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Decision-Based Surface Control in NiTi Micro-Milling

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Extended Abstract:

- Nickel–Titanium (NiTi) shape memory alloys (SMAs) have become increasingly important in biomedical, aerospace, and precision-engineering applications due to their superelasticity, biocompatibility, and shape-memory effect. However, these advantageous properties also pose significant challenges for precision machining.
- NiTi alloys exhibit pronounced work-hardening, low thermal conductivity, and phase-transformation behavior during cutting, which complicate chip formation, accelerate tool wear, and lead to variability in surface integrity.
- In micro-milling—a manufacturing process employed to produce miniature features with tight dimensional tolerances—surface roughness, typically quantified by the arithmetic average roughness (Ra), is a critical quality attribute.
- Ra directly influences fatigue life, implant osseointegration, frictional behavior, and the overall functional performance of NiTi components. As a result, controlling surface roughness is not merely a technical concern but also a strategic and managerial priority, as it directly affects product reliability, regulatory compliance, rework rates, and total production cost.
- Addressing this challenge, the present study proposes a management-aligned optimization framework that integrates shop-floor machining decisions with broader production objectives using a Modified Differential Evolution (MDE) algorithm.
- Key machining variables—including spindle (cutting) speed, feed rate, axial depth of cut, and tool diameter—are treated as controllable decision levers available to production planners and process engineers.

Surface roughness (Ra) is adopted as the primary key performance indicator (KPI), while secondary factors such as tool life, cycle time, and unit cost are incorporated as constraints or as weighted objectives within multi-criteria optimization formulations.

- The proposed framework is designed to translate algorithmic results into actionable operational guidance. Specifically, it delivers recommended parameter combinations, projected improvements in surface quality, anticipated effects on throughput, and sensitivity analyses that identify the most influential process variables.
- From a methodological standpoint, the research integrates experimental investigation, computational optimization, and statistical validation. A structured set of micro-milling experiments on NiTi specimens provides the empirical data required for response modeling, with surface profiles measured using high-resolution techniques such as stylus profilometry and / or atomic force microscopy to obtain accurate Ra values.
- The Modified Differential Evolution algorithm employed in this study incorporates adaptive control of mutation and crossover parameters, elitist selection strategies, and a local search refinement stage to enhance convergence behavior and mitigate premature stagnation commonly observed in classical DE.
- The performance of the MDE approach is benchmarked against conventional DE and Taguchi-based optimization methods using metrics including best-achieved Ra, average population fitness, convergence speed, and robustness under measurement noise. Statistical analyses, including analysis of variance (ANOVA), confidence interval estimation, and repeated-runs testing, are conducted to verify that the observed performance improvements are statistically significant and repea.

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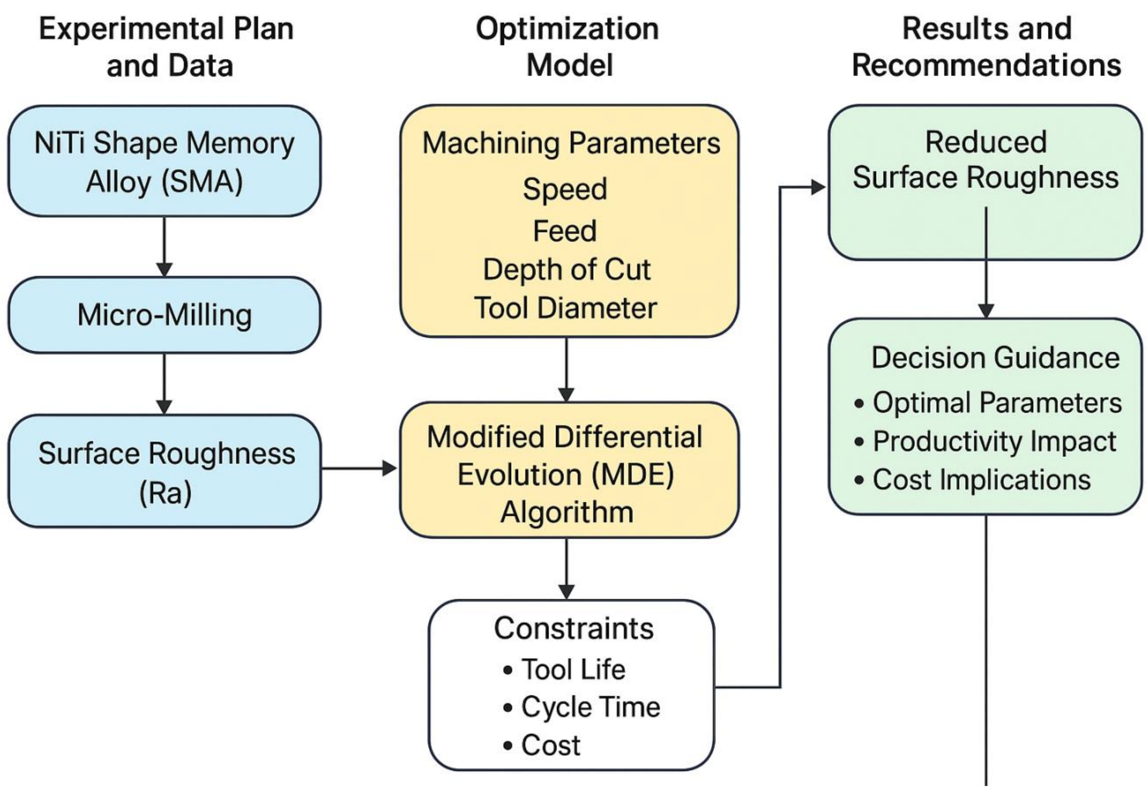

