APPLICATION OF FUZZY LOGIC AND REGRESSION ANALYSIS FOR MODELING SURFACE ROUGHNESS IN FACE MILLING

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Abstract: Examining how machining settings affect surface finish in face milling is the goal of this study. This study describes an innovative use of artificial intelligence to the simulation of surface roughness. The purpose of this work is to develop empirical models using fuzzy logic and regression analysis. The predicted surface roughness values of these models are then contrasted. The results showed that the suggested technique may significantly increase the accuracy of the product performance. The outcomes demonstrate the effectiveness of using fuzzy logic modelling to accurately estimate surface roughness in dry machining.

Key words: Face milling, Regression analysis, Fuzzy logic.

1. Introduction

Manufacturing process and system research is increasingly evaluating processes to improve their efficiency, productivity, and quality. The end product's quality is determined by how closely it corresponds to certain specifications, such as dimensions and surface quality. Surface finish, surface texture, and surface roughness are used to define and identify surface quality. The most frequent metric for determining surface quality is roughness (Ra) [1], [2]

Due to imperfections emerging on machined surfaces, which are mostly caused by process deficiencies and imbalances, manufacturing methods do not allow for the theoretical surface roughness to be achieved. Because of these factors, measurement processes are required, as they allow one to determine the true state of surfaces in order to manufacture parts with more accuracy. To figure out the surface quality, you'll need to use theoretical models that allow you to make predictions based on response characteristics [3].

Many analytical methods for forecasting surface roughness have also been developed and employed. Lajis et al. (2008) established a mathematical model for predicting tool life in hardened steel end milling[4]. The creation of mathematical models for tool life in end milling steel utilising high-speed steel slot drills under dry conditions was proposed by Alauddinel et al [5]. Palanikumar et al. described response surface regression and analysis of variance (ANOVA)[6]

Choudhary et al. [7]and Grzenda et al.[8] found that the modelling of surface quality in machining operations has primarily used Artificial Neural Networks and fuzzy set theory.

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Rajasekaran et al. [9]investigated the effect of machining parameter combinations on surface finish in turning and used fuzzy modelling to predict surface roughness values..
Razali et al. [10]deployed FL in this study to predict cutting speed and feed rate of peripheral end milling process at given hardness of material, radial depth of cut and cutter diameter. There were two types of fuzzy models had been designed and developed throughout in his study. Two types of fuzzy model were designed to evaluate the effectiveness and efficiency of introducing cutter diameter as another input into the system. Author concluded the relationship between the material hardness, radial depth of cut and diameter of the tool with recommended cutting speed and feed can be described by the theory of fuzzy sets. Ren et al [11] presents the experimental study for turning process in machining by using Takagi–Sugeno–Kang (TSK) fuzzy modeling to accomplish the integration of multi-sensor information and tool wear information. The experimental results show its effectiveness and a satisfactory comparison with several other AI methods. But for tool condition monitoring, none of existing methods can overcome the defect that the models are difficult to estimate the errors of approximation
The purpose of this study is to offer a novel mathematical approach for determining surface roughness. The model, like the majority of the models offered, connects the elements of the cutting parameters. Cutting speed, feed rate, depth of cut were chosen as machining conditions in this investigation. Using these cutting parameters, fuzzy and regression models were created and compared.
Surface roughness is influenced by a variety of factors, including cutting tool and work piece qualities, tool geometry, and machine tool stiffness; however, machining parameters, such as cutting speed, feed, and depth of cut, are thought to be the most important. The machining factors, such as cutting speed, feed and depth of cut were modelled for surface roughness in face milling machining of Magnesium calcium alloy using DLC coated carbide cutting inserts in the current study.
The fuzzy logic and fuzzy inference system (FIS) is a powerful tool for detecting and controlling complex nonlinear systems. Fuzzy logic is used to make predictions. The fuzzy logics theory, pioneered by Zadeh [12], has proven to be beneficial in dealing with uncertain and ambiguous data. The capacity of fuzzy logic to address issues in the absence of precise mathematical models makes it particularly appealing. This idea has been shown to be effective in dealing with linguistically specified aims. Fuzzy sets can define linguistic concepts like 'low,''medium,' and 'high' [13].
Surface roughness modelling in face milling is a complex operation. In order to know surface quality and dimensional properties, theoretical models must be used for prediction, therefore traditional ways to model the surface roughness must be used. There are considerable differences between simulation findings and experimental data in the turning results. The findings showed that fuzzy logic can accurately predict surface roughness in milling. In this work, the impact of factors and their interactions on machining is thoroughly examined and described.
The contribution of this study is that it not only uses fuzzy logic for modelling, but it also compares two modelling methods, the standard regression approach and fuzzy logic. A

