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Fuzzy logic modeling of ultimate tensile strength and cost in fused deposition modeling process of additive manufacturing

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Abstract: Additive manufacturing is the modern technology that uses a computer-aided design product data to create its real physical replica. In the industry already exist a vast number of different additive manufacturing processes that use various types of materials, from polymers to metals, to create new products and prototypes. Fused deposition modeling (FDM) is one of the well-known additive manufacturing processes. It is able to create products that can be treated and used further in the manufacturing process. These products have very acceptable mechanical properties. These properties mostly depend and vary according to process parameters values and can be optimized by setting process parameters on appropriate levels. In this paper, a fuzzy logic modeling approach was used to analyze the influence of variable process parameters: top and bottom surface layers' number, fill spacing, and layer resolution on ultimate tensile strength and manufacturing cost. Experiments were conducted on the PLA (Polylactic Acid) biodegradable material but it can be also tested on some other materials such as ABS, PC, PSU, PEEK and etc. Developed models were used to describe the process and determine process parameters values that lead to maximal tensile strength and minimal cost. Findings in this paper can be significant for users involved in this type of process to obtain a higher quality product and desirable savings.

1. Introduction

Fused deposition modeling (FDM) is one rapidly growing technology of additive manufacturing (AM). It was developed almost 30 years ago. At that time, it was mainly focused on building conceptual models, but today it is present in the field of electronics, industry (machines, automobile, and space) but also in medicine, science, architecture, and military. The basic principle of FDM is that the melted polymer in a wire form passes through the nozzle. The polymer cures at room temperature, and thus, the heat of the melted material should be maintained a little above the curing temperature. The head of the extruder moves in the x-y plane, and after the production of the first layer, the platform moves down on the z-axis, thus extruding the new layer. The process of applying a new layer repeats, and a model is generated [1-3]. Depending on the geometry of the model, the extruder can build a supporting material for the model, which can be easily removed after printing. The surface of the model tends to be rough, and the model can be additionally processed after the printing, using techniques such as milling, grinding, and turning. Depending on the type of the used polymer, it can be treated with various chemicals to gain a smooth finish. For FDM, various polymers can be used: acrylonitrile butadiene styrene (ABS), polylactic acid (PLA), polycarbonates (PC), polypropylene (PP), polyethylene – high density (PE-HD) and polyethylene – low density (PE-LD) [3]. Investment is relatively small, as well as maintenance cost, material waste, and energy consumption [3]. Furthermore, an application is relatively simple, the material is stable and can be processed afterward. Several prototypes can be manufactured at one extrusion, and finally, low-cost products can be obtained, at least for low-cost 3D printers. On the other hand, the lack of this technology for building prototypes is that the created parts need to be finally processed after printing, and models usually require printing support. Furthermore, the process is sensitive to temperature changes. Dimensional accuracy of the model can be low and sharp edges cannot be produced due to the circular nozzle that shape the final product cross section [1]. Usually, material density is lower in the direction vertical to the printing direction, and the mechanical properties of the parts depend on the position of the product on the working surface (platform), especially in the z-axis direction [4, 5].

Considering the significant impact in most of the science and technology fields, the numerous studies on the efficiency of parameters of the FDM process is not surprising [6-19]. The main focus of these studies was based on the research on the impact of various parameters that can affect the success of the process such as layer thickness, raster angle, and width, the orientation of the part build, air gap, strength (flexural and impact) [6-9]. Furthermore, numerous researches were conducted to investigate the influence of the FDM process parameters on the obtained samples properties: surface roughness [10], dimensional accuracy [11], material behavior (elasticity) [12], build time [13] and mechanical properties [14]. In most of the previous researches, efforts have been made to explain the relationship between the input process parameters obtained on the obtained samples properties using mathematical modeling methods [9-16, 18-19]. Several of research works were based on various optimization and modeling techniques such as response surface methodology (RSM), Taguchi method, full factorial, gray relational, fractional factorial, artificial neural network (ANN), fuzzy logic and genetic algorithms (GA) [17]. Nancharaiah et al. [10] studied the influences of process parameters such as layer thickness, road width, raster angle, and air gap on the surface finish of FDM processed ABS part through the Taguchi method and variance analysis (ANOVA) technique. The main conclusion was that surface roughness could be improved by using a lower value of layer thickness and air gap [10]. Peko et al. [16] utilized the design of experiments (DOE) approach in order to create mathematical models that can describe the influence of process parameters on maximal ultimate tensile strength and cost of the obtained samples. DOE was prepared using D-optimal response surface design. Optimization results showed that the samples with the best combination of tensile strength and cost were samples produced with 11 surface layers, fill spacing 15 mm, and layer resolution 70 µm. According to these results, it is possible to create samples that have 77.8 % of maximal UTS obtained in this research, but these samples also cost 45.9 % less than those with the maximal value of UTS [16]. Onwubolu et al. [18] analyzed the influence of layer thickness, part orientation, raster angle, raster width, and air gap on the tensile strength of test specimens. Mathematical models relating the response to the process parameters were developed using the group method of data handling (GMDH). Optimal process parameters that lead to maximized tensile strength were defined through the application of differential evolution (DE) algorithm. Sood et al. [19] made an extensive study to understand the effect of five FDM parameters such as layer thickness, part build orientation, raster angle, raster width, and air gap on the compressive stress of test specimens. They also developed statistically validated predictive equations using an artificial neural network approach and regression analysis and found optimal parameter settings through quantum-behaved particle swarm optimization (QPSO).

