ISSN No.: 2455-6130
Special Issue – RAISE2024, 2025,, pp. 37-49

website: www.ijoetr.com

International Journal of Emerging Trends in Research

Optimization of Fused Deposition Modelling Process Parameters by Using a Grey Fuzzy Logic Technique

Dr. Balasubramanyam. N[1], Mrs.B. Rajitha[2], Karri.Aswini[3]
[1]Dept. of Mechanical Engineering, S.V.University College of Engineering Tirupati, Andhra Pradesh
[2]Department of Physics, Sri Padmavathi Mahila Visvavidyalayam Tirupati, Andhra Pradesh
[3]Department of Basic Sciences and Humanities, Sri Padmavathi Mahila Visvavidyalayam Tirupati, A.P

* Corresponding author. E-mail: balu.phd28@gmail.com

Abstract

This paper presents the optimization of process parameters for multi-response characteristics of Fused Deposition Modelling (FDM) using Grey Fuzzy Relational Analysis (GFRA) