Int. J. Adv. Eng. Pure Sci. 2023, 35(1): 72-80
DOI: 10.7240/jeps.1201547

RESEARCH ARTICLE / ARAŞTIRMA MAKALESİ

Prediction of The Production Quality During Flat Bottom Drilling of Low Lead Brass Alloy Using Fuzzy Logic and Regression Models

Nima ZOGHIPOUR [1,2], Yusuf KAYNAK[2]

[1] *Torun Bakır Alaşımları Metal Sanayi ve Ticaret A.Ş., Gebze,Kocaeli, Turkey*

[2] *Department of Mechanical Engineering, Marmara University, Istanbul,Turkey*

Abstract
The approved restrictive rules on the containment of Lead element in the chemical composition of the brass alloys which are utilized in drinking water and pumping systems have resulted in developing of new material generations. Neglection or limitation of this element has faced the industry with some serious problems such as lower machinability as compared to the conventional ones. Furthermore, since the most application of the manufactured components from these alloys corresponds to the fluids transfer, the permeability property between the parts and their surface becomes prominent. In other words, any burrs or extra material which are left on the surfaces of manufactured components will make assembly troublesome, causing seals to tear, and permeability problems in the user's hands. In this study, the quality of the machined blind holes with flat bottom drills with various geometries including radial, axial rake angle as well as the cutting edge-radius have been investigated for machining of low-lead brass alloy. Moreover, it has attempted to develop fuzzy logic and regression models in order to predict the machined holes burr height and surface quality. The model predictions have been compared with the experimental data. The obtained results have demonstrated that the developed models are able in predicting of the product quality.
Keywords: Flat bottom drilling, Brass, Machinability, Fuzzy logic

I. INTRODUCTION

Brass materials with the main element of Zinc are categorized in the family of the copper-based alloys. Due to the excellent properties such as strength, formability, recyclability and corrosion resistance, brass alloys are widely used in the sterile, water and pumping components [1]. In order to intensify the forming and machining process efficiency of these alloys several elements one of which is Lead are being added to the chemical composition [2]. On the grounds of the toxic and harmful nature of this element, the use of Lead is prohibited/limited in most European countries and USA by accepted and published rules [3-6]. This restriction has led to the decrease in the brass formability and machinability. As a result, new challenges have emerged that must be resolved in order to expand this material change globally. In this scope, few authors have researched the machinability of these alloys. [7].

The friction behavior of leaded and lead-free brasses was studied by Gane et al. [8] with cutting and sliding tests. According to his results, the friction stress for lead-free brass was measured two times of the leaded one. In a performed investigation by Trent et al. [9, 10], it was concluded that the adding Lead element in the brass composition results in the reduction in the cutting forces, shortens the chips and the tool wear. They explained the reason behind this occurrence as adhering of Lead to the tool contact area and acting as an “internal lubricant” [10]. Bushlya et al. [11] studied the wear mechanisms of uncoated and coated cemented carbide tools for machining lead-free silicon brass. They found that the main reason for the tool failure is the crater formation on the rake face. Schultheiss et al. [12] focused on the machinability of CuZn39Pb3 and CuZn21Si3P brasses. Their work presented a profound level of differences in machinability in terms of tool coating types and their wear during machining of these two materials according to the properties and behavior. Nobel et al. [13] analysed the effect of microstructure on the chip formation, cutting forces, tool temperatures and tool wear is during external turning. Toulfatzis et al. [14] studied the machinability of three lead-free brass alloys, CW510L, CW511L and C27450 in a comparison with leaded brass CW614N with turning experiments. Zoghipour et al. [15] studied the effect of drilling process on surface integrity characteristics of lead-free brass alloy by focusing on the dimensional accuracy and the surface quality of the holes, subsurface characteristics including microhardness and microstructure. Hua et al. [16] studied the influences of the cutting-edge geometry, cutting conditions, and workpiece hardness in micro drilling of lead-free brass alloy. According to their results,

Corresponding Author: Nima ZOGHIPOUR, Tel: +90 262 677 15 15, e-posta: nima.zoghipour@gmail.com

Submitted: 09.11.2022, **Revised:** 01.01.2023, **Accepted:** 11.02.2023

sharpen edge with chamfer cutting edge leads to higher compressive residual stress, and hardness. In a similar study Hua et al. [16], Kato et al. [17] studied the effects of web thinning, the helix angle, and the nick geometry on chip evacuation in micro drilling on lead-free brass alloy. Timata et al. [18] carried out an experimental study in drilling forging brass using a special tungsten carbide drilling tool and measured the exit burr height and workpiece diameter. They found that the most influencing parameters on the exit burr height and workpiece diameter are spindle speed and feed rate. Zoghipour et al. [19] considered the effects of the tools geometries, feed rates and rotational speeds in drilling of hot forged lead-free brass alloys with various copper content. They used artificial neural networks modelling, and genetic algorithm-based optimization methods to predict and minimize the cutting forces, dimensional accuracy error, and surface quality of the holes.

