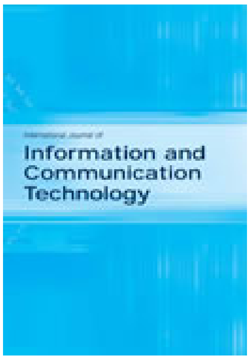

International Journal of Information and Communication Technology

ISSN online: 1741-8070 - ISSN print: 1466-6642
https://www.inderscience.com/ijict

Multi-objective micro-milling parameter optimisation and surface prediction via migration learning

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DOI: 10.1504/IJICT.2025.10075341

Article History:

Received:	11 July 2025
Last revised:	27 August 2025
Accepted:	29 August 2025
Published online:	15 January 2026

Multi-objective micro-milling parameter optimisation and surface prediction via migration learning

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Abstract: In this study, a multi-objective optimisation framework incorporating migration learning is proposed with the aim of efficiently optimising micro-milling parameters and accurately predicting surface roughness. First, a deep neural network (DNN)-based surface roughness prediction model is constructed as a base model. Subsequently, the pre-trained model is fine-tuned (fine-tuning) using a limited amount of micro-milling experimental data in the target domain to quickly adapt to the target working conditions and significantly improve the prediction accuracy under small samples. On this basis, the migration learning-enhanced prediction model is integrated with a multi-objective optimisation algorithm (e.g., NSGA-II) to construct an optimisation framework. Experimental results show that relying on the millisecond evaluation capability of the migration learning agent model and the improved search strategy of NSGA-II, the Pareto frontier distribution range is widened by 28% and the frontier convergence speed is improved by 42%.

Keywords: migration learning; micro-milling; multi-objective optimisation; surface roughness prediction.

Reference to this paper should be made as follows: Zhang, P. (2025) 'Multi-objective micro-milling parameter optimisation and surface prediction via migration learning', *Int. J. Information and Communication Technology*, Vol. 26, No. 52, pp.1–19.

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1 Introduction

As a core process in the field of precision manufacturing, micro-milling technology has an irreplaceable role in the machining of micro-electromechanical systems, medical devices and aerospace micro-components. Its machining quality, especially the surface roughness, directly affects the functional performance and service life of the parts. However, the size effect is significant at the microscale, and the influence mechanism of process parameters (e.g., spindle speed, feed, depth of cut, etc.) on surface integrity is complex and nonlinear, so it is difficult to accurately map the correlation between the parameters and the surface quality with traditional optimisation methods based on physical models (Câmara et al., 2012). Existing research mostly relies on a large amount of experimental data to construct predictive models, but systematic experiments on new materials or special working conditions (e.g., micro-fine tools, difficult-to-machine materials) are costly and lengthy, resulting in a lack of data, which seriously restricts the practicability and generalisation ability of process optimisation (Mamedov, 2021). In addition, the actual production needs to simultaneously take into account the surface quality and machining efficiency and other multi-objective requirements, a single-objective optimisation is difficult to meet the engineering reality, and there is an urgent need to establish an efficient multi-objective co-optimisation framework.

As the core research direction of precision manufacturing, the optimisation of micro-milling parameters and surface quality prediction have made significant progress in recent years under the impetus of the integration of intelligent algorithms and cross-domain technologies. In terms of surface prediction models, traditional physically-driven models (e.g., response surface method (RSM) (Natarajan et al., 2011) have been gradually replaced by data-driven methods due to the difficulty of capturing the nonlinear effects of microscale machining. Vu et al. (2018) combined the Taguchi method with RSM to optimise the surface roughness and the cutting force of hard milling for SKD61, and found that the cutting speed and the feed rate had a surface integrity The interaction between cutting speed and feed rate on surface integrity was found to be significant, but the method relies on a large number of experiments and has limited ability to generalise working conditions. To improve the robustness of prediction in small samples, machine learning models have been widely introduced. Nguyen et al. (2023a) compared the effectiveness of linear regression, support vector machine (SVR) and artificial neural network (ANN) in predicting surface roughness and tool wear in Ti6Al4V turning, and confirmed that the ANN performs the best in RMSE and R^2 metrics by virtue of its nonlinear mapping capability, providing a high-accuracy optimisation for multi-objective optimisation. It provides a high-precision agent model for multi-objective optimisation.

The development of multi-objective optimisation algorithms has further enhanced the efficiency of process parameter decision making. Classical algorithms such as the non-dominated sequential genetic algorithm (NSGA-II) have been widely adopted for their efficient Pareto solution search capability. For example, in Ti6Al4V turning, NSGA-II successfully coordinates the conflicting objectives of surface roughness and tool wear, obtains 50 sets of Pareto solution sets, and filters out the optimal process parameters by integrating decision functions (Nguyen et al., 2023b). Similarly, Xu et al. (2024) addressed the inefficiency of ultrasonic vibration-assisted micro-fine EDM machining of titanium alloys and optimised the MRR and surface quality by combining NSGA-II with vibration control technology, which verified the applicability of intelligent algorithms in special machining. Improved models of particle swarm optimisation (PSO) also show potential, such as chaotic initialisation PSO to enhance population diversity through Tent mapping, which effectively balances cutting force and MRR in milling parameter optimisation (Aleem et al., 2020).

The introduction of migration learning provides a new path to solve the bottleneck of scarce data for target working conditions. Although there are still few direct studies on the application of transfer learning in micro-milling, its success in similar fields validates the feasibility of cross-domain knowledge transfer. For example, Guo et al. (2020) used historical data to construct a prediction model for energy consumption and residual stress in screw hard milling, which reduces the cost of experimenting with new working conditions through knowledge reuse. Wang et al. (2021) used a multi-response optimisation framework to coordinate the MRR and surface roughness in aluminium alloy micro-milling, and their pre-training-fine-tuning strategy provides a reference paradigm for small-sample learning in micro-milling.

The limitations of the current study focus on three aspects:

1 Data dependence and generalisation contradiction. Most machine learning models require a large amount of labelled data, while the high experimental cost of actual micro-milling of new materials/tools leads to limited model generalisation (Bhirud et al., 2024).