The main aim of this paper is to create mathematical models that should serve for description and prediction of the influence of additive manufacturing process parameters on the mechanical properties and cost of the obtained samples. As mentioned above, most of the previous researches deal with visual, mechanical, and physical properties of the obtained FDM samples, while in this research, economic perspective was also taken into consideration. The input process parameter was top and bottom surface layers number, fill spacing, and layer resolution. According to the comprehensive review paper published by Omar et al. [17], many studies have investigated the effects of FDM process parameters on ABS built part. However, in the case of other FDM materials, very little work has been done both in terms of material characterization and FDM process optimization. Therefore, considerable work remains to be done in DOE's for part fabrication and process optimization involving other FDM polymers such as PC, PPSF, PC-ABS, PC-ISO, elastomer, and nylon-12 [17]. For this reason, for the analysis in this paper PLA material is conducted. PLA is a biodegradable polymer, in contrast to ABS, which is not biodegradable but can be recycled. PLA has low printing temperature, and it can print sharper corners in comparison to ABS. Also, in contrast to ABS, it is significant in printing models for which the form is more important than its function [20-22].

Mathematical modeling in this paper will be conducted using the artificial intelligence method of fuzzy logic (FL). Fuzzy logic modeling provides a way to better understand the process behavior by allowing the functional mapping between input and output observations [23, 24]. Afterward, the quality of the obtained mathematical model will be estimated using the mean absolute percentage error (MAPE) and the coefficient of determination (R^2) between experimental and predicted response values. The created model will be used to determinate optimal area of input process parameters values that lead to maximal ultimate tensile strength and minimal cost of manufacturing. Obtained models should serve as a valuable tool in additive manufacturing investigation.

2. Experimental procedure

In order to develop mathematical models, design of experiment method (DOE) was utilized. These mathematical models will be able to predict output process responses and show the impact of variable input process parameters on them. In this paper, DOE was prepared using Taguchi L18 experimental plan. The impact of fill spacing, layer resolution and the number of top and bottom surface layers on built samples maximal tensile strength and manufacturing cost are investigated. Variable process parameters represent additive manufacturing machine settings that can be adjusted by operator. Fixed input parameters are building material: PLA, print mode: custom, print strength: strong, print pattern: honeycomb, outer walls: 1. Variable process parameters values and obtained ultimate tensile strength values as well as cost for all experimental samples are shown in Table 1. Cost was calculated as:

