ISSN 1392-1207. MECHANIKA. Vol. 32, No. 3, 2026: 228–240

Machine Learning for Prediction of Surface Roughness in Stellite 6 Turning: A Comparative Study of ANN, Random Forest and Support Vector Regression Models

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https://doi.org/10.5755/j02.mech.43720

1. Introduction

The surface integrity of a manufactured component is fundamental to its long-term operational performance and service life. The quality of the finished surface profoundly influences several crucial material properties, notably wear resistance, corrosion susceptibility, and fatigue strength [1, 2]. Among the quantitative parameters used to characterize this finish, surface roughness (*Ra*) stands as the most globally established and critical metric for evaluating machining quality and verifying strict dimensional compliance [3].

The material under investigation, Stellite 6, is a cobalt-based superalloy frequently deployed across challenging industrial sectors, including aerospace, power generation, and petrochemical industries. This utilization stems from its exceptional resistance to elevated temperatures, chemical corrosion, and severe abrasion [4]. However, the very mechanical attributes that ensure its superior reliability, specifically its high intrinsic hardness and thermal stability. The ensuing high cutting-zone temperatures, accelerated tool deterioration, and poor chip formation often result in undesirable and inconsistent surface finishes during standard turning operations [5]. Consequently, the accurate control and prior prediction of *Ra* during the machining of Stellite 6 presents a notable manufacturing challenge.

Traditional methodologies used to model the relationship between machining inputs (e.g., cutting speed, feed rate, depth of cut) and the resulting *Ra* have historically relied upon simple empirical equations or linear regression methodologies. These approaches are generally inadequate for capturing the intricate, non-linear dependencies and multi-variable interactions that characterize the turning process of superalloys [6]. To circumvent these inherent limitations, advanced data-driven methodologies, specifically Machine Learning (ML) techniques, have emerged as powerful alternatives capable of modeling complex input-output relationships with enhanced fidelity [7].

Arvind and Periyarsamy [8] focused on enhancing the surface grinding inputs for AISI 1035 steel, specifically examining the impact of grinding wheel abrasive grain size, depth of cut (DOC), and feed rate. Their methodology integrated two distinct modeling approaches: the Taguchi method and Response Surface Methodology (RSM). The primary response variables under consideration were the roughness metrics *Ra* and *Rz*. Their comparative findings postulated that RSM offered marginally superior optimization capability over the Taguchi method, particularly when small variations in the operative parameters were introduced.

Mane, S. et al. explored the use of predictive modeling techniques to improve the hard turning of AISI 52100 steel under minimum quantity lubrication conditions. Their work focused on estimating surface roughness and cutting temperature by applying Response Surface Methodology alongside Artificial Neural Networks.

The analysis showed that both methods are capable of accurately describing the process behavior; however, the ANN approach provided marginally better prediction accuracy. In addition, the study identified a set of cutting parameters that make it possible to achieve a smoother surface finish while effectively controlling heat generation during machining [9].

Bagci, E. and Işık, B. investigated surface roughness behavior during the turning of unidirectional glass fibre–reinforced plastic (GFRP) composites. In their study, cutting speed, feed rate, and depth of cut were systematically varied while machining was performed using cermet cutting tools.

The primary objective was to develop reliable predictive models for surface quality by applying two different computational approaches: Response Surface methodology (RSM) and Artificial Neural Networks (ANNs). The outcomes demonstrated that robust models could be established to effectively predict the surface finish of the machined components [10].

Saidi, R. et al. in their research optimized the turning process for the Stellite 6 (Co-Cr-Mo) superalloy to achieve minimal insert flank wear and surface roughness (*Ra*). The experiments were structured using a Taguchi L18 design, and Response Surface Methodology (RSM) was employed to develop predictive mathematical models based on four key factors (tool nose radius, feed rate, cutting depth, and cutting speed). The resulting RSM models were highly accurate, with low maximum prediction errors (13.82% for wear, 10.90% for *Ra*), successfully identifying the optimal parameter combination for achieving the best balance of tool longevity and part quality [11].

Tibakh, I. et al. optimized the dry face milling of Polyoxymethylene Co-polymer (POM C) to enhance surface quality (*Ra*) and productivity (*MRR*). The study com-

pared predictive models from response surface methodology (RSM) and support vector machine (SVM), validated by ANOVA. The highly accurate SVM models were then used with a genetic algorithm (GA) to determine the optimal cutting parameters for minimizing roughness and maximizing productivity [12].

Saidi, R. et al. developed and validated Artificial Neural Networks (ANNs) to predict the three cutting force components (*Fx, Fy, Fz*) during the turning of the superalloy Stellite 6. The models used four machining parameters (tool nose radius, cutting speed, feed rate, cutting depth) as inputs and demonstrated high predictive accuracy based on low error metrics (RMSE, MAPE, MAD). This confirms the potential of ANNs for real-time process control [13].

In a related study, Kishore et al. [14] investigated the grinding performance of Inconel 625, analyzing the results across three lubrication conditions: dry, wet, and Minimum Quantity Lubrication (MQL). Their analysis concentrated on two key performance indicators: tangential forces and resultant surface roughness. The study employed a dual-modeling strategy, utilizing both RSM and a set of four distinct machine learning (ML) architectures: MultiLayer Perceptron (MLP), k-Nearest Neighbors (KNN), and Support Vector Machine (SVM) featuring two different kernel functions. In terms of predictive accuracy, the research concluded that the KNN model provided a more robust prediction of surface roughness compared to the other evaluated ML models. Furthermore, the MQL technique was empirically shown to yield the most favorable *Ra* values among the tested lubrication environments.

Prashanth et al. [15] assessed the predictive capabilities of several machine learning algorithms for modeling the grinding process of Inconel 751. Their methodology involved training models: specifically Support Vector Regression (SVR), Gaussian Process Regression (GPR), and a boosted tree ensemble technique to forecast multiple process responses, including tangential grinding forces, normal grinding forces, temperature, and surface roughness (*Ra*). The input variables for the models comprised cutting velocity, depth of cut, feed rate, and ambient environmental conditions. The authors ultimately determined that the GPR algorithm achieved superior predictive accuracy compared to the other evaluated ML models in this particular application.

Reddy et al. [16] focused on developing predictive models for *Ra* using a full factorial design executed on a CNC Lathe with a Carbide tool. They contrasted the performance of a second-order multiple regression model against an Artificial Neural Network (ANN). Their results demonstrated a clear advantage for the ANN model, which exhibited superior predictive capability over the traditional multiple regression technique.

Dubey et al. [17] explored the effect of nanofluids during the turning of AISI 304 steel. Their experimental design, based on RSM, aimed to predict *Ra* as a function of conventional cutting parameters (cutting speed, DOC, feed rate) supplemented by a non-conventional parameter: n8anoparticle concentration. They employed Minimum Quantity Lubrication (MQL) utilizing carrier fluid (CF) enriched with alumina nanoparticles (with average sizes of 30 nm and 40 nm).

Previous studies have investigated surface roughness (*Ra*) prediction using various machine-learning (ML) techniques for different materials and machining conditions. However, a systematic comparison of multiple ML regression models for Stellite 6 turning under identical experimental conditions remains limited.

This study aims to evaluate and compare four ML models, namely ANN-MLP, ANN-RBF, Random Forest (RF), and Support Vector Regression (SVR), using a common dataset obtained from 27 Stellite 6 turning experiments. A unified modeling framework with hyperparameter optimization was applied to ensure a fair comparison based on R^2, RMSE, and MAE performance indicators. The experimental data were processed in a Python environment for model development, training, and validation. The objective is not to introduce a new ML algorithm, but to identify the most suitable predictive approach for estimating surface roughness and analyzing the nonlinear relationship between cutting parameters (tool nose radius, cutting speed, feed rate, and depth of cut) and Ra.

The results highlight the effectiveness of ML approaches, particularly the Random Forest model, for Ra prediction in Stellite 6 turning. However, considering the limited dataset size, further validation using larger datasets and industrial-scale applications is required to confirm the generalization capability of the developed models.

2. Experimental Framework

The material selected for the machining investigation was the cobalt-based alloy Stellite 6, which exhibited an average hardness of 41 HRC. The alloy's complex chemical composition consists of 28.25% Chromium, 3.74 % Tungsten, 1.17% Molybdenum, 1.11% Carbon, 1.89% Iron, 2.32 % Nickel, 0.57% Manganese, (e.g.1.20 % Silicium, 0.004 % Phosphorus), 0.001% Sulfur, and the remaining balance being of Cobalt.

