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RESEARCH ARTICLE

Surface roughness prediction for CNC-turned C45-steel utilising adaptive neuro-fuzzy inference systems

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ABSTRACT - The surface roughness, *Ra* of mechanical products, is an important parameter commonly used to evaluate the surface quality of a part after machining. Therefore, developing accurate prediction models for surface roughness is essential for optimizing manufacturing processes without multiple and repetitive experiments, leading to significant savings in both cost and time. This study examines the impact of turning parameters, including cutting speed, *V*, feed rate, *f*, and depth of cut, *d*, on *Ra* and develops a predictive model for the turning of C45 steel. The Taguchi method and the analysis of variance (ANOVA) were used to design the experiments and analyze the effects of machining parameters on *Ra*. Additionally, a predictive model for *Ra* was developed using the Adaptive Neuro-Fuzzy Inference System (ANFIS), and the efficiency of this model was evaluated based on the coefficient of determination, R^2, and the Root Mean Square Error (RMSE). The results of the ANOVA analysis showed that all three cutting parameters had significant effects on *Ra*. However, the *f* parameter had the most significant influence on *Ra* at 90.35%, followed by *V* and *d* at 1.9% and 3.24%, respectively. The developed ANFIS prediction model with Gaussian membership functions for *Ra* achieved R^2 of 0.989 for training and 0.963 for testing and RMSE of 0.112 and 0.223, respectively. These results indicate that the ANFIS model can predict Ra relatively accurately based on cutting parameters. Thus, the results of this research can be useful in C45 steel turning operations, which further enables assessment and improvement of cutting parameters to reduce *Ra*, thereby improving product quality.

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1. INTRODUCTION

Surface roughness is an important parameter commonly used to evaluate the surface quality of a part after machining. It dramatically affects friction, wear resistance, fatigue and other mechanical parts that are especially essential for the automotive, aerospace, and mechanical manufacturing industries [1]. Therefore, developing prediction models of surface roughness helps manufacturers find the best cutting parameters to achieve the required surface quality. Traditionally, surface roughness and other performance indexes are mainly analyzed and predicted based on the empirical models that relate to single-factor machining conditions such as cutting speed, feed rate, and tool construction. Regression analysis and other statistical methods were also used to quantify features of surface roughness and the factors that might influence it. However, as the more complex machining processes, these traditional methods have encountered limitations in accuracy and reliability [2].

Recently, many studies have aimed to develop predictive models for surface roughness to optimize production performance. They have produced trustworthy and efficient systems for assessing and influencing surface roughness in machining processes with various modeling strategies based on machine learning [3]. Ghani and Choudhury [4] emphasized the importance of selecting appropriate machining parameters to achieve high product quality and extended tool life. However, balancing these factors to give the desired surface quality is complex and time-consuming. Misaka et al. [5] integrated an analytical tool model with measurement data from CNC turning using the Co-Kriging method. Ficko et al. [6] investigated the influence of process parameters in water jet cut, including traverse speed, depth of cut, and abrasive mass flow rate, on surface roughness. They developed a predictive model based on a feed-forward Artificial Neural Network (ANN) and then used the k-fold cross-validation method to validate. Vasanth et al. [7] also utilized ANNs and regression models to predict surface roughness during the turning process of hardened SS410 steel based on factors such as cutting force, cutting temperature, tool wear, and tool vibration. Their study results concluded that the ANN model predicted surface roughness better than the regression model. Therefore, many other studies utilizing ANN for prediction have also been published in this field [7-9]. However, neural networks also have disadvantages, including the fact that the process is concealed or a 'black box' in nature, proneness to overfitting, requiring much computational power, and the empirical nature of model development [10-12].

Fuzzy systems are artificial intelligence applied in several engineering fields because they offer straightforward interpretation and quantification of knowledge in linguistic terms [10]. In contrast with conventional mathematical equations, fuzzy systems use fuzzy IF-THEN rules to describe the system's operation and give an approximate idea of

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the functions performed [13]. A significant benefit of fuzzy systems is their ability to emulate complex and ambiguous human knowledge. Therefore, fuzzy systems use linguistic terms to describe the behavior of systems, even when a primary mathematical model cannot accommodate them. In recent years, there has been a concern in the design of neuro-fuzzy systems in combination with neural networks. This combination leads to superior and more flexible ways of modeling complicated systems. Among them, one of the best approaches is the ANFIS, which combines the principles of ANNs and fuzzy logic to develop accurate models of highly complex systems within a short period [14]. This is because ANFIS takes advantage of smoothness from the fuzzy principle and adaptiveness from the neural network training structure [15]. Therefore, ANFIS has been applied in various fields, such as control systems [16, 17], industry [18-21], image processing [22], and some other fields.

