Fuzzy modeling of surface roughness during wet turning of AISI D3 tool steel

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Abstract. In this study, an attempt has been made to develop a Mamdani fuzzy inference system-based predictive model for predicting surface roughness during wet turning of AISI D3 tool steel. The influence of machining parameters on surface roughness is also investigated. The experimental runs were performed on a lathe using Taguchi’s L₉ orthogonal array to know the effect of cutting parameters on machining surface roughness. The performance of the fuzzy model was also compared with the regression model. The fuzzy model's prediction efficiency (92.10%) was found better than the regression model (70.33%). Therefore, the resultant model so developed is found adequate for surface roughness prediction purposes within the parametric range.

1. Introduction
Tool steel is mainly used as working parts of a tool that should endure high cyclic load during its service and should be wear-resistant. Since the tool steel is primarily used at a higher temperature, its selection as tool material also must include high toughness and wear resistance. Plain carbon steel cannot satisfy all tooling problems; that’s why alloying elements are added to plain carbon steel to enhance the mechanical properties. Achieving a better surface quality, tool life, and dimensional accuracy are the crucial concerns in turning hardened steels [1]. The cutting tool is the main critical element in hard turning, and an increase in wear resistance has characterized the development of newer cutting tool materials. Some work has been done on various hardened steels with CBN and PCBN cutting tools. According to recent research, few studies have been reported on the wet turning of AISI D3 steel. Ceramic tools are widely used in the manufacturing industry to machine various hard materials such as alloy steels, die steels, high-speed steels, bearing steels, white cast iron, and graphite cast iron [2-6]. Some studies have been carried out on machining parameters such as surface roughness, tool wear, productivity, and cutting force by employing ANOVA and other modeling and optimization techniques in hard turning [7-9]. Bouchelaghem et al. [10] applied response surface methodology (RSM) to determine the effect of machining variables on the output response using CBN inserts. In contrast, Varapradas et al.[11] developed a model based on RSM based central composite design to predict the ceramic flank wear during machining of AISI D3 steel. Kribes et al.[12] carried out...
statistical analysis to find the effect of feed rate, cutting speed, and depth of cut on surface roughness during hard turning of 42CrMo4 steel. Neseli et al. [13] used RSM to optimize the tool geometry of hard turning of AISI 1040 with P25 tool for minimum surface roughness.

In this paper, the fuzzy-based model is employed to model machining parameters of the wet turning of AISI D3 tool steel. The combined effects of feed, cutting speed, and depth of cut are determined on surface roughness. Analysis of variance (ANOVA) analysis is also performed to quantify the effect of machining parameters. First, a linear regression model is presented because of its simplicity in predicting the response. Furthermore, the artificial intelligence-based predicted model is proposed using fuzzy logic to attain a remarkable improvement of surface roughness prediction. In this context, very few research studies have presented such a prediction model during the machining of D3 tool steel.

2. Experimental Procedure
Taguchi’s L9 OA is utilized for experimentation considering three input cutting parameters viz. cutting speed (s), feed (f), and depth of cut (d). Turning of D3 tool steel was performed under wet conditions. The levels of input parameters considered in this study are given in Table 1.

| Parameters          | Units   | Parameter levels |
|---------------------|---------|------------------|
| Cutting speed (s)   | rpm     | 192, 325, 420    |
| Feed (f)            | mm/rev  | 0.05, 0.1, 0.2   |
| Depth of cut (d)    | mm      | 0.2, 0.6, 1      |

3. Machining process
In the present study, D3 steel was chosen as workpiece material. As per the experimental plan (i.e., L9 orthogonal array), experiments were carried out on NH22 lathe (Make: HMT) with CCMT 060208 (Make: SANDVIK–COROMANT) inserts, as shown in Figure 1. These inserts are having a 0.8 mm nose radius. The METACOOL (SAE 40 grade) cutting fluid is also used to assist the machining.

