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Application of Fuzzy Logic in the Analysis of Surface Roughness of Thin-Walled Aluminum Parts

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Abstract

This paper presents the development and application of fuzzy logic in the milling of thin-walled parts for the purpose of analyzing surface roughness. Surface roughness is an important performance indicator of finished components. Depending on conditions such as feed ratio and wall thickness, different machining strategies can be applied. The objective was to analyze and determine the influence of the machining conditions on surface roughness. The model for analyzing and determining surface roughness of the aluminum alloy AL 7075 was trained (design rules) and compared by using the experimental data. The average deviation of the compared data for surface roughness was 12.3%. The effect of the feed ratio, wall thickness and machining strategy as well as their interactions in machining are thoroughly analyzed and presented in this study.

Keywords Thin-walled parts · Aluminum · Fuzzy logic · Design of experiments · Surface roughness

Abbreviations

MRR	Material removal rate
Ra	Surface roughness—arithmetic mean roughness (μm)
Rz	Surface roughness—max. height roughness (μm)
CNC	Computer numerical control
MISO	Multi-input–single-output
MIMO	Multi-input–multiple-output
Al	Aluminum
ANN	Artificial neural network
MMC	Metal matrix composites
MLP	Multi-layer perceptron
RBF	Radial basis function
PSO	Particle swarm optimization
ANFIS	Adaptive network-based fuzzy interface system
FIS	Fuzzy interface system
MF	Membership functions
3D	Three dimensional

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1 Introduction

Thin-walled components made of aluminum alloys, due to their excellent physical and mechanical characteristics, are used as structural parts in various branches of the electro-mechanical industry, especially in the air and auto industries [1–3].

There are several recommendations on how basic classification of thin-walled parts is carried out. Thin-walled parts are such parts whose value of wall thickness is much smaller compared to other dimensions of the part. According to paper [4], the basic classification of thin-walled parts can be performed by:

- Small height-to-thickness ratio 15:1
- Moderate height-to-thickness ratio < 30:1
- Very large height-to-thickness ratio > 30:1.

Thin-walled parts can be obtained by casting, forging, injection molding, additive manufacturing technologies,

machining technologies (turning, milling, grinding, etc.), or electrical discharge machining. In this paper the focus is on machining by milling, because milling is one of the most common machining methods used in thin-walled part processing [5].

Machining of thin-walled parts reduces the processing time by creating one flow of monolithic parts. Thin-walled parts are made from blank material, which eliminates the need for manufacturing multiple parts that make one assembly unit [6, 7]. Due to the excellent strength-to-weight ratio and advantages in terms of machining costs, thin-walled parts have significant advantages over the conventional monolithic parts [8].

The machining of thin-walled structures is performed by removing material up to 95% of its weight. Machining processes for such complex structures are very long and demanding. Due to such a large amount of removed material, it is necessary to achieve high productivity. On the other hand, high productivity implies the application of sharper machining parameters which can cause vibrations during processing. These vibrations reduce the accuracy and quality of processing, sometimes leading to permanent deformation or even damage to parts. These problems are caused by many factors of the manufacturing process, such as the elements of the machining system (machine tool, cutting tool and fixtures), cutting conditions, strategies, coolant, etc [9–13].

Material removal rate (MRR) plays a significant role in the machining of thin-walled parts, because on the one hand, increase in MRR leads to reduced processing time, while on the other hand, it must be ensured that surface quality does not fall significantly.

The quality of finished products is defined by how closely the finished product adheres to certain specifications, including dimensions and surface quality. Surface quality is defined and identified by the combination of surface finish, surface texture, and surface roughness. Surface roughness (R_a) is the most common index for determining surface quality [14].

Baranek et al. [15] investigated the effects of the method of material removal on surface quality of thin-walled structures. The results of the research pointed to the optimal strategies with the application of cooling and lubrication assets which gave the best results in terms of dimensional accuracy and surface quality. Ab-Kadir et al. [8] performed a comparison of milling strategies for the machining of thin-walled aluminum parts. On the basis of the obtained results, they concluded that the limitations regarding surface roughness, machining time and accuracy of wall thickness are very important from the aspect of achieving high productivity of machining thin-walled parts.

Das et al. [16] conducted a comparative study of strategic approaches to the machining of thin-walled parts. They used five different machining strategies to achieve defined

dimensional accuracy and surface quality. Based on the experimental results, they concluded that the progressive increase in the axial depth of cut and constant feed provide better surface quality. Jiao et al. [17] studied the influence of the number of revolutions in high speed machining on surface quality of thin-walled parts made of SiCp/Al material.

Chandrasekaran et al. [18] developed an ANN based model for the prediction of surface roughness for various machining parameters. Fang et al. [19] described how the multi-layer perceptron (MLP) and the radial basis function (RBF) neural network models were developed to predict surface roughness in the machining of 2024-T351 aluminum alloy. The models take into account the effects of the tool-edge radius (via the ratio of the feed ratio to the tool-edge radius), the cutting speed, cutting forces, and cutting vibrations on the machined surface roughness. The results show that in comparison to the RBF model, the MLP model offers significantly higher accuracy of prediction for the machined surface roughness, especially for the maximum roughness height.