In the machining field, many studies have published evidence of the effectiveness of ANFIS in predicting surface roughness and other indices based on experimental cutting parameters. For example, Kumar and Hynes [23] have used an integrated ANFIS and Genetic Algorithm (GA) to predict and optimize the surface roughness of thermally drilled holes in galvanized steel. Their results showed that the predicted surface roughness correlates with the experimental of 99.235 %, thus proving that the developed ANFIS-based model is quite efficient. Similarly, Kannadasan et al. [24] developed an intelligent prediction model based on ANFIS methodology capable of predicting performance parameters such as surface roughness and geometric tolerances in CNC machining. The experimental results demonstrated that this model could serve manufacturers well in predicting these indices based on different machining parameters and thus help them achieve necessary performance indices. In another study, Balonji et al. [25] employed ANN and ANFIS approaches to predict the surface roughness of machining aluminium Al6061 material. These models were combined with GA and Particle Swarm Optimization to improve the prediction model's performance. The results showed that population size, acceleration values, membership functions, neurons, and layers significantly impacted the prediction performance of the proposed models. In addition, there are studies related to applying the ANFIS model in machining prediction, and their conclusion showed similar results with high prediction performance [26-28]. Overall, these study results help to advance the existing knowledge about the effectiveness of ANFIS for estimating surface roughness and other values characteristic of machining operations. Combining different optimization algorithms with ANFIS and experiments with different influencing parameters improves the accuracy and applicability of these prediction models.

C45 steel, also called 1045 steel, belongs to a group of medium carbon steel with high tensile strength used in many manufacturing sectors [29]. It has high carbon content and good machinability, thus used in turning, milling, drilling, and grinding operations [30]. However, the type of machining operation and cutting parameters significantly affect the efficiency and surface quality of parts, which renews the need for the development of predictive models. This paper aims to consider the effects of three turning parameters, including V, f, and d, on Ra during the turning of C45 steel and develop a prediction model based on the machining parameters. The experimental plan was designed using the Taguchi method, and ANOVA analysis was used to investigate the effects of three turning parameters on Ra. Then, the ANFIS method was employed to develop a prediction model for Ra and evaluate the performance of the model. The findings from this study can be useful in C45 steel turning operations, which further enables assessment and improvement of cutting parameters to reduce Ra, thereby improving product quality.

2. METHODS AND MATERIAL

2.1 Design of Experiments

The turning experiments were conducted using C45 steel workpieces with a diameter of 40 mm and a length of 200 mm, mounted on an EL-550 TM model lathe machine. This machine features a main spindle power of 5.5 kW, and PV cutting oil coolant was applied during the process, as depicted in Figure 1. One end of each workpiece was secured in a chuck, while a revolving center supported the opposite end. The machining involved a 30 mm stroke on the workpiece to evaluate the surface roughness.

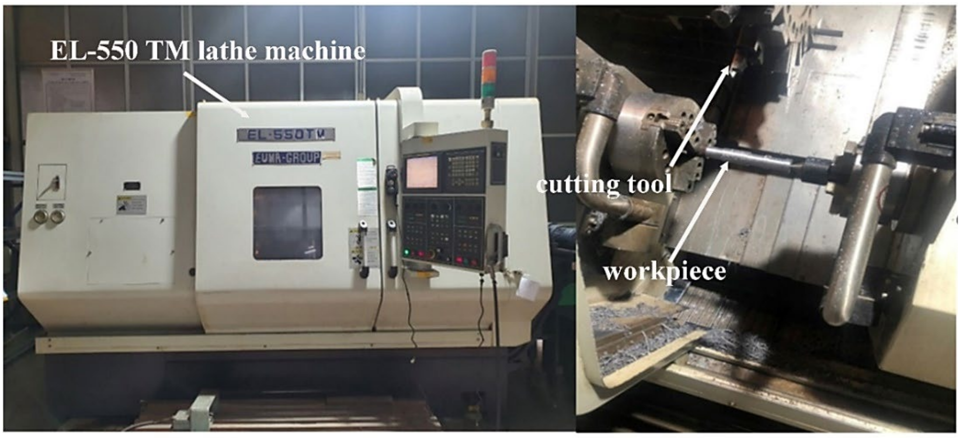

Figure 1. EL-550 TM model lathe machine and experiment workpiece

The workpieces' main chemical composition and mechanical properties are detailed in Table 1, according to the manufacturer's specifications and without any additional treatments or surface preparations before the experiment. The cutting tool used was a CCMT 120408-VL, an uncoated carbide tool with a sharp 80-degree rhombic angle and a 7-degree relief angle. Surface roughness and *Ra* measurements were subsequently taken with a TR200 roughness tester, with a display resolution of 0.001 µm. This tester uses a stylus with a 5 µm radius, which moves linearly along the machined surface to record the roughness data.

