Available online at
https://jmeche.uitm.edu.my/

e-ISSN: 2550-164X

Journal of Mechanical Engineering 23(2) 2026, 57 – 74

Journal of Mechanical Engineering

Performance Analysis of Genetic Algorithm (GA), Particle Swarm Optimization (PSO), and Simulated Annealing (SA) for Surface Roughness Optimization in Aluminum Alloy Milling

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ARTICLE INFO

Article history:
Received 20 July 2025
Revised 22 July 2025
Accepted 24 January 2026
Online first
Published 15 May 2026

Keywords:
Genetic algorithm
Particle swarm optimization
Simulated annealing
Surface roughness
Milling

DOI:
10.24191/jmeche.v23i2.7790

ABSTRACT

Surface roughness (*Ra*) is one of the most important response indicators used to evaluate machining quality. Although various metaheuristic optimization algorithms have been applied in machining optimization, there remains limited comparative evidence regarding their relative performance under consistent modeling and computational conditions. Therefore, this study aims to evaluate and compare the performance of three widely applied metaheuristic optimization algorithms, namely Genetic Algorithm (GA), Particle Swarm Optimization (PSO), and Simulated Annealing (SA), in minimizing *Ra* during the milling of aluminum alloys. A predictive model for *Ra* is first constructed using the Group Method of Data Handling (GMDH). Among the eight functions tested in the GMDH network, the double-variable model provides the highest accuracy with an R^2 of 0.9990, *RMSE* of 0.0042, and *MAPE* of 0.2985 for training, and an R^2 of 0.9962, *RMSE* of 0.0083, and *MAPE* of 0.5724 for validation. This model is subsequently integrated into the optimization stage, where GA, PSO, and SA are implemented under consistent computational conditions to ensure a fair comparison. The optimal *Ra* values obtained by the algorithms are 0.6448 for GA, 0.6445 for PSO, and 0.6472 for SA. PSO achieves the best overall performance due to its rapid convergence, high stability, and small variance across repeated runs. GA produces competitive results with moderate variability, whereas SA converges more slowly and yields a wider spread of solutions. The findings confirm that PSO is the most effective algorithm among the three for surface roughness optimization in aluminum alloy milling and provide practical guidance for selecting machining parameters.

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https://doi.org/10.24191/jmeche.v23i2.7790

INTRODUCTION

Surface roughness (*Ra*) is one of the most important response indicators used to evaluate machining quality, as it directly affects service life, loading capacity, friction behavior, and assembly precision of mechanical components. Numerous studies have shown that *Ra* is affected by various technological factors such as cutting speed, feed rate, depth of cut, and tool geometry, among others (Darwish, 2000; Yadav et al., 2022). In the machining of aluminum alloys, controlling surface roughness is often more complex due to characteristics such as high ductility and a tendency to form burrs. These characteristics lead to complex, nonlinear interactions between cutting parameters, making optimal selection highly sensitive and complicating the achievement of consistent surface integrity (Armansyah et al., 2024; Pimenov et al., 2023). While empirical and statistical methods have traditionally been used to model Ra, their effectiveness is limited by an inability to fully capture these nonlinearities. Furthermore, these methods often require extensive experimental data to produce reliable models, leading to high costs and significant time investments (Aurrekoetxea et al., 2022).

To address these limitations, intelligent optimization and machine learning approaches have increasingly gained attention. Artificial Neural Networks (ANN), in particular, have shown strong capability for modeling complex nonlinear relationships between cutting parameters and surface roughness, exhibiting higher predictive accuracy than traditional linear models (Abu-Mahfouz et al., 2017; Khorasani & Yazdi, 2017; Armansyah et al., 2025; Vasconcelos et al., 2024; Zain et al., 2010). Nonetheless, ANN performance depends heavily on training data volume and network configuration; insufficient or imbalanced datasets may lead to overfitting and reduced generalization ability (Tu, 1996). In this context, the Group Method of Data Handling (GMDH) presents a compelling alternative for building predictive models. As a self-organizing neural network algorithm, GMDH automatically optimizes its structure through inductive learning, selectively building increasingly complex polynomials to model the underlying process without substantial prior assumptions. This key characteristic allows GMDH to effectively navigate the trade-off between model complexity and prediction accuracy, significantly reducing the risk of overfitting (Madala & Ivakhnenko, 2019). For machining optimization problems where experimental data is often costly to obtain, GMDH's ability to generate models from relatively small datasets makes it particularly advantageous for establishing a reliable objective function (Ebtehaj et al., 2015; Tran, 2024). However, developing a predictive model is only the first step in the optimization process. The subsequent challenge involves efficiently locating the optimal machining parameters.

Among optimization methods, metaheuristic optimization algorithms, which are capable of exploring high-dimensional and multimodal solution spaces, have become promising tools in machining optimization (Zain et al., 2011). The Genetic Algorithm (GA) performs a global search through operations mimicking natural selection. Although GA is effective in finding near-global optima for complex engineering problems, its performance relies on proper parameter settings to avoid premature convergence (D'Angelo & Palmieri, 2021). Despite these limitations, GA has been applied in various machining optimization studies. For example, Bhushan (2023) investigated cutting forces during the dry turning of AA7075/15 wt% SiC (20–40 µm) composites on a Computer Numerical Control (CNC) machine, using Response Surface Methodology (RSM) combined with GA. The results demonstrated that the parameters derived from GA significantly reduced cutting force compared to those obtained from other optimization methods. Similarly, Bousnina et al. (2024) developed a hybrid GA-ANN model to optimize machining parameters for 2017A alloy, achieving $R^2 > 0.97$ for surface quality, cost, and energy predictions. Compared to RSM, the GA-ANN model improved the mean squared error by 90.91% for energy, 96.55% for cost, and 40.18% for surface roughness. Numerous other studies have reported similar advantages of GA in parameter optimization across manufacturing processes (Panwar et al., 2021; Shang et al., 2024; Wang et al., 2024; Wang et al., 2025).

