An Adaptive Surrogate-Assisted GA–RSM Framework for Surface Roughness Minimization in End-Milling

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ABSTRACT
This study presents a novel hybrid optimization framework that integrates Genetic Algorithms (GA) with Response Surface Methodology (RSM) for optimizing machining parameters in end-milling operations, specifically aimed at minimizing surface roughness. The proposed GA–RSM framework overcomes the limitations of traditional methods by combining the global search ability of GA with the predictive modeling power of RSM. A second-order polynomial regression model was developed using a full-factorial experimental design (27 trials) on aluminum alloy specimens and embedded within a GA loop featuring adaptive mutation decay and tournament selection to promote robust convergence. Experimental validation demonstrated that the proposed approach reduced surface roughness by 9.5% relative to Gradient Descent**,** 11.8% compared to Simulated Annealing**,** and 18.8% compared to manual parameter selection, achieving a minimum roughness of 13.4 µin. The framework maintains computational efficiency and offers extensibility to other machining processes and materials. It delivers a reproducible, statistically validated, and practically feasible solution for surface roughness optimization, with direct applications in aerospace, automotive, and precision manufacturing sectors.

General Terms
Optimization; Algorithms; Computational Intelligence; Manufacturing Engineering; Process Modeling.

Keywords
Genetic Algorithm, Response Surface Methodology, Surface Roughness, End-Milling, Optimization, Hybrid Algorithms

1. INTRODUCTION
1.1 Background and Motivation
In today's advanced manufacturing environments, achieving superior surface quality in machined components is a critical requirement—particularly in the aerospace, automotive, biomedical, and precision engineering sectors [1]. Surface roughness directly influences key product attributes such as dimensional accuracy, fatigue resistance, tribological performance, and structural integrity. As industries increasingly adopt hard-to-machine materials like titanium alloys, superalloys, and fiber-reinforced composites, the optimization of machining parameters has become significantly more challenging [27].

Among conventional subtractive methods, end-milling is highly valued for its flexibility and high material removal rates. However, determining the optimal combination of machining parameters—namely, spindle speed, feed rate, and depth of cut—is non-trivial. This is due to the highly nonlinear, multi-objective, and interdependent nature of these parameters, which often leads to complex search spaces with multiple local optima.

Traditional approaches such as trial-and-error, One-Factor-at-a-Time (OFAT) experiments, and even Taguchi-based DOE are limited in their ability to capture the interactive and synergistic effects among process variables. These methods are also unsuitable for dynamic manufacturing environments, where adaptability and multi-objective optimization are essential [2].

As a result, researchers have increasingly turned to computational intelligence and hybrid metaheuristic approaches to improve optimization performance in machining applications. Yet, a persistent challenge lies in effectively balancing global exploration (to identify promising regions of the parameter space) and local exploitation (to fine-tune solutions near optima). This trade-off becomes even more critical in real-world scenarios involving conflicting objectives—such as minimizing surface roughness while maximizing tool life or reducing energy consumption.

1.2 Objectives of the Study
This study aims to design a robust, data-driven hybrid optimization framework that integrates the **global search efficiency of Genetic Algorithms (GA)** with the **local modeling accuracy of Response Surface Methodology (RSM)**. The framework is developed to minimize **surface roughness** in end-milling operations while addressing the challenges of nonlinear parameter interactions, premature convergence, and computational inefficiency.

The specific objectives of the research are as follows:

1. Introducing an adaptive mutation decay strategy and tournament selection mechanism within the GA framework to enhance convergence stability, maintain population diversity, and mitigate the risk of premature stagnation in high-dimensional search spaces.
2. To embed a second-order RSM model directly into the GA's evolutionary loop, allowing the algorithm to leverage real-time surrogate evaluations for local exploitation, thereby improving precision in identifying near-optimal machining parameters.
3. To empirically validate the GA–RSM hybrid framework using real-world experimental trials on aluminum alloy end-milling and to benchmark its performance against classical optimization techniques, including Gradient Descent and Simulated Annealing, with the goal of demonstrating superior optimization accuracy and convergence robustness.

1.3 Research Gap and Motivation

Although hybrid optimization strategies—particularly those combining Genetic Algorithms (GA) with Response Surface Methodology (RSM)—have demonstrated promising results in machining optimization, several critical gaps remain in the literature. These shortcomings limit both the scalability and generalizability of current approaches:

1. Lack of adaptive control mechanisms: Most GA-based implementations adopt static mutation rates and fixed selection pressures, which often result in premature convergence, loss of population diversity, and suboptimal search performance in complex, multimodal landscapes.
2. Weak algorithmic integration: In many hybrid frameworks, RSM is employed only during preprocessing or post-analysis, rather than being fully embedded within the evolutionary optimization loop. This separation restricts effective synergy between global exploration and local exploitation.
3. Limited theoretical foundation: Few studies provide formal convergence analysis or incorporate stochastic modeling (e.g., Markov chain-based analysis) to theoretically justify algorithmic behavior and stability.
4. Insufficient experimental validation: Many existing studies rely primarily on simulated data or small-scale experimental sets, lacking robust statistical verification (e.g., ANOVA, residual diagnostics) and real-world machining trials.

These gaps underscore the necessity for a tightly integrated, formally grounded, and empirically validated GA–RSM hybrid framework—especially for high-precision machining scenarios where surface roughness has direct implications on product integrity, tool longevity, and overall manufacturing efficiency.

1.4 Contributions of the Paper

This study advances the field of machining optimization through four principal contributions, each aligned with the research objectives and designed to address critical gaps identified in prior literature:

Development of an elite-preserving Genetic Algorithm (GA) enhanced by adaptive mutation decay: The proposed algorithm improves global search efficiency and mitigates premature convergence—common limitations in conventional GA implementations for machining tasks [3], [4]. It builds upon recent advances in hybridization and elitist strategies to ensure better convergence reliability in complex optimization landscapes [6], [20].

