SURFACE ROUGHNESS OPTIMIZATION IN EDM CONSIDERING GRAPHITE ELECTRODE TYPE USING GAUSSIAN PROCESS REGRESSION

TỐI ƯU HÓA ĐỘ NHÁM BỀ MẶT TRONG GIA CÔNG XUNG ĐIỆN EDM CÓ XÉT ĐẾN LOẠI VẬT LIỆU ĐIỆN CỰC GRAPHITE BẰNG MÔ HÌNH HỒI QUY QUÁ TRÌNH GAUSSIAN

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ABSTRACT

In this study, a Gaussian Process Regression (GPR) model was developed to predict and optimize surface roughness (Ra) in electrical discharge machining (EDM), considering the influence of graphite electrode types. A Box–Behnken Design (BBD) was employed, involving four process parameters discharge current (IP), servo voltage (SV), pulse on-time (T_{on}), pulse off-time (T_{off}) and the electrode material type (TOG), to systematically collect experimental data. The GPR model was trained on the collected dataset and achieved a high coefficient of determination (R^2), demonstrating its superior ability to capture nonlinearities and stochastic variations in Ra during EDM. Single-objective optimization was performed using MATLAB®'s fmincon algorithm to identify the optimal combination of process parameters that minimizes surface roughness. The results confirm the effectiveness of GPR in predicting and optimizing Ra, while highlighting the significant impact of graphite electrode material type on surface quality. The proposed method offers strong potential for broader applications in precision electro-discharge machining process optimization.

Keywords: *Electrical discharge machining (EDM); Surface roughness; Gaussian Process Regression (GPR); Single-objective optimization; Graphite electrode material; Predictive modeling.*

TÓM TẮT

Trong nghiên cứu này, một mô hình hồi quy quá trình Gaussian (Gaussian Process Regression – GPR) đã được xây dựng để dự đoán và tối ưu hóa độ nhám bề mặt (Ra) trong quá trình gia công xung điện (EDM), có xét đến ảnh hưởng của loại vật liệu điện cực graphite. Thiết kế thí nghiệm Box–Behnken (BBD) với bốn thông số đầu vào gồm cường độ dòng điện (IP), điện áp phóng điện (SV), thời gian phát xung (T_{on}), thời gian ngắt xung (T_{off}) và loại vật liệu điện cực graphite đã được sử dụng nhằm thu thập dữ liệu thực nghiệm. Mô hình GPR được huấn luyện trên bộ dữ liệu thu thập được, cho kết quả hệ số xác định (R^2) cao, thể hiện khả năng mô hình hóa chính xác tính phi tuyến và sự biến thiên ngẫu nhiên của Ra trong quá trình EDM. Quá trình tối ưu hóa được thực hiện bằng thuật toán fmincon trong MATLAB®, nhằm tìm ra tổ hợp thông số công nghệ tối ưu cho mục tiêu *giảm thiểu độ nhám bề mặt. Kết quả nghiên cứu khẳng định tính hiệu quả của phương pháp GPR trong việc dự đoán và tối ưu hóa Ra, đồng thời cho thấy ảnh hưởng rõ rệt của loại vật liệu điện cực graphite đến chất lượng bề mặt. Phương pháp đề xuất mở ra triển vọng áp dụng rộng rãi trong tối ưu hóa quá trình gia công điện hóa chính xác.*

Từ khóa: *Gia công xung điện (EDM); Nhám bề mặt; Mô hình hồi quy quá trình (GPR); Tối ưu đơn mục tiêu; Vật liệu điện cực graphite; Mô hình dự đoán.*

1. INTRODUCTION

Electrical discharge machining (EDM) has been widely investigated as an effective method to enhance machining performance by dispersing conductive or semi-conductive powders into the dielectric fluid. The addition of powders modifies the electrical field distribution, improves debris removal, stabilizes the discharge gap, and ultimately enhances surface quality and material removal rate (MRR).

