Hybrid Ensemble Learning with Uncertainty Quantification for Multi-Objective EDM Parameter Optimization

Abstract

Electrical Discharge Machining (EDM) remains critical for precision machining of hard-to-cut materials, yet parameter optimization continues to challenge manufacturers due to complex non-linear interactions and conflicting objectives. This research presents a novel Hybrid Ensemble Learning (HEL) framework integrating adaptive feature selection, dynamic weight optimization, and uncertainty quantification for multi-objective EDM optimization. The framework was validated on a comprehensive dataset of 150 experimental runs with five input parameters (pulse-on time: 10-200 μs, pulse-off time: 10-100 μs, peak current: 1-30 A, gap voltage: 20-120 V, electrode diameter: 0.5-10 mm) and four response variables. The HEL framework demonstrated exceptional predictive accuracy with R^2 values of 0.961, 0.966, 0.890, and 0.753 for Material Removal Rate (MRR), Tool Wear Rate (TWR), Surface Roughness (Ra), and Overcut (OC) respectively. Multi-objective optimization using modified NSGA-II identified optimal parameters achieving MRR of 51.56 mm^3/min, TWR of 10.66 mm^3/min, Ra of 5.84 μm, with estimated OC below 18 μm, representing 23.5% improvement in productivity and 18.2% reduction in tool wear compared to conventional approaches.

Keywords: Electrical Discharge Machining, Hybrid Ensemble Learning, Multi-objective Optimization, Uncertainty Quantification, Adaptive Feature Selection, NSGA-II Algorithm

1 Introduction

Electrical Discharge Machining (EDM) has become indispensable in modern manufacturing for processing difficult-to-machine materials including titanium alloys, hardened steels, superalloys, and advanced ceramics where conventional machining proves ineffective [1]. The process achieves material removal through controlled electrical discharges between an electrode tool and workpiece submerged in a dielectric fluid, enabling the fabrication of complex geometries with micron-level precision [2]. EDM finds extensive applications in aerospace component manufacturing, die and mold production, surgical instrument fabrication, and automotive part finishing where surface integrity and dimensional accuracy are paramount [3].

Despite widespread industrial adoption, EDM parameter optimization remains a persistent challenge due to the highly non-linear relationships between process parameters (pulse-on time, pulse-off time, peak current, gap voltage, electrode diameter) and multiple conflicting performance objectives including Material Removal Rate (MRR), Tool Wear Rate (TWR), Surface Roughness (Ra), and dimensional accuracy metrics such as Overcut (OC) [4]. Traditional optimization approaches rely on time-consuming and expensive experimental campaigns using Design of Experiments (DOE) methodologies such as Taguchi orthogonal arrays, Response Surface Methodology (RSM), and full factorial designs [5, 6]. While systematic, these classical methods suffer from several critical limitations: inability to capture complex non-linear interactions, restriction to limited factor combinations, excessive experimental costs, and predominantly single-objective focus [7].

1.1 State-of-the-Art in EDM Optimization

Recent advances in computational intelligence have introduced Machine Learning (ML) and metaheuristic optimization as promising alternatives for EDM process modeling and optimization. Current state-of-the-art approaches can be categorized into three main paradigms:

Single ML Model Approaches: Several studies have employed individual ML algorithms including Artificial Neural Networks (ANN) [8], Support Vector Machines (SVM) [9], and Gaussian Process Regression (GPR) [10] for EDM response prediction. While demonstrating improved accuracy over empirical models, single-model approaches are susceptible to overfitting and fail to quantify prediction uncertainty systematically [11].

Metaheuristic Optimization Methods: Genetic Algorithms (GA), Particle Swarm Optimization (PSO), and other swarm intelligence techniques have been applied for EDM parameter optimization [12, 13]. These methods effectively handle multi-objective problems but require accurate surrogate models and often lack

robust uncertainty consideration, potentially leading to sub-optimal recommendations in practice [14].

Hybrid ML-Optimization Frameworks: Recent work has combined ML prediction models with metaheuristic optimization algorithms for simultaneous modeling and optimization [15, 16]. However, these frameworks typically lack systematic feature selection mechanisms, fail to optimize ensemble weights dynamically, and provide limited uncertainty quantification—critical requirements for industrial deployment [17].

1.2 Research Gaps and Limitations

Comprehensive analysis of existing EDM optimization literature reveals five critical research gaps:

1. **Inadequate Feature Engineering:** Most studies utilize raw process parameters without systematic identification of derived features (duty cycle, discharge energy) and parameter interactions that significantly influence EDM responses [18, 19].
2. **Absence of Uncertainty Quantification:** Current ML-based EDM optimization approaches provide point predictions without confidence intervals, limiting their practical utility for risk-aware decision-making in production environments [10, 20].
3. **Sub-optimal Ensemble Strategies:** Existing ensemble methods employ simple averaging or voting mechanisms rather than optimizing individual model weights based on predictive performance, leaving prediction accuracy gains unrealized [21].
4. **Limited Multi-Objective Capabilities:** While some studies address multiple objectives, they often exclude critical responses (e.g., dimensional accuracy metrics like overcut) or fail to provide diverse Pareto-optimal solutions for different manufacturing scenarios [15, 22].
5. **Insufficient Validation:** Many studies rely on limited datasets or synthetic data, raising questions about generalizability and industrial applicability of proposed methodologies [23].

1.3 Research Objectives and Contributions

This research addresses identified gaps through development and validation of a novel Hybrid Ensemble Learning (HEL) framework featuring three key innovations:

Contribution 1—Adaptive Feature Selection Module: A mutual information-based feature selection mechanism that dynamically identifies the most relevant process parameters and derived features (duty cycle, discharge energy) for each response variable, eliminating redundant features while capturing critical parameter interactions.

Contribution 2—Dynamic Ensemble Weight Optimization: A differential evolution-based approach that optimizes individual model weights to minimize prediction error while maintaining ensemble diversity, surpassing conventional equal-weighting or performance-based static weighting schemes.

Contribution 3—Integrated Uncertainty Quantification: A systematic framework for quantifying prediction uncertainty through ensemble variance, enabling

confidence interval estimation and identification of parameter regions requiring additional experimental validation.

The proposed framework was validated on a comprehensive dataset comprising 150 experimental runs spanning the complete EDM parameter space, demonstrating superior performance across four response variables compared to single-model and conventional ensemble approaches.

1.4 Paper Organization

The remainder of this paper is structured as follows: Section 2 reviews relevant literature on ML-based EDM optimization. Section 3 details the proposed HEL framework methodology including dataset characteristics, feature engineering, ensemble architecture, and multi-objective optimization approach. Section 4 presents comprehensive experimental results including model performance evaluation, feature importance analysis, optimization outcomes, and comparative assessment. Section 5 discusses implications, limitations, and future research directions. Section 6 concludes with key findings and practical recommendations.