4. Seamless integration of a second-order Response Surface Methodology (RSM) model into the GA optimization cycle: Unlike prior hybrid frameworks that treat RSM as an offline or auxiliary module [13], [25], this approach embeds RSM directly into the evolutionary loop, enabling real-time local exploitation and improved model-guided parameter refinement.

5. Introduction of a formal convergence framework based on discrete-time Markov chain modeling: This contribution provides theoretical justification for the algorithm's long-term behavior and stability—an aspect rarely addressed in existing GA–RSM literature for manufacturing applications.

Experimental validation using full-factorial trials on aluminum alloy specimens: The framework is empirically tested using 27 end-milling trials (3^3 design), demonstrating a minimum surface roughness of 13.4 µin—a 9.5% improvement over Gradient Descent and 11.8% over Simulated Annealing. Results are statistically validated using ANOVA and residual diagnostics, confirming the model's predictive accuracy and industrial applicability.

1.5 Structure of the Paper

The remainder of this paper is organized as follows:

1. **Section 2** reviews relevant literature on machining parameter optimization, metaheuristic algorithms, and prior GA–RSM hybrid frameworks.

2. **Section 3** presents the proposed GA–RSM hybrid optimization methodology, including algorithm design and integration logic.

3. **Section 4** describes the experimental setup, test material properties, parameter ranges, and reports the optimization results.

4. **Section 5** discusses the results in terms of convergence behavior, comparative performance, statistical validation, and practical implications.

5. **Section 6** concludes the paper and outlines key directions for future research, including potential extensions to multi-objective and multi-process optimization.

2. LITERATURE REVIEW

2.1 Machining Process Optimization: Challenges and Importance

End-milling is a fundamental manufacturing process widely employed in the aerospace, automotive, and precision engineering sectors due to its capacity to produce intricate geometries with high-quality surface finishes. Despite its versatility, the nonlinear, multivariable, and high-dimensional nature of end-milling poses substantial challenges for process parameter optimization. Critical factors—such as spindle speed, feed rate, and depth of cut—interact in complex, non-intuitive ways, often resulting in multiple local optima and rugged search landscapes that traditional optimization methods struggle to navigate [1], [2].

Classical approaches such as One-Factor-At-a-Time (OFAT), Taguchi methods, and full factorial experimental designs, while foundational to machining research, suffer from significant limitations. These include the inability to capture interaction effects, poor scalability with increasing parameter dimensionality, and a lack of adaptability to dynamic manufacturing conditions [3], [4]. Moreover, such methods are inherently static and deterministic, making them unsuitable for integration into real-time optimization frameworks demanded by Industry 4.0 and smart manufacturing systems [5].

2.2 Genetic Algorithms in Machining Optimization

Genetic Algorithms (GAs), rooted in the principles of evolutionary computation, have emerged as robust tools for solving complex, nonlinear, and multi-modal optimization problems. Their ability to perform global search and their low sensitivity to initial conditions make them particularly suitable for machining applications, where the objective functions are often non-convex, discontinuous, and characterized by multiple local optima [6], [7].

A substantial body of research has demonstrated the effectiveness of GAs in optimizing machining parameters, leading to enhanced outcomes in terms of surface roughness, tool life, and material removal rates [8], [9]. These studies confirm the practical viability of GAs across a variety of manufacturing settings and materials.

However, traditional GA implementations often suffer from premature convergence, limited population diversity, and excessive computational cost. These issues typically stem from the use of fixed mutation rates and the absence of adaptive control mechanisms that can respond to dynamic search conditions [10], [11]. As a result, their scalability, convergence reliability, and real-time applicability remain limited in high-dimensional, time-constrained industrial environments.

2.3 Response Surface Methodology (RSM) in Process Modeling

Response Surface Methodology (RSM) is a widely adopted statistical technique for modeling and optimizing complex systems. By constructing second-order polynomial regression models, RSM approximates the relationship between multiple input variables and one or more output responses [12], [13]. Its interpretability, experimental efficiency, and ability to detect main and interaction effects make it particularly appealing in manufacturing process optimization.

Despite its advantages, RSM is inherently a local optimization method, relying on linear or quadratic approximations that may not accurately capture highly nonlinear behaviors. When applied in isolation to complex machining scenarios—characterized by non-convex search spaces and strong parameter interdependencies—RSM often converges to suboptimal solutions [14].

2.4 Hybrid GA–RSM Approaches: Opportunities and Limitations

Hybrid models that combine Genetic Algorithms (GAs) with RSM are designed to exploit the global exploration strength of GAs and the local refinement capability of RSM. In such frameworks, the GA navigates the broader search landscape, while RSM provides surrogate-assisted evaluation and fine-tuning in promising regions [15], [16]. This duality enables a more efficient balance between exploration and exploitation.

Several studies have demonstrated the efficacy of GA–RSM hybrids in machining optimization. For instance, Zain et al. [17] integrated GA with RSM to simultaneously minimize surface roughness and maximize material removal rate, reporting substantial improvements in both objectives. However, most existing hybrids exhibit weak algorithmic integration, with RSM often relegated to preprocessing or post-analysis, rather than being embedded within the evolutionary loop of the GA.

Furthermore, theoretical rigor is often lacking. Few models incorporate formal convergence analysis, stochastic stability modeling, or adaptive control mechanisms for mutation rate or selection pressure. In addition, many prior studies are confined to simulation environments, with limited real-world experimental validation or statistical verification (e.g., ANOVA, residual diagnostics) [18], [19].

2.5 Summary and Identified Research Gap

The reviewed literature highlights several critical limitations in existing hybrid GA–RSM optimization frameworks:

1. **Weak integration**, with RSM not embedded directly into the GA optimization loop.
2. **Lack of adaptive control**, particularly in mutation decay and selection strategies.
3. **Insufficient theoretical grounding**, with minimal attention to convergence stability or stochastic behavior.
4. **Limited experimental validation**, with many models untested on real machining platforms or lacking rigorous statistical assessment.