All the performed studies in the literature confirm the existence of Lead benefits in the machining process, and report lower and problematic machining properties for the low-lead and lead-free brass alloys. Furthermore, considering that most of the studies are associated with standard machining operations, it is seen that the industry requirements need high performance and efficient processes, one of which passes through the correct cutting tool design and its application. Therefore, in this study different flat bottom drills with various geometries including radial, axial rake angle as well as the cutting edge-radius have been utilized in order to form blind holes in low-lead brass alloy. The quality of the generated holes has been considered according to industrial component requirements. For this purpose, fuzzy logic and regression models have been developed in order to predict the machined holes burr height and surface quality. The model predictions have been compared with the experimental data.

II. MATERIAL AND METHODS

2.1. Experimental Tests

The workpieces used in this study was hot extruded round bars of 60 mm diameter and 28 mm length low-lead type of brass alloys CuZn38As (CW511L). The mechanical properties and chemical composition of the test materials is presented in Table 1. Ø8 mm diameter carbide flat bottom drill with given geometric specifications in Table 2 were utilized during the experiments. The designed flat bottom drill is demonstrated in Fig. 1. The cutting speed and the feed rate were kept constant at 100 m/min and 0.125 mm/rev during through hole drilling using 25 Bar of internal cooling flood. The machining experiments were conducted on a four axis Fanuc Robodrill –D21LiB5 CNC milling center having maximum spindle speed of 10000 rpm and 14.2 kW. In order to study the formed burrs height at entry of the machined holes Keyence digital optic microscope was used. The measurements for every drilled hole were executed from four different points. The surface quality of the holes bottom was evaluated with Mitutoyo Contracer CV-2100M4. All experiments have been carried out three times and the average result is reported. Fig. 2 shows the experimental setup and the machined product requirements in this study.

Table 1. The chemical composition of the studied brass alloys [20]

	E, GPa	Machinability, %	Composition	Cu	Zn	Pb	Sn	Fe	Ni	Al	As
CuZn38As (CW511L)	100	40	%Min.	61.5	Rem.	-	-	-	-	-	0.02
			%Max.	63.5	Rem.	0.2	0.1	0.1	0.3	0.05	0.15

Table 2. The geometric specification of the utilized cutting tools

Parameter	Diameter (mm)	Helix angle (deg)	Radial rake angle (deg)	Axial rake angle (deg)	Cutting edge-radius (μm)
Flat Bottom Drill	8	30	6	-2	10
			8	0	15
			10	2	20

2.2. Fuzzy Logic Modeling

The ability of behaving similar to mankind's decisions, fuzzy logic has gained a broad application with different purposes. A fuzzy logic system is consisted of the following steps as illustrated in Fig. 3;

- Fuzzification, in which the crisp data converts into fuzzy data or Membership Functions (MFs)
- Fuzzy Inference, in which the control rules to derive the fuzzy output combines with the membership functions. By using these membership functions the output of a fuzzy controller is derived from fuzzifications of both inputs and outputs
- Defuzzification, in which the output converts to crisp variable using different methods.