Particle Swarm Optimization (PSO) is based on the social movement and interaction of swarming animals such as birds or fish. The algorithm converges quickly but is sensitive to the adjustment of its

https://doi.org/10.24191/jmeche.v23i2.7790

inertia weight and acceleration coefficients (Sekyere et al., 2024). However, PSO has demonstrated strong performance in machining parameter optimization (Raghavendra et al., 2025; Yusup et al., 2012). For instance, Lmalghan et al. (2018) investigated the effects of machining parameters on cutting force, surface roughness, and power consumption in milling AA6061 aluminum by using RSM, PSO, and desirability approaches. Their results demonstrated that PSO performs comparably to conventional methods in optimizing multiple response variables. Xu et al. (2020) developed a method for predicting tool wear width and optimizing cutting parameters in the milling process through a novel ANFIS-PSO approach. Similarly, Gadagi & Adake (2021) also conducted a constrained multi-objective optimization of turning process parameters using GA and PSO techniques. Collectively, these studies demonstrate the strong applicability of PSO in machining optimization problems.

Simulated Annealing (SA), a stochastic optimization method inspired by the annealing process in metallurgy, offers an alternative approach by probabilistically accepting inferior solutions in early search stages to escape local optima. This exploration mechanism improves global search capability while preserving solution diversity (Suppapitnarm et al., 2000). SA has been successfully applied in various precision machining tasks, including geometric accuracy enhancement, surface roughness minimization, and tool-path optimization (Chávez-García & Castillo-Villar, 2018; Sibalija, 2018). Its conceptual simplicity and strong ability to avoid local minima make SA particularly suitable for highly nonlinear machining environments.

Despite the extensive individual application of GA, PSO, and SA in machining optimization, a critical research gap remains to be addressed. Specifically, most existing studies have not conducted a direct and systematic comparison of all three algorithms under identical conditions, particularly using the same predictive model based on GMDH for aluminum alloy milling. Most published works examine these algorithms individually or in pairs, often employing different modeling techniques, materials, and objectives. These variations make it difficult to compare results and fail to provide manufacturers with reliable guidance on which algorithm is more effective for reducing surface roughness. Consequently, there is a lack of clear, consistent guidance on which algorithm best balances efficiency, accuracy, and convergence speed.

This study presents a comprehensive comparison of GA, PSO, and SA for optimizing cutting parameters, specifically cutting speed, feed rate, and depth of cut, with the single objective of minimizing surface roughness in aluminum alloy milling. First, the GMDH algorithm was used to build a highly accurate predictive model for *Ra* to serve as the objective function for the optimization methods. Then, based on this model, GA, PSO, and SA were applied to the same dataset, using the same optimization settings and evaluation criteria. The study analyzes their convergence characteristics, solution stability, and ability to identify suitable machining parameters. This methodology establishes a consistent basis for comparing the three algorithms and helps clarify their respective strengths and weaknesses when used with a GMDH-derived objective function. The findings aim to support more informed decision-making in machining parameter optimization, thereby contributing to improved surface quality and production efficiency.

MATERIALS AND METHODS

Materials, tools, and machining equipment

To ensure that the machining experiments could be reproduced reliably, all tests were performed under strictly controlled process conditions. The experiments were conducted on 7075 aluminum alloy samples sized (100 × 65 × 10 ± 1) mm. As provided by the manufacturer, the alloy contains 87.1–91.4% aluminum, 0.18–0.28% chromium, and 1.2–2.0% copper, plus trace amounts of other elements, with a density of 2.81 g/cm^3.

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All machining operations were performed on a MORI SEIKI MV JUNIOR vertical machining center equipped with a Fanuc 10M control unit (Fig. 1). A water-soluble coolant (Venus GPX) was supplied at a concentration of 2.5 to 3.0% to maintain stable thermal conditions, facilitate chip evacuation, and minimize tool–workpiece adhesion. A solid carbide end mill with three flutes, a diameter of 10 mm, and a cutting-edge angle of 55 degrees was used consistently across all experiments to avoid tool-related variability.

Surface roughness (*Ra*) was measured after each trial using a Mitutoyo TR200 profilometer. To obtain a representative roughness value for each machining condition, measurements were performed at three distinct positions along the machined surface, aligning with the tool travel direction. The final *Ra* value assigned to each experimental run was calculated as the arithmetic mean of these three measurements, thereby reducing potential random errors and enhancing the accuracy of the recorded surface finish.

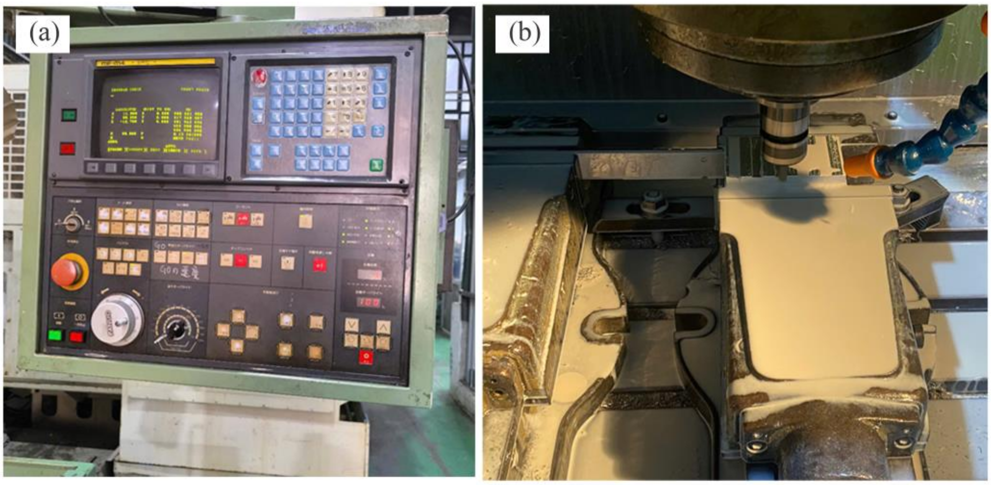

Fig. 1. CNC machine used in the experiment: (a) control panel; (b) machining zone and workpiece setup.