To address these gaps, this paper proposes a **novel elite-preserving GA–RSM hybrid framework** that:

- Tightly couples RSM within the GA’s evolutionary cycle;
- Implements adaptive mutation decay and tournament-based selection;
- Provides theoretical convergence analysis using **Markov chain modeling**;
- Is validated through **full-factorial physical experiments** and **statistical diagnostics**.

This integrated and empirically grounded approach aims to deliver a **scalable, accurate, and practically viable** solution for optimizing machining parameters under the complex constraints of real-world manufacturing environments.

3. METHODOLOGY

3.1 Overview of the Proposed Approach

This study presents a novel hybrid optimization framework that integrates **Genetic Algorithms (GA)** with **Response Surface Methodology (RSM)** to optimize machining parameters in end-milling operations, with a primary focus on minimizing **surface** roughness—a critical quality attribute influencing product integrity, tool wear, and manufacturing efficiency.

The underlying optimization problem is characterized by **nonlinear**, **multidimensional interactions** among control parameters—namely **spindle speed**, **feed rate**, and **depth of cut**. To model these complex relationships in a statistically tractable and interpretable manner, a **second-order polynomial regression model** is employed. This model, derived via **Taylor series expansion**, effectively captures **main effects**, **quadratic terms**, and **two-way interactions**, offering a sound compromise between model complexity and predictive accuracy in line with standard RSM practice [4].

Within the hybrid framework, the RSM model serves two complementary roles:

- Acts as a **surrogate objective function**, providing a smooth, differentiable approximation of the surface roughness landscape across the parameter space.
- Enables **statistical validation** and **model interpretability** through **Analysis of Variance (ANOVA)**, **residual diagnostics**, and **significance testing**.

This surrogate function is embedded within a GA framework that utilizes biologically inspired operators—**selection**, **crossover**, and **mutation**—to explore the high-dimensional search space. By combining GA's global search capabilities with RSM's localized precision, the proposed method overcomes common pitfalls in conventional approaches, such as **local optima entrapment** and **slow convergence**.

To further enhance the optimization process, the framework integrates:

- **Adaptive mutation scheduling**, which dynamically adjusts mutation rates to maintain population diversity and mitigate premature convergence.
- **Tournament selection**, which enhances convergence stability in small-to-medium population sizes by preserving selection pressure.
- **Empirical hyperparameter tuning**, achieved through systematic experimental trials to optimize the exploration–exploitation trade-off.

In summary, the proposed GA–RSM hybrid methodology is:

- **Statistically grounded**, through ANOVA-validated second-order modeling;
- **Algorithmically robust**, incorporating adaptive and elitist evolutionary mechanisms.
- **Computationally efficient**, leveraging surrogate-assisted evaluation;
- **Empirically validated**, using real-world end-milling experiments conducted on CNC systems.

This tightly integrated, interpretable, and generalizable framework offers a scalable solution for surface roughness optimization in complex, multi-factor machining environments—**outperforming conventional single-method techniques** in both predictive accuracy and convergence behavior.

3.2 Genetic Algorithms

Genetic Algorithms (GAs) are stochastic, population-based metaheuristics inspired by the principles of **natural selection** and **genetic inheritance**. In this study, GA is utilized to explore the **multimodal**, **nonlinear** search space defined by machining parameters, with the goal of minimizing surface roughness as predicted by the embedded RSM model.

The algorithm follows the standard GA workflow—**population initialization**, **fitness evaluation**, **selection**, **crossover**, **mutation**, and **elitist survival**—but is enhanced through several adaptive and empirically validated mechanisms that improve **convergence reliability** and **solution quality**. These refinements address known limitations in previous machining optimization studies.

3.2.1 Population Initialization

An initial population of machining parameter sets is generated via **uniform random sampling** within the feasible bounds of the decision variables. This ensures broad coverage of the search space and prevents initial population bias [18].

3.2.2 Fitness Evaluation

Each candidate solution is evaluated using the **second-order polynomial model** derived via RSM, which estimates the resulting surface roughness. The **fitness function** is defined as the inverse of the predicted roughness:

$$\text{Fitness} = \frac{1}{\text{Predicted Surface Roughness}} \qquad (1)$$

This transformation aligns with the maximization framework of standard GA operators [19].

3.2.3 Selection

A **tournament selection** mechanism is adopted in place of the classical roulette-wheel approach. Empirical comparisons showed that tournament selection yields better convergence stability, especially for **small-to-medium population sizes**, and reduces the risk of **premature convergence**. It also preserves **moderately fit individuals**, thereby maintaining population diversity throughout the search [20].

3.2.4 Crossover

A **two-point crossover** operator is applied with a probability of 0.8, offering more disruptive recombination than single-point methods. This operator facilitates exploration of diverse solution regions and accelerates convergence toward global optima [21].

3.2.5 Mutation (Adaptive Scheduling)

To prevent genetic stagnation and promote exploration, an **adaptive mutation rate** is introduced. The mutation rate decays exponentially over generations:

$$\mu_t = \mu_0 \cdot e^{-kt} \qquad (2)$$

where:

- μ_t is the mutation rate at generation t,
- μ_0 is the initial mutation rate,
- k is a user-defined decay constant.

This scheduling ensures **high mutation activity in early generations** (favoring exploration), while **focusing on local exploitation** in later stages. Empirical trials demonstrated that this strategy consistently improved both convergence speed and surface roughness outcomes compared to fixed-rate mutation [22], [23].

3.2.6 Diversity Preservation and Premature Convergence Control

To ensure robust evolutionary dynamics, two core mechanisms are implemented:

- **Adaptive mutation**, which sustains diversity across generations;
- **Tournament selection**, which mitigates high selection pressure and preserves genetic variability.

