

# Collaborative Optimization of Micro-Textured Tool Parameters Using Support Vector Machine and Swarm Intelligence Algorithms

Xuejun Wang<sup>1</sup>, Feng Guo<sup>2</sup>, and Yiran Wan<sup>3</sup>

<sup>1</sup> Instructor, Shandong Huayu Institute of Technology, 968 Daxue East Road, Decheng District, Dezhou, Shandong, 253034, China, E-mail: xuejunw1@outlook.com (corresponding author).

<sup>2</sup> Instructor, Shandong Huayu University of Technology, China, E-mail: fengguo@heu.uu.me

<sup>3</sup> Process Engineer, Dezhou Xitai Hydraulic Co., Ltd. Tianqu Industrial Zone, Decheng District, Dezhou, Shandong, 253000 China, E-mail: yiranwang23@heu.uu.me

Engineering Management

Received January 27, 2026; revised March 17, 2026; accepted September 20, 2026  
Available online September 27, 2026

**Abstract:** This study puts forward a collaborative optimization model for micro-textured tool parameters that integrates a Support Vector Machine (SVM) with swarm intelligence algorithms. The model aims to identify optimal cutting parameters for micro-textured tools. First, an optimized SVM predicts cutting performance indicators with high accuracy. Then, swarm intelligence algorithms efficiently search for optimal parameter combinations in multi-objective optimization. These parameter combinations are fed back into the SVM prediction model to achieve collaborative optimization. Results from the experiments demonstrate that the model achieves prediction accuracies of 97.8% for cutting force and 97.6% for cutting temperature after training. The model's loss value is reduced to 0.12. In the actual processing, the wear scar's cross-sectional area is only 1237  $\mu\text{m}^2$  at a load of 40 N when the micro-textured tool with optimal values obtained by the proposed method is used for cutting. Moreover, the wear rate is only 10.02 %. This indicates that the proposed method exhibits greater stability and flexibility than the reference models.

**Keywords:** Support vector machine (SVM); swarm intelligence algorithms; micro-textured tool; collaborative parameter optimization; multi-objective particle swarm optimization.

Copyright © Journal of Engineering, Project, and Production Management (EPPM-Journal).  
DOI 10.32738/JEPPM-2026-137

## 1. Introduction

A micro-textured tool is a new type of cutting tool in which surface patterns are designed to be embedded in predetermined areas of the tool to improve the tribological characteristics of the contact interface between the tool and the chip during cutting (Xu et al., 2025). Optimizing micro-texture tool parameters is highly significant in machining. In addition to prolonging tool life, it can greatly improve machining quality and efficiency (Wang et al., 2023; Yang et al., 2024a). In this context, the importance of optimizing micro-texture tool parameters using intelligent algorithms has been increasingly highlighted (Li et al., 2024). However, existing optimization methods often lack effective mechanisms for collaborative optimization across multiple parameters. They struggle to achieve a reasonable balance among multiple optimization objectives. This limitation restricts further improvement in cutting performance. An efficient and accurate multi-parameter collaborative optimization method is required to overcome current technical bottlenecks (Sristi and Zaman, 2024). To address this problem, this study puts forward a collaborative optimization model for micro-textured tool parameters that integrates a Support Vector Machine (SVM) with a Multi-Objective Particle Swarm Optimization (MOPSO) algorithm. The purpose of this model is to determine optimal parameter combinations and perform precise optimization. The model begins by constructing an improved support vector machine. It follows by implementing an improved MOPSO algorithm to efficiently explore these Pareto-optimal solutions. The model identifies the optimal parameter combination of the micro-textured tools. This model is expected to serve as a reliable assistant in optimizing parameter combinations for micro-textured tools and engineering practices. It will also facilitate the advancement of intelligence in this field. This study is novel in that it integrates the accurate prediction capabilities of SVM with the global optimization function of

MOPSO. This combination forms a complete optimization cooperation system and ensures that the optimal parameter combinations are better suited to engineering practice.

## 2. Previous Studies

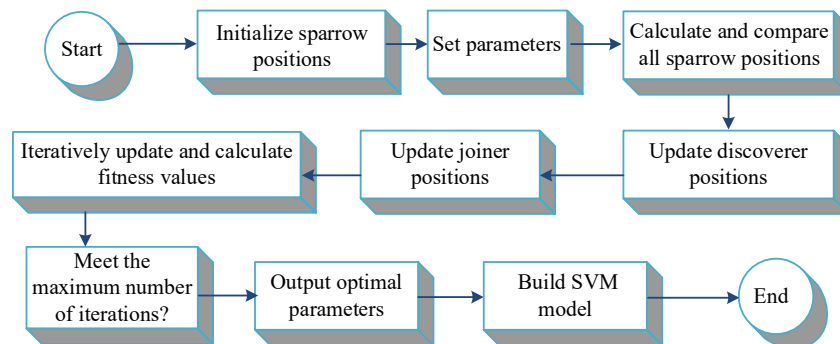
The selection of parameters in micro-textured tools directly affects the cutting performance, service life, and machining quality of the tools, making parameter optimization a research hotspot in this field. Sen et al. (2025) employed TOPSIS to optimize the parameters of micro-textured tools, with the predicted responses deviating from experimental results by only 5% on average. To enhance tool machining efficiency during spray cooling, Bhushan (2023) developed a multi-objective optimization model for micro-textured tool parameters and solved it using NSGA-II. The experimental results demonstrated that the parameters obtained from the study were effective in practical applications. Feng et al. (2023) analyzed the shape, dimensions, and working conditions of tool micro-textures and developed five tools with different shapes using a genetic algorithm. The optimized tools performed better in the cutting process. To determine the optimal parameters for cutting tools, Zhao et al. (2024) applied the firefly algorithm. The results of the experiment clearly demonstrated the effectiveness of the parameter sets determined using the firefly approach in the finishing process of thin-walled aluminum alloy shells.