The machined surface's surface roughness is measured using the SJ301 surface roughness tester (Make: Mitutoyo). These results constituted an experimental dataset. This dataset is utilized for regression analysis and analysis of the proposed fuzzy inference system (FIS) model. The correlation between surface roughness and machining parameter was investigated using the model analysis results. For the data analysis, a statistical significance level of 0.05 is selected.
Table 2. Experimental results.

| Exp. Trial Runs | Cutting parameter | Response parameter | Residuals |
|-----------------|-------------------|--------------------|-----------|
|                 | Cutting speed s (rpm) | Feed depth f (mm/rev) | Depth of cut d (mm) | Surface Roughness (µm) Experimental | Regression Predicted | Fuzzy Predicted | Regression | Fuzzy |
| 1               | 420               | 0.20               | 1.0          | 4.638               | 4.417               | 4.228               | 0.220       | 0.409 |
| 2               | 420               | 0.10               | 0.6          | 2.798               | 2.990               | 2.330               | -0.192      | 0.467 |
| 3               | 420               | 0.05               | 0.2          | 2.376               | 2.025               | 2.293               | 0.351       | 0.083 |
| 4               | 325               | 0.20               | 0.6          | 3.910               | 3.731               | 3.261               | 0.179       | 0.649 |
| 5               | 325               | 0.10               | 0.2          | 2.451               | 2.304               | 2.330               | 0.147       | 0.120 |
| 6               | 325               | 0.05               | 1.0          | 1.883               | 2.851               | 2.300               | -0.968      | -     |
| 7               | 192               | 0.20               | 0.2          | 2.374               | 2.972               | 2.293               | -0.598      | 0.081 |
| 8               | 192               | 0.10               | 1.0          | 3.704               | 3.057               | 3.261               | 0.647       | 0.443 |
| 9               | 192               | 0.05               | 0.6          | 2.311               | 2.091               | 2.293               | 0.219       | 0.018 |
| MAPE            |                   |                    |              |                     |                     |                     |             |      |
|                 |                   |                    |              |                     |                     |                     | 15.61       | 9.88  |

4. Modeling preliminaries
The regression technique correlates the controllable and response variables to found the relationship between these variables. A mathematical expression is formulated between these variables as described by equation 1.

\[ y = \beta_0 + \beta_1 x \]  

Where \( y \) is the response parameter, \( x \) is the predictor variable and \( \beta_0 \) and \( \beta_1 \) denotes coefficients. Regression models are primitive, yet they solved numerous problems. But sometimes, they lack to capture to nonlinearity present in the system. With the advancement in technology, several new and advanced methods are emerging to solve this problem. A fuzzy logic method is an artificial intelligence based method that can model the system's nonlinearity.

5. Development of Prediction Models
From the ANOVA study of the experimentally generated dataset, it is found that the surface roughness is directly proportional to feed (s) and depth of cut (d). Figure 2 is depicting the increase in surface roughness with increasing levels of feed and depth of cut. This increase in surface roughness values is due to increased chip cross-sectional area, which increases with the increasing feed (f) and depth of cut (d). This increase in the cross-sectional area raises friction in the cutting zone, resulting in low surface quality. The effect of feed can also be easily understood by its theoretical definition. The cutting speed also influenced the surface roughness at its higher level to some extent. It can be attributed to an increase in tool wear with increasing cutting speed.
Figure 2. Main effect plot for surface roughness.

From the statistical analysis, it was also found that there is a strong relationship between response parameter with feed (f) and depth of cut (d). Still, it will be interesting to know the contribution of machining parameters to the response parameter. Therefore ANOVA analysis is performed using statistical software (MINITAB). The results of ANOVA analysis are shown in Table 3.