Methods

Experimental design

The Taguchi Orthogonal Array (OA) method was employed to determine the required number of experimental runs while reducing experimental cost and maintaining statistical reliability. Three machining parameters were selected for evaluation: cutting speed (*S*, rpm), feed rate (*f*, mm/rev), and depth of cut (*d*, mm). Each parameter was assigned five levels, where *S* ranged from 3000–5000 rpm, *f* from 0.20–1.00 mm/rev, and *d* from 0.25–1.25 mm. Based on these factors and levels, a total of 25 runs were generated using the L25 (5^3) orthogonal array, as shown in Table 1, while the corresponding level values are summarized in Table 2.

To reduce material cost and minimize the number of required workpiece samples, the cutting paths for all experimental conditions were programmed to run in parallel tracks across several workpieces. Each track (groove) corresponds to one machining condition from the Taguchi L25 array, with cutting parameters varying according to the assigned settings. This approach ensures consistent material properties across all tests, reduces experimental cost, and maintains comparability while still enabling accurate measurement of surface roughness for each individual cutting condition.

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Table 1. L25 Taguchi Orthogonal Array

Run no.	*S*	*f*	*d*	Run no.	*S*	*f*	*d*	Run no.	*S*	*f*	*d*
1	1	1	1	10	2	5	1	19	4	4	2
2	1	2	2	11	3	1	3	20	4	5	3
3	1	3	3	12	3	2	4	21	5	1	5
4	1	4	4	13	3	3	5	22	5	2	1
5	1	5	5	14	3	4	1	23	5	3	2
6	2	1	2	15	3	5	2	24	5	4	3
7	2	2	3	16	4	1	4	25	5	5	4
8	2	3	4	17	4	2	5				
9	2	4	5	18	4	3	1				

Table 2. Cutting conditions and corresponding levels

Level	*S* (rpm)	*f* (mm/rev)	*d* (mm)
1	3000	0.20	0.25
2	3500	0.40	0.50
3	4000	0.60	0.75
4	4500	0.80	1.00
5	5000	1.00	1.25

Prediction model using GMDH

The Group Method of Data Handling (GMDH) is a machine learning technique used to develop prediction models based on experimental data (Abdel-Aal et al., 2009). It functions by automatically generating and selecting mathematical models in the form of nonlinear polynomials to optimize prediction accuracy. The structure consists of a multi-layer network, with each layer containing neuron sets formed by combining neurons from the previous layer using mathematical functions (Fig. 2).

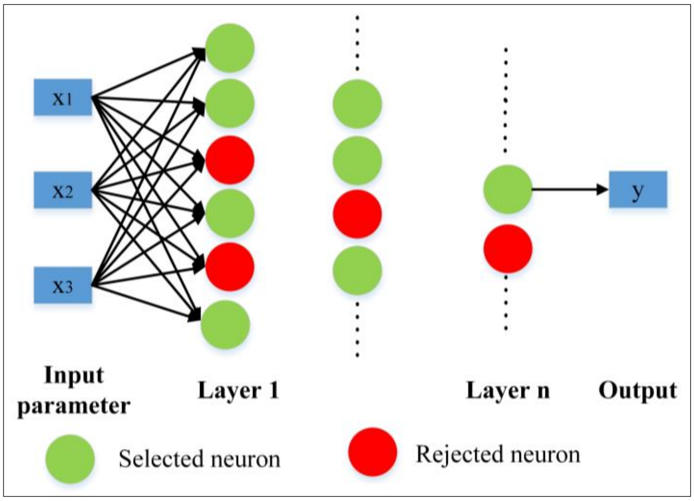

Fig. 2. GMDH model with three input parameters and one output (Tran, 2024).

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In predictive modeling, GMDH approximates a function ($\hat{f}$) to estimate the output ($\hat{y}$) from an input vector X ($x_1, x_2, \ldots, x_n$) such that the estimate closely matches the actual output y.

$$y_i = f(x_{i1}, x_{i2}, x_{i3}, \ldots, x_{in})\ with\ \mathrm{i} = 1, 2, \ldots, \mathrm{m} \tag{1}$$

The GMDH-based neural network can be designed to predict output values ($\hat{y}$) for any input vector X as demonstrated in Equation 2:

$$\hat{y_i} = \hat{f}(x_{i1}, x_{i2}, x_{i3}, \ldots, x_{in})\ with\ \mathrm{i} = 1, 2, \ldots, \mathrm{m} \tag{2}$$

Using a discrete form of the complex Volterra series, the generalized relationship between inputs and output can be expressed as:

$$y = a_0 + \sum_{i=1}^{n} a_i x_i + \sum_{i=1}^{n}\sum_{j=1}^{n} a_{ij} x_i x_j + \sum_{i=1}^{n}\sum_{j=1}^{n}\sum_{k=1}^{n} a_{ijk} x_i x_j x_k + \cdots \tag{3}$$

where a_0, a_i, a_{ij}, a_{ijk}, ... are coefficients indicating the interaction levels of the inputs with the system output.

To evaluate a model's accuracy and generalizability, three performance indicators are employed, including the coefficient of determination (R^2), root mean square error (*RMSE*), and mean absolute percentage error (*MAPE*). A higher R^2 indicates a better fit between the predicted and actual values, while lower *RMSE* and *MAPE* values reflect greater prediction accuracy and overall model performance.

Genetic Algorithm (GA)

The Genetic Algorithm (GA) is an optimization method based on natural evolution, consisting of main steps: initializing a random population, evaluating fitness through an objective function, selecting the best individuals, performing crossover to combine genetic information, and mutation to maintain diversity (Alhijawi & Awajan, 2024). This process repeats over multiple generations until convergence criteria are met, aiming to find the optimal solution in a broad search space. The general workflow is shown in Fig. 3.