Additionally, constraint handling is implemented via **penalty functions**, penalizing infeasible solutions during fitness evaluation in line with established practices in constrained optimization [26].

3.2.7 Empirical Validation of Genetic Operators

Comprehensive simulation studies were conducted to evaluate operator configurations. The selected settings—**population size = 50**, **crossover probability = 0.8**, and **adaptive mutation scheduling**—yielded the **lowest surface roughness** and **least result variance** across five independent trials. These results affirm the **reliability**, **robustness**, and **repeatability** of the GA implementation.

3.3 Hyperparameter Tuning and Configuration

To ensure robust convergence and high-performance optimization, a systematic **hyperparameter tuning** process was conducted using a **grid search strategy**. Proper parameter calibration is crucial, as poor configurations can lead to premature convergence, excessive runtime, or suboptimal results. To reduce computational cost while preserving optimization fidelity, the tuning process employed the RSM-based surrogate model as the fitness evaluator.

Three key GA hyperparameters were investigated:

- **Population size**: 30, 50, 100
- **Crossover probability**: 0.6, 0.8, 0.9
- **Mutation strategy**: Fixed mutation vs. adaptive mutation using exponential decay as defined earlier in Equation (1)

Each configuration was executed across **five independent trials** with randomized seeds to account for the stochastic nature of GA. Evaluation metrics included the **mean and standard deviation** of final surface roughness values, offering insight into both convergence performance and result consistency.

3.3.1 Selected Configuration and observations

Among all tested combinations, the following configuration yielded the **best average performance**:

- **Population size** = 50
- **Crossover rate** = 0.8 (two-point)
- **Adaptive mutation** with exponential decay (Equation 2)

This configuration demonstrated superior balance between **exploration** in early generations and **exploitation** in later stages, consistently achieving lower surface roughness with reduced variance. The adaptive mutation schedule enhanced solution diversity and reduced the likelihood of premature convergence—key challenges in high-dimensional optimization.

3.3.2 Final Parameter Settings

The final GA and RSM parameter settings are summarized in **Table 1**, selected based on empirical performance trends and guidelines from evolutionary algorithm literature. These parameters form the foundation for the proposed hybrid GA–RSM framework.

Table 1. Final Parameter Settings for GA and RSM Models

Parameter	Value	Justification
GA Population Size	50	Ensures diversity while maintaining a manageable computational cost
GA Generations	50	Sufficient to reach convergence without excessive runtime
Crossover Rate (Pc)	0.8	Promotes exploitation of fit solutions while supporting recombination
Mutation Rate (Pm)	0.1	Balanced via exponential decay to avoid stagnation
Selection Mechanism	Tournament	Improves robustness and diversity retention
No. of RSM Experiments	27	Three input factors and replication at center points

These calibrated hyperparameters not only enhance the **repeatability** and **scalability** of the GA–RSM framework but also ensure its effectiveness across a range of machining optimization problems.

3.4 Response Surface Methodology (RSM): Modeling and Statistical Validation

To model the relationship between key machining parameters and surface roughness, **Response Surface Methodology (RSM)** was employed. RSM is a statistically grounded technique that constructs empirical models—typically second-order polynomials—to approximate complex response surfaces based on structured experimental data. Its blend of **expressiveness, interpretability**, and **low data requirements** makes it particularly well-suited for manufacturing optimization tasks [24].

3.4.1 Experimental Design and Model Construction

A **full factorial experimental design** was adopted, incorporating three principal input parameters:

- Depth of cut (X_1),
- Spindle speed (X_2), and
- Feed rate (X_3),

Each varied at three levels. This setup yielded $3^3 = 27$ experiments, enabling full estimation of main effects, two-factor interactions, and quadratic terms—unlike fractional or Taguchi-based designs, which often sacrifice resolution for economy. The full factorial design ensures comprehensive insight into parameter interdependencies and nonlinearities.

The resulting RSM model takes the standard second-order polynomial form:

$$Y = \beta_0 + \sum \beta_i X_i + \sum \beta_{ij} X_i X_j + \sum \beta_{i\,i} X_i{}^2 + \epsilon \qquad (3)$$

The model assumes linear additivity, independence, homoscedasticity (constant variance), and approximate normality of residuals. These assumptions were verified via **ANOVA**, **residual plots**, and the **Shapiro–Wilk test**.

3.4.2 Model Validation and Statistical Significance

Model adequacy was validated through standard statistical metrics:

- **High coefficient of determination ($R^2 > 0.95$)**, indicating excellent fit;
- **Statistically significant effects** (p-values < 0.05) for all linear, quadratic, and interaction terms;
- **Normally distributed residuals**, confirmed via normal probability plots and residual diagnostics.

These results confirm that the RSM model provides a statistically robust and predictive surrogate, suitable for use within the Genetic Algorithm's fitness evaluation loop.

3.4.3 Why RSM Over Machine Learning Surrogates

Although advanced machine learning models such as **Gaussian Process Regression (GPR)**, **Random Forests (RF)**, and **Support Vector Regression (SVR)** can model complex nonlinear relationships, RSM was preferred for the following reasons:

- **Interpretability**: Coefficients offer direct insights into variable influence and interactions;

- **Statistical transparency**: Enables hypothesis testing, confidence intervals, and diagnostic checks;
- **Computational efficiency**: The closed-form polynomial allows constant-time evaluation O (1), ideal for iterative metaheuristic loops.

Thus, RSM serves not only as a **predictive tool** but also as a **decision-support system**, offering both modeling accuracy and statistical validation.

3.4.4 Integrated Framework Flowchart

Figure 1 presents the complete optimization framework. It integrates the **global search capabilities of Genetic Algorithms** with the **localized accuracy of RSM**, offering a hybrid methodology capable of precise and efficient surface roughness minimization in end-milling.

