PREDICTION OF SURFACE ROUGHNESS IN FINISH MILLING OF 6061 ALUMINIUM ALLOY USING ARTIFICIAL NEURAL NETWORK AND EXTREME LEARNING MACHINE

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Abstract - Surface roughness is a key indicator of surface quality in milling processes. This study presents a comparative evaluation of polynomial regression, Artificial Neural Network (ANN), and Extreme Learning Machine (ELM) models for predicting surface roughness during finish milling of 6061 aluminium alloy. Experimental data were obtained using a Taguchi L27 design with cutting speed, feed rate, and depth of cut as inputs. Model generalisation was further assessed through six additional experiments with parameter combinations outside the original design. All models achieved high accuracy within the experimental domain; however, predictive performance decreased under unseen conditions. ANN and ELM showed better generalisation than polynomial regression. Although their performance difference was moderate, ELM provided more consistent prediction accuracy across validation tests. The results highlight the importance of external validation and offer practical guidance for model selection in milling with limited data.

Keywords - Milling; Surface roughness; Taguchi method; Artificial Neural Network; Extreme Learning Machine

1. Introduction

Surface roughness (Ra) is a critical indicator of surface integrity and functional quality in machining processes, as it directly affects fatigue life, wear resistance, friction behaviour, and dimensional accuracy of machined components [1–3]. In milling operations, Ra is governed by complex interactions among cutting parameters, tool geometry, cutting mechanics, and workpiece material properties. Among these factors, cutting speed, feed rate, and depth of cut are widely recognised as the most influential parameters affecting surface finish [4–6].

Aluminium alloy 6061 is extensively used in aerospace, automotive, mould manufacturing, and precision engineering applications owing to its favourable strength-to-weight ratio, corrosion resistance, and good machinability. Nevertheless, achieving stable, low surface roughness during finish milling of 6061 remains challenging, particularly under high-productivity cutting conditions [7]. As a result, accurate prediction of surface roughness has become an important research topic to support process planning, quality control, and optimisation in milling operations.

Conventional approaches for surface roughness prediction commonly rely on statistical techniques such as regression analysis, Taguchi methods, and analysis of variance (ANOVA). These methods are effective for identifying significant factors and determining optimal machining conditions with a limited number of experiments [8, 9]. However, regression-based models generally assume linear or low-order polynomial relationships, which may not adequately capture the nonlinear and coupled effects inherent in machining processes [10].

Recently, machine learning (ML) techniques have attracted increasing attention due to their ability to model complex nonlinear relationships directly from experimental data. Artificial Neural Networks (ANNs) have been widely applied to predict surface roughness in turning and milling and have demonstrated strong nonlinear approximation capabilities [11, 12]. Nevertheless, ANN models often require careful tuning of network architecture and training parameters and may exhibit reduced generalisation performance when trained on limited datasets [13]. Extreme Learning Machine (ELM) has emerged as an efficient alternative to conventional ANN models. ELM is a single-hidden-layer feedforward neural network in which hidden-layer parameters are randomly assigned and output weights are analytically determined using a least-squares solution. This learning mechanism significantly reduces training time while maintaining strong generalisation performance, particularly for small-to medium-sized datasets commonly encountered in machining experiments [14–16].

Although numerous studies have investigated surface roughness prediction using regression analysis or ANN-based models, systematic comparisons among regression, ANN, and ELM for finish milling of aluminium alloys remain limited. Moreover, the robustness of these models under machining conditions outside the original experimental design has not been sufficiently explored.

Therefore, this study aims to develop and compare polynomial regression [17], ANN, and ELM models for predicting surface roughness (Ra) in the finish milling of 6061 aluminium alloy. The models are developed using experimental data from a Taguchi L27 design with cutting speed, feed rate, and depth of cut as factors. Beyond the original 27 experiments, six supplementary milling experiments conducted outside the design matrix are used to evaluate the model's generalisation capability.