comparison of the fuzzy logic model and the regression approach revealed that the fuzzy logic model produces a significantly higher divergence of the measured values of the model.

2. Proposed Algorithm

To investigate how the process parameters affects the Surface integrity several experiments were conducted. Experimental setup to conduct milling experiments is shown in Fig 1. Work material, Mg-Ca 1.0 alloy in the form of plates 80 mm x 60 mm x 10 mm is used in dry face milling. CNC milling center Hardinge VMC 600 II) with a max spindle speed of 3800 rpm has been used to carry out experiments. DLC coated carbide cutting inserts (Make- HITACHI) were used and the cutting diameter is 50 mm. The experiment was carried out for different levels of cutting speed, feed and depth of cut as per the Table 1.

Fig. 1 Experimental Setup

Table 1 Levels of experimental parameters

Cutting speed Vc (m/min)	**Feed *f* (mm/rev)**	**Depth of cut a_p (mm)**
350	0.15	0.15
450	0.2	0.2
550	0.3	0.25

3. Experiment and Result

3.1 Regression modeling

The trials in this investigation were carried out utilising a central composite design with three levels of each element, as shown in Table I. With the parameters listed in Table 2, a total of 20 tests were conducted. Surface roughness is measured with a Mitutoyo surface roughness tester after machining (model SJ-201, make—Mitutoyo). When measuring the surface roughness parameter Ra, a sampling length of 2.5 mm was used. Kistler dynamometer Type 9257 was used to measure cutting forces. Surface roughness characteristics were estimated using experimental data that was entered into the model (see Table 3). The regression analysis was used to develop the above empirical equation for predicting surface roughness in dry face milling.

CCD evaluates the interaction of parameters by formulating a polynomial model. The 2nd order model predicted surface roughness values for the machining process with 0.35 percent error, at a 95 percent confidence level for adequacy

Table 2 Experimental, estimated values and difference

Expt No.	Speed (m/min)	Feed (mm/rev)	Depth of cut (mm)	Roughness Exp. Value (μm)	Roughness Regression Value (μm)	Roughness Fuzzy Value (μm)	Regression Difference (%)	Fuzzy Difference (%)
1	450.00	0.225	0.200	0.208	0.20682	0.208	0.567	0
2	550.00	0.300	0.250	0.224	0.22416	0.225	-0.071	-0.446
3	450.00	0.225	0.115	0.202	0.20243	0.205	-0.213	-1.485
4	350.00	0.300	0.250	0.274	0.27413	0.265	-0.047	3.285
5	550.00	0.150	0.150	0.142	0.14164	0.155	0.254	-9.155
6	450.00	0.225	0.200	0.202	0.20682	0.208	-2.386	-2.970
7	450.00	0.225	0.200	0.210	0.20682	0.208	1.514	0.952
8	450.00	0.098	0.200	0.143	0.14351	0.16	-0.357	-11.888
9	618.17	0.225	0.200	0.166	0.16613	0.16	-0.078	3.614
10	550.00	0.300	0.150	0.218	0.21793	0.22	0.032	-0.917
11	450.00	0.225	0.200	0.206	0.20682	0.208	-0.398	-0.971
12	350.00	0.150	0.250	0.198	0.19784	0.209	0.081	-5.556
13	350.00	0.150	0.150	0.192	0.19162	0.209	0.198	-8.854
14	281.82	0.225	0.200	0.250	0.25019	0.256	-0.076	-2.400
15	450.00	0.225	0.200	0.207	0.20682	0.208	0.087	-0.483
16	450.00	0.225	0.284	0.213	0.21289	0.208	0.052	2.347
17	450.00	0.351	0.200	0.272	0.27181	0.256	0.070	5.882
18	450.00	0.225	0.200	0.208	0.20682	0.208	0.567	0.000
19	550.00	0.150	0.250	0.148	0.14786	0.160	0.095	-8.108
20	350.00	0.300	0.150	0.268	0.26791	0.23	0.034	14.179
Fuzzy average error = 4.17 %					Regression average error = 0.36 %			