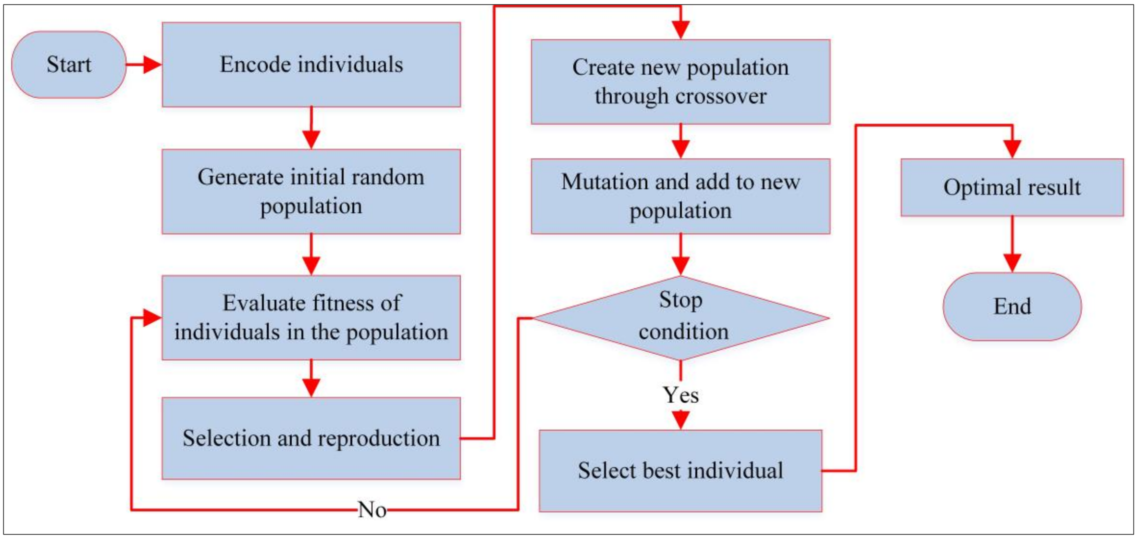

Fig. 3. Optimization flowchart using Genetic Algorithm (GA).

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Particle Swarm Optimization (PSO)

The PSO algorithm is an optimization technique inspired by the collective behavior of animals, such as fish schools or bird flocks in their search for optimal solutions (Wang et al., 2018). It begins by initializing a population of particles, each representing a potential solution. Each particle has its own position and velocity vectors X_i and V_i (Fig. 4).

To achieve the objective, the trajectories of the particles are updated through their velocity and position at each iteration, according to Equations 4 and 5. P_i^{best} represents the particle's personal best position, and G_i^{best} represents the global best position in the search space. The movement trajectory of each particle is updated in each iteration using the following formulas:

$$V_i^{(t+1)} = \omega \times V_i^{(t)} + C_1 \times r_1 \times (P_i^{best} - X_i^{(t)}) + C_2 \times r_2 \times (G_i^{best} - X_i^{(t)}) \tag{4}$$

$$X_i^{(t+1)} = X_i^{(t)} + V_i^{(t+1)} \tag{5}$$

where ω is the inertia weight; C_1 and C_2 are cognitive and social coefficients; r_1 and r_2 are random numbers within the interval [0, 1].

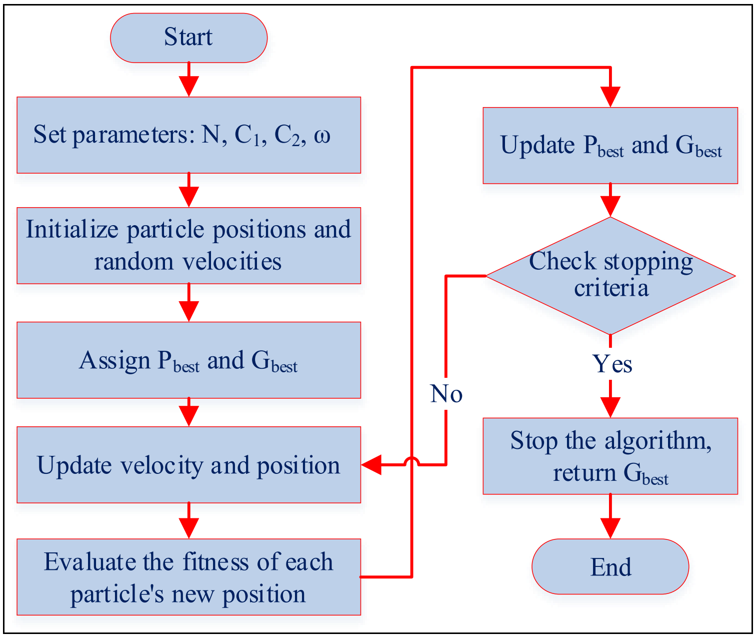

Fig. 4. Optimization flowchart using PSO.

Simulated Annealing (SA)

Based on the principles of metallurgical annealing, Simulated Annealing (SA) is a computational method that replicates the process of heating and slowly cooling materials to find optimal solutions. (Delahaye et al., 2018). The algorithm starts with a high-temperature state. In each iteration, a new state is generated by perturbing the current state. If the new state is better, it is accepted; if worse, it may still be accepted with a certain probability, allowing the system to escape local minima. The temperature is systematically reduced following a predefined cooling scheme, progressively focusing the search area until

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converging toward the best solution. The process terminates when the temperature reaches a threshold or no significant improvement is observed (Fig. 5).