The experimental phase focused on straight turning operations performed on three separate workpieces. To systematically test the variables of the adopted experimental design, each component was carefully subdivided into distinct testing zones using machined grooves (Fig. 1). The investigation systematically varied the key cutting parameters: the tool nose radius (*r*), the cutting speed (*V*), the feed rate (*f*), and the cutting depth (*d*). The specific combinations of these parameters (factors and levels) are detailed in Table 1.

Machining operations were performed on a SN 40C lathe manufactured by the Czech company "TOS TRENCIN," which is characterized by a 6.6 kW spindle power. Furthermore, the specific chemical composition of the workpiece material, the Co-Cr-Mo alloy Stellite 6, including the precise percentages of each constituent element, is detailed in Table 1.

The selected turning input parameters were tool nose radius, cutting speed, feed rate, and depth of cut, while surface roughness (*Ra*) was considered as the response variable. The experimental investigation was conducted according to a Taguchi L27 orthogonal array design, involving four factors at three levels, resulting in a total of 27 experiments as presented in Table 2. The experimental program specifically varied the tool nose radius (*r*) across three distinct values: 0.2 mm, 0.4 mm, and 0.8 mm. These radii were selected for their suitability in turning the Co-Cr-Mo alloy Stellite 6. PVD coated tungsten carbide inserts with PVD (Ti, Al) N2 (CNGG type, SGF geometry and 1105 nuance) were selected for machining. Synthetic conventional oil

(20%) was used for cutting fluid. The turning process was based on the geometry of SANDVIK ISO Type CNGG and SGF 1105, which resulted in a better overall wear resistance. The tool holder is PCLNR 2020 K. Their geometry of the active part, as shown in Fig. 1, is the same for the following angles: cutting edge angle ($\chi_r = +95°$), inclination angle ($\lambda = -6°$), rake angle ($\gamma = -6°$), and clearance angle ($\alpha = 0°$), respectively.

Surface roughness (*Ra*) was measured using a Mitutoyo Surftest SJ-201P equipped with a 2 μm diamond stylus. Measurements were performed along the feed direction using a 0.8 mm cut-off length, a 4 mm evaluation length (5 cut-offs), and a traverse speed of 0.5 mm/s with a Gaussian filter according to ISO 4287. Three traces were recorded at uniformly distributed positions (120° apart) on each machined surface, and the reported *Ra* value corresponds to their average. The instrument was calibrated before each test using a certified reference standard, with a repeatability of ±0.02 μm and an overall uncertainty of ±5%.

3. Machine Learning Algorithms

The accurate prediction of surface roughness (*Ra*) in precision machining is a critical application for data-driven methods. To effectively model the complex, non-linear relationship between input cutting parameters and the resulting surface finish, this study utilizes and compares three prominent Machine Learning (ML) regression algorithms. These include the Support Vector Regression (SVR**)**, known for its ability to define decision boundaries with maximum margin and handle high-dimensional data; the Artificial Neural Network (ANN), leveraged for its deep pattern recognition capabilities and powerful non-linear mapping; and the Random Forest, valued for its ensemble approach that mitigates overfitting and enhances robustness. A comparative assessment across these methods allows us to determine the most effective predictive strategy for roughness estimation in the experimental setup.

3.1. Mathematical formulation of support vector regression

Support Vector Regression (SVR) represents the direct adaptation of the established Support Vector Machine (SVM) algorithm for addressing continuous regression tasks, and it has been widely applied in solving complex forecasting problems. Mechanistically, SVR operates by mapping the input data into a high-dimensional feature space using designated kernel functions, where it then constructs an optimal hyperplane. A significant attribute of SVR is its intrinsic robustness against overfitting, achieved by minimizing the margin errors within a specified tolerance (epsilon-insensitivity loss function), thereby promoting excellent generalization performance on unseen data [18].

The Support Vector Regression (SVR) model is an extension of the foundational Support Vector Machine (SVM) algorithm, specifically tailored for continuous value prediction tasks, and has demonstrated broad utility in complex forecasting applications [19].

Support Vector Regression (SVR) stands as a powerful adaptation of Support Vector Machines (SVM) specifically tailored for regression tasks. Unlike traditional methods that minimize squared errors, SVR focuses on finding a function that deviates from the true targets by a margin, ε, while keeping the model's complexity low. This approach

Table 1

Levels and cutting conditions values

Level	Factors			
	r, mm	*V*, m/min	*f*, mm/rev	*d*, mm
1	0.2	30	0.08	0.15
2	0.4	55	0.12	0.30
3	0.8	80	0.16	0.45

Table 2

Experimental results of surface roughness when varying cutting conditions

Trail No.	Inputs				Outputs
	r, mm	*V*, m/min	*f*, mm/rev	*d*, mm	*Ra,* μm
1	0.2	30	0.08	0.15	0.98
2	0.2	30	0.08	0.30	0.95
3	0.2	30	0.08	0.45	1.04
4	0.2	55	0.12	0.15	1.91
5	0.2	55	0.12	0.30	1.78
6	0.2	55	0.12	0.45	1.42
7	0.2	80	0.16	0.15	2.65
8	0.2	80	0.16	0.30	2.10
9	0.2	80	0.16	0.45	2.28
10	0.4	30	0.12	0.15	1.10
11	0.4	30	0.12	0.30	1.25
12	0.4	30	0.12	0.45	1.18
13	0.4	55	0.16	0.15	1.70
14	0.4	55	0.16	0.30	1.83
15	0.4	55	0.16	0.45	1.60
16	0.4	80	0.08	0.15	0.53
17	0.4	80	0.08	0.30	0.68
18	0.4	80	0.08	0.45	0.60
19	0.8	30	0.16	0.15	1.30
20	0.8	30	0.16	0.30	1.12
21	0.8	30	0.16	0.45	1.10
22	0.8	55	0.08	0.15	0.53
23	0.8	55	0.08	0.30	0.36
24	0.8	55	0.08	0.45	0.46
25	0.8	80	0.12	0.15	0.91
26	0.8	80	0.12	0.30	0.64
27	0.8	80	0.12	0.45	0.72

defines a band of tolerance, known as the ε-insensitive tube, effectively ignoring errors that fall within this band.

The underlying regression function is formally defined as:

$$f(x) = w^T \cdot x + b, \tag{1}$$

where w is the vector of weights and b is the bias term. The model's complexity, often equated to its flatness or inverse regularization, is measured by the magnitude of $\|w\|^2$.

3.1.1. Epsilon support vector regression

The goal of Epsilon Support Vector Regression (ε-SVR) is to find a regression function $f(x)$ such that the error between $f(x)$ and the training data y is less than ϵ for the majority of data points, while keeping $\|w\|$ as small as possible (to regularize the model). Errors greater than ε are penalized by the slack variables ξ_i (for overestimation) and ξ_i^* (for underestimation).