Table 3 Equations of Regression Model

Sr. No.	Responses	Equations
1	Surface Roughness	0.2093- 0.000292 Cutting Speed + 0.4850 Feed + 0.015 Depth of cut + 0.000000 Cutting Speed*Cutting Speed +0.0525 Feed*Feed + 0.118 Depth of cut*Depth of cut - 0.000000 Cutting Speed*Feed- 0.000000 Cutting Speed*Depth of cut - 0.000 Feed*Depth of cut

2	Cutting Force	14.15- 0.01916 Cutting Speed+ 18.26 Feed- 0.6 Depth of cut+ 0.000007 Cutting Speed* Cutting Speed- 15.7 Feed*Feed + 13.4 Depth of cut*Depth of cut - 0.0001 Cutting Speed*Feed + 0.0001 Cutting Speed*Depth of cut - 0.1 Feed*Depth of cut

3.2 Fuzzy modeling

Membership functions, fuzzy logic operators, and if-then rules are all used in the fuzzy inference process. A FIS's basic structure consists of three conceptual components: a rule base containing a set of fuzzy rules; a database defining the membership functions (MF) used in the fuzzy rules; and a reasoning mechanism that performs the inference procedure on the rules to derive an output. (See Figure 2)[14]

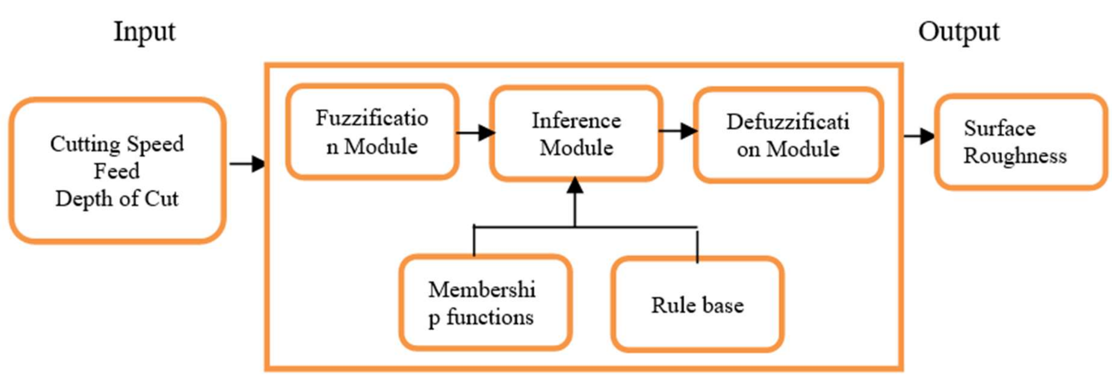

Fig. 2 Fuzzy inference system [14]

The rules have been constructed using the input parameters which are the Speed, Feed rate and Depth of cut. Surfac e roughness of the milled surface is the output parameter. Three membership functions are used for each input variable, which are High, Medium and Low. Three membership functions are selected for the output response Very smooth, Smooth. Rough Mamdani Inferencing system is selected for model development as shown in Fig 3.