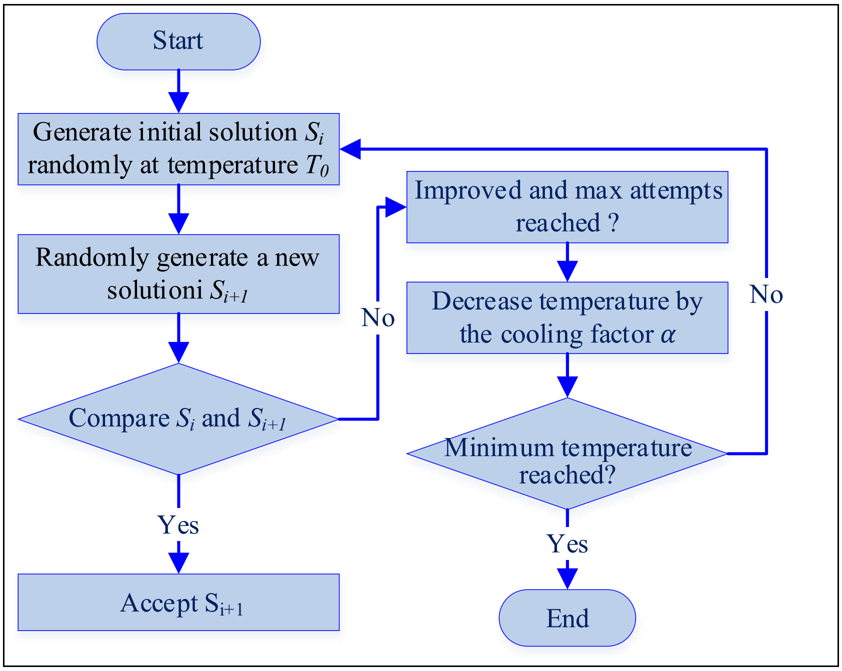

Fig. 5. Optimization flowchart using SA.

RESULTS AND DISCUSSION

Influence of milling process parameters on *Ra*

To evaluate the influence of machining parameters on *Ra*, an ANOVA was performed. The results in Table 3 indicate that *f* has the strongest effect, contributing 79.68% of the total variance. This can be attributed to the fact that increasing *f* results in thicker chips, leading to higher cutting forces and greater tendencies for chatter and vibration (Hanincová et al., 2024). These factors result in increased *Ra*. Additionally, at higher feed rates, the helical motion of the tool becomes more distinct, creating deeper and wider grooves on the machined surface. *S* is also statistically significant ($p < 0.001$) and a contribution of 20.06%. This is due to higher cutting speeds can improve surface quality by reducing the built-up edge and decreasing cutting forces (Aydin & Ozcatalbas, 2003; Gökkaya, 2010). However, although *d* is known to influence surface characteristics through its role in material removal and chip formation, its impact was limited in this study. The *d* parameter shows no statistically significant effect ($p = 0.075$). This result is due to the fact that the selected range of the *d* parameter was narrow, thereby failing to produce sufficient variation to show a statistically significant effect on *Ra*. Fig 6. illustrates the influence of *S, f,* and *d* parameters on *Ra*.

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Table 3. ANOVA results for *Ra*

Source	*DF*	Seq *SS*	Contribution	Adj *SS*	Adj *MS*	*F*	*p*
S	4	0.089	20.06%	0.089	0.022	453.3	0.000
f	4	0.353	79.68%	0.353	0.088	1800.5	0.000
d	4	0.001	0.12%	0.001	0.000	2.80	0.075
Error	12	0.001	0.13%	0.001	0.000		
Total	24	0.443	100.00%				

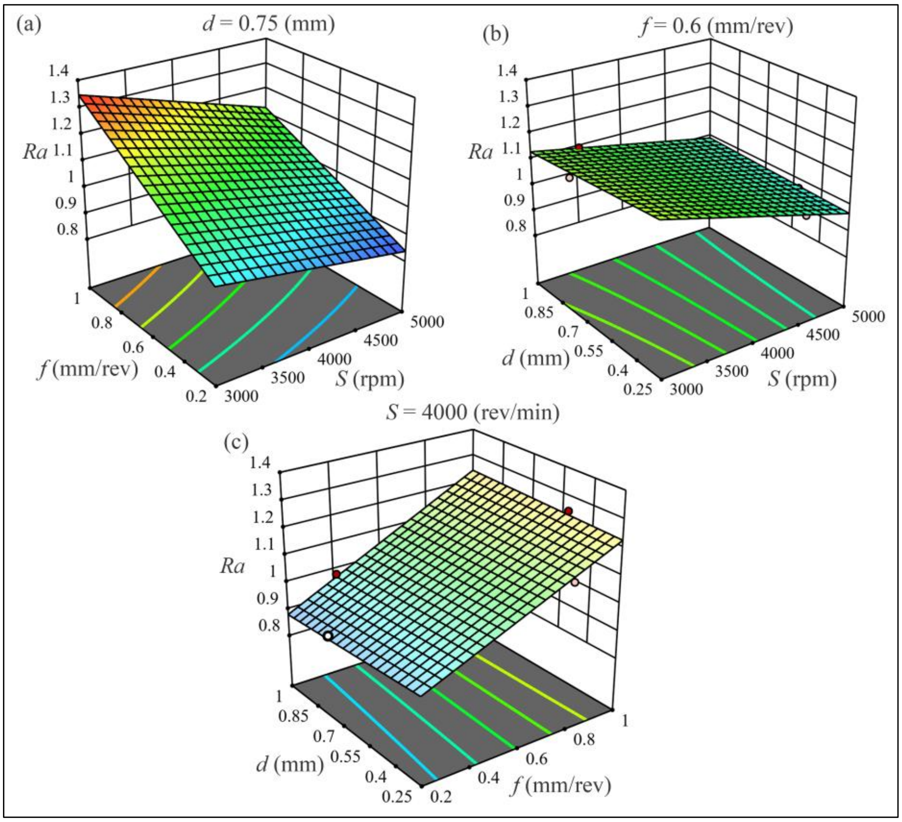

Fig. 6. The influence of *S, f, d* parameters on *Ra.*

Prediction model

In this study, the GMDH was employed to develop a predictive model for *Ra* as a function of machining parameters. To ensure the reliability of the model, a 10-fold cross-validation procedure was implemented, thereby reducing the risk of performance overestimation and enhancing the generalization capability of the predictive model.