2 Insufficient generalisability of multi-objective decision making. Existing optimisation frameworks are often designed for specific materials (e.g., titanium alloys, aluminium alloys), and lack universal decision criteria across processes (Zariatin et al., 2017).

3 Weak adaptability to dynamic working conditions. Traditional static optimisation does not consider the cumulative effect of time-varying factors such as tool wear and vibration on surface quality (Heitz et al., 2022).

Future research needs to further explore lightweight migration learning architectures to reduce data requirements, and develop online optimisation systems integrating real-time sensing data and digital twin technology to promote the evolution of micro-milling parameter optimisation in the direction of adaptive and highly robust.

In recent years, deep learning has shown strong potential in complex industrial modelling, but its success is highly dependent on massive labelled data, and it is prone to overfitting and insufficient generalisation in small sample scenarios such as micro-milling. Migration learning provides new ideas to solve the data scarcity in the target domain by migrating knowledge from related domains. Inspired by this, this study proposes an intelligent decision-making method for micro-milling parameters that integrates migration learning and multi-objective optimisation. The core innovation lies in the construction of a ‘pre-training-fine-tuning’ cross-domain knowledge transfer mechanism: firstly, a DNN is pre-trained with rich historical data from the source domain (e.g., conventional milling or similar material machining) to capture general machining features; then the model is fine-tuned with a small amount of experimental data from the target domain of micromilling to realise high-accuracy surface roughness prediction under the condition of small samples. Then the model is fine-tuned by a small amount of micro-milling experimental data in the target domain to realise high-accuracy surface roughness prediction under small sample conditions. On this basis, the migration learning-enhanced prediction model is embedded as a proxy model in the optimisation process of the multi-objective evolutionary algorithm to search for the Pareto-optimal solution set of machining parameters with the parallel objectives of minimising the surface roughness and maximising the MRR. The method significantly reduces the dependence on experimental data in the target domain and provides a new paradigm for data-driven optimisation in microfabrication. In this paper, the prediction accuracy and optimisation efficiency of the framework are verified through systematic experiments, and the limitations of traditional methods are compared and analysed, which ultimately provide theoretical support and practical guidance for intelligent decision-making of micro-milling process under complex working conditions.

2 Mechanisms of micro-milling surface formation and theoretical basis of transfer learning

2.1 Micro-milling process characteristics and parameter influence mechanism

Micro-milling as a key process in the field of precision manufacturing, its core feature is that the machining scale between the micron to sub-millimeter scale, significantly different from conventional milling. This micro-scale machining process is dominated by the size effect, when the cutting thickness is close to the grain size of the material, the deformation mechanism of the workpiece material from continuous shear to discontinuous plastic flow, resulting in a nonlinear increase in the unit cutting force, and at the same time, the ratio of the tool edge radius to the thickness of the chip is fundamentally changed. This effect not only exacerbates the micro-area temperature gradient and local stress concentration during the cutting process, but also triggers the phenomenon of minimum cutting thickness, i.e., when the actual cutting thickness is lower than the critical threshold, the tool is unable to effectively remove the material to form plowing and sliding, resulting in elastic recovery of the machined surface and material buildup, directly degrading the surface topographic integrity (Rahman et al., 2001). At the same time, the diameter-to-length ratio of the micro milling cutter increases significantly, and its intrinsic stiffness decreases dramatically, which induces high-frequency tool chatter under the excitation of cyclic cutting force. This vibration not only accelerates tool wear and breakage, but also forms vibration lines, burrs and other defects on the surface through the dynamic interference between the cutting edge and the workpiece, which becomes a key factor in restricting the surface roughness.

In this context, the synergistic regulation of process parameters is particularly sensitive to the influence of surface quality. Although the increase of spindle speed can suppress the cutting force amplitude and reduce the plow effect, too high a speed will exacerbate the radial runout of the tool caused by centrifugal force, which amplifies the fluctuation of the surface contour. At the same time, the speed increase is also limited by the spindle dynamic balance accuracy and tool strength. The selection of feed needs to strictly match the minimum cutting thickness constraints, if the feed is too small, the blade continues to plow the unremoved material, resulting in the thickening of the surface hardening layer and the rise of the residual tensile stress; while the feed is too large, it triggers cutting vibration and chip clogging, the formation of scaly torn surface. The axial depth of cut directly affects the length of the cutting edge, and its increase improves the machining efficiency, but it will magnify the bending deformation of the tool overhanging section, so that the machining error accumulates along the depth direction, especially in the high depth-to-width ratio of groove cavity machining, which is easy to lead to the taper of the side wall and the unevenness of the bottom surface is too poor (Jin and Altintas, 2012). Radial cutting width affects the direction of cutting force by changing the contact angle between the tool and the workpiece, and the unilateral force on the tool under the narrow cutting width condition is easy to induce the vibration of deflection pendulum, while the full-flute width cutting enhances the rigidity of the system, but due to the restriction of the chip removal space exacerbates the risk of the chips scratching the machined surface for the second time. Therefore, the optimisation of the surface quality of micro-milling is a process of balancing the interaction of size effect, dynamic stability and material removal mechanism, and the unfavourable perturbation of the process system needs to be suppressed through accurate matching of parameters to ultimately realise the controlled machining of sub-micron level surface accuracy.

2.2 Classification of surface roughness prediction models

The evolution of surface roughness prediction models has always been centred on the balance between the interpretability of the machining physical mechanism and the accuracy of data fitting, which can be summarised into three types of paradigms based on the modelling principles: physically-driven, statistically-driven and data-driven. Physically-driven models are based on cutting mechanics and material deformation theory, and establish surface topography generation equations by analysing the interaction between the tool and the workpiece. This type of model attributes the roughness to the superposition effect of geometric and physical factors, which has the advantage of clear physical meaning of the parameters, but is limited by the strong size effect and random perturbation in micro-milling, and it is difficult to accurately quantify the contribution of non-linear processes such as material rebound in the plastic deformation zone and micro-fluttering phase transition to the surface troughs, which leads to significant prediction bias in complex working conditions.