Table 1. Main chemical composition and mechanical properties of C45 steel

Chemical Composition (wt.%)					
C	Mn	Si	P	S	Cr
0.42 - 0.5	0.5 - 0.8	0.15 - 0.35	max 0.025	max 0.025	0.2 - 0.4
Mechanical Properties					
Yield Strength (MPa)		Tensile breaking (MPa)		Elongation (%)	Hardness (HRC)
350		610		15	23

The number of experimental samples is crucial in studies of machining predictive modelling. Many experimental samples allow for an increase in the accuracy of predictions and the model's reliability. Specifically, a large sample size results in greater power to detect the effects of the cutting parameters. In addition, it helps minimize variability and increases the accuracy of the estimates for each parameter. However, many samples will affect the experimental setup and processing cost. In this study, a CNC lathe machine conducted a series of cutting experiments based on the Taguchi method. This method can minimize the total number of experiments, providing accuracy and consistency. A factorial-based method uses the orthogonal array to assign the factors selected for an experiment [31]. Three critical cutting parameters, such as cutting speed, *V*, feed rate, *f*, and depth of cut, *d*, were considered based on a Taguchi L27 orthogonal array. Each parameter was evaluated at multiple specific levels, which were established based on recommendations from the tool chip manufacturer, insights from prior research, and the cutting parameters currently employed in the factory's turning processes. The specific levels and values for each parameter are detailed in Table 2.

Table 2. Taguchi L27 experimental design

No.	*V* (m/min)	*f* (mm/rev)	*d* (mm)	No.	*V* (m/min)	*f* (mm/rev)	*d* (mm)
1	100	0.05	0.50	15	150	0.10	1.50
2	100	0.05	1.00	16	150	0.15	0.50
3	100	0.05	1.50	17	150	0.15	1.00
4	100	0.10	0.50	18	150	0.15	1.50
5	100	0.10	1.00	19	200	0.05	0.50
6	100	0.10	1.50	20	200	0.05	1.00
7	100	0.15	0.50	21	200	0.05	1.50
8	100	0.15	1.00	22	200	0.10	0.50
9	100	0.15	1.50	23	200	0.10	1.00
10	150	0.05	0.50	24	200	0.10	1.50
11	150	0.05	1.00	25	200	0.15	0.50
12	150	0.05	1.50	26	200	0.15	1.00
13	150	0.10	0.50	27	200	0.15	1.50
14	150	0.10	1.00				

A larger number of experimental samples typically leads to higher prediction accuracy when constructing an accurate prediction model. However, a strategic approach was adopted to balance the need for sufficient data with the goal of minimizing experimental costs. Surface roughness measurements were conducted on three sections of the machined cylindrical part, each section separated by an angle of 120°. This method helps minimize result dispersion and maintain an acceptable number of samples by ensuring diverse yet representative data collection from different aspects of the same piece.

2.2 ANFIS Model

ANFIS is a model that integrates the neural network and fuzzy logic system. Specifically, fuzzy inference systems are adequate for representing expert knowledge but do not possess capabilities for automated learning. However, the neural networks perform well in the training from sample data, especially when specialist knowledge is limited, but does not possess knowledge representation capability. Figure 2 illustrates the ANFIS structure, which comprises three inputs such as cutting speed, *V*, feed rate, *f*, and depth of cut, *d*, and one output, *Ra*. The model consists of five layers, including input nodes, rule nodes, average nodes, following nodes, and output nodes [14].

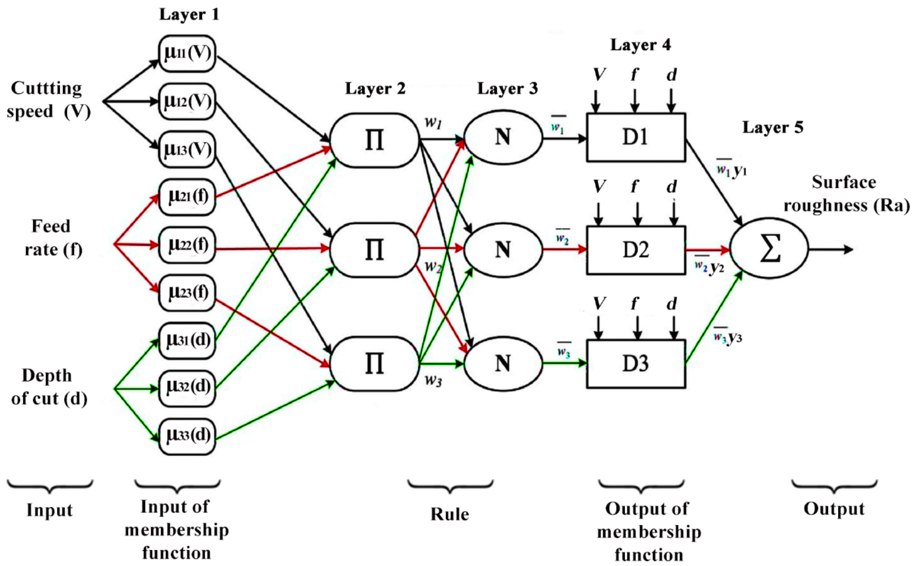

Figure 2. ANFIS architecture with three inputs of *V*, *f*, *d* and one output of *Ra*

The first layer in the ANFIS model is the input nodes layer, also known as the fuzzification layer. The membership relationship between the input and output functions of this layer can be defined as follows [32]:

$$\begin{gathered} O_{1,r} = \mu_{1i}(V) \\ O_{1,r} = \mu_{2j}(f) \\ O_{1,r} = \mu_{3k}(d) \\ \text{For } i, j, k = 1, 2, 3 \end{gathered} \tag{1}$$