SVM is a supervised learning model that leverages support vector algorithms to process data, recognize patterns, and perform classification and regression tasks. For example, Zhou et al. (2023) proposed three hybrid SVM models and evaluated their performance in rockburst prediction. The experimental results demonstrated that these three optimization algorithms greatly enhanced the SVM models' ability to predict rockbursts, facilitating the use of machine learning for such prediction tasks in mining. To enhance the prediction performance of SVM, Pande et al. (2023) improved it using different kernel functions and applied it to multi-scale drought index prediction. The experimental results demonstrated that the SVM model, optimized with sequential minimal optimization, achieved the best predictive performance, benefiting water resource management decisions. Ge et al. (2023) applied SVM to predict milling tool wear, enabling precise real-time tracking of tool conditions during milling. Experiments indicated that the model surpassed alternative approaches in prediction accuracy, offering practical guidance for industrial operations. MOPSO is a widely used swarm intelligence algorithm for multi-objective optimization, with clear advantages. For instance, Hu et al. (2023) proposed an improved multi-objective optimization algorithm combining a fuzzy-based graph clustering algorithm with MOPSO to enhance the ability to find optimal solutions. The experimental results showed that this method outperformed comparison algorithms in both accuracy and convergence. Given the limitations of existing micro-textured tool parameter optimization methods and the advantages of SVM and MOPSO in multi-objective optimization, this study proposes a collaborative optimization model integrating SVM and MOPSO for micro-textured tool parameters. This model combines the powerful fitting capability of SVM with the multi-objective solving capability of MOPSO, achieving accurate and efficient optimization of micro-textured tool parameters.

## 3. SVM-PSO Model for Micro-Textured Tool Parameter Optimization

### 3.1. Construction of an SVM-Based Parameter Optimization Prediction Model

The shape, size, and other characteristics of micro-textured tools greatly influence machining performance. Accurate prediction of cutting performance corresponding to different parameter combinations plays a key role in tool design optimization (Tong and Qu, 2023). SVM establishes a nonlinear mapping between parameters and cutting performance at a low cost. It enables the prediction of fast performance. After optimization algorithms adjust the kernel function and related parameters, SVM achieves higher prediction accuracy (Liu et al., 2025). MSISSA enhances the conventional sparrow search algorithm by incorporating adaptive weighting strategies, Lévy flights, and a dynamic spiral search method. It converges to the global optimal solution more efficiently (Dar et al., 2025). Applying MSISSA to the optimization of the SVM kernel function and parameters further improves the SVM's prediction accuracy for micro-textured tool performance. The optimization process is shown in Fig. 1.



**Fig. 1.** Optimization process of SVM using MSISSA

As shown in Fig. 1, the algorithm first initializes the sparrow population. It then sets relevant parameters, including SVM optimization parameters and constraint conditions. The algorithm compares and records the positions of all sparrows. It calculates their fitness values and ranks them. The adaptive weighting strategy updates the discoverers' positions. The calculation process is shown in Eq. (1).

$$x_{i,j}(t+1) = \begin{cases} w(t) \cdot x_{i,j}(t) \cdot \exp\left(\frac{-i}{a \cdot t_{\max}}\right) & \text{if } R < ST \\ w(t) \cdot x_{i,j}(t) + Q \cdot L & \text{if } R \geq ST \end{cases} \quad (1)$$

In Eq. (1),  $w$  represents a nonlinear variation within the range [0,1].  $x_{i,j}$  is the position of a sparrow individual,  $R$  is the warning value released when sparrows encounter danger, and  $ST$  represents the migration threshold. The positions of the sentinels are then modified according to the Lévy flight strategy. The calculation process is shown in Eq. (2).

$$X_j(t) = X_j(t) + L \oplus \text{levy}(\lambda) \quad (2)$$

In Eq. (2),  $X_j(t)$  is the position of the  $j$ -th sparrow at the  $t$ -th iteration, and  $L$  represents the step size control parameter. Through continuous iterative updating, the algorithm calculates the fitness value after each iteration. It then updates the joiners' positions using the variable spiral search strategy. The calculation process is shown in Eq. (3).

$$x_{i,j}(t+1) = \begin{cases} \varphi \cdot Q \cdot \exp\left(\frac{X_w - X_{i,j}(t)}{i^2}\right) & \text{if } i > n/2 \\ X_{i,j}(t) + |X_{i,j}(t) - X_p(t)| \cdot A^* \cdot L \cdot \varphi & \text{otherwise} \end{cases} \quad (3)$$

In Eq. (3),  $\varphi$  represents the spiral search factor, and  $A$  represents a matrix. The algorithm then checks whether the maximum number of iterations is reached. If not, it returns to the step of comparing and recording all sparrow positions until the condition is satisfied. If the condition is met, the algorithm records and outputs the optimal parameters. It uses these parameters to develop the SVM surrogate model. Lastly, the study uses the SVM model optimized by MSISSA to predict optimal Micro-textured tool parameters. It gives a better optimal classification plane. The operation flow of the MSISSA-SVM micro-textured tool parameter optimization prediction model is shown in Fig. 2.

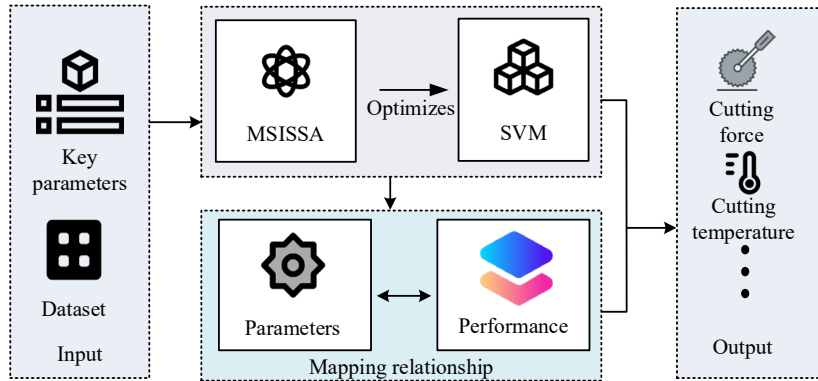


Fig. 2. MSISSA-SVM micro-textured tool parameter optimization prediction model

As shown in Fig. 2, the model takes key micro-textured tool parameters as input variables. It uses cutting force and cutting temperature as output performance indicators. The model collects experimental or simulation data under different parameter combinations. It then inputs the data into the dynamically adjusted SVM model optimized by MSISSA for parameter combination prediction. Specifically, the fitting capability of MSISSA-SVM enables rapid calculation of cutting force and temperature for any given combination of parameters. This process accurately predicts parameter–performance relationships and provides reliable performance data for subsequent parameter optimization. For a given set of micro-textured parameters, the prediction output of MSISSA-SVM is shown in Eq. (4).