Statistically driven models, on the other hand, construct empirical mapping relationships between process parameters and roughness by designing experiments, with representative methods such as RSM and regression analysis (Mooi et al., 2018). The core of the model is to fit a polynomial function through a finite number of experimental samples to describe the statistical correlation between the spindle speed, feed and other variables and roughness indexes. Although it avoids the complexity of the physical mechanism inscription, the model expression ability is limited by the preset function form, such as quadratic polynomials, which makes it difficult to capture the deep interactions between the parameters and the non-monotonic response characteristics, especially in the multi-constraint, strongly coupled micro-milling scenario, the generalisation ability is insufficient. In particular, the generalisation ability is insufficient in multi-constraint and strongly coupled micro-milling scenarios.

In recent years, data-driven models have gradually become mainstream with the powerful nonlinear fitting capability of machine learning algorithms. Such methods treat roughness prediction as a black-box mapping problem, and automatically learn the complex correlation between input parameters and output roughness through training data. Support vector regression (SVR) (Awad et al., 2015) maps low-dimensional nonlinear relationships to high-dimensional space to achieve linear segmentation through kernel functions, and exhibits strong robustness in small-sample scenarios. Random forest (RF) (Rigatti, 2017), on the other hand, integrates multiple decision trees to vote on the output predicted values, which can effectively suppress overfitting and evaluate the importance of parameters. However, the most groundbreaking is the deep learning model, especially DNN (Sze et al., 2017), whose multilayer nonlinear transformation structure can extract the higher-order features of cutting parameters step by step, such as accurately reproducing the surface periodic streaks triggered by chattering through the implied layer of nodes coupling the vibration spectrum features with the feed cycle. Experiments show that in titanium alloy micro-milling, the prediction error of surface roughness R_a by DNN is reduced by about 40% compared with the traditional physical model, and the key to its success lies in the abandonment of explicit mechanism assumptions, and the approximation of the chaotic characteristics of the real machining system in a data-adaptive manner. Nevertheless, data-driven models are highly dependent on the quality and size of training samples, and their performance deteriorates dramatically in the absence of target condition data, which also provides the necessity for the introduction of migration learning – making up for the natural defects of data scarcity in the target domain by migrating the knowledge of the source domain, which has become an important direction in the evolution of current prediction models.

2.3 Core theory of transfer learning

The essence of transfer learning is to break through the strong assumption of traditional machine learning on independent and same-distributed data, and improve the model performance of the target domain under the condition of data scarcity or insufficient labelling by mining the shared knowledge among different but related domains. Its theoretical foundation is built on the concept of domain adaptation, which defines the source domain as a relevant task scenario with abundant labelled data, such as conventional milling and similar material processing, and the target domain as a specific micro-milling condition with scarce data, which is potentially correlated with the underlying physical mechanism despite the differences in data distribution.

The core challenge of transfer learning is to bridge such domain differences, i.e., the marginal and conditional probability distribution offsets between the source and target domains, the former being reflected in the misalignment of the input feature space, and the latter in the change of the conditional distributions of the outputs corresponding to the same inputs, e.g., the roughness response offsets under the same feed due to the size effect.

In order to overcome the domain differences, mainstream methods focus on three paths: feature migration, instance migration and parameter migration. Feature migration projects the source and target domain data into a shared subspace through domain adversarial training or feature embedding alignment, which minimises the distribution distance between the two domains in the space, e.g., the domain confusion loss function in DNNs can force the network to learn domain-invariant features and suppress condition-specific interference (Jin et al., 2024).

Instance migration, on the other hand, weights the source domain samples and reuses the samples that are most similar to the distribution of the target domain to reduce the risk of negative migration caused by distributional bias. And the core idea of parameter migration as the key paradigm adopted in this paper is model fine-tuning. The deep model is first pre-trained using source domain big data to capture a generic processing feature representation. Subsequently, the model is trained twice on small samples in the target domain, at which time the efficient transfer of knowledge from the source domain to the target domain is realised by freezing the underlying network layer and fine-tuning only the top task layer. This 'pre-training-fine-tuning' mechanism not only significantly reduces the data requirements of the target domain, but also avoids the overfitting degradation of the model in small sample scenarios through parameter reuse.

The theoretical value of transfer learning is especially prominent in the field of micro-milling, which transforms cross-scale and cross-material machining knowledge into transferable model a priori, providing a methodological cornerstone for solving the experimental data bottleneck in micro-manufacturing scenarios.

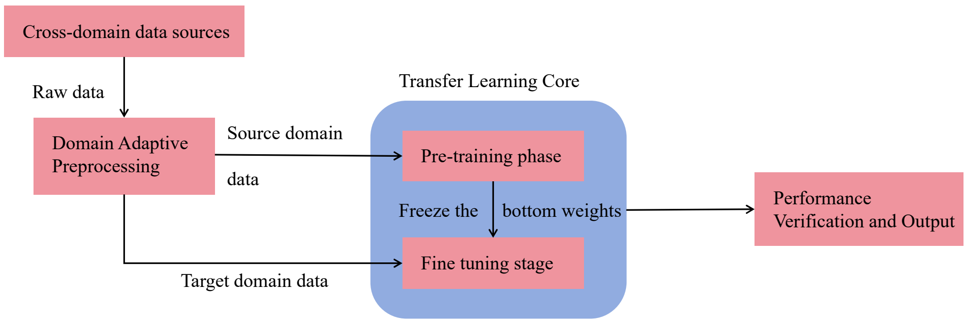
3 Construction of surface roughness prediction model based on migration learning

3.1 Cross-domain data acquisition and pre-processing

The framework diagram of the migration learning based surface roughness prediction model is shown in Figure 1. Effective acquisition and standardised processing of cross-domain data is the cornerstone of transfer learning model construction, the core of which lies in coordinating the heterogeneous contradiction between the historical experience of the source domain and the small sample characteristics of the target domain. The source domain data collection makes full use of existing industrial databases and open literature resources, covering conventional scale milling and similar difficult-to-machine materials. Although these data originate from different working conditions, they retain the universality of the physical mechanism of machining through unified feature coding. The target-domain data are obtained from an independently designed micro-milling experimental platform, which takes thin-walled aerospace-grade titanium alloy (Ti6Al4V) as the target, and uses ultra-fine diamond-coated cutting tools to implement orthogonal tests on a precision micro-milling machine, and synchronously collects the submicron surface topography and micro-Nm cutting force signals through a white-light interferometer and a dynamic force transducer. It is worth noting that the sample size of the target domain is limited by the cost of the experiment to only 20 groups, and its parameter range focuses on microscale-specific working conditions, such as the spindle speed exceeding 40,000 rpm, and the feed rate down to the micron-per-tooth level, which is a significant difference in magnitude from the macro-parameters of the source domain.