Although surface roughness in milling is influenced by many factors, including stepover and toolpath strategy, the present study deliberately focuses on cutting speed, feed rate, and depth of cut, as these parameters are widely recognised as the most influential contributors to surface roughness variation in milling operations and are most commonly investigated in both experimental and data-driven modelling studies [4–6]. Other machining parameters, such as stepover and toolpath strategy, were kept constant across all experiments to isolate the effects of the selected variables and ensure a controlled, fair comparison between predictive models. This parameter selection is consistent with the objective of the present work, which is to evaluate the predictive performance and generalisation behaviour of regression- and machine-learning-based models rather than to conduct a comprehensive parametric study of all milling factors.

Moreover, unlike many previous studies that focus on a single predictive technique, this study provides a systematic comparison between conventional polynomial regression and two ANN-based learning models (ANN and ELM) under identical experimental conditions**.** In addition, the generalisation capability of the models is explicitly evaluated using additional experimental data outside the original Taguchi design space**,** a factor that has rarely been addressed in previous studies on 6061 aluminium alloy milling. The contribution of this study is primarily comparative and application-oriented, aiming to provide practical insight into the predictive performance and generalisation behaviour of different modelling approaches rather than proposing a new prediction algorithm.

2. Experimental method

2.1. Experimental design and machining parameters

The experimental data used in this study were obtained from a finish milling experiment conducted on 6061 aluminium alloy. A Taguchi L27 (3^3) orthogonal array was employed to systematically investigate the effects of three cutting parameters on surface roughness (Ra), namely cutting speed (v), feed rate (f), and depth of cut (t). Each factor was examined at three levels, as presented in Table 1 [17]. The cutting tool is a Lasting Victory 884L-Z (100410) end mill. The parameter levels are presented in Table 1, based on the manufacturer's maximum recommended values.

Table 1. *Levels of the investigated factors*

Symbol	Unit	Low	Medium	High
v	m/min	25	60	95
f	mm/t	0.04	0.06	0.08
t	mm	0.2	0.5	0.8

2.2. Machining conditions and surface roughness measurement

The experiments were conducted on a VCN-430A SG machining center (Mazak, Japan). Prior to finishing milling, a roughing operation was performed to remove surface irregularities using a 12 mm-diameter, four-flute carbide end mill (spindle speed of 1600 rpm) with a cutting depth of 1 mm. Both roughing and finishing operations used a side-milling strategy with conventional cutting, and the effective length of the machined surface was 110 mm. The spindle speed in finishing milling was calculated according to the selected cutting speed (Table 1) and the tool diameter (10 mm) used in the finishing operation, while other machining parameters were kept constant. Throughout both roughing and finishing operations, coolant was continuously applied to ensure stable cutting conditions. During the experiments, v, f, and t were varied according to the Taguchi design, while other machining parameters, including tool geometry and cooling conditions, were kept constant to minimise their influence on surface roughness. Figure 1 shows the aluminium alloy specimen used for machining, with dimensions of 120×110×30 mm.

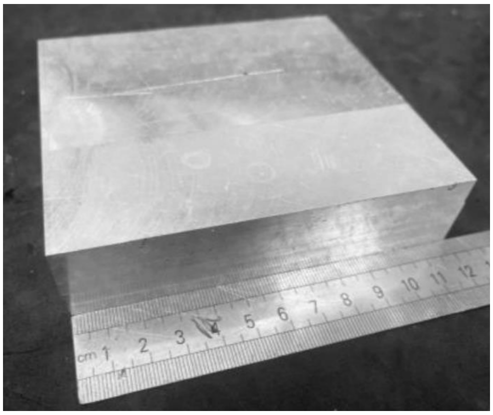

Figure 1. *Experimental specimen [17]*

As the machining process was performed using a side-milling strategy, the machined surface was generated along the side of the end mill as the tool moved along the edge of the workpiece. Therefore, the concept of stepover, commonly used in face milling or surface pocketing operations, does not apply to this experimental configuration. Instead, the cutting engagement was governed by the selected depth of cut (t) and the feed motion along the machining direction.

All finishing-milling experiments were performed using the same tool type and geometry (Lasting Victory 884L-Z end mill, 10 mm diameter, four cutting edges). The experiments were conducted sequentially according to the Taguchi L27 experimental matrix, and each specimen was machined individually. To evaluate the potential influence of tool wear and material adhesion, additional verification experiments were conducted after completing the 27 Taguchi experiments, using the same cutting parameters as in experiments No. 1 and No. 2. The results showed negligible differences in surface roughness, indicating that tool wear had minimal influence on the dataset [17].