Pandian et al. [20] used an artificial neural network to predict cutting forces during high-speed machining, while the particle swarm optimization (PSO) was used to obtain optimum cutting speed and feed ratio. Dutta et al. [6] examined the optimal process parameters in order to obtain efficient thin wall machining using the firefly algorithm. Based on the experimental tests, they concluded that the tool diameter has the largest impact on surface roughness. In paper [21], the optimization of thin-walled structures using hybrid methods of artificial intelligence was performed.

Kovac et al. [22] applied fuzzy logic and regression analysis for modeling surface roughness in face milling. Hossain and Ahmad [23] developed the adaptive network-based fuzzy interface system (ANFIS) to predict surface roughness when milling aluminum parts using end mills, taking into account the cutter axis inclination angle, spindle speed, feed ratio, radial depth of cut, and axial depth of cut.

It is evident that to date a very limited amount of work has been produced using fuzzy logic techniques in modeling surface roughness of thin-walled aluminum parts. In addition to the feed ratio, which is one of the most important parameters of the milling of thin-walled parts, adding types of strategies and wall thickness as input parameters to the fuzzy model contributes to better understanding of the machining process.

According to the literature, the effect of various machining parameters on the finished surface quality has been investigated, but the absence of machining strategy and wall thickness and their effect on surface roughness has also been observed. It is assumed that these two non-classical input parameters have a major impact on surface quality. Therefore, in this paper, the use of fuzzy logic for analyzing surface roughness of thin-walled aluminum parts is presented.

The originality of applying fuzzy logic is reflected in the fact that previous research was mainly based on the development of models with classical machining parameters.

In this study, different wall thicknesses, feed rates and machining strategies were used, while the cutting speed and depth of cut were constant. The experiment was performed for rough cutting conditions with the aim of obtaining the best surface roughness. The finishing cut is not applicable because it is often long-lasting and therefore increases the machining or production cost. The object of the research was the line-type aluminum alloy thin-walled structure machining, with wall thickness ranging from 0.5 to 1.5 mm, which is moderately low compared to wall height 30:1.

2 Experimental Procedures

2.1 Experimental Setup

A prismatic shape was used as a blank for machining the samples, with the dimensions of $70 \times 40 \times 40$ mm. In Fig. 1a, the dimensions of the finished part are added. The experiments were performed on machining the aluminum alloy 7075-T6 (AlZnMgCu1.5), which was chosen due to its relatively low price, great strength and high density, thermal properties, etc. The chemical composition of 7075-T6 aluminum alloy is: Al (87.1–91.4%), Zn (5.1–6.1%), Mg (2.1–2.9%), Cu (1.2–2.0%), Fe ($\leq$0.5%), Si ($\leq$0.4%), Mn ($\leq$0.3%), Cr (0.18–0.28%), Ti ($\leq$0.20%), Zr ($\leq$0.25%). The tensile strength of this alloy is $\sigma = 560$ MPa, the modulus of elasticity is $E = 72$ GPa, the elongation at break is 7% and the hardness is 150 HBW.

Experimental investigations were carried out on the CNC vertical machining center—EMCO Mill 450, using emulsion as a cooling and lubricating agent, Fig. 1b. A cutting tool—high speed steel milling cutter was selected for machining the thin-walled aluminum parts. Its usable length is 32 mm which meets the requirements of the thin-walled geometry. The diameter is 10 mm and it has two teeth. The tool type was selected based on the recommendations from the tool manufacturer's catalog for the machining of aluminum materials [24]. The identification of the milling cutter, Fig. 1c, is R216.32-10025-AK32.

SolidWorks 2014 was selected to define the 3D model, while the MasterCAMX7 was used to generate program control (NC code).

2.2 Design of Experiments

The experiment plan setup was realized using the design-expert software. For this case, central composite was chosen. The total number of experiments was 33. The experiment plan envisaged three variable factors, two numeric
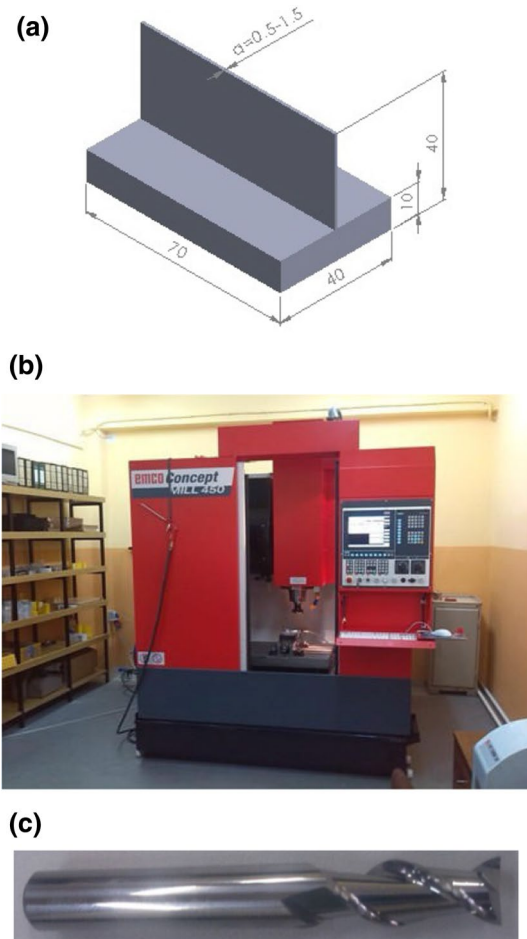