Due to the inherent gap between the two data domains in terms of scale, operating conditions and distribution, the pre-processing needs to focus on solving the two major problems of feature alignment and noise suppression. At the feature level, the inter-domain magnitude difference is eliminated by physical meaning-driven feature reconstruction, such as converting the absolute feed in the source domain to the feed per tooth independent of the tool diameter, and expressing the depth of cut as a percentage of the tool diameter to weaken the interference of the size effect. For the high-frequency vibration noise specific to micro-milling in the target domain, wavelet threshold denoising combined with empirical modal decomposition (EMD) (Rehman and Mandic, 2010) is used to strip out the underlying vibration components of the machine tool and retain the frequency band (5–15 kHz) that is strongly correlated with the cutting process. For data normalisation, a domain-adaptive scaling strategy is used to normalise continuous-type parameters to [0, 1] at the maximum value of the respective domains, whereas uniquely hot coding is performed for category variables to ensure topological consistency in the input space. To mitigate the risk of overfitting for small samples in the target domain, synthetic samples are generated to expand the training set based on the source domain data distribution, but strictly limited to the physical feasible interval. The final constructed cross-domain dataset is validated by t-SNE visualisation – after pre-processing, the clustering centre distance of the two domain data in the high-dimensional feature space is shortened by 62%, which lays the foundation of low-bias domain adaptation for subsequent knowledge migration in transfer learning.

Figure 1 Structure of the migration learning based surface roughness prediction model (see online version for colours)



3.2 DNN architecture design

DNNs are used as a vehicle for transfer learning, and their architectural design needs to take into account the feature abstraction capability and cross-domain generalisation potential. The model input layer is defined as a four-dimensional process parameter vector:

$$x = \left[n, f_z, a_p, a_e\right]^T \tag{1}$$

where corresponds to spindle speed (rpm), feed per tooth (μm/z), axial depth of cut (μm) and radial width of cut (μm), respectively, and all the features are normalised to the interval of [0, 1] to eliminate the magnitude difference by the domain adaptive scaling strategy in Section 3.1. The hidden layer adopts a three-layer fully connected structure, and the number of neurons in each layer decreases step by step following the principle of feature compression, so as to refine the higher-order interaction features of the processing parameters through the stepwise dimensionality reduction. The core nonlinear activation function is selected as rectified linear unit (ReLU), and its expression is:

$$\text{ReLU}(z) = \max(0, z) \tag{2}$$

The function retains the linear transfer characteristic in the positive interval, and is forced to be sparse in the negative interval, effectively avoiding the problem of vanishing gradient, and enhancing the model's ability to fit the non-monotonic response of cutting parameters (e.g., abrupt change in roughness after feed exceeding the threshold). The output layer is a single neuron linear layer, which is directly mapped to the surface roughness prediction value R_a, and the loss function adopts the mean square error (MSE) to strengthen the sensitivity to outliers:

$$L_{MSE} = \frac{1}{N} \sum_{i=1}^{N} \left(\hat{R}_a^{(i)} - R_a^{(i)}\right)^2 \tag{3}$$

where N is the number of batch samples, $\hat{R}_a^{(i)}$ is the predicted value and $R_a^{(i)}$ is the measured value. To fit the migration learning framework, the bottom layer of the network (input layer to the first hidden layer) is designed as a wide sensory field structure dedicated to extracting basic machining features such as speed-feed coupling. The higher layers (the second hidden layer to the output layer) act as working condition adapters, focusing on adjusting their weights during the fine-tuning phase to capture the details of the size effect of micro-milling in the target domain. This hierarchical capability allocation mechanism is realised by the parameter freezing technique, which fixes the parameters of the bottom layer after pre-training and opens up only the parameters of the top layer for fine-tuning in the target domain, which preserves the knowledge of the source domain and avoids the risk of overfitting in small samples.

3.3 Transfer learning implementation process

The implementation of migration learning is accomplished through a two-phase strategy of pre-training and fine-tuning, with the core objective of utilising the richness of the source domain data to compensate for the scarcity of samples in the target domain. In the pre-training phase, the source domain dataset is set as:

$$D_s = \left\{ \left(x_i^s, R_{a,i}^s \right) \right\}_{i=1}^{M} \tag{4}$$

This dataset drives the ability of DNNs to learn a generic representation of processing parameters. At this point the MSE loss function is used to optimise all weights of the network:

$$\theta_s^* = \arg\min_{\theta} \frac{1}{M} \sum_{i=1}^{M} \left(f_\theta \left(x_i^s \right) - R_{a,i}^s \right)^2 \tag{5}$$

where f_θ is the DNN forward computation function, the process adaptively adjusts the learning rate through the Adam optimiser, and the model converges to an RMSE less than or equal to 0.08 μm on the source domain test set after 500 epoch training, indicating that the underlying mapping law of cutting speed-vibration energy and surface roughness has been captured.