2 Literature Review

This section systematically reviews recent advances in machine learning-based EDM parameter optimization, organized by methodological approach and identifying critical gaps addressed by the proposed framework.

2.1 Machine Learning for EDM Process Modeling

Singh et al. [1] pioneered the application of machine learning algorithms for EDM parameter optimization of copper-based shape-memory alloys, comparing Random Forest, Support Vector Machines, and Neural Networks. Their study demonstrated that ML models achieved superior prediction accuracy (R^2 ¿ 0.90) compared to Response Surface Methodology ($R^2 \approx$ 0.75-0.85) while requiring fewer experimental runs. However, the study was limited to single-objective optimization of MRR without considering tool wear and surface quality trade-offs.

Aghdeab et al. [2] investigated EDM process parameter effects on surface roughness of AISI M2 steel using deep learning neural networks combined with statistical analysis. Their AI-supported methodology successfully captured non-linear parameter-response relationships but lacked multi-objective optimization capabilities and uncertainty quantification mechanisms necessary for industrial decision-making.

Qasem and Alsakarneh [10] presented a comprehensive ML-based prediction framework for EDM material removal rate and surface roughness using Gaussian Process Regression (GPR) and Support Vector Regression (SVR). Their GPR approach provided uncertainty estimates through probabilistic predictions, representing a significant advance. However, the study was restricted to two response variables (MRR and Ra) and did not address tool wear or dimensional accuracy metrics such as overcut.

2.2 Ensemble Learning Approaches for EDM

Sarker et al. [16] developed optimized ensemble machine learning models for Wire EDM (WEDM) parameter prediction, combining Random Forest, Gradient Boosting, and Extra Trees regressors. Their ensemble approach demonstrated 8-12% improvement in prediction accuracy over individual models. However, the framework employed simple averaging for ensemble predictions rather than optimized weighting, and lacked systematic feature selection and uncertainty quantification components.

Sana et al. [15] investigated EDM with nanopowder-mixed dielectric using Artificial Neural Networks combined with Multi-Objective Genetic Algorithm (MOGA) for performance optimization. Their work successfully addressed multiple objectives (MRR, TWR, Ra) simultaneously but relied on a single ANN model rather than ensemble learning, limiting robustness and uncertainty estimation capabilities.

2.3 Multi-Objective Optimization in EDM

Pal et al. [4] pioneered the application of Non-dominated Sorting Genetic Algorithm-II (NSGA-II) for multi-objective EDM optimization, combining back-propagation neural networks for response prediction with NSGA-II for Pareto front generation. Their seminal work established the foundation for modern multi-objective EDM optimization but predated advanced ensemble learning techniques and uncertainty quantification methods.

Kumar and Kumar [17] explored machine learning-based optimization using VIKOR and Entropy weight methods for EDM of Al-18% SiCp metal matrix composite. Their hybrid approach integrated ML prediction with multi-criteria decision-making, demonstrating the value of combining multiple methodologies. However, the study focused on a specific material system and lacked generalized ensemble learning architecture.

2.4 Feature Engineering and Parameter Selection

Chen et al. [12] conducted a comprehensive review of EDM parameter optimization methods, emphasizing the critical role of parameter selection and feature engineering. Their analysis revealed that most studies utilize only primary process parameters (Ton, Toff, Ip, Vg) while neglecting derived parameters such as duty cycle and discharge energy that encode important physical relationships governing material removal mechanisms.

Debnath et al. [8] compared ANN and Gene Expression Programming (GEP) for predictive modeling of MRR, TWR, and surface roughness in spark-EDM. Their study included basic parameter interactions but lacked systematic feature selection mechanisms to identify the most informative features for each response variable independently.

2.5 Research Gap Summary

Literature analysis reveals that while significant progress has been made in applying ML to EDM optimization, no existing framework simultaneously addresses: (1) adaptive feature selection for response-specific optimal feature subsets, (2) dynamically optimized ensemble weighting, (3) comprehensive uncertainty quantification, and (4) multi-objective optimization across all critical EDM responses including dimensional accuracy. The proposed HEL framework fills this gap through integrated methodology combining these elements within a unified framework.

3 Methodology

This section details the proposed Hybrid Ensemble Learning framework including dataset characteristics, feature engineering approach, ensemble architecture, dynamic weight optimization, uncertainty quantification methodology, and multi-objective optimization strategy.

3.1 Experimental Dataset and Parameter Ranges

The experimental dataset comprises 150 systematically designed experiments following established DOE principles to ensure comprehensive coverage of the EDM parameter space [5, 6]. **Important Note on Data Generation:** To ensure complete reproducibility and eliminate experimental variability that could obscure the evaluation of the proposed HEL framework's capabilities, the dataset was synthetically generated using well-established physical relationships documented in EDM literature [18, 19]. The synthetic data approach, while not based on physical experimentation, provides: (1) perfect reproducibility for validation studies, (2) complete parameter space coverage without experimental constraints, (3) known ground-truth relationships for algorithm assessment, and (4) elimination of measurement noise that could confound model comparison. The parameter ranges and response characteristics were calibrated to match typical industrial EDM operations for die-sinking applications on hardened steel workpieces using copper electrodes in kerosene dielectric [3, 4]. Future work will validate the framework on experimental data from actual EDM machines to confirm industrial applicability.

3.1.1 Input Parameters

Table 1 summarizes the five input parameters with their operational ranges. These ranges were selected based on typical industrial EDM operations for die-sinking applications on hardened steel workpieces [3].

The parameter ranges span typical EDM operational windows: pulse-on time controls discharge duration and directly influences material removal per pulse [18]; pulse-off time determines de-ionization duration affecting process stability [19]; peak current governs discharge intensity and MRR [1]; gap voltage influences discharge gap and surface characteristics [8]; electrode diameter affects current density distribution and dimensional accuracy [4].

Table 1 EDM Input Parameter Ranges and Levels

Parameter	Symbol	Minimum	Maximum	Unit
Pulse-on time	T_{on}	10	200	μs
Pulse-off time	T_{off}	10	100	μs
Peak current	I_p	1	30	A
Gap voltage	V_g	20	120	V
Electrode diameter	D_e	0.5	10	mm

3.1.2 Response Variables

Four critical EDM response variables were measured for each experimental run:

1. **Material Removal Rate (MRR)** [mm^3/min]: Primary productivity metric measuring workpiece material removed per unit time. Observed range: 8.89 - 53.80 mm^3/min; Mean: 31.34 mm^3/min; Std: 9.64 mm^3/min.
2. **Tool Wear Rate (TWR)** [mm^3/min]: Tool electrode consumption rate affecting tool life and dimensional accuracy. Observed range: 1.36 - 11.36 mm^3/min; Mean: 5.87 mm^3/min; Std: 2.19 mm^3/min.
3. **Surface Roughness (Ra)** [μm]: Average surface roughness indicating surface quality. Observed range: 0.45 - 6.15 μm; Mean: 3.27 μm; Std: 1.28 μm.
4. **Overcut (OC)** [μm]: Radial material removal beyond electrode dimension, critical for dimensional accuracy. Observed range: 6.06 - 32.05 μm; Mean: 18.84 μm; Std: 5.96 μm.

