# INFLUENCE OF ARTIFICIAL NEURAL NETWORK ARCHITECTURE DEPTH ON SURFACE ROUGHNESS PREDICTION IN FINISH MILLING OF 6061 ALUMINIUM ALLOY

## ẢNH HƯỞNG CỦA ĐỘ SÂU KIẾN TRÚC MẠNG NƠ-RON NHÂN TẠO ĐẾN DỰ ĐOÁN ĐỘ NHÁM BỀ MẶT TRONG GIA CÔNG PHAY TINH HỢP KIM NHÔM 6061

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## ABSTRACT

*Surface roughness (Ra) is a critical indicator of surface quality in milling processes and is strongly influenced by cutting parameters and their nonlinear interactions. The present study investigates the effect of the depth of the Artificial Neural Network (ANN) architecture on surface roughness prediction during finish milling of 6061 aluminium alloy. Experimental data were obtained from a Taguchi L27 design and divided into training and internal testing datasets, while six additional experiments conducted outside the original design space were used for external validation. ANN models with 1, 2, 3, and 4 hidden layers were developed and systematically compared using standard statistical indicators. The results show that all ANN models achieve high prediction accuracy on internal testing data; however, their generalisation performance differs significantly under unseen machining conditions. The ANN model with two hidden layers consistently provides the best balance between accuracy and robustness, whereas deeper architectures exhibit clear overfitting behaviour. The findings confirm that moderate ANN depth is more suitable for surface roughness prediction in machining applications with limited experimental data.*

**Keywords:** *Surface roughness; Finish milling; Artificial neural network; Network depth; Generalisation performance; Taguchi method.*

## TÓM TẮT

*Độ nhám bề mặt (Ra) là một chỉ số quan trọng phản ánh chất lượng bề mặt trong quá trình gia công phay và chịu ảnh hưởng mạnh mẽ bởi các thông số cắt cũng như sự tương tác phi tuyến giữa chúng. Nghiên cứu này nhằm khảo sát ảnh hưởng của độ sâu kiến trúc mạng nơ-ron nhân tạo (ANN) đến khả năng dự đoán độ nhám bề mặt trong quá trình phay tinh hợp kim nhôm 6061. Dữ liệu thực nghiệm được thu thập từ thiết kế Taguchi L27 và được chia thành tập huấn luyện và tập kiểm tra nội bộ, trong khi sáu thí nghiệm bổ sung được thực hiện ngoài không gian thiết kế ban đầu được sử dụng cho mục đích kiểm chứng bên ngoài. Các mô hình ANN với một, hai, ba và bốn lớp ẩn được xây dựng và so sánh một cách có hệ thống thông qua các chỉ số thống kê tiêu chuẩn. Kết quả cho thấy tất cả các mô hình ANN đều đạt độ chính xác dự đoán cao trên tập kiểm tra nội bộ; tuy nhiên, khả năng khái quát hóa của chúng có sự khác biệt đáng kể khi áp dụng trong các điều kiện* ☞

*gia công chưa từng gặp. Mô hình ANN với hai lớp ẩn cho thấy sự cân bằng tốt nhất giữa độ chính xác và tính ổn định, trong khi các kiến trúc sâu hơn thể hiện rõ hiện tượng quá khớp (overfitting). Các kết quả này khẳng định rằng độ sâu ANN ở mức trung bình là phù hợp hơn cho việc dự đoán độ nhám bề mặt trong các ứng dụng gia công với bộ dữ liệu thực nghiệm hạn chế.*

**Từ khóa:** *Độ nhám bề mặt; Phay tinh; Mạng nơ-ron nhân tạo; Độ sâu mạng; Khả năng khái quát hóa; Phương pháp Taguchi.*

## 1. INTRODUCTION

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

Aluminium alloy 6061 is widely used in aerospace, automotive, mould manufacturing, and precision engineering applications due to its favourable strength-to-weight ratio, corrosion resistance, and good machinability. However, achieving a stable, predictable surface roughness during finish milling of 6061 aluminium alloy remains challenging, particularly under productivity-driven cutting conditions. Consequently, accurate prediction of surface roughness has become an important research topic for supporting process planning, quality assurance, and machining optimisation [7].

Conventional approaches for surface roughness modelling commonly rely on statistical techniques such as regression analysis, Taguchi methods, and analysis of variance (ANOVA). These techniques are effective for identifying significant factors and optimising machining parameters with a limited number of experiments [8, 9]. Nevertheless, regression-based models usually assume linear or low-order polynomial relationships between cutting parameters and surface roughness, which may not adequately capture the nonlinear and coupled effects inherent in milling processes, especially outside the original experimental domain [10].

