OPTIMIZATION OF SURFACE ROUGHNESS IN MICRO-MILLING OF NITI SHAPE MEMORY ALLOYS USING MODIFIED DIFFERENTIAL EVOLUTION ALGORITHM

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ABSTRACT

This study is conducted to observe the optimal effect of feed per tooth to cutting edge radius ratio, nanoparticle composition in percentage, and cutting environment on the surface roughness (Ra) of Nickel-Titanium (NiTi) Shape Memory Alloys (SMAs) in micro-milling. NiTi alloys are challenging to machine due to their high ductility and temperature sensitivity, often resulting in significant Ra. In this connection, surface quality was enhanced through Minimum Quantity Lubrication (MQL) in combination with solid lubrication using Boron Nitride (BN) nanoparticles. The Taguchi method developed a regression model from the experimental machining data. This Ra regression model was used as a fitness function for the Modified Differential Evolution (MDE) algorithm. Hence, the outcome of this study demonstrated that the MDE optimization technique can identify the process parameters that achieve reduced Ra. MDE application significantly reduces the Ra to 0.7115 µm, which is lower than experimental data (0.7210 µm) and standard Differential Evolution (DE) optimization (0.7122 µm). In conclusion, this research shows how the parameter optimization process can benefit from a combination of regression modeling with the MDE algorithm, yielding the results necessary for sustainable and efficient NiTi SMA machining.

Keywords: *Micro-milling, Nickel-Titanium, Differential Evolution, Surface Roughness, Minimum Quantity Lubrication*

1.0 INTRODUCTION

Nickel-Titanium (NiTi) Shape Memory Alloys (SMAs) are employed in many applications across industries because of their unique mechanical and functional properties, including superelasticity, biocompatibility, and shape memory effect [1-2]. These properties make NiTi alloys necessary for biomedical devices, aerospace components, and robotic actuators, where they need dimensional stability and mechanical reliability [3-4]. Nevertheless, materials in this class pose a significant challenge for machining applications because of their high ductility, temperature sensitivity, and severe work hardening [5-6]. However, traditional machining techniques tend to suffer from high tool wear, compromised surface integrity, and burr formation. Thus, optimizing the machining strategy to reach the desired surface quality while maintaining tool life is mandatory.

This is an important consideration for biomedical implants and within micro-electromechanical systems, wherein micro-milling emerges as an efficient machining method of NiTi alloy [7]. However, the processes of machining NiTi alloys must consider the specific behaviors of NiTi alloys at the microscale level, for example, size effect, ploughing, and elastic recovery, as these phenomena affect machining performance [8]. Micromachining affects both efficiency and the economy and function in the long run. Due to the prevailing rough Ra, which adversely affects fatigue life, corrosion resistance, and component reliability, optimization of machining parameters such as feed per tooth, cutting edge radius ratio, and cutting environment becomes necessary to minimize surface imperfections [9-10].

Various methods have been proposed to optimize machining parameters and improve surface quality, ranging from classic optimization methods, such as the Taguchi and Response Surface Methodology (RSM) [11-12]. Such approaches have been extensively utilized to derive optimal machining conditions from test data but require many trials, making them impractical and resource oriented. While traditional optimization techniques remain popular with machinists, there is considerable interest in advanced optimization techniques, such as Genetic Algorithms (GA), Particle Swarm Optimization (PSO), which is a swarm-based algorithm [13], and Differential Evolution (DE) which is a population-based algorithm [14-16]. These can potentially implement a time and cost-efficient solution for complex nonlinear machining problems. DE is a comparatively more robust algorithm for multi-objective optimization. Nonetheless, it suffers from a slow convergence rate and premature convergence problems [17]. Hence, to overcome these limitations, researchers have proposed Modified Differential Evolution (MDE) variants by enhancing DE optimization capabilities through a hybrid search strategy, adaptive parametric control, and local search mechanism [18-19].

The introduction of MDE in improving machining shows significant potential in optimizing process parameters and reducing roughness [20]. The algorithm offers a formal structure to identify the best machining conditions for obtaining a better MDE surface finish while machining NiTi alloys under the micro-milling process. For instance, the Taguchi method was used to construct a regression model between the machining parameters (feed axial, feed per tooth, cutting edge radius ratio, and nanoparticle-based lubrication methods) and the surface roughness values [21]. The obtained regression model acts as the fitness function for the algorithm of MDE, which efficiently explores the search space and identifies optimal parameter settings for higher machining performance. Optimally tuning control parameters is crucial in complex engineering applications with interacting processes. A recently developed MDE algorithm can optimize control parameters for microgrid frequency regulation and active suspension control, thereby improving the system's stability and overall performance [22-23].

Until now, owners in micro-milling, in addition to optimizing the process parameters, have played a significant role in lubrication strategies and improving surface finish and tool life. Minimum Quantity Lubrication (MQL) and solid lubricants like Boron Nitride (BN) nanoparticles have been suggested to reduce friction and dissipate heat and tool wear [19,24]. MQL sprays a specific quantity of lubricant into the cutting zone, which contains an environmental effect while improving machining [25]. This adhesiveness, thus, is essential in enhancing lubrication efficiency, fracturing, reducing Ra, and increasing the durability of the tool and the workpiece owing to the addition of BN nanoparticles [26]. By optimizing lubrication parameters in conjunction with machining conditions, a holistic approach can be adopted toward achieving more desirable surface finishes in micro-milling NiTi alloys [27-28].

The optimization of Ra in micro-milling of Nickel-Titanium Shape Memory Alloys (NiTi SMAs) is achieved through the Modified Differential Evolution (MDE) algorithm. By integrating Taguchi-based regression modeling with MDE, optimal machining parameters are systematically determined to minimize Ra. The application of Minimum Quantity Lubrication (MQL) combined with Boron Nitride (BN) nanoparticles further enhances machining performance. These results advance machining optimization methodologies, demonstrating MDE's capability to achieve superior surface finish quality while adhering to green and sustainable manufacturing principles. This research provides valuable insights applicable to these industries in which high-precision NiTi components are essential, including biomedical, aerospace, and robotics sectors, where surface integrity and component reliability are critical.

2.0 EXPERIMENTAL PROCEDURE

2.1 Methodology

During micro-milling of NiTi SMAs, Ra is affected by many factors, such as the machining parameters, lubrication methods, workpiece characteristics, and tool geometry. A new method to improve machining performance is to achieve a lower Ra under the MDE technique by optimizing the feed per tooth to cutting edge radius ratio, nanoparticle concentration, and cutting environment. The experimental investigation was conducted in four phases to achieve the optimal machining parameters for minimizing the Ra of NiTi alloys in micro-milling. The general methodology phases are illustrated in Figure 1, with further detail provided as follows:

Analysis of Machining Experimental Data

Ra responses were analyzed from the machining experimental data set, and the effect of process parameters like the feed per tooth to cutting edge radius ratio, nanoparticle concentration in MQL, and cutting environment on the Ra response. The results of this study were based on experimental data reported by Zailani & Mativenga [21], where micro-milling operations were carried out on NiTi SMAs under varying lubrication conditions. These conditions are dry machining, MQL with graphene, and BN nanoparticles. Few clarifications have been done in the manuscript.