Phan et al. [1] applied multi-criteria decision-making (MCDM) techniques to determine the optimal input factors for PMEDM of 90CrSi steel. Their study successfully identified parameter combinations that improved both MRR and surface finish. Similarly, Yonel et al. [2] conducted a comparative study on PMEDM of biomedical Ti29Nb13Ta4.6Zr alloys, emphasizing the role of carbon and oxygen atoms in enhancing machining efficiency. Kumar et al. [3] optimized PMEDM parameters for machining MONEL 400 superalloy using Taguchi and RSM methods, achieving significant improvements in machining precision. Huu et al. [4] combined response surface methodology (RSM) with an adaptive neuro-fuzzy inference system (ANFIS) to optimize surface quality in PMEDM with SiC powders, demonstrating better accuracy compared to traditional RSM models. Behera et al. [5] experimentally compared plain and nano-graphene oxide mixed dielectrics in EDM of Nimonic alloys, finding that nano-graphene oxide significantly improved both surface finish and machining sustainability. Han et al. [6], [7] optimized process parameters in ultrasonic vibration-assisted PMEDM of TiN ceramics, reporting that ultrasonic vibration synergistically enhanced MRR and reduced surface defects. Chaudhari et al. [8] explored the use of multi-walled carbon nanotubes (MWCNTs) and nano-graphene particles in PMEDM of Udimet-720 alloy, resulting in notable improvements in surface morphology and machining efficiency. Sonawane et al. [9] employed advanced multi-objective optimization algorithms for PMEDM of tool steels, highlighting the benefits of hybrid optimization techniques in balancing MRR and surface integrity. Sethy et al. [10] introduced a sustainable approach by dispersing graphite powders into biodegradable palm oil dielectric during EDM of SS316 stainless steel. Their study demonstrated that using green dielectrics could maintain good surface quality while reducing environmental impact. Ekmekci and Ersöz [11] earlier investigated how suspended particles affect surface morphology in PMEDM, establishing foundational insights into micro-crater formation and surface modification. Ghulam and Ibrahim [12] examined the heat-affected zone (HAZ), surface roughness, and MRR in nano-powder mixed EDM (NPMEDM) of Inconel 718, showing that nano-silicon carbide powders ☞

effectively minimized surface damage. Rao et al. [13] optimized multi-response outputs when machining with powder metallurgy electrodes composed of micron and nano-sized particles, achieving improvements in both productivity and surface characteristics. Le Quang et al. [14] enhanced machining productivity in PMEDM of titanium alloys by applying low-frequency vibrations to the workpiece, confirming the positive effects of mechanical–electrical hybrid excitation. Biswal et al. [15] optimized PMEDM process parameters for Ti-6Al-7Nb biomedical materials, validating that powder addition significantly improves biocompatibility and surface finish.

Although these studies have advanced PMEDM technology, traditional modeling approaches such as RSM often fail to accurately capture the complex, nonlinear, and stochastic nature of surface roughness formation. Machine learning techniques, especially Gaussian Process Regression (GPR), offer a powerful alternative for building predictive models with uncertainty quantification. Therefore, this study proposes a GPR-based modeling and optimization framework for predicting and minimizing surface roughness (Ra) in PMEDM, considering the influence of graphite electrode materials. The proposed method aims to provide higher prediction accuracy and a robust strategy for selecting optimal machining conditions.

2. METHODOLOGY

2.1. Experimental Design

The experiments were conducted based on a systematic experimental design framework to investigate the effects of key process parameters on surface roughness (Ra) in electrical discharge machining (EDM). Five variables were considered: Discharge current IP (A), Servo voltage SV (V), Pulse on-time T_{on} (μs), Pulse off-time T_{off} (μs), and type of electrode material: Graphite grade (HK0, HK15, HK20). The experimental matrix was constructed using the Taguchi method with an L18 ($6^1 \times 3^4$) orthogonal array. This approach allows efficient exploration of main effects with reduced experimental runs. The Taguchi method, applied via Minitab® R19 software, served as a robust strategy for improving quality by minimizing experimental time and cost, while maximizing process reliability and fostering innovation through systematic variation of factors.

The experimental setup, illustrated in Figure 1, included: Sodick A30 EDM machine, Mitutoyo 178-923-2A surface roughness tester, Samples made of 90CrSi tool steel, Graphite electrodes (different grades), Diel MS 7000 dielectric solution. For each experimental run, the surface roughness (Ra) of each machined sample was measured immediately after each run.