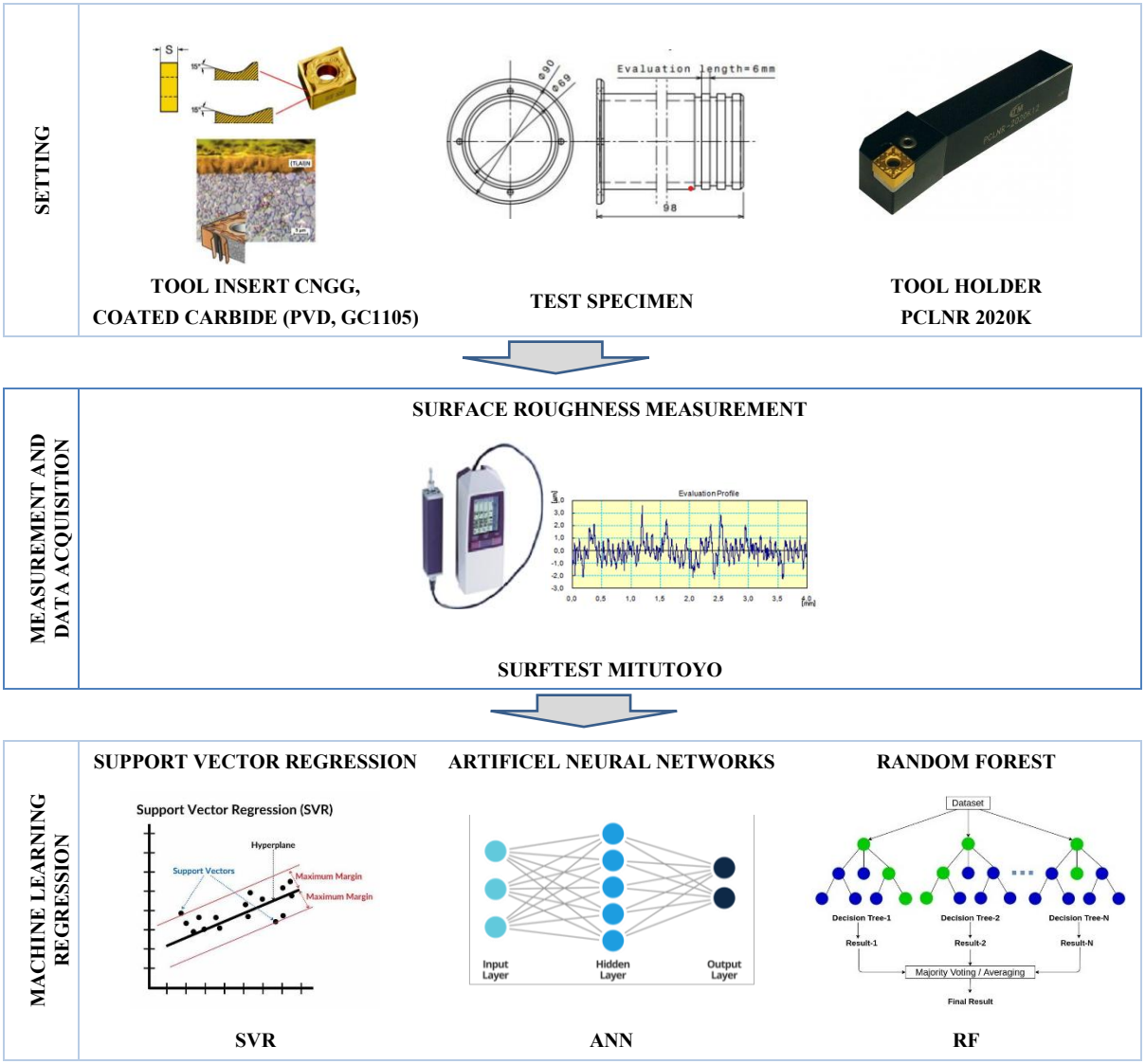


Fig. 1 Experimental design diagram: workpiece, tool geometry, acquisition system and machine learning regression

The Primal Optimization Problem

The optimization seeks to minimize the model's regularization term plus the weighted penalty for errors outside the ε-tube:

$$min_{w,b,\xi,\xi^*} \frac{1}{2}\|w\|^2 + C\sum_{i=1}^{m}\left(\xi_i + \xi_i^*\right), \tag{2}$$

Subject to the constraints:
for all data points $i = 1, \ldots, m$ (error on the positive side)

$$y_i - \left(w^T \cdot x_i + b\right) \le \varepsilon + \xi_i, \tag{3}$$

for all data points $i = 1, \ldots, m$ (error on the negative side)

$$\left(w^T \cdot x_i + b\right) - y_i \le \varepsilon + \xi_i^*, \tag{4}$$

the slack variables must be non-negative

$$\xi_i \ge 0, \quad \xi_i^* \ge 0. \tag{5}$$

Here:

$C \succ 0$ is the regularization parameter, controlling the penalty cost for points outside the tube ;

$\varepsilon \succ 0$ is the fixed width of the insensitive tube (margin) ;

ξ_i and ξ_i^* are the slack variables that measure the extent to which a point lies outside the ε-tube.

The Dual Optimization Problem

By applying Lagrange multipliers, we transform this into the dual problem, which is far easier to solve computationally

$$min_{\alpha,\alpha^*} \frac{1}{2}\sum_{i=1}^{m}\sum_{j=1}^{m}\left(\alpha_i^* + \alpha_i\right)\left(\alpha_j^* + \alpha_j\right)K\left(x_i, x_j\right) + \\ +\varepsilon\sum_{i=1}^{m}\left(\alpha_i^* + \alpha_i\right) - \sum_{i=1}^{m}\left(\alpha_i^* - \alpha_i\right). \tag{6}$$

Subject to the constraints:

$$\sum_{i=1}^{m}\left(\alpha_i^* - \alpha_i\right) = 0, \tag{7}$$

where $0 \le \alpha_i, \alpha_i \le C$.

$K(x_i, x_j)$ is the kernel function. The weight vector w is implicitly defined by the solution of the dual problem:

$$w = \sum_{i=1}^{m} \left(\alpha_i^* - \alpha_i\right) \cdot x_i . \tag{8}$$

Data points x_i for which $(\alpha_i^* - \alpha_i) \neq 0$ are the support vectors.

3.1.2. Nu support vector regression

The Nu Support Vector Regression (υ-SVR) variant introduces the parameter υ in place of a fixed ε. The critical distinction is that υ (where $\upsilon \in (0, 1]$) directly controls an upper bound on the fraction of training errors and a lower bound on the fraction of support vectors. Importantly, the margin of insensitivity, ρ, is no longer a fixed hyperparameter but is instead treated as an optimization variable within the formulation.

The Primal Optimization Problem

$$min_{w,b,\xi,\xi^*,\rho} \frac{1}{2}\|w\|^2 + C\left(\upsilon\rho + \frac{1}{m}\sum_{i=1}^{m}\left(\xi_i + \xi_i^*\right)\right). \tag{9}$$

Subject to the constraints:

$$\begin{aligned} & y_i - \left(w^T \cdot x_i + b\right) \leq \rho + \xi_i, \\ & \left(w^T \cdot x_i + b\right) - y_i \leq \rho + \xi_i^*, \\ & \xi_i \geq 0, \ \xi_i^* \geq 0, \\ & \rho \geq 0, \end{aligned} \tag{10}$$

where: $\upsilon \in (0, 1]$ is the parameter that sets the desired fraction of support vectors and bounds the fraction of errors; ρ is the width of the insensitive tube, now optimized by the solver.

3.1.3. Kernel functions

The kernel function $K(x_i, x_j)$ is the core element of the Kernel Trick. It allows the SVR model to implicitly map the input data into a higher-dimensional feature space where non-linear relationships can become linear, without ever explicitly calculating the coordinates in that space.

Linear Kernel

The linear kernel is the simplest form, representing the dot product of the input features. It is typically used when the underlying relationship between variables is already expected to be linear

$$K\left(x_i, x_j\right) = x_i^T x_j . \tag{11}$$

Radial Basis Function (RBF) Kernel

The RBF kernel, often referred to as the Gaussian kernel, is the most popular choice for non-linear SVR. It implicitly maps the data into an infinite-dimensional space, effectively allowing the decision boundary to be arbitrarily complex

$$K\left(x_i, x_j\right) = exp\left(-\gamma \left\|x_i - x_j\right\|^2\right), \tag{12}$$

where $\gamma \succ 0$ is a critical parameter that dictates the influence of a single training example; a small γ results in a wider influence, while a large γ results in a narrow, highly localized influence.

3.2. Random Forest Regressor (RFR)

The Random Forest (RF) algorithm, shown in Fig. 2, is a supervised learning technique widely used for both classification and regression tasks. Its strength lies in the principle of ensemble learning, where multiple decision trees are generated using different samples of the original dataset. Each tree provides its own prediction, and the final output is obtained by aggregating these individual results, either through majority voting or averaging, depending on the problem type. By combining several diverse trees instead of relying on a single model, RF effectively reduces overfitting, captures complex relationships within the data, and delivers more stable and accurate predictions. This collective decision-making process is what makes RF one of the most reliable and versatile algorithms in machine learning.

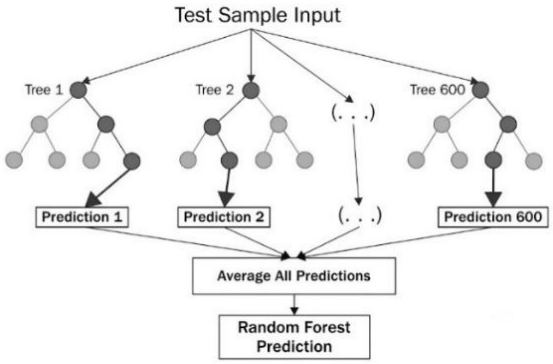


Fig 2. Illustration of Random Forest algorithm

3.3. Artificial neural networks models – MLP and RBF

Artificial Neural Networks (ANNs) position themselves as a powerful and direct alternative to traditional statistical analysis methods [20]. They can easily replace techniques such as autocorrelation, linear or multivariable regression, and other trigonometric or statistical analysis tools. The main appeal of neural networks lies in their exceptional ability to derive a general and reliable solution even when dealing with complex, noisy, or imprecise datasets. This unique characteristic allows them to probe raw information to detect and extract underlying patterns and trends that would be far too complex to be perceived by human intuition or to be isolated by conventional computing techniques. They thus excel where classic analyses reach their limits.