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Development of the Regression Model

A Ra model was developed to correlate machining parameters (feed per tooth to cutting edge radius, cutting environment) with nanoparticle concentration. A regression model was created using the Taguchi method to systematically study the effect of input parameters, utilizing an L4 orthogonal array. The model was built and analyzed by Minitab statistical software, which allowed these data to be analyzed by regression analysis and the significance of both linear parameters. The efficiency of this model was investigated based on the Analysis of Variance (ANOVA) to determine which parameter affected the model's accuracy in predicting Ra. The validated regression model was embedded as the fitness function in the MDE optimization module to compute optimal machining conditions.

Optimization using Modified Differential Evolution (MDE)

The MDE technique determined the optimal machining parameters for achieving the lowest possible Ra. This algorithm minimizes Ra by efficiently exploring the solution space and refining parameter selection. Adaptive mutation strategies and local search mechanisms were added to improve optimization performance, allowing MDE to prevent premature convergence and improve exploration efficiency. MDE was developed using the Matrix Laboratory (MATLAB) framework, and calculations were performed to find the frequencies of machining parameters that gave the lowest roughness values.

Evaluation and Verification of Optimization Results

The optimized machining parameters were compared with measurements to validate the MDE algorithm. The identified optimum parameters were then used for a verification experiment to verify their accuracy and effectiveness in Ra minimization. This phase validated that the proposed optimization approach successfully improved machining performance while yielding reliable parameter recommendations to improve surface quality.

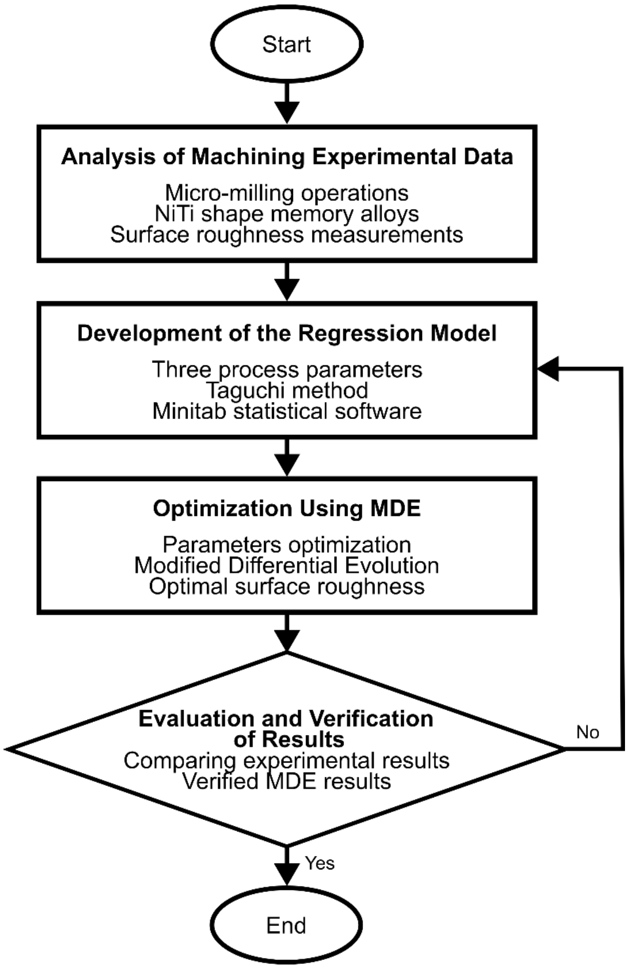

Figure 1: Flowchart of overall methodology.

2.2 Experimental Design

This study was referenced to the experimental study conducted by Zailani & Mativenga [21] involving measuring the Ra values during the micro-milling of NiTi SMAs. Experiments were performed on a Mikron HSM 400 high-speed machining center, as shown in Figure 2. These experiments aimed to ascertain the influences of machining parameters such as feed per tooth to cutting edge radius ratio (f/re), the composition of nanoparticles (wt.%), and cutting environment (MQL with graphene or BN nanoparticles), on output response of Ra. The workpiece used was a NiTi alloy block with dimensions 70 mm×20 mm×8 mm, selected due to its widespread application in high-precision industries. The cutting tool was a two-flute fine-grain solid carbide end mill cutter with a 500-micron diameter coated with AlTiN to enhance tool wear resistance and prolong machining performance. Before each test, the cutting tools were analyzed using a Scanning Electron Microscope (SEM) to examine their cutting-edge quality. A Keyence VK-X200K 3D Laser Scanning Microscope was used to ensure accurate measurement of Ra values. The machining process was conducted under MQL conditions, incorporating graphene and BN nanoparticles as solid lubricants. The influence of nanoparticle concentration was studied at 0.5 wt.% and 1.0 wt.%, as previous research suggested that excessive nanoparticle concentration may lead to adverse effects on Ra due to increased particle interactions.

According to the design of the experiment, the micro-milling process parameters for NiTi SMA were selected based on previous machining studies. They were arranged using the Taguchi L4 orthogonal array. The combinations of experimental parameters used in the study are presented in Table 1. The cutting velocity was set at 35 m/min (23,000 rpm), with a depth of cut of 30 μm to simulate high-precision machining conditions. The MQL system used in the study employed Coolube® 2210 biodegradable cutting lubricant, and the MQL flow rate was maintained at 0.75 ml/min with a velocity of 13.3 m/s. To optimize lubricant delivery, the MQL nozzle was positioned 15 mm away from the workpiece at a 60° angle to the spindle axis, as recommended in previous studies for maximizing lubricant coverage and penetration. Nanofluids were prepared by sonicating graphene and BN nanoparticles in the base cutting fluid for six hours at 100 W power and 37 kHz frequency, as shown in Figure 3. This ensured that the nanoparticles remained uniformly suspended, preventing agglomeration and ensuring consistent lubrication throughout the machining process. A Kruss Drop Shape Analyser DSA100 was used to measure static contact angles, confirming that nanoparticle addition significantly improved fluid wettability, with graphene (0.5 wt.%) reducing contact angle by over 30%, thereby enhancing the lubricant's ability to spread across the cutting zone.

Figure 2: Mikron HSM 400 high-speed machining.

Table 1: Experimental Parameters and Their Levels [21]

Factor	Level 1	Level 2
Feed per tooth to cutting edge radius ratio (f/re)	0.4	2.0
Nanoparticle composition (wt.%)	0.5	1.0
Cutting environment	MQL + Boron Nitride	MQL + Graphene

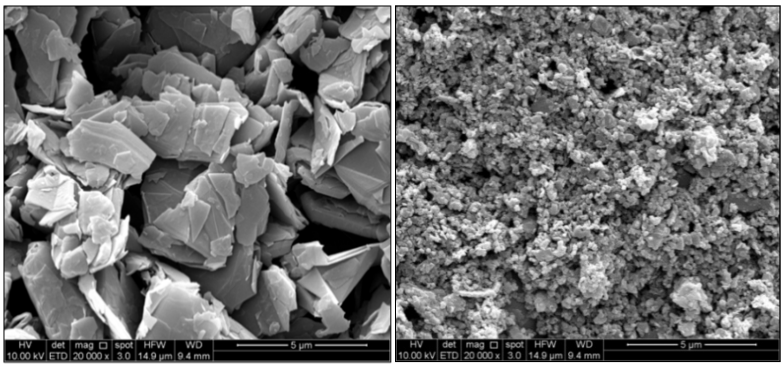

Figure 3: SEM nanoparticle images at 5 μm scale of (left) graphene and (right) boron nitride.