The second layer in the ANFIS model is the rule nodes layer, also known as the product layer. This layer consists of two fixed nodes labelled *Π* and produces an output w, which represents the weight functions of the third layer [32]:

$$O_{2,r} = w_r = \mu_{1i}(V) \times \mu_{2j}(f) \times \mu_{3k}(d) \ \text{ For i, j, k =1, 2, 3.} \tag{2}$$

The third layer in the ANFIS model is the average nodes layer. This layer involves the normalized layer, which contains a fixed node labelled *N*. The outputs of this layer can be calculated as follows [32]:

$$O_{3,r} = \overline{w_r} = \frac{w_r}{\sum_{r=1}^{3} w_r} \ \text{ for r =1, 2, 3} \tag{3}$$

$$O_{3,r} = \overline{w_r} \times y_r = \overline{w_r}(p_r V + q_r f + r_r d + s_r) \text{ for } r = 1, 2, 3 \tag{4}$$

The fuzzy if-then rules from Takagi and Sugeno [33] are as follows:

If V is $\mu_{11}(V)$, f is $\mu_{21}(f)$, and d is $\mu_{31}(d)$, then $y_1=p_1\times V+q_1\times f+r_1\times d+s_1$

If V is $\mu_{21}(V)$, f is $\mu_{22}(f)$, and d is $\mu_{32}(d)$, then $y_2=p_2\times V+q_2\times f+r_2\times d+s_2$

If V is $\mu_{31}(V)$, f is $\mu_{32}(f)$, and d is $\mu_{33}(d)$, then $y_3=p_3\times V+q_3\times f+r_3\times d+s_2$

where $\mu_{1i}(V)$, $\mu_{2j}(f)$, *and* $\mu_{3k}(d)$ are the fuzzy sets, and y_i is the output set within the fuzzy region specified by the fuzzy rule. The parameters p_i, q_i, r_i and s_i are determined during the training process.

The fifth layer in the ANFIS model is the output nodes layer, also known as the defuzzification layer. This layer comprises a single fixed node labelled Σ, which summarises all incoming signals to produce the output. Hence, the output *Ra* can be expressed as follows [32]:

$$O_{5,r} = Ra = \sum_{r=1}^{3} (\overline{w_r} \times y_r) \tag{5}$$

For ANFIS model evaluation, the coefficient of determination, R^2 and Root Mean Square Error (RMSE). were used. R^2 is used as an index for measuring the model adequacy and for the significance of the overall variance of the dependent variable. However, R^2 does not indicate or define the actual size of prediction errors. For this reason, other parameters, such as RMSE, are used to test the validity of the results. RMSE quantifies the average prediction error in the same units as the target variable. A small RMSE value means that the model's predicted results are closer to the actual results. The combination of using R^2 and RMSE gives a balance between the size of the total model and the exactness of expectation, which allows accuracy in evaluating the quality and efficacy of the ANFIS model [34]. The equation of R_2 and RMSE are shown in Eqs. (6) and (7).

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(\hat{R}a - Ra)^2}{\sum_{i=1}^{n}(Ra - \bar{R}a)^2} \quad 0 \leq R^2 \leq 1 \tag{6}$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(\hat{R}_a - R_a)^2} \quad 0 \leq RMSE \leq +\infty \tag{7}$$

where n is the number of data, Ra is the value of predicted datasets, $\bar{R}$a is the average of Ra, and $\hat{R}$a is the average experimental datasets. The best fit developed- model can be determined in the case that RMSE values are closer to 0 and R^2 values closer to 1.

This study used the Fuzzy Logic Toolbox of Matlab R2018b software (MathWorks, Natick, Massachusetts) to develop a prediction model based on ANFIS. The 81 data sets were randomly divided into the training data set (75%) and the checking data set (25%). The training data set was utilized to train the ANFIS model. In contrast, the checking data set was employed to assess the accuracy and effectiveness of the trained ANFIS model in adapting learning content. The system was designed by selecting three inputs and inputting them into the network (3*3*3) with the Gaussian function type (see Figure 3). The membership functions for each of the three inputs were established as defaults. Additionally, training of the ANFIS model was set up with 100 epochs.