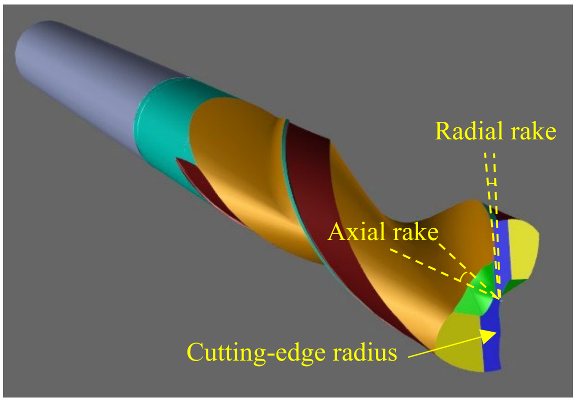


Fig 1. The designed flat bottom drill cutting tool

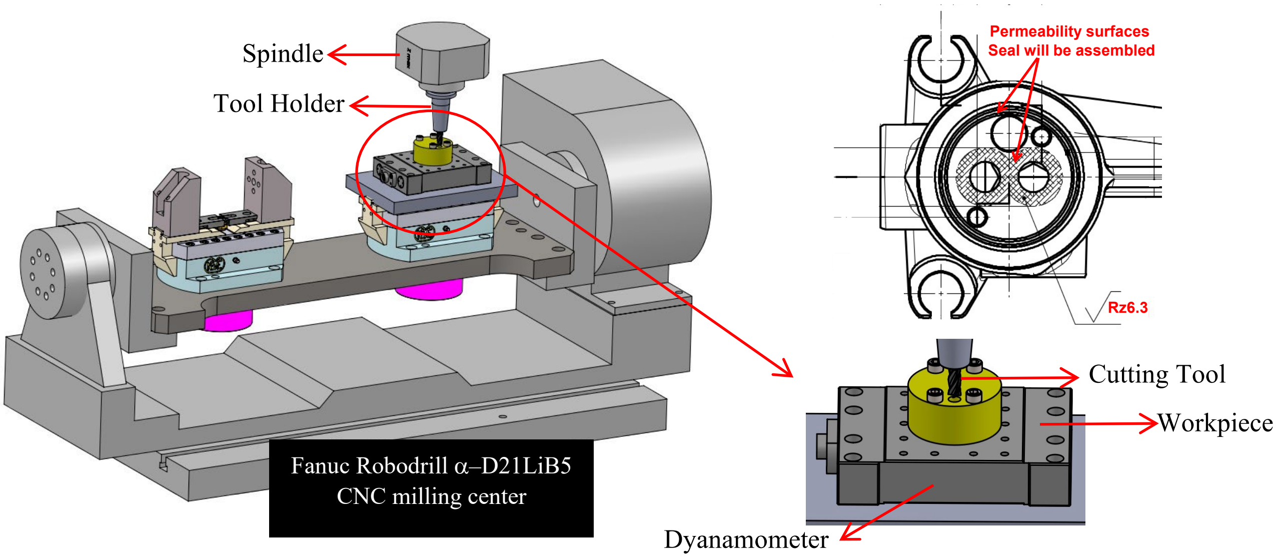


Fig. 2. The test setup in this study and the machined product requirement

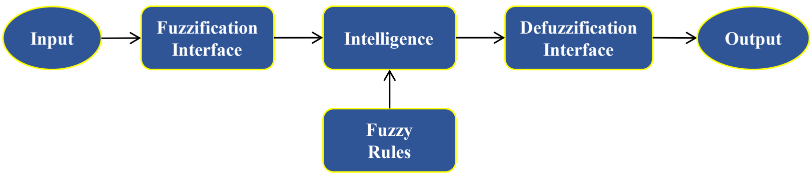


Fig. 3. The schematic of a fuzzy logic system

2.3. Regression modeling

The regression analysis was introduced in order to inspect the statistical relationship between one or more independent variables and dependent variables by Galton [21]. The parabolic regression is one the widespread used models for the purpose of inspections due to its simplicity and applicability. This model can be expressed as in below:

$$y_i = b_0 + b_1 x_i + b_2 x_i^2 + \cdots + b_n x_i^n + \varepsilon \quad (1)$$

$$\varepsilon = y_i - \hat{y}_i \quad (2)$$

where y_i is dependent variable, x_i stands for the independent variable, b_0, b_1, b_2, b_n are the parameter coefficients and ε is the model error [22]. The regression coefficients can be obtained by the Eq. 3:

$$b = (\acute{x}x)^{-1}\acute{x}y \quad (3)$$

Furthermore, multiple regressions are a collection of numerical and factual strategies useful for modeling and analyzing issues in which the reaction of intrigued is influenced by a several variables [22,23].

III. RESULTS AND DISCUSSIONS

3.1. Fuzzy Logic Modeling

Mamdani FIS type was used and Gaussian membership function (gauss2mf) was deployed to return the fuzzy membership computed values using a combination of two Gaussian membership functions in the model. Subsequently, the linguistic coding was used as illustrated in Table 3. The generated inputs in the model are displayed in Fig. 4.

Table 3. The utilized linguistic coding for the developed model

Radial rake angle (deg)	Axial rake angle (deg)	Cutting edge radius (μm)	Burr height (μm)	Rz (μm)
6=L 8=M 10=H	-2=L 0=M 2=H	10=L 15=M 20=H	L<350 350≤M≤425 425<H≤500 VH>500	L<5 5≤M≤5.8 5.8<H≤6.3 VH>6.3

where, L, M, H, VH represent low, medium, high and very high, respectively. The model was performed by 27 rules in total. The schematic developed rules based fuzzy logic model in this study is demonstrated in Fig. 5. Mean of Maximum (MoM) method was used for defuzzification. Therefore, the fuzzy output is a result of minimum and maximum compositional operations tracking.