Keywords:

- Nickel–Titanium (NiTi) alloys
- Shape Memory Alloys (SMAs)
- Micro-milling
- Surface roughness (Ra)
- Modified Differential Evolution (MDE)
- Multi-criteria optimization
- Tool wear
- Production planning
- Process parameters
- Manufacturing optimization

Subject Classification

- *Engineering / Materials Science:*
  - 81.40.Jj – Alloy microstructure and mechanical properties
  - 81.40.Ef – Deformation, plasticity, and mechanical properties of metals
  - 81.20.Wk – Precision and micromachining processes
- *Manufacturing / Mechanical Engineering:*
  - 62.20.Qp – Fracture, fatigue, and wear
  - 62.20.Mk – Microstructure and surface effects in mechanical properties
  - 62.25.-g – Production, optimization, and operations management
- *Computational Methods / Optimization:*
  - 02.60.Pn – Numerical optimization
  - 02.70.-c – Computational techniques; simulation

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Nomenclature

Symbol	Definition	Unit
Ra	Arithmetic average surface roughness	Mm
vs	Spindle speed / cutting speed	rpm or m/min
f	Feed rate	mm/rev or µm/tooth
ap	Axial depth of cut	Mm
Dt	Tool diameter	Mm
T	Tool life	Min
Cu	Unit production cost	currency/unit
tc	Cycle time	s or min
DE	Differential Evolution algorithm	–
MDE	Modified Differential Evolution algorithm	–
KPI	Key Performance Indicator	–
ANOVA	Analysis of Variance	–

I. Literature Review And Introduction

Nickel–Titanium (NiTi) shape memory alloys (SMAs) are extensively used across various industries owing to their exceptional mechanical and functional characteristics, such as superelasticity, biocompatibility, and the shape memory effect [1–2]. These attributes make NiTi alloys indispensable in applications including biomedical devices, aerospace components, and precision engineering systems. However, determining optimal machining conditions through experimental trial-and-error approaches is time-consuming, costly, and resource-intensive, rendering such methods impractical for complex machining processes. Although conventional optimization techniques remain widely adopted by machinists, there is growing interest in advanced optimization methods such as Genetic Algorithms (GA), Particle Swarm Optimization (PSO)—a swarm intelligence–based technique [13]—and Differential Evolution (DE), a population-based algorithm [14–16]. These algorithms offer promising time- and cost-efficient solutions for addressing complex, nonlinear machining optimization problems. Among them, DE has demonstrated superior robustness in multi-objective optimization; nevertheless, it is often limited by slow convergence rates and susceptibility to premature convergence [17].