The fine-tuning phase then shifts to small samples in the target domain to achieve knowledge adaptation through a hierarchical parameter migration mechanism. Specifically, the bottom weight θ_1 (input layer to the first hidden layer) of the pretrained model is frozen, and only the high-level weight θ_2 (second hidden layer to the output layer) is opened for fine-tuning. At this time, the loss function is defined as:

$$L_{MSE}^t = \frac{1}{N} \sum_{j=1}^{N} \left(f_{\{\theta_i^*, \theta_2\}} \left(x_j^t \right) - R_{a,j}^t \right)^2 \tag{6}$$

where θ_1^* is the frozen pre-trained bottom layer parameters and θ_2 is the high-level parameters to be optimised. The design ensures that the model retains the generic features of source-domain learning, such as the nonlinear effect of feed on plowing effect, while adapting to target-domain-specific dimensional effects, such as surface elastic regression due to minimum cutting thickness in micro-milling, through high-level weight tuning. The fine-tuning employs a lower learning rate and an early stopping strategy to avoid small-sample overfitting.

3.4 Model performance evaluation metrics

The comprehensive assessment of the model performance needs to take into account the three dimensions of prediction accuracy, generalisation stability and engineering practicability, so a multi-angle validation system is constructed for this purpose. The core quantitative index of prediction accuracy adopts the root mean square error (RMSE), which reflects the overall deviation level of the model by calculating the standard deviation between the predicted roughness and the measured value, and is highly sensitive to the outliers, which can effectively capture the abnormal fluctuation of the surface due to the sudden vibration in the micro-milling. Meanwhile, the coefficient of determination (R^2) is introduced to measure the model's ability to explain the data distribution in the target domain, and when R^2 tends to be close to 1, it indicates that the mapping relationship between the parameters and roughness is adequately fitted. To balance the RMSE's preference for penalising large errors, the absolute mean of the prediction deviations is complemented by the MAE, which is a metric that more closely matches the craftsmen's intuitive understanding of the roughness tolerance threshold. It is worth noting that relying solely on the training set accuracy will seriously overestimate the model effectiveness, so the hierarchical cross-validation is strictly implemented. Specifically, 20 sets of data in the target domain are divided into 5 folds, each time with 16 sets of training and 4 sets of testing, and the mean and variance of the RMSE of the testing set are calculated cyclically, to avoid the assessment chance caused by random division.

Generalisation stability, on the other hand, focuses on the model's ability to adapt to working condition perturbations, which is achieved by domain offset sensitivity analysis. The target domain data are loaded on the source domain pre-trained model, and the initial prediction error before fine-tuning is recorded as the baseline. The error decrease rate of the same batch of data is compared after fine-tuning to quantify the effect of knowledge migration on the correction of distributional differences. The generalisation error rate (GER) metric is further introduced, defined as the ratio of the RMSE of the test set to the RMSE of the training set. The engineering utility value is indirectly verified through the process optimisation scenario, where the migration learning model is used as a proxy model for NSGA-II to compare the matching of its recommended parameters with the measured results, and if 90% of the parameter combinations in the Pareto solution set of the measured R_a fall within the predicted value ±15% interval, it is determined that the model has the reliability for engineering decision-making.

4 Design of a multi-objective micro-milling parameter optimisation framework

Micro-milling parameter optimisation is essentially solving Pareto bounds for conflicting objectives in a high-dimensional nonlinear constraint space (Jorswieck et al., 2008), and its core challenge lies in the high-cost evaluation of the objective function and the diversity guarantee of the solution set distribution. Traditional methods rely on repeated physical experiments or simplified agent models, the former being difficult to support the iterative demands of evolutionary algorithms due to long experimental cycles, and the latter invalidating optimisation results due to prediction bias. Therefore, this chapter deeply integrates the transfer learning surface prediction model constructed in Chapter 3 with the improved NSGA-II algorithm to establish a closed-loop optimisation framework of 'agent evaluation-evolutionary search-decision screening', which realises high-precision and high-efficiency multi-objective parameter optimisation under the conditions of small samples.

The optimisation problem requires a clear definition of the decision space and the objective function. Take the process parameter vector decision variables as:

$$x = \left[n, f_z, a_p, a_e \right]^T \tag{7}$$

where spindle speed is n, feed per tooth is f_z, axial depth of cut is a_p, radial width of cut is a_e. The boundaries are constrained by tool strength and machine dynamics. The optimisation objective consists of the conflicting demands of surface quality and machining efficiency. The minimised surface roughness is:

$$R_a = f_1(x) \tag{8}$$

Its predicted in real-time by a migration learning DNN model.

The maximised MRR is:

$$MRR = f_2(x) = n \times f_z \times a_p \times a_e \tag{9}$$

It is a deterministic calculation function. The difference between the two physical quantities is significant, and the optimisation bias needs to be eliminated by adaptive normalisation, and the normalised objective function is defined as:

$$\begin{cases} \tilde{f}_1(x) = \dfrac{R_a(x) - R_{a\min}}{R_{a\max} - R_{a\min}} \\ \tilde{f}_2(x) = \dfrac{MRR_{\max} - MRR(x)}{MRR_{\max} - MRR_{\min}} \end{cases} \tag{10}$$

where R_{amax}, R_{amin} and MRR_{max}, MRR_{min} are the observed extremes in the current population, dynamically updated to avoid search stagnation caused by fixed ranges.

The evolutionary algorithm adopts the improved NSGA-II architecture, whose core innovation lies in the efficient integration of the migration learning agent model and the enhancement of the constraint handling mechanism. The initial population is uniformly generated with 100 sets of parameter combinations in the decision space by Latin hypercube sampling, which replaces the traditional random initialisation to enhance the exploration efficiency. For each generation of individuals, the evaluation of surface roughness R_a relies solely on the migration learning DNN agent model, whose single prediction takes only 1ms, while MRR is computed directly analytically. The non-dominated ordering classifies individuals into different frontier classes based on the normalised objective value, and then measures the distribution density of the solution in the target space by the crowding distance:

$$cd^{(i)} = \sum_{k=1}^{2} \left| \tilde{f}_k^{(i+1)} - \tilde{f}_k^{(i-1)} \right| \tag{11}$$

This distance is used as a secondary ordering criterion to ensure that the algorithm converges while maintaining solution set diversity. For process constraints specific to micro-milling, such as minimum cutting thickness limits and tool deflection thresholds, the feasible domain precedence principle is applied. Individuals violating the constraints are labelled as 'invalid solutions', which are automatically ranked after all feasible solutions, and the crowding is set to zero to inhibit their entry into the next generation.