The variation of the average entry burr height and surface roughness in a combined mode of the influencing cutting tool geometries is demonstrated in Fig. 6. The developed fuzzy model for the machining responses is given in Fig. 7. The lowest predicted average burr height and surface roughness values in the fuzzy logic model were 294.320 and 5.74 μm, respectively. It is seen that as compared with experimental results; the developed model has predicted the same cutting tool geometry for the minimum burr height. Furthermore, it has recognized two of three geometric parameters of the tool correctly. Along with the fuzzy logic system, in order to model the quality of the drilled hole, quadratic polynomial functions were used to predict the responses. The generated functions are illustrated in Table 3. The confidence coefficients for the burr height and surface roughness functions were %.80.04 and %96.31, respectively. The lowest predicted average burr height and surface roughness values in

the fuzzy logic model were 331.946 and 5.03 μm, respectively. The regression model has only determined the same cutting tool geometry for burr height in a comparison with experimental results. The fuzzy logic average entry burr height and surface quality prediction error are %11.01 and %2.98, respectively. On the other hand, these percentages were %12.26 and %7.15 in the regression model. Table 5 illustrates the measured and predicted results for the process with their calculated error. The model's average entry burr height and surface roughness graphs are demonstrated in Fig. 8. Beyond the predicted and measured result values, it is seen that the model predictions have demonstrated a good trend with the variation of the radial, axial rake angles and cutting-edge radius. Consequently, both models can be used in the industrial and academic applications since they can give an acceptable range of confidence in their prediction results.