$$Cost = mass\ of\ piece\ (g) * material\ price\ (EUR/g) \quad (1)$$

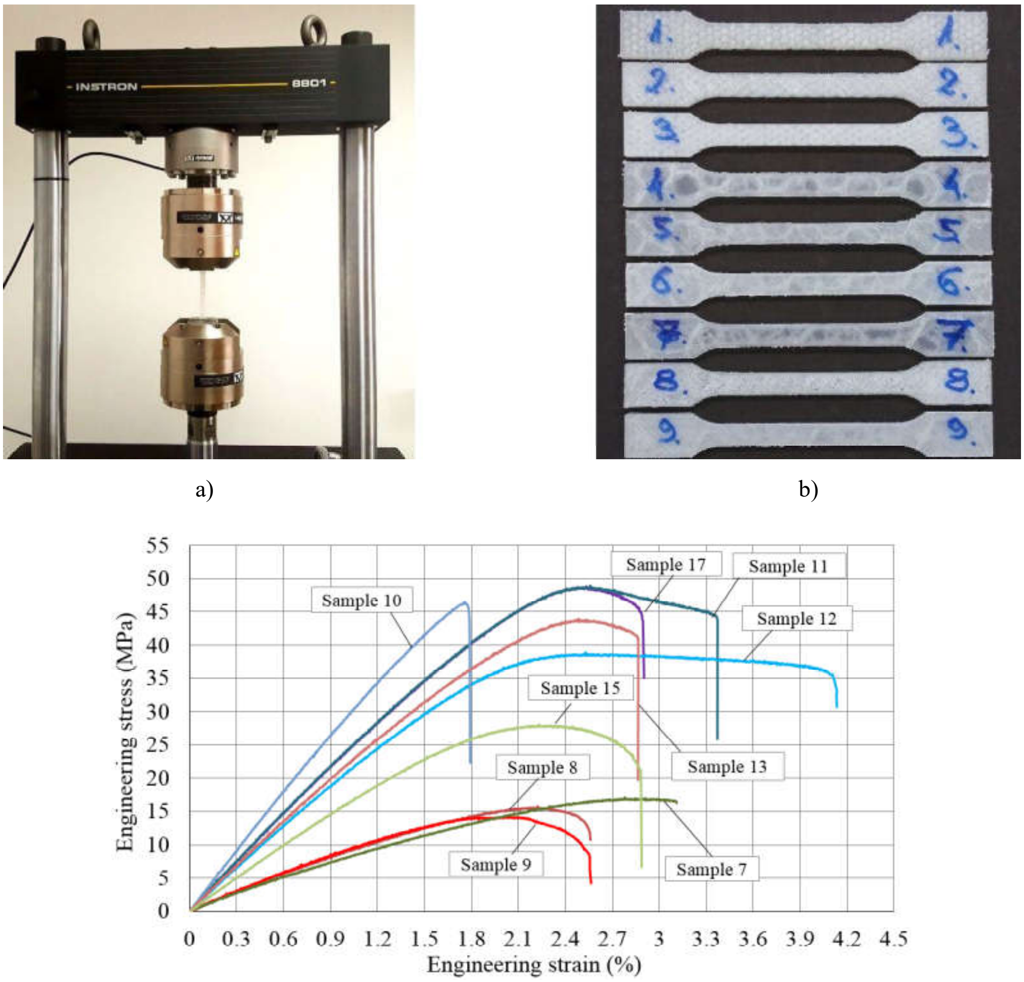
Table 1. Design of experiment and results

No. of experiment	Top and bottom surface layers number	Fill spacing (mm)	Layer resolution (μm)	Ultimate tensile strength, UTS (MPa)	Cost (EUR)
1.	3	2	70	25.150	1.77
2.	3	2	200	14.758	1.49
3.	3	2	300	15.258	1.59
4.	3	8.5	70	17.399	1.08
5.	3	8.5	200	15.818	1.16
6.	3	8.5	300	16.860	1.25
7.	3	15	70	17.130	0.94
8.	3	15	200	15.835	1.11
9.	3	15	300	14.372	1.09
10.	15	2	70	46.561	2.21
11.	15	2	200	49.046	1.84
12.	15	2	300	38.911	1.53
13.	15	8.5	70	43.994	1.71
14.	15	8.5	200	48.693	1.78
15.	15	8.5	300	28.092	1.53
16.	15	15	70	42.134	1.64
17.	15	15	200	48.861	1.77
18.	15	15	300	38.662	1.53

Experimental work was conducted on a CubePro (3D Systems) additive manufacturing machine. Experimental samples were generated according to HRN EN ISO 527:2012 standard (Figure 1b). Building material was applied in layers in z-axis while building platform lies in an x-y plane. Furthermore, ultimate tensile strength evaluation was performed on universal testing machine ''Instron 8801'' (Figure 1a). After the testing was finished a few random stress-strain diagrams for different experimental samples were generated (Figure 1c).

3. Fuzzy logic modeling

Fuzzy logic modeling is one of the most important modeling approaches in the field of artificial intelligence. It is very useful for modeling complex processes where the limited understanding of the physical laws that describe the underlying process does not allow development of accurate mathematical models. For complex processes where there are a few numerical data and where only ambiguous or imprecise information is available, fuzzy logic modeling provides a way to better understand the process behavior by allowing the functional mapping between input and output observations [23, 24]. The fuzzy system consists of four components (Figure 2): the fuzzification module, the fuzzy inference module, the defuzzification module, and the knowledge base. Fuzzification module converts all input variables into fuzzy (linguistic) variables using membership functions. A membership function is a curve that defines how each point in the input and output space is mapped to a membership value (or degree of membership) between 0 and 1. There are many available membership functions like triangular, trapezoidal, Gaussian etc. [24, 25]. The fuzzy inference module uses the knowledge base containing the fuzzy IF-THEN rules and the membership functions to obtain the fuzzy (linguistic) output values for the corresponding inputs. Finally, the defuzzification module converts the aggregated fuzzy output into a non-fuzzy value [24].