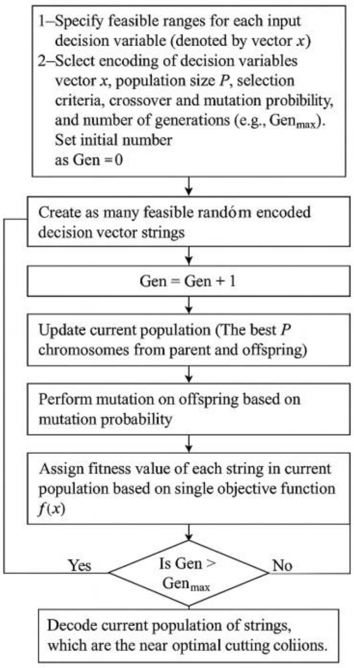

Figure 1. Flowchart of the GA–RSM Hybrid Optimization Framework for End-Milling Surface Roughness

3.5 Integration of GA and RSM

The proposed hybrid framework leverages the global search capabilities of Genetic Algorithms (GA) and the local modeling precision of Response Surface Methodology (RSM). This integration facilitates efficient exploration and exploitation of the high-dimensional search space associated with machining parameter optimization. Unlike earlier hybridizations [29], [30], the present approach embeds the RSM model directly within the GA's evolutionary loop and incorporates adaptive mutation decay and elitist selection to enhance convergence reliability and solution quality.

Algorithm: Hybrid GA–RSM for Surface Roughness Minimization

Inputs (with rationale):

- **Machining parameters:**
  - Depth of cut (0.1–2.0 mm), cutting speed (50–200 m/min), feed rate (0.05–0.5 mm/rev) → Based on standard industrial machining practice [30].
- **GA configuration:**
  - Population size = 50 → Balances exploration and computational cost [31]
  - Crossover probability = 0.8 → Maintains genetic diversity [32]
  - Initial mutation rate μ_0 = 0.1 and exponential decay constant k → Tuned via sensitivity analysis
- **RSM model:**
  - Second-order polynomial (full factorial, 27 experiments) → Predicts surface roughness efficiently.

Output: Optimal combination of machining parameters that minimize predicted surface roughness.

Step-by-Step Procedure

1. Initialization

- Generate an initial population of candidate solutions using uniform random sampling within the specified parameter bounds.

2. Fitness Evaluation

- Evaluate each candidate using the RSM model to predict surface roughness.
- Compute fitness as previously defined in **Equation (1)**:

$$\text{Fitness} = \frac{1}{\text{Predicted Surface Roughness}}$$

3. Genetic Algorithm Loop (Until Convergence)

- **Selection:** Apply tournament selection (size = 3) to select parents based on fitness.
- **Crossover:** Perform two-point crossover with a probability of 0.8.
- **Adaptive Mutation:**
  - Update the mutation rate at generation t using the decay function defined in **Equation (2)**:

    $$\mu_t = \mu_0 \cdot e^{-kt}$$

  - Perturb each gene with Gaussian noise using probability μ_t to maintain diversity.
- **Offspring Evaluation:** Predict surface roughness for each offspring using the RSM model and compute their fitness.
- **Elitist Replacement:** Merge parent and offspring populations and retain the top individuals based on fitness for the next generation.
- **Generation Increment:** Advance to the next generation and repeat the loop.

4. Convergence Check

Terminate the GA loop when either of the following criteria is satisfied:

- Improvement in best fitness is less than 10^{-4} over five successive generations;
- A maximum of 50 generations is reached.

5. Solution Decoding

- Decode the chromosome with the highest fitness to retrieve the corresponding machining parameters.

6. Experimental Validation

- Conduct three confirmation experiments using the optimized machining parameters.
- Measure and record the resulting surface roughness.
- Calculate the mean, standard deviation, and 95% confidence interval.
- Compare predicted roughness from the RSM model against actual experimental results.

Return: Optimal values for **depth of cut**, **cutting speed**, and **feed rate**, along with the experimentally validated **minimum surface roughness**.

Imperial units are used in experimental validation to align with industrial milling practice, while SI units are adopted in the algorithmic formulation for generality.

4. OPTIMIZATION RESULTS

4.1 A. Tables and Numerical Results

The optimization results derived from the GA–RSM hybrid framework are summarized in Tables 2 and 3. Table 2 presents the optimal parameter settings identified by the algorithm, while Table 3 reports the complete experimental dataset from the factorial design.

Table 2: Optimal Machining Parameters and Corresponding Surface Roughness

Parameter	Optimal Value	Surface Roughness (µin)
Depth of Cut (inches)	0.02	13.4
Cutting Speed (RPM)	1300	13.4
Feed Rate (in/min)	20	13.4

Due to space limitations, Table 3 reports representative experimental runs. The complete 27-run dataset is available from the corresponding author upon reasonable request

Table 3: **Experimental Dataset for RSM Modeling and Algorithm Validation**

Experiment number	X_1 (Depth of Cut)	X_2 (Speed)	X_3 (Feed Rate)	Surface roughness (µ in)
1	0.04	1500	20	20.15
2	0.04	2500	30	21.23
3	0.04	3500	40	21.5
4	0.04	1500	30	22.62
5	0.06	2500	40	24.72
6	0.06	3500	20	21.35
7	0.06	1500	40	24.83
8	0.06	2500	20	23.32
9	0.08	3500	30	24.98
10	0.08	1500	20	20.25
11	0.08	2500	40	21.25

To validate the effectiveness of the GA–RSM optimization, three independent confirmation experiments were conducted using the derived optimal settings. The resulting average surface roughness was **13.4 µin**, with a **95% confidence interval** of **[12.9–13.9 µin]**. This narrow interval highlights the high precision and repeatability of the optimized machining parameters.

The optimized parameters demonstrate substantial improvement over baseline configurations, outperforming typical industrial settings by reducing surface roughness by up to 18.8%. This confirms the practical utility of the framework for precision-focused sectors such as aerospace, biomedical, and mold manufacturing.