A Mikron HSM 400 high-speed machining center and a Keyence VK-X200K 3D Laser Scanning Microscope were used to perform the milling process and measure the Ra values of the machined NiTi alloy. The Ra values were recorded at multiple points along the machined surface to ensure repeatability and consistency of results. The results of the ANOVA revealed that nanoparticle composition had the most significant influence on Ra (44%), followed by feed per tooth to cutting edge radius ratio (28%) and cutting environment (17%). The study found that BN nanoparticles (0.5 wt.%) produced the lowest Ra (Ra < 1 µm) due to their smaller size (80–100 nm), which allowed them to penetrate better into the tool-workpiece interface. However, larger graphene nanoplatelets (5 µm) exhibited slightly higher Ra. This is due to their larger sizes, which leads to increased interaction with the workpiece and causes micro-scratches. A decrease in feed per tooth to cutting edge radius ratio (0.4) positively affected Ra, predating ploughing, and favoured smoother cutting. The study further noted that higher concentrations of nanoparticles (1.0 wt.%) increased the Ra due to the excessive collisions of particles released with higher kinetic energy on the machined surface.

The effect of chilled air and MQL was also studied to improve the surface finish further. As shown in Figure 4, using a Vortex Tube Cold Air Gun, which applies chilled air, dramatically reduced tool wear and improved machining performance considerably. The cold air gun was able to generate temperatures around −21.0°C at a wind speed of 8.0 m/s and flow velocity of 14 m/s. The chilled air resulted in over 20% less Ra than the unchilled condition, indicating its capability to decrease thermal deformation and residual stress on the machined surface. The integrated cooling and lubrication system effectively enhanced the adhesion of nanoparticles, resulting in a more stable lubrication film and decreased adhesion effect. Moreover, the decreased cutting temperature reduced tool wear, enhancing surface integrity and durability. It indicates that systematic processes like optimized nanoparticle concentration, choosing the correct feed rate, and providing additional cooling arrangements can drastically improve the surface finish when micro-milling NiTi alloys. The results highlight the need to properly use nanoparticle size and concentration to achieve ideal surface quality in high-precision machining.

Figure 4: Adjustable Vortex Tube Cold Air Gun.

2.3 Experimental Details

This machining work was conducted by Zailani & Mativenga [21] on a Mikron HSM 400 high-speed machining centre, which used NiTi alloy blocks as a workpiece. The cutting tool was a two-flute fine-grain solid carbide end mill (500-µm diameter, AlTiN-coated). The cutting speed for each test was 35 m/min (23,000 rpm), and the depth of cut was 30 µm. The MQL system applied Coolube® 2210 biodegradable cutting lubricant with graphene and BN nanoparticles (0.5 and 1.0 wt.%). The lubricant was delivered at a flow rate of 0.75 ml/min, with a nozzle positioned 15 mm from the workpiece at a 60° angle to the spindle axis. The nanofluids were sonicated for six hours to ensure even dispersion. Ra measurements were conducted using a Keyence VK-X200K 3D Laser Scanning Microscope, with readings taken at multiple points along the machined surface. The ANOVA results confirmed that BN (0.5 wt.%) achieved the best surface finish, attributed to its smaller particle size and better tool-workpiece interface penetration. A lower feed per tooth to cutting edge radius ratio (0.4) also improved Ra values by minimizing ploughing effects. Chilled air cooling was introduced to improve machining outcomes, reducing tool wear and lowering Ra by over 20%. The findings highlight the importance of selecting appropriate nanoparticle size, concentration, and cooling mechanisms in high-precision micro-milling.

2.4 Introduction to Differential Evolution

DE is a stochastic optimization method that addresses complex optimization problems via an evolutionary strategy. As introduced by Storn & Price [15], the algorithm's ability to effectively tackle nonlinear, multimodal functions has led to its extensive use in engineering applications. DE functions within a population-based framework like GA. However, DE employs three main operators to drive solution improvements when the algorithm uses selection pressure or recombination probabilities to evolve the solution: mutation, crossover, and selection. A mutation is an operator that perturbs the existing solutions to generate a mutant vector based on the difference between randomly chosen members of the current population as stated in Equations (1) – (4) [15]:

Scheme DE/rand/1
$$v_{i,G+1} = x_{r1,G} + F.(x_{r2,G} - x_{r3,G}), \tag{1}$$

Scheme DE/best/1
$$v_{i,G+1} = x_{best,G} + F.(x_{r1,G} - x_{r2,G}), \tag{2}$$

Scheme DE/best/2
$$v_{i,G+1} = x_{best,G} + F.(x_{r1,G} + x_{r2,G} - x_{r3,G} - x_{r4,G}), \tag{3}$$

Scheme DE/rand-to best/1
$$v_{i,G+1} = x_{i,G} + \lambda.(x_{best,G} + x_{i,G}) + F.(x_{r2,G} - x_{r3,G}), \tag{4}$$

where $v_{i,G+1}$ is a mutant vector for the next generation at index *i* = 1, 2, 3, …, *NP*; *NP* is a population size; $x_{r1,G}$ is a target vector for the current generation at random index integer *r*1; *r*1, *r*2, *r*3, *r*4 ϵ {1, 2, …, *NP*}; *F* is the scaling factor, whose value is $(0 \leq F \leq 2)$, so-called mutation rate, used in this study that controls the amplification of the differential variation of $(x_{r2,G} - x_{r3,G})$, whereas $\lambda = F, x_{best,G}$ is the best vector of the population and $x_{i,G}$ is a vector index *i* at the current generation [15]. The value of *F* will control the robustness and speed of the search. Low values of *F* will increase the rate of convergence and the risk of being trapped in local optima [29].

The crossover operation exchanges information between the target and mutant vectors to generate a trial vector. The trial vector is constructed in Equation (5) as follows [15]:

$$u_{i,G+1} = u_{ji,G+1} = \begin{cases} \mathrm{v_{ji,G+1}\ if(rand(j) \leq CR)\ or\ j = ranr(i)} \\ \mathrm{x_{ji,G}\ if(rand(j) > CR)\ or\ j \neq ranr(i)} \end{cases}, \mathrm{j = 1,2,\ldots,D} \tag{5}$$

where $u_{ji,G+1}$ is the trial vector at index *j* and *i* = 1, 2, 3, …, *NP*; *D* is the size of the vector or called a dimensional vector. The Crossover Rate (*CR*) ϵ [0, 1] has to be chosen by the user, whereas *rand*(*j*) is the output of a uniform random number generator in the range of [0, 1], and *rand*(*i*) is a randomly chosen index in the range of [1, 2, …, *D*] that is taken from the mutant to ensure that the trial vector does not duplicate all the target vector, $x_{ji,G}$, to get at least one parameter from the mutant vector, $v_{ji,G+1}$. This crossover operation is a type of one-point crossover.