All 27 experiments are shown in Table 2. Surface roughness Ra (μm) was measured using a HANDYSURF+35 (ACCRETECH) contact-type profilometer. The measurements were conducted with a sampling length of 0.8 mm and a cut-off length of 4.0 mm, in accordance with the JIS 2001/2013 standards. For each experimental run, three Ra measurements were taken at different locations along the machined surface, and the mean value was used for subsequent analysis. The measurement locations were spaced approximately 50 mm apart along the machining direction over the effective machined length of 110 mm, and all measurements were performed at the centre of the machined surface width. The profilometer's stylus movement direction was aligned with the milling feed direction to ensure consistent evaluation of surface roughness along the toolpath.

Table 2. *Experimental matrix and values of R_a [17]*

No.	**Cutting parameters**			**R_a** (µm)
	v (m/min)	**f** (mm/t)	**t** (mm)	
1	25	0.04	0.2	0.184
2	25	0.06	0.5	0.395
3	25	0.08	0.8	0.906
4	25	0.04	0.5	0.224
5	25	0.06	0.8	0.406
6	25	0.08	0.2	0.756
7	25	0.04	0.8	0.247
8	25	0.06	0.2	0.363
9	25	0.08	0.5	0.887
10	60	0.04	0.2	0.205
11	60	0.06	0.5	0.409
12	60	0.08	0.8	0.757
13	60	0.04	0.5	0.289
14	60	0.06	0.8	0.450
15	60	0.08	0.2	0.642
16	60	0.04	0.8	0.325
17	60	0.06	0.2	0.375
18	60	0.08	0.5	0.709
19	95	0.04	0.2	0.186
20	95	0.06	0.5	0.405
21	95	0.08	0.8	0.805
22	95	0.04	0.5	0.199
23	95	0.06	0.8	0.455
24	95	0.08	0.2	0.723
25	95	0.04	0.8	0.224
26	95	0.06	0.2	0.361
27	95	0.08	0.5	0.783

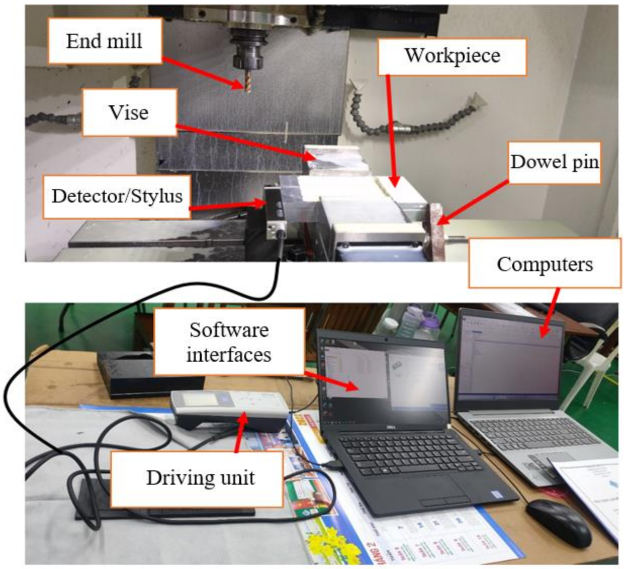

Figure 2. *The experimental setup and Ra measurement*

This measurement strategy was adopted to reduce the influence of local surface irregularities, tool entry and exit effects, and edge-related disturbances, thereby ensuring that the reported Ra values are representative of the steady-state cutting conditions. The experimental setup and measurement procedure are illustrated in Fig. 2.

2.3. Dataset preparation for predictive modelling

The dataset obtained from the Taguchi L27 design consists of 27 samples, each defined by three input variables (v, f, and t) and one output variable (Ra). These data were used to develop and evaluate three predictive models: polynomial regression, ANN, and ELM.