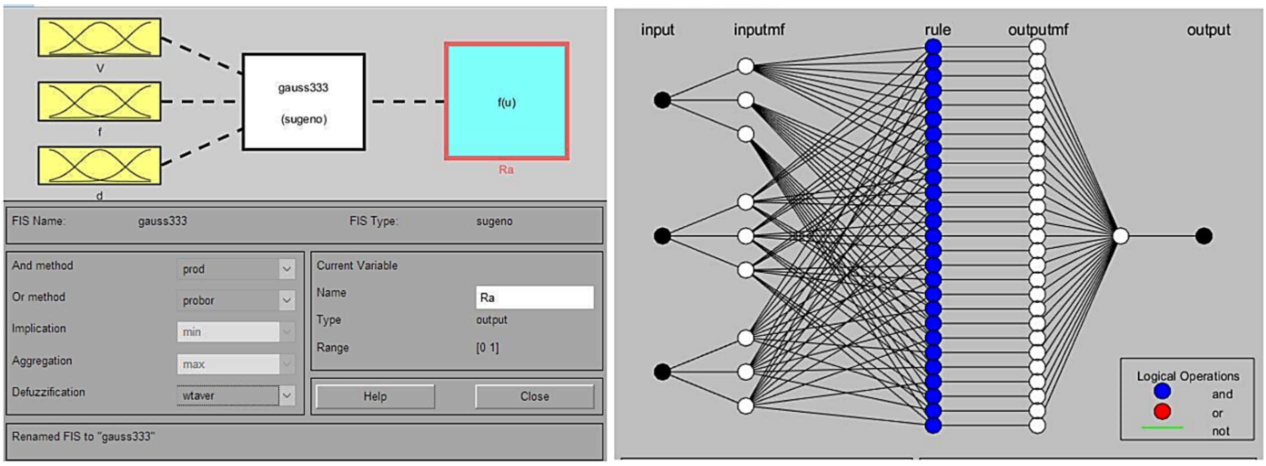

Figure 3. ANFIS network for predicting Ra using the Fuzzy Logic toolbox

3. RESULTS AND DISCUSSION

3.1 Influence of Cutting Parameters on *Ra*

ANOVA is a commonly employed statistical technique for investigating the impact of inputs on outputs in manufacturing operations, with a focus on significant parameters [35]. To determine significance, the P-value statistical index is utilized. The analysis in this study was conducted at a 5% significance level, corresponding to a 95% confidence level [36]. The ANOVA outcomes for surface roughness are provided in Table 3.

Table 3. Analysis of variance for *Ra*

Source	DF	Seq SS	Contribution	Adj SS	Adj MS	F-Value	P-Value
V	2	2.006	2.03%	2.006	1.0028	18.34	0.000
f	2	89.340	90.36%	89.340	44.6698	816.84	0.000
d	2	3.483	3.52%	3.483	1.7416	31.85	0.000
Error	74	4.047	4.09%	4.047	0.0547		
Lack-of-Fit	20	2.680	2.71%	2.680	0.1340	5.30	0.000
Pure Error	54	1.367	1.38%	1.367	0.0253		
Total	80	98.875	100.00%				

The results of the ANOVA analysis indicate significant effects of the cutting parameters V, f, and d on Ra. Specifically, the parameter f was the most influential, accounting for approximately 90.36% of the total variability in Ra, with an F-value of 816.84 and $p<0.05$, indicating a highly significant effect. This finding is consistent with previous studies that showed that f had the highest impact on surface roughness in turning processes [37-39]. These investigations show that increasing feed rates cause higher cutting forces and more grooves or scratches per revolution on the work surface, thus creating higher surface roughness. The parameters V and d also showed significant influence with $p<0.05$; however, these two parameters only contributed 2.03% and 3.52% of the variability, respectively. The model summary results showed that the R^2 value of 0.9591 means that the model is useful in explaining the variations of the response variable. Furthermore, the prediction sum of squares (PRESS) was 4.84857, and the predictive R^2 was 0.9510, suggesting good predictive power. However, a large lack of fit suggests that additional parameters and interactions in the model may not capture all underlying data interactions, which requires further examination.

Cutting parameters contour plots referring to *Ra* are depicted in Figure 4. These plots show that *Ra* decreases as the cutting speed increases from 100 to 200 mm/min. This improvement is largely due to the higher spindle speed, which helps eliminate the built-up edge (BUE) phenomenon, and the increased temperature in the cutting zone that softens the area locally, facilitating easier chip separation and reducing surface scratches [40]. Furthermore, an increase in feed rate from 0.05 to 0.15 mm/rev was observed to increase *Ra*. Additionally, increasing the depth of cut from 0.5 to 1.5 mm also resulted in a higher *Ra*. The larger contact area between the workpiece and the cutting tool because of the increased depth of cut results in the removal of more material and thus increases cutting force and, consequently, surface roughness during machining [37].