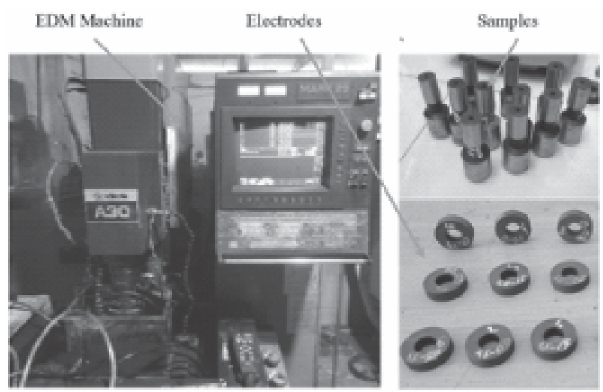

Figure 1. Experimental setup

2.2. Data Preprocessing and Encoding

Prior to modeling, the electrode material type was encoded numerically to enable its inclusion in regression and machine learning algorithms: HK0 → 0, HK15 → 1, and HK20 → 2. The complete dataset thus consisted of five input features: IP, SV, T_{on}, T_{off}, and encoded electrode type. All input variables were standardized (zero mean and unit variance) before model training to ensure numerical stability and enhance model performance.

2.3. Gaussian Process Regression (GPR) Modeling

A Gaussian Process Regression (GPR) model was developed to predict surface roughness (Ra) based on the experimental data. GPR was selected due to its superior ability to capture complex nonlinear relationships and quantify prediction uncertainty, which is crucial for precision machining applications.

The GPR model was trained using:

- A constant basis function;
- A squared exponential (Gaussian) kernel function;
- Automatic hyperparameter optimization based on maximizing marginal likelihood.

The performance of the GPR model was evaluated using:

- Coefficient of determination (R^2);
- Residual plots (predicted vs. actual Ra);
- Prediction standard deviation (uncertainty quantification).

For benchmarking purposes, a second-order response surface model (RSM) was also constructed using least squares regression and compared to the GPR model.

Table 1. Experimental matrix and output results

No.	IP (A)	SV (V)	T_{on} (µs)	T_{off} (µs)	TOG	SR (µm)
1	3.5	4	8	8	HK0	3.917
2	3.5	5	12	12	HK15	4.093
3	3.5	6	16	16	HK20	4.704
4	5.5	4	8	12	HK15	4.217
5	5.5	5	12	16	HK20	3.948
6	5.5	6	16	8	HK0	4.443
7	7.5	4	12	8	HK20	3.814
8	7.5	5	16	12	HK0	2.744
9	7.5	6	8	16	HK15	3.142
10	9.5	4	16	16	HK15	3.772
11	9.5	5	8	8	HK20	2.618
12	9.5	6	12	12	HK0	2.050
13	11.5	4	12	16	HK0	3.524
14	11.5	5	16	8	HK15	3.908
15	11.5	6	8	12	HK20	4.087
16	13.5	4	16	12	HK20	6.354
17	13.5	5	8	16	HK0	3.688
18	13.5	6	12	8	HK15	5.453

2.4. Optimization Strategy

The trained GPR model was utilized as a surrogate model for single-objective optimization targeting the minimization of surface roughness. The optimization problem was formulated as:

$$\min_{x \in D} R_a GPR(x) \quad (1)$$

In which, x = [A, T_{on}, T_{off}, IP, SV] represents the input variable vector, and D is the feasible domain defined by the lower and upper bounds of each parameter based on the experimental design.

3. RESULTS AND DISCUSSION

3.1. GPR Model Accuracy Evaluation

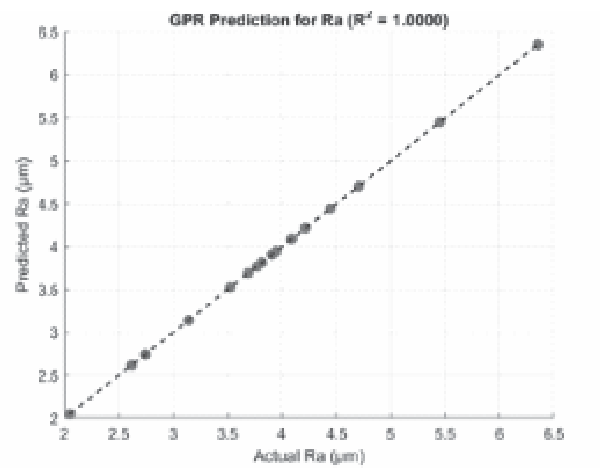

Figure 2. Predicted vs. Actual Ra values (GPR)