$$y(x) = \sum_{i=1}^n a_i^* y_i K(x, x_i) + b \quad (4)$$

In Eq. (4),  $a_i^*$  represents the Lagrange multiplier obtained from SVM training.  $y_i$  is the output label of the training samples.  $K(x, x_i)$  is the kernel function, where the RBF function is selected.  $b$  represents the bias term.

### 3.2. Design of a Multi-Objective Optimization Algorithm Based on MOPSO

The constructed MSISSA-SVM micro-textured tool parameter optimization surrogate model accurately and efficiently predicts cutting force and cutting temperature for given parameter combinations. However, in the actual optimization process of micro-textured tool parameters, it is necessary to consider both cutting force and cutting temperature. Single parameter adjustment cannot achieve multi-objective collaborative optimization. Therefore, multi-objective optimization methods are required to obtain optimal parameter combinations that satisfy the constraints (Hoang, 2023). The multi-objective function is constructed as shown in Eq. (5).

$$\begin{cases} \min f(a,b,c,d) = (F_{total(a,b,c,d)}, T_{cut(a,b,c,d)}, R_{a(a,b,c,d)}) \\ s.t. (a,b,c,d) \in \Omega \end{cases} \quad (5)$$

In Eq. (5),  $\min f(a,b,c,d)$  represents the function variable representing multi-objective optimization,  $T_{cut(a,b,c,d)}$  maximum temperature of the cutting region,  $R_{a(a,b,c,d)}$  represents the surface roughness of the machined workpiece. Relevant constraints are set simultaneously. Considering practical micro-textured tool parameters, the constraints are defined as in Eq. (6).

$$\begin{cases} 90\mu m \leq a \leq 130\mu m \\ 40\mu m \leq b \leq 80\mu m \\ 60\mu m \leq c \leq 140\mu m \\ 40\mu m \leq d \leq 80\mu m \end{cases} \quad (6)$$

In Eq. (6),  $a$  represents the edge margin.  $b$  represents the texture width.  $c$  represents the texture spacing.  $d$  represents the texture depth. MOPSO is a common multi-objective optimization algorithm. It introduces an external archive to store the non-dominated solutions produced by the optimization process and applies a crowding-distance sorting method to maintain the diversity of the archive, thereby avoiding entrapment in local optima. However, the conventional MOPSO algorithm has slow convergence and an uneven distribution of solutions. To further improve the global optimization capability of the MOPSO algorithm for multi-objective optimization of micro-textured tool parameters, an exponentially declining non-linear inertia weight and an iteration-dependent learning factor are employed. The operation flow of IMOPSO is shown in Fig. 3.

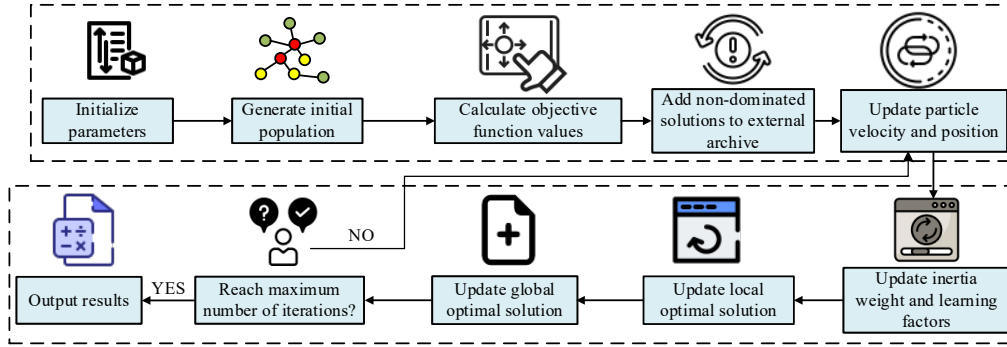


Fig. 3. Operation flow of IMOPSO algorithm

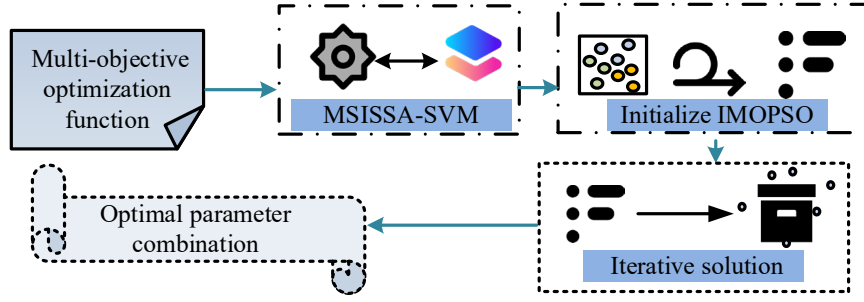
As shown in Fig. 3, the algorithm first initializes all particle swarm parameters. It then generates the initial population and computes the corresponding objective function values. According to Pareto dominance, non-dominated solutions are added to the external archive, and global and local best solutions for the particles are determined. The algorithm then updates particle positions and velocities, inertia weights, learning factors, and the best local solutions according to the relevant Eqs. The exponentially decreasing nonlinear inertia weight is shown in Eq. (7).