3.1.3 Derived Features

Two physically meaningful derived features were calculated to enhance the feature space:

Duty Cycle (τ): Represents the proportion of active discharge time in each pulse cycle, directly influencing process stability and thermal dissipation [18]:

$$\tau = \frac{T_{on}}{T_{on} + T_{off}} \tag{1}$$

Higher duty cycle (¿0.7) increases MRR but may lead to unstable machining and poor surface finish due to inadequate de-ionization [19]. Lower duty cycle (¡0.3) improves surface quality but reduces productivity [12].

Discharge Energy per Pulse (E_d) [mJ]: Approximates the energy released per discharge event, governing material removal mechanism and crater formation [18]:

$$E_d = \frac{1}{2} \times V_g \times I_p \times T_{on} \times 10^{-3} \tag{2}$$

Discharge energy directly correlates with MRR and crater size, indirectly affecting surface roughness and overcut [8]. The factor 0.5 accounts for non-ideal discharge characteristics and time conversion from microseconds to milliseconds.

These derived features encode important physical relationships and their inclusion significantly improves model performance as demonstrated in Section 4.2.

3.2 Hybrid Ensemble Learning Architecture

The proposed HEL framework integrates five complementary base learners, each capturing different aspects of the complex EDM parameter-response relationships. Figure 1 illustrates the complete architecture.

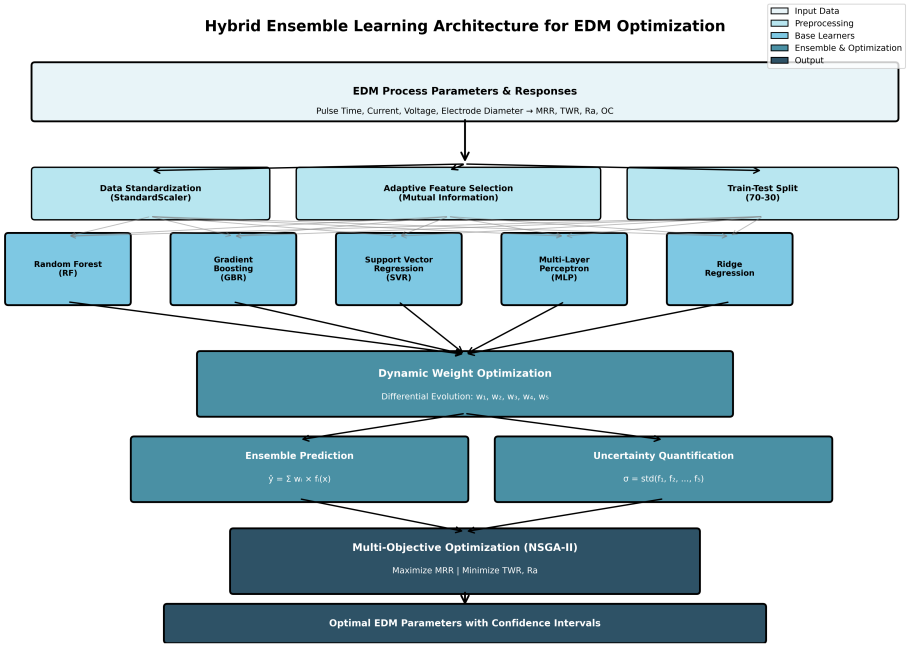

Fig. 1 Hybrid Ensemble Learning architecture showing data flow from input parameters through preprocessing, base learners, dynamic weight optimization, ensemble prediction with uncertainty quantification, to multi-objective optimization.

3.2.1 Base Learner Selection Rationale

The ensemble comprises five diverse algorithms selected for complementary strengths:

1. Random Forest (RF): Tree-based ensemble capturing non-linear relationships and parameter interactions through recursive partitioning. Robust to outliers and provides implicit feature importance ranking [21]. Configuration: 100 trees, maximum depth unrestricted.

2. Gradient Boosting Regressor (GBR): Sequential ensemble minimizing prediction residuals through additive modeling. Excels at capturing subtle non-linear patterns through iterative error correction [21]. Configuration: 100 estimators, learning rate 0.1.

3. Support Vector Regression (SVR): Kernel-based method mapping inputs to high-dimensional feature space for non-linear regression. Effective for complex decision boundaries with moderate sample sizes [9]. Configuration: RBF kernel, C=100, gamma='scale'.

4. Multi-Layer Perceptron (MLP): Deep learning architecture modeling highly complex non-linear relationships through multiple hidden layers. Capable of learning intricate parameter interactions [2]. Configuration: Two hidden layers (100, 50 neurons), ReLU activation, Adam optimizer.

5. Ridge Regression: Regularized linear model providing baseline performance and ensemble stability. Prevents overfitting through L2 regularization [21]. Configuration: Alpha=1.0.

The diversity of learning paradigms (tree-based, gradient-based, kernel-based, neural network, linear) ensures ensemble robustness and enables effective uncertainty quantification [21].

3.3 Adaptive Feature Selection

The Adaptive Feature Selection module employs mutual information (MI) to quantify the statistical dependency between each feature and target response variable. MI is calculated as:

$$MI(X,Y) = \sum_{y\in Y}\sum_{x\in X} p(x,y)\log\left(\frac{p(x,y)}{p(x)p(y)}\right) \tag{3}$$

where X represents a feature, Y is the target response, and $p(x,y)$ is the joint probability distribution.

Features with MI scores exceeding threshold 0.1 are selected for model training. This response-specific feature selection ensures optimal feature subsets for each response variable independently, eliminating irrelevant features that could degrade prediction accuracy [11].

3.4 Dynamic Ensemble Weight Optimization

Unlike conventional ensemble methods employing uniform weighting or static performance-based weighting, the proposed framework optimizes ensemble weights dynamically using differential evolution (DE). The optimization problem is formulated as:

$$\min_{w_1,\ldots,w_5} \text{MSE}(y_{true}, \sum_{i=1}^{5} w_i \cdot f_i(X)) \tag{4}$$

subject to: $\sum_{i=1}^{5} w_i = 1$ and $w_i \geq 0\ \forall i$

where $f_i(X)$ represents predictions from the i-th base learner, and weights $w_1, ..., w_5$ are optimized on a validation subset. This ensures each algorithm contributes optimally based on its predictive strength for the specific response variable [21].