In recent years, machine learning (ML) techniques have been increasingly adopted in machining research due to their strong ability to model nonlinear relationships directly from experimental data. Artificial Neural Networks (ANNs), in particular, have been widely applied to surface roughness prediction in turning and milling processes and have demonstrated superior predictive accuracy compared with traditional regression models [11, 12]. Despite these advantages, ANN performance is strongly influenced by network architecture, especially the number of hidden layers and neurons. Inappropriate network depth may lead to underfitting or overfitting, particularly when the available experimental dataset is small [13].

Several studies have reported that increasing the depth of ANN models does not necessarily guarantee improved predictive performance in machining applications, and excessive network complexity may degrade generalisation capability [14, 15]. However, systematic investigations of the influence of ANN depth on prediction accuracy and robustness, especially under small-sample conditions typical of machining studies, remain limited.

Recent studies have demonstrated the increasing application of artificial intelligence techniques for surface roughness prediction in machining processes. For example, recent reviews have highlighted that machine learning and deep learning models are effective in capturing the complex interactions between cutting parameters and surface quality, even under data-limited conditions [16]. Furthermore, recent experimental studies have shown that artificial neural networks can accurately predict surface roughness based on cutting parameters such as cutting speed, feed rate, and depth of cut, with feed rate often identified as the dominant factor [17]. In addition, AI-based approaches have been successfully applied in various machining processes, including EDM, where deep learning models have demonstrated strong predictive capability despite the inherent complexity and variability of the process [18].

Therefore, the objective of the present study is to systematically investigate the effect of ANN architecture depth on surface roughness prediction in the finish milling of 6061 aluminium alloy. Using a Taguchi L27 experimental dataset, ANN models with 1, 2, 3, and 4 hidden layers are developed and evaluated. The dataset is divided into training and internal testing subsets, and the generalisation capability of each ANN model is further assessed using six additional milling experiments conducted outside the original experimental design. By comparing predictive accuracy and robustness using standard statistical indicators, this study aims to identify an ANN architecture that provides an optimal balance between prediction accuracy and generalisation capability for surface roughness prediction in milling applications.

## 2. EXPERIMENTAL METHOD

### 2.1. Experimental data and machining parameters

*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 |

*Table 2. Experimental matrix and values of Ra.*

| No. | Cutting parameters | | | Ra (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 |

☞

The experimental data used in this study were obtained from finish-milling tests performed on 6061 aluminium alloy. The experiments were originally designed using a Taguchi L27 ($3^3$) orthogonal array to examine the influence of three primary machining parameters on surface roughness (Ra): v, f, and t. Each parameter was investigated at three discrete levels, as detailed in Table 1 [19].

The Taguchi L27 design was selected due to its efficiency in exploring the parameter space while maintaining statistical adequacy with a limited number of experimental runs. A total of 27 milling experiments were conducted, and the corresponding surface roughness values were recorded as the fundamental dataset for the present investigation.

### 2.2. Milling procedure and surface roughness measurement

All milling experiments were carried out on a VCN-430A SG machining center (Mazak, Japan) under finish milling conditions using a Lasting Victory 884L-Z (100410) end mill. Before the finishing operation, a preliminary roughing pass was applied to each workpiece to ensure uniform initial surface conditions. During the experiments, v, f, and t were varied according to the Taguchi design, whereas all other machining variables, including tool geometry and cooling conditions, were maintained constant to minimise their influence on surface roughness.

Surface roughness Ra (µm) was measured using a HANDYSURF+35 (ACCRETECH) contact profilometer. Measurements were conducted with a sampling length of 0.8 mm and a cut-off length of 4.0 mm, following the requirements of the JIS 2001/2013 standard. For each experimental run, three measurements were taken at different locations along the machined surface, and the average Ra value was used in subsequent analyses to improve measurement reliability.

### 2.3. Data partitioning for ANN modelling

To evaluate the predictive capability of the ANN models, the experimental dataset obtained from the Taguchi L27 design was divided into distinct subsets. Out of the 27 experimental samples, 21 samples were used for network training, while the remaining six samples (listed in Table 3 [19]) were reserved exclusively for internal testing. This fixed data-splitting strategy was consistently applied across all ANN configurations to ensure an unbiased comparison of model performance.