Fig. 1 3D part drawing (**a**), CNC machine (**b**) and cutting tool (**c**) on which the experiment was performed

and one non-numeric factor. The numerical factors were wall thickness and feed ratio. The wall thickness values were 0.5, 0.65, 1.00, 1.35, and 1.50 mm. The feed ratio interval was from 150 mm/min to 350 mm/min. The non-numeric factor was the machining strategy. The machining strategies used in the MasterCAM software included:

- Tool path strategy—PATH 1 (Parallel Spiral)
- Tool path strategy—PATH 2 (Zigzag)
- Tool path strategy—PATH 3 (True Spiral)

The following strategy for the order of treatment of the sides of the thin-walled part was adopted during the experiments: the first machining pass was executed on the left side of the thin-walled structure; then the second and the third machining pass were executed on the right side; next, the fourth and the fifth machining pass were executed on the left side, and so on up to the twentieth pass at the bottom of the thin-walled structure as shown in Fig. 2.
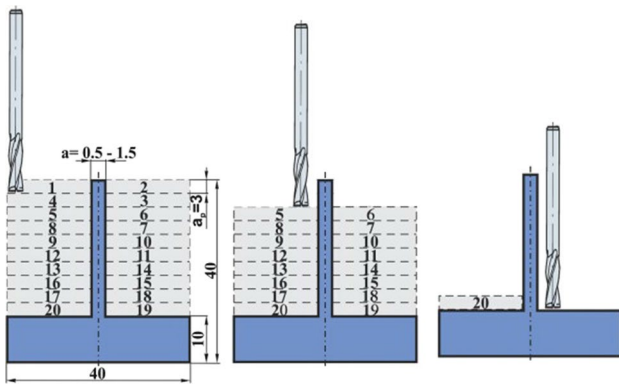
Fig. 2 Machining passes sequence for the milling of thin-walled parts [25]

The experimental machining parameters are given in the Table 1, while the experimental results are shown in the Table 2. The measured value of the thin-walled structure was surface roughness—Ra. Measurement of surface roughness was performed with the INNOVATEST device, perpendicular to the direction of the movement of the cutter on both sides of the wall. The device can measure the parameters Ra (0.03–6.35) μm and Rz (0.2–25.3) μm. Measurement was performed with a 2 μm diamond tip and a resolution of 0.01 μm.

For each part, four measurements of surface roughness of both sides of the wall were performed at a distance of 15 mm from the end edges of Fig. 3. The measurement position influences the results of roughness measurement, since the lower edge of the wall is more stable than the upper one, and measurement is done with the entire height of the treated surface of the wall. Figure 4 gives an overview of two machined parts with different wall thicknesses.

3 Fuzzy Logic

Fuzzy logic is a method that is widely used today and provides great possibilities for solving problems in the automatic managing and processing of information. The process of fuzzy inference involves membership functions, fuzzy logic operators, and if–then rules [22, 26]. The basic structure of a FIS consists of three conceptual components: a rule base which contains a selection of fuzzy rules; a database which defines the membership functions (MF) used in the fuzzy rules; and a reasoning mechanism which performs the inference procedure upon the rules to derive an output, Fig. 5. The parameters of the if–then rules define a fuzzy region of the input space, and the output parameters (which represent the consequence in fuzzy modeling) specify the corresponding output [21].

There are three types of fuzzy inference systems in wide use: Mamdani-type, Sugeno-type and Tsukamoto-type [27–29].Mamdani FIS is the best known or most commonly used one in developing fuzzy models and was applied in this paper, too. Also, Mamdani FIS can be used directly for both multi-input–single-output (MISO) systems and multi-input-multiple-output (MIMO) systems. The design of the fuzzy logic system was divided into three phases. The first was to define a fuzzy variable, followed by forming a set of all fuzzy subsets of variables with the appropriate membership functions. In the third phase fuzzy rules were formed. Input variables in the fuzzy system were: wall thickness, feed ratio and machining strategy. The output variable was surface roughness—Ra. MATLAB fuzzy logic tool was used for the calculation. For the set problem, the structure of the set system was defined, Fig. 6.

The fuzzy expressions for different input parameters are shown in Table 3. For example, parameters for wall thickness were defined as "Lowest", "Low", "Medium", "High" and "Highest", as shown in Table 3. The degree of membership was equal to 1, and the corresponding current values were 0.50, 0.65, 1.00, 1.35, and 1.50. The feed ratio values were 150.00, 179.29, 250.00, 320.71, and 350.00. Each experiment resulted in certain output parameters that were classified into the corresponding fuzzy set of output variable.