The study of neural networks encompasses a diverse family of computational models. For addressing ubiquitous machine learning challenges, particularly classification and regression, specific architectures have become standard academic tools. Among the most popular and frequently cited in literature are the Multi-Layer Perceptron (MLP) and the Radial Basis Function (RBF) network [21,

22]. Reflecting this widespread application and utility, both the MLP and RBF architectures were selected and implemented as core components of the current research methodology.

3.3.1. Multi-layer perceptron model

The Multi-Layer Perceptron (MLP) is recognized as one of the most versatile and influential network architectures within the neural network domain. Due to its robustness and proven efficacy, the MLP model has become a foundational tool that dominates research across a multitude of disciplines. Its applications span from critical fields like medicine and engineering to fundamental areas such as advanced mathematical modeling and theoretical computations.

MLP networks consist of an input layer, one or more hidden layers and an output layer. The output of the network is determined by the activation of the units in the output layer as follows:

$$x_0 = f\left(\sum_h x_h \cdot w_{h0}\right), \tag{13}$$

where $f()$ is activation function, x_h is activation of the hidden layer node and w_{h0} is the interconnection between the hidden layer node and the output layer node. The most used activation function is the sigmoid and it is given as follows:

$$x_0 = \frac{1}{1+exp\left(-\sum_h x_h \cdot w_{h0}\right)}. \tag{14}$$

The activation level of the nodes in the hidden layer is determined in a similar fashion.

3.3.2. Radial basis function model

The Radial Basis Function (RBF) neural network operates fundamentally within the supervised learning framework. Developed independently by various research groups, RBF networks are widely utilized as a popular and highly efficient alternative to the Multi-Layer Perceptron (MLP) architecture (Fig. 3).

A core advantage is their notable proficiency in modeling complex, nonlinear data. Furthermore, RBF networks offer a compelling training efficiency: they can often be trained in a single, non-iterative stage, which stands in contrast to the multi-step, iterative process required by MLPs. This characteristic enables RBF models to rapidly learn and adapt to a given application [23].

The output of the network is derived from [24]

$$y_k\left(x\right) = \sum_{j=1}^{M} w_{kj} \cdot \phi_j\left(x\right) + w_{k0}, \tag{15}$$

where M is the number of basis functions, x the input data vector, w_{kj} represents a weighted connection between the basis function and output layer and ϕ_j is the nonlinear function of unit j, which is typically a Gaussian of the form

$$\phi_j\left(x\right) = exp\left(-\frac{\left\|x-\mu_j\right\|^2}{2\sigma_j^2}\right). \tag{16}$$

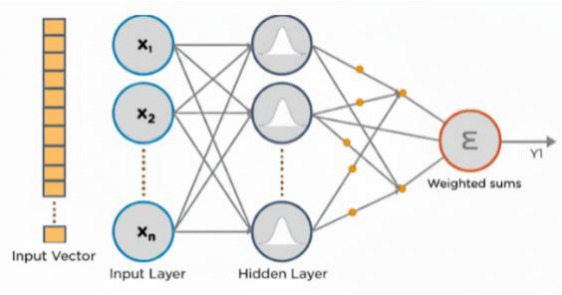


Fig. 3 MLP and RBF neural network structure used in the study

Here x and μ are the input and the center of RBF unit respectively. σ_j is the spread of the Gaussian basis function [24].

4. Performance Metrics

The application of multiple performance metrics is essential when comparing models like the Support Vector Regression (SVR), Artificial Neural Networks (ANN), and Random Forest. Since these algorithms operate on fundamentally different principles: SVR uses maximum margin principles, ANN uses complex non-linear hidden layers, and Random Forest uses ensemble decision trees. A single metric is insufficient to declare a definitive "best" model.

In this study, three metrics are used to compare model performance based on different aspects of error and fit: To rigorously assess the predictive capabilities of the models developed for estimating the surface roughness (Ra), three distinct performance metrics were employed.

The accuracy and generalization of each model were verified by evaluating the Mean Square Error (MAE), the Root Mean Square Error (RMSE), and the Coefficient of Determination (R^2).

4.1. Mean absolute error

The Mean Absolute Error (MAE) is a fundamental metric for evaluating regression model performance. It quantifies the average magnitude of error by calculating the arithmetic mean of the absolute differences between the model's predicted outcomes and the actual observed data points. MAE is highly interpretable because it measures error linearly, ensuring that a value closer to zero signifies greater model accuracy and precision

$$MAE = \frac{1}{N}\sum_{i=1}^{N}\left|y_{i.\,exp} - y_{i.\,pred}\right|, \tag{17}$$

where N is the experiments number, $y_{i.pred}$ and $y_{i.exp}$ are the predicted and experimental values of the i-th experiment, respectively.

4.2. Root mean square error

The Root Mean Square Error (RMSE) is closely related to another statistical measure: the standard deviation of the residuals. In essence, residuals are simply the vertical distances measured between the actual data points and the regression line (the "best-fit" line). The RMSE itself is an indicator of the distribution of these residuals, effectively showing how concentrated the data points are around that best-fit line. A more intuitive way to think about it is that

RMSE illustrates how well the line fits the data. Calculation-wise, the RMSE is derived by taking the square root of the average of the squared differences between your observed (actual) values and the model's predicted values

$$RMSE = \sqrt{\frac{\sum_{i=1}^{N}\left(y_{i.\,exp} - y_{i.\,pred}\right)^2}{N}}, \tag{18}$$

where N is the experiments number, $y_{i.pred}$ and $y_{i.exp}$ are the predicted and experimental values of the i-th experiment, respectively.

4.3. Coefficient of determination

The Coefficient of Determination (R^2) is an essential statistical measure that indicates how well a regression model fits the observed data. It quantifies the proportion of the variance in the target variable that the model is able to explain. R^2 is specific to the dataset used and cannot be compared across different data sets. The maximum value is 1.0 (a perfect fit), and 0.0 means the model is no better than simply predicting the mean. In rare instances, R^2 can be negative, which signifies that the model performs worse than the baseline mean prediction

$$R^2 = 1 - \frac{\sum_{i=1}^{N}\left(y_{i.\,exp} - y_{i.\,pred}\right)^2}{\sum_{i=1}^{N}\left(y_{i.\,exp} - y_{i.\,average}\right)^2}, \tag{19}$$

where N is the experiments number, $y_{i.pred}$ and $y_{i.exp}$ are the predicted and experimental values of the i-th experiment, respectively, and $y_{i.average}$ is the average value.

4.5. Mean squared error

The Mean Squared Error (MSE) is defined as the average of the squared differences between the predicted values ($y_{i.pred}$) and the actual true values ($y_{i.exp}$), where N is the total number of data points

$$MSE = \frac{1}{N}\sum_{i=1}^{N}\left(y_{i.\,exp} - y_{i.\,pred}\right)^2. \tag{20}$$

5. ML Models Implementation

To execute this study, Python has been utilized as the primary programming language. Python is a high-level, interpreted, and object-oriented programming language with dynamic semantics.

Python truly stands out due to its remarkably extensive standard library. This robust, built-in resource offers countless modules with customizable functionalities, allowing developers to save substantial time and effort by eliminating the need to write fundamental code repeatedly. Beyond the standard library, Python is supported by a rich ecosystem of specialized libraries and frameworks.

These ready-made packages are particularly effective for simplifying the complex implementation of Artificial Intelligence (AI) and Machine Learning (ML) algorithms, providing elegant, pre-written solutions for a wide range of common programming tasks. Python offers a wide variety of libraries for artificial intelligence and machine learning:

- Keras, TensorFlow, and Scikit-learn for machine learning;
- NumPy for high-performance scientific computing and data analysis;
- SciPy for advanced computing;
- Pandas for general-purpose data analysis;
- and Seaborn for data visualization.

6. Analysis and Discussion

In this study, we employed three different ML algorithms to develop surface roughness prediction models, namely, Random Forest (RF), Support Vector Regression (SVR) and Artificial Neural Network (ANN). The complete set of hyperparameter values (optimum) is listed in Table 3.

The available experimental dataset consisted of 27 Stellite 6 turning trials. The data were randomly divided into training (80%) and testing (20%) subsets using a fixed random seed to ensure reproducibility. Data scaling was performed using the training set parameters before model training. Hyperparameter tuning was conducted only on the training data to prevent information leakage from the test set. All models were developed and evaluated using the experimental dataset (Table 3 and Table 4).