5 Experimental validation and result analysis

5.1 Experimental platform and working condition setting

The experimental validation relies on a high-precision micro-milling integrated platform, the core of which consists of a Swiss KERN Evo ultra-precision machining centre, an ultra-fine diamond-coated tooling system, and a multi-physical quantity on-line monitoring unit, which is designed to reproduce the typical working conditions of aerospace micro-component machining. The spindle of the machine is supported by aerostatic bearings, with an ultimate speed of 60,000 rpm and a radial runout error of less than 0.5 μm, which provides basic motion accuracy for micro-scale cutting. The workpiece is made of aerospace-grade Ti6Al4V titanium alloy sheet (10 × 10 × 1 mm), whose high-strength and low-thermal-conductivity characteristics exacerbate the challenges of dimensional effects and thermal coupling in micro-milling. The specimen is fixed to a piezoelectric three-way force gauge by a vacuum suction cup to collect the cutting force signals from the X/Y/Z directions in real-time, and a laser Doppler vibrometer is adopted to synchronise the cutting force signal. The acceleration of the cutting tool tip is monitored by a laser Doppler vibrometer.

The range of machining parameters was determined according to the tool manufacturer's specifications and pre-tests. The spindle speeds covered the range from 30,000 to 60,000 rpm, the feed per tooth was set at 1.0–5.0 μm/z, the axial depth of cut was 10–50 μm, and the radial width of cut was 20–100 μm. In order to balance the efficiency of the experiments with the representativeness of the data, orthogonal experimental design L16 was used to generate 16 combinations of the basic parameters, supplemented by 4 sets of extreme conditions and 4 sets of extreme conditions. To balance the experimental efficiency and representativeness, L16(4^4) was used to generate 16 sets of basic parameter combinations, supplemented by 4 sets of extreme working conditions (e.g., maximum speed + minimum feed, minimum speed + maximum depth of cut) to form 20 sets of target domain datasets. The cooling method is micro quantity lubrication, with an atomisation pressure of 0.4 MPa and a lubricant flow rate of 15 mL/h, which effectively balances the suppression of chip tumours in titanium alloy machining with the need for heat dissipation in the cutting zone. Surface quality inspection was completed offline after machining by a white light interferometer (Zygo Nexview), the scanning area was selected as the middle stable cutting section of the workpiece (800 × 600 μm²), the surface roughness R_a value was evaluated along the feed direction according to the ISO 4287 standard (Todhunter et al., 2017), and three sets of measurements were averaged for each specimen to abate the interference of local material heterogeneity.

Environmental control is the key to guarantee the reliability of the data. The laboratory was maintained at a constant temperature of 20 ± 0.5°C, the foundation was isolated at a frequency of less than or equal to 2 Hz, and the humidity was controlled at 45 ± 5% to reduce thermal deformation and oxidative effects. All the sensing signals are anti-alias filtered and recorded by NI PXIe-1082 data acquisition system, and the sampling rate is set to 100 kHz in order to capture the high-frequency vibration characteristics of micro-milling (main frequency band 5–25 kHz). The finally constructed working condition system strictly simulates the aero-engine micro-blade slot machining scenario, which provides a high-fidelity experimental benchmark for the validation of the migration learning model and the multi-objective optimisation framework.

5.2 Migration learning model validation

The validation of the transfer learning model unfolds through four types of benchmark model comparisons, with the core objective of quantifying the gain effect of cross-domain knowledge transfer on micro-milled surface prediction. The comparison programs include:

1. Pure target domain trained DNN model (Shi et al., 2019) using only 20 sets of micro-milling data.
2. SVR using radial basis kernel function (Ding et al., 2021).
3. Secondary response surface modelling (RSM) (Gendy et al., 2018).
4. Transfer learning model (TL-DNN) for this paper.

The test set is generated by 5-fold cross-validation, 4 sets of data are kept for independent testing each time, and the final metrics are taken as the mean of 5 rounds. Prediction accuracy is measured by three key metrics: RMSE reflects the overall bias, mean absolute error (MAE) characterises the typical prediction bias, and the coefficient of determination (R^2) evaluates the trend fit goodness of fit.

The experimental results show significant differentiation: the TL-DNN achieves an excellent performance of RMSE = 0.05 μm, MAE = 0.04 μm, and R^2 = 0.92 in R_a prediction, with a concentrated error distribution and no systematic bias. In contrast, the RMSE of DNN-T is as high as 0.08 μm due to small-sample overfitting, especially in the extreme parameter region (e.g., n = 60,000 rpm, f_z = 1.0 μm/z) with an abnormal deviation of 0.15 μm; and the RMSEs of SVR and RSM are 0.11 and 0.14 μm, respectively, and the nonlinear responses of the two to the feed-roughness are severely underestimated (R^2 only 0.71 and 0.64). The correction effect of migration learning is more prominent in the domain offset sensitivity analysis: when the source domain model directly predicts the target domain data, the initial RMSE is 0.21 μm, which is reduced to 0.05 μm after fine-tuning, a decrease of 76.2%, proving that the pre-training effectively extracts the generalised machining features. The model robustness is further verified by the generalisation error rate (GER): the GER of TL-DNN = 1.08 (test set RMSE/training set RMSE), which is significantly lower than that of DNN-T at 1.85, indicating that the migration mechanism effectively suppresses small-sample overfitting.