Finally, the selection process presented in Equation (6) ensures that only the best-performing solutions are advanced to the next generation. Once the trial vector, $u_{i,G+1}$ has been generated, a greedy criterion is applied to compare it with the target vector, $x_{i,G}$. It is selected if the trial vector has a better objective function value than the target vector. Otherwise, the target vector is retained. The selection process in DE is outlined as follows:

$$x_{i,G+1} = \begin{cases} u_{i,G+1} \; if (f(u_{i,G+1}) < f(x_{i,G})) \\ x_{i,G} \; otherwise \end{cases}, \tag{6}$$

where f (.) denotes the objective function. The process of selection is repeated until the termination criterion is defined.

The DE algorithm workflow consists of five important steps within an iterative optimization process, as illustrated in Figure 5. First, it will start with problem formulation, initializing the population, and defining the dimensional size. This is followed by a perturbation stage that applies mutation, crossover, and selection strategies to produce better candidate solutions. The stopping criterion determines whether optimization continues or terminates based on specified criteria, like reaching a maximum number of iterations or achieving convergence. If not, the process goes through the perturbation stage again. When it is, the algorithm stops. This structure ensures that DE is effective for challenging optimization problems through efficient global exploration and solution refinement.

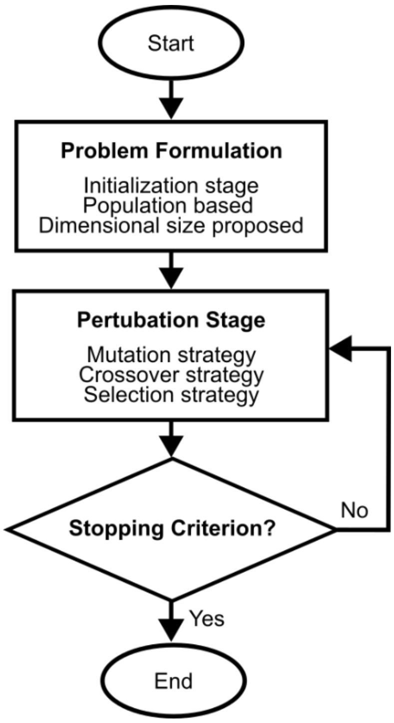

Figure 5: Workflow basic for DE algorithm.

3.0 RESULTS AND DISCUSSION

3.1 Regression Modeling Development Using Taguchi Method

The Taguchi method is a statistical approach to optimize process parameters with minimal experimental runs while maintaining robust performance. It employs Orthogonal Arrays (OA) to systematically study the influence of multiple factors on a response variable. In this study, the L4 OA was selected to analyze the effects of three machining parameters on Ra. Other than that, the three factors refer to the three different cutting parameters (feed per tooth to cutting edge radius ratio, composition of nanoparticles, and cutting environment), each having two different levels. The three cutting parameters selected for the experiment are given in Table 1. The L4 OA accommodates three factors, each with two levels. However, developing the regression model with three factors using only four experimental runs is insufficient. This is because a regression model with three factors utilizes all degrees of freedom, leaving no room for error estimation. To solve the problem, a replication approach was used to increase statistical reliability. In addition, replication provides degrees of freedom for error and to avoid overfitting [30]. Using the replication approach, the total number of experiments is eight runs.

Table 2 presents experimental parameters and their corresponding Ra responses, both experimental and predicted. The factors considered include the feed per tooth to cutting edge radius ratio (A), the composition of nanoparticles (B), and the cutting environment (C), where BN and graphene are represented as -1 and 1, respectively. Experimental versus predicted Ra results and their respective error margins are detailed in the table below. This shows a high correlation between experimental and predicted Ra, indicating the model's reliability in capturing the impact of machining parameters on Ra. Higher feed per tooth ratios (A = 2.0) yield increased Ra compared to lower feed values (A = 0.4), yielding smoother surfaces. The cutting environment (C) also seems to influence the results, as BN (C = -1) tends to yield lower roughness values than graphene (C = 1). This study shows the importance of the process parameters in controlling the surface quality during micro-milling.

Table 2: Experimental Parameters and Their Responses.

Trial Number	Factors			Response	
	A (Feed per tooth to cutting edge radius ratio)	B (Composition of nanoparticles)	C (Cutting environment)	Surface Roughness (Experimental)	Surface Roughness (Predicted)
1	2.0	1.0	-1	0.933	0.9545
2	0.4	1.0	1	0.949	0.9315
3	0.4	0.5	-1	0.723	0.7120
4	0.4	0.5	-1	0.721	0.7120
5	2.0	0.5	1	0.841	0.8575
6	0.4	1.0	1	0.914	0.9315
7	2.0	0.5	1	0.874	0.8575
8	2.0	1.0	-1	0.976	0.9545

Statistical analysis software Minitab was utilized to explore the regression coefficient of the developed model. The significance of cutting parameters was conducted using ANOVA. Table 3 displays the ANOVA output. It is also a good fit, with the results showing a P-value corresponding to a significance level lesser than 0.05. This means the independent variable is a significant predictor of the response. The F-value of 42.66 indicates that the regression model explains a significant proportion of the variation in the data. The size of the residual error is small, which is a good indication that the model describes the data well with relatively slight unexplained variation.

Table 3: Analysis of Variance.

Source	DF	SS	MS	F	P
Regression	3	0.071785	0.023928	42.66	0.002
Residual Error	4	0.002243	0.000561		
Total	7	0.074029			

The machine learning model accuracy was estimated using the Coefficient of Determination (R^2). The R^2 value was 0.97 or, in other words, 97%, which indicated that the model's predictions closely correlated with the actual data. The results also indicate that the model is appropriate for simulating the micro-milling process considering the Ra values. The regression equation for the model is presented in Equation (7):

$$\mathbf{Ra = 0.563 + 0.0527A + 0.316B - 0.0306C}, \tag{7}$$

where Ra signifies the roughness of the surface, A is the feed per tooth to cutting edge radius ratio, B is the composition of the nanoparticles, and C is the cutting environment.

Thus, the Taguchi method-based regression model predicted the relationship between machining parameters and Ra in the micro-milling of NiTi SMAs. The analysis confirmed that the feed-per-tooth to cutting-edge-radius ratio, nanoparticle composition, and cutter setup conditions significantly affect Ra, with optimal results achieved using BN nanoparticles and appropriate feed ratios. Again, the model showed good prediction accuracy, as indicated by the high correlation between experimental and predicted data, with an R^2 value of 97%. The validation of the fit ensured that the regression equation was a good fit, allowing for optimization. The validated regression equation served as the fitness function for the MDE algorithm. Thus, the union of statistical modeling and optimization methods allows for a systematic and efficient means to obtain the optimal parameters of NiTi machining for superior surface quality without requiring a prohibitively extensive experimental trial.

3.2 Modified Differential Evolution Optimization

DE is one of the most effective stochastic optimization algorithms used today, and it is widely used in engineering applications to solve complex and nonlinear problems. Despite its effectiveness, well-known issues of standard DE include premature convergence, low optimization speed, and parameter rigidity [31]. These limitations may prevent it from performing well in machining optimization, where accurate control of parameters is key to attaining excellent Ra. To ameliorate the mode of optimization in the procedure of MDE, an improved elitism strategy to keep the best solutions, an improved search mechanism that balances global and local exploration ability, and a constant probabilistic selection mechanism to ensure diversity and avoid over-exploitation. These enhancements accelerate convergence, promote solution diversity, and prevent the algorithm from becoming trapped in local optima, resulting in a more viable implementation of MDE for machining parameter optimization. In machining optimization, MDE is adopted as an integrated approach with the regression model obtained from the Taguchi method. This model is a fitness function for MDE in determining important machining parameters, including feed per tooth, cutting edge radius ratio, nanoparticle concentration, and cutting environment. Subsequently, it employs MDE with MATLAB, iteratively refining these parameters to reduce Ra. It performs significantly better than standard DE for high-precision NiTi-SMA machining.