The performance of ML models was measured using MAE, RMSE, and R^2.

6.1. Random forest regressor

The Random Forest (RF) algorithm, an ensemble machine learning method that builds a multitude of decision trees to enhance prediction stability and generalization [25]. The final prediction is achieved by aggregating the results from these trees.

Following normalization, the data was split into training and testing subsets using an 80% to 20% ratio. Hyperparameter optimization was performed using grid search to ensure optimal performance.

For the target variable *Ra* (Surface roughness) and the inputs variables (cutting parameters: r, V, f and d), the optimal hyperparameters identified were: maximum depth = 10, minimum samples split = 2, and number estimators = 50 (Table 3).

6.2 Support vector regression (SVR)

The Support Vector Machine (SVM) is a robust machine learning algorithm [26]. For implementation, the dataset underwent normalization before being rigorously partitioned into 80% training and 20% testing subsets.

Crucially, the SVR model's predictive performance was optimized through a systematic grid search procedure, which identified different optimal hyperparameter sets for the two SVR-type, Epsilon-SVR and Nu-SVR and two type of kernel, linear and RBF for the target (*Ra*) and inputs variables (cutting parameters):

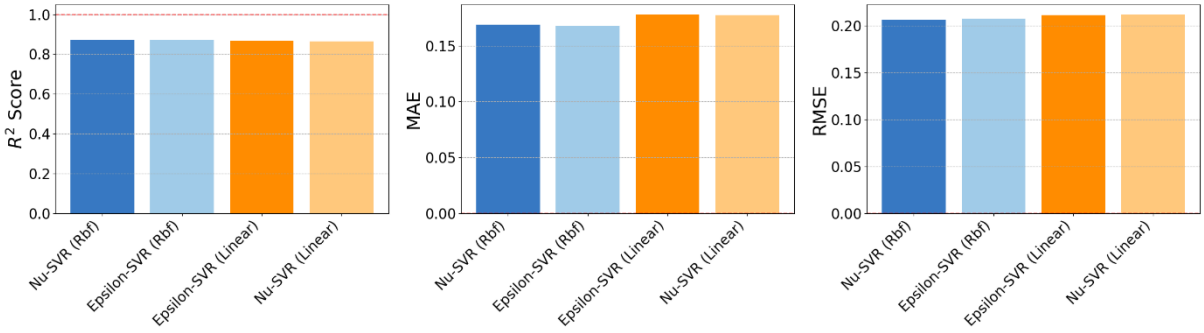
- For the Epsilon-SVR: The optimal configuration was determined to be kernel = RBF, C = 10, gamma = 0.01 and Epsilon = 0.01.
- For the Nu-SVR, the optimal settings included kernel = RBF, C = 10, gamma = 0.01 and Nu = 0.9.

This analysis confirms the nature of the relationship between the input variables and the target variable *Ra*. The enormous performance difference between the RBF (non-linear) and Linear (linear) kernels decisively proves that the physical relationship between the input parameters and *Ra* is strongly non-linear.

Linear models are insufficient to capture the complexity of the process. The graphs provide visual confirmation of the numerical results (see Fig. 4 and Fig. 5).

This graph is the visual evidence for the analysis above (Fig. 4). The bars for RBF models are significantly higher for R^2 and lower for errors than those of Linear models, proving the non-linear nature of the data (Fig. 4).

These maps are optimization tools (Fig. 5). The darkest color area (minimum MSE) identifies the optimal hyperparameter combination. This confirms that optimization is critical and the best SVR model results from a precise tuning of *C* (regularization) and Gamma (kernel width).



a b c

Fig. 4 Comparison of optimal SVR RBF vs Linear Kernel performances (TEST Set): a – Coefficient of Determination (R^2); b – Mean Absolute Error (MAE); c – Root Mean Squared Error (RMSE)

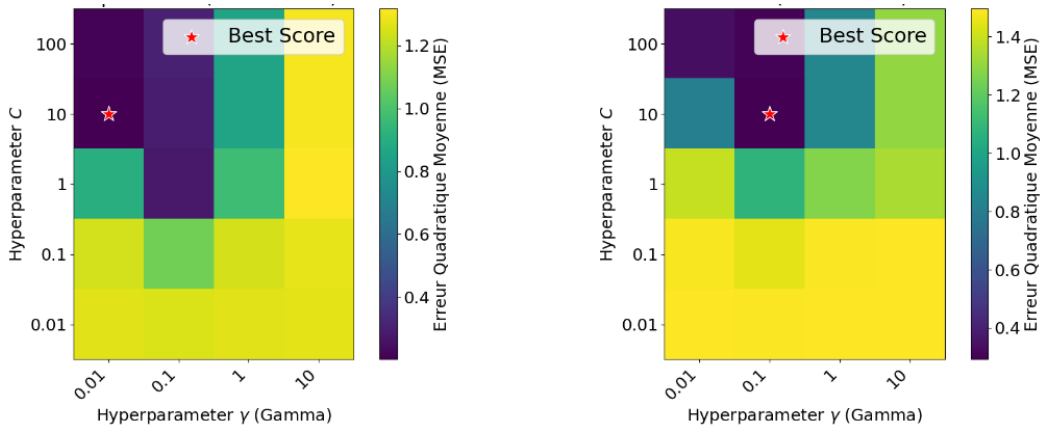


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Fig. 5 Comparison heatmaps: *C* vs Gamma SVR (RBF Kernel): a – Epsilon-SVR (Best MSE); b – Nu-SVR (Best MSE)

6.3. Artificial Neural Network

Artificial Neural Networks (ANNs) are powerful machine learning algorithms built upon a network of interconnected artificial neurons. These models excel at processing complex data, recognizing intricate patterns, and generating meaningful outputs.

Structurally, the network generally consists of at least three parts: an input layer, one or more hidden layers, and an output layer.

In this study, the objective of these models was to predict the surface roughness (*Ra*) based on four primary input variables: *r* (tool nose radius), *V* (cutting speed), *f* (feed rate), and *d* (depth of cut).

Before training, the raw dataset was pre-processed via normalization and subsequently partitioned into a standard 80% (training) and 20% (testing) split. Optimal hyperparameters were systematically identified using a grid search methodology (Table 3).

Two configurations were used in this model:

ANN-MLP Model: The ANN-MLP (Multi-Layer Perceptron) architecture was configured with two hidden layers of sizes (100, 50) neurons. The model utilized the 'adam' solver for weight optimization and the 'Relu' activation function. The initial learning rate (Alpha) was set to 0.0001.

ANN-RBF Model: The ANN-RBF (Radial Basis Function Network) model, a distinct architecture, was also evaluated. This model's structure was defined by setting the number of centers to 10. The Sigma parameter, controlling the width of the basis functions, was set to 0.1. The Random State was fixed at 42 for reproducible results.

The comparison of these regression models (ANN-MLP, SVR, RFR, RBF) is carried out to identify the most accurate and reliable algorithm for predicting surface roughness (*Ra*) on unseen data.

The evaluation (average of metrics on the test set after 5 trials) positions the ANN-MLP as the most successful model in generalization, with the lowest errors (MAE 0.1490, RMSE 0.1925) and the highest R^2 (0.8890).

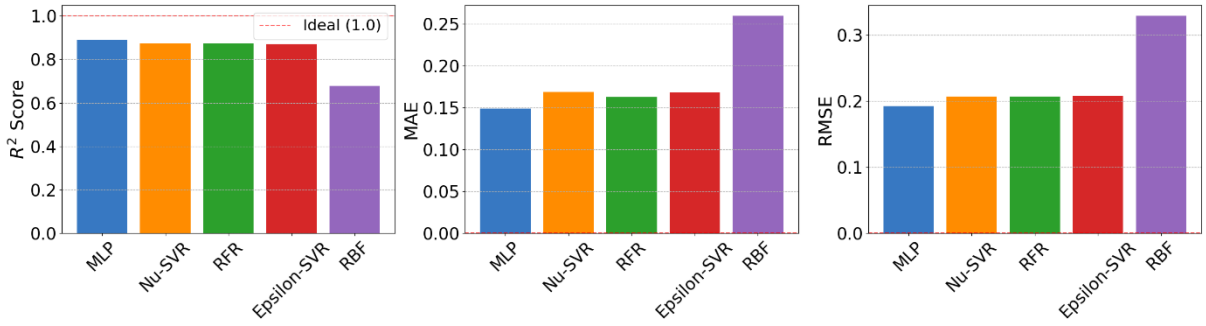

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Fig. 6 Comparison of optimal ML models performances (TEST Set): a – Coefficient of Determination (R^2) ; b – Mean Absolute Error (MAE) ; c – Root Mean Squared Error (RMSE)

The SVR and RFR models follow closely (R^2 around 0.87). The ANN-RBF is the least suitable for this application, showing the lowest R^2 (0.6769) (see Table 4 and Fig. 6).