*Table 3. Six subset datasets for testing models.*

| No. | Cutting parameters | | | Ra (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 |

*Table 4. The six new experiments.*

| 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 |

In addition to the internal testing dataset, six supplementary milling experiments conducted outside the original Taguchi design were employed for external validation. These additional experiments, summarised in Table 4 [19], were not involved in the training or internal testing processes and were used solely to assess the generalisation capability of the ANN models under unseen machining conditions.

### 2.4. Artificial neural network architecture

ANNs were employed to establish the nonlinear mapping between machining parameters and surface roughness. The network input layer consisted of three cutting parameters (v, f, and t) and an additional bias neuron, while the output layer corresponded to the predicted Ra value. Before training, min–max normalisation was applied to improve numerical stability and facilitate network convergence [13].

To investigate the influence of network depth on prediction performance, four ANN architectures with 1, 2, 3, and 4 hidden layers were developed. The detailed configurations of these networks, including the number of neurons in each layer and the optimal number of training epochs, are provided in Table 5. The number of neurons in each hidden layer was selected based on preliminary trials to balance model complexity and prediction accuracy. Larger network configurations were initially tested; however, they resulted in unstable training and an increased risk of overfitting. Therefore, moderate network sizes were adopted to ensure stable convergence and reliable generalisation performance. A sigmoid activation function was adopted for all hidden layers, and the networks were trained using the Adam optimisation algorithm, known for its efficient convergence in nonlinear regression problems [17].

*Table 5. Detailed configurations of ANN networks.*

| ANN | 1-Layer | 2-Layer | 3-Layer | 4-Layer |
|---|---|---|---|---|
| Structure | 4-18-1 | 4-8-5-1 | 4-24-9-7-1 | 4-25-22-22-2-1 |
| Epochs | 2767 | 3000 | 882 | 887 |

The optimal training duration for each ANN model was determined based on the minimum validation error in order to reduce the risk of overfitting. All ANN models were trained using identical datasets and training conditions to ensure consistency in performance evaluation.

### 2.5. Performance evaluation criteria

The prediction accuracy of the developed ANN models was assessed using multiple statistical indicators, including the coefficient of determination ($R^2$), mean absolute error (MAE), mean absolute percentage error (MAPE), and root mean squared error (RMSE). Model performance was first evaluated on the internal test dataset and subsequently examined in external validation experiments. This two-level evaluation framework enables a comprehensive assessment of both prediction accuracy and generalisation capability, which is particularly important for machining studies based on limited experimental data [11].

## 3. RESULTS AND DISCUSSION

### 3.1. Performance of ANN models on internal testing dataset

Fig. 1 and Table 6 show the predictive performance of the four ANN configurations evaluated using the internal testing dataset ☞

consisting of six samples selected from the Taguchi L27 design (Table 3). All ANN models exhibit high prediction accuracy, with coefficients of determination ($R^2$) exceeding 0.99, indicating that neural networks can effectively capture the nonlinear relationship between cutting parameters and surface roughness.

Among the investigated architectures, the 2-layer ANN model demonstrates the best overall performance, achieving the highest $R^2$ value (0.9970) and the lowest error metrics (MAE = 0.0124 µm, RMSE = 0.0154 µm). This result suggests that a moderate network depth provides sufficient representational capacity to model nonlinear interactions among cutting parameters without introducing excessive complexity.

The 1-layer ANN model shows inferior accuracy compared with deeper architectures, which can be attributed to its limited modelling capacity. Conversely, increasing the number of hidden layers beyond two does not lead to further improvement. Both 3-layer and 4-layer ANN models exhibit slightly higher prediction errors despite their increased structural complexity, indicating diminishing returns with increasing network depth.

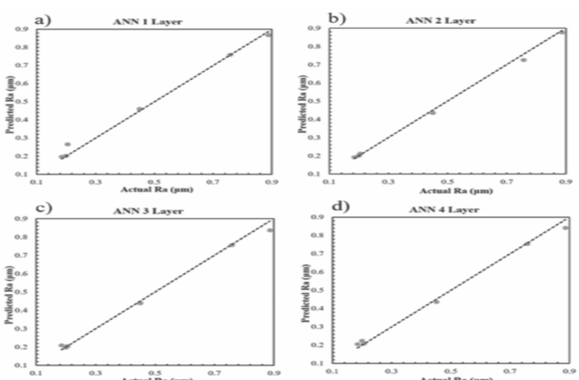


*Figure 1. Comparison of predicted and actual Ra values using different layers: (a) 1-layer, (b) 2-layer, (c) 3-layer, (d) 4-layer.*