The number of membership functions used for the first output response was nine, i.e., A, B, C, D, E, F, G, H, I, while for the second output it was eight: A, B, C, D, E, F, G, H. More precise results can be obtained by using a greater number of membership functions. Hence, nine and eight membership functions were selected for the present work. Each fuzzy set

Table 1 Experimental parameters						
Number of revolutions	rpm	2000				
Wall thickness	mm	0.5	0.65	1.0	1.35	1.5
Feed ratio	mm/min	150	179.29	250	320.71	350
Tool diameter	mm	10				
Tool material	–	H10F				
Number of teeth	–	2				
Flute helix angle	–	25°				
Depth of cut	mm	3 (consistent)				

Table 2 Experimental data

No.	Wall thickness (mm)	Feed ratio (mm/min)	Machining strategy	Surface roughness Ra (µm)	Fuzzy surface roughness Raf (µm)
1.	1.35	250	PATH 1	0.5	0.61
2.	1.35	320.71	PATH 1	0.6	0.83
3.	1.5	150	PATH 1	1	1.10
4.	1	350	PATH 1	1.1	1.00
5.	1	250	PATH 1	1.1	0.91
6.	0.65	179.29	PATH 1	1.2	1.33
7.	0.65	320.71	PATH 1	1.2	1.31
8.	1	179.29	PATH 1	1.2	1.32
9.	0.5	250	PATH 1	1.4	1.32
10.	1	250	PATH 1	1.4	0.91
11.	1	250	PATH 1	1.4	0.91
12.	1	179.29	PATH 2	2	2.07
13.	0.5	250	PATH 2	2	2.07
14.	0.65	320.71	PATH 2	2.1	2.08
15.	1	350	PATH 2	2.1	2.39
16.	0.65	179.29	PATH 2	2.2	2.08
17.	1.35	250	PATH 2	2.2	2.06
18.	1	250	PATH 2	2.2	2.30
19.	1.5	150	PATH 2	2.4	2.41
20.	1	250	PATH 2	2.4	2.30
21.	1	250	PATH 2	2.5	2.30
22.	1.35	320.71	PATH 2	3	2.87
23.	1	179.29	PATH 3	0.4	0.56
24.	1.35	320.71	PATH 3	0.4	0.67
25.	1.35	250	PATH 3	0.5	0.61
26.	1	350	PATH 3	0.6	0.71
27.	0.65	320.71	PATH 3	0.7	0.72
28.	1.5	150	PATH 3	0.7	0.72
29.	1	250	PATH 3	0.7	0.69
30.	1	250	PATH 3	0.7	0.69
31.	1	250	PATH 3	0.7	0.69
32.	0.65	179.29	PATH 3	0.8	0.83
33.	0.5	250	PATH 3	0.8	0.85
Average error 12.3%					

was defined by a separate membership function. The membership functions for wall thickness, feed ratio and machining strategy are shown in the Fig. 7.

Fuzzy logic uses membership functions representing an arbitrary curve. Although there are a number of available membership functions, such as triangular, trapezoidal, Gaussian, etc., in this paper we used the Gaussian type for tool life and cutting temperature modeling. The symmetric Gaussian function depends on two parameters, where σ and c are given:

$$f(x, \sigma, c) = e^{\frac{-(x-c)}{2\sigma^2}} \tag{1}$$

where c is the mean value (center), and σ is the standard deviation (width of the 'base' curve).

The concept of fuzzy reasoning for the four-input and two output fuzzy logic unit is described as follows: The fuzzy rule base consists of a group of IF-THEN statements with three inputs: x_1 (wall thickness), x_2 (feed ratio) and x_3 (machining strategy) and one output: y_1 (surface roughness). Thus, the general form of rule base systems with multiple inputs and multiple outputs is:

Input : x_1 *is* A_1 *and* x_2 *is* B_1 *and* x_3 *is* C_1

R_1 : x_1 *is* A_1 *and* x_2 *is* B_1 *and* x_3 *is* C_1 *THEN* y_1 *is* D_1

R_2 : x_1 *is* A_2 *and* x_2 *is* B_2 *and* x_3 *is* C_2 *THEN* y_1 *is* D_2

⋮

R_i : x_1 *is* A_i *and* x_2 *is* B_i *and* x_3 *is* C_i *THEN* y_1 *is* D_i

Output: y_1 *is* D}

$$\tag{2}$$

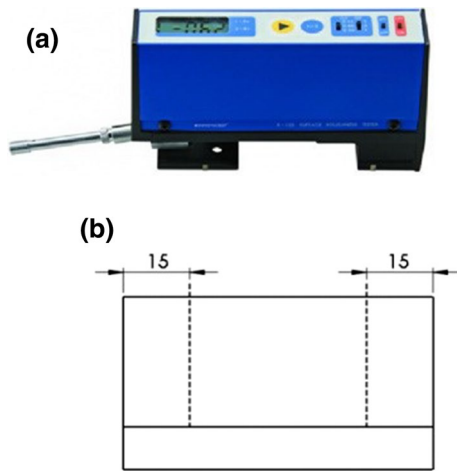**(a)**

(b)