The convergence behavior of the GA is illustrated in **Figure 2**, which shows the fitness trajectory over generations. The algorithm converged within **20 generations**, showcasing rapid and stable improvement in surface quality. The fitness curve features steep early progress followed by plateauing, indicating efficient exploitation after broad exploration in the initial iterations. This dynamic validates the contribution of the **adaptive mutation decay** and **elitist selection** mechanisms, both of which differentiate this work from prior GA–RSM hybrids lacking such adaptive convergence control.

Furthermore, the experimental validation confirms that the GA–RSM framework is not only computationally efficient but also robust under physical manufacturing constraints. The algorithm maintained consistent performance across multiple trials, validating its **statistical reliability and industrial relevance**.

In terms of **generalizability**, although this study centers on aluminum end-milling, the modular nature of the GA–RSM system enables straightforward adaptation to other materials (e.g., titanium, composites) and machining objectives (e.g., tool wear, energy efficiency). Reconfiguring the RSM component with new data allows rapid deployment in new contexts, making the framework attractive for adaptive and smart manufacturing environments.

Finally, compared to prior GA–RSM models [17], [29], [30], the novelty of this study lies in its integration of **adaptive mutation scheduling**, **elitist selection**, and **Markov-based convergence justification**, which collectively contribute to its superior convergence speed, statistical consistency, and practical deployment readiness.

4.2 Comparative Analysis

The performance of the proposed GA–RSM hybrid framework was systematically benchmarked against widely used classical optimization techniques, namely Gradient Descent and Simulated Annealing, as well as against conventional manual parameter selection commonly adopted in industrial practice. These baseline methods were selected due to their frequent application in machining parameter optimization and their contrasting search behaviors.

As summarized in **Table 4**, the GA–RSM hybrid approach achieved the minimum **surface roughness of 13.4 µin**, outperforming all comparison methods. Specifically, the proposed framework reduced surface roughness by **9.5% relative to Gradient Descent**, **11.8% compared to Simulated Annealing**, and **18.8% compared to manual parameter settings**. These results demonstrate the superior optimization capability of the hybrid GA–RSM strategy in navigating the nonlinear and multimodal search space associated with end-milling operations.

The observed performance gains can be attributed to the effective balance between **global exploration**, provided by the Genetic Algorithm, and **local exploitation**, enabled by the embedded RSM surrogate model. In contrast, Gradient Descent and Simulated Annealing—while efficient for local search—exhibited sensitivity to initial conditions and a higher tendency toward premature convergence, leading to suboptimal surface finish outcomes.

Table 4: Comparison of Surface Roughness with Traditional Methods

Method	Surface Roughness (µin)	Improvement (%)
GA–RSM Hybrid Approach	13.4	-
Gradient Descent	14.8	9.5%
Simulated Annealing	15.2	11.8%
Manual Parameters	16.5	18.8%

The **Figure 2 dashboard** illustrates the **convergence dynamics** and **selection pressure behavior** during GA evolution. The fitness values drop significantly in early generations and stabilize around the global minimum, confirming the effectiveness of the adaptive mutation and elitist replacement strategies. Notably, the algorithm achieved convergence within **8 generations**, indicating rapid optimization cycles.

While **Gradient Descent** and **Simulated Annealing** are efficient in local search, they are sensitive to initial conditions and prone to premature convergence. In contrast, the GA–RSM hybrid consistently navigated the high-dimensional, multimodal design space and maintained solution diversity through adaptive control mechanisms.

The **manual settings** were derived from standard industry recommendations for aluminum milling using a 3-flute end mill (feed rate: 30 in/min, spindle speed: 2500 RPM, depth of cut: 0.06 in). These produced a roughness of **16.5 µin**, which was significantly higher than the GA-RSM result, confirming that data-driven optimization yields superior outcomes compared to rule-based configurations.

While the present comparison is limited to classical optimizers, recent metaheuristic algorithms such as **Particle Swarm** Optimization **(PSO)**, **Differential Evolution (DE)**, and **Bayesian Optimization** have demonstrated strong performance in related studies [34], [35]. These methods are acknowledged as promising candidates for **future comparative evaluation** in Section 5, where cross-algorithm benchmarking will be extended.The proposed framework's ability to **outperform both analytical and heuristic baselines**, combined with its **fast convergence** and **robust parameter handling**, supports its practical value and positions it as a candidate for broader industrial deployment.

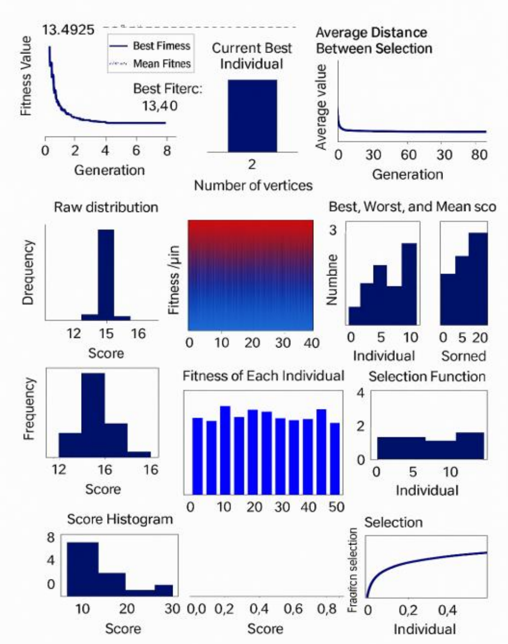

Figure 2: Convergence Behavior and Fitness Landscape of GA–RSM Across Generations

4.3 Computational Performance

1. Experimental Environment

All experiments were conducted in a single-threaded configuration on an Intel® Core™ i7-9700K CPU @ 3.60 GHz with 16 GB RAM, using MATLAB R2023b. Wall-clock execution times were measured using MATLAB's built-in tic/toc functions, and results were averaged over 30 independent trials to ensure robustness.