*Table 6. Performance comparison of different ANN models with six subset datasets.*

| Model | $R^2$ | MAPE | MAE | RMSE |
|---|---|---|---|---|
| ANN 1-layer | 0.9909 | 7.119 | 0.0179 | 0.0269 |
| ANN 2-layer | 0.9970 | 3.018 | 0.0124 | 0.0154 |
| ANN 3-layer | 0.9933 | 3.849 | 0.0148 | 0.0231 |
| ANN 4-layer | 0.9932 | 5.657 | 0.0184 | 0.0233 |

Compared with the polynomial regression (PG) model reported in a previous study [17], the ANN configurations exhibit clear differences in predictive performance. Specifically, the 2-layer ANN model consistently demonstrates superior accuracy compared with the PG model ($R^2$ = 0.9961, MAE = 0.0136 µm, RMSE = 0.0176 µm), as reflected in its higher coefficient of determination and lower prediction errors. This result highlights the advantage of a moderately deep ANN architecture in capturing nonlinear and coupled effects among cutting parameters. In contrast, the remaining ANN models (one-, three-, and four-hidden-layer configurations) exhibit predictive performance comparable to that of the PG model. Although these ANN models can model nonlinear relationships, their overall accuracy does not show a substantial improvement over the conventional regression approach. This observation suggests that increasing ANN depth beyond an optimal level does not necessarily enhance predictive capability and may limit the advantage of ANN over polynomial regression when the available dataset is small.

### 3.2. External validation using six new experiments

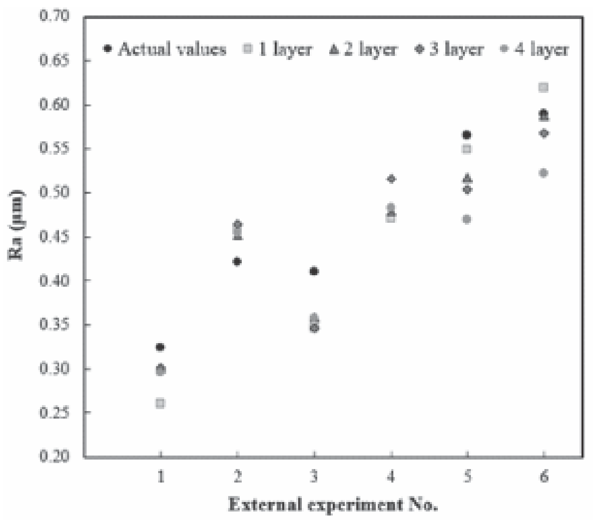


*Figure 2. Comparison of predicted and actual Ra values of 6 additional experiments for different models.*

Fig. 2 shows the generalisation capability of the ANN configurations, which was further evaluated using six additional milling experiments conducted outside the original Taguchi design (Table 4). The corresponding prediction results are presented in Table 7.

*Table 7. Performance comparison of different models with six new experiments.*

| Model | $R^2$ | MAPE | MAE | RMSE |
|---|---|---|---|---|
| ANN 1-layer | 0.7946 | 8.625 | 0.0349 | 0.0419 |
| ANN 2-layer | 0.8715 | 6.313 | 0.0275 | 0.0333 |
| ANN 3-layer | 0.7534 | 9.516 | 0.0430 | 0.0460 |
| ANN 4-layer | 0.6741 | 10.062 | 0.0482 | 0.0556 |

A clear performance differentiation is observed when the models are applied to unseen machining conditions. The 2-layer ANN model again provides the best generalisation performance, achieving the highest $R^2$ (0.8715), the lowest MAE (0.0275 µm), and the lowest RMSE (0.0333 µm). These results confirm that the ANN 2-layer architecture maintains robust predictive accuracy beyond the training domain.

In contrast, the predictive performance of deeper architectures deteriorates significantly during external validation. The 3-layer and 4-layer ANN models exhibit pronounced reductions in $R^2$ and substantial increases in prediction errors, indicating poor generalisation capability. This behaviour highlights the susceptibility of overly complex networks to overfitting when trained on small experimental datasets.

Furthermore, compared with the PG model reported in a previous study [16], all ANN models exhibit improved predictive performance under external validation. Although the PG model demonstrated acceptable accuracy within the experimental range, its prediction capability deteriorated markedly when applied to unseen machining conditions, resulting in higher prediction errors ($R^2$ = 0.6366, MAE = 0.0529 µm, RMSE = 0.0559 µm). In contrast, the ANN-based models exhibit lower errors and higher coefficients of determination across the six new experiments, indicating superior robustness. Notably, the performance advantage is most pronounced for the 2-layer ANN model, which consistently outperforms the PG model in both accuracy and stability.