Table 3

Optimum parameters for ML models

ML Models	Optimum parameters
RFR	Maximum depth: 10, Minimum samples split: 2, Number estimators: 50
ANN-MLP	Activation: Relu, Alpha: 0.0001, Hidden layer sizes: (100, 50), Solver: adam
Nu-SVR	C: 10, Gamma: 0.01, Kernel: RBF, Nu: 0.9
Epsilon-SVR	C: 10, Epsilon: 0.01, Gamma: 0.01, Kernel: RBF
ANN-RBF	Number centers: 10, Random State: 42, Sigma: 0.1

Table 4

Performance metrics for ML models (5 tests)

ML models	MAE	RMSE	R^2
ANN-MLP	0.1490	0.1925	0.8890
Nu-SVR	0.1688	0.2066	0.8721
RFR	0.1623	0.2066	0.8721
Epsilon-SVR	0.1682	0.2073	0.8712
ANN-RBF	0.2594	0.3284	0.6769

6.4. Performance ML models evaluation

This analysis is based on the performance of five distinct regression ML models: Random Forest Regressor (RFR), ANN Multi-Layer Perceptron (ANN-MLP), Nu-SVR, Epsilon-SVR, and ANN Radial Basis Function (ANN-RBF) utilized to predict surface roughness (*Ra*). The predictions are based on four key input variables: tool nose radius (*r*), cutting speed (*V*), feed rate (*f*), and depth of cut (*d*).

The systematic comparison of these diverse algorithms is essential to benchmark their efficacy and identify the most reliable and accurate predictor for *Ra* in this specific application domain. The performance metrics: Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), and the Coefficient of Determination (R^2) are calculated as the average performance across 27 rigorous test set evaluations, providing a robust measure of each model's capacity for generalization to unseen data. These comprehensive results are summarized in detailed tables and visualized through explanatory histograms (Table 5 and Fig. 7).

The RFR and the ANN-MLP models demonstrated virtually identical and superior generalization performance. Both are confirmed as highly effective and stable choices. RFR achieved the highest R^2 (0.9394) and the lowest MAE (0.1115), meaning it explains nearly 94% of the variance in the data and exhibits the smallest average absolute prediction error. ANN-MLP followed extremely closely with an R^2 of 0.9365 and a MAE of 0.1116 (Table 5).

Both SVR variants provided strong, but secondary, performance with R^2 values clustered around 0.89. Their associated errors (RMSE=0.193) are notably higher than the top two models, suggesting they are less precise but still highly capable alternatives.

ANN-RBF model, while statistically strong (R^2 of 0.8907), demonstrated the highest errors (RMSE = 0.1946) among the top four contenders, indicating the lowest capacity for accurately capturing the complex relationships for this specific application (Table 5).

Table 4 presents the model performance obtained from five train/test evaluation runs, while Table 5 summarizes the prediction performance using the complete experimental dataset (27 trials). The difference in model ranking is related to the validation strategy, as ANN-MLP showed the best performance during split-based evaluations, whereas RFR achieved the highest accuracy when considering the full dataset evaluation.

Table 5

Performance metrics for machine learning models (27 tests)

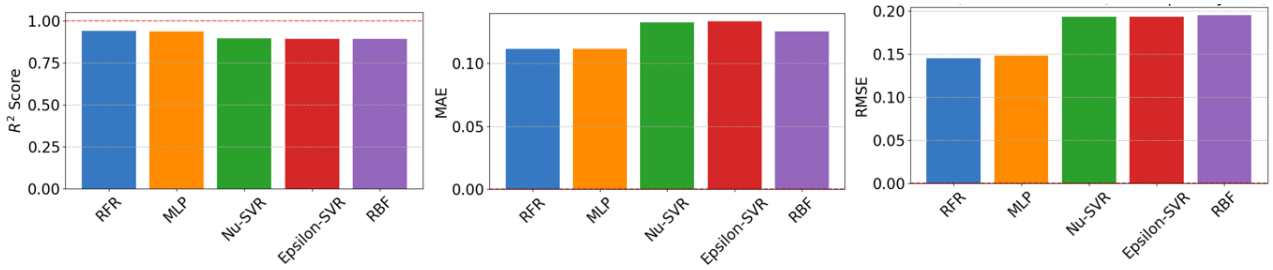
ML models	MAE	RMSE	R^2
RFR	0.1115	0.1449	0.9394
ANN-MLP	0.1116	0.1483	0.9365
Nu-SVR	0.1325	0.1929	0.8926
Epsilon-SVR	0.1332	0.1932	0.8923
ANN-RBF	0.1254	0.1946	0.8907

Based on the highest (R^2) and the lowest (MAE) and (RMSE), the Random Forest Regressor (RFR) is selected as the optimal and most robust model for predicting surface roughness (*Ra*) using the specified input variables.

This bar chart clearly shows that the RFR and Epsilon-SVR (RBF) achieve the highest R^2 bars (close to 1.0)

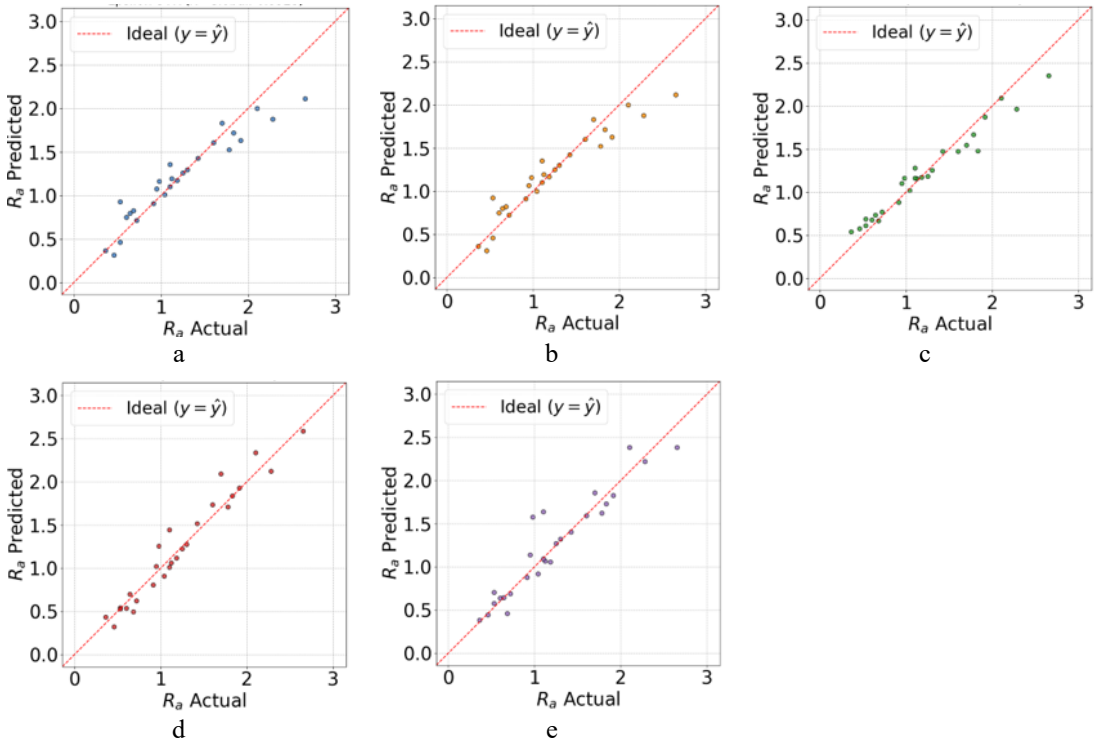
and the lowest error bars (MAE and RMSE close to 0), confirming their superiority in generalization on unseen data (Fig. 7).