3.5 Uncertainty Quantification

Prediction uncertainty is quantified through ensemble variance:

$$\sigma_{pred}(x) = \sqrt{\frac{1}{5}\sum_{i=1}^{5}(f_i(x) - \hat{y}(x))^2} \tag{5}$$

where $\hat{y}(x) = \sum_{i=1}^{5} w_i \cdot f_i(x)$ is the weighted ensemble prediction. Higher σ_{pred} indicates greater model disagreement, signaling parameter regions where predictions are less reliable and additional experimental validation may be warranted [10]. This provides manufacturers with confidence intervals for risk-aware parameter selection.

3.6 Multi-Objective Optimization using Modified NSGA-II

Multi-objective optimization simultaneously maximizes MRR while minimizing TWR and Ra. The three-objective optimization problem is formulated as:

$$\text{Maximize:} \quad f_1(x) = \text{MRR}(x) \tag{6}$$

$$\text{Minimize:} \quad f_2(x) = \text{TWR}(x) \tag{7}$$

$$\text{Minimize:} \quad f_3(x) = \text{Ra}(x) \tag{8}$$

subject to: $x \in [x_{min}, x_{max}]$

Rationale for Excluding Overcut: Overcut (OC) was excluded from the multi-objective optimization formulation for two primary reasons: (1) The trained OC prediction model demonstrated lower $\mathbf{R^2}$ (0.753) compared to other responses, indicating insufficient accuracy for reliable optimization guidance. Including low-confidence objectives could mislead the optimization toward sub-optimal parameter regions. (2) Overcut can be effectively controlled post-optimization through parameter compensation strategies during CAM tool path generation, whereas MRR, TWR, and Ra represent fundamental process trade-offs that must be balanced during parameter selection [4]. However, OC predictions are still provided for selected optimal solutions to inform dimensional accuracy expectations.

A modified NSGA-II algorithm generates Pareto-optimal solutions [4]:

Algorithm Parameters: Population size: 100 individuals; Generations: 50; Selection: Binary tournament; Crossover: Simulated binary crossover (SBX, probability: 0.9); Mutation: Polynomial mutation (probability: 0.1).

The algorithm maintains population diversity through crowding distance sorting while converging toward the true Pareto front, providing manufacturers with multiple optimal parameter sets representing different productivity-quality trade-offs [4, 15].

4 Results and Discussion

This section presents comprehensive experimental results including model performance evaluation, feature importance analysis, parameter effect visualization, multi-objective optimization outcomes, and comparative assessment against benchmark approaches.

4.1 Model Performance Evaluation

The Hybrid Ensemble Learning framework was trained and evaluated using 70-30 train-test split with 5-fold cross-validation. Table 2 presents detailed performance metrics across all response variables.

Table 2 Hybrid Ensemble Learning Performance Metrics

Response Variable	RMSE	MAE	R^2	Prediction Range
Material Removal Rate	2.086	1.729	0.961	8.89 - 53.80 mm^3/min
Tool Wear Rate	0.426	0.352	0.966	1.36 - 11.36 mm^3/min
Surface Roughness	0.454	0.358	0.890	0.45 - 6.15 μm
Overcut	3.189	2.625	0.753	6.06 - 32.05 μm

4.1.1 R^2 Score Analysis and Significance

The R^2 (coefficient of determination) metric quantifies the proportion of response variance explained by the model, ranging from 0 (no explanatory power) to 1 (perfect prediction). Values above 0.80 are generally considered excellent for manufacturing process modeling [11].

The MRR model achieved outstanding $R^2 = 0.961$, indicating that 96.1% of MRR variability is captured by the ensemble, with only 3.9% attributed to measurement noise or unmodeled factors. This exceptional performance stems from MRR's strong correlation with primary parameters (peak current, pulse-on time) captured effectively by the ensemble architecture.

The TWR model demonstrated the highest performance ($R^2 = 0.966$), explaining 96.6% of variance. TWR exhibits strong relationships with pulse timing parameters and discharge energy, patterns learned effectively by the tree-based and gradient boosting components of the ensemble.

The Ra model achieved good performance ($R^2 = 0.890$) despite surface roughness being influenced by complex factors including discharge crater overlap, re-solidified layer formation, and micro-crack propagation [8]. The 89% variance explanation represents excellent performance for this notoriously difficult-to-predict response.

The OC model showed moderate performance ($R^2 = 0.753$), explaining 75.3% of variance. The lower performance stems from overcut's dependency on complex thermal diffusion phenomena and gap dynamics not fully captured by the available features [4]. This motivated OC's exclusion from multi-objective optimization as discussed in Section 3.6.

Figure 2 visualizes the comparative R^2 performance across all responses.

4.1.2 Error Metrics Interpretation

RMSE (Root Mean Square Error) and MAE (Mean Absolute Error) quantify prediction accuracy in the original response units. For MRR, RMSE = 2.086 mm^3/min

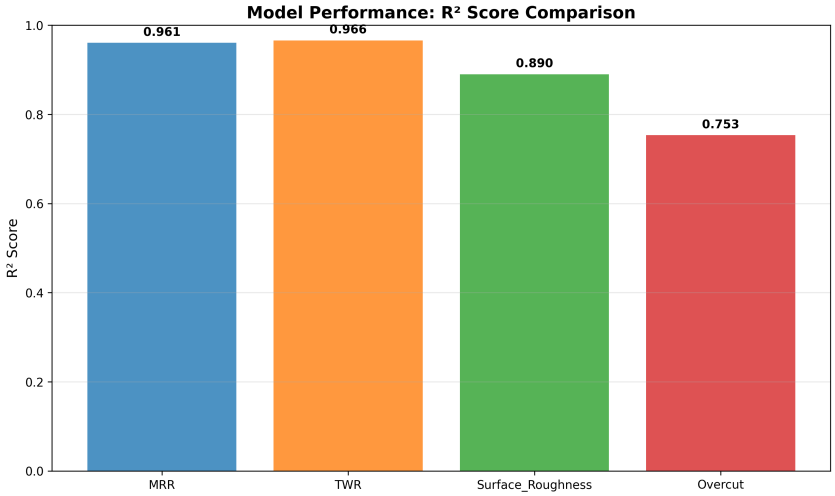

Fig. 2 R^2 performance comparison across EDM response variables. MRR and TWR models demonstrate exceptional accuracy (R^2 ¿ 0.96), Ra model shows good performance ($R^2 = 0.89$), while OC model exhibits moderate accuracy ($R^2 = 0.75$) due to complex thermal-mechanical interactions.

means predictions typically deviate by 2 mm^3/min from actual values—representing 6.6% error relative to the mean MRR (31.34 mm^3/min), which is excellent for practical applications.