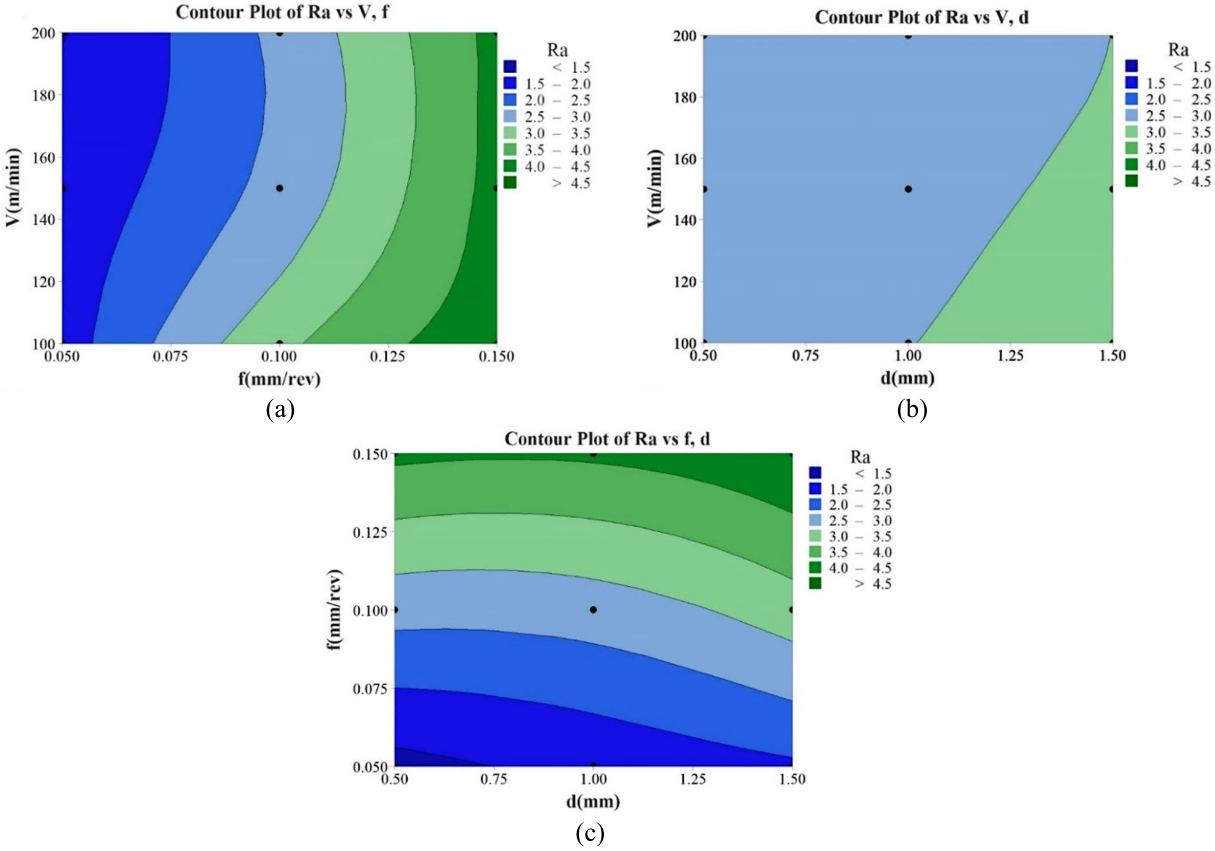

Figure 4. Contour plots for the influence of cutting parameters on *Ra*

3.2 ANFIS Model Evaluation

After the training process was complete, the efficiency of the ANFIS model was tested to identify the best fuzzy parameters. The grid partition method was used to structure the ANFIS model. This method involves partitioning the input space into smaller areas so that each area is related to a set of fuzzy rules and creating the membership functions of the input variables. The results after training are shown in Table 4, and the structure of the fuzzy inference system rules is illustrated in Figure 5.

Table 4. ANFIS results after the training process

No.	Parameter	Value
1	Number of nodes:	78
2	Number of linear parameters:	27
3	The number of nonlinear parameters:	18
4	Total number of parameters:	45
5	Number of training data pairs:	56
6	Number of checking data pairs:	0
7	The number of fuzzy rules:	27

