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Comparison Of Fuzzy Logic And Neural Network Models For Surface Roughness Prediction İn Turning Of AISI 304 Stainless Steel

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Abstract: *This study presents a comparative analysis of fuzzy logic and neural network-based predictive models for estimating surface roughness (Ra) in the turning of AISI 304 stainless steel. Experimental trials were conducted using a two-axis CNC lathe, with cutting speed, feed rate, and depth of cut as input parameters. A full factorial design of experiments was used, and Ra measurements were obtained using a Mitutoyo SJ-210 surface roughness tester. A Mamdani-type fuzzy inference system and a feedforward neural network (3-10-1 structure, trained using the Levenberg-Marquardt algorithm in MATLAB) were developed. The performance of each model was evaluated in terms of RMSE and R^2. The neural network model achieved an RMSE of 0.155 µm and R^2 of 0.98, slightly outperforming the fuzzy logic system. Results indicate that both models provide reliable surface roughness predictions and can support intelligent manufacturing systems.*

Keywords: *AISI 304, surface roughness, CNC turning, fuzzy logic, neural network, MATLAB*

1. INTRODUCTİON

Stainless steels, particularly AISI 304, are widely employed in the manufacturing industry due to their exceptional corrosion resistance, formability, and weldability. However, their low thermal conductivity and high work-hardening tendency make them difficult to machine efficiently (Gao et al., 2023). Surface roughness, a critical quality indicator in machining operations, significantly affects functional performance parameters such as friction, wear resistance, fatigue strength, and dimensional precision (Aydın et al., 2013; Zhou et al., 2019).

In turning operations, surface roughness is predominantly influenced by cutting parameters, including cutting speed (Vc), feed rate (f), and depth of cut (ap). Among these, feed rate is generally considered the most critical factor affecting Ra values, as supported by both empirical studies and modeling approaches (Naresh et al., 2021). While conventional statistical models like regression and Taguchi methods have been traditionally used for surface quality prediction, they often fall short in capturing complex nonlinearities inherent in machining processes (Chandrakasan et al., 2010).

To overcome these limitations, artificial intelligence (AI) techniques have emerged as powerful alternatives for predictive modeling in manufacturing. Among these, fuzzy logic (FL) systems and artificial neural networks (ANNs) have shown significant promise due to their ability to approximate uncertain and nonlinear relationships based on experimental data. FL uses linguistic rules and membership functions to represent expert knowledge and manage ambiguity, making it especially suitable for manufacturing environments where exact mathematical modeling is challenging (Chandrakasan et al., 2010; Aydın et al., 2013). On the other hand, ANNs offer adaptive learning capabilities and robust generalization performance without requiring predefined rule sets, as emphasized by Xu et al. (2023) and Gao et al. (2023).

This study aims to develop and compare fuzzy logic and neural network models for predicting surface roughness in AISI 304 stainless steel turning processes. The models are trained on experimental data obtained through a fractional factorial design, considering three input variables—Vc, f, and ap—and one output variable, Ra. The results are evaluated using statistical metrics such as RMSE and R^2, and the predictive accuracy of each model is assessed. The research contributes to intelligent process planning and real-time surface quality estimation, supporting smart manufacturing applications.

2. Experimental Procedure

2.1 Material and Equipment

The experiments were carried out on cylindrical AISI 304 stainless steel bars (100 mm diameter × 250 mm length) using a 2-axis CNC lathe. Cutting inserts were of type WNMG 080408. All tests were conducted under dry cutting conditions. Ra measurements were recorded using a Mitutoyo SJ-210 surface roughness tester as per ISO 4287 standards.

2.2 Cutting Parameters and DOE Three levels were defined for each input:

- Cutting speed (Vc): 120, 170, 250 m/min
- Feed rate (f): 0.10, 0.25, 0.40 mm/rev
- Depth of cut (ap): 1.0, 1.5, 2.0 mm A half-factorial design was used, totaling 11 experiments. Each condition was selected to represent a meaningful range of industrial turning parameters.

2.3 Data Set Table 1 presents the experimental data including cutting parameters and corresponding measured Ra values.

Experiment No	Cutting Speed (Vc, m/min)	Feed Rate (f, mm/rev)	Depth of Cut (ap, mm)	Surface Roughness (Ra, µm)
1	120	0.10	1.0	0.42
2	250	0.10	1.0	0.34
3	120	0.40	1.0	3.52
4	250	0.40	1.0	3.74
5	250	0.40	2.0	4.10
6	120	0.40	2.0	3.40
7	250	0.10	2.0	0.42
8	120	0.10	2.0	1.62
9	170	0.25	1.5	1.42
10	170	0.25	1.5	1.38
11	170	0.25	1.5	1.38

The measured surface roughness (Ra) values ranged from 0.34 to 4.10 µm. Feed rate had the most significant influence on Ra, followed by interactions between cutting speed and depth.