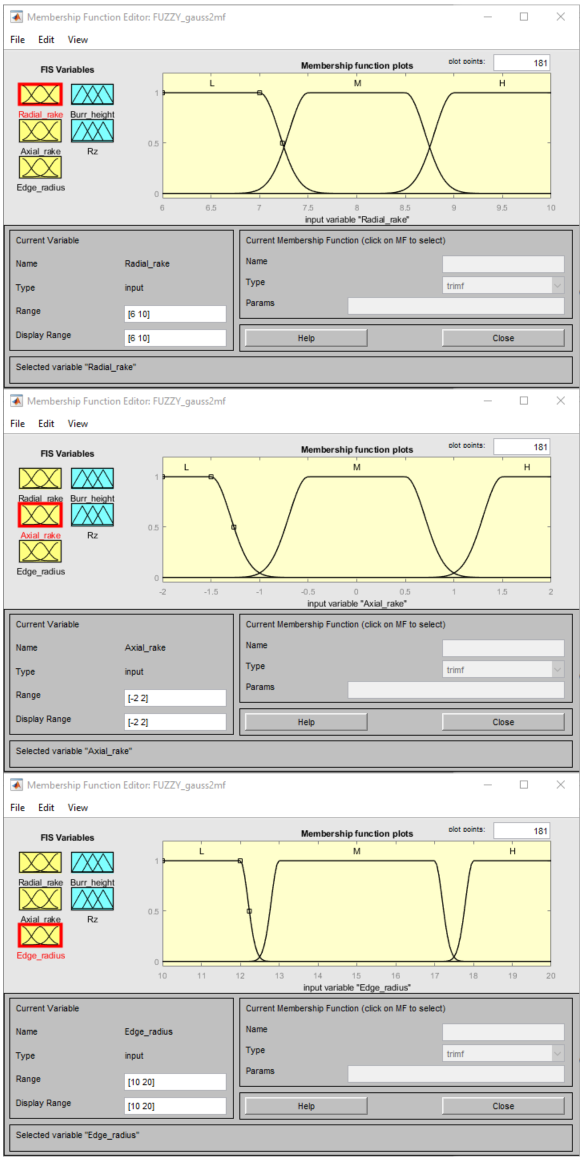


Fig. 4. The generated inputs FIS model

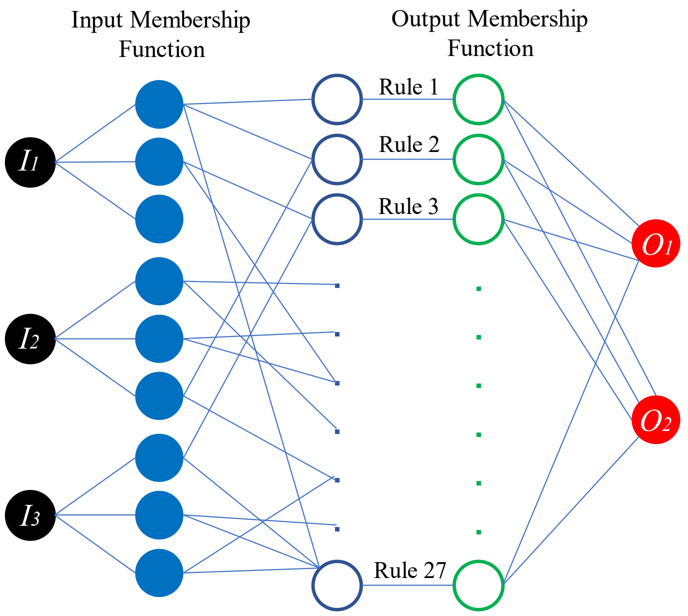
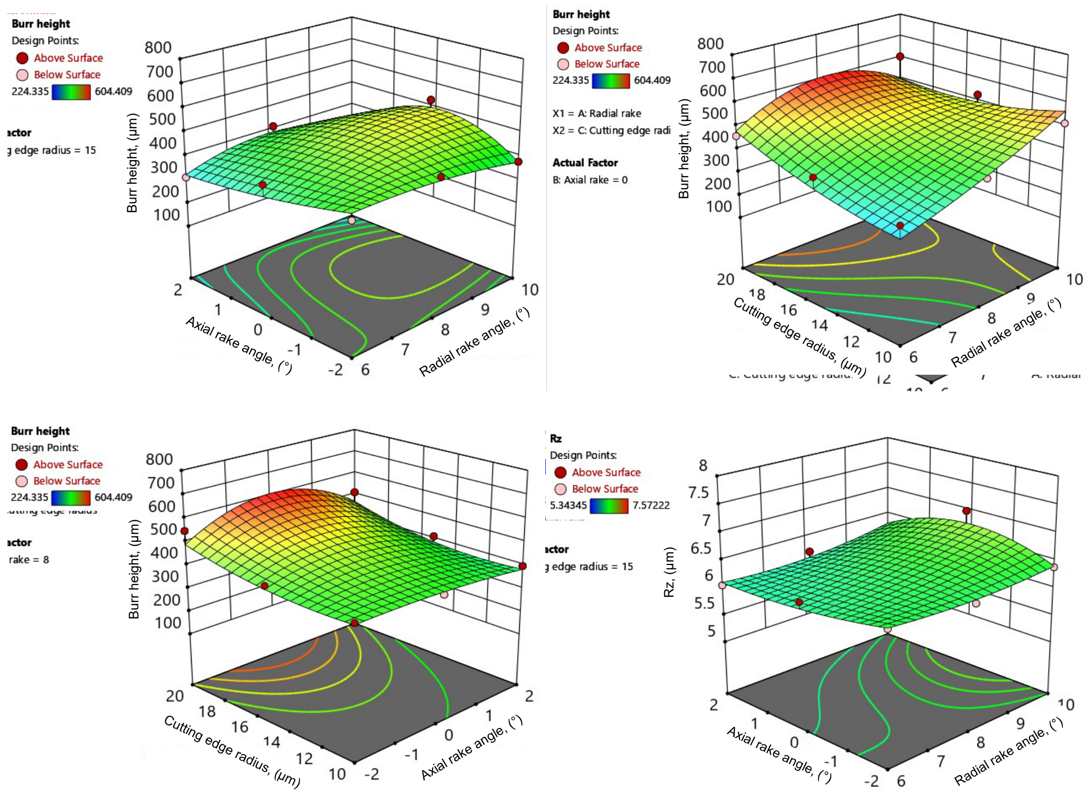


Fig. 5. The schematic of the developed fuzzy logic model



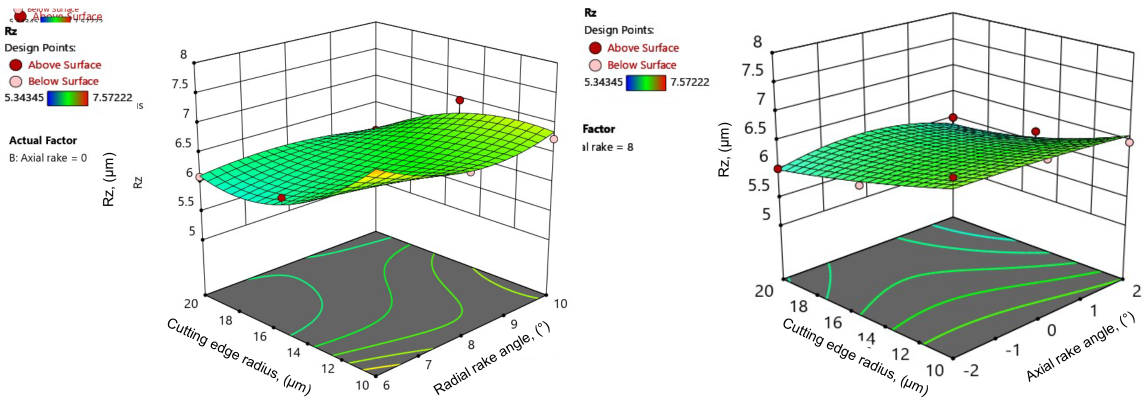


Fig. 6. The variation of the average entry burr height and surface roughness in a combined mode of the influencing cutting tool geometries