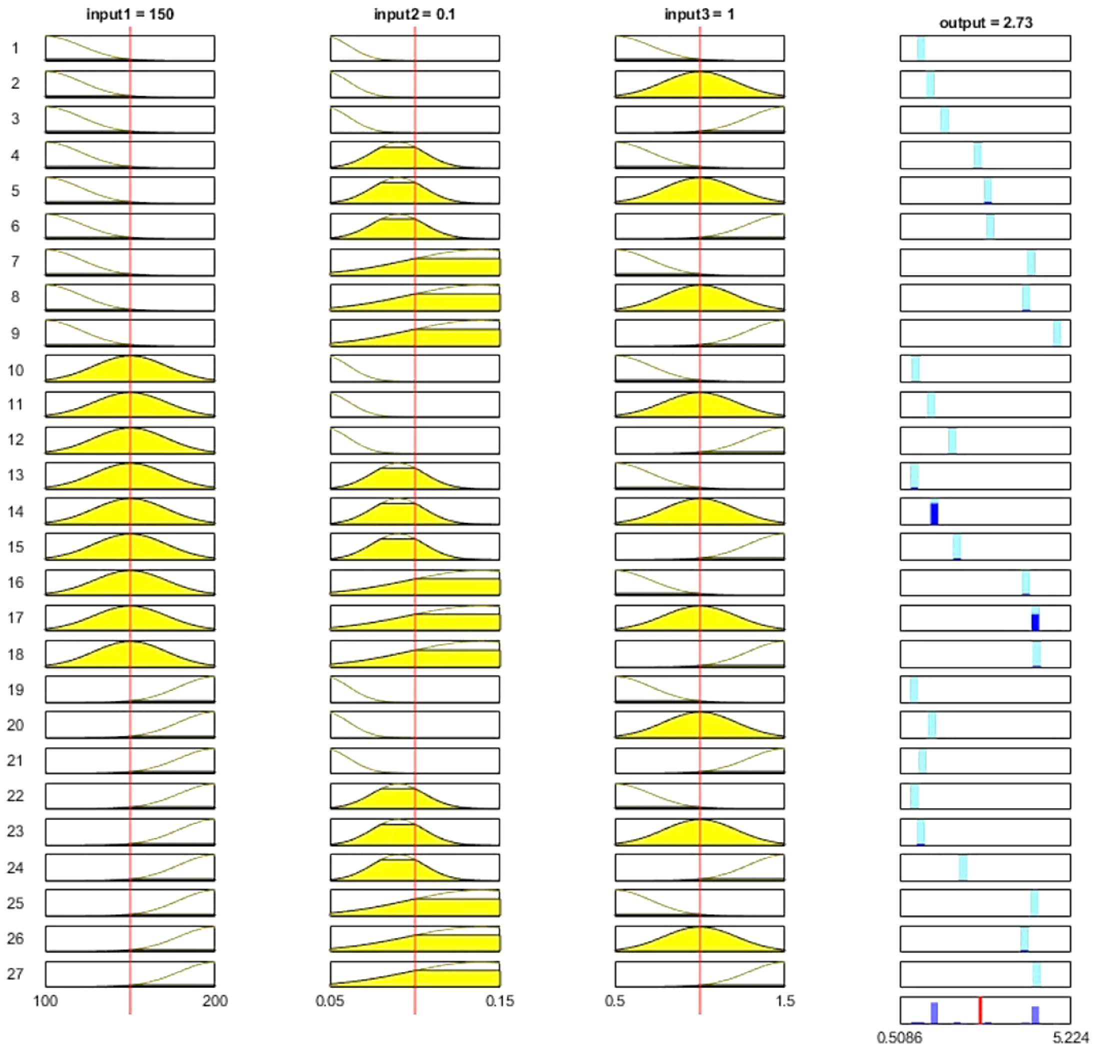

Figure 5. Twenty-seven rules of the ANFIS model

Two evaluation parameters were utilized to assess the performance of the selected ANFIS prediction model, namely R^2 and RMSE. The calculated R^2 values were 0.989 for the training dataset and 0.963 for the testing dataset, demonstrating the model's accuracy in prediction. Specifically, an R^2 of 0.989 for the training dataset indicates that the model has explained 98.9% of the variation in the dependent variable, which is quite a good fit for the training data. On the other hand, the testing dataset suggests that the model shows 96.3% of the test dataset's variance. While this is below the value observed within the training set, it remains above the acceptable threshold of a good predictor. These high levels of precision are further affirmed in the graphs presented in Figures 6a and 6b. These figures show that most of the actual values of *Ra* are closely fitted to the regression line, suggesting that the model appropriately reflects the tendency of the predictors influencing Ra. In addition, no systematic deviation from the regression line was found, indicating no obvious error patterns that can invalidate the model's reliability [41].

RMSE was used to quantify the average difference between the predicted values and the actual observed values, serving as a measure of the model's predictive accuracy. The value for RMSE of the ANFIS training and test sets was 0.112 and 0.213, respectively. The results indicate a slight increase in the testing dataset, which suggests that the model generalizes well. This implies that the ANFIS model has captured the training data well and operates satisfactorily on other data, which is crucial for *Ra* prediction. Figures 6c and 6d emphasize this result by comparing the predicted values from the ANFIS model with the actual values of *Ra*. Compared with the actual values, the predicted values are also near the actual values, which shows that the proposed ANFIS models might accurately predict Ra based on the cutting speed, feed rate, and depth of cut.

This study has several limitations that should be acknowledged. Firstly, the predictive model developed only considers three cutting parameters: cutting speed, feed rate, and depth of cut. These parameters were chosen because they can be easily adjusted in actual machining processes. However, numerous other factors, such as cooling conditions, machine vibration, and tool material, can impact surface roughness in machining processes. Future studies should, therefore, expand the range of factors considered to develop a more comprehensive and reliable prediction model. Secondly, the model presented in this study does not immediately apply to other machining contexts or materials without modifications. Retraining and customization are necessary to adapt the model to different scenarios. The ANFIS model developed here also used a specific structure (3*3*3) and Gaussian membership functions. While effective for this study, these may not be optimal for all applications, and other models may achieve higher performance. However, such techniques as ANFIS are valuable in automated manufacturing systems despite their above-detailed limitations. These models are very important in controlling part quality, especially concerning surface roughness on machined parts. Future work includes the continued extension and adaptation of ANFIS, including considering the impact of more factors that might influence the ANFIS and experimenting with different structures for the proposed model. This offers much potential for increasing the quality of the manufacturing process, particularly in real-time data integration, which might further improve the mentioned models' predictive power in the context of automated manufacturing.