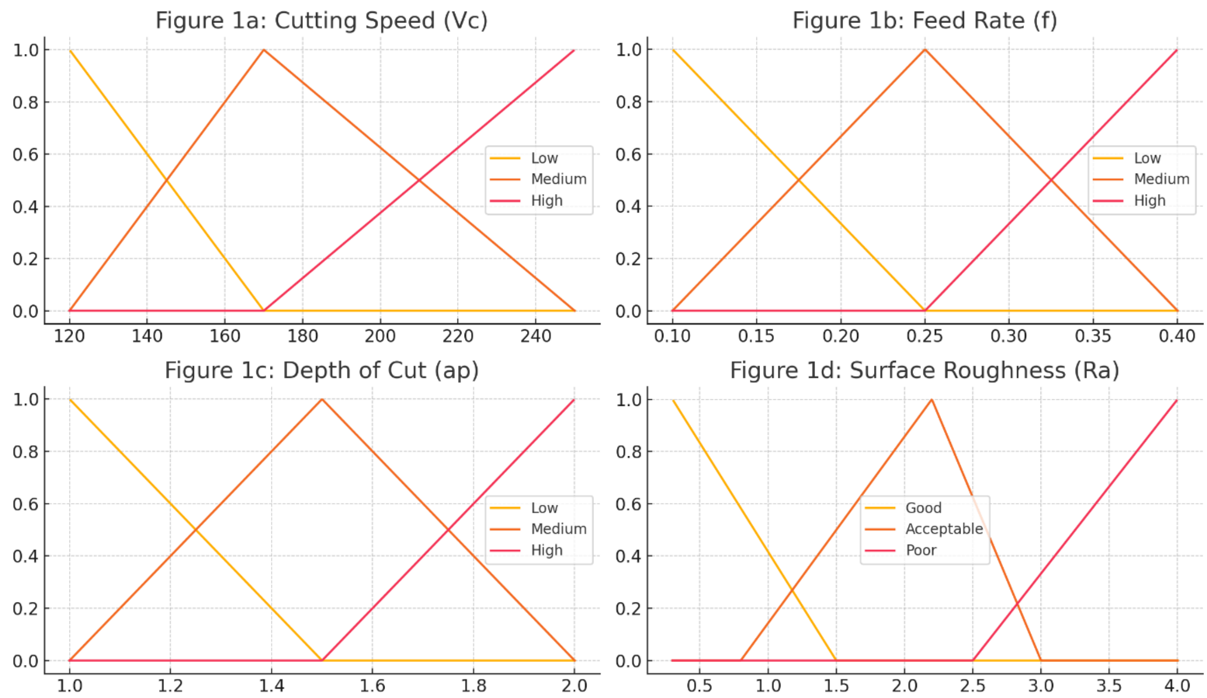
3. Fuzzy Logic Modeling

A Mamdani-type fuzzy inference system was constructed in MATLAB using triangular membership functions for both input and output variables. The input parameters—cutting speed (Vc), feed rate (f), and depth of cut (ap)—were each divided into three fuzzy sets: Low, Medium, and High. The output variable, surface roughness (Ra), was categorized into three sets: Good, Acceptable, and Poor.

The system utilized a total of 15 fuzzy rules, which were derived from machining knowledge and observed data trends. For example:

- If Vc is Low AND f is Low AND ap is Low THEN Ra is Good
- If Vc is High AND f is High AND ap is High THEN Ra is Poor

The rules were combined using the minimum (AND) operator and the max-min composition method. The centroid method was used for defuzzification. The fuzzy logic model showed good performance particularly in predicting surface roughness at lower and mid-range values. Its interpretability made it useful for understanding parameter interactions, although extreme values were predicted with slightly less precision. Figure 1 illustrates the triangular membership functions used for the fuzzy logic model:



- **Figure 1a**: Membership functions for Cutting Speed (Vc)
- **Figure 1b**: Membership functions for Feed Rate (f)
- **Figure 1c**: Membership functions for Depth of Cut (ap)
- **Figure 1d**: Membership functions for Surface Roughness (Ra)

4. Neural Network Modeling The neural network model was implemented using MATLAB's Neural Network Toolbox, aiming to capture complex nonlinear relationships between machining parameters and surface roughness. A multilayer feedforward neural network (MLFFNN) architecture was used. The input layer consisted of three neurons representing the input features: cutting speed (Vc), feed rate (f), and depth of cut (ap). These were connected to a single hidden layer composed of 10 neurons using a tangent sigmoid activation function. The output layer consisted of one neuron with a linear activation function to predict surface roughness (Ra). Figure 2 presents the architecture of the developed neural network model.