a) b)

c)

Figure 1. a) Universal tensile testing machine "Instron 8081", b) few experimental samples, c) Stress-strain diagrams for the few samples

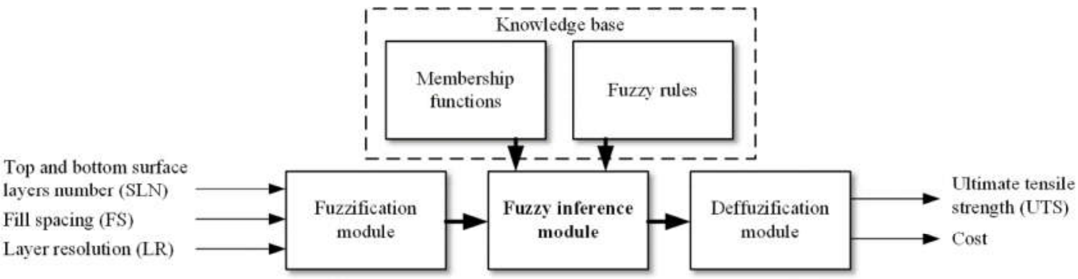


Figure 2. Structure of the fuzzy logic system with three input process parameters and two output responses

In this paper, for the purpose of FDM process analysis, Mamdani fuzzy inference system was used. Process parameters: top and bottom surface layers number (SLN) fill spacing (FS), layer resolution (LR) were considered as inputs, while ultimate tensile strength (UTS) and cost were considered as outputs. For SLN input two membership functions were used: Low and High, while for FS and LR inputs three membership functions were used: Low, Medium and High.

On the other side, for both outputs, five membership functions were used: Low (L), Low-Medium (LM), Medium (M), Medium-High (MH), High (H). Gaussian membership functions were employed to describe the fuzzy sets of inputs and outputs. Membership functions and their ranges are shown in Figure 3.

After selection of membership functions, based on conducted experiments, a set of 18 fuzzy IF-THEN rules with three inputs (SLN, FS, LR) and two outputs (UTS, Cost) was constructed. Each of these rules plays an important role in generating the fuzzy logic model and the accuracy of the numerical output [24, 26]. These rules are shown in Table 2. Fuzzy inference process was defined by the following: and method: min, or method: max, implication: min, aggregation: max and defuzzification method: centroid.

Centroid method is a widely accepted method of deffuzification where the deffuzified output z* is obtained by:

$$z* = \frac{\int \mu A(z) z dz}{\mu A(z) dz} \quad (2)$$

where $\mu_A(z)$ is the aggregated membership function and z is the output variable (the center value of the regions).

Table 2. Set of fuzzy rules

1. If (SLN is Low) and (FS is Low) and (LR is Low) then (UTS is M)(Cost is MH)	10. If (SLN is High) and (FS is Low) and (LR is Low) then (UTS is H)(Cost is H)
2. If (SLN is Low) and (FS is Low) and (LR is Medium) then (UTS is L)(Cost is M)	11. If (SLN is High) and (FS is Low) and (LR is Medium) then (UTS is H)(Cost is MH)
3. If (SLN is Low) and (FS is Low) and (LR is High) then (UTS is L)(Cost is M)	12. If (SLN is High) and (FS is Low) and (LR is High) then (UTS is MH)(Cost is M)
4. If (SLN is Low) and (FS is Medium) and (LR is Low) then (UTS is LM)(Cost is L)	13. If (SLN is High) and (FS is Medium) and (LR is Low) then (UTS is MH)(Cost is MH)
5. If (SLN is Low) and (FS is Medium) and (LR is Medium) then (UTS is L)(Cost is L)	14. If (SLN is High) and (FS is Medium) and (LR is Medium) then (UTS is H)(Cost is MH)
6. If (SLN is Low) and (FS is Medium) and (LR is High) then (UTS is LM)(Cost is LM)	15. If (SLN is High) and (FS is Medium) and (LR is High) then (UTS is M)(Cost is M)
7. If (SLN is Low) and (FS is High) and (LR is Low) then (UTS is LM)(Cost is L)	16. If (SLN is High) and (FS is High) and (LR is Low) then (UTS is MH)(Cost is M)
8. If (SLN is Low) and (FS is High) and (LR is Medium) then (UTS is L)(Cost is L)	17. If (SLN is High) and (FS is High) and (LR is Medium) then (UTS is H)(Cost is MH)
9. If (SLN is Low) and (FS is High) and (LR is High) then (UTS is L)(Cost is L)	18. If (SLN is High) and (FS is High) and (LR is High) then (UTS is MH)(Cost is M)