In addition to training and validating the ELM and ANN models, the experimental dataset was divided into training and validation subsets, as summarised in Table 3. Specifically, 21 samples were randomly selected for model training, and the remaining 6 for validation. The dataset was randomly divided into training and validation subsets to reduce selection bias and ensure a representative sample distribution for model evaluation. After data splitting, all input and output variables were normalised using min–max scaling to the range [0,1] using Eq. 1. The normalisation parameters were determined exclusively from the training dataset and subsequently applied to the validation dataset to avoid data leakage and ensure an unbiased evaluation of model performance. The same data partitioning and normalisation strategy was consistently applied to all predictive models to enable a fair comparison.

$$x_{norm} = (x - x_{min})/(x_{max} - x_{min}) \quad (1)$$

It should be noted that practical constraints in machining experiments limit the dataset size; however, this scale is typical for Taguchi-based studies in manufacturing and is sufficient for comparative evaluation of predictive models under controlled conditions.

Table 3. *The predicted R_a within the experimental range*

No.	**Cutting parameters**			**R_a** (µm)
	V (m/min)	**F** (mm/t)	**T** (mm)	
1	25	0.04	0.2	0.184
9	25	0.08	0.5	0.887
10	60	0.04	0.2	0.205
12	60	0.08	0.8	0.757
14	60	0.06	0.8	0.450
22	95	0.04	0.5	0.199

Although the experimental dataset consists of 27 samples obtained from a Taguchi L27 design, such dataset sizes are common in machining experiments due to the high cost and time associated with experimental trials. In this study, ANN and ELM models are employed primarily for comparative evaluation with conventional regression models rather than for large-scale predictive deployment. To mitigate limitations associated with the small dataset, moderate model complexity was adopted, and the predictive capability of the models was further examined through six additional experiments not included in the original design matrix.

In the present study, the term "generalisation capability" refers to the ability of predictive models to estimate surface roughness for machining conditions not included in the training dataset but within the investigated parameter range. It should be noted that, due to the limited size of the experimental dataset, the results should not be interpreted as a strict theoretical demonstration of generalisation in the machine learning sense. Instead, the additional six milling experiments serve as a practical external validation to examine how the models perform when applied to new machining conditions. Therefore, the comparison presented in this work should be interpreted as an evaluation of model robustness under limited experimental data rather than a definitive assessment of model superiority.

2.4. Development of predictive models

A polynomial regression model (Eq. 2) was employed as a conventional statistical baseline to describe the relationship between the cutting parameters and surface roughness, as established in a previous study [17].

$$\begin{aligned} Ra = {} & 0.287 - 0.0687v - 41.89f + 0.1618t \\ & +542.5f^2 + 0.7097vf - 0.003744 \\ & -9.59vft + 37.8f^2 - 2.73ft^2 \\ & +0.06025\, v^2f^2 \end{aligned} \tag{2}$$

ELM is a learning algorithm developed for single-hidden-layer feedforward neural networks (SLFNs) and is recognised for its high computational efficiency and strong generalisation capability. In ELM, the input weights and hidden-layer biases are randomly assigned, whereas the output weights are analytically determined via a least-squares solution, thereby eliminating the need for iterative gradient-based optimisation [14–16]. In the present study, the ELM model was configured with 12 hidden neurons and employed a hyperbolic tangent ($tanh$) activation function in the hidden layer to predict surface roughness (Ra) from the selected machining parameters.

ANNs are widely used machine learning models that can approximate complex, highly nonlinear relationships between input and output variables. A typical ANN architecture consists of an input layer, one or more hidden layers, and an output layer, in which information is transmitted via weighted connections and nonlinear activation functions. In the present study, ANN models were developed to predict surface roughness (Ra) as a function of v, f, and t. Two network configurations were investigated, consisting of one and two hidden layers with 5 and 12 neurons, respectively. A sigmoid activation function was employed in all layers. Network training was carried out using the Adam optimisation algorithm with 2500 training epochs and a batch size of 4.

The dataset was randomly divided into training and validation subsets consisting of 21 and 6 samples, respectively. To avoid potential data leakage during model development, the min–max normalisation parameters were calculated exclusively from the training dataset, and the same scaling transformation was subsequently applied to the validation dataset. The maximum number of training epochs for the ANN model was set to 2500 to ensure convergence of the optimisation process. However, the training loss stabilised well before the final epoch, indicating that the network parameters had reached a stable solution. In addition, relatively simple network architectures were intentionally adopted to limit model complexity, given the small dataset size.