3.2.1 Modifications to DE for Improved Optimization

Optimizing machining processes is a complex problem, requiring a solution that balances exploration (searching for increasingly better solutions) and exploitation (searching around promising solutions) through an efficient algorithm. MDE is an improved DE algorithm with adaptive mechanisms embedded in the standard of the DE framework to find an optimal solution for machining parameters as quickly as possible while keeping diversity among the solutions and ensuring robustness. A major challenge in optimizing the machining process, including micro-milling of NiTi alloys, is the action of the process parameters and Ra, which is complex and nonlinear. MDE conquers these issues by introducing an adaptive mutation strategy, improved selection mechanisms, and enhanced global and local exploration balance. These adjustments guarantee swift, accurate determination of optimal machining conditions while avoiding both premature convergence and stagnation of local optima.

The improvements primarily focus on the component level. A key advantage of the MDE algorithm is its adaptive mutation and crossover strategies, which dynamically adjust the mutation rate (*F*) and *CR* to ensure suitable convergence behavior and prevent becoming trapped in local optima. Unlike standard DE, which employs fixed mutation parameters, MDE utilizes a probability-based approach to alternate between two candidate mutation strategies, ensuring a better global search capability while retaining strong local refinement. The adaptive mutation strategy can be represented as [32]:

$$v_i = \begin{cases} x_{r1} + F \cdot (x_{r2} - x_{r3}), & if\ rand(0,1) < p \\ x_{r1} + F \cdot (x_{r2} - x_{r3}) + F \cdot (x_{r4} - x_{r5}), & otherwiese \end{cases} \tag{8}$$

where $x_{r1}, \dots, x_{r5}$ are randomly selected individuals from the population, and $rand(0,1)$ represents a uniform random number and probability, p is introduced to realize the mutation strategy self-adaption. From Equation (8), the value p is initially set to 0.5. After evaluating all offspring, those successfully transferred to the next generation are labeled as ns_1 and ns_2, respectively, while the discarded offspring from Equation (8) are named nf_1 and nf_2. These parameters (ns_1, ns_2, nf_1, nf_2) will be cumulatively updated after each learning stage. Update the probability p by learning as shown in Equation (9) as follows [23]:

$$p = \frac{ns_1 \times (ns_2 + nf_2)}{ns_2 \times (ns_1 + nf_1) + ns_1 \times (ns_2 + nf_2)} \tag{9}$$

With these enhancements combined, MDE emerges as a more robust and efficient optimization method in machining contexts, ensuring faster convergence rates, enhanced accuracy, and superior adaptability in identifying prime process qualities. In Figure 6, the result comparison of standard DE and MDE is presented, where it is observed that MDE is superior to standard DE in terms of both convergence speed and accuracy of the final solution. MDE overcomes the limitations of standard DEs, particularly in machining optimization tasks where there is a complex interaction between various parameters hitting towards the performance outcome. The improvements introduced in MDE, including adaptive mutation, self-tuning parameters, and enhanced selection mechanisms, align with the latest advancements in evolutionary algorithms. This ensures robust and efficient optimization in machining and other engineering applications.

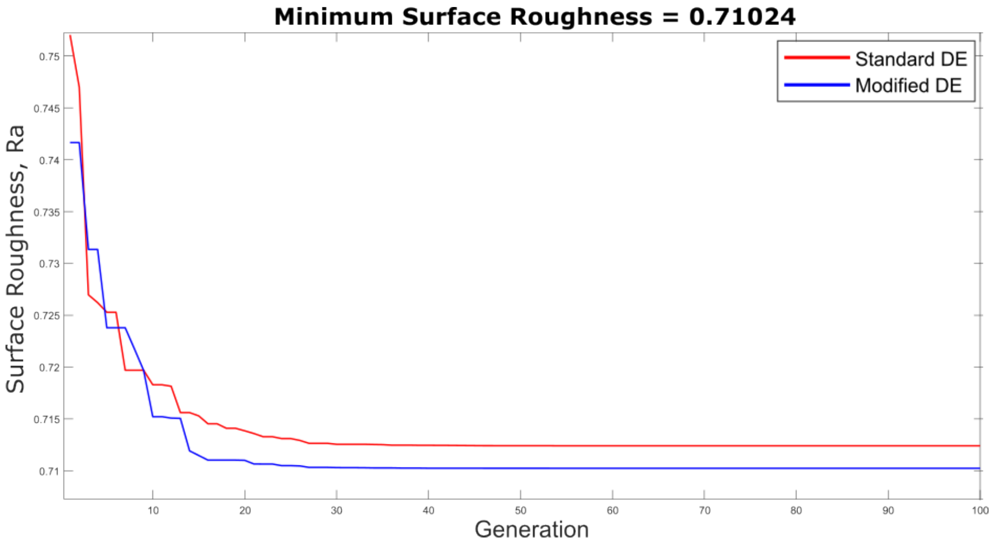

Figure 6: Convergence of Standard DE and MDE algorithms for minimizing Ra.

3.2.2 Implementation of MDE in Machining Optimization

Implementing MDE in machining optimization involves systematically integrating the algorithm with regression modeling to refine machining parameters. As mentioned in Section 2.4, the regression model is developed using the Taguchi method, establishing relationships between machining parameters and Ra. The regression model was confirmed, validating its effectiveness in predicting Ra based on the identified parameters. Each parameter in the MDE algorithm is directly linked to the corresponding variables in the regression model, as presented in Equation (7), ensuring a structured optimization process for achieving minimum Ra. This model serves as the fitness function in MDE, guiding the algorithm toward optimal machining conditions. The regression equation predicts Ra based on key machining parameters, allowing the algorithm to minimize roughness without excessive experimental trials. By iteratively optimizing the feed per tooth to cutting edge radius ratio, nanoparticle concentration, and cutting environment, MDE efficiently identifies the most favorable machining conditions. Table 4 summarizes the relationship between the machining parameters in the regression model and the corresponding symbols used in the MDE algorithm, along with their respective ranges.

The optimization problem is formulated as a minimization function in the MDE algorithm setting, aiming to reduce Ra by selecting the optimal combination of machining parameters. The decision variables include the feed per tooth to cutting edge radius ratio, nanoparticle concentration, and cutting environment (MQL + BN and MQL + graphene). In MDE algorithms, the parameter values are determined based on the lower and upper boundaries set within a predefined range, as listed in Table 4. The specific lower and upper boundaries for each parameter used in the optimization process are presented in Table 5. Constraints such as machine limits (spindle speed, feed rate) and lubrication feasibility are imposed to ensure realistic parameter selection. By defining a structured search space, MDE explores feasible solutions while maintaining compliance with practical machining conditions. These constraints prevent the selection of unrealistic values, ensuring that the algorithm identifies machining settings that yield improved Ra while maintaining process efficiency.