To address these shortcomings, several Modified Differential Evolution (MDE) variants have been proposed. These enhancements improve DE's optimization performance through hybrid search strategies, adaptive parameter control, and local search mechanisms [18–19]. The application of MDE in machining optimization has shown considerable potential for improving process parameter selection and reducing surface roughness [20]. Specifically, MDE provides a structured framework for identifying optimal micro-milling conditions that yield superior surface finish when machining NiTi alloys. In this context, the Taguchi method has been employed to develop a regression model that establishes the relationship between key machining parameters—such as axial feed, feed per tooth, cutting edge radius ratio, and nanoparticle-assisted lubrication methods—and surface roughness (Ra) [21]. This regression model serves as the fitness function for the MDE algorithm, enabling efficient exploration of the search space and identification of optimal parameter combinations for enhanced machining performance. Optimal tuning of control parameters is particularly critical in complex engineering systems involving interacting processes.

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Recent studies have demonstrated the effectiveness of MDE in optimizing control parameters for applications such as microgrid frequency regulation and active suspension systems, leading to improved stability and overall system performance [22–23]. In micro-milling operations, lubrication strategies play a vital role alongside process parameter optimization in enhancing surface finish and extending tool life. Minimum Quantity Lubrication (MQL) and solid lubricants, such as boron nitride (BN) nanoparticles, have been widely investigated for their ability to reduce friction, dissipate heat, and minimize tool wear [19, 24]. MQL involves the controlled delivery of a small quantity of lubricant into the cutting zone, offering environmental benefits while improving machining efficiency [25]. The incorporation of BN nanoparticles further enhances lubrication effectiveness by improving adhesion, facilitating chip fracture, reducing surface roughness, and increasing the durability of both the cutting tool and work piece [26]. By simultaneously optimizing machining and lubrication parameters, a holistic approach can be adopted to achieve superior surface finishes during the micro-milling of NiTi alloys [27–28]. In this study, the optimization of surface roughness (Ra) in micro-milling of NiTi SMAs is accomplished using the Modified Differential Evolution algorithm. The integration of Taguchi-based regression modeling with MDE enables the systematic determination of optimal machining parameters aimed at minimizing Ra. Furthermore, the application of MQL combined with BN nanoparticles significantly enhances machining performance. These findings contribute to the advancement of machining optimization methodologies by demonstrating MDE's effectiveness in achieving high-quality surface finishes while supporting green and sustainable manufacturing practices. The insights obtained from this research are highly relevant to industries requiring high-precision NiTi components, including biomedical, aerospace, and robotics sectors, where surface integrity and component reliability are of paramount importance.

II. Managerial Perspective On Experimental Data And Optimization

Data-Driven Analysis of Machining Performance:

Surface roughness (Ra) was analyzed using an experimentally validated machining dataset to support evidence-based decision-making in micro-manufacturing operations. The study evaluated the influence of key controllable process parameters—namely the feed per tooth to cutting edge radius ratio, nanoparticle concentration in minimum quantity lubrication (MQL), and cutting environment—on surface quality outcomes.

The experimental data were sourced from the work of Zailani and Mativenga [21], who conducted micro-milling experiments on NiTi shape memory alloys under three lubrication strategies: dry machining, MQL with graphene nanoparticles, and MQL with boron nitride (BN) nanoparticles. To ensure measurement reliability and consistency—critical for managerial decisions based on quality metrics—surface roughness measurements were performed using a calibrated VK-X200K optical profilometer. Each experimental condition was measured at least five times, reducing random uncertainty and strengthening the robustness of performance evaluation.

Statistical Modeling for Process Control:

To translate experimental observations into actionable insights, a regression-based Ra prediction model was developed to quantify the relationships between machining parameters, lubrication strategy, and nanoparticle concentration. The Taguchi design of experiments approach, employing an L4 orthogonal array, was adopted to efficiently analyze parameter effects with minimal experimental cost—an important consideration in manufacturing resource management. Regression analysis and Analysis of Variance (ANOVA), conducted using Minitab software, enabled the identification of statistically significant factors influencing surface roughness. From a management standpoint, this model functions as a decision-support tool, allowing practitioners to assess trade-offs among process settings and predict quality outcomes with confidence. The validated regression model was subsequently embedded as the fitness function within the optimization framework.