In addition, the selection of hyperparameters for ANN and ELM was based on achieving an appropriate balance between model complexity and generalisation performance, considering the limited size of the experimental dataset. Preliminary tests with different numbers of hidden neurons were conducted, and moderate network sizes were selected to minimise the risk of overfitting. For the ELM model, 12 hidden neurons were used, as further increasing the number did not yield a noticeable improvement in prediction accuracy. For the ANN model, two network configurations with 5 and 12 hidden neurons were examined to investigate the influence of network size on prediction performance. This strategy allows the effect of model complexity to be assessed without performing exhaustive hyperparameter optimisation, which is beyond the primary scope of the present study.

The predictive performance of the polynomial regression, ANN, and ELM models was first evaluated using experimental data within the design space defined by the Taguchi L27 matrix. Model accuracy was assessed using standard statistical indicators, including the coefficient of determination (R^2), mean absolute error (MAE), mean absolute percentage error (MAPE), and root mean squared error (RMSE).

Table 4. *The six new experiments [17]*

No.	**Cutting parameters**			**Ra** (μm)
	V (m/min)	***F*** (mm/t)	***T*** (mm)	
1	35	0.05	0.3	0.324
2	35	0.065	0.6	0.421
3	50	0.05	0.7	0.410
4	50	0.07	0.3	0.471
5	80	0.065	0.7	0.566
6	80	0.07	0.6	0.589

To further evaluate the models' generalisation capability, six additional milling experiments were conducted using cutting-parameter combinations not included in the original Taguchi design. These experiments, presented in Table 4, were excluded from the model training process and used exclusively for external validation. The predictive performance of all models on these unseen data was evaluated using the same statistical indicators to ensure a rigorous and unbiased comparison.

3. Results and discussion

3.1. Experimental results and characteristics of surface roughness

Table 2 summarises the experimental results obtained from the Taguchi L27 design for finish milling of 6061 aluminium alloy. The measured surface roughness values range from 0.184 µm to 0.906 µm, indicating a significant influence of cutting parameters on surface quality. Such a wide variation in Ra is typical in milling processes, where *f* and *t* strongly affect surface generation mechanisms, including tool–workpiece interaction and chip formation [17]. Across the experimental runs, lower Ra values are consistently associated with lower *f* (0.04 mm/tooth) and smaller *t* (0.2 mm), while higher Ra values are observed at larger *f* and *t*. This trend is consistent with classical machining theory and previously reported experimental studies on the milling of aluminium alloys, in which the *f* is recognised as the dominant factor governing surface roughness [4, 5]. These experimental results provide a reliable dataset for developing and comparing predictive models, as they cover a sufficiently broad parameter space and include both low- and high-roughness regimes.

3.2. Prediction performance within the experimental range

Figure 4 compares the predicted and experimentally measured surface roughness (Ra) values obtained from polynomial regression, ELM, and ANN. Apparent differences in prediction accuracy are evident among these modelling approaches. Table 5 presents a performance comparison of polynomial regression, ANN, and ELM models, evaluated on data within the experimental range. All three models exhibit high coefficients of determination ($R^2 > 0.99$), indicating a strong fit to the Taguchi L27 dataset.

Table 5. *Performance comparison of different regression models*

Model	R2	MAPE	MAE	RMSE
Polynomial regression	0.9961	4.6463	0.0136	0.0176
ELM	0.9951	2.9355	0.0133	0.0197
ANN	0.9970	3.0184	0.0124	0.0154

The polynomial regression model achieves an R^2 of 0.9961, indicating its ability to capture the overall trend in Ra variation within the designed experimental domain. However, its prediction error, reflected by an MAPE of 4.65%, is higher than that of the machine-learning-based models. This limitation arises from the inherent assumption of a predefined polynomial relationship between inputs and outputs, which limits its ability to capture complex nonlinear interactions among cutting parameters [10].

The ANN model yields the highest R^2 (0.9970), the lowest MAE (0.0124 µm), and the lowest RMSE (0.0154 µm) among the three approaches. This result demonstrates the strong nonlinear approximation capability of ANN when trained and evaluated within the same experimental domain. Nevertheless, ANN performance is known to be sensitive to network architecture and training conditions, particularly when datasets are small [13].