Fig. 9 indicates the black curve (experimental *Ra* values) the real *Ra* fluctuations across the 27 trials. Predicted Curves with ML (RFR, Eps-SVR)**:** These curves follow the black curve very closely, even in peaks and troughs, demonstrating an exceptional fit. Other Curves: The ANN (MLP and RBF) predictions are visible, but they might show slight smoothing or greater deviations from the actual peaks, indicating a lower capacity to fit local variations (Table 6).



a b c

Fig. 7 Comparison of ML models performances: a – Coefficient of Determination (R^2); b – Mean Absolute Error (MAE); c – Root Mean Squared Error (RMSE)



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d e

Fig. 8 Comparison of Experimental *Ra* vs Predicted ML models *Ra*: a – Epsilon-SVR (R^2 Global: 0.8923); b – Nu-SVR (R^2 Global: 0.8926); c - RFR (R^2 Global: 0.9394); d – MLP (R^2 Global: 0.9365); e – RBF (R^2 Global: 0.8907)

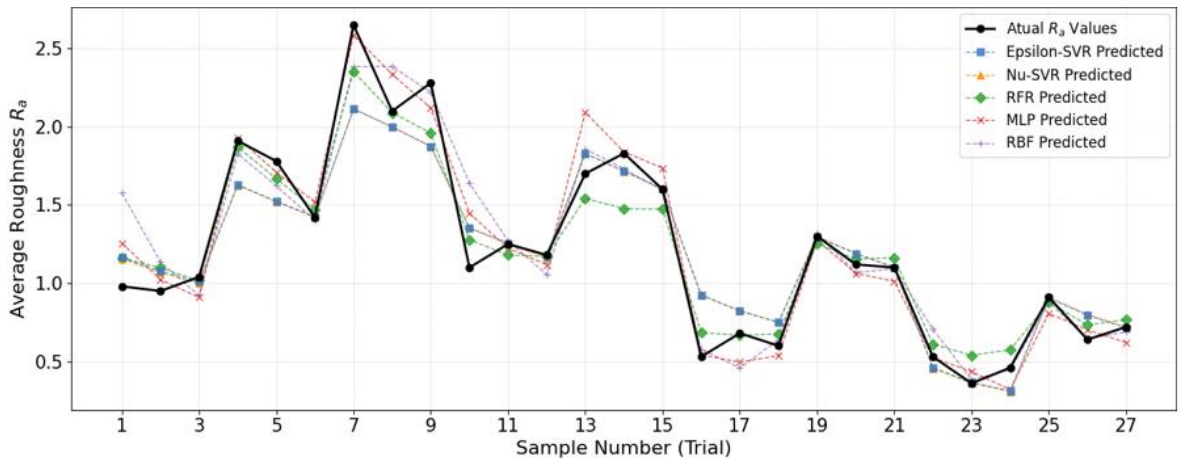

Fig. 9 Experimental *Ra* vs Predicted ML models *Ra*

Table 6

Experimental and predicted ML models surface roughness values

Test	Experimental	Predited ML models				
	Ra, μm	Epsilon-SVR	Nu-SVR	RFR	ANN-MLP	ANN-RBF
1	0.98	1.16	1.16	1.16	1.26	1.58
2	0.95	1.08	1.07	1.10	1.02	1.14
3	1.04	1.01	1.00	1.02	0.91	0.92
4	1.91	1.63	1.63	1.87	1.93	1.83
5	1.78	1.52	1.52	1.67	1.71	1.62
6	1.42	1.43	1.42	1.47	1.52	1.40
7	2.65	2.11	2.12	2.35	2.59	2.38
8	2.1	2.00	2.00	2.09	2.34	2.38
9	2.28	1.87	1.87	1.96	2.12	2.22
10	1.1	1.35	1.35	1.28	1.45	1.64
11	1.25	1.26	1.25	1.18	1.22	1.27
12	1.18	1.17	1.16	1.17	1.12	1.06
13	1.7	1.83	1.83	1.54	2.09	1.86
14	1.83	1.72	1.71	1.48	1.84	1.73
15	1.6	1.60	1.60	1.47	1.74	1.59
16	0.53	0.93	0.92	0.68	0.54	0.58
17	0.68	0.82	0.82	0.67	0.50	0.46
18	0.6	0.75	0.75	0.68	0.54	0.64
19	1.3	1.29	1.30	1.25	1.27	1.32
20	1.12	1.19	1.19	1.15	1.06	1.07
21	1.1	1.10	1.10	1.16	1.01	1.09
22	0.53	0.46	0.45	0.61	0.52	0.71
23	0.36	0.37	0.36	0.54	0.43	0.38
24	0.46	0.31	0.31	0.57	0.32	0.45
25	0.91	0.90	0.91	0.88	0.81	0.88
26	0.64	0.80	0.80	0.73	0.70	0.64
27	0.72	0.71	0.72	0.77	0.62	0.69

7. Conclusions

The core finding of this study is the successful application of advanced machine learning (ML) methodologies to reliably predict surface roughness (*Ra*) during the challenging turning of the cobalt-based superalloy, Stellite 6. By rigorously training and comparing three distinct Python-based regression ML models: Artificial Neural Networks (ANN), Support Vector Regression (SVR), and Random Forest Regressor (RFR), on a comprehensive dataset derived from 27 turning trials, we have enabled a comparative evaluation of different ML approaches for surface roughness prediction in Stellite 6 turning.

Among the investigated models, the Random Forest Regressor (RFR) achieved the best predictive performance. The RFR model performance was exceptional across all statistical benchmarks, registering an impressive R^2 of 0.9394 and demonstrating minimal prediction errors (RMSE of 0.1449 and MAE of 0.1115). This high level of accuracy highlights the model's intrinsic capability to successfully map the complex, non-linear relationships linking cutting parameters (tool nose radius, cutting speed, feed rate, and depth of cut) to the final surface finish (Surface roughness *Ra*).

The ensemble learning strategy inherent in the Random Forest proved significantly more robust in managing the inherent data variability compared to the single-model SVR. While SVR (particularly the RBF-kernel Epsilon-SVR) offered commendable results, the RFR's approach was ultimately more stable and reliable. This outcome serves as a strong methodological recommendation that researchers addressing similar high-variability prediction tasks in manufacturing should prioritize ensemble modeling techniques.

This research provides a vital, data-driven solution that fills a critical gap in manufacturing science. The validated RFR model is more than a theoretical finding; it represents a ready-to-deploy practical asset capable of enabling in-process quality assurance and real-time monitoring. This capability promises to enhance the reliability and predictability of machining operations for high-value components made from Stellite 6.

To build upon this predictive success and translate it into comprehensive process control and optimization, future

investigations should strategically focus on several key areas:

- Incorporating significantly larger and more diverse datasets will be crucial to enhance model generalization, boost predictive confidence, and mitigate the risk of overfitting to the initial experimental domain.
- While the RFR excels, future studies should explore and benchmark its performance against other advanced machine learning architectures (e.g., Gradient Boosting Machines or Deep Learning) to maximize predictive performance.
- The high-fidelity RFR predictor should be immediately employed within multi-objective optimization algorithms (such as Genetic Algorithms) to quickly identify optimal machining conditions that simultaneously minimize surface roughness and maximize productivity.
- It is essential to validate the model's resilience and generality by incorporating a broader spectrum of transient operational factors, including complex phenomena like tool wear progression and cutting zone temperature measurements.
- The current successful methodology should be extended to predict other critical facets of component integrity, such as fatigue resistance and corrosion susceptibility, broadening the impact of ML in material performance analysis.

In conclusion, the results highlight the effectiveness of ML techniques for predicting surface roughness in Stellite 6 turning, with the Random Forest model providing the best performance among the investigated approaches.