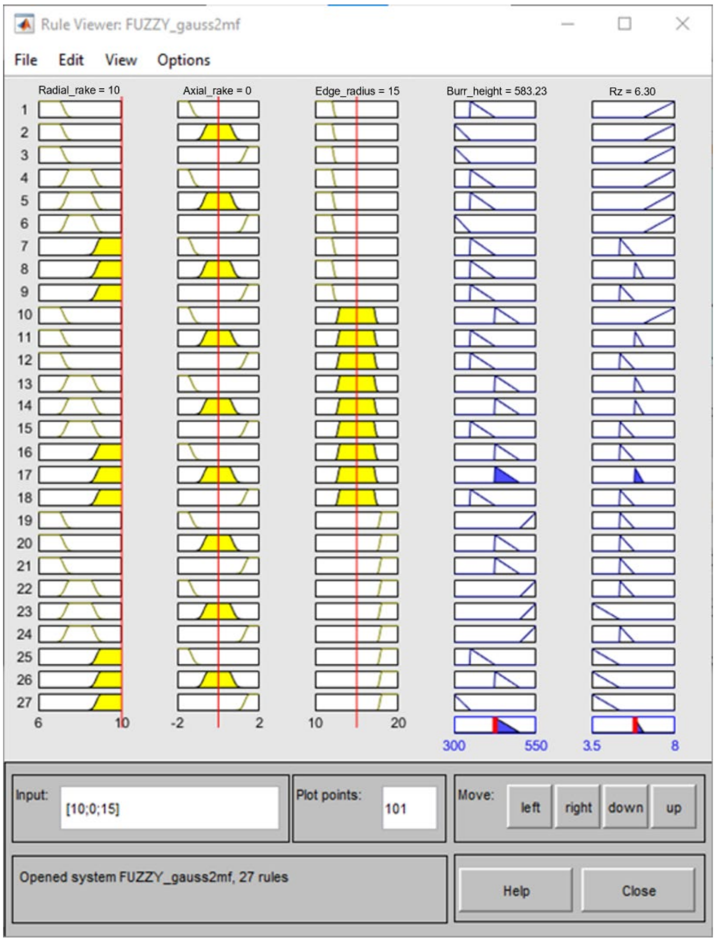


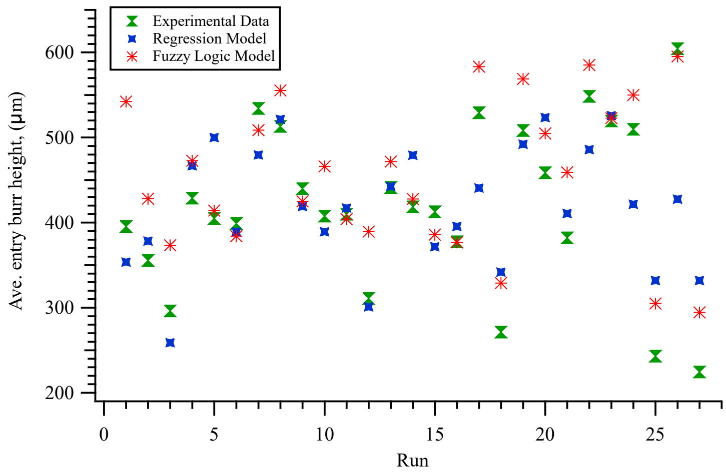
Fig. 7. The developed fuzzy logic model in this study

Table 4. The developed regression models

		A	B	C	AB	AC	BC	A^2	B^2	C^2	ABC	A^2B	A^2C	AB^2	AC^2	B^2C	BC^2
Burr	479.03	66.91	-19.28	96.04	8.59	-59.75	3.34	-50.2	-72.01	33.76	12.85	-28.98	-66.88	-87.98	5.32	-57.89	4.68
Rz	6.35	0.29	-0.11	-0.24	-0.04	0.05	0.006	0.09	-0.14	0.09	-0.11	0.01	-0.25	-0.23	-0.41	-0.11	0.05