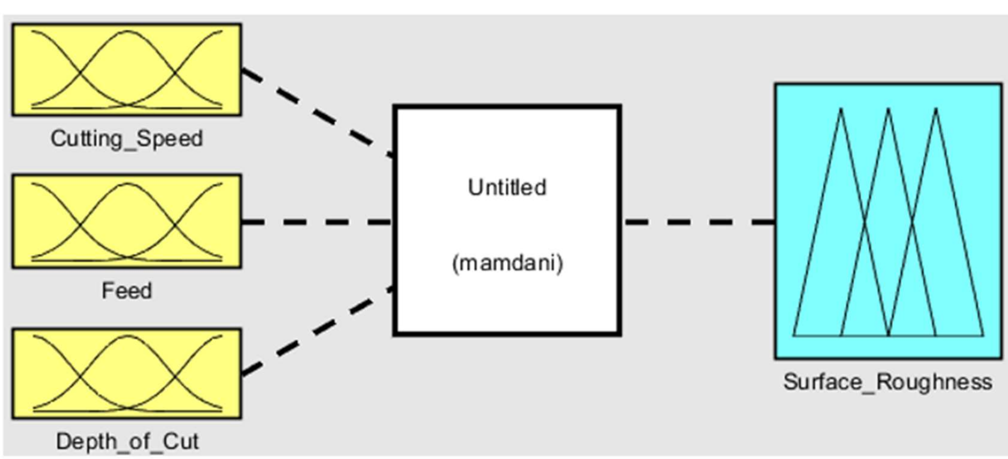

Fig. 3 Mamdani Inferencing System

3.3 Membership Functions for Fuzzy Variables

Fuzzy logic toolbox has several membership functions such as Traingular, Trapezoidal, Sigmoid etc. In this model, Traingular membership function is selected for both Inout and Outout variables to develop the model. The input variables have been divided in three levels and output varialbes is divided into three levels depending on the experimental results. Membership fucnitons for both the input as well as output is shown in figure 3 and the rules for the model are shown in the Fig. 4.

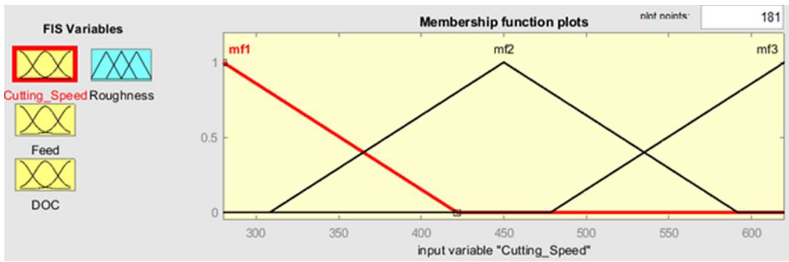

Fig. 4 Membership functions for cutting speed, Feed, Depth of cut and for surface roughness