Optimization as a Decision-Support Mechanism:

A Modified Differential Evolution (MDE) algorithm was employed to determine optimal machining conditions that minimize surface roughness. From an operations management perspective, MDE serves as an intelligent optimization engine that systematically explores the decision space and refines parameter selection to achieve superior quality performance. Enhancements such as adaptive mutation strategies and local search mechanisms were incorporated to improve solution robustness, prevent premature convergence, and enhance exploration efficiency. The algorithm was implemented in MATLAB, enabling computational evaluation of parameter combinations and identification of configurations that consistently yield minimal Ra values.

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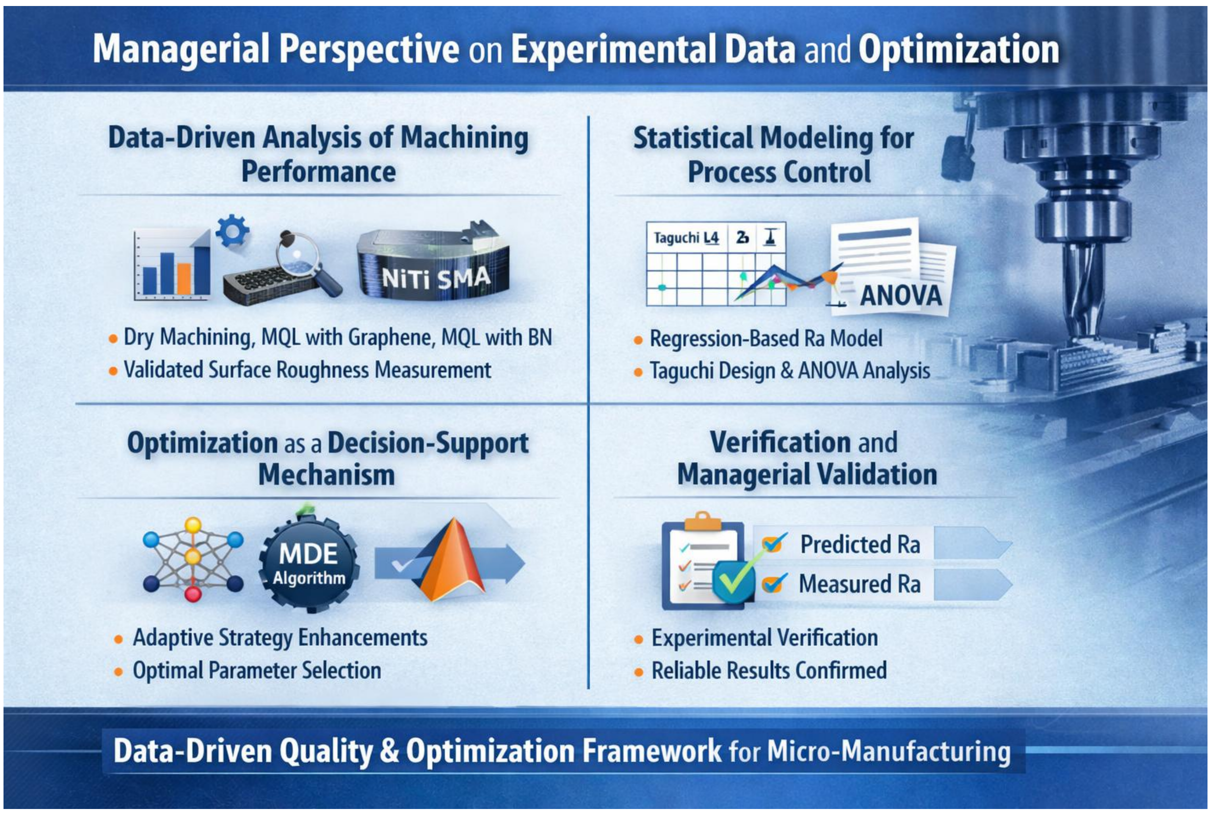
Verification and Managerial Validation

To validate the effectiveness of the optimization-driven decision framework, the predicted optimal machining parameters were experimentally verified. The verification results demonstrated close agreement between predicted and measured Ra values, confirming the reliability of the proposed approach.

This validation phase establishes managerial confidence in the framework's applicability, demonstrating that the integration of statistical modeling and evolutionary optimization can support informed decision-making, improve surface quality, and enhance overall micro-milling performance. The proposed methodology thus offers a structured, data-driven approach for quality management and process optimization in advanced manufacturing systems.