Overall, the results from the six additional experiments clearly indicate that ANN models provide better generalisation capability than the conventional polynomial regression approach. This confirms that ANN- ☞

based modelling is more suitable for surface roughness prediction under varying machining conditions, where extrapolation beyond the original experimental design is required.

### 3.3. Effect of ANN depth on prediction accuracy and practical implications

The combined results from internal testing and external validation clearly demonstrate that ANN depth plays a crucial role in determining both prediction accuracy and generalisation capability.

To further explain this observation, the superior performance of the 2-layer ANN can be interpreted from both machine learning and machining perspectives. From a modelling standpoint, a two-layer architecture provides sufficient capacity to capture the nonlinear interactions among cutting parameters without introducing excessive complexity. When the dataset is limited (27 samples), deeper networks tend to memorise training data rather than learn general patterns, leading to overfitting and poor generalisation.

From a machining perspective, surface roughness in finish milling is primarily governed by feed marks, tool–workpiece interaction, and material deformation mechanisms. These relationships are nonlinear but not extremely complex. Therefore, a moderately complex model (2-layer ANN) is sufficient to approximate the physical behaviour of the system, whereas deeper networks introduce redundant degrees of freedom that are not supported by the available data.

This trend is evident in the present study. Although the 3-layer and 4-layer ANN models achieve reasonable accuracy during internal testing, their performance degrades markedly when applied to new experimental data. Such behaviour is consistent with well-established findings in machine learning literature, which indicate that deeper neural networks require substantially larger datasets to achieve stable generalisation performance [13-15].

In addition, the influence of cutting parameters on surface roughness can be explained from a machining perspective. From a physical standpoint, feed rate (f) directly determines the feed mark spacing and is widely recognised as the dominant factor influencing surface roughness in milling. Higher feed rates increase the height of residual scallops, resulting in larger Ra values. Cutting speed (v) affects tool–workpiece interaction and material deformation behaviour. At higher cutting speeds, improved cutting conditions and reduced built-up edge formation generally lead to smoother surfaces. Depth of cut (t), although less influential in finish milling, affects cutting stability and vibration, which can indirectly influence surface quality.

In contrast, the ANN 2-layer model provides an optimal balance between model complexity and data availability. Its superior performance across both internal and external evaluations suggests that moderate-depth architectures are better suited to machining applications, where experimental data are often scarce due to cost and time constraints. Similar observations have been reported in previous studies on ANN-based modelling of machining processes, where simpler or moderately complex networks outperform deeper architectures under small-sample conditions [11, 12].

From a practical standpoint, these findings highlight the importance of carefully selecting ANN architecture for surface roughness prediction. Rather than increasing network depth indiscriminately, the focus should be on achieving an appropriate balance between model complexity and dataset size. The results of this study indicate that a 2-layer ANN offers a robust and computationally efficient solution for surface roughness prediction in finish milling of 6061 aluminium alloy, making it suitable for integration into machining process planning and decision-support systems.

## 5. CONCLUSIONS

This study investigated the effect of the depth of the Artificial Neural Network (ANN) architecture on the prediction of surface roughness (Ra) during finish milling of 6061 aluminium alloy. Using experimental data derived from a Taguchi L27 design, ANN models with one to four hidden layers were developed and evaluated through a consistent data partitioning strategy, including internal testing and external validation using six additional experiments conducted outside the original experimental domain.

The results demonstrate that ANN depth has a pronounced influence on both prediction accuracy and generalisation capability. Although all ANN models exhibit high accuracy on the internal testing dataset, their performance differs significantly when applied to unseen machining conditions. The ANN model with two hidden layers consistently achieves the best balance between accuracy and robustness, outperforming both shallower and deeper architectures in terms of $R^2$, MAE, and RMSE. In contrast, deeper networks with three and four hidden layers show clear signs of overfitting, resulting in degraded generalisation performance despite increased model complexity.

In addition, compared with the PG model reported in the previous study, the ANN-based models, particularly the two-hidden-layer configuration, demonstrate superior robustness and generalisation capability under external validation conditions. This indicates that ANN provides a more reliable modelling approach than conventional regression when extrapolation beyond the original experimental design is required.

Overall, the findings confirm that increasing ANN depth does not necessarily improve predictive performance when the available dataset is limited. For machining applications characterised by small experimental datasets, a moderately deep ANN architecture offers superior reliability. Consequently, the 2-layer ANN emerges as an effective and practical tool for surface roughness prediction in milling, providing valuable support for machining process planning and quality control.

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