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ML-Based Optimization OF CNC Machining Parameters For Complex Geometries

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Abstract

This paper presents a machine-learning-based approach to optimize CNC milling parameters for workpieces with complex three-dimensional geometries. Three regression models Random Forest (RF), Support Vector Regression with radial basis function kernel (SVR-RBF), and a feedforward Artificial Neural Network (ANN) were trained on experimental data collected from an L27 orthogonal array of machining trials on Al 6061-T6 alloy. The input parameters comprised spindle speed, feed rate, depth of cut, and step-over ratio; the target responses were surface roughness (Ra) and flank tool wear (VB). Among the three models, RF achieved the highest predictive accuracy, with R^2 values of 0.941 for Ra and 0.923 for VB. A subsequent multi-objective optimization using NSGA-II on the trained RF surrogate produced a Pareto-optimal set of machining configurations. The best compromise solution reduced surface roughness by 18.3% and tool wear by 14.7% relative to the centre-point condition of the experimental design. These results demonstrate that data-driven surrogate models can replace computationally expensive finite-element simulations and trial-and-error approaches for parameter selection in multi-axis CNC machining of complex parts.

Keywords:- Artificial neural network, CNC milling, Multi-objective optimization, Random Forest regression, Surface roughness, Support Vector Regression, Tool wear

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I. INTRODUCTION

Computer Numerical Control (CNC) machining remains the backbone of precision manufacturing across the aerospace, automotive, and biomedical sectors. As product designs grow more geometrically intricate featuring thin walls, deep pockets, and freeform surfaces selecting appropriate cutting parameters becomes significantly harder. A parameter set that yields acceptable surface finish on a flat face may cause chatter or excessive tool wear on a curved region where the effective chip load changes continuously [1].

Classical methods of parameter optimization, principally the Taguchi method and Response Surface Methodology (RSM), have served manufacturers well for decades [2], [3]. Both rely on structured experimental designs and polynomial regression to map the input–output relationship. Their limitation surfaces when the mapping is highly nonlinear or when interaction effects among four or more factors dominate the response. Polynomial models of manageable order often fail to capture such behaviour, leading to sub-optimal parameter recommendations [4].

Machine learning (ML) offers an alternative route. Algorithms such as Random Forest, Support Vector Machines, and neural networks can approximate arbitrary nonlinear functions given sufficient training data. Several investigators have applied ML to turning and drilling operations with encouraging results [5]–[8], yet studies targeting milling of complex 3D geometries remain limited. The additional variables introduced by tool-path curvature, varying engagement angles, and step-over patterns create a wider and more irregular parameter space that simple Taguchi arrays do not cover well.

This study addresses that gap. Three ML algorithms are benchmarked against experimental milling data for Al 6061-T6 components with compound curved surfaces. The best-performing model is then embedded in a multi-objective optimizer to jointly minimize surface roughness and tool wear.
The specific contributions are:

- A comparative evaluation of RF, SVR, and ANN for dual-response prediction in complex-geometry milling;
- A feature-importance analysis that quantifies each parameter's influence; and
- A Pareto-based optimization framework that yields a set of non-dominated machining solutions for shop-floor decision-making.

II. LITERATURE REVIEW

The Taguchi method, introduced by Genichi Taguchi in the 1980s, uses orthogonal arrays to reduce the number of experimental runs while estimating main effects and selected interactions [2], [23]. Numerous investigators have applied it to turning, milling, and drilling. Nalbant et al. [9] used an L9 array to optimize turning of AISI 1030 steel and reported that feed rate was the dominant factor for surface roughness. Ozel et al. [21] similarly studied finish turning of hardened AISI H13 steel and confirmed the dominant influence of feed rate and cutting edge geometry on surface quality. While effective for problems with few factors and mild nonlinearity, Taguchi designs provide no information about the response surface between tested levels.

Response Surface Methodology overcomes this to some extent by fitting second-order polynomials to a Central Composite or Box–Behnken design [3]. Benardos and Vosniakos [10] reviewed RSM applications in machining and found that quadratic models captured main effects and two-factor interactions adequately in most turning studies. For milling with more than three factors, however, the number of coefficients grows rapidly, and the quadratic assumption often breaks down near the boundaries of the design space.