The network configuration was defined with a maximum of 30 layers, a polynomial order of up to 16, and a convergence tolerance of 10^{-4}, enabling the model to represent nonlinear interactions without compromising numerical stability. Table 4 summarizes the performance of eight GMDH function types evaluated using R^2, *RMSE*, and *MAPE* for both training and validation datasets. The results show the

https://doi.org/10.24191/jmeche.v23i2.7790

significant different variation in model performance across function types. Specifically, linear functions and single-variable polynomial functions exhibit limited predictive capability, indicating that *Ra* is governed by complex nonlinear interactions rather than dependencies on individual machining parameters. Although the quadratic two-variable function demonstrates improved accuracy, it still falls short of the optimal performance required for reliable prediction.

In contrast, the double-variable function achieves outstanding predictive accuracy, with R^2 values of 0.9990 for training and 0.9962 for validation, accompanied by the lowest *RMSE* and *MAPE* among all examined models. The results confirm the model's strong generalization ability and absence of overfitting. Although the triple-variable function provides greater structural flexibility, it does not yield further improvements and may introduce redundant complexity that contributes to noise amplification. Therefore, the double-variable function was selected as the objective function for the subsequent optimization using GA, PSO, and SA.

Table 4. Performance of GMDH-based prediction models using different functions

Function Type	Training			Validation		
	R^2	*RMSE*	*MAPE*	R^2	*RMSE*	*MAPE*
Linear (1 variable)	0.7865	0.0615	5.0645	0.7508	0.0665	5.3593
Linear (2 variables)	0.9881	0.0145	1.0543	0.9784	0.0196	1.2666
Linear (3 variables)	0.9868	0.0153	1.1476	0.9573	0.0275	1.8529
Quadratic (1 variable)	0.7930	0.0606	5.0038	0.7176	0.0708	5.7539
Quadratic (2 variables)	0.9974	0.0068	0.5667	0.9886	0.0142	1.0655
Cubic (1 variable)	0.7939	0.0605	4.9885	0.6953	0.0735	5.9983
Double-variable function	0.9990	0.0042	0.2985	0.9962	0.0083	0.5724
Triple-variable function	0.9837	0.0170	0.5825	0.9772	0.0196	0.6224

The final GMDH model represents *Ra* through three intermediate variables (*A, B*, and *C*), each derived from nonlinear polynomial combinations of the cutting parameters, as presented in Equation 6. This multilayer polynomial formulation enables the model to capture higher-order nonlinearities and complex interactions among the machining parameters that conventional regression approaches typically fail to describe. In addition, the hierarchical structure of GMDH allows the model to automatically identify and select the most appropriate functional forms based on the characteristics and quality of the empirical data.

$$\begin{aligned}
B &= 0.389687 + 0.425567 \times d + 0.011968 \times d^2 + 0.000362 \times S - 0.000124 \times d \times S \\
C &= 1.103357 + 0.2606 \times f + 0.169483 \times f^2 - 0.000044 \times S - 3.871179\times10^{-9} \times S^2 - 0.000012 \times f \times S \\
A &= -\ 0.580249 + 1.130448 \times B - 0.386204 \times B^2 + 0.97446 \times C + 0.161984 \times C^2 - 0.302019 \times B \times C \\
Ra &= 0.640378 + 0.541213 \times f + 0.069943 \times f^2 - 0.515667 \times A + 0.883799 \times A^2 - 0.593214 \times f \times A
\end{aligned} \tag{6}$$

Optimization using GA, PSO, and SA

The optimization process using GA, PSO, and SA was implemented in the MATLAB environment to determine the minimum *Ra* based on the objective function derived from the GMDH model. To ensure that the comparison among the three algorithms was fair and not influenced by discrepancies in configuration, the parameters of GA, PSO, and SA were established under equivalent computational effort and exploitation capacity. Both GA and PSO were configured with a population or swarm size of 50, whereas SA functioned under its inherent single-solution mechanism. The maximum number of iterations for all

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algorithms was kept approximately the same, and the total number of objective function evaluations was maintained at comparable levels through unified stopping criteria. Control parameters such as crossover and mutation rates (for GA), inertia weight and learning coefficients (for PSO), and the initial temperature and cooling factor (for SA) were selected based on standard configurations widely recommended in the literature. By harmonizing these settings, the performance differences observed among GA, PSO, and SA reflect the intrinsic characteristics of each algorithm rather than tuning biases, thereby ensuring objectivity and reliability of the comparative evaluation.

The detailed parameter settings were as follows. For GA, a population size of 50 was employed, with a crossover rate of 0.8 and a mutation rate of 0.1 to balance global exploration and local refinement. Tournament selection was adopted, and the algorithm was terminated after 100 generations. For PSO, 50 particles were used, with an inertia weight (w) decreasing gradually from 0.7 to facilitate the transition from exploration to exploitation. The personal and social learning coefficients (C_1 = C_2 = 1.5) were selected following common practice in many PSO implementations. The maximum number of iterations was set at 100. The SA algorithm was initialized with a starting temperature of 1000 (T_0), a cooling factor of 0.95, and 50 iterations per temperature level, following the conventional SA design for continuous optimization. In addition, both GA and PSO applied supplemental stopping criteria of 5000 objective function evaluations or no improvement over 20 consecutive iterations.

Evaluation results indicate that the three optimization algorithms exhibit distinct differences in solution quality, convergence speed, and stability. In terms of the final solution quality, PSO achieved the best performance, yielding the minimum surface roughness value of Ra = 0.6445 over 30 independent runs (Fig. 7(a)). GA and SA produced nearly equivalent results, with values of approximately 0.6448 and 0.6472, respectively. Although the numerical difference is marginal, it suggests that PSO exploits the search space more effectively, demonstrating a stronger tendency to converge near the global optimum for this specific problem. The corresponding optimal cutting parameters identified by each algorithm are summarized in Table 5.