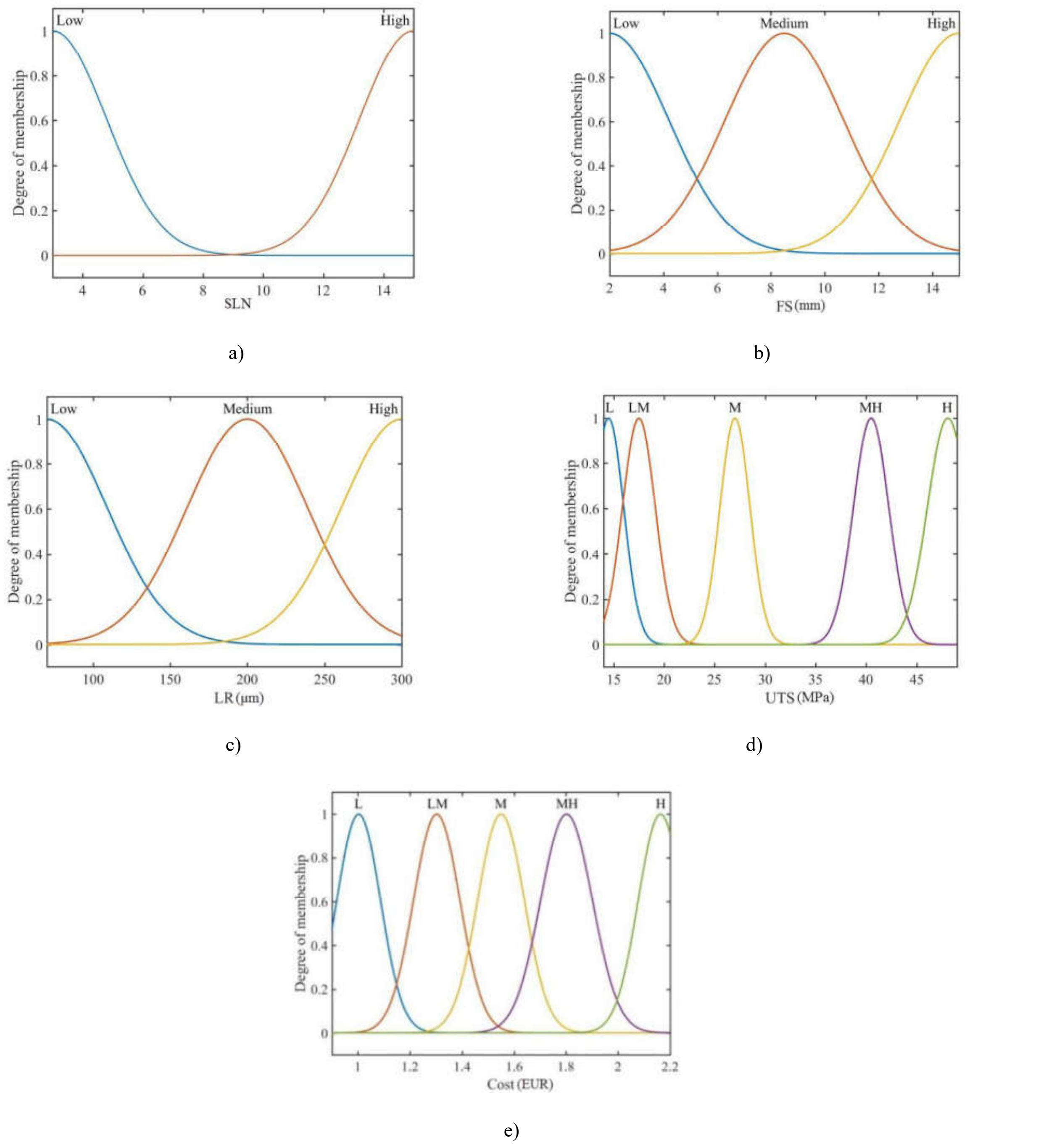
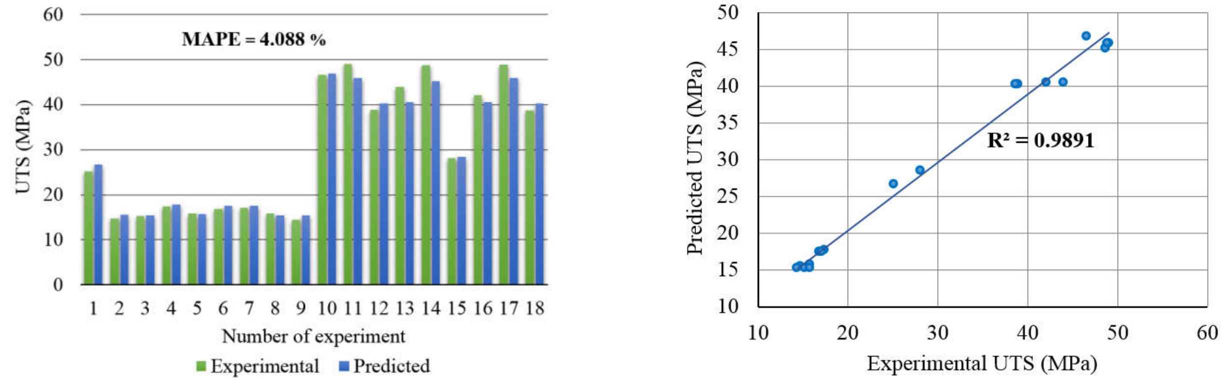