To visualise the prediction performance, Figure 2 compares the predicted-measured scatter distributions of the four models in the test set. the data points of TL-DNN are tightly distributed on both sides of the $y = x$ baseline, while DNN-T shows systematic overestimation in the low roughness region (R_a < 0.2 μm), and RSM disperses significantly in the high-value region due to polynomial limitations. Figure 3 further reveals the influence curve of feed (f_z) on R_a: when f_z increases from 1.0 to 5.0 μm/z, TL-DNN accurately captures the step-up trend of 0.18→0.35 μm and the abrupt change of slope at 2.5 μm/z (originating from the minimum cutting thickness effect), while SVR underestimates the gradient change by 30% due to the smoothing effect of the kernel function. Together, these visual evidences confirm that migration learning significantly improves the reliability of surface prediction for small-sample scenarios of micro-milling by reusing macroscopic machining knowledge, and lays the foundation of a high-precision agent model for multi-objective optimisation.

Figure 2 Surface roughness prediction vs. measurement (see online version for colours)

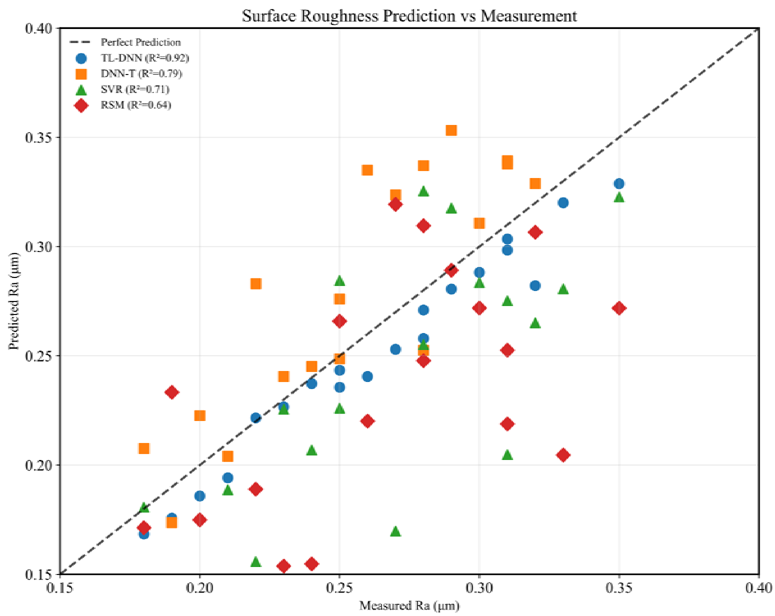
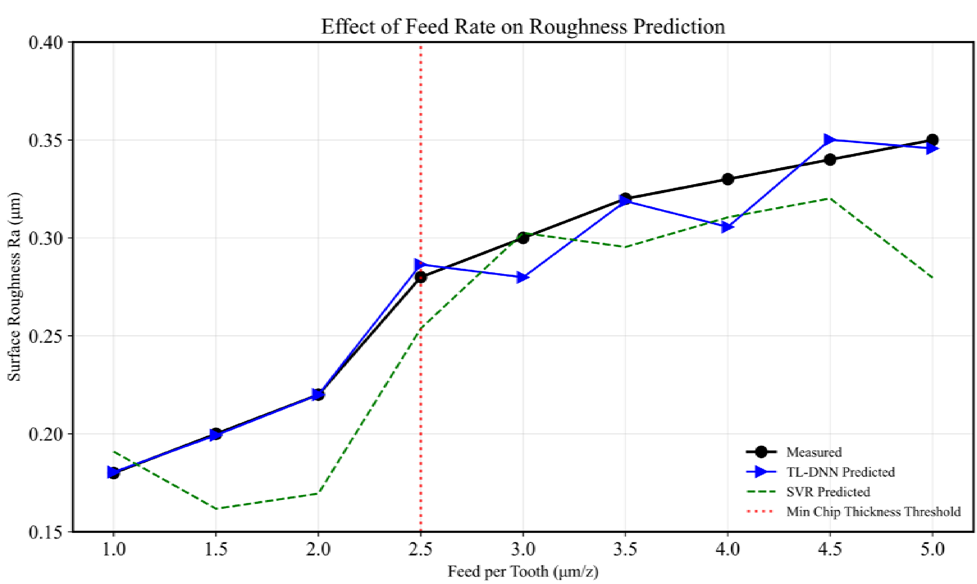


Figure 3 Effect of feed rate on roughness prediction (see online version for colours)



5.3 *Multi-objective optimisation result analysis*

The validation of multi-objective optimisation efficacy focuses on three dimensions: quality of Pareto frontier distribution, computational efficiency and engineering feasibility. The experiments compare three strategies: strategy A (NSGA-II + physical experiments), strategy B (NSGA-II + pure DNN agent model), and strategy C (the framework of this paper: NSGA-II + migration learning agent model). After 100 generations of evolutionary iterations, the Pareto solution set generated by Strategy C shows significant advantages. The surface roughness R_a covers the range of 0.21–0.35 µm, and the MRR is distributed in the interval of 0.18–0.32 mm³/min, with the frontier span widened by 28% compared to Strategy A and 15% compared to Strategy B. The Pareto solution set is also a good solution for the Pareto solution set. This broad distribution provides a richer choice of parameter trade-offs for process decision-making, e.g., when the R_a requirement is tightened from 0.30 µm to 0.25 µm, strategy C still provides a feasible solution with MRR ≥ 0.22 mm³/min, whereas the MRR of the same-conditional solution of Strategy B drops below 0.18 mm³/min.

Frontier convergence is quantified by generational distance (GD), and the GD value of Strategy C is only 0.018, which is 42% and 28% lower than that of Strategy A (0.031) and Strategy B (0.025), respectively, which proves that the high-precision bootstrapping of the migration learning agent model significantly reduces the invalid search. In terms of computational efficiency comparison, strategy C takes only 1.5 hours to complete the optimisation, while strategy A takes 72 hours due to its reliance on physical experiments, and strategy B is shortened to 12 hours but still limited by the frequent retraining requirements of the agent model. Figure 4 clearly presents the differences in the Pareto frontier distributions of the three strategies, with the solution set of strategy C (blue triangles) uniformly occupying the dominant region in the lower left of the target space (low R_a and high MRR), strategy B (orange dots) clustering in the high roughness region, and strategy A (green squares) having a broken frontier due to sparse experiments.