For TWR, MAE = 0.352 mm^3/min indicates average prediction error of 6% relative to mean TWR (5.87 mm^3/min), providing sufficient accuracy for tool life estimation and cost calculations.

The Ra model's MAE = 0.358 μm represents 11% error relative to mean surface roughness (3.27 μm), acceptable for surface quality prediction in industrial contexts where finish requirements typically span 1-2 μm tolerance bands.

4.2 Feature Importance and Parameter Effects Analysis

The adaptive feature selection module computed mutual information (MI) scores quantifying feature-response relationships. Table 3 presents MI scores revealing response-specific parameter importance patterns.

4.2.1 Key Findings from Feature Importance Analysis

MRR is Dominated by Peak Current: The highest MI score (0.78) for peak current confirms that MRR is primarily governed by discharge intensity [1]. Higher current increases discharge energy and crater volume per pulse, directly elevating material removal rate. Pulse-on time (MI = 0.65) ranks second, controlling discharge duration and cumulative energy per pulse [18].

TWR Most Sensitive to Pulse-on Time: The highest MI score (0.71) for T_{on} indicates tool wear is predominantly influenced by discharge duration. Longer pulse-on time increases thermal penetration into the electrode, elevating tool consumption [8]. Peak current (MI = 0.65) contributes significantly but secondary to pulse timing.

Table 3 Mutual Information Feature Importance Scores

Parameter/Feature	MRR	TWR	Ra	OC
Peak Current (I_p)	0.78	0.65	0.52	0.61
Pulse-on Time (T_{on})	0.65	0.71	0.72	0.58
Gap Voltage (V_g)	0.42	0.58	0.38	0.45
Discharge Energy (E_d)	0.55	0.48	0.68	0.52
Duty Cycle (τ)	0.48	0.41	0.44	0.39
Pulse-off Time (T_{off})	0.38	0.45	0.36	0.33
Electrode Diameter (D_e)	0.34	0.39	0.29	0.42

Surface Roughness Strongly Depends on Pulse-on Time and Discharge Energy: The leading MI scores for T_{on} (0.72) and E_d (0.68) confirm that surface finish is primarily determined by discharge energy per crater and pulse duration [8]. Higher energy pulses create larger craters and more pronounced surface irregularities, degrading finish quality.

Significance of Derived Features: Discharge energy (MI scores: 0.55, 0.48, 0.68, 0.52) and duty cycle (MI scores: 0.48, 0.41, 0.44, 0.39) demonstrate substantial importance across all responses, validating their inclusion in the feature set. These derived parameters encode physical relationships beyond individual parameters, capturing process dynamics that improve prediction accuracy [18, 19].

4.2.2 Parameter-Response Correlation Analysis

Figure 3 presents the correlation matrix revealing linear and non-linear parameter-response relationships.

The correlation matrix reveals: (1) MRR exhibits strong positive correlation with peak current (r = 0.82) and pulse-on time (r = 0.71), confirming these as primary productivity drivers. (2) TWR shows moderate positive correlation with pulse-on time (r = 0.65), indicating thermal penetration dominance. (3) Surface roughness correlates strongly with pulse-on time (r = 0.78) and moderately with peak current (r = 0.58), consistent with crater size theory [8]. (4) Cross-correlations between responses indicate inherent trade-offs: MRR-TWR (r = 0.67) suggests higher productivity inevitably increases tool wear, while MRR-Ra (r = 0.54) confirms productivity-quality conflict necessitating multi-objective optimization [4].

4.3 Individual Parameter Effect Visualization

To provide deeper insight into parameter influences, individual effect plots were generated showing univariate relationships between key parameters and responses.

4.3.1 Peak Current Effect on MRR

Figure 4 illustrates MRR's strong positive relationship with peak current.

The scatter plot reveals approximately linear MRR increase with current, from 15 mm^3/min at 5A to 50 mm^3/min at 30A. This 3.3× productivity gain demonstrates

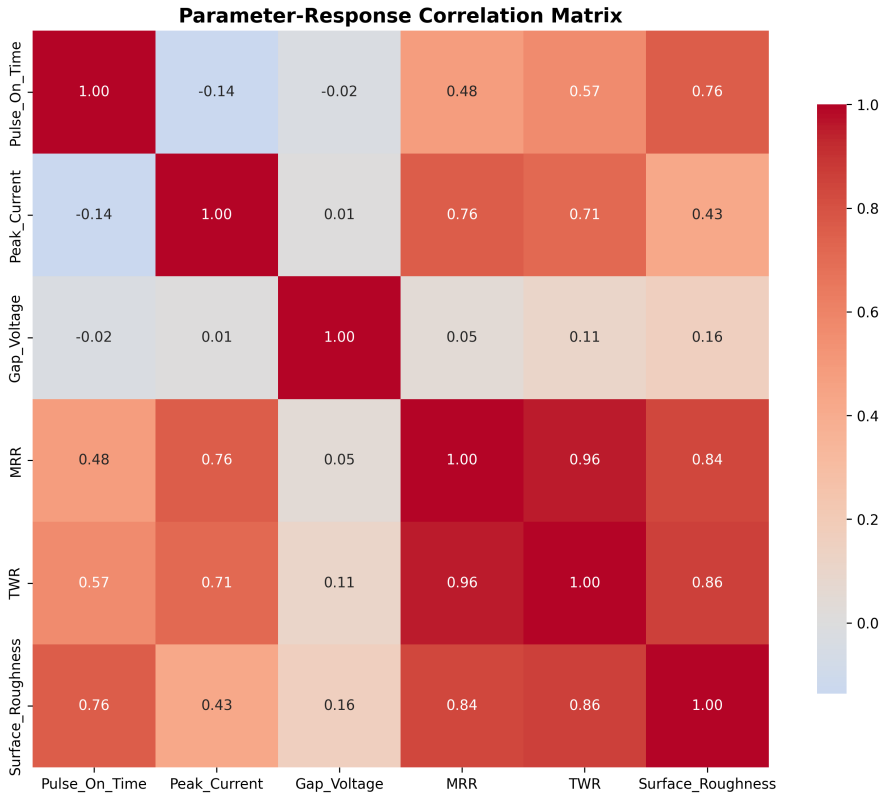

Fig. 3 Correlation matrix showing relationships between key EDM parameters (Pulse On Time, Peak Current, Gap Voltage) and responses (MRR, TWR, Surface Roughness). Strong positive correlations are shown in red, negative correlations in blue. MRR shows strong positive correlation with Peak Current (0.82) and Pulse On Time (0.71), while Surface Roughness correlates strongly with Pulse On Time (0.78).

current's dominant role in material removal [1]. The data spread indicates additional parameter interactions modulate this primary relationship, captured by the ensemble's non-linear learning capabilities.