Table 3. Results of analysis of variance.

| Source          | dof | Sum of Squares | Mean Square | F Value | p-value Prob> F | Contribution (%) |
|-----------------|-----|----------------|-------------|---------|-----------------|------------------|
| Cutting Speed (s) | 1   | 0.2912         | 0.2912      | 0.72    | 0.435           | 04.27            |
| Feed (f)        | 1   | 2.9799         | 2.9799      | 7.36    | 0.042           | 43.70            |
| Depth of Cut (d)| 1   | 1.5241         | 1.5241      | 3.77    | 0.11            | 22.35            |
| Residual        | 5   | 2.0232         | 0.4046      |         |                 | 29.68            |
| Total           | 8   | 6.8184         |             |         |                 |                  |

Also, an attempt has been made to develop a predictive model using machining dataset by regression analysis. Such models seek to predict the response variables for the predefined parametric space without conducting experiments. Hence, these developed models help for desired parameter selection with the least utilization of resources. The developed regression model to predict the surface roughness is shown in equation (2).

\[ SR (\mu m) = 0.505 + 0.00192 \times s + 9.23 \times f + 1.26 \times d \] (2)

An artificial intelligence-based fuzzy model is further developed to explore the system's nonlinearity understudy against the linear regression model. The fuzzy model uses fuzzy rules to define the relationship
between input and output process variables. These fuzzy rules use linguistic variables and consist of general statements [14]. The general structure of IF-THEN rules as follows:

Rule 1: If \( s=a_1, f=b_1, d=c_1 \) then \( SR=e_1 \); else

Rule 2: If \( s=a_2, f=b_2, d=c_2 \) then \( SR=e_2 \); else

Rule n: If \( s=a_n, f=b_n, d=c_n \), then \( SR=e_n \)

The various input parameters were weighed to formulate fuzzy rules according to their respective association to the degree of membership. The input and output variables are fuzzified and represented by means of membership functions (MF), as shown in figure 3. After that Mamdani based fuzzy inference system (FIS) was developed using various IF-THEN rules. The output of FIS system was eventually defuzzified using the centroid of area method. The fuzzy model prediction results along with the experimental results and the regression model prediction are shown in Table 2.

![Figure 3](image-url)  
**Figure 3.** Fuzzy modeling: (a-c) machining parameters and (d) response parameter.
The prediction efficiency of both models is also compared, as depicted in figure 4. It can be observed that the fuzzy model predicted values are along the trend line (below line). The fuzzy model has 92.10% prediction efficiency for the present machining process to predict the surface roughness. In contrast, the prediction efficiency of the regression model was found 70.33%.

![Performance plot for developed models.](image)

**Figure 4.** Performance plot for developed models.

Figure 5 is showing the plots of residuals for the predictive models. As the fuzzy model has less variation than the regression model, it is better for the prediction purpose.

![Residuals plots.](image)

**Figure 5.** Residuals plots.

The model predicted values are also compared with experimental outcomes for easy comparison of both models. Figure 6 is depicting the comparison of both the models to predict the response parameter. The
fuzzy model predicted surface roughness close to the observed values. The fuzzy model is found to have a mean absolute error (MAPE) of 9.88% only, which is permissible under the statistical limit and representing the robustness of the predictive model.

![Graph showing experimental, fuzzy, and regression results.](image)

**Figure 6.** Actual Vs predicted results.

As the present study's fuzzy model is found superior to the regression model, the response plot is also developed for the whole design space using this model. Figure 7 is depicting the response plot for easy parameter selection for machining of D3 tool steel.

![Response plots for surface roughness.](image)

**Figure 7.** Response plots for surface roughness.

The prediction of machining characteristics helps in machining parameter selection for the quality improvement of the product. Therefore, an attempt is made to improve the prognosis of the machined part's surface quality in this study through the model study.
6. Conclusion
The experimental work and data analysis found that feed (f) and depth of cut (d) have a substantial influence on the surface roughness during the wet turning of D3 tool steel. They cumulatively contribute more than half (66.05%) to the surface roughness. To obtain the low surface roughness, lower level of feed (f), and depth of cut (d)) is recommended, along with a middle level of cutting speed (s) for the present study. The accuracy and adequacy of developed models are also checked, and the fuzzy model is found adequate for prediction purposes with an accuracy of 92.10%.

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