Table 5. Optimal cutting parameters and *Ra* values obtained by GA, PSO, and SA

Algorithm	*S* (rpm)	*f* (mm/rev)	*d* (mm)	Predicted *Ra* (μm)
GA	4988.7	0.20	0.25	0.6448
PSO	5000.0	0.20	0.25	0.6445
SA	4950.9	0.20	0.25	0.6472

Regarding convergence behavior, PSO again demonstrates superiority by attaining a low *Ra* value within a small number of iterations and maintaining stability until the process concludes (Fig. 7(b)). This rapid convergence is consistent with the theoretical underpinnings of PSO, where each particle dynamically updates its position based on both personal experience (P_{best}) and the collective knowledge of the swarm (G_{best}). Such cooperative information exchange enables PSO to quickly identify promising regions within the solution space, thus accelerating convergence. GA also demonstrates a relatively stable convergence trajectory, though minor oscillations are present due to the inherent randomness of crossover and mutation. These stochastic operators are essential for maintaining population diversity, yet they occasionally cause short-term degradation in solution quality, a behavior commonly reported in previous evolutionary optimization studies. This finding is strongly aligned with trends reported in prior studies. For example, Yusup et al. (2012) and Abu-Mahfouz et al. (2021) demonstrated that PSO consistently outperforms GA in convergence speed and stability when optimizing surface roughness in turning and milling operations.

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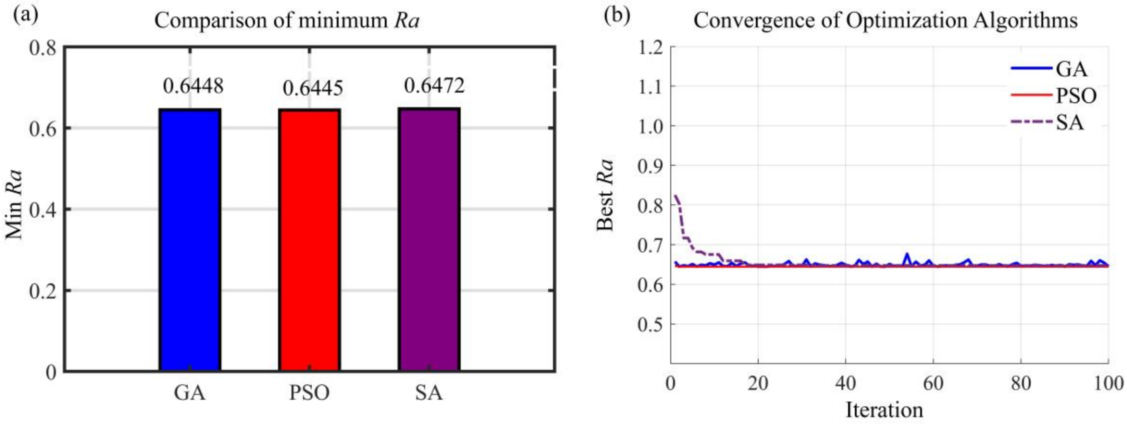

Fig. 7. (a) Comparison of minimum *Ra* values and (b) convergence curves for GA, PSO, and SA optimization.

The distribution of optimal *Ra* values across multiple independent runs provides additional evidence of the relative stability of each algorithm. As shown in Fig. 8(a), PSO exhibits the smallest variance and the tightest value range, indicating superior repeatability. This stability arises from PSO's collaborative search mechanism, which continuously aligns particle trajectories through shared learning, thereby reducing stochastic fluctuations while preserving exploration capability. The superior consistency of PSO is also consistent with trends reported in recent studies, where PSO methods demonstrated lower inter-run variance and more reliable convergence behavior compared with other evolutionary algorithms (Fathi et al., 2025; Hayat et al., 2023). GA also displays a relatively stable distribution, although several outliers are present. These deviations are indicative of the stochastic behavior of crossover and mutation, which, while beneficial for escaping local minima, may sometimes lead to suboptimal search directions. This observation is consistent with previous findings that GA performance is strongly influenced by selection pressure and mutation intensity (Simoncini et al., 2007). Katoch et al. (2021) also concluded that although GA is capable of reaching high-quality solutions, its stability is strongly dependent on parameter configuration, which corresponds well with the larger variance observed for GA in the present study. In this study, SA exhibited the widest distribution and the largest number of outliers, indicating lower stability compared to GA and PSO. This result is consistent with findings reported in the recent literature (Jia & Lichti, 2017). The reason is its probabilistic acceptance mechanism, which, although theoretically advantageous for escaping local optima at high temperatures, introduces substantial variability in the final solution quality across repeated executions. This characteristic has been reaffirmed by several studies (Franzin & Stützle, 2019; Lu et al., 2014). Thus, the dispersed distribution of solutions obtained in the present work is fully aligned with existing research.