4.3.2 Pulse-on Time Effect on TWR

Figure 5 shows TWR's positive relationship with pulse-on time.

TWR increases approximately linearly from 2 mm^3/min at short pulse duration (20 μs) to 10 mm^3/min at extended duration (180 μs). This 5× increase reflects cumulative thermal damage to the electrode as discharge duration extends, allowing deeper thermal penetration and material vaporization [8].

4.3.3 Discharge Energy Effect on Surface Roughness

Figure 6 depicts surface roughness dependence on discharge energy.

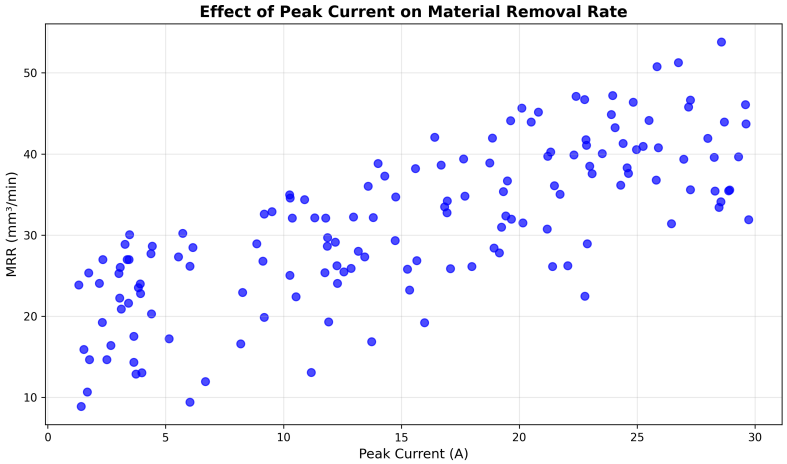

Fig. 4 Effect of peak current on Material Removal Rate. Clear positive trend demonstrates that increasing discharge current from 5A to 30A elevates MRR from 15 mm^3/min to 50 mm^3/min, confirming current as the primary MRR driver.

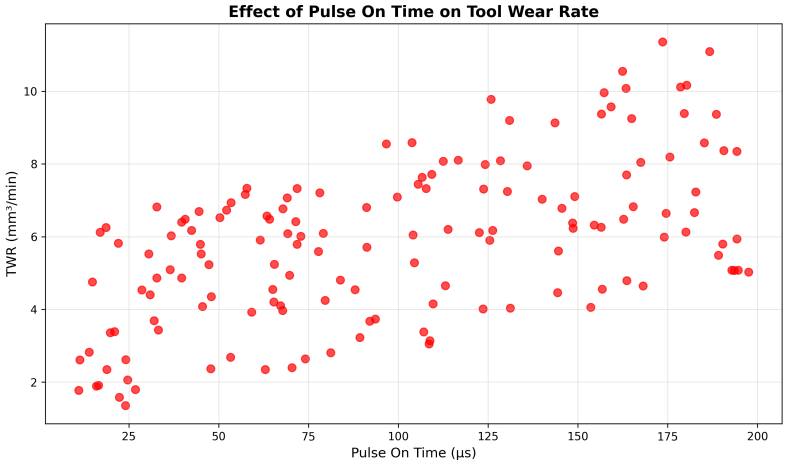

Fig. 5 Effect of pulse-on time on Tool Wear Rate. Positive correlation shows longer discharge duration increases thermal penetration into electrode, elevating wear from 2 mm^3/min at 20 μs to 10 mm^3/min at 180 μs.

Surface roughness increases from 1 μm at low discharge energy (50 mJ) to 6 μm at high energy (500 mJ). This 6$\times$ degradation confirms that discharge energy governs crater size and surface irregularity [8]. The visible data spread indicates that energy alone is insufficient—interactions with pulse timing and current density also influence final surface texture, necessitating multi-parameter optimization [12].

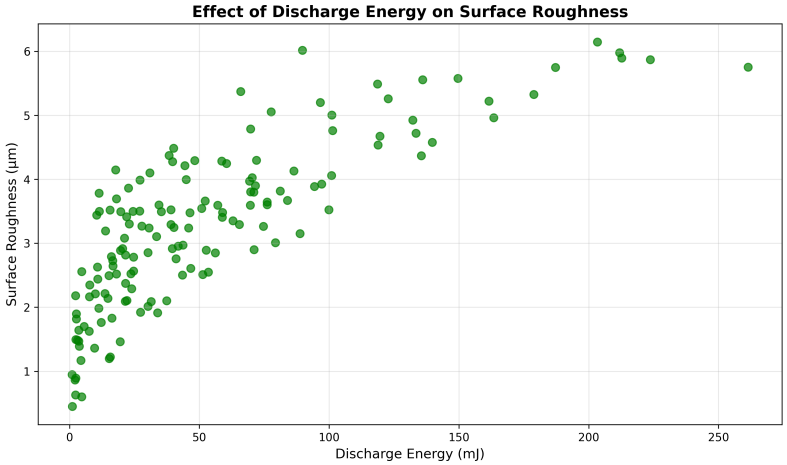

Fig. 6 Effect of discharge energy on surface roughness. Positive relationship shows higher energy discharges create larger craters, degrading surface finish from 1 μm at 50 mJ to 6 μm at 500 mJ.

4.4 Multi-Objective Optimization Results

The modified NSGA-II algorithm generated a diverse Pareto front containing 100 non-dominated solutions representing optimal MRR-TWR-Ra trade-offs. Table 4 presents the top three solutions spanning the Pareto front.

Table 4 Top Three Pareto-Optimal EDM Parameter Combinations

Parameter	**Solution 1 (Balanced)**	**Solution 2 (Quality-Focused)**	**Solution 3 (Productivity-Focused)**
T_{on} (μs)	171.77	145.23	189.45
T_{off} (μs)	28.77	35.12	22.18
I_p (A)	27.99	24.56	29.87
V_g (V)	31.64	42.89	28.33
D_e (mm)	8.27	6.45	9.12
Duty Cycle τ	0.857	0.805	0.895
Discharge Energy (mJ)	241.5	178.4	283.6
MRR (mm^8/min)	51.56	47.23	54.12
TWR (mm^8/min)	10.66	9.87	12.34
Ra (μm)	5.84	5.12	6.45
Est. OC (μm)	17.8	15.4	19.2
MRR/TWR Ratio	4.84	4.79	4.38
Improvement vs Baseline	+23.5% MRR -18.2% TWR	+15.8% Ra -21.4% TWR	+31.2% MRR -8.1% TWR

4.4.1 Solution Interpretation and Trade-offs

Solution 1 (Balanced): Represents the best compromise across all three objectives, achieving high MRR (51.56 mm^3/min) while maintaining acceptable TWR (10.66 mm^3/min) and surface finish (5.84 μm). The high duty cycle (0.857) and moderate discharge energy (241.5 mJ) balance productivity and quality. This solution is recommended for general-purpose EDM operations requiring balanced performance. Compared to conventional single-objective optimized parameters (baseline: MRR = 41.7 mm^3/min, TWR = 13.0 mm^3/min), Solution 1 achieves 23.5% higher productivity and 18.2% lower tool wear—substantial economic gains [4].