$$w' = w_0 + \frac{2r_4}{3}(1 - w_0)^{i/n} \quad (7)$$

In Eq. (7),  $w'$  represents the inertia weight.  $r_4$  represents a constant within [0,1]. The improved learning factor is shown in Eq. (8).

$$\begin{cases} c_1 = c_{1min} + (c_{1max} - c_{1min}) \times \frac{k}{2n} \\ c_2 = c_{2min} + (c_{2max} - c_{2min}) \times \frac{k}{2n} \end{cases} \quad (8)$$

With the improved learning factor, the algorithm better adapts to the multi-objective optimization requirements of micro-textured tool parameters in both early and late iterations. The external archive is then updated based on the new solutions to maintain the best global solution. The algorithm checks whether the maximum number of iterations is reached. If it is reached, the optimal solution is output. If not, the algorithm continues to update particle positions and velocities, inertia weights, learning factors, and local best solutions until the final condition is satisfied. On this basis, the study combines the MSISSA-SVM prediction model with the IMOPSO algorithm for multi-objective optimization of micro-textured tool parameters. This combination forms the MSISSA-SVM-IMOPSO micro-textured tool parameter optimization model. Its operation flow is shown in Fig. 4.

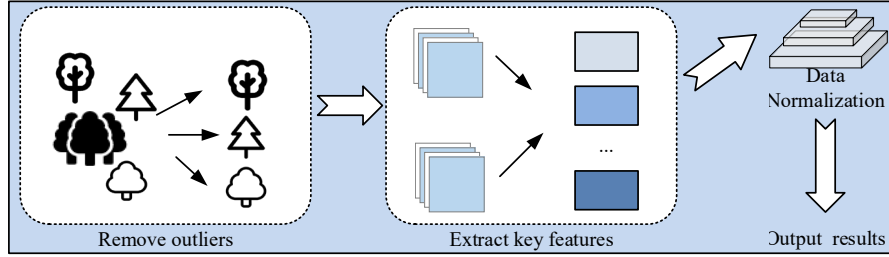


**Fig. 4.** MSISSA-SVM-IMOPSO micro-textured tool parameter optimization model

In Fig. 4, the algorithm first takes key micro-textured tool parameters as optimization variables. It constructs the multi-objective optimization function and sets constraints. The trained MSISSA-SVM surrogate model predicts tool performance indicators for different parameter combinations. These results serve as input to the fitness function of the proposed IMOPSO algorithm. Next, the initial values of the particle swarm of the proposed IMOPSO algorithm and the set of important parameters are determined. In the proposed algorithm, the multi-objective problem is addressed through iterative processes. Upon reaching the maximum number of iterations or achieving convergence, the iterative process stops. In this scenario, the non-dominated solutions maintained in the external archive are considered the multi-objective solution set for the micro-textured tool parameters, i.e., the optimal parameters.

### 3.3. Improvement of Parameter Optimization Model with IF-PCC Preprocessing

The constructed MSISSA-SVM-IMOPSO micro-textured tool collaborative parameter optimization model is strongly influenced by the quality and amount of training data. If the training data contain bias or are incomplete, the SVM model may produce errors when predicting micro-textured tool performance, thereby affecting the effectiveness of parameter optimization (Yang et al., 2024b; Rathod et al., 2023). Therefore, before performing parameter optimization, the study designs a data preprocessing algorithm that uses Isolation Forest (IF) and the Pearson Correlation Coefficient (PCC) to improve the quality of the input data. The workflow of the IF-PCC algorithm is shown in Fig. 5.



**Fig. 5.** IF-PCC data preprocessing algorithm workflow

As shown in Fig. 5, the first step uses IF to detect outliers in the micro-textured tool dataset. IF constructs multiple isolation trees and recursively partitions the samples at random. Outlier samples are easier to isolate and receive higher anomaly scores, enabling outlier detection. The average path length of each isolation tree is calculated as shown in Eq. (9).

$$c(n) = 2H(n-1) - \frac{2(n-1)}{n} \quad (9)$$

In Eq. (9),  $H$  is the harmonic number. Based on this, the anomaly score of each data point is calculated as shown in Eq. (10).

$$s(x, n) = 2 \frac{E(h(x))}{c(n)} \quad (10)$$

In Eq. (10), analyzing anomaly scores allows the removal of outliers from the data. Next, PCC quantifies the strength of linear correlation between core features in the micro-textured tool dataset and the target variables. This step identifies key features in the data. The calculation is shown in Eq. (11).

$$r = \frac{\sum_{i=1}^m (x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum_{i=1}^n (x_i - \bar{x})^2} \cdot \sqrt{\sum_{i=1}^n (y_i - \bar{y})^2}} \quad (11)$$

In Eq. (11),  $m$  represents the number of samples. Finally, the data are normalized. The normalization process is shown in Eq. (12).

$$x_{norm} = \frac{x - x_{min}}{x_{max} - x_{min}} \quad (12)$$

In Eq. (12),  $x$  represents the original feature of a sample. The study then integrates the IF-PCC data preprocessing stage into the MSISSA-SVM-IMOPSO model and enhances the collaborative interaction between MSISSA-SVM and IMOPSO. The resulting final parameter optimization model is named the IPMSI micro-textured tool collaborative optimization model. Its operation flow is shown in Fig. 6.