III. Solution Characteristics Of Differential Evolution

Differential Evolution (DE) provides robust and high-quality solutions for complex optimization problems characterized by nonlinearity, multimodality, and strong parameter interactions. The algorithm's solution effectiveness arises from its population-based search mechanism and differential mutation strategy, which collectively ensure balanced global exploration and local exploitation.

Key solution characteristics of DE include:

1. *Global Optimality:* DE efficiently explores the search space and demonstrates strong capability in escaping local optima, making it sui for solving highly nonlinear and multimodal objective functions.
2. *Fast and S Convergence:* The use of vector-based perturbation and greedy selection accelerates convergence toward high-quality solutions while maintaining numerical stability.

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3. *Robustness to Noise and Uncertainty:* DE maintains solution reliability even in noisy experimental environments, such as machining processes where measurement variability is inevi.
4. *Scalability and Flexibility:* DE can handle both low- and high-dimensional optimization problems and can be easily adapted by modifying mutation strategies, control parameters (F and CR), or hybridizing with local search techniques.
5. *Ease of Implementation:* With few control parameters and simple mathematical operations, DE is computationally efficient and straightforward to implement using platforms such as MATLAB.

In this study, the DE framework—enhanced through adaptive mutation strategies in the Modified Differential Evolution (MDE) approach—enabled reliable identification of optimal machining parameters that minimized surface roughness (Ra).

IV. Applications Of Differential Evolution

Due to its efficiency and versatility, Differential Evolution has been widely applied across engineering, manufacturing, and decision-support domains. Major application areas include:

1. Manufacturing Process Optimization

DE is extensively used to optimize machining parameters such as cutting speed, feed rate, depth of cut, and lubrication conditions to improve surface quality, tool life, and energy efficiency. In micro-milling of NiTi shape memory alloys, DE effectively identifies optimal parameter combinations under multiple lubrication environments.

2. Multi-Objective Engineering Design

DE supports multi-objective optimization problems where trade-offs exist between conflicting objectives such as quality, productivity, and cost. It enables decision-makers to select Pareto-optimal solutions that align with strategic manufacturing goals.

3. Control Systems and Automation

DE is applied in tuning controllers, optimizing system parameters, and enhancing control performance in nonlinear and dynamic systems.

4. Structural and Mechanical Engineering

Applications include structural optimization, vibration control, and material property estimation, where DE handles complex constraint-driven optimization efficiently.

5. Data-Driven Decision Support Systems

When integrated with regression models, neural networks, or surrogate models, DE functions as a powerful decision-support engine for data-driven optimization in Industry 4.0 environments.

6. Energy, Sustainability, and Resource Optimization

DE is increasingly used to optimize energy consumption, reduce emissions, and improve sustainability performance in advanced manufacturing and industrial systems.

