	5	0.477

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Table 2. Estimated coefficients and statistical significance of the quadratic regression model for HWR

Term	Coefficient	p-value	Significance
Intercept	8.5578	0.0479	Significant
A	0.1298	0.7541	Not significant
Ton	-0.3594	0.0999	Marginal
Toff	-0.5212	0.0203	Significant
IP	0.1681	0.3093	Not significant
SV	-1.4459	0.1346	Not significant
A × Ton	0.0094	0.5016	Not significant
A × Toff	-0.0196	0.1665	Not significant
A × IP	-0.0030	0.7883	Not significant
A × SV	-0.0081	0.8836	Not significant
Ton × Toff	-0.0106	0.1425	Not significant
Ton × IP	-0.0084	0.1466	Not significant
Ton × SV	0.0033	0.9077	Not significant
Toff × IP	-0.0025	0.6562	Not significant
Toff × SV	0.0768	0.0110	Significant
IP × SV	0.0003	0.9894	Not significant
A^2	0.0103	0.6589	Not significant
Ton^2	0.0179	0.0008	Significant
$Toff^2$	0.0135	0.0087	Significant
IP^2	0.0013	0.6743	Not significant
SV^2	0.0550	0.4746	Not significant

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Table 3. Performance comparison of GPR models (kernel basis) using R^2 and adjusted R^2

Kernel Function	Basis Function	R^2	Adjusted R^2
Squared Exponential	Constant	0.9726	0.9691
Squared Exponential	Linear	0.9723	0.9689
Squared Exponential	Pure Quadratic	0.9726	0.9691
Rational Quadratic	Constant	0.7330	0.6997
Rational Quadratic	Linear	0.9724	0.9689
Rational Quadratic	Pure Quadratic	0.9723	0.9689
Matern 3/2	Constant	0.8085	0.7846
Matern 3/2	Linear	0.9726	0.9691
Matern 3/2	Pure Quadratic	0.9726	0.9691
Matern 5/2	Constant	0.8075	0.7834
Matern 5/2	Linear	0.9726	0.9691
Matern 5/2	Pure Quadratic	0.9726	0.9691

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Table 5. Local sensitivity of HWR with ±10% variation around the optimum

Parameter	HWR (-10%)	HWR (+10%)	Sensitivity (-)	Sensitivity (+)
A (µm)	0.0560	0.0548	-0.0149	0.0120
Ton (µs)	0.1363	0.0222	-0.1078	-0.1000
Toff (µs)	0.0614	0.0454	-0.0142	-0.0058
IP (A)	0.0110	0.0733	0.0390	0.0233
SV (V)	0.0500	0.0653	0.0000	0.0763

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Contribution of Individual Authors to the Creation of a Scientific Article (Ghostwriting Policy)

The authors equally contributed to the present research, at all stages from the formulation of the problem to the final findings and solution.

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Conflict of Interest

The authors have no conflicts of interest to declare.