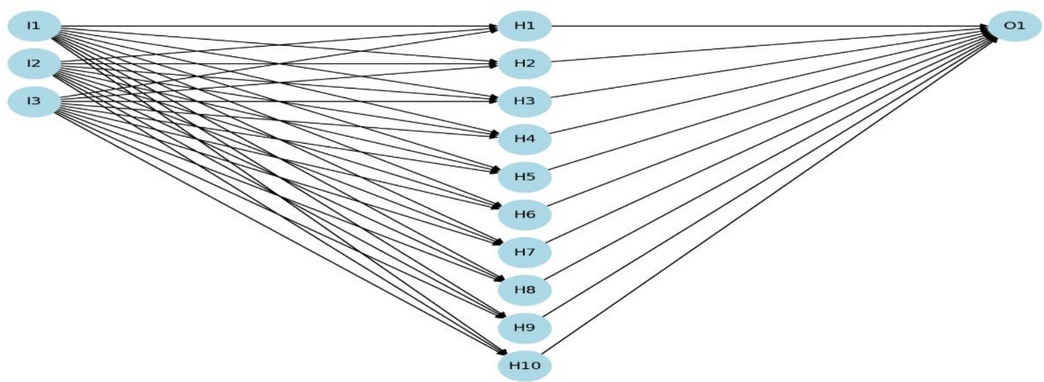


Figure 2. Neural Network Architecture Used in the Study

Prior to training, the data were normalized to improve convergence. The dataset was divided into three subsets: 70% for training, 15% for validation, and 15% for testing. The Levenberg–Marquardt backpropagation algorithm was selected due to its robustness and efficiency in training small- to medium-sized datasets.

During training, the model's performance was monitored through the mean squared error (MSE) on validation data. Early stopping was implemented to prevent overfitting. Once trained, the model was evaluated on the test dataset.

The neural network demonstrated strong generalization ability, with an RMSE of 0.155 µm and a coefficient of determination (R^2) of 0.98 on the test set. The predicted Ra values closely matched the

experimental measurements. Residual analysis revealed random distribution, indicating good model fit. Compared to the fuzzy logic model, the neural network achieved slightly better predictive accuracy, especially for samples with extreme Ra values, which are generally harder to model with rule-based systems.
In conclusion, the neural network proved effective in surface roughness prediction, leveraging its capacity to learn from data patterns without explicit rule formulation.

Table 1. Experimental Results and Model Predictions

Experiment No	**Vc (m/min)**	**f (mm/rev)**	**ap (mm)**	**Actual Ra (µm)**	**Fuzzy Predicted Ra (µm)**	**NN Predicted Ra (µm)**
1	120	0.10	1.0	0.42	0.53	0.48
2	250	0.10	1.0	0.34	0.39	0.36
3	120	0.40	1.0	3.52	3.25	3.39
4	250	0.40	1.0	3.74	3.55	3.65
5	250	0.40	2.0	4.10	3.91	4.00
6	120	0.40	2.0	3.40	3.20	3.33
7	250	0.10	2.0	0.42	0.55	0.47
8	120	0.10	2.0	1.62	1.65	1.70
9	170	0.25	1.5	1.42	1.35	1.40
10	170	0.25	1.5	1.38	1.31	1.34
11	170	0.25	1.5	1.38	1.32	1.36

Figure 3 compares the actual surface roughness values obtained from experiments with the values predicted by the fuzzy logic and neural network models. The graph demonstrates the effectiveness of both models in approximating the true Ra values, with the neural network performing slightly better in terms of closeness to actual results.