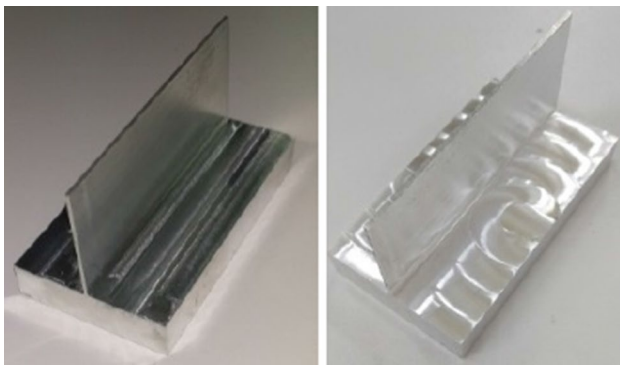**Fig. 3** INNOVATEST device (**a**) and the measurement plan (**b**)

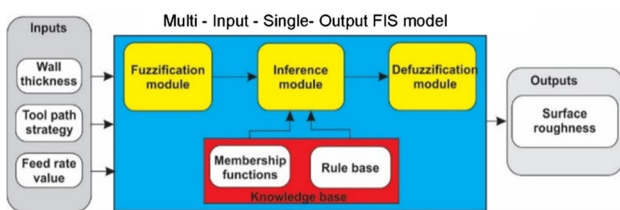**Fig. 4** Final shape of two parts with different tool path strategies (left—Parallel Spiral, right—True Spiral)

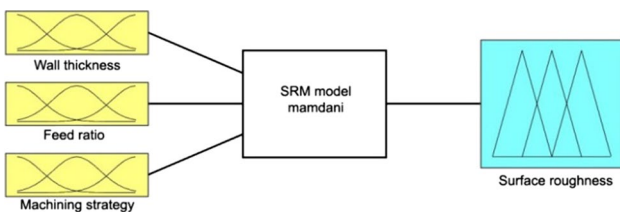**Fig. 5** Fuzzy inference system with three inputs and one output

Fig. 6 Mamdani fuzzy model input–output diagram

where x_1, x_2, x_3 are variables describing the process status and representing the input size of a fuzzy system, while y_1 represents the output variable of a fuzzy system. A_i, B_i, C_i, D_i and E_i are linguistic values defined by fuzzy sets on the ranges: x_1, x_2, x_3 and y_1 respectively. After that, the implication function modifies the fuzzy set to a degree specified by the antecedent. The most common way to modify the output fuzzy set is truncation using the MIN function. Each rule from the previous set of rules can be viewed as a fuzzy implication, so that the i-th rule can be defined as:

$$\mu_{Ri} = \mu_{(A_i \wedge B_i \wedge C_i \wedge D_i \wedge E_i \wedge F_i \wedge G_i \Rightarrow H_i)(x_1,x_2,x_3,y_1,y_2,y_3,y_4,y_5)}$$
$$= \left[\mu_{Ai}(x_1) \wedge \mu_{Bi}(x_2) \wedge \mu_{Ci}(x_3) \right] \Rightarrow \mu_{Di}(y_1) \quad (3)$$

We used the Mamdani MIN implication operator, whereby the implication operator takes as input the membership function of the antecedent $\mu_{Ai}(x_1) \wedge \mu_{Bi}(x_2) \wedge \mu_{Ci}(x_3)$ while $\mu_{Di}(y_1)$ is the consequent. Every rule has a weight (number between 0 and 1) which is applied to the number given by the antecedent.

Finally, a defuzzification method is used to transform the fuzzy output into a non-fuzzy value y_0. Defuzzification is carried out by using the centroid defuzzification method. It produces the center area of the possibility distribution of the inference output. It is also one of the most frequently used defuzzification methods using the centroid of the area under the membership function for calculation:

$$y_1' = \frac{\sum_{i=1}^{n} y_1 \mu_{Di}(y_1)}{\sum_{i1}^{n} \mu_{Di}(y_1)} \quad (4)$$

where y_1' represents defuzzied outputs (the output for a given input vector, which was predicted by T and θ values in this study); μ_{Di} represents the aggregated membership functions; y_1 represents the output variable (the center value of the regions).The rule bank for the system was based on experimental data. Table 3 shows the rule bank for MISO model. IF–THEN was also employed in the inference element to determine the output. The nonfuzzy values y_1 give the output values which are shown in numerical form.

4 Results and Discussion

The results obtained by the Mamdani fuzzy system of reasoning, using rules that were defined on the basis of experimental data, show agreement with the experiment. This shows that the selected types of membership functions (gaussmf) type reasoning mechanism by the method