The ELM model also exhibits excellent predictive performance within the experimental range, with an R^2 of 0.9951 and a MAPE of 2.9355%, which is lower than those of both polynomial regression and ANN. The competitive accuracy of ELM highlights its ability to approximate nonlinear relationships effectively while maintaining a simple network structure and fast training process [14, 15].

Overall, within the experimental range, ANN and ELM outperform conventional polynomial regression, confirming the advantage of machine-learning-based approaches for predicting surface roughness in milling.

In addition, although all models exhibit very high R^2 values within the experimental range, these results primarily reflect the models' fitting capabilities and may be influenced by the limited dataset size. In particular, ANN- and ELM-based models are known to be susceptible to overfitting when evaluated solely on in-sample data.

Overall, although all models exhibit very high R^2 values within the experimental range, these results mainly reflect fitting capability under limited data conditions. Given the small training dataset, such high R^2 values should not be interpreted as evidence of strong predictive reliability, but rather as an indication of potential overfitting when models are evaluated on in-sample data alone.

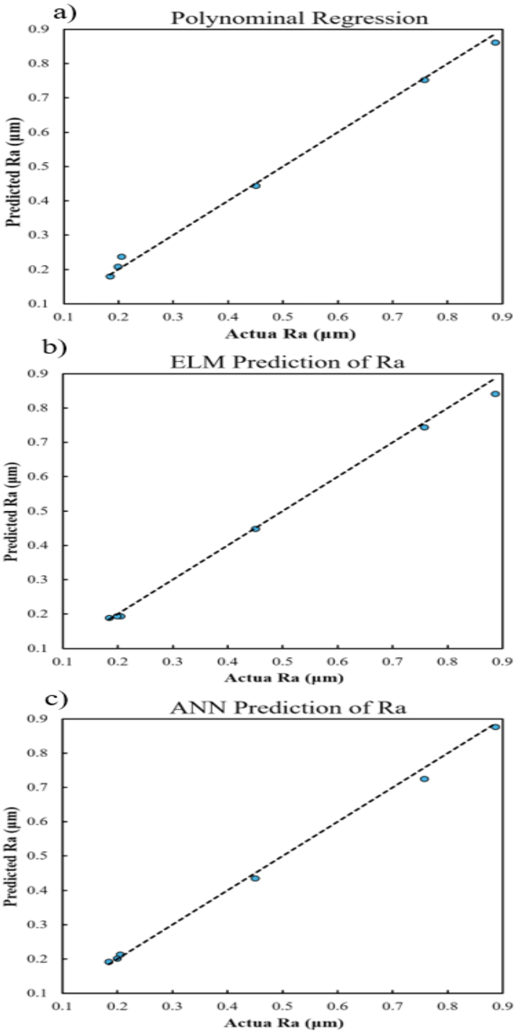

Figure 3. *Comparison of predicted and actual Ra values using different models: (a) Polynomial Regression, (b) ELM, (c) ANN*

3.3. External validation using six new experiments

In contrast, both ANN and ELM demonstrate significantly better generalisation performance. The ANN model achieves an R² value of 0.8715, with MAE and RMSE values of 0.0275 µm and 0.0333 µm, respectively. These results indicate that ANN retains reasonable predictive accuracy on unseen data, although its performance deteriorates compared with that within the training domain. The ELM model exhibits comparable and stable performance, with an R² of 0.8365 and an MAPE of 5.96%. Although the prediction accuracy of ANN and ELM is comparable in terms of R², ELM exhibits a lower MAPE (5.96% compared with 6.31% for ANN), indicating more consistent relative prediction accuracy across the six unseen experiments. Moreover, the ELM's prediction errors exhibit less fluctuation across different cutting conditions, suggesting more stable generalisation behaviour under limited data availability. This stability can be attributed to the analytical learning mechanism of ELM, which avoids iterative weight updates and reduces the risk of convergence to local minima, a common issue in gradient-based ANN training when datasets are small [14–16].