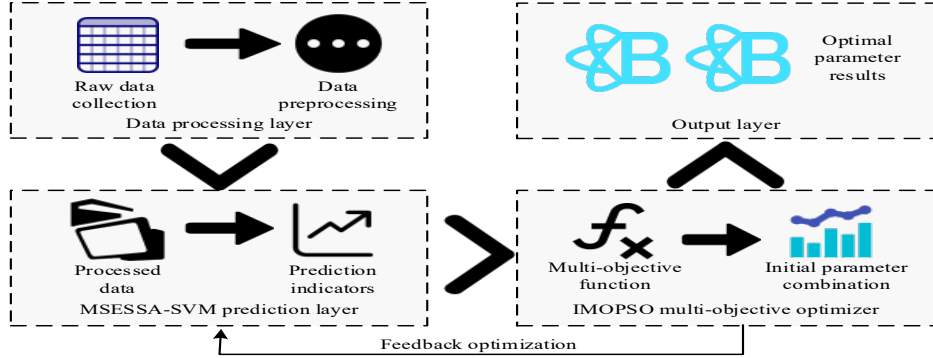


Fig. 6. IPMSI micro-textured tool collaborative optimization model

As shown in Fig. 6, the model first takes the original micro-textured tool dataset as input. The data preprocessing algorithm improves data quality. MSISSA then optimizes SVM parameters, and the MSISSA-SVM prediction model is constructed using the optimal parameters to map micro-textured tool parameters to performance indicators. The process then enters the IMOPSO multi-objective optimization stage. Relevant parameters and constraints are set, the particle swarm is initialized, and multi-objective optimization is performed to find the initial parameter combination for the micro-textured tool. Meanwhile, high-quality particle parameters generated during iterations are fed back into the SVM model, dynamically optimizing its predictive accuracy and establishing a positive collaborative mechanism. Finally, when the iteration converges, the Pareto optimal solution set is output, representing the optimal micro-textured tool parameters.

#### 4. Performance of Micro-Textured Tool Collaborative Parameter Optimization Model

##### 4.1. Performance Verification of the IPMSI Model

To verify the performance of the proposed IPMSI model, this study compared it with Kriging Model-Non-dominated Sorting Genetic Algorithm II (Kriging-NSGA-II), Back Propagation-NSGA-III (BP-NSGA-III), and Atom Search Optimization-BP (ASO-BP). First, based on the actual dimensions and surface structure of micro-textured tools, an accurate simulation tool model was constructed in the simulation software. Then, simulation conditions, such as machining materials and cutting parameters, were set to simulate the cutting process and obtain simulation data, including tool wear and cutting force, which were compiled into the final dataset. The study strictly adhered to the hyperparameter tuning symmetry principle, with all comparison groups employing identical tuning budgets and computational resource allocations—including standardized maximum iteration counts, initial population sizes, and function evaluation frequencies per iteration—while preserving only inherent differences in model architecture and algorithmic logic. The experiment was conducted on a hardware platform equipped with an Intel Xeon Gold 6248R CPU, NVIDIA RTX 3090 GPU (24GB), and 64GB of memory. The average training time of the IPMSI model was 128.4 seconds, the average multi-objective optimization time was 345.2 seconds, the average GPU memory usage was 1824 MB, and the CPU memory usage was 12.7GB. The computational resource consumption was reasonable, and the model demonstrated good practical applicability. This study first set the IPMSI model parameters, as shown in Table 1.

After clarifying the core parameter configuration of the IPMSI model through Table 1, this study further applied the model to predict cutting force and temperature. First, the prediction accuracy was compared for both outputs, with the results presented in Fig. 7.

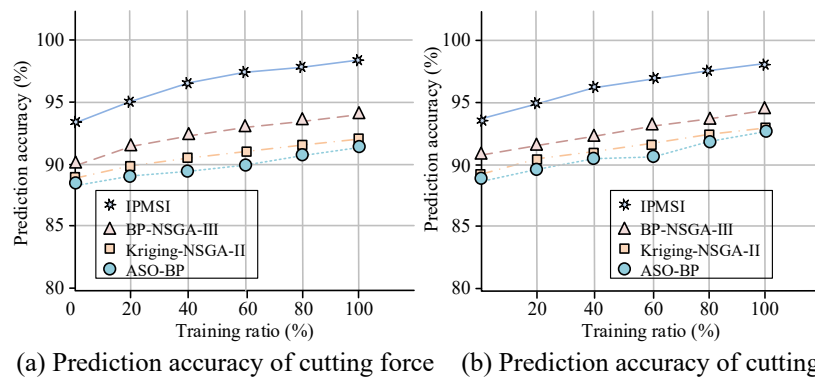
As shown in Fig. 7(a), the IPMSI model achieved a prediction accuracy of 97.8% for cutting force after training was completed, which was significantly higher than the 94.3%, 92.1%, and 91.7% of the three comparison models. As shown in Fig. 7(b), the MSISSA-SVM surrogate model maintained prediction accuracy above 94% for cutting temperature throughout, reaching 97.6% after training, surpassing the three comparison models. In summary, the IPMSI model demonstrated reliability and stability in predicting the performance of micro-textured tools. Next, the convergence behavior and Pareto-optimal solution ratios of the four algorithms in multi-objective parameter optimization were evaluated, with the results illustrated in Fig. 8.

As shown in Fig. 8(a), the loss of the IPMSI model decreased to 0.12 after training was completed, which was significantly lower than the 0.20, 0.27, and 0.51 of the three comparison models. As shown in Fig. 8(b), the proportion of Pareto-optimal solutions of the IPMSI model remained in the lead throughout, reaching 36.2% when training was completed, while the other three comparison models all remained below 34%. In summary, the IPMSI model demonstrated

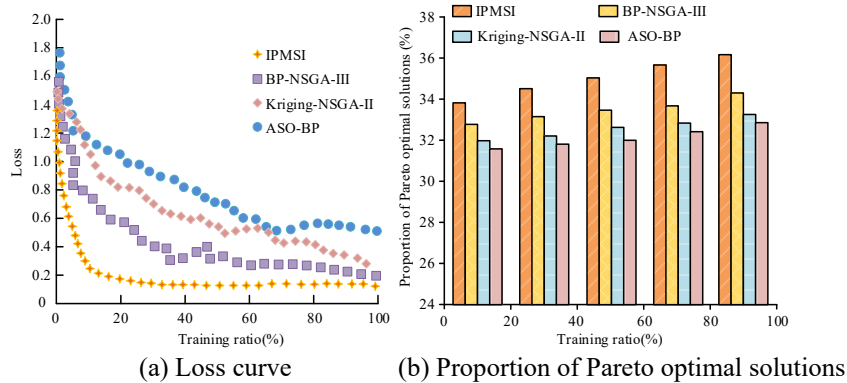
clear advantages in the multi-objective optimization of micro-textured tool parameters, enabling rapid convergence to the optimal solution region while effectively maintaining solution diversity.