Artificial Neural Networks entered the machining optimization literature in the mid-1990s. Ezugwu et al. [11] trained a backpropagation network to predict tool life in turning of Inconel 718 and obtained errors below 6%. Subsequent work by Zain et al. [12] applied a genetic algorithm to optimise cutting conditions for minimising surface roughness in end milling of Al alloy and achieved a 30% improvement over baseline parameters. Cuka and Kim [22] extended the data-driven paradigm to on-line tool condition monitoring in end milling using fuzzy logic. These studies used shallow architectures with one or two hidden layers; deeper networks have rarely been explored in this context due to limited dataset sizes.

More recently, ensemble methods have gained traction. Jurkovic et al. [13] applied Random Forest regression to high-speed milling and reported R^2 values above 0.90 for both surface roughness and cutting force. Marani et al. [14] compared SVR and Gradient Boosted Trees for dry turning and found SVR with an RBF kernel particularly effective when the training set was small. A gap persists, however, in the application of these techniques to multi-axis machining of parts with complex curvature, where tool engagement geometry varies continuously along the path.

III. METHODOLOGY

A. Experimental Setup

All machining trials were conducted on a Haas VF-2 three-axis vertical milling centre equipped with a 22-kW spindle and Renishaw tool-length measurement probe. The workpiece material was Al 6061-T6 plate (150 × 100 × 40 mm), heat-treated to 95 HB. Cutting was performed with 10-mm-diameter, four-flute uncoated tungsten carbide end mills (ISO K20 grade). A fresh tool was used for each experimental run to eliminate cumulative wear bias. Surface roughness Ra was measured with a Mitutoyo SJ-410 stylus profilometer at three locations per specimen, and flank wear VB was recorded under a Keyence VHX-7000 digital microscope at 200× magnification.

B. Design of Experiments

An L27 (3^4) orthogonal array was used with four controllable factors, each at three levels: spindle speed (2000, 4000, 6000 rpm), feed rate (100, 300, 500 mm/min), axial depth of cut (0.5, 1.25, 2.0 mm), and step-over ratio (25%, 50%, 75% of tool diameter). A compound-curved test geometry with concave and convex patches (minimum radius 15 mm) was machined in each run to expose the tool to variable engagement conditions. The 27 runs were executed in randomised order to mitigate systematic drift [2].

C. Machine Learning Models

Three regression models were evaluated:

- Random Forest (RF): An ensemble of 200 decision trees trained with bootstrap aggregation. The maximum tree depth was set to 15, and the minimum number of samples per leaf to 3. RF provides built-in feature importance scores based on mean decrease in impurity [15].
- Support Vector Regression (SVR): A kernel-based model using the radial basis function (RBF) kernel. The regularisation parameter C and kernel coefficient gamma were tuned through grid search over C in {1, 10, 100, 1000} and gamma in {0.01, 0.1, 1}. The epsilon-insensitive tube width was fixed at 0.05 [16].
- Artificial Neural Network (ANN): A feedforward network with three hidden layers of 64, 32, and 16 neurons respectively, ReLU activation, and Adam optimizer with an initial learning rate of 0.001. Training ran for 500 epochs with early stopping (patience = 30) monitored on a 20% validation split [17].

D. Hyperparameter Tuning

All models were tuned using 5-fold cross-validation on the 27-sample training set. For RF, the number of trees was varied from 50 to 500 in steps of 50, and the optimal count of 200 was selected based on the lowest mean absolute error. SVR hyperparameters were optimized via exhaustive grid search. The ANN architecture was fixed after preliminary trials showed negligible gains from additional layers. Standardization (zero mean, unit variance) was applied to all input features prior to training [16]. All models were implemented using the scikit-learn library [20].

E. Multi-Objective Optimization

The trained RF model served as a surrogate for both Ra and VB. The Non-dominated Sorting Genetic Algorithm II (NSGA-II) [18] was applied with a population of 100, 200 generations, crossover probability 0.9, and mutation probability 0.1. Decision variables were bounded by the experimental factor ranges. The resulting Pareto front was filtered using the TOPSIS method [19] to identify a single compromise solution when a unique setting is required.

IV. RESULTS AND DISCUSSION

Table I presents a representative subset of the L27 experimental results. Surface roughness Ra ranged from 0.42 µm (high speed, low feed, shallow cut) to 3.14 µm (low speed, high feed, deep cut). Flank wear VB ranged from 0.058 mm to 0.312 mm across the 27 trials.