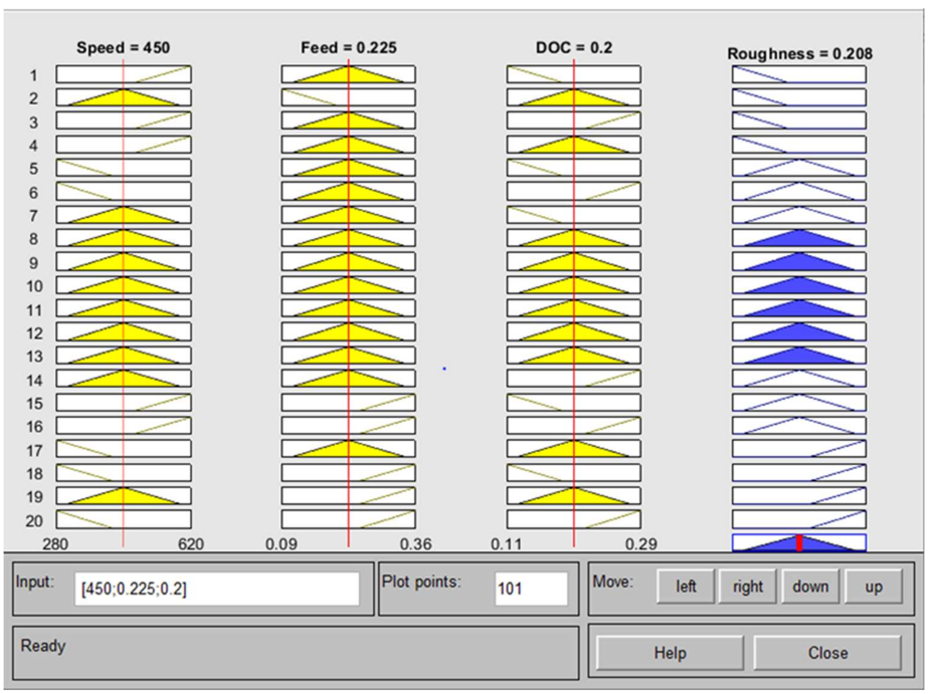

Fig. 5 Rules for Fuzzy logic

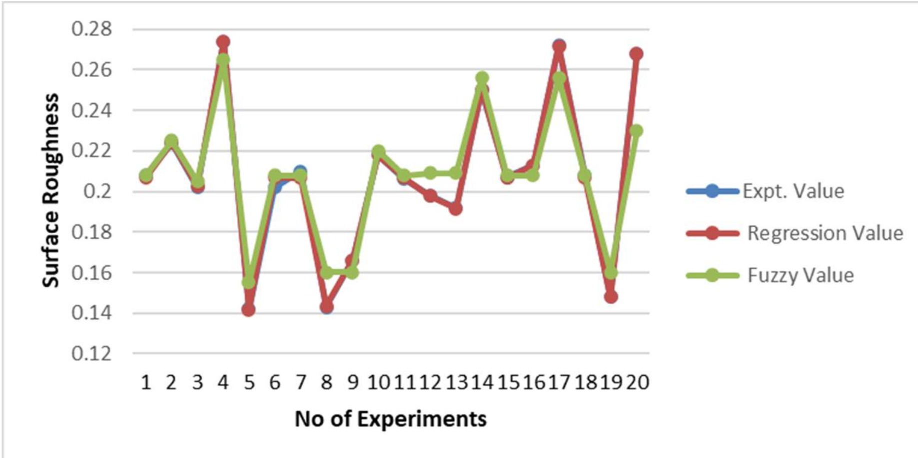

Fig. 6 Correlation between experimental value, fuzzy predicted and regression model

For fuzzy logic using the value of conditions, based on the experiment is defined by 20 rules. All cutting conditions were used to obtain the regression model. Table 2 shows the compared values obtained by experiment, and estimated by models fuzzy logic and regression analysis. The Fig. 6 shows the correlation between experimental value, fuzzy predicted and regression model. The average deviation of the fuzzy model is 4.17 % while average deviation of the regression model is 0.36 %. Research showed that regression analysis model gives more accurate prediction on surface roughness. Results obtained by Mamdani fuzzy system of reasoning, using rules (see Fig 5) that are defined on the basis of experimental data, show agreement with experiment. This shows that the selected types of membership function type reasoning mechanism by the method of MIN - MAX and selected defuzzification centroid method are a good choice (Fig. 4).

4. Conclusion

The amount of data that was used to create the "Mamdani" models' error results is not a factor; rather, the error model depends on the set of rules and the avoidance of rule overlap. Fuzzification and defuzzification phases can be effectively performed by choosing a membership function and its parameters. Although developing a fuzzy model is more difficult than a regression model . When milling magnesium calcium alloy, the surface roughness can be predicted using the model once it has been evaluated for suitability. The findings show that while surface roughness increases with increased feed, it decreases with increased cutting speed. Surface roughness is at least influenced by cut depth. The ideal outcome is attained while cutting with a low depth of cut. The model's efficacy is limited by the range and factor research. By taking into account variables and parameter ranges, the model's suitability can be increased still further. For each set of rules that form and combination emerge with too many solutions, the membership function must be defined. Fuzzy logic implementation can be used successfully for this purpose.