	No.	Wall thickness (mm)	Feed ratio (mm/min)	Machining strategy	Surface roughness Ra (µm)
Table 3 Set of rules for FIS model	1.	HIGH	MEDIUM	PATH 1	A
	2.	HIGH	HIGH	PATH 1	B
	3.	HIGHEST	LOWEST	PATH 1	D
	4.	MEDIUM	HIGHEST	PATH 1	D
	5.	MEDIUM	MEDIUM	PATH 1	D
	6.	LOW	LOW	PATH 1	E
	7.	LOW	HIGH	PATH 1	E
	8.	MEDIUM	LOW	PATH 1	E
	9.	LOWEST	MEDIUM	PATH 1	E
	10.	MEDIUM	LOW	PATH 2	F
	11.	LOWEST	MEDIUM	PATH 2	F
	12.	LOW	HIGH	PATH 2	F
	13.	MEDIUM	HIGHEST	PATH 2	F
	14.	LOW	LOW	PATH 2	F
	15.	HIGH	MEDIUM	PATH 2	F
	16.	MEDIUM	MEDIUM	PATH 2	F
	17.	HIGHEST	LOWEST	PATH 2	G
	18.	HIGH	HIGH	PATH 2	H
	19.	MEDIUM	LOW	PATH 3	A
	20.	HIGH	HIGH	PATH 3	A
	21.	HIGH	MEDIUM	PATH 3	A
	22.	MEDIUM	HIGHEST	PATH 3	B
	23.	LOW	HIGH	PATH 3	B
	24.	HIGHEST	LOWEST	PATH 3	B
	25.	MEDIUM	MEDIUM	PATH 3	B
	26.	LOW	LOW	PATH 3	C
	27.	LOWEST	MEDIUM	PATH 3	C

of MIN–MAX and the selected defuzzification centroid method (center of gravity) are a good choice.

The average deviation of the fuzzy values for surface roughness was 12.3%. The relative error of the model was slightly above average. According to the current literature, a model is considered successful if it has an error up to 10% [30, 31]. In this paper, the obtained model was used to analyze and examine the effect of input parameters on surface quality. Therefore, the relative error of the fuzzy model is considered acceptable.

Figure 8 illustrates the comparison of experimental and fuzzy values for surface roughness. It has been proved that the method used in this paper is feasible and could be used to determine surface roughness within the acceptable error rate for milling thin-walled aluminum parts. The comprised lines seem to be close to each other, indicating good agreement. Figure 9 shows the three-dimensional surface profile obtained during fuzzy logic modeling for the effect of machining parameters wall thickness, feed ratio and machining strategy on surface roughness, where any two of the inputs vary and one of the inputs must be held constant. It can be seen how strong the influence of machining strategy on surface roughness is for various wall thicknesses and constant feed rates. Figure 9a–c show that path 2 of the machining strategy has a high impact on surface roughness. The most significant factor that affects surface roughness is machining strategy.

Any change in the machining strategy leads to a corresponding change in surface roughness. The machining strategy Zigzag (Path 2) gives a high value of surface roughness, Parallel Spiral (Path 1) and True Spiral (Path 3) give a lower value of surface roughness, while path 3 of the machining strategy gives the lowest value of roughness, Fig. 10. The
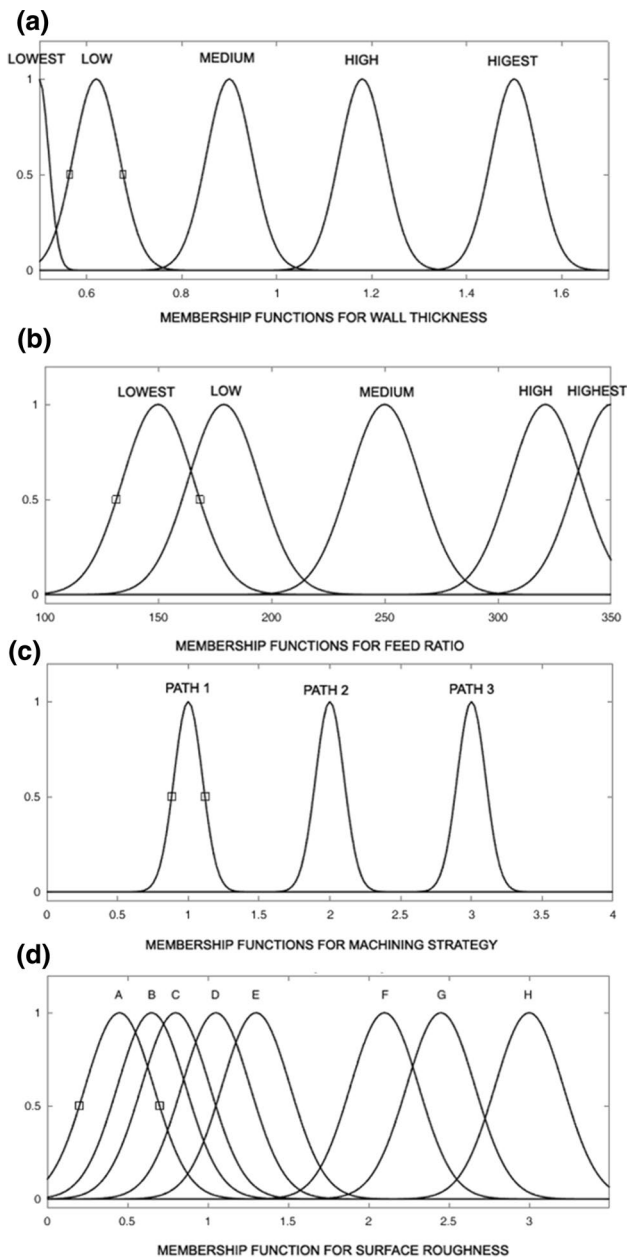
(a)

(b)

(c)

(d)

Fig. 7 Membership functions of outputs: **a** wall thickness; **b** feed ratio; **c** machining strategy; and membership of output: **d** surface roughness

influence of wall thickness on the change in surface roughness is similar to the impact of feed ratio.