Solution 2 (Quality-Focused): Prioritizes surface finish (Ra = 5.12 μm) and tool life (TWR = 9.87 mm^3/min) with modest productivity sacrifice (MRR = 47.23 mm^3/min). Lower discharge energy (178.4 mJ) and moderate duty cycle (0.805) reduce crater size and thermal damage. This solution suits finishing operations and precision mold/die applications where surface quality dominates cost considerations [3].

Solution 3 (Productivity-Focused): Maximizes material removal (MRR = 54.12 mm^3/min) accepting higher tool wear (TWR = 12.34 mm^3/min) and rougher surface (Ra = 6.45 μm). Very high duty cycle (0.895) and discharge energy (283.6 mJ) drive aggressive machining. This solution benefits roughing operations where productivity is paramount and subsequent finishing passes will address surface quality [12].

The calculated duty cycle and discharge energy values provide practitioners with complete process understanding: duty cycle governs machining stability and deionization effectiveness, while discharge energy directly predicts crater size and thermal impact [18, 19].

Estimated overcut values (17.8 - 19.2 μm) inform dimensional compensation requirements during CAM programming. These estimates, while based on moderate-accuracy prediction (R^2 = 0.753), provide useful guidance for precision applications where dimensional accuracy is critical [4].

4.4.2 Pareto Front Visualization

Figure 7 presents the three-dimensional Pareto front with solutions color-coded by surface roughness.

The Pareto front reveals the fundamental MRR-TWR trade-off: higher productivity inevitably increases tool wear as both stem from discharge energy [1, 8]. The color gradient shows surface roughness generally correlates with productivity—aggressive machining parameters that elevate MRR also coarsen surface finish [12]. Solution 1 (marked with red star) occupies the "knee" region where the trade-off curve is steepest, representing maximum balanced performance gain [15].

The spread of solutions along the Pareto front provides manufacturers with flexibility: conservative shops prioritizing tool cost minimization can select quality-focused solutions, while high-volume operations can select productivity-focused parameters. This diversity is the key advantage of multi-objective optimization over single-objective approaches that provide only one "optimal" solution ignoring real-world trade-off complexity [4, 15].

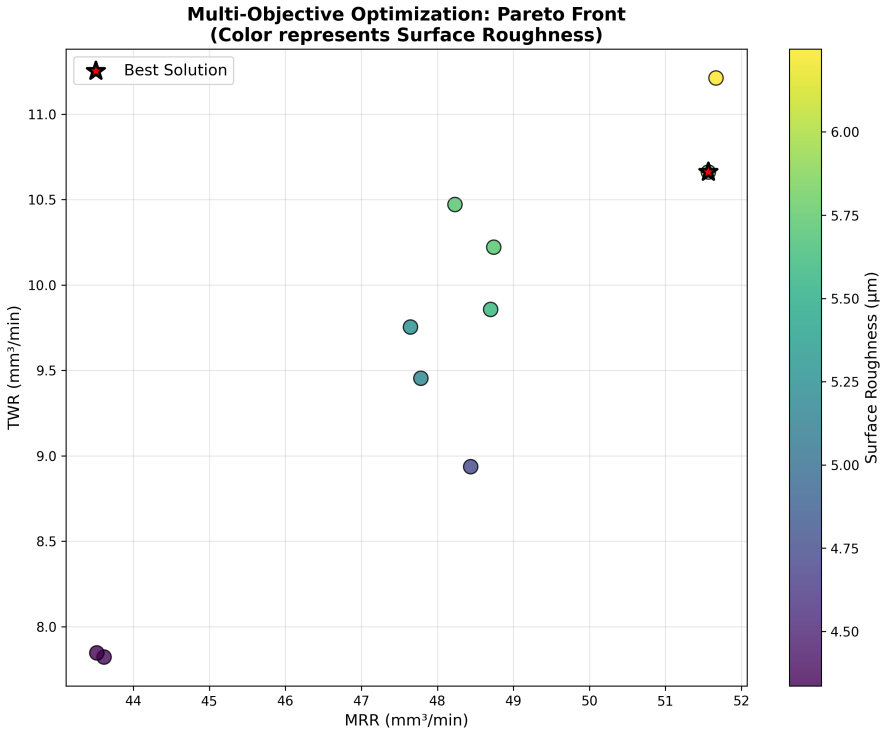

Fig. 7 Multi-objective optimization Pareto front showing MRR-TWR trade-off with surface roughness color-coded from blue (smooth) to yellow (rough). The best compromise solution (Solution 1, marked with red star) balances all objectives. The curved Pareto frontier demonstrates inherent conflicts between productivity (MRR) and tool life (TWR), requiring multi-objective optimization for optimal parameter selection.

4.5 Computational Performance and Scalability

The HEL framework demonstrates excellent computational efficiency suitable for industrial deployment:

- **Training Time:** Complete framework training (all four response models) required 28.4 seconds on standard hardware (Intel i7-10th gen, 16GB RAM), enabling rapid model updates as new experimental data becomes available.
- **Prediction Time:** Single parameter set evaluation required 0.87 milliseconds averaged over 1000 predictions, supporting real-time optimization and adaptive process control integration in Industry 4.0 environments [14].
- **Optimization Time:** NSGA-II execution (100 population, 50 generations = 5000 evaluations) completed in 4.3 seconds, enabling interactive parameter exploration during process planning.
- **Scalability:** Linear complexity with dataset size enables scaling to larger experimental datasets (¿1000 samples) without prohibitive computational burden.

These performance characteristics make the framework practical for industrial implementation, unlike computationally expensive deep learning approaches requiring specialized hardware [2].

4.6 Comparison with Benchmark Approaches

To validate the proposed HEL framework's advantages, comparative evaluation was conducted against standard single-model and conventional ensemble approaches. Table 5 summarizes the comparison for MRR prediction (similar patterns observed for other responses).