Table 5. The obtained results in this study

				Experimental Results		Regression Model Results				Fuzzy Logic Model Results			
Run	Radial rake angle, (°)	Axial rake angle, (°)	Cutting edge radius, (μm)	Entry burr height, (μm)	Rz Bottom, (μm)	Entry burr height, (μm)	Rz Bottom, (μm)	% Burr Error	% Rz Error	Entry burr height, (μm)	Rz Bottom, (μm)	% Burr Error	% Rz Error
1	6	-2	10	395.33	7.57	353.57	8.01	10.563	5.81	452.18	7.21	14.38	4.76
2	6	0	10	355.46	7.25	378.16	7.56	6.386	4.28	427.96	7.24	20.40	0.14
3	6	2	10	296.02	7.25	258.74	7.87	12.593	8.55	373.24	6.97	26.09	3.86
4	8	-2	10	428.68	6.9	466.73	6.32	8.876	8.41	472.59	6.86	10.24	0.58
5	8	0	10	404.88	6.68	499.92	6.99	23.475	4.64	413.98	6.94	2.25	3.89
6	8	2	10	398.87	6.47	389.09	6.76	2.451	4.48	384.03	6.94	3.72	7.26
7	10	-2	10	534.11	6.43	479.50	5.87	10.225	8.71	508.55	6.71	4.79	4.35
8	10	0	10	513.02	6.74	521.27	6.23	1.610	7.57	555.31	6.83	8.24	1.34
9	10	2	10	439.66	6.84	419.03	6.47	4.691	5.41	424.97	6.83	3.34	0.15
10	6	-2	15	407.59	6.37	389.08	5.97	4.541	6.28	465.94	6.66	14.32	4.55
11	6	0	15	409.77	6.27	417.02	6.69	1.769	6.70	403.94	6.59	1.42	5.10
12	6	2	15	310.77	6.05	300.95	6.32	3.160	4.46	389.29	6.32	25.27	4.46
13	8	-2	15	441.19	6.25	442.50	6.74	0.297	7.84	471.58	6.27	6.89	0.32
14	8	0	15	418.37	6.21	479.03	6.86	14.500	10.47	427.56	6.35	2.20	2.25
15	8	2	15	412.64	6.19	371.54	6.45	9.960	4.20	385.72	6.13	6.52	0.97
16	10	-2	15	377.44	6.38	395.51	6.95	4.788	8.93	376.76	6.17	0.18	3.29
17	10	0	15	529.00	6.97	440.63	6.37	16.705	8.61	583.23	6.3	10.25	9.61
18	10	2	15	271.23	6.14	341.73	6.55	25.995	6.68	328.89	6.13	21.26	0.16
19	6	-2	20	508.28	6.09	492.11	6.41	3.180	5.25	568.72	6.1	11.89	0.16
20	6	0	20	458.45	6.09	523.40	6.66	14.168	9.36	504.66	6.14	10.08	0.82
21	6	2	20	382.04	6.07	410.67	5.03	7.494	17.13	458.99	5.84	20.14	3.79
22	8	-2	20	548.23	6.01	485.78	5.03	11.392	16.31	585.01	5.88	6.71	2.16
23	8	0	20	519.24	6.11	525.65	6.30	1.235	3.11	522.72	5.95	0.67	2.62
24	8	2	20	509.65	6	421.51	5.50	17.295	8.33	549.75	5.87	7.87	2.17
25	10	-2	20	242.96	5.59	331.95	5.80	36.626	3.76	304.8	5.74	25.45	2.68
26	10	0	20	604.41	5.99	427.50	6.20	29.270	3.51	595.11	5.97	1.54	0.33
27	10	2	20	224.34	5.34	331.95	5.10	47.969	4.49	294.32	5.81	31.20	8.80



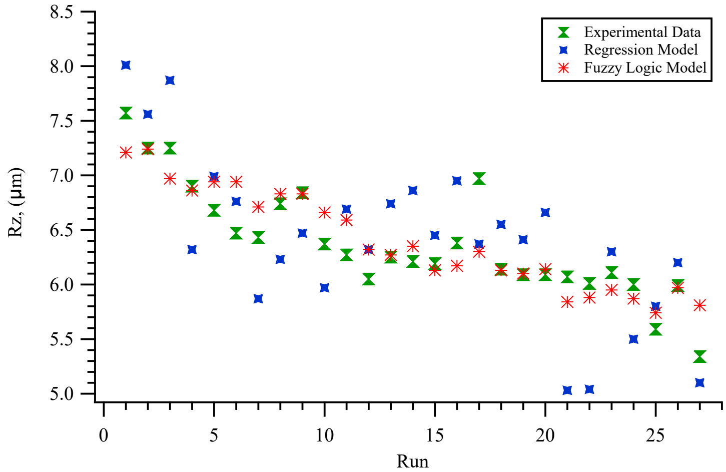


Fig. 8. Comparison of the model predictions with the experimental results

IV. CONCLUSION

This paper discusses the development of fuzzy logic and regression models to predict the average burr height the hole entry, and surface quality of a drilled specimens on low lead brass alloy. After several trial-and-error attempts, the accurate and effective types of fuzzification and defuzzification methods were determined. Moreover, a regression model was also developed to predict the responses as well. Afterall, the predicted results were compared with the experimental ones. The fuzzy logic average entry burr height and surface quality prediction error are %11.01 and %2.98, respectively. On the other hand, these percentages were %12.26 and %7.15 in the regression model. Both models are in good agreement with the achieved experimental results. Therefore, the developed models can be effectively used in to predicting the average entry burr height and surface quality. Consequently, these models can be helpful to neglect several costly experiments to predict the drilling responses as well as optimized cutting specially in industrial and academic applications.