**Table 1.** Model parameter settings

| Algorithm | Specific parameter                  | Span      |
|-----------|-------------------------------------|-----------|
| MSISSA    | Inertia weight                      | [0,1]     |
|           | Lévy flight step size               | [1,3]     |
|           | Uniformly distributed random number | [-1,1]    |
| SVM       | Penalty factor                      | [1,0]     |
|           | Kernel function                     | RBF       |
| IMOPSO    | Population size                     | [0.4-0.9] |
|           | Inertia weight                      | [0,1]     |
|           | Learning factor                     | [1,2.5]   |
|           | Maximum size of external archive    | [100-200] |



**Fig. 7.** Prediction accuracy for cutting temperature and cutting force



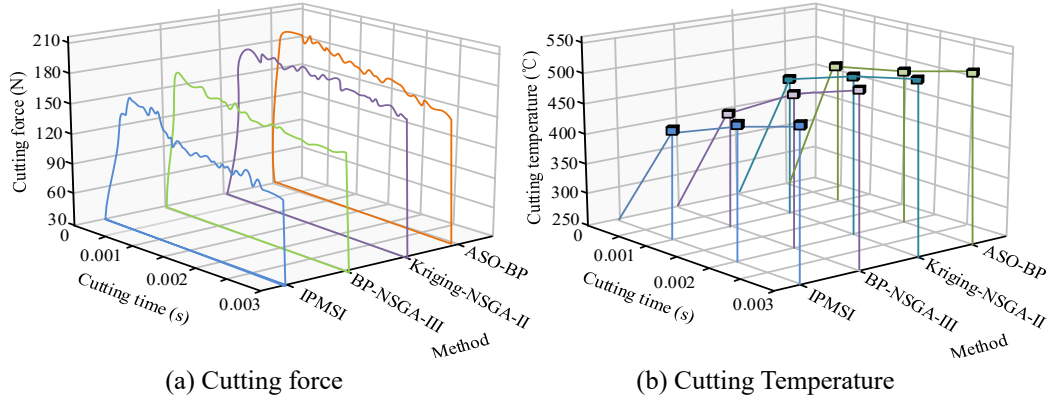
**Fig. 8.** Loss curves and proportion of Pareto optimal solutions

#### 4.2. Analysis of Practical Application Performance of IPMSI Model

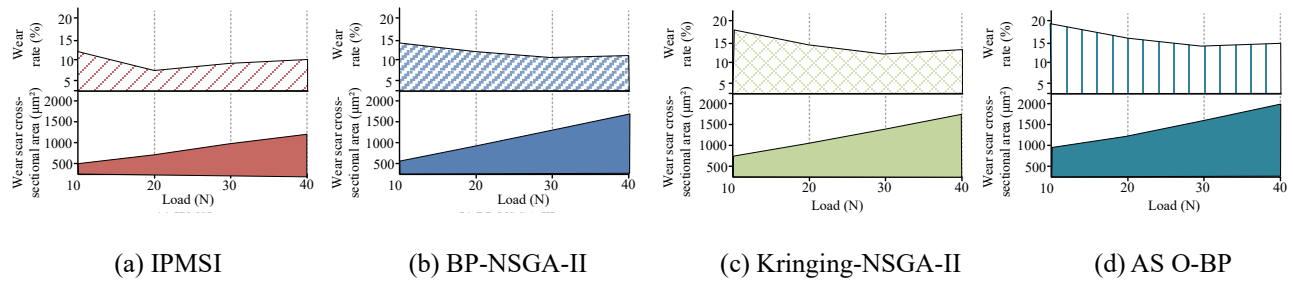
Four models were employed to optimize cutting parameters for tools, obtaining the optimal parameter combination. Based on these parameter sets, simulated micro-textured tools were fabricated and imported into cutting simulation software to simulate indicators such as tool wear, cutting force fluctuations, and machined surface roughness. Using TC4 titanium alloy as the cutting material, a geometric model consistent with the actual workpiece was constructed. Cutting experiments were conducted under unified conditions to compare the optimization effects of different models, with the results shown in Fig. 9.

According to Fig. 9(a), the optimized micro-textured tool exhibited the lowest cutting force throughout the titanium alloy cutting process. When the cutting time reached 0.03s, the cutting force decreased to 105.3 N, which was significantly lower than the three comparison tools. Fig. 9(b) indicates that, although the proposed model's cutting temperature increased slightly, it reached only 501.4°C at a cutting time of 0.03s, remaining lower than that of the three comparison tools and within the safe tolerance range of the tool material. This indicated that after optimizing the cutting parameters, the overall cutting performance of this model surpassed that of the other models. Next, the wear scar cross-sectional area

and wear rate of the tool cutting after parameter optimization were compared, and the comparison results are shown in Fig. 10.



**Fig. 9.** Cutting force and cutting temperature of optimized tools



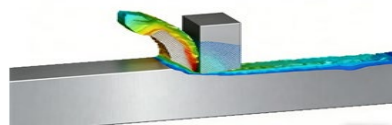
**Fig. 10.** Wear scar cross-sectional area and wear rate of optimized tools

Fig. 10(a) shows that the micro-textured tool optimized by the IPMSI model exhibited the minimum wear cross-section under all load conditions. At a load of 40 N, the measured value was only 1237  $\mu\text{m}^2$ , with a wear rate of 10.02%. In Figs. 10(b), (c), and (d), the corresponding wear cross-sections of tools optimized by the three comparison models increased markedly at 40 N, all exceeding 1400  $\mu\text{m}^2$ , while the wear rates remained above 11%. These results indicate that tools optimized using IPMSI parameters can effectively reduce the frictional contact area at the tool–workpiece interface. To conduct a more comprehensive evaluation of the model's performance, the study selected multiple generations of models and optimizers for comparative assessment, as detailed in Table 2.