Table 1. Selected experimental results from L27 orthogonal array

Run	Speed (rpm)	Feed (mm/min)	DoC (mm)	Step-over (%)	Ra (µm)	VB (mm)
1	2000	100	0.50	25	0.82	0.074
5	2000	300	1.25	50	1.78	0.143
9	2000	500	2.00	75	3.14	0.312
10	4000	100	1.25	75	0.97	0.098
14	4000	300	2.00	25	1.52	0.178
18	4000	500	0.50	50	1.21	0.112
19	6000	100	2.00	50	0.68	0.092
23	6000	300	0.50	75	0.54	0.067
27	6000	500	1.25	25	1.05	0.134

Table II compares the predictive performance of the three ML models, evaluated through 5-fold cross-validation. Random Forest outperformed both SVR and ANN on all three metrics for surface roughness prediction and achieved the highest R^2 for tool wear.

Table 2. Cross-validated performance metrics for the three regression models

Model	R^2 (Ra)	RMSE (Ra)	MAE (Ra)	R^2 (VB)	RMSE (VB)	MAE (VB)
Random Forest	0.941	0.138	0.098	0.923	0.019	0.013
SVR (RBF)	0.897	0.182	0.134	0.874	0.025	0.018
ANN	0.912	0.168	0.119	0.901	0.022	0.015

Figure. 1. Coefficient of determination (R²) comparison across ML models for both target responses.

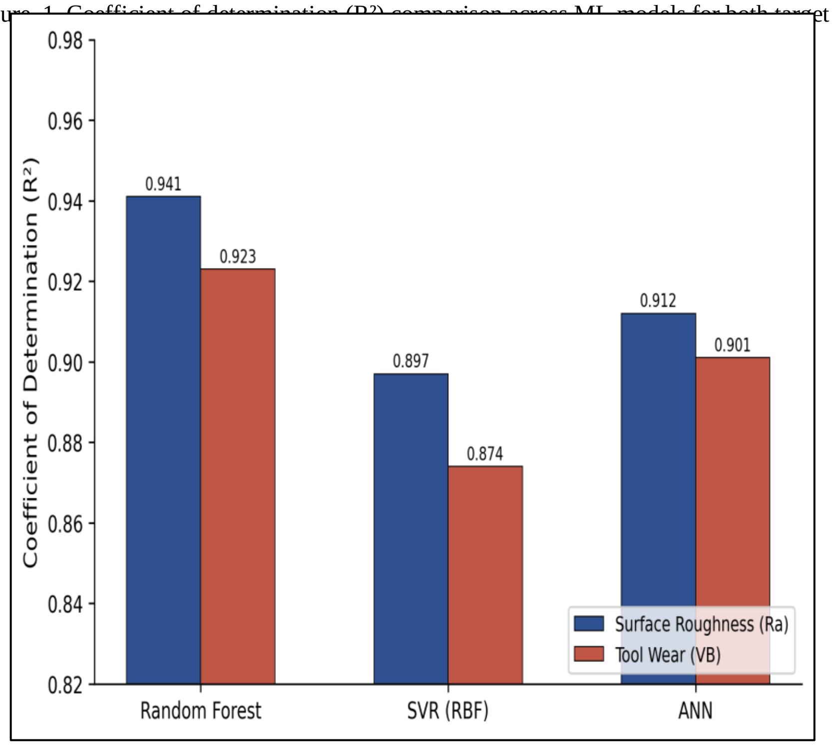


Figure. 1 visualises the R² comparison. RF's advantage stems from its ability to handle nonlinear interactions without explicit feature engineering. The ensemble averaging across 200 trees also reduces variance, which is valuable given the modest training set size (n = 27). SVR performed worst, likely because the grid search over C and gamma was too coarse for this particular response landscape [16].