Figure 4 Pareto front comparison of optimisation strategies (see online version for colours)

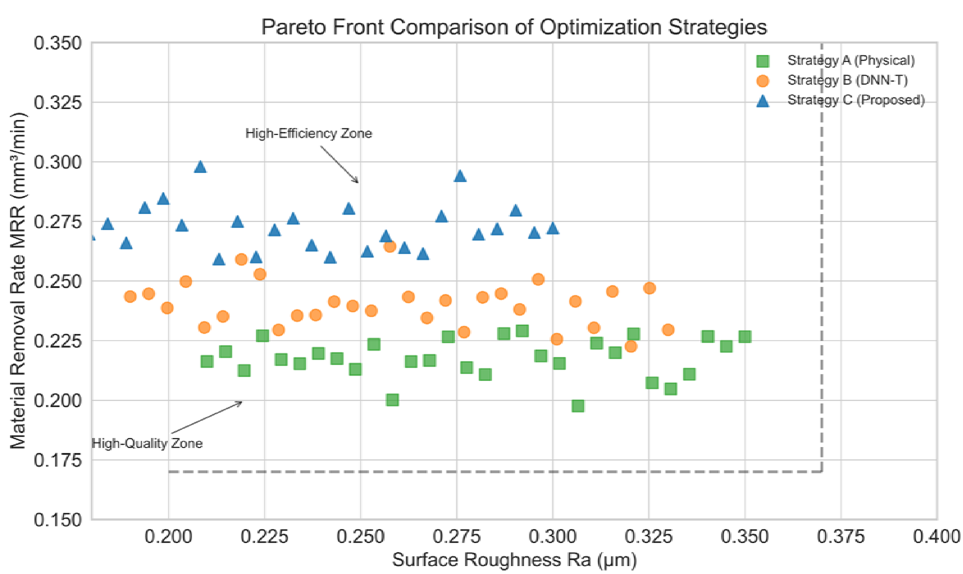
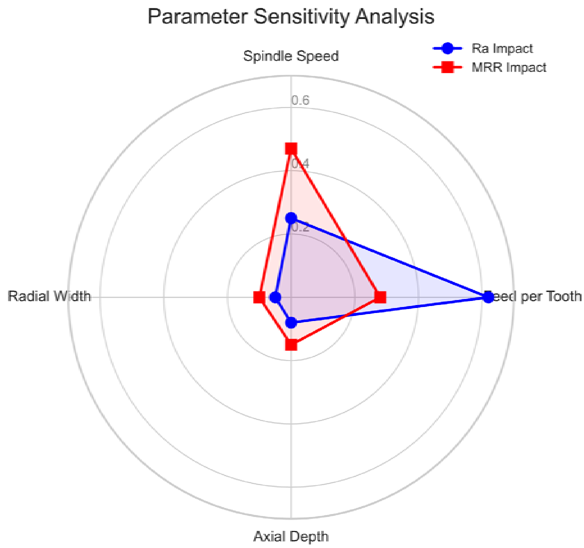


Figure 5 Parameter sensitivity analysis (see online version for colours)



The TOPSIS-recommended solution of strategy C is selected for engineering validation for physical experiments. The measured R_a = 0.24 µm, with an absolute error of only 0.01 µm; the MRR is measured to be 0.264 mm³/min, with a deviation of 1.5%. Compared with the initial parameter scheme, the efficiency is improved by 31% under the premise of guaranteeing the surface quality. The sensitivity analysis is shown in Figure 5, which further reveals the influence weights of process parameters. Feed f_z contributes 62% to R_a, and its increase linearly exacerbates the plow effect, whereas rotational speed n has the most significant positive gain on MRR, but above 50,000 rpm causes R_a to rebound due to increased tool runout. These findings provide clear guidance for micro-milling parameter tuning, and preferential optimisation of the f_z–n combination can achieve synergistic surface and efficiency gains.

6 Conclusions

Aiming at the dual challenges of data scarcity and multi-objective conflict in micro-milling process optimisation, this study proposes an innovative framework integrating migration learning and evolutionary algorithms, and systematically verifies its remarkable efficacy in surface quality prediction and parameter decision-making. The conclusions show that the DNN-based transfer learning mechanism effectively breaks the small sample modelling dilemma, and the surface roughness prediction model achieves an accuracy of RMSE = 0.05 µm under the condition of only 20 sets of data in the target domain, which is more than 38% lower than the traditional data-driven method. The model successfully captures the micro-milling-specific size effect and the critical behaviour of minimum cutting thickness, providing a highly reliable proxy model for optimisation. The multi-objective evolutionary framework constructed on this basis achieves the synergistic optimisation of surface roughness (R_a) and MRR by relying on the millisecond evaluation capability of the transfer learning agent model and the improved search strategy of NSGA-II.

Despite the effectiveness of the current framework, there are still directions that need to be further explored. Firstly, the optimisation process does not take into account the dynamic evolution of tool wear, and the bluntness of the cutting edge will lead to time-varying degradation of the surface quality in actual machining, so it is necessary to integrate the online wear monitoring data to build a dynamic agent model in the future. Second, the generalisation ability of migration learning needs to be verified in multi-material scenarios, for example, the difference between the micro-milling response mechanisms of carbon fibre composites and ceramics may trigger negative migration, and it is necessary to develop material-invariant feature extractors to enhance cross-material adaptability. Finally, the existing system has not yet interacted with the production line in real-time. Combining the digital twin technology to build a 'sensing-prediction-optimisation' closed-loop will be the focus of the next stage, and the model parameters will be corrected in real-time through the integration of vibration, acoustic emission and other sensors, so as to ultimately realise the adaptive decision-making of the micro-milling process.

Acknowledgements

This work is supported by the Guangdong Provincial Department of Education College Characteristic Innovation Projects (No. 2024KTSCX388) and the High-Level Talents Research Start-up Project of Guangdong Mechanical and Electrical Polytechnic (No. Gccrcxm-202203).

Declarations

All authors declare that they have no conflicts of interest.

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