Figure 3. Membership functions for a) top and bottom surface layers number, b) fill spacing, c) layer resolution, d) ultimate tensile strength, e) cost

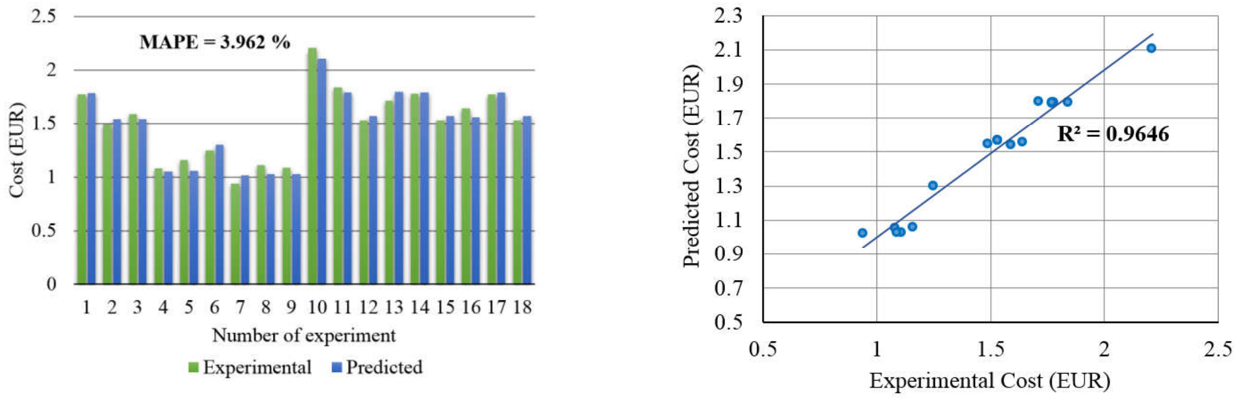
4. Results and discussion

In order to assess the prediction accuracy of the developed fuzzy logic model, the prediction and experimental data were compared. These comparison results with calculated mean absolute percentage errors (MAPE) and coefficients of determination (R^2) for both outputs are shown in Figures 4 and 5.



a) b)

Figure 4. a) mean absolute percentage error between experimental and predicted data for UTS, b) coefficient of determination between experimental and predicted data for UTS