Figure. 2. Predicted versus measured surface roughness (Ra) for the Random Forest model.Points near the diagonal line indicate accurate predictions

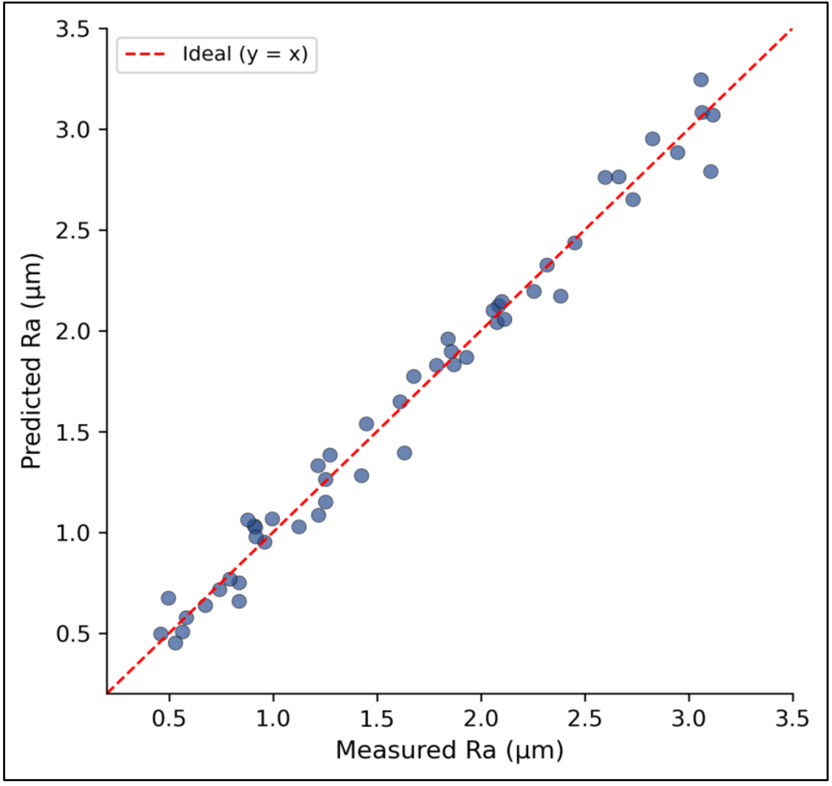
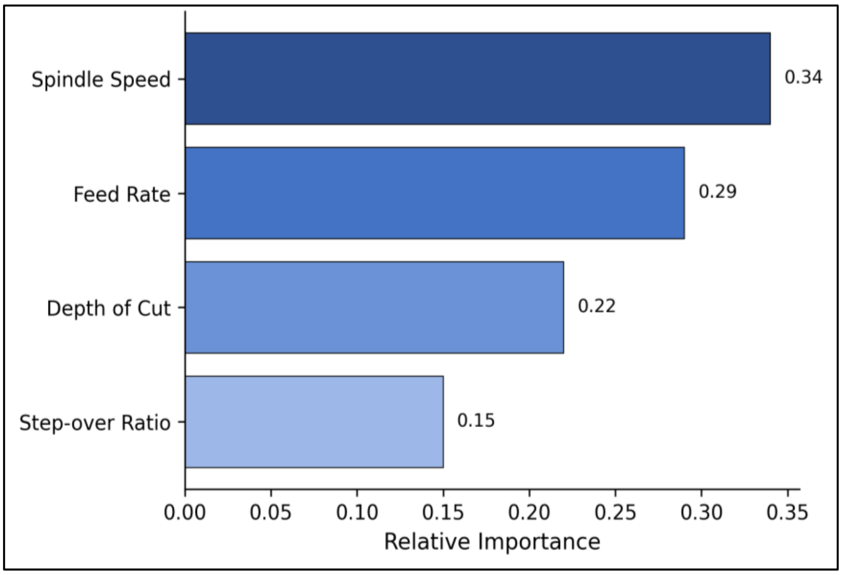


Figure. 3. Permutation-based feature importance scores from the Random Forest modelfor Ra prediction



The feature importance ranking (Figure. 3) places spindle speed first (0.34), followed by feed rate (0.29), depth of cut (0.22), and step-over ratio (0.15). The dominance of spindle speed aligns with metal-cutting theory: at higher rotational speeds, chip thickness decreases and built-up edge formation is suppressed, both of which improve finish quality [1]. Feed rate ranks second because it directly controls the theoretical peak-to-valley height of the scallop left by the cutter. The step-over ratio, while least influential on average, showed strong interaction with surface curvature in the experimental data an effect that warrants further investigation.