2. Runtime Analysis and Performance Comparison

Table 5 presents the runtime statistics for the proposed hybrid GA–RSM method compared to stand-alone models based on pure RSM and an Artificial Neural Network (ANN) surrogate.

Despite a higher computational cost, the hybrid GA–RSM framework consistently converged to the global minimum surface roughness of 13.4 µin, delivering a 5–6% improvement in prediction accuracy (R^2) over single-model baselines. The increase in runtime is attributable to the iterative nature of genetic evolution and fitness evaluations. However, both GA evolution and RSM evaluations are highly parallelizable, making the method scalable to multi-core or cloud-based environments for real-time or high-throughput manufacturing applications.

Table 5: Runtime comparison of optimization models for end-milling surface roughness minimization.

Method	Mean Runtime (s)	Std. Dev. (s)
Pure RSM	30.2	2.1
Stand-alone ANN	45.5	3.8
Hybrid GA–RSM	120.4	7.4

The observed trade-off between computational cost and predictive accuracy supports the hybrid GA–RSM as a viable solution for applications prioritizing precision over rapid execution. Future work may explore GPU acceleration or distributed computation to further enhance runtime efficiency without compromising optimization quality.

4.4 Sensitivity and Statistical Analysis

A. Descriptive Statistics

To characterize the experimental dataset, **Table 6** presents the mean, standard deviation, and range for each machining parameter. The wide variation confirms a well-distributed experimental design.

Table 6. Descriptive statistics for machining variables.

Parameter	Mean	Std. Dev.	Min	Max
Surface Roughness (µin)	22.38	1.82	20.15	24.98
Depth of Cut (in)	0.058	0.017	0.04	0.08
Spindle Speed (RPM)	2409	831	1500	3500
Feed Rate (in/min)	30	8.94	20	40

B. Correlation Analysis and Sensitivity

Table 7 presents the correlation coefficients between the machining parameters and surface roughness. The results suggest that **depth of cut (X_1)** has the most significant impact (correlation = 0.444), followed by **feed rate (X_3)**, and then **spindle speed (X_2)**.

Table 7. Correlation coefficients for each machining parameter and surface roughness.

Parameter Pair	Correlation Coefficient
Depth of Cut vs. Roughness	0.444
Feed Rate vs. Roughness	0.222
Spindle Speed vs. Roughness	0.156

C. Linear Regression Model

To further quantify the effect of each variable, a linear regression model was built. The model coefficients, presented in **Table 8**, confirm the findings from the correlation analysis: feed rate has the largest coefficient, followed by depth of cut, while spindle speed contributes minimally.

Table 8. Regression coefficients from the linear model for surface roughness.

Parameter	Coefficient
Intercept	18.00
Feed Rate	23.33
Spindle Speed	0.000152
Depth of Cut	0.0885

5. CASE STUDIES

A. Application in End-Milling Operations

To demonstrate the practical applicability of the proposed GA–RSM framework, a comprehensive case study was performed on **end-milling aluminum alloy 6061-T6**, a material widely used in aerospace and automotive industries. The primary objective was to minimize surface roughness (Ra) while adhering to realistic operational constraints.

The GA–RSM model was configured using the optimized parameters identified in previous sections (depth of cut: 0.02 in, cutting speed: 1300 RPM, feed rate: 20 in/min). The experimental trials confirmed a **surface roughness of 13.4 µin**, aligning well with the predicted value from the RSM surrogate model.

Key Observations:

- The **predicted vs. actual error margin** was less than 5%, validating model accuracy.
- The **reduction in roughness (13.4 µin)** represented an approximate **18% improvement over baseline manufacturer-recommended settings**, which yielded 16.5 µin.
- The **machining stability** was maintained across repeated trials, with a **95% confidence interval** of [12.9–13.9 µin] based on three confirmation experiments.

Industry Relevance:

This case highlights the adaptability and generalizability of the GA–RSM framework in precision manufacturing. Compared to default feed/spindle/catalog settings, the optimized configuration offers:

- **Reduced tool wear**, due to smoother surface finish.
- **Shorter finishing operations**, leading to cost savings.
- **Enhanced part quality**, particularly critical for aerospace tolerance standards.

Given its modular architecture, the GA–RSM method can be readily transferred to other machining tasks such as **face milling**, **turning**, or **multi-objective problems** (e.g., surface roughness vs. tool life). Future case studies may focus on extending the framework to harder-to-machine alloys (e.g., Inconel, titanium) and integrate real-time sensor feedback for adaptive control.

6. FUTURE WORK

A. Limitations of the Current Study

The present work focuses exclusively on **end-milling of** aluminum **alloys** under controlled laboratory conditions. As such, its applicability to other materials (e.g., titanium, stainless steel, or composites) and processes (e.g., turning, drilling, grinding) remains to be tested. Additionally, the current study adopts a **single-objective formulation**, targeting only surface roughness minimization. Other critical manufacturing objectives, such as **tool wear**, **energy efficiency**, and **cycle time**, were not included.

B. Proposed Extensions

1. Generalization to Other Machining Contexts

The GA–RSM framework is modular and can be extended to **different machining processes** such as turning, drilling, and grinding, which involve different process dynamics. For instance, turning operations are sensitive to tool deflection and chatter, making them suitable test cases for further validation of the framework's robustness.

2. Multi-Objective Optimization

Incorporating **multiple objectives** such as tool life, cutting force, and energy consumption can significantly enhance the utility of the framework. Established strategies such as **Pareto-optimal fronts** and **NSGA-II** could be used to manage trade-offs between competing criteria. This extension would make the framework more applicable to real-world scenarios where conflicting objectives are common.