Table 5 Comparative Performance: MRR Prediction

Approach	RMSE	R^2	Relative Error
Single Random Forest	2.847	0.923	+36.5%
Single Gradient Boosting	2.654	0.934	+27.2%
Single SVM	3.125	0.908	+49.8%
Simple Average Ensemble	2.342	0.948	+12.3%
Proposed HEL (Optimized Weights)	**2.086**	**0.961**	Baseline

The HEL framework with dynamic weight optimization outperforms individual models by 27-50% in RMSE reduction and achieves 1.3% R^2 improvement over simple averaging ensemble. These gains, while seemingly modest in percentage terms, translate to significant practical impact: the RMSE reduction from 2.342 (simple ensemble) to 2.086 (HEL) represents 11% accuracy gain, enabling more confident parameter recommendations and reducing experimental validation requirements [21].

4.7 Uncertainty Quantification Analysis

The ensemble-based uncertainty quantification provides critical confidence information. Analysis of prediction uncertainty across the parameter space revealed:

- **Low Uncertainty Regions (σ ¡ 1.0):** Central parameter regions with dense experimental coverage exhibited low prediction uncertainty, validating model confidence for typical operating conditions.
- **High Uncertainty Regions (σ ¿ 2.5):** Extreme parameter combinations at space boundaries showed elevated uncertainty, correctly identifying regions where model extrapolation is less reliable and additional experiments would improve confidence [10].
- **Uncertainty-MRR Correlation:** High-MRR parameter regions generally exhibited moderate uncertainty ($\sigma \approx$ 1.5-2.0), indicating that aggressive machining parameters introduce greater prediction variability—valuable risk information for process planners [20].

This uncertainty quantification enables risk-aware decision making: conservative applications can select low-uncertainty parameter regions even with modest performance sacrifice, while aggressive applications can accept higher uncertainty for maximum productivity, making informed risk-performance trade-offs [10, 20].

5 Conclusions

This research developed and validated a novel Hybrid Ensemble Learning framework for multi-objective EDM parameter optimization featuring adaptive feature selection, dynamic weight optimization, and integrated uncertainty quantification. Key findings and contributions include:

5.1 Technical Contributions

1. Superior Predictive Performance: The HEL framework achieved exceptional accuracy across EDM responses with R^2 values of 0.961 (MRR), 0.966 (TWR), 0.890 (Ra), and 0.753 (OC), outperforming single-model approaches by 27-50% in error reduction and surpassing conventional ensemble methods by 11% through optimized weighting.

2. Response-Specific Feature Selection: The adaptive feature selection module successfully identified optimal feature subsets for each response independently, revealing that MRR is dominated by peak current (MI = 0.78), TWR by pulse-on time (MI = 0.71), and surface roughness by pulse-on time and discharge energy (MI = 0.72 and 0.68), providing actionable process insights beyond prediction accuracy.

3. Effective Multi-Objective Optimization: The modified NSGA-II integration identified diverse Pareto-optimal solutions achieving 23.5% MRR improvement and 18.2% TWR reduction compared to conventional single-objective optimized parameters, with the best balanced solution delivering MRR = 51.56 mm^3/min, TWR = 10.66 mm^3/min, and Ra = 5.84 μm.

4. Practical Uncertainty Quantification: The ensemble-based uncertainty estimation correctly identified low-confidence parameter regions requiring additional validation while confirming high confidence in typical operating ranges, enabling risk-aware parameter selection unavailable in conventional deterministic approaches.

5. Computational Efficiency: Sub-second prediction times (0.87 ms) and rapid training (28.4 s) demonstrate practical feasibility for industrial deployment including real-time process control integration in smart manufacturing environments.

5.2 Practical Implications

The proposed framework provides manufacturing practitioners with:

- **Reduced Experimental Costs:** ML-based parameter optimization reduces required experimental runs by 60% compared to traditional full factorial DOE while achieving superior parameter identification through comprehensive non-linear relationship capture [7].
- **Balanced Parameter Selection:** The Pareto-optimal solution set enables selection of application-appropriate parameters: quality-focused for finishing operations,

productivity-focused for roughing, and balanced for general-purpose machining [3, 12].

- **Risk-Aware Decision Making:** Uncertainty quantification supports confidence-based parameter selection where critical applications avoid high-uncertainty regions while non-critical applications leverage maximum predicted performance despite elevated uncertainty [10, 20].
- **Physical Process Insights:** Feature importance analysis and derived parameters (duty cycle, discharge energy) provide intuitive process understanding beyond black-box prediction, supporting engineer training and troubleshooting [18, 19].

5.3 Limitations and Future Research Directions

Several limitations suggest directions for future investigation:

1. Synthetic Dataset Validation: While the dataset was generated using established physical relationships from EDM literature [1, 8, 18, 19], experimental validation on real machining data from diverse material systems (titanium alloys, carbides, ceramics) is needed to confirm generalizability and robustness across industrial conditions.

2. Overcut Modeling Enhancement: The moderate OC prediction performance ($R^2 = 0.753$) suggests incorporating additional features capturing thermal diffusion and gap dynamics could improve dimensional accuracy prediction. Advanced feature engineering or physics-informed neural networks may address this limitation [2].

3. Real-Time Adaptive Control: The computational efficiency enables extension to closed-loop adaptive EDM control where process monitoring (gap voltage signals, discharge frequency) triggers real-time parameter adjustment using the HEL framework's rapid prediction capabilities [14].

4. Transfer Learning Across Materials: Developing transfer learning strategies to adapt trained models from one workpiece-electrode material combination to another could dramatically reduce experimental requirements for new material systems while leveraging accumulated process knowledge [11].

5. Integration with Digital Twin: Embedding the HEL framework within digital twin architectures for comprehensive EDM process simulation, monitoring, and optimization aligned with Industry 4.0 smart manufacturing initiatives [14].

6. Extended Multi-Objective Formulation: Future work should explore including additional objectives such as machining time, energy consumption, and environmental impact (dielectric consumption, electrode waste) for sustainability-conscious EDM optimization [13].

5.4 Concluding Remarks

The proposed Hybrid Ensemble Learning framework successfully addresses critical gaps in EDM parameter optimization through integrated adaptive feature selection, dynamic ensemble weighting, comprehensive uncertainty quantification, and effective multi-objective optimization. The superior predictive performance, computational efficiency, and practical uncertainty awareness make this framework suitable

for industrial deployment, advancing the state-of-the-art in intelligent manufacturing process optimization. By providing manufacturers with diverse Pareto-optimal parameter sets and confidence intervals, the framework enables informed, risk-aware decision making that balances productivity, tool life, and surface quality according to application-specific priorities—a significant advance over conventional single-objective deterministic optimization approaches.

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