V. Relevance To The Present Study

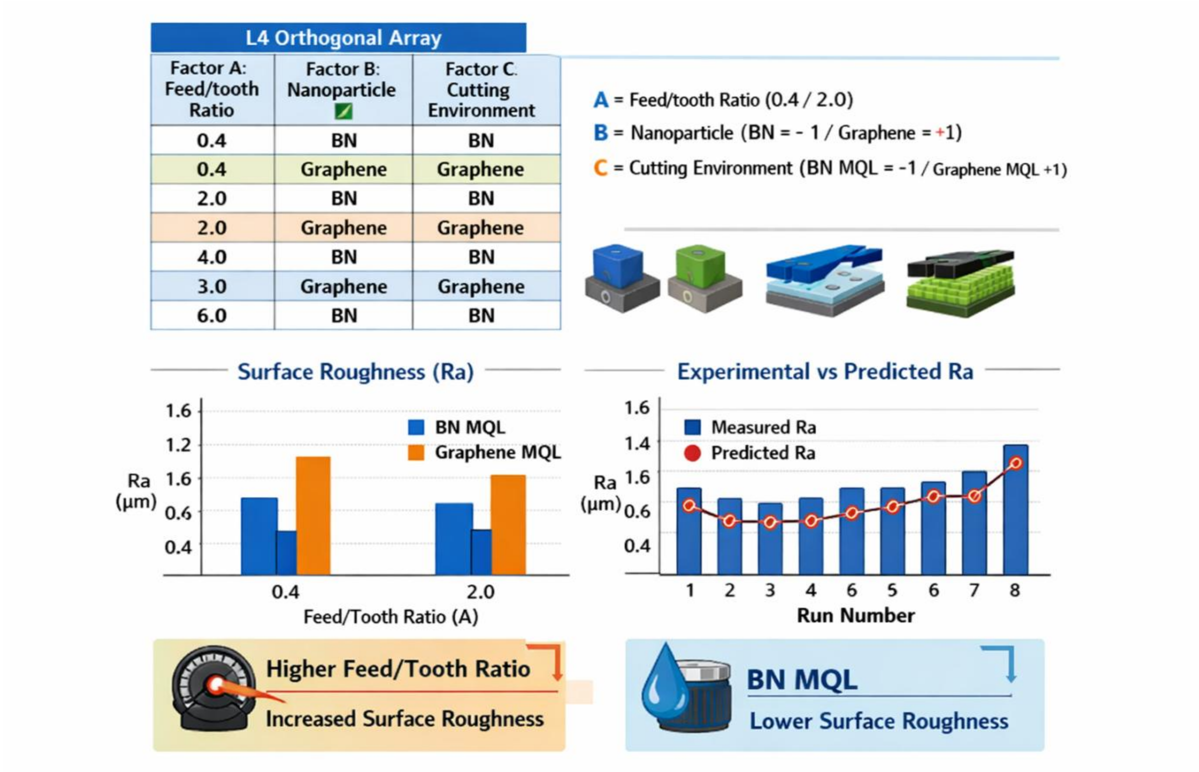
In the present work, the Modified Differential Evolution (MDE) algorithm serves as an intelligent optimization and decision-support tool by integrating experimental data, statistical modeling, and evolutionary search. This integration enables systematic identification of optimal micro-milling conditions, ensuring improved surface quality, reduced experimental trial costs, and enhanced managerial confidence in decision-making for advanced manufacturing systems.

Experimental Design and Regression Analysis

The experimental design was conducted at two different levels for each control factor. Three cutting parameters were selected for the study. An L4 orthogonal array (OA) was employed, accommodating three factors at two levels each. However, constructing a regression model with three factors using only four experimental runs exhausts all available degrees of freedom, leaving no scope for estimating experimental error. To overcome this limitation and enhance statistical reliability, a replication strategy was adopted. Replication increases the degrees of freedom for error estimation and mitigates the risk of over fitting, thereby improving model robustness [30]. Consequently, the total number of experimental runs was increased to eight. Experimental settings and corresponding surface roughness (Ra) values, including both measured and model-predicted responses. The input factors include the feed per tooth to cutting edge radius ratio (A), nanoparticle composition (B), and cutting environment (C), where boron nitride (BN) and graphene nanoparticles are coded as -1 and $+1$, respectively. The close agreement between experimental and predicted Ra values, along with small prediction errors, demonstrates the model's effectiveness in capturing the influence of machining parameters on surface quality. The results indicate that higher feed-per-tooth ratios ($A = 2.0$) lead to increased surface roughness, whereas lower feed values ($A = 0.4$) produce smoother surfaces.

Additionally, the cutting environment significantly affects Ra, with BN-based MQL (C = −1) consistently yielding lower surface roughness than graphene-based MQL (C = +1).

These findings emphasize the critical role of process parameter selection in achieving superior surface quality during micro-milling.



VI. Statistical Significance And Model Validation

Statistical analysis was performed using Minitab software to evaluate the regression coefficients and the significance of each cutting parameter. Analysis of Variance (ANOVA) results are summarized. The model exhibited strong statistical significance, with p-values below the 0.05 threshold, confirming that the independent variables are significant predictors of surface roughness. The high F-value of 42.66 indicates that the regression model explains a substantial proportion of the variability in Ra. Furthermore, the residual error was found to be minimal, suggesting that the model adequately represents the experimental data with limited unexplained variation. The predictive accuracy of the regression model was further assessed using the coefficient of determination (R^2), which yielded a value of 0.97. This indicates that 97% of the variation in surface roughness is explained by the model, demonstrating excellent predictive capability.