In this study, several combinations of initial population size (*NP*), the mutation rate (*F*), the *CR*, and the number of generations (*GEN*) were tested using MATLAB programming to achieve the optimal Ra value. The optimization was aimed at minimizing Ra in the machining process by selecting the best combination of these parameters. Population sizes of 10, 30, 50, 70, and 90 were tested in the program, and the algorithm was executed 100 times for each NP value. Based on the experiments, the minimum and constant Ra value of 0.711 µm was obtained using a population size of 50, approximately 16 times the number of process parameters. When the population increased to 70 and 90, there were no significant changes in the achieved Ra value, confirming that $NP = 50$ was the optimal setting.

Table 4: Relationship Between the MDE Algorithm Symbols and the Regression Model.

Setting	Regression Model	MDE symbols	Range
Fitness function	*Ra*	f	-
Number of process parameters	3 × 1 matrix	D	3
Minimum surface roughness	*Ra (minimum)*	f_{best}	-
Feed per tooth to cutting edge radius ratio	*A*	X_1	0.4 – 2.0
Composition of nanoparticles	*B*	X_2	0.5 – 1.0%
Cutting environment	*C*	X_3	-1(BN)–1 (Graphene)

Table 5: Lower and Upper Boundary Setting for Each Parameter

Parameters	Lower boundary	Upper boundary
Feed per tooth to cutting edge radius ratio, *A*	0.4	2.0
Composition of nanoparticles, *B*	0.5	1.0
Cutting environment, *C*	-1	1

Additionally, it was found that using 100 generations produced the minimum and stable Ra value. Increasing the number of iterations beyond this did not yield significant improvements. Meanwhile, for the mutation rate (*F*) used in the mutation stage of the algorithm, values ranging from 0.1 to 0.9 were tested to determine the optimal setting, with the *CR* being varied at 0.2, 0.6, and 0.8. After running 100 trials, the final parameter settings that resulted in the minimum Ra value were identified, as presented in Table 6. These findings confirm that the chosen settings effectively optimize the Ra in the machining process.

Table 6: MDE Parameters Setting for the Optimal Solution.

Parameter	Setting value
Population size, *NP*	50
Mutation rate, *F*	0.15
Crossover rate, *CR*	0.6
Number of generations, *GEN*	100

Thus, when testing the MDE algorithm for machining optimization, regression modeling provides a systematic approach for evaluating machining parameters to minimize Ra. Utilizing the Taguchi-based regression model as the fitness function, MDE effectively explores optimal machining conditions while adhering to practical constraints such as machine limits and lubrication feasibility. A structured approach to optimization packed with important decision variables such as the mass ratio of the feed per tooth to the radius of the cutting edge, concentration, and cutting environment of the nanoparticles guarantees optimal machining conditions. Through extensive MATLAB simulations, the study determined that an initial population size of 50, 100 generations, a mutation rate (*F*) within the tested range, and an optimized *CR* led to the lowest and most stable Ra value of 0.7115 µm. These results confirm the potential of MDE for machining improvements and the method's ability to deliver accurate Ra minimization and ensure process expediency.

3.3 Summary of Findings

The results obtained from the MDE optimization technique demonstrate significant improvements in minimizing the Ra in the micro-milling of NiTi SMAs. Figure 7 shows the convergence of performance for each machining parameter, highlighting how the optimization process improved the ratio of feed per tooth to cutting edge radius, nanoparticle composition, and cutting environment to attain an optimum solution. The results confirm that the MDE algorithm efficiently predicts the optimal combination of machining parameters, leading to consistent and reduced Ra. These results are consistent with the findings from regression modeling covered in Section 3.1, wherein the feed ratio per tooth to the cutting-edge radius and nanoparticle composition were highlighted as key parameters impacting Ra. The convergence trend also confirms the efficiency of MDE over standard DE, demonstrating its capability to prevent premature stagnation and enhance optimization performance.

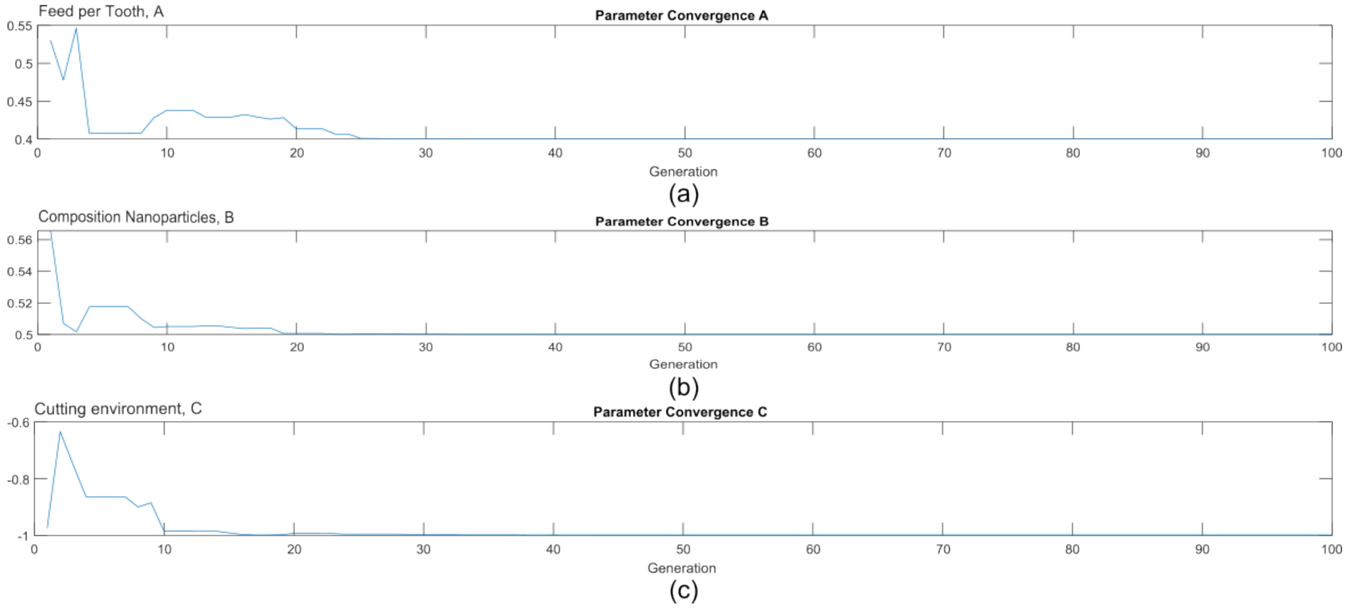

Figure 7: Performance convergence for each machining parameter.

A sensitivity analysis of the MDE results reveals the algorithm's robustness across various parameter settings, reinforcing its practical applicability in high-precision machining industries. The convergence profiles in Figure 8 indicate that MDE maintains stability even with initial population size and mutation rate variations, as tested in Section 3.2.1. Compared to the experimental baseline, the 1.3% reduction in Ra (from 0.7210 µm to 0.7115 µm) may seem modest. However, it represents a significant enhancement in surface integrity for NiTi components used in biomedical and aerospace applications, where even minor improvements can extend fatigue life and reliability [33]. The synergy between the regression model developed in Section 3.1 and the MDE algorithm demonstrates a data-driven approach to machining optimization, offering a scalable framework for future studies on other difficult-to-machine materials. These findings confirm that MDE meets and exceeds the performance expectations set in earlier sections, providing a reliable tool for achieving superior surface finishes in micro-milling processes.