**Table 2.** Comparison of cutting performance optimization results for different model combinations

| Combination of groups | Surrogate model type | Multi-objective optimizer | Minimum cutting force (N) | Minimum cutting temperature (°C) |
|-----------------------|----------------------|---------------------------|---------------------------|----------------------------------|
| IPMSI                 | MSISSA-SVM           | IMOPSO                    | 105.6                     | 502.8                            |
| GP-NSGA-II            | Gaussian Process     | NSGA-II                   | 128.5                     | 512.1                            |
| RF-SPEA2              | Random Forest        | SPEA2                     | 137.9                     | 523.7                            |
| XGBoost-MOPSO         | XGBoost              | MOPSO                     | 158.8                     | 537.5                            |

According to Table 2, the minimum cutting force of the IPMSI model combination reaches 105.6 N, which is about 17.8% lower than the GP-NSGA-II combination's 128.5 N, about 23.4% lower than the RF-SPEA2 combination's 137.9 N, and about 33.5% lower than the XGBoost MOPSO combination's 158.8 N. In terms of minimum cutting temperature, the IPMSI model is 502.8°C, which is about 1.8% lower than GP-NSGA-II's 512.1°C, about 4.0% lower than RF-SPEA2's 523.7°C, and about 6.5% lower than XGBoost MOPSO's 537.5°C. This further confirms the IPMSI model's comprehensive cutting performance in complex cutting environments. To demonstrate the actual cutting performance of the micro-textured tool after parameter optimization in the IPMSI model, the study presents simulation images of the cutting process, as shown in Fig. 11.



**Fig. 11.** Simulation of cutting process

As shown in Fig. 11, the micro-textured tool optimized by the IPMSI model exhibits smooth chip discharge during the cutting process, and the contact area between the tool front face and the chips shows clear intermittent characteristics. This practical application fully demonstrates the effectiveness and superiority of the IPMSI model in the collaborative optimization of micro-textured tool parameters, providing strong support for its promotion and application in actual industrial production.

## 5. Conclusion

This study innovatively proposed an IPMSI collaborative optimization model for micro-textured tool parameters. This model first employed an SVM optimized with MSlSSA parameters to build a prediction model, enabling accurate characterization of the mapping between input parameters and performance metrics. Subsequently, the IMOPSO algorithm was applied to perform multi-objective optimization and generate optimal combinations of tool parameters, thereby enhancing overall tool performance. The experimental results showed that in terms of model performance, the proposed model achieved prediction accuracies of 97.8% and 97.6% for cutting force and cutting temperature after training was completed. In practical terms, when the tool cutting time optimized by the proposed model reached 0.03s, the cutting force decreased to 105.3 N, and the cutting temperature was only 501.4°C. Micro-texture reduces cutting force by reducing tool-chip friction through oil storage and chip guidance, but excessively reducing the contact area can cause local stress concentrations and exacerbate the accumulation of cutting heat. The optimized parameter combination achieved a balance between reducing friction and force and controlling temperature, thereby not only strengthening the physical mechanism of chip lubrication but also avoiding increased local heat generation. These results demonstrate that the proposed IPMSI model offers significant advantages for optimizing micro-textured tool parameters and provides new insights and perspectives in related fields. However, the effectiveness of the optimized tool in extreme operating scenarios was not evaluated, and the model's general applicability remains to be enhanced. At the same time, it was shown that micro-texture geometric parameters significantly affect cutting performance, providing a quantitative basis for the customized design of micro-textured tools under different working conditions. Therefore, future research can investigate this aspect further. The research results can promote enterprises to shift the design of micro-textured cutting tools from empirical trial and error to data-driven quantitative optimization, shorten the research and development cycle, and reduce trial production costs. Meanwhile, managers can develop process selection criteria based on the trade-off between parameters and performance, thereby ensuring cutting performance while avoiding local thermal damage and improving production stability.

## Author Contributions

Xuejun Wang contributed to conceptualization, supervision and manuscript revision. Feng Guo contributed to the investigation, data analysis and draft preparation. Yiran Wang contributed to data collection and validation.

## Funding

The research is supported by the School Grants platform for Scientific Research of Shandong Huayu University of Technology in 2025: CNC tool manufacturing process research and development center (PT2025KJX001).

## Institutional Review Board Statement

Not applicable.

## Declaration of Artificial Intelligence (AI) Tools

The authors confirm that no AI tools were used in the preparation of this manuscript. The authors reviewed and verified all content and take full responsibility for the accuracy and integrity of the manuscript.