The fuzzy results shown above were also confirmed by the ANOVA (Table 4) analysis using the main effects plot. As it can be seen from Fig. 11, surface roughness increases with the change of machining strategy. From this figure, the effects of each parameter at different levels can be observed. The best surface roughness was achieved when wall thickness was 1.35 mm, and the most unfavorable roughness was achieved when it was 0.5 mm. Feed ratio had the following influence on surface roughness: the most favorable variant was when feed was 350 mm/min, and the most unfavorable was for feed variants of 150 mm/min and 250 mm/min. The factor machining strategy gave the best results for surface roughness when path 3 of the machining strategy was used and the most unfavorable results were obtained when path 2 was used.

5 Conclusion

In the present research, according to Central Composite Design, a number of experiments with different machining conditions including feed ratio, wall thickness and machining strategies were performed and analyzed using fuzzy logic and the ANOVA. In the machining of the aluminum alloy AL 7075-T6, the effect of machining parameters on surface roughness was examined.

Fuzzy logic can be successfully applied for this purpose. The application of fuzzy logic in the analysis of surface roughness resulted in the deviation of 12.3% with respect to the experimental results. The model is only applicable within the range of the experiment plan. The contribution of this paper is not only in the comparison of the obtained experimental data for surface roughness using fuzzy logic, but also in the examination of machining parameters which have the greatest impact on surface roughness.

The effects of parameters and their interactions in machining were thoroughly analyzed and presented in this study. Based on the ANOVA analysis and the fuzzy model, it can be concluded that in order to achieve minimum surfaces roughness, the best strategy for machining is path 3(True Spiral). On the other hand, the strategy path 2(Zigzag) resulted in the greatest surface roughness. In addition, the remaining parameters such as feed ratio and wall thickness have less influence on surface roughness.

Finally, it can be concluded that the application of fuzzy logic for the purpose of analyzing input parameters and obtaining the best possible solution has been successfully implemented. The model adequacy can be further improved by considering more variables and ranges of parameters.
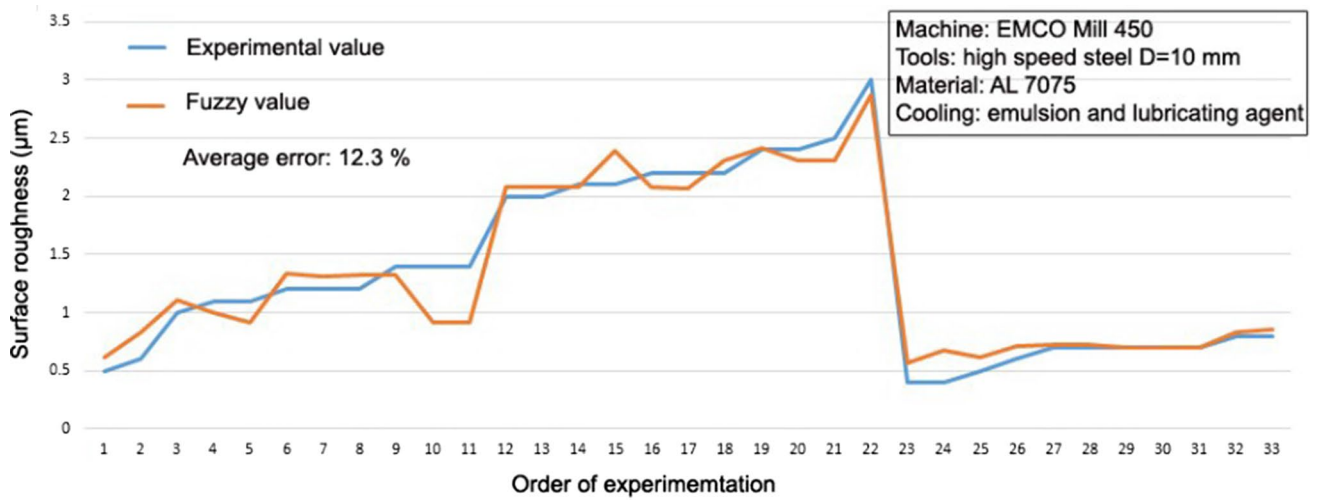
Fig. 8 Comparison of experimental data and fuzzy values with the average relative error
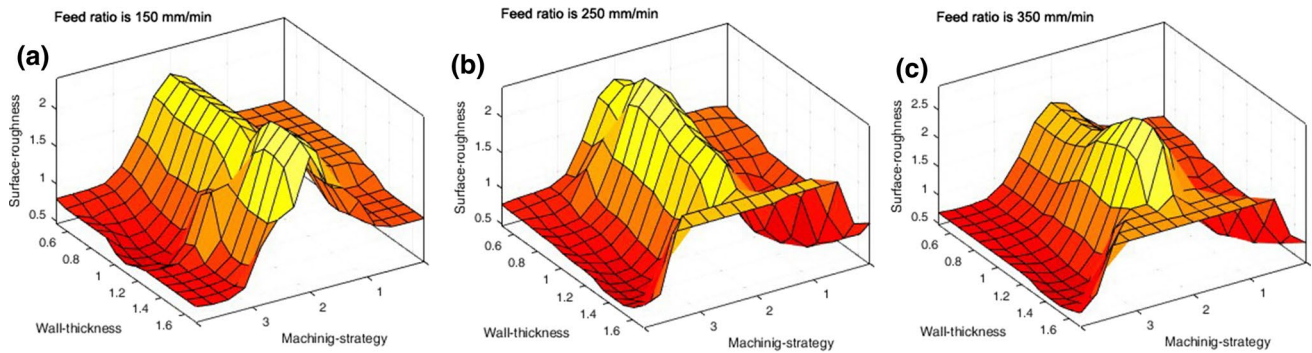