Table 7 summarizes the machining parameters and resulting Ra values obtained from the experimental process, standard DE, and MDE. The optimized results indicate that MDE successfully identified the best machining conditions, achieving a Ra of 0.7115 µm, lower than the experimental (0.7210 µm) and DE-optimized (0.7122 µm) values. The selection of BN nanoparticles as the optimal lubrication medium aligns with previous findings in Section 2.3, where BN demonstrated superior tribological performance in reducing cutting friction and heat generation. Moreover, the fine-tuned feed per tooth to cutting edge radius ratio (0.4) minimizes the ploughing effect and improves the final surface finish.

Overall, the results confirm that the integration of regression modeling with the MDE algorithm provides a robust optimization framework for minimizing Ra in the micro-milling of NiTi alloys. These results further reinforce the conclusions made in Section 3.2.1 on MDE's superior performance over traditional optimization techniques based on MDE's improved convergence speed, adaptive searching, and more accurate solutions. This optimization strategy leads to an enhanced surface finish and is exceptionally beneficial for high-precision NiTi components in biomedical applications and aerospace parts. Further investigation can incorporate optimization strategies in lubrication and multi-objective optimization techniques for better surface quality and prolonging tool life at the same time.

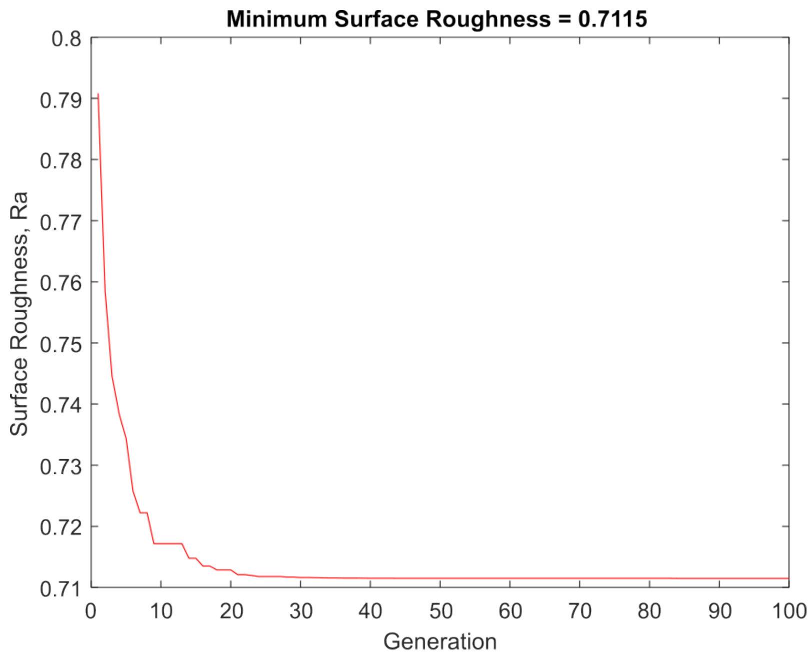

Figure 8: MDE convergence profile for Ra optimization.

Table 7: Comparison of overall results between Experimental, DE, and MDE approaches.

Variables	Experimental	DE	MDE
Feed per tooth to cutting edge radius ratio, *A*	0.4000	0.4005	0.4000
Composition of nanoparticles, *B*	0.5000	0.5009	0.5000
Cutting environment, *C*	-1 (BN)	-1 (BN)	-1 (BN)
Surface Roughness, Ra (µm)	0.7210	0.7122	0.7115

4.0 CONCLUSION

The MDE has proven effective for Ra optimization in micro-milling NiTi SMAs, producing optimized outcomes that far exceed the results of traditional optimization techniques. With MDE being coupled with regression modeling in the study, the ideal machining parameters, such as feed per tooth to edge radius ratio, antioxidant nanoparticle composition, and cutting environment, were successfully identified, which yielded the least Ra. The findings ascertain the superiority of MDE over conventional DE, characterized by faster convergence, better parameter adjustment, and improved optimization accuracy. MDE refined the machining conditions, as 0.7115 µm is the optimal Ra, in which the solid lubricant with BN nanoparticles acted as the best lubricant to minimize tool-workpiece friction and maintain machining stability. The results underline the importance of advanced optimization techniques in high-precision manufacturing of NiTi alloys, relevant to industries as diverse as biomedical, aerospace, and robotics applications.

Moreover, this study convincingly demonstrates the potential of combining intelligent optimization algorithms with empirical modeling to enhance machining performance while minimizing the required number of experimental trials. Building on this success, MDE can serve as a platform for future research into multi-objective optimization techniques for machining processes that minimize Ra while extending tool life. In addition, integrating real-time adaptive control mechanisms and advanced lubrication strategies can further enhance the optimization process, ensuring sustainable and efficient manufacturing practices. The knowledge acquired from this study guides researchers and practitioners who endeavor to attain optimum surface finish in the micro-milling of advanced materials such as NiTi SMAs.

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REFERENCES

[1] T. Duerig, A. Pelton, and D. Stöckel, ‘An overview of nitinol medical applications’, Materials Science and Engineering: A, vol. 273–275, pp. 149–160, 1999. doi: 10.1016/s0921-5093(99)00294-4.

[2] K. Otsuka and X. Ren, ‘Physical metallurgy of Ti-Ni-based shape memory alloys’, Prog Mater Sci, vol. 50, no. 5, pp. 511–678, 2005. doi: 10.1016/j.pmatsci.2004.10.001.

[3] M. H. Elahinia, M. Hashemi, M. Tabesh, and S. B. Bhaduri, ‘Manufacturing and processing of NiTi implants: A review’, Prog Mater Sci, vol. 57, no. 5, pp. 911–946, 2012. doi: 10.1016/j.pmatsci.2011.11.001.

[4] D. Mantovani, ‘Shape memory alloys: Properties and biomedical applications’, JOM, vol. 52, no. 10, pp. 36–44, 2000. doi: 10.1007/s11837-000-0082-4.

[5] Y. Kaynak, H. E. Karaca, R. D. Noebe, and I. S. Jawahir, ‘Tool-wear analysis in cryogenic machining of NiTi shape memory alloys: A comparison of tool-wear performance with dry and MQL machining’, Wear, vol. 306, no. 1–2, pp. 51–63, 2013. doi: 10.1016/j.wear.2013.05.011.

[6] K. Weinert and V. Petzoldt, ‘Machining of NiTi based shape memory alloys’, Materials Science and Engineering: A, vol. 378, no. 1-2 SPEC., pp. 180–184, 2004. doi: 10.1016/j.msea.2003.10.344.

[7] A. Aramcharoen and P. T. Mativenga, ‘Size effect and tool geometry in micromilling of tool steel’, Precis Eng, vol. 33, no. 4, pp. 402–407, 2009.

doi: 10.1016/j.precisioneng.2008.11.002.

[8] X. Liu, R. E. DeVor, and S. G. Kapoor, 'An analytical model for the prediction of minimum chip thickness in micromachining', J Manuf Sci Eng, vol. 128, no. 2, pp. 474–481, 2006. doi: 10.1115/1.2162905.