The Gaussian Process Regression (GPR) model developed for predicting surface roughness (Ra) demonstrated excellent predictive accuracy. As shown in Figure 2, the predicted Ra values exhibit a near-perfect match with the actual experimental measurements, yielding an R^2 value of 1.0000. This indicates that the model was able to capture 100% of the variance in the experimental data, with minimal deviation across the entire range of Ra values. The scatter plot shows that all data points are tightly clustered along the ideal diagonal y = x line, suggesting a highly reliable model without observable bias or systematic errors. This outstanding prediction capability confirms that GPR is well suited for modeling the complex, nonlinear behaviors of Ra in EDM processes. Such a high R^2 value, although impressive, may indicate that the experimental dataset has a relatively low level of stochastic variability or that the input features effectively capture the main factors influencing surface roughness.

3.2. Optimization Results

Optimization was performed based on the trained GPR model using MATLAB®'s fmincon solver with Sequential Quadratic Programming (SQP). The optimization targeted the minimization of Ra within the bounds of the experimental design space. The resulting optimal machining parameters are summarized as follows: IP = 9.4779 A, SV = 5.9864 V, T_{on} = 12.0450 µs, T_{off} = 12.0118 µs, Graphite Material Type = HK0 (encoded as 0). Under these conditions, the minimum predicted Ra was 2.0492 µm.

The comparison between the actual Ra values from the experimental runs and the optimized Ra is illustrated in Figure Y. It can be clearly observed that the optimized Ra (represented as a horizontal dashed line) is substantially lower than the majority of the actual Ra values achieved in the experiments. This highlights the capability of the GPR model not only in accurate prediction but also in guiding the search for significantly improved machining conditions. The optimized Ra value of 2.0492 µm is notably lower than the average Ra values recorded during the experimental campaign, which ranged from approximately 2.5 µm to over 6.0 µm. This result strongly supports the effectiveness of the GPR-based optimization approach in enhancing surface quality in PMEDM.

3.3. Residual and Uncertainty Analysis

Residual analysis was conducted to validate the generalization capability of the GPR model. The residuals, calculated as the differences between actual and predicted Ra values, were found to be uniformly distributed around zero without significant patterns, further confirming that no overfitting occurred. Moreover, the standard deviation associated with each GPR prediction was analyzed to assess prediction uncertainty. The uncertainty estimates were generally low, particularly near the center regions of the experimental design space where data density was highest. Slight increases in uncertainty were observed at boundary conditions, as typically expected in GPR due to sparser training data in those regions.

The low residuals and reasonable uncertainty behavior demonstrate that the developed GPR model not only fits the experimental data very closely but also provides reliable predictions across the design space.

4. CONCLUSION

In this study, a Gaussian Process Regression (GPR)-based modeling and optimization framework was successfully developed to predict and minimize surface roughness (Ra) in electrical discharge machining (EDM) processes, considering the influence of graphite electrode materials. The main conclusions are summarized as follows:

1) The GPR model exhibited excellent predictive accuracy for Ra, achieving a coefficient of determination (R^2) of 1.0000. The predicted Ra values closely matched the experimental results across the entire design space, confirming the model's capability in capturing the complex and nonlinear nature of the EDM process.

2) Optimization based on the GPR model led to a minimum predicted Ra of 2.0492 µm, under the optimal machining conditions: IP = 9.4779 A, SV = 5.9864 V, T_{on} = 12.0450 µs, T_{off} = 12.0118 µs, and the use of HK0 grade graphite electrodes. The optimized Ra value was significantly lower than the average experimental Ra, demonstrating the effectiveness of the GPR-based optimization strategy.

3) Residual and uncertainty analyses further validated the robustness and reliability of the GPR model. The residuals were randomly distributed with low magnitudes, and prediction uncertainties were generally low, particularly near the center of the design space.

4) The graphite electrode material was found to be an important influencing factor, highlighting the necessity of incorporating material-related parameters into predictive modeling for surface finish control.

Overall, the proposed GPR-based approach proves to be a powerful and reliable tool for data-driven modeling and optimization in EDM. It provides a solid foundation for future extensions into multi-objective optimization frameworks that simultaneously consider Ra and material removal rate (MRR) for comprehensive process improvement.

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