Fig. 9 Fuzzy 3D-plot of surface roughness where wall thickness and machining strategy are variable values for different feed ratio: **a** 150 mm/min; **b** 250 mm/min and **c** 350 mm/min
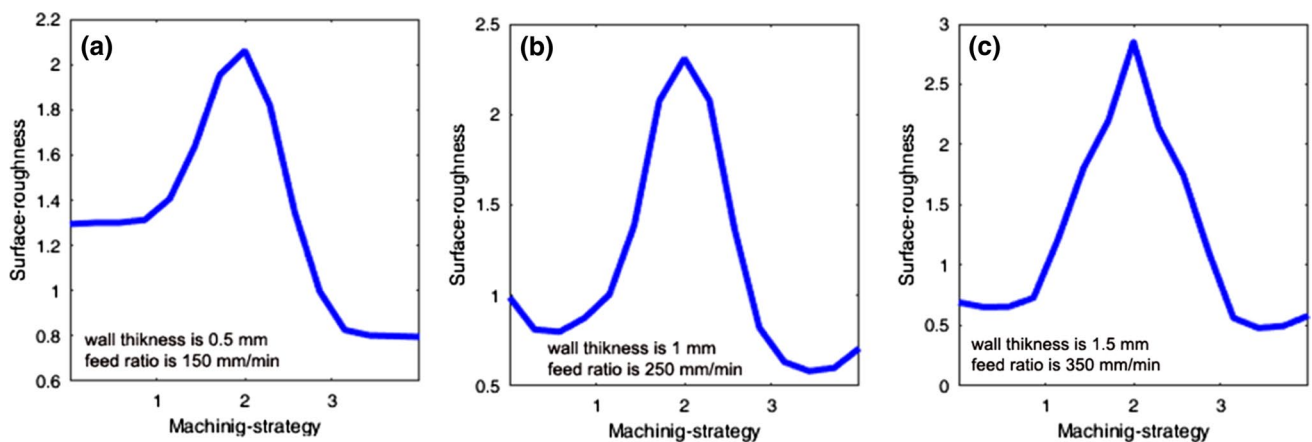

Fig. 10 Fuzzy 2D-plot of surface roughness where wall thickness and feed ratio are held constant: **a** 0.5 mm and 150 mm/min; **b** 1 mm and 250 mm/min; and **c** 1.5 mm and 350 mm/min

Table 4 ANOVA results

Input factors	Degree of freedom	Sum of square	Mean square	F value	P value	Contribution %
Wall thickness	4	0.2183	0.05457	0.73	0.579	0.68
Feed ratio	3	0.1027	0.03424	0.46	0.713	0.42
Machining strategy	2	15.8370	7.91848	106.28	0.000	98.90
Error	23	1.7137	0.07451	–	–	
Total	32	1.6070	0.09453	–	–	100
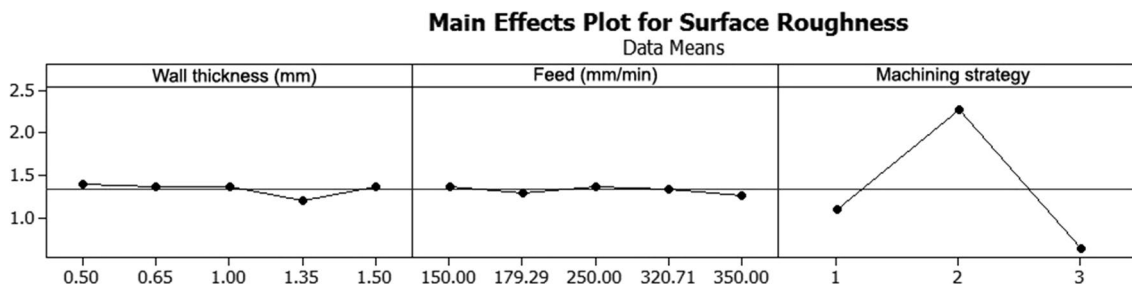
Fig. 11 ANOVA based main effects plot of input parameters on surface roughness

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