5. REFERENCES

[1] J. C. Chen and M. Savage, "A Fuzzy-Net-Based Multilevel In-process Surface Roughness Recognition System in Milling Operations," pp. 670–676, 2001.

[2] G. Q. M. L. G. J. Ciurana, "Surface roughness monitoring application based on artificial neural networks for ball-end milling operations," pp. 607–617, 2011, doi: 10.1007/s10845-009-0323-5.

[3] & T. Sivarao, S., Castillo, "Machining quality pre- dictions: comparative analysis of neural network and fuzzy logic. International Journal of Electrical & Computer Sciences," Int. J. Electr. Comput. Sci. IJECS-IJENS, vol. 9, pp. 451–456, 2000.

[4] M. A. Lajis, M. Engineering, M. Engineering, M. Engineering, L. G. Turnad, and M. Engineering, "Prediction of Tool Life in End Milling of Hardened Steel AISI D2," vol. 4, pp. 592–602, 2008.

[5] E. Baradie, "Prediction of tool life in end milling surface methodology y," vol. 71, no. 97, pp. 0–9, 1997.

[6] K. Palanikumar, N. Muthukrishnan, and K. S. Hariprasad, "Surface roughness parameters optimization in machining A356/SiC/20p metal matrix composites by PCD tool using response surface methodology and desirability function," Mach. Sci. Technol., vol. 12, no. 4, pp. 529–545, 2008, doi: 10.1080/10910340802518850.

[7] A. K. C. J. A. H. M. K. Tiwari, "Data mining in manufacturing : a review based on the kind of knowledge," pp. 501–521, 2009, doi: 10.1007/s10845-008-0145-x.

[8] M. Grzenda, A. Bustillo, and P. Zawistowski, "A soft computing system using intelligent imputation strategies for roughness prediction in deep drilling," pp. 1733–1743, 2012, doi: 10.1007/s10845-010-0478-0.

[9] T. R. K. P. B. K. Vinayagam, "Application of fuzzy logic for modeling surface roughness in turning CFRP composites using CBN tool," pp. 191–199, 2011, doi: 10.1007/s11740-011-0297-y.

[10] S. Z. Razali, S. V. Wong, and N. Ismail, "Fuzzy logic modeling for peripheral end milling process," IOP Conf. Ser. Mater. Sci. Eng., vol. 17, no. 1, 2011, doi: 10.1088/1757-899X/17/1/012050.

[11] K. Ren, Qun and Balazinski, Marek and Baron, Luc and Jemielniak, "TSK Fuzzy Modeling for Tool Wear Condition in Turning Processes: An Experimental Study," Eng. Appl. Artif. Intell, vol. 24, no. 2, pp. 260–265, 2011.

[12] L. A. Zadeh, "The concept of a linguistic variable and its application to approximate reasoning-I," Inf. Sci. (Ny)., vol. 8, no. 3, pp. 199–249, 1975, doi: 10.1016/0020-0255(75)90036-5.

[13] Subramonian Sivarao, "Mamdani Fuzzy Inference System Modeling to Predict Surface Roughness in Laser Machining," Int. J. Intell. Inf. Technol. Appl., vol. 2, no. 1, pp. 12–18, 2009.

[14] P. Kovac, D. Rodic, V. Pucovsky, B. Savkovic, and M. Gostimirovic, "Application of fuzzy logic and regression analysis for modeling surface roughness in face milliing," J. Intell. Manuf., vol. 24, no. 4, pp. 755–762, 2013, doi: 10.1007/s10845-012-0623-z.