## References

- Alhussen, A., Vinoth, N., Jenis, A., Surendran, S., Ganesh, V. D., and Thangaraj, S. J. J. (2025). Development of Weighted Ensemble Deep Learning Network for Surface Roughness Prediction and Flank Wear Measurement. *Journal of Materials Engineering and Performance*, 34(5), 3648-3672.
- Bahrami, B., Khayyambashi, M. R., and Mirjalili, S. (2024). Multiobjective placement of edge servers in MEC environment using a hybrid algorithm based on NSGA-II and MOPSO. *IEEE Internet of Things Journal*, 11(18), 29819-29837.
- Bhushan, R. K. (2023). Minimising tool wear by optimisation (ANOVA) of cutting parameters in machining of 7075Al Alloy SiC particle composite. *Australian Journal of Mechanical Engineering*, 21(2), 499-517.
- Dar, A. A., Hirani, T., Arora, V., and Kakkar, S. (2025). Predictive Analytics for Personalized Debt Management: Leveraging Machine Learning to Provide Actionable Financial Advice. *FinTech and Sustainable Innovation*, 1, A4.
- Feng, X., Meng, C., Lian, W., and Wei, J. (2023). Optimization analysis of microtexture size parameters of tool surface for turning GH4169. *Ferroelectrics*, 607(1), 186-207.
- Ge, Y., Zhang, J., Song, G., and Zhu, K. (2023). An effective LSSVM-based approach for milling tool wear prediction. *The International Journal of Advanced Manufacturing Technology*, 126(9), 4555-4571.
- Hoang, X. T. (2023). Multi-objective optimization of turning process by FUCA method. *Strojnícky časopis-Journal of Mechanical Engineering*, 73(1), 55-66.
- Hu, L., Yang, Y., Tang, Z., and He, Y., Li, X.. (2023). FCAN-MOPSO: An improved fuzzy-based graph clustering algorithm for complex networks with multiobjective particle swarm optimization. *IEEE Transactions on Fuzzy Systems*, 31(10), 3470-3484.
- Li, Q., Shi, H., Ma, C., Xie, L., Yin, C., and Shi, Y. (2024). Effect of Micro-Texture on Cutting Performance of PCBN Cutter. *Journal of Nanoelectronics and Optoelectronics*, 19(4), 433-439.

- Liu, Y., Yang, S., Xiao, Z., and Hua, P. (2025). Improving Coating Mechanical Properties and Cutting Performance of Carbide Tools Through Combined Technology of Micro-textures and AlCrN Coatings. *Metallurgical and Materials Transactions B*, 56(1), 212-236.
- Pande, C. B., Kushwaha, N. L., Orimoloye, I. R., Kumar, R., Abdo, H. G., Tolche, A. D., and Elbeltagi, A. (2023). Comparative assessment of improved SVM method under different kernel functions for predicting multi-scale drought index. *Water Resources Management*, 37(3), 1367-1399.
- Rathod, N. J., Chopra, M. K., Chaurasiya, P. K., Vidhate, U. S., and Dasore, A. (2023). Optimization on the turning process parameters of SS 304 using Taguchi and TOPSIS. *Annals of Data Science*, 10(5), 1405-1419.
- Sristi, N. A., and Zaman, P. B. (2024). A review of textured cutting tools' impact on machining performance from a tribological perspective. *The International Journal of Advanced Manufacturing Technology*, 133(9), 4023-4057.
- Sen, B., Bhowmik, A., Rachhh, N., Patil, N., Khatibi, A., and Kumar, R. (2025). Exploring cryo-MQL medium for hard machining of hastelloy C276: a multi-objective optimization approach. *International Journal on Interactive Design and Manufacturing (IJIDeM)*, 19(7), 4773-4786.
- Tong, X. and Qu, Q. (2023). Optimizing the micro-texture and cutting parameters of ball-end milling cutters to achieve milling stability. *Proceedings of the Institution of Mechanical Engineers, Part E: Journal of Process Mechanical Engineering*, 237(2), 326-335.
- Wang, C., Ge, Y., Ma, J., Yu, Z., Zhang, K., Liu, T., Guo, X., and Huang, S. (2023). Effects of parameter selection strategy on tool wear when milling 3D-printed functionally graded materials with textured tool under minimum quantity lubrication. *The International Journal of Advanced Manufacturing Technology*, 125(3), 1615-1632.
- Xu, T., Xie, L., Ma, C., and Li, Q. (2025). Investigation of cutting performance of coated micro-textured tools for cutting aluminum alloys. *Mechanical Sciences*, 16(1), 195-208.
- Yang, S., Liu, L., and He, C. (2024a). Study on milling behavior of TiAlN coated tool with variable distribution density micro-texture. *Machining Science and Technology*, 28(1), 74-97.
- Yang, S., Guo, Y., Xiao, Z., and Wang, D. (2024b). Study on cutting performance of micro-textured ball-end milling cutter with multiple distribution density under the action of cutting edge. *Journal of Mechanical Science and Technology*, 38(4), 1753-1764.
- Zhao, H., Cao, Y., Bai, Y., Yao, H., and Tian, C. (2024). Numerical simulation and tool parameters optimization of aluminum alloy transmission intermediate shell. *Scientific Reports*, 14(1), 4241-4253.
- Zhou, J., Yang, P., Peng, P., Khandelwal, M., and Qiu, Y. (2023). Performance evaluation of rockburst prediction based on PSO-SVM, HHO-SVM, and MFO-SVM hybrid models. *Mining, Metallurgy & Exploration*, 40(2), 617-635.



Xuejun Wang was born in September 1971, is of Han ethnicity and a native of Jinan City, Shandong Province. He graduated from Southwest University of Science and Technology in 2008 with a specialization in Mechanical Design, Manufacturing and Automation, the field in which he continues to conduct research. He worked as a technician at the Fourth Branch of China Hydropower 13th Bureau (1990–1998) and as a teacher at the Technical School of China Hydropower 13th Bureau (1998–2003). Since 2003, he has taught at Shandong Huayu Institute of Technology. He has published two EI conference papers, led six university-level research projects, holds one invention patent and four utility model patents, and has received two Science and Technology awards from the Shandong Machinery Industry Association.



Feng Guo was born in June 1989, is of Han ethnicity and a native of Dezhou City, Shandong Province. He earned his master's degree in mechanical engineering and Mechatronics from Odessa National Technical University in Ukraine. He has served as a faculty member at Shandong Huayu University of Technology since 2010. He has published five papers, led one municipal-level research project, participated in four university-level research projects, and holds one authorized invention patent and six utility model patents.



Yiran Wang was born in March 2001 and is of Han ethnicity, with her native place in Jinan City, Shandong Province. She graduated from Shandong University of Science and Technology with a bachelor's degree in materials chemistry (2019–2023). Her research interests include materials and mechanical engineering. Since 2025, she has been employed as a process engineer at Dezhou Xitai Hydraulic Co., Ltd. Her academic achievements include co-authoring two EI conference papers and co-authoring the authorization of one invention patent.