određivanja između eksperimentalnih i predviđenih podataka za UTS

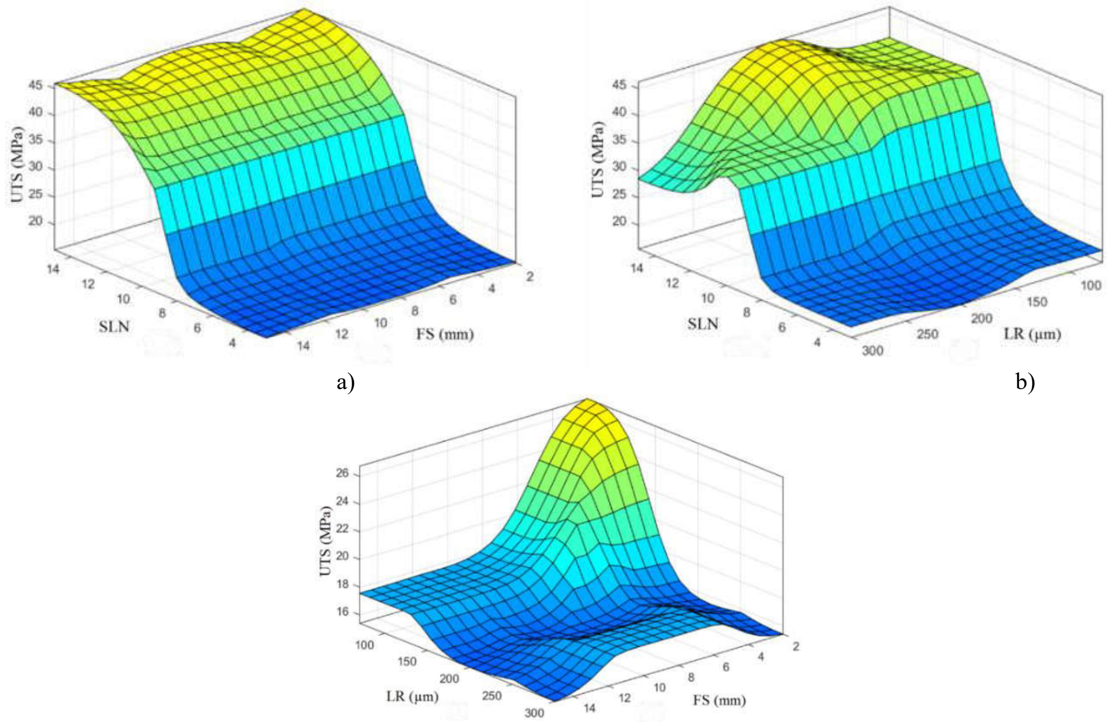
a) b)

Figure 5. a) mean absolute percentage error between experimental and predicted data for cost, b) coefficient of determination between experimental and predicted data for cost

From the results in Figures 4 and 5, it is clear that developed fuzzy logic model has a good prediction performance. Once developed and validated fuzzy logic model can be used to analyze the effects of the fused deposition modeling process parameters on the ultimate tensile strength (UTS) and cost.

In order to that, three 3D surface plots for each of outputs were generated using a developed fuzzy logic model. These response surfaces are shown in Figures 6 and 7.

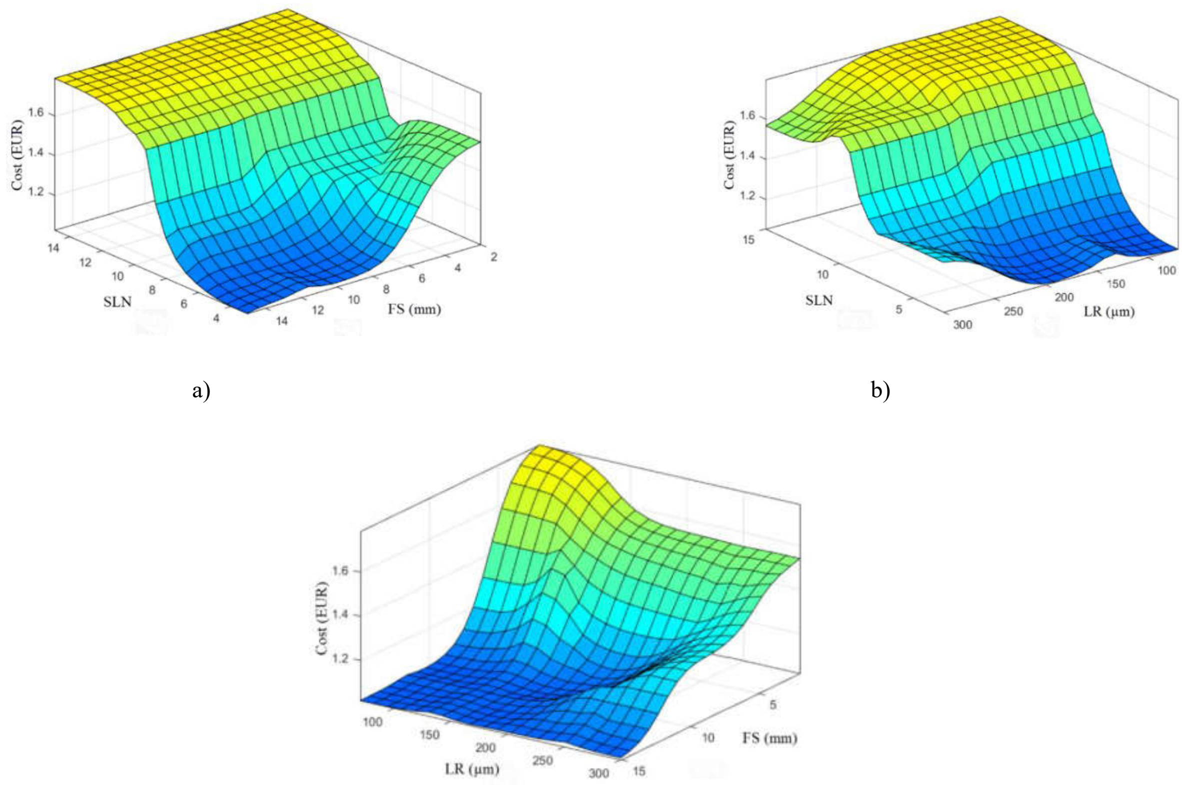
From the Figures 6 and 7, it can be observed that ultimate tensile strength and cost are quite sensitive to all fused deposition modeling process parameters. It is clear, from the Figure 6a) that higher top and bottom surface layers number at the layer resolution of 200 µm result with higher ultimate tensile strength. The fill spacing parameter doesn't have an influence on the ultimate tensile strength values change. At the same time, from the Figure 7a) it is obvious that, at the layer resolution of 200 µm, the area with higher ultimate tensile strength has also higher manufacturing cost values. In the area of the low top and bottom surface layers number, higher fill spacing values result in lower costs while in the area of the high top and bottom surface layers number fill spacing parameter doesn't affect the change in the manufacturing costs.