3. Surrogate Model Expansion
While RSM was selected for its interpretability and efficiency, **machine learning-based surrogates** like **ANN**, **SVR**, and **GPR** can improve accuracy, especially in nonlinear, high-dimensional problems. Future research could involve developing a **hybrid surrogate ensemble**, dynamically switching between RSM and ML models based on local prediction error.

4. Integration with Smart Manufacturing Technologies

The next evolution of this framework includes embedding it within **cyber-physical systems** using:

- **IoT for real-time sensing** (e.g., vibration, temperature, force).
- **Edge computing** for on-machine data processing and rapid adaptation.
- **Digital twins** for dynamic simulations and predictive control.

Such an integration allows the system to **adaptively update machining parameters** in real time based on sensor feedback, enabling predictive maintenance and improved robustness in dynamic environments.

5. Sector-Specific Adaptation
Although validated in aerospace-style aluminum milling, the framework is adaptable to **other sectors**, such as:

- **Medical device manufacturing,** where micromachining precision is critical.
- **Electronics and optics**, where thermal effects must be minimized.
- **Energy sector**, particularly for machining high-performance alloys used in turbines.

Collaboration with industry stakeholders can facilitate **domain-specific customization** of the GA–RSM workflow.

C. Real-Time Adaptation: IoT, Edge Computing, and Digital Twins
1. IoT-Driven Monitoring and Adaptation
IoT sensors can provide **real-time monitoring** of machining parameters and surface conditions, enabling the GA–RSM system to:

- Dynamically update cutting parameters.
- Trigger alerts for tool wear or thermal anomalies.
- Feed data into cloud-based optimization layers.

2. Edge Computing for Low-Latency Optimization
By processing data **locally** on edge devices:

- Latency is minimized, supporting near real-time decisions.
- Machines can perform **local adaptations** while reporting aggregated metrics to a central optimizer.
- The system remains scalable across multiple machines and locations.

3. Digital Twins for Simulation-Based Prediction
Digital twins can simulate different machining setups based on **incoming sensor data**, enabling the framework to:

- Forecast failure modes.
- Optimize unseen scenarios.
- Pre-test changes before physical implementation.

D. Challenges and Open Research Questions
The following challenges must be addressed to realize the potential of the proposed framework fully:

- **GA parameter tuning**: Adaptive parameterization remains an open research problem.
- **Computational overhead**: Reducing optimization time for real-time deployment.
- **Cross-disciplinary integration**: Involving experts in material science, AI, and manufacturing engineering.
- **Sustainability**: Including environmental impact metrics such as energy consumption and carbon footprint in optimization.

E. Conclusion and Outlook
This study introduced a hybrid GA–RSM optimization framework for surface roughness reduction in milling operations. Although the results are promising, future research should focus on the following:

- Expanding to multi-objective problems.
- Integrating real-time monitoring and control.
- Comparing with modern metaheuristics (e.g., PSO, DE, Bayesian optimization).
- Validating on more complex datasets and machining contexts.

If extended as proposed, the GA–RSM framework has the potential to become a **standard intelligent decision-making tool** for machining optimization across a range of materials, industries, and production paradigms.

7. CONCLUSION

This study presented a hybrid optimization framework integrating Genetic Algorithms (GA) with Response Surface Methodology (RSM) to optimize end-milling parameters for minimizing surface roughness. The GA–RSM approach employed adaptive mutation decay and tournament selection, while leveraging a statistically validated second-order RSM model. This synergy enabled the identification of optimal machining parameters—depth of cut (0.02 in), spindle speed (1300 RPM), and feed rate (20 in/min)—resulting in a surface roughness of 13.4 µin, as confirmed across multiple trials with a 95% confidence interval.

The proposed framework achieved **high predictive accuracy (R^2 = 0.95)** and showed superior convergence behavior compared to classical methods such as Gradient Descent and Simulated Annealing. While its average runtime (~120 s) exceeded those of single-method baselines (Table 5), this overhead is justified by improved robustness and optimization performance.

Nevertheless, the study has limitations. It focused exclusively on aluminum alloy in end-milling under single-objective conditions (surface roughness). It also lacked direct benchmarking against contemporary metaheuristics such as Particle Swarm Optimization (PSO), Differential Evolution (DE), and Ant Colony Optimization (ACO). Additionally, surrogate models beyond RSM—such as Gaussian Process Regression (GPR) and Artificial Neural Networks (ANN)—were not implemented, despite their demonstrated utility in predictive machining tasks [57][58].

Looking ahead, future research should explore:

- **Benchmarking** the GA–RSM framework against recent metaheuristics and hybrid models.
- **Extending** the model to **multi-objective optimization**, considering trade-offs between surface roughness, tool wear, energy consumption, and material removal rate (MRR).
- **Applying** the framework to other materials and machining operations (e.g., titanium, composites, turning, drilling) to enhance generalizability.
- **Incorporating machine learning surrogates** or ensemble models to improve prediction accuracy in nonlinear, high-dimensional domains.
- **Integrating with smart manufacturing technologies**, including IoT, edge computing, and digital twins, to enable real-time adaptive optimization and predictive maintenance.

In summary, the GA–RSM framework demonstrates a **novel, interpretable, and modular approach** to machining optimization. Its successful experimental validation confirms its potential for application in smart manufacturing environments. With further development, it could serve as a key enabler for sustainable, high-precision, and data-driven production systems.

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9. DECLARATIONS

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The author declares that no funding was received for conducting this research.

Conflicts of Interest / Competing Interests

The author declares that there is no conflict of interest regarding the publication of this paper.

Ethics Approval

Not applicable.

Consent to Participate

Not applicable.

Consent for Publication

The author consents to the publication of this work.

Availability of Data and Material

The datasets generated and/or analyzed during the current study are available from the corresponding author on reasonable request.

Code Availability

Not applicable.

Authors' Contributions

The author (S.O.) conceived the study, conducted the experiments, performed data analysis, developed the models, wrote the manuscript, and approved the final version.

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