To further validate the robustness of the optimized solution, a sensitivity analysis was conducted using the developed GMDH model. *f* was identified as the most influential machining parameter affecting surface roughness, contributing 79.68% of the total variance in *Ra*. Therefore, *f* was varied within its experimental range (0.20–1.00 mm/rev), while *S* and *d* were fixed at the PSO-optimized values of 5000 rpm and 0.25 mm, respectively. Fig. 8(b) shows the predicted relationship between *Ra* and *f*. The results show a consistent increase in *Ra* with increasing *f*, rising from 0.6446 µm to 0.9046 µm at *f* values of 0.20 mm/rev and 1.00 mm/rev, respectively. This corresponds to an approximately 40.3% increase in *Ra* over the tested range. The relationship between *f* and *Ra* also explains why all three optimization algorithms consistently converged toward the lower bound of the feed rate range, as any increase in feed rate leads to a direct and substantial degradation of the surface finish.

https://doi.org/10.24191/jmeche.v23i2.7790

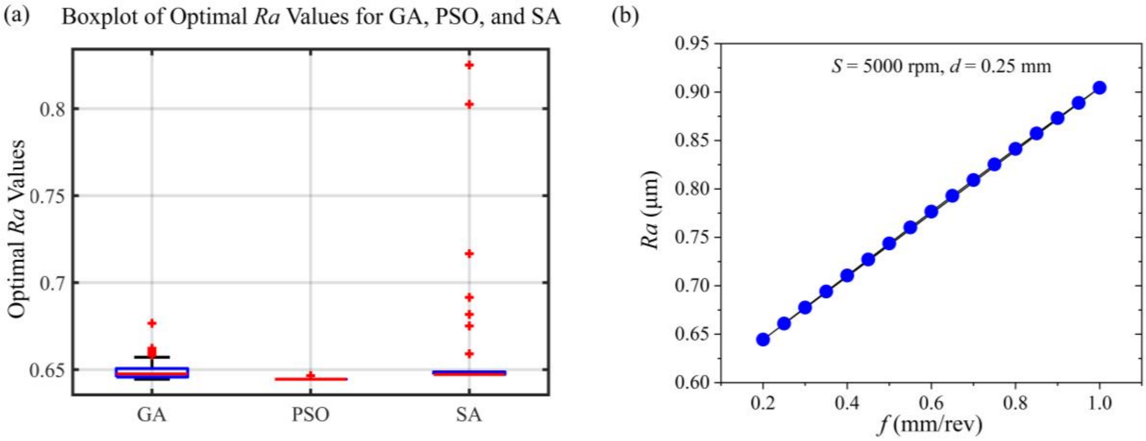

Fig. 8. (a) Statistical distribution of optimal *Ra* values for GA, PSO, and SA and (b) sensitivity of *Ra* to *f* under PSO-optimized conditions.

Overall, the combined results clearly demonstrate that PSO provides the most comprehensive performance among the three algorithms for optimizing surface roughness in machining operations. PSO not only delivers the best solution quality but also offers rapid convergence and high stability, making it particularly suitable for real-world applications that demand reliable and repeatable optimization outcomes. Although GA performs reasonably well, its run-to-run variability limits its practical reliability. SA proves to be the least effective for this problem due to its slow convergence, lower stability, and lack of competitive final solution quality. These findings suggest that PSO is a highly promising and effective candidate for parameter optimization in manufacturing processes where consistency and optimality are critical requirements.

CONCLUSION

This study optimized *Ra* in aluminum alloy milling using a combined approach of experimental design, GMDH predictive modeling, and metaheuristic optimization, providing practical guidance for improving surface quality and supporting more efficient, cost-effective machining in industrial applications. Based on the results from experimentation, modeling, and optimization, the main conclusions are as follows:

(i) Feed rate (*f*) is the most influential parameter affecting *Ra*, contributing 79.68%, followed by spindle speed (*S*) with 20.06%. Depth of cut (*d*) shows no significant effect within the tested range.

(ii) Among eight GMDH function types, the double-variable model provides the highest predictive accuracy, achieving R^2 values of 0.9990 (training) and 0.9962 (validation). This confirms that *Ra* exhibits complex nonlinear interactions, and the selected GMDH model effectively captures these relationships without signs of overfitting.

(iii) The optimization results demonstrate that PSO achieves the lowest *Ra* value (0.6445), which corresponds to a marginal but consistent improvement of approximately 0.05% over GA and 0.42% over SA. PSO also exhibits the fastest and most stable convergence, with the smallest variance across multiple runs. GA provides competitive performance but shows moderate fluctuations and variability, while SA yields the highest *Ra* value (0.6472), converges more slowly, and displays the widest distribution of solutions, indicating the lowest stability among the three algorithms.

However, this study also has several limitations that should be taken into consideration. First, the dataset used in the research is relatively limited. Although 10-fold cross-validation helps minimize bias, a larger dataset could significantly enhance the accuracy and stability of the model. Second, while the GA, PSO, and SA algorithms have produced promising results, each algorithm has its own strengths and weaknesses. Therefore, the comparison among these three methods may not fully reflect their overall performance, particularly in the context of other optimization problems. Finally, the optimal *Ra* values obtained from these algorithms can be considered “optimal” under the current experimental conditions, but they may not represent the ideal targets in practical manufacturing scenarios. Determining optimal values in real-world applications requires balancing quality requirements and machining costs and should be adjusted according to the specific characteristics of each application.

ACKNOWLEDGMENTS

The authors sincerely thank the reviewers for their valuable feedback and the editorial board for considering this manuscript.

CONFLICT OF INTEREST STATEMENT

The authors agree that this research was conducted in the absence of any self-benefits, commercial or financial conflicts and declare the absence of conflicting interests with the funders.

AUTHORS’ CONTRIBUTIONS

The authors confirm their contribution to the paper as follows: study conception and design: V. T. Pham, C.C. Tran; data collection: V. T. Nguyen, V. T. Tran; analysis and interpretation of results: V. T. Pham, V. T. Tran; draft manuscript preparation: C.C. Tran, V.T. Tran. All authors reviewed the results and approved the final version of the manuscript.

DECLARATION OF GENERATIVE AI IN THE WRITING PROCESS

During the preparation of this work, the authors used Grammarly.com to improve the language. After using this tool, the authors reviewed and edited the content as needed and take full responsibility for the content of the publication.

DATA AVAILABILITY/ SUPPLEMENTARY MATERIALS

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

https://doi.org/10.24191/jmeche.v23i2.7790

ETHICS STATEMENT

The authors declare that this research did not involve human or animal subjects. All experimental procedures were performed following the institutional Safety, Health, and Environmental (HSE) protocols of Vietnam National University of Forestry.

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