References

1. **Patil, P. J.; Patil, C. R.** 2016. Analysis of process parameters in surface grinding using single objective Taguchi and multi-objective grey relational grade, Perspectives in Science 8: 367-369. https://doi.org/10.1016/j.pisc.2016.04.077.
2. **Dogra, M.; Sharma, V. S.; Dureja, J. S.; Gill, S. S.** 2018. Environment-friendly technological advancements to enhance the sustainability in surface grinding-A review, Journal of Cleaner Production 197: 218-231. https://doi.org/10.1016/j.jclepro.2018.05.280.
3. **Weiss, B.; Lefebvre, A.; Sinot, O.; Marquer, M.; Tidu, A.** 2015. Effect of grinding on the sub-surface and surface of electrodeposited chromium and steel substrate, Surface and Coatings Technology 272: 165-175. https://doi.org/10.1016/j.surfcoat.2015.04.009.
4. **Ranga, P.; Gupta, E. D.** 2016. Review on effects of input parameters and design of experiments on surface grinding process in EN31 material, International Journal of Scientific Engineering and Technology 5(5): 232-238.
5. **Külekcı, M. K.** 2013. Analysis of process parameters for a surface-grinding process based on the Taguchi method, Materials and Technology 47: 105-109.
6. **Mirifar, S.; Kadivar, M.; Azarhoushang, B.** 2020. First Steps through Intelligent Grinding Using Machine Learning via Integrated Acoustic Emission Sensors, Journal of Manufacturing and Materials Processing 4(2): 35. https://doi.org/10.3390/jmmp4020035.
7. **Kara, F.; Köklü, U.; Kabasakaloğlu, U.** 2020. Taguchi optimization of surface roughness in grinding of cryogenically treated AISI 5140 steel, Materials Testing 62(10): 1041-1047. https://doi.org/10.3139/120.111583.
8. **Aravind, M.; Periyasamy, S.** 2014. Optimization of Surface Grinding Process Parameters By Taguchi Method And Response Surface Methodology, International Journal of Engineering Research and Technology 3(5):1721-1727.
9. **Mane, S.; Patil, R. B.; Al-Dahidi, S.** 2025. Predictive Modeling of Surface Roughness and Cutting Temperature Using Response Surface Methodology and Artificial Neural Network in Hard Turning of AISI 52100 Steel with Minimal Cutting Fluid Application, Machines 13(4): 266. https://doi.org/10.3390/machines13040266
10. **Bagci, E.; Işık, B.** 2006. Investigation of surface roughness in turning unidirectional GFRP composites by using RS methodology and ANN, The International Journal of Advanced Manufacturing Technology 31(1): 10-17. https://doi.org/10.1007/s00170-005-0175-x
11. **Saidi, R.; Mabrouki, T.; Fathallah, B. B.; Belhadi, S.; Yallese, M. A.** 2025. Study of Insert Flank Wear and Surface Roughness Evolutions During Turning of Stellite 6 Based on RSM and Desirability Approaches, Mechanika 31(4): 415-427. https://doi.org/10.5755/j02.mech.40674.
12. **Tibakh, I.; Yallese, M. A.; Belhadi, S.** 2024. Quality and productivity improvement in the milling of polyoxymethylene co-polymer (POM C) using RSM, SVM and genetic algorithm, Surface Review and Letters 33(6): 2550029. https://doi.org/10.1142/S0218625X25500295.
13. **Saidi, R.; Fathallah, B.B.; Mabrouki, T.; Belhadi, S.; Yallese, M.A.** 2020. Prediction of Forces Components During the Turning Process of Stellite 6 Material Based on Artificial Neural Networks, in: Aifaoui, N., et al. Design and Modeling of Mechanical Systems - IV. CMSM 2019. Lecture Notes in Mechanical Engineering. Springer, Cham. https://doi.org/10.1007/978-3-030-27146-6_43.
14. **Kishore, K.; Chauhan, S. R.; Sinha, M. K.** 2023. Application of machine learning techniques in environmentally benign surface grinding of Inconel 625, Tribology International 188: 108812. https://doi.org/10.1016/j.triboint.2023.108812.
15. **Prashanth, G. S.; Sekar, P.; Bontha, S.; Balan, A. S. S.** 2023. Grinding parameters prediction under different cooling environments using machine learning techniques, Materials and Manufacturing Processes 38(2): 235-244. https://doi.org/10.1080/10426914.2022.2116043.
16. **Reddy, B. S.; Padmanabhan, G.; Reddy, K. V. K.** 2008. Surface Roughness Prediction Techniques for CNC Turning, Asian Journal of Scientific Research 1(3): 256-264. https://doi.org/10.3923/ajsr.2008.256.264.
17. **Dubey, V.; Sharma, A. K.; Pimenov, D. Y.** 2022. Prediction of Surface Roughness Using Machine Learning Approach in MQL Turning of AISI 304 Steel by Varying Nanoparticle Size in the Cutting Fluid, Lubricants

10(5): 81.
https://doi.org/10.3390/lubricants10050081.
18. **Lagat, A. K.; Waititu, A. G.; Wanjoya, A. K.** 2018. Support Vector Regression and Artificial Neural Network Approaches: Case of Economic Growth in East Africa Community, American Journal of Theoretical and Applied Statistics 7(2): 67-79.
https://doi.org/10.11648/j.ajtas.20180702.13
19. **Vijayakumar, S.; Wu, S.** 1999. Sequential Support Vector Classifiers and Regression. In Proc. International Conference on Soft Computing (SOCO'99): 610-619.
20. **Singh, T. N.; Kanchan, R.; Verma, A. K.; Singh, S.** 2003. An intelligent approach for prediction of triaxial properties using unconfined uniaxial strength, Mining Engineering Journal 5(4): 12-16.
21. **McGarry, K. J.; Wermter, S.; MacIntyre, J.** 1999. Knowledge extraction from radial basis function networks and multilayer perceptrons, In IJCNN'99 International Joint Conference on Neural Networks. Proceedings (Cat. No. 99CH36339) 4: 2494-2497.
22. **Lim, T. S.; Loh, W. Y.; Shih, Y. S.** 2000. A Comparison of Prediction Accuracy, Complexity, and Training Time of Thirty-Three Old and New Classification Algorithms, Machine Learning 40(3): 203-228.
https://doi.org/10.1023/A:1007608224229.
23. **Venkatesan, P.; Anitha, S.** 2006. Application of a radial basis function neural network for diagnosis of diabetes mellitus, Current Science 91(9): 1195-1199. Available at:
http://eprints.nirt.res.in/id/eprint/789.
24. **Foody, G. M.** 2004. Supervised image classification by MLP and RBF neural networks with and without an exhaustively defined set of classes, International Journal of Remote Sensing 25(15): 3091-3104.
https://doi.org/10.1080/01431160310001648019
25. **Grillone, B.; Danov, S.; Sumper, A.; Cipriano, J.; Mor, G.** 2020. A review of deterministic and data-driven methods to quantify energy efficiency savings and to predict retrofitting scenarios in buildings, Renewable and Sustainable Energy Reviews 131: 110027.
https://doi.org/10.1016/j.rser.2020.110027
26. **Ghosh, S.; Dasgupta, A.; Swetapadma, A.** 2019. Study on Support Vector Machine based Linear and Non-Linear Pattern Classification, In 2019 nternational Conference on Intelligent Sustainable Systems (ICISS): 24-28.
https://doi.org/10.1109/ISS1.2019.8908018.

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MACHINE LEARNING FOR PREDICTION OF SURFACE ROUGHNESS IN STELLITE 6 TURNING: A COMPARATIVE STUDY OF ANN, RANDOM FOREST AND SUPPORT VECTOR REGRESSION MODELS

S u m m a r y

In recent years, the landscape of predictive modeling has been significantly transformed by the adoption of sophisticated methodologies, collectively known as soft computing techniques. The surface condition of a machined part plays a crucial role in its overall performance. It can significantly affect properties such as wear behavior, resistance to corrosion, and fatigue strength. Among the various indicators used to evaluate this finish, surface roughness (*Ra*) remains one of the most important criteria for assessing the quality of a machined surface.

Stellite 6 is a cobalt-based alloy widely employed in applications that demand high wear resistance and withstand elevated temperatures. While its mechanical strength makes it highly reliable in harsh environments, it also makes the alloy difficult to machine, particularly when aiming to achieve a good surface finish. The problem is framed using the Design of Experiments (DOE) to measure the Ra of Stellite 6 turning: a total of 27 experiments were performed. The main contribution of this study is the comparison of ANN-MLP, ANN-RBF, RF, and SVR models for Ra prediction in Stellite 6 turning. To better anticipate surface roughness during turning, this study investigates the performance of several machine learning (ML) models developed in Python. Three algorithms: Artificial Neural Networks (ANN), Random Forests (RF), and Support Vector Regression (SVR) were trained using an experimental dataset that includes tool nose radius, cutting speed, feed rate, and depth of cut.

Model performances were assessed using coefficient of determination (R^2), root mean squared error (RMSE), and mean absolute error (MAE) metrics. Among the evaluated models, the RF achieved the highest prediction accuracy, followed by ANN and then SVR. The results highlight the capability of Python-based machine learning approaches to capture the nonlinear relationships between cutting parameters and surface roughness. The Random Forest Regressor (RFR) demonstrates the best ability to predict surface roughness (*Ra*), closely followed by the Epsilon-SVR using the RBF kernel. RFR is less sensitive to data scaling and effectively fits the complex non-linear relationships in the synthetic dataset.

The results demonstrate the potential of ML models for surface roughness prediction in Stellite 6 turning. However, further validation using larger datasets and industrial applications is needed.

Keywords: Stellite 6, surface roughness, machine learning.

Received November 27, 2025
Accepted June 19, 2026