a) b)

c)

Figure 6. Effects of FDM process parameters on the UTS a) LR = 200 μm, b) FS = 8.5 mm, c) SLN = 3



a) b)

c)

Figure 7. Effects of FDM process parameters on the cost a) LR = 200 μm, b) FS = 8.5 mm, c) SLN = 3

Figure 6b) shows that, at the fill spacing of 8.5 mm, layer resolution doesn't show influence on the ultimate tensile strength in the area of the low top and bottom surface layers number, while at the high top and bottom surface layers number, lowering layer resolution result in the ultimate tensile strength increment. On the other side, Figure 7b) shows that, at the fill spacing of 8.5 mm, low top and bottom surface layers number and the layer resolution of 70 µm result in the low costs. From the Figure 6c) it can be observed that lowering of the layer resolution at the fill spacing of 2 mm and in the area of the low top and bottom surface layers number, results in the higher ultimate tensile strength values. On the other fill spacing levels, the layer resolution parameter doesn't show significant influence on the ultimate tensile strength. Increasing of the fill spacing parameter at the layer resolution of 70 µm lead to the lowering of the ultimate tensile strength. On the other layer resolution levels, the fill spacing change doesn't affect the ultimate tensile strength. Figure 7c) shows that increasing of fill spacing results in lower costs at the all three layers resolution levels and in the area of the low top and bottom surface layers number. At the fill spacing of 2 mm lowering of layer resolution parameter lead to a noticeable increment of costs while at the fill spacing of 15 mm layer resolution doesn't show influence on the manufacturing costs. In the area of fill spacing parameter middle value, a costs increment is visible at the layer resolution of 300 µm. Further analysis of 3D response surfaces obtained from the fuzzy logic model can help to find an optimal result of ultimate tensile strength and costs and their process parameters values. Optimal solutions are compromising. They lead to maximal possible ultimate tensile strength values that will at the same time result with the acceptable manufacturing costs. Layer resolution parameter can be varied only on three levels and due to that, the optimal solutions will be defined for each of these levels. Optimization results are shown in Table 3.

Table 3. *Optimization results

$LR_{opt.}$, (µm)	$SLN_{opt.}$	$FS_{opt.}$(mm)	$UTS_{opt.}$ (MPa)	$Cost_{opt.}$ (EUR)
70	15	15	40.515	1.557
200	15	2	45.912	1.788
		8.5	45.248	1.788
		15	45.912	1.788
300	15	2	40.331	1.568
		15	40.331	1.568

5. Conclusion

In this paper, the influence of the fused deposition modeling process parameters: top and bottom surface layers number, fill spacing and layer resolution on the ultimate tensile strength and additive manufacturing cost was analyzed. The experimental work was carried out on the specimens generated from the PLA plastic material. Experimental results were used to establish a relationship between inputs and analyzed responses. Modeling was conducted using a fuzzy logic approach. The generated model was validated using statistical measures such as mean absolute percentage error and coefficient of determination between experimental and predicted responses values. After the prediction accuracy of the developed model was done, the effects of parameters and their interactions were explained using response surfaces obtained from the fuzzy logic model. From these figures, it was clear that tensile strength and costs are proportional what means that higher tensile strength leads to higher costs. Also, the developed model was effective for further analysis and optimization procedure. According to that, the process parameters values that lead to maximal tensile strength and acceptable manufacturing cost were found (Table 3). Obtained observations are useful for users involved in this kind of additive manufacturing process. Future research will focus on the examination, modeling, and optimization of other mechanical properties of FDM specimens built by ABS plastic material.

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