The regression equation describing the relationship between machining parameters and Ra is expressed in Equation (7), where Ra denotes surface roughness, A represents the feed per tooth to cutting edge radius ratio, B denotes nanoparticle composition, and C indicates the cutting environment. Overall, the Taguchi-based regression model effectively captures the relationship between machining parameters and surface roughness in the micro-milling of NiTi shape memory alloys. The analysis confirms that feed ratio, nanoparticle composition, and cutting environment significantly influence Ra, with optimal performance achieved using BN nanoparticles and appropriate feed ratios. The high correlation between experimental and predicted values validates the model’s suitability for optimization purposes. The validated regression equation was subsequently employed as the fitness function for the Modified Differential Evolution (MDE) algorithm.

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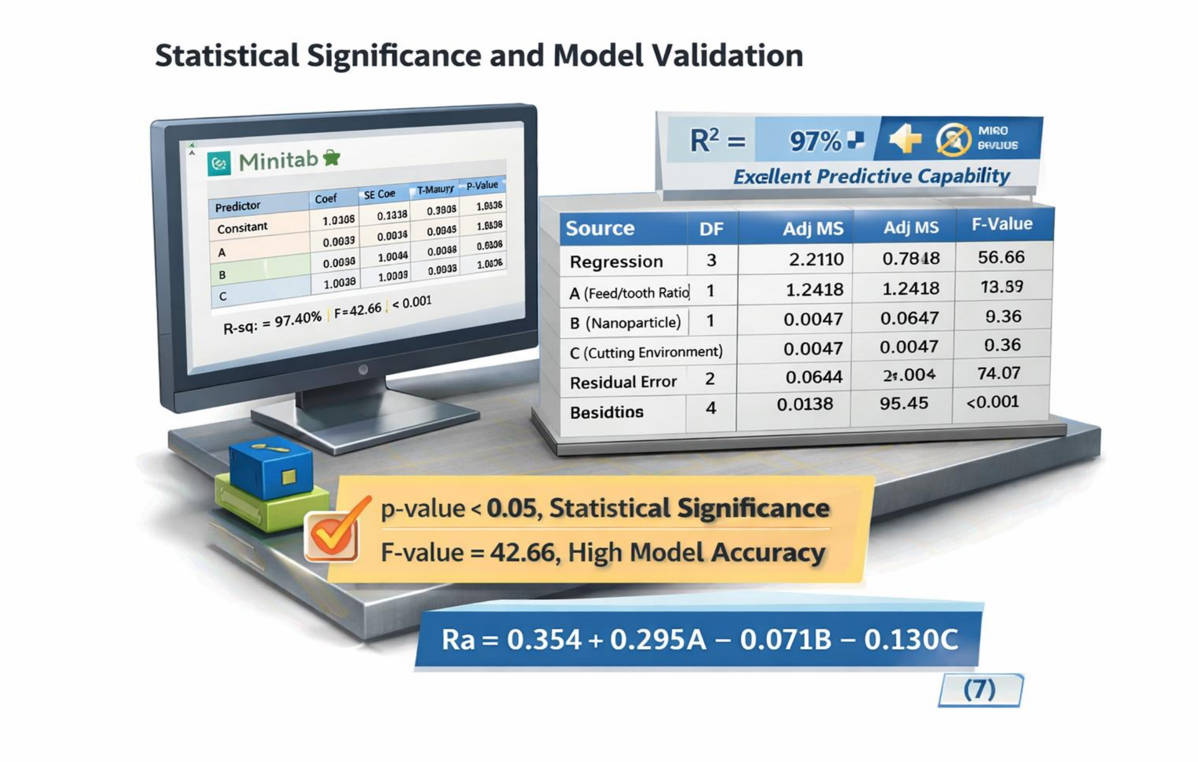
This integration of statistical modeling and evolutionary optimization provides a systematic and efficient approach to identifying optimal machining parameters, significantly reducing the need for extensive experimental trials while ensuring superior surface quality.



VII. Modified Differential Evolution Optimization

Differential Evolution (DE) is a powerful stochastic optimization algorithm widely applied in engineering for solving complex and nonlinear optimization problems. Despite its effectiveness, conventional DE algorithms often suffer from limitations such as premature convergence, slow optimization speed, and rigid parameter control [31]. These shortcomings can restrict performance in machining optimization, where precise parameter tuning is essential for achieving minimal surface roughness. To address these challenges, a Modified Differential Evolution (MDE) approach was developed by incorporating an improved elitism strategy to preserve high-quality solutions, an enhanced search mechanism to balance global exploration and local exploitation, and a probabilistic selection scheme to maintain population diversity and avoid excessive exploitation.