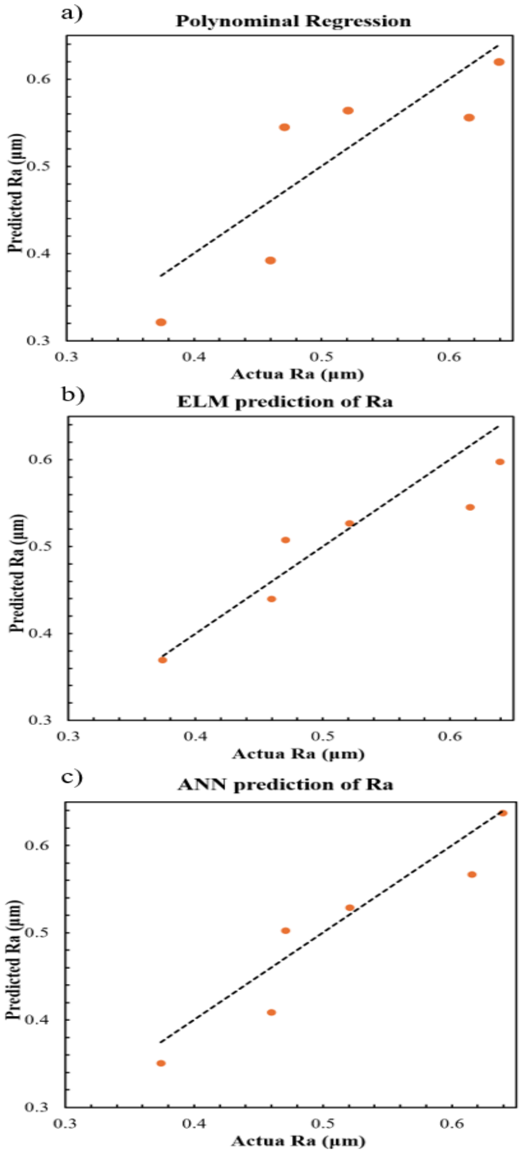

Figure 4. *Comparison of predicted and actual R_a values of 6 additional experiments for different models*

Nevertheless, given the limited size of the experimental dataset, the results should be interpreted cautiously, and the models are primarily intended to provide a comparative evaluation of predictive behaviour rather than a broadly generalisable machine learning solution.

As noted, practical constraints in machining experiments limit the dataset size. The use of additional experiments outside the original design space is intended to compensate for this limitation partially and to provide insight into the robustness and generalisation capability of the developed models.

Table 6. *Performance comparison of different models with six new experiments*

Model	R2	MAPE	MAE	RMSE
Polynomial regression	0.6366	12.2593	0.0529	0.0559
ELM	0.8365	5.9613	0.0299	0.0376
ANN	0.8715	6.3133	0.0275	0.0333

Moreover, the degradation in prediction accuracy observed for the regression model under extrapolation conditions suggests that surface roughness is highly nonlinearly sensitive to cutting parameters, especially when parameter combinations deviate from the original experimental design. Machine-learning-based models are therefore better suited to capturing parameter sensitivity in practical milling operations.

The noticeable reduction in prediction performance observed during external validation confirms that high in-sample accuracy does not necessarily translate into reliable prediction under unseen machining conditions. This result highlights the importance of external validation for evaluating the true generalisation capability of data-driven models in machining applications.

4. Conclusions

This study compared polynomial regression, ANN, and ELM models for predicting surface roughness (Ra) in the finish milling of 6061 aluminium alloy. The models were developed using a Taguchi L27 experimental dataset and further evaluated using six additional experiments conducted outside the original design to assess their generalisation capability.

Within the experimental range, all models exhibited high prediction accuracy, with R² values exceeding 0.99. ANN provided the best fitting performance, while ELM achieved lower relative prediction errors, reflecting its strong nonlinear modelling capability. When applied to unseen experimental conditions, the polynomial regression model showed a significant loss of accuracy, whereas ANN and ELM maintained substantially better predictive performance. While the performance difference between ANN and ELM is moderate, ELM offers a more stable, computationally efficient alternative, particularly advantageous for machining applications with limited experimental data.

Although the number of experimental samples is limited (L27), the results remain meaningful for practical machining applications, where data availability is often constrained. Overall, the results suggest that machine-learning-based approaches can provide improved predictive performance compared with conventional regression models under the conditions investigated. ELM, in particular, offers a favourable balance between accuracy, robustness, and computational efficiency, making it a promising predictive tool for surface quality estimation and machining process planning.

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