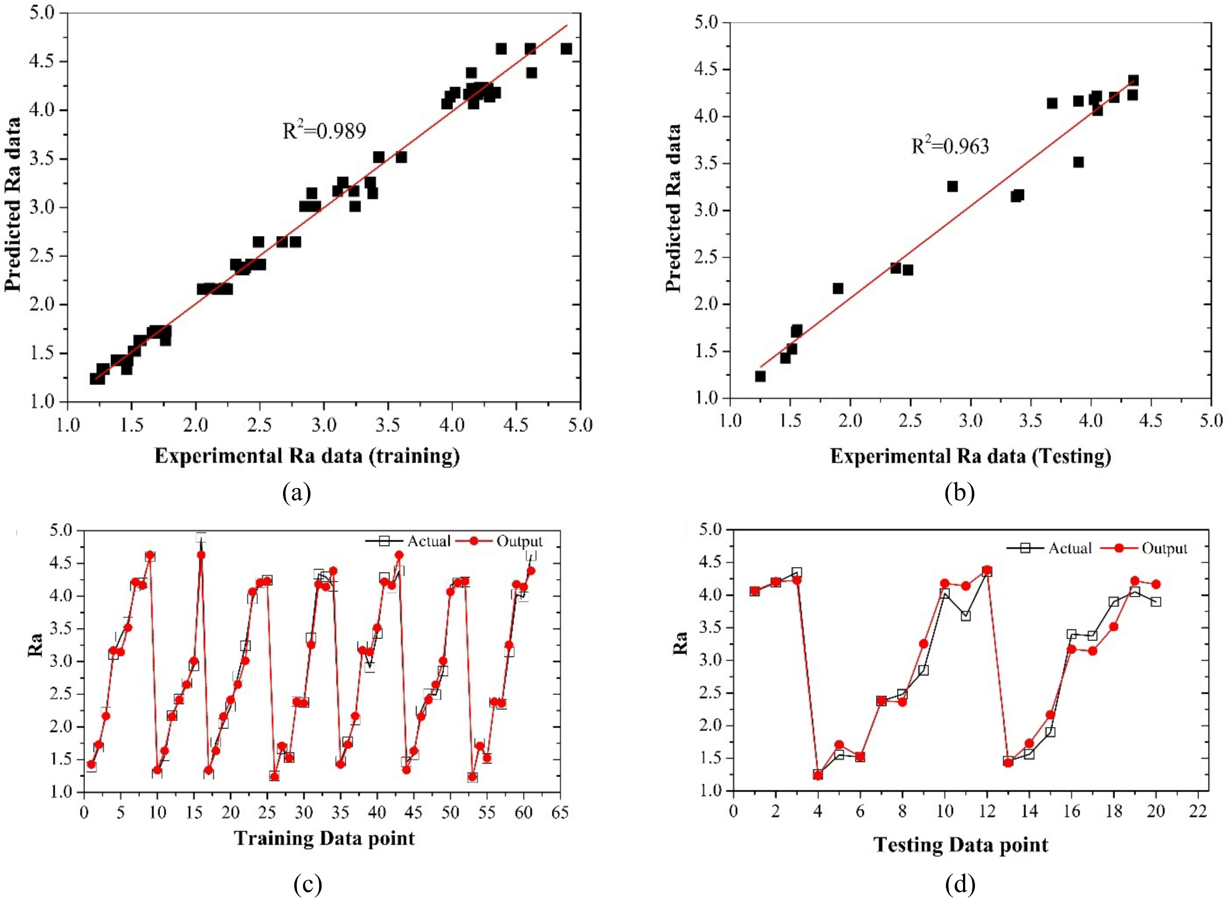

Figure 6. (a,b) Correlation coefficient of ANFIS model and (c,d) comparison of the experimental and predicted data

4. CONCLUSIONS

This study investigated the impact of machining parameters, namely cutting speed, feed rate, and depth of cut, on *Ra* in the turning of C45 steel. Subsequently, an ANFIS is employed to develop a prediction model for *Ra*. Subsequently, an ANFIS is employed to develop a prediction model for *Ra*. The results obtained from the ANOVA demonstrated that the feed rate had the most significant influence on the generated *Ra*, followed by cutting speed and depth of cut. Furthermore, an effective prediction model for *Ra* was successfully developed using ANFIS. The prediction model's performance evaluation indicated that near-real *Ra* predictions can be achieved by combining information from the cutting parameters. As a result, the proposed model can serve as a valuable reference for enhancing surface quality control, optimizing machining parameters, and improving both the production process and product quality.

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CONFLICT OF INTEREST

The authors declare no conflicts of interest to report regarding the present study.

AUTHORS CONTRIBUTION

C. C. Tran (Methodology; Data Curation; Writing - Original Draft; Project Administration)
V. T. Nguyen (Formal Analysis; Software; Writing - Review & Editing)

AVAILABILITY OF DATA AND MATERIALS

The data supporting this study's findings are available on request from the corresponding author.

ETHICS STATEMENT

Not applicable

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