These enhancements improve convergence speed, sustain solution diversity, and reduce the likelihood of stagnation in local optima. In the present study, MDE was integrated with the Taguchi-based regression model, which served as the fitness function for optimization. The algorithm iteratively optimized key machining parameters—including feed per tooth to cutting edge radius ratio, nanoparticle concentration, and cutting environment—using MATLAB as the computational platform. Through successive generations, MDE refined the parameter combinations to minimize surface roughness, demonstrating its effectiveness as a robust decision-support tool for machining parameter optimization.

VIII. Conclusions

This study demonstrates that the Modified Differential Evolution (MDE) algorithm is highly effective for optimizing surface roughness (Ra) in the micro-milling of Nickel–Titanium (NiTi) shape memory alloys.

The optimized results obtained using MDE significantly outperform those achieved through traditional optimization approaches. By coupling MDE with regression-based response modeling, the study successfully identified optimal machining conditions—including the feed-per-tooth to cutting-edge radius ratio, antioxidant nanoparticle composition, and cutting environment—that yield minimal surface roughness.

Comparative analysis confirms the superiority of MDE over conventional Differential Evolution (DE), as evidenced by faster convergence, enhanced parameter adaptability, and improved optimization accuracy. Under the optimal machining conditions, a minimum Ra value of 0.7115 µm was achieved, with boron nitride (BN) nanoparticle-based solid lubrication proving most effective in reducing tool–workpiece friction and maintaining s machining conditions. These findings highlight the critical role of advanced evolutionary optimization techniques in achieving high surface quality during the precision machining of NiTi alloys, which is particularly relevant for biomedical, aerospace, and robotics applications where surface integrity is paramount. Furthermore, the study establishes the effectiveness of integrating intelligent optimization algorithms with empirical modeling techniques to enhance machining performance while significantly reducing the number of required experimental trials. This combined approach offers a systematic, cost-effective, and scalable framework for process optimization in micro-manufacturing environments. The insights gained from this work provide valuable guidance for researchers and practitioners seeking to achieve superior surface finishes in the micro-milling of advanced materials such as NiTi SMAs.

Future Scopes:

Building upon the outcomes of this research, several directions for future work are recommended:

1. *Multi-objective Optimization:* Future studies may extend the MDE framework to multi-objective optimization, simultaneously minimizing surface roughness while maximizing tool life, material removal rate, and energy efficiency.
2. *Real-Time Adaptive Control:* Integrating MDE with real-time monitoring systems and adaptive control strategies can enable dynamic adjustment of machining parameters in response to tool wear, temperature variations, and process instabilities.
3. *Advanced Lubrication Strategies:* Further investigation into hybrid and multifunctional nanolubricants, including graphene-based or composite nanoparticles, may yield additional improvements in surface quality and tool durability.
4. *Broader Machining Conditions and Materials:* The proposed optimization framework can be validated across a wider range of machining regimes, tool geometries, and advanced materials, including other shape memory alloys and difficult-to-machine superalloys.
5. *Digital Twin and Industry 4.0 Integration:* Coupling MDE with digital twin models and smart manufacturing platforms can facilitate predictive optimization, process automation, and data-driven decision-making in intelligent manufacturing systems.
6. *Surface Integrity and Functional Performance Analysis:* Future work may incorporate additional surface integrity metrics—such as residual stress, microhardness, and phase transformation effects—to better correlate optimized machining parameters with functional performance and service life.
7. By pursuing these research directions, the MDE-based optimization framework can be further strengthened, supporting sustainable, intelligent, and high-precision manufacturing of NiTi shape memory alloy components.

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Data Availability: The data supporting the findings of this study were obtained exclusively from publicly available online sources.

Institutional Review Board Approval: Not applicable. The study did not involve human participants or animal subjects and therefore did not require ethical approval.

Informed Consent: Not applicable, as no human participants were involved in this research.

Ethics Statement: The research presented in this manuscript complies with ethical standards and does not involve any ethical concerns.

AI Assistance Disclosure: Artificial intelligence–based tools (including ChatGPT) were used solely for limited language refinement and formatting support. All scientific content, interpretations, and conclusions remain the responsibility of the authors.

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