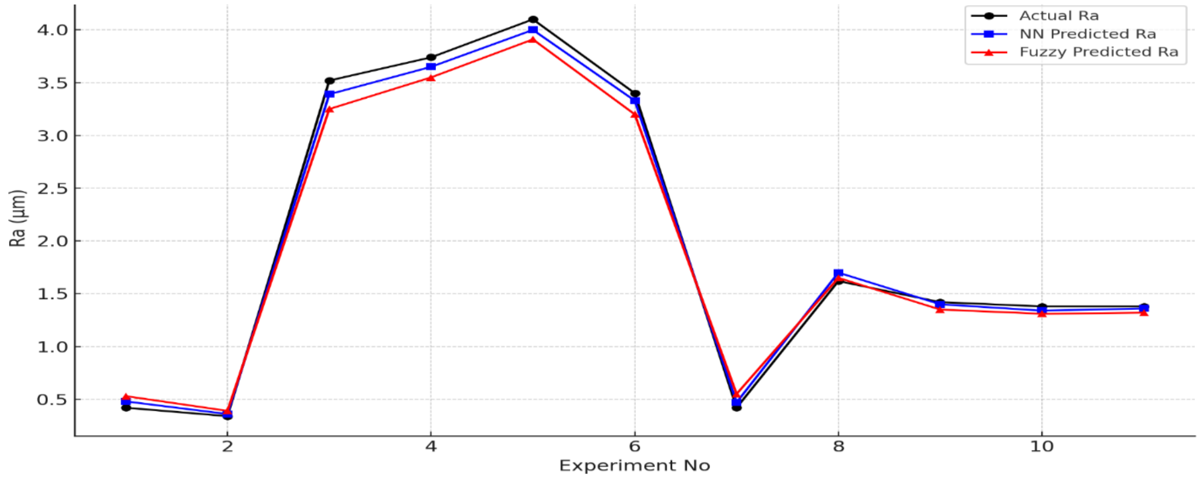


Figure 3. Actual nd Predicted Surface Roughness (Ra)
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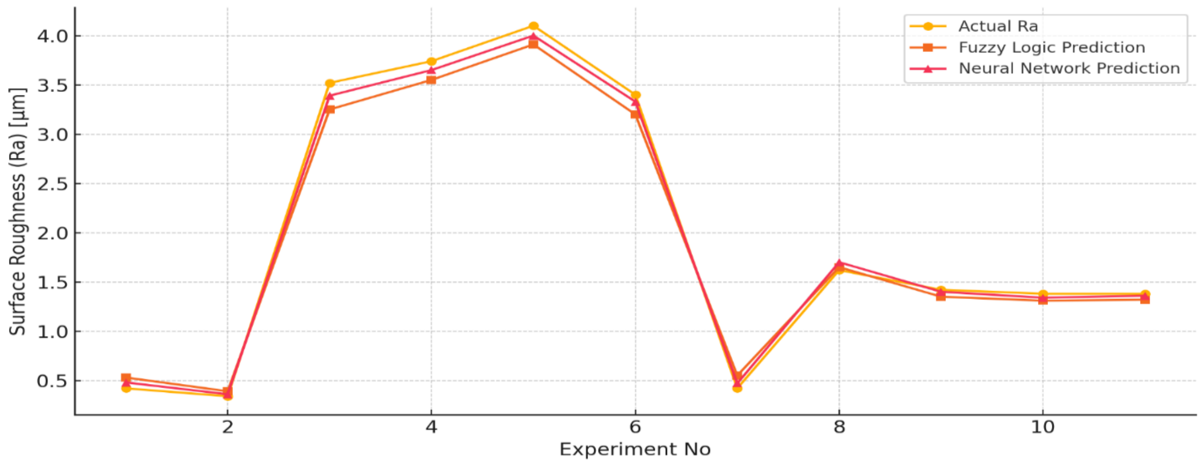

Figure 4 provides another visual comparison between actual Ra values and those predicted by both the fuzzy logic and neural network models across all experiments.
In conclusion, the neural network proved effective in surface roughness prediction, leveraging its capacity to learn from data patterns without explicit rule formulation.

5. CONCLUSİON

This study explored the use of two intelligent modeling techniques—fuzzy logic and neural networks—for predicting surface roughness during the turning of AISI 304 stainless steel. The experimental results clearly showed that feed rate was the most influential parameter on surface roughness, in agreement with prior research (Aydın et al., 2013; Chandrakasan et al., 2010). High feed rates resulted in deeper tool marks and higher Ra values, while lower feeds produced smoother surfaces.
The fuzzy logic model, based on expert-derived rules and triangular membership functions, demonstrated reasonable prediction performance. However, the neural network model showed superior accuracy with an RMSE of 0.155 µm and R^2 of 0.98, validating its strong learning ability without requiring an explicit rule base—consistent with findings from Naresh et al. (2021), Zhou et al. (2019), Gao et al. (2023), and Xu et al. (2023), which emphasize deep learning and hybrid modeling in surface finish predictions.
Overall, both methods proved viable for predictive modeling of surface roughness, but neural networks offered a slight edge in precision and generalization. These findings support the application of intelligent systems for process optimization and quality prediction in advanced manufacturing environments.

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