ACKNOWLEDGEMENTS

The authors thank TUBITAK (The Scientific and Technological Research Council of Turkey) for partially supporting this work under project number 118C069.

REFERENCES

[1] K. Aytekin, Characterization of machinability in lead-free brass alloys, PhD thesis, KTH Royal institute of technology, Sweden (2018).

[2] M. Adineha, H. Doostmohammadi, Microstructure, mechanical properties and machinability of Cu–Zn–Mg and Cu–Zn–Sb brass alloys, ***Journal of Materials Science and Technology***, 35(12), 1504–1514, (2019).

[3] https://www.copper.org/applications/rodbar/pdf/A7038-brass-for-european-potable-water-applications.pdf

[4] https://rohs.exemptions.oeko.info/fileadmin/user_upload/RoHS_Pack_9/Exemption_6_c_/Exemption_6c__2015-10-mitsubishi-shindoh-rohs.pdf

[5] D. Peters, Bismuth Modified Cast Red Brasses to Meet U.S. Drinking Water Standards, ***Copper Development Association***, (1995).

[6] D. Davies, Bismuth in copper and copper base alloys: a literature review, Technical Report, ***Copper Development Association***, (1993).

[7] L. Amaral, R. Quinta, T.E. Silva, R.M. Soares, S.D. Castellanos, A.M.P. de Jesus, Effect of lead on the machinability of brass alloys using polycrystalline diamond cutting tools, ***Journal of Strain Analysis for Engineering Design***, 53(8), 602–615, (2018).

[8] N. Gane, The effect of lead on the friction and machining of brass, ***Journal of Philosophical Magazine A***, 43(3), (1981).

[9] E.M. Trent, P.K. Wright, Metal Cutting, 4th ed., Butterworth-Heinemann, Stoneham, MA, USA, (2000).

[10] E.M. Trent, Metal cutting and the tribology of seizure: III temperatures in metal cutting, ***Journal of Wear***, 128, 65–81, (1988).

[11] V. Bushlya, D. Johansson, F. Lenrick, J. E. Ståhl, F. Schultheiss, Wear mechanisms of uncoated and coated cemented carbide tools in machining lead-free silicon brass, ***Journal of Wear***, (376-377), 143-151, (2017).

[12] F. Schultheiss, D. Johansson, V. Bushlya, J. Zhou, K. Nilsson, J. E. Ståhl, Comparative study on the machinability of lead-free brass, ***Journal of Cleaner Production***, 149, 366-377, (2017).

[13] C. Nobel, F. Klocke, D. Lung, S. Wolf, Machinability Enhancement of Lead-Free Brass Alloys, ***Journal of Procedia CIRP***, 14, 95-100, (2014).

[14] A. I. Toulfatzis, G. A. Pantazopoulos, C. N. David, D. S. Sagris, A. S. Paipetis, Machinability of Eco-Friendly Lead-Free Brass Alloys: Cutting-Force and Surface-Roughness Optimization, ***Journal of Metals***, 8, 250, (2018).

[15] N. Zoghipour, E. Tascioglu, G. Ataya, Y. Kaynak, Machining-induced surface integrity of holes drilled in lead-free brass alloy, ***Journal of Procedia CIRP***, 87, 148-152, (2020).

[16] J. Hua, R. Shivpuri, X. Cheng, V. Bedekar, Y. Matsumoto, F. Hashimoto, T. R. Watkins. Effect of feed rate, workpiece hardness and cutting edge on subsurface residual stress in the hard turning of bearing steel using chamfer + hone cutting edge geometry, ***Journal of Materials Science and Engineering A***, 394, 238–248, (2005).

[17] H. Kato, S. Nakata, N. Ikenaga, Improvement of chip evacuation in drilling of lead-free brass using micro drill, ***International Journal of Automation Technology***, 8, (2014).

[18] M. Timata, C. Saikaew. Influences of spindle speed and feed rate on exit burr height and workpiece diameter in drilling forging brass, ***Solid state phenomena***, 279, 67-71, (2018).

[19] N. Zoghipour, G. Atay, Y. Kaynak, Modeling and optimization of drilling operation of lead-free brass alloys considering various cutting tool geometries and copper content, ***Journal of Procedia CIRP***, 102, 246-251, (2021).

[20] https://sarbak.com.tr/dokuman/alasimlar/en/S511.pdf

[21] F. Galton, Regression towards mediocrity in hereditary stature, ***The Journal of the Anthropological Institute of Great Britain and Ireland***, 15, 246–263, (1886).

[22] I. J. Jeong, K. J. Kim, An interactive desirability function method to multiresponse optimization, European Journal of Operational Research, 195, 412–426, (2009).

[23] D. C. Montgomery, ***Design and Analysis of Experiments***, John Wiley, New York, NY, USA, 2nd. (1984).