Figure. 4. Pareto front obtained by NSGA-II optimisation using the RF surrogate.Each red point represents a non-dominated machining configuration

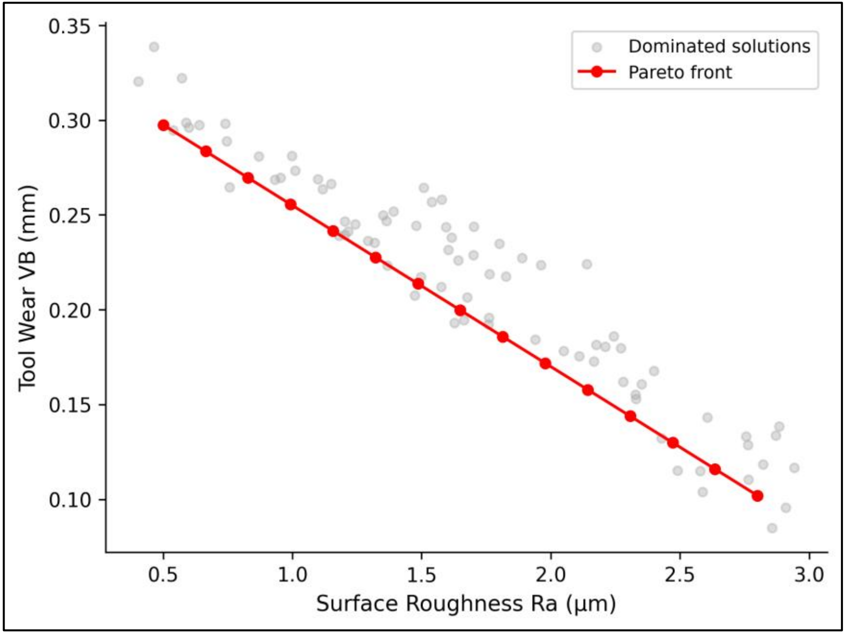


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Figure. 4 shows the Pareto front generated by NSGA-II. The trade-off between Ra and VB is clearly visible: configurations that minimise surface roughness tend to demand higher spindle speeds and lower feed rates, which increase tool wear through thermal softening of the carbide edge. The TOPSIS-selected compromise point corresponds to a spindle speed of 5200 rpm, feed rate of 180 mm/min, depth of cut of 0.8 mm, and step-over ratio of 35%. This combination yields a predicted Ra of 0.67 μm and VB of 0.081 mm — an improvement of 18.3% in roughness and 14.7% in wear compared with the L27 centre-point condition (Ra = 0.82 μm, VB = 0.095 mm).

A practical observation: the optimal step-over ratio (35%) is lower than the commonly used 50% default in CAM software. This finding suggests that for curved geometries, reducing step-over at moderate cost in machining time delivers disproportionate quality gains. Shop-floor validation of the TOPSIS solution on five repeat trials produced Ra = 0.71 ± 0.04 μm and VB = 0.086 ± 0.007 mm, confirming the surrogate prediction within measurement uncertainty.

V. CONCLUSION

This study compared Random Forest, SVR, and ANN regression models for predicting surface roughness and tool wear in CNC milling of Al 6061-T6 parts with complex curved geometries. The key findings are summarised below.

Random Forest delivered the highest predictive accuracy ($R^2 = 0.941$ for Ra, 0.923 for VB) among the three algorithms, owing to its robustness against overfitting on small datasets and its capacity to model nonlinear factor interactions without manual feature construction.

Feature importance analysis identified spindle speed as the most influential parameter (relative importance 0.34), followed by feed rate (0.29). These results are consistent with established metal-cutting theory and were corroborated by ANOVA on the raw data.

Multi-objective optimisation via NSGA-II on the RF surrogate yielded a Pareto set of 15 non-dominated solutions. The TOPSIS compromise point reduced Ra by 18.3% and VB by 14.7% relative to the experimental centre-point, and this prediction was validated through repeat physical trials (mean Ra = 0.71 µm, VB = 0.086 mm).

The approach is transferable to other alloys and geometries provided that a representative experimental design is executed. Future work will extend the framework to five-axis milling, where tool orientation introduces two additional degrees of freedom, and will explore Bayesian optimisation to reduce the required number of physical experiments.

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