[9] M. Ansari and I. A. Khan, 'Investigation on the performance of wire electrical discharge machining (WEDM) using aluminium matrix composites (AMCs) micro-channel', Engineering Research Express, vol. 5, no. 3, 2023. doi: 10.1088/2631-8695/acf5ca.

[10] L. Kumar, A. Jain, K. Kumar, and G. K. Sharma, 'Influence of surface polishing on the degradation behavior of biodegradable Magnesium alloy', Engineering Research Express, vol. 5, no. 4, 2023. doi: 10.1088/2631-8695/ad04ac.

[11] D. C. Montgomery, Design and Analysis of Experiments. John Wiley & Sons, 2017.

[12] Philip J. Ross, Taguchi Techniques for Quality Engineering. McGraw-Hill, 1996.

[13] J. Kennedy and R. Eberhart, 'Particle swarm optimization', in IEEE International Conference on Neural Networks - Conference Proceedings, 1995, pp. 1942–1948.

[14] C. Y. Nee, M. S. Saad, A. Mohd Nor, M. Z. Zakaria, and M. E. Baharudin, 'Optimal process parameters for minimizing the surface roughness in CNC lathe machining of Co28Cr6Mo medical alloy using differential evolution', International Journal of Advanced Manufacturing Technology, vol. 97, no. 1–4, 2018. doi: 10.1007/s00170-018-1817-0.

[15] R. Storn and K. Price, 'Differential Evolution - A Simple and Efficient Heuristic for Global Optimization over Continuous Spaces', Journal of Global Optimization, vol. 11, no. 4, pp. 341–359, 1997. doi: 10.1023/A:1008202821328.

[16] M. Z. Zakaria, Z. Mansor, A. Mohd Nor, M. S. Saad, M. S. Mohamad, and R. B. Ahmad, 'NARMAX model identification using multi-objective optimization differential evolution', International Journal of Integrated Engineering, vol. 10, no. 7, 2018. doi: 10.30880/ijie.2018.10.07.018.

[17] M. Z. Zakaria et al., 'Perturbation parameters tuning of multi-objective optimization differential evolution and its application to dynamic system modeling', J Teknol, vol. 75, no. 11, 2015. doi: 10.11113/jt.v75.5335.

[18] J. Brest, S. Greiner, B. Bošković, M. Mernik, and V. Zumer, 'Self-adapting control parameters in differential evolution: A comparative study on numerical benchmark problems', IEEE Transactions on Evolutionary Computation, vol. 10, no. 6, pp. 646–657, 2006. doi: 10.1109/TEVC.2006.872133.

[19] Y. Zhang, C. Li, D. Jia, D. Zhang, and X. Zhang, 'Experimental evaluation of the lubrication performance of MoS2/CNT nanofluid for minimal quantity lubrication in Ni-based alloy grinding', Int J Mach Tools Manuf, vol. 99, pp. 19–33, Dec. 2015. doi: 10.1016/J.IJMACHTOOLS.2015.09.003.

[20] S. Das, S. S. Mullick, and P. N. Suganthan, 'Recent advances in differential evolution-An updated survey', Swarm Evol Comput, vol. 27, pp. 1–30, 2016. doi: 10.1016/j.swevo.2016.01.004.

[21] Z. A. Zailani and P. T. Mativenga, 'Boron and graphene nanoparticles as solid lubricant in micro milling of nickel titanium shape memory alloys', International Journal of Machining and Machinability of Materials, vol. 24, no. 3–4, pp. 262–279, 2022. doi: 10.1504/ijmmm.2022.125199.

[22] A. Kumar and S. K. Mallik, 'Measurement-based ZIP load modelling using opposition based differential evolution optimization', Engineering Research Express, vol. 5, no. 3, 2023. doi: 10.1088/2631-8695/ace81c.

[23] J. Zou and X. Zuo, 'Active suspension LQR control based on modified differential evolutionary algorithm optimization', Journal of Vibroengineering, vol. 26, no. 5, pp. 1150–1165, 2024. doi: 10.21595/jve.2024.23953.

[24] V. S. Sharma, M. Dogra, and N. M. Suri, 'Cooling techniques for improved productivity in turning', Int J Mach Tools Manuf, vol. 49, pp. 435–453, 2009, [Online]. Available: https://api.semanticscholar.org/CorpusID:110396290

[25] N. R. Dhar, M. W. Islam, S. Islam, and M. A. H. Mithu, 'The influence of minimum quantity of lubrication (MQL) on cutting temperature, chip and dimensional accuracy in turning AISI-1040 steel', J Mater Process Technol, vol. 171, no. 1, pp. 93–99, Jan. 2006. doi: 10.1016/J.JMATPROTEC.2005.06.047.

[26] N. Suresh Kumar Reddy and P. Venkateswara Rao, 'Experimental investigation to study the effect of solid lubricants on cutting forces and surface quality in end milling', Int J Mach Tools Manuf, vol. 46, no. 2, pp. 189–198, Feb. 2006. doi: 10.1016/J.IJMACHTOOLS.2005.04.008.

[27] A. J. Asalekar and D. V. A. Rama Sastry, 'Enhancing high-speed CNC milling performance of Ti6Al4V alloy through the application of ZnO-Ag hybrid nanofluids', Engineering Research Express, vol. 6, no. 2, 2024.
doi: 10.1088/2631-8695/ad476d.

[28] A. Mohammed S. Ahmed and S. K. Shather, 'Optimizing the five magnetic abrasive finishing factors on surface quality using Taguchi-based grey relational analysis', Engineering Research Express, vol. 6, no. 1, 2024.
doi: 10.1088/2631-8695/ad2d99.

[29] W. S. Sakr, R. A. EL-Sehiemy, and A. M. Azmy, 'Adaptive differential evolution algorithm for efficient reactive power management', Applied Soft Computing Journal, vol. 53, pp. 336–351, 2017.
doi: 10.1016/j.asoc.2017.01.004.

[30] O. Muribwathoho, V. Msomi, and S. Mabuwa, 'An Analysis Comparing the Taguchi Method for Optimizing the Process Parameters of AA5083/Silicon Carbide and AA5083/Coal Composites That Are Fabricated via Friction Stir Processing', Applied Sciences (Switzerland), vol. 14, no. 20, 2024.
doi: 10.3390/app14209616.

[31] E. Reyes-Davila, E. H. Haro, A. Casas-Ordaz, D. Oliva, and O. Avalos, 'Differential Evolution: A Survey on Their Operators and Variants', Archives of Computational Methods in Engineering, vol. 32, no. 1, pp. 83–112, 2025.
doi: 10.1007/s11831-024-10136-0.

[32] H. M. J. Mustafa, M. Ayob, M. Z. A. Nazri, and G. Kendall, 'An improved adaptive memetic differential evolution optimization algorithms for data clustering problems', PLoS One, vol. 14, no. 5, 2019.
doi: 10.1371/journal.pone.0216906.

[33] I. S. Jawahir et al., 'Surface integrity in material removal processes: Recent advances', CIRP Ann Manuf Technol, vol. 60, no. 2, pp. 603–626, 2011.
doi: 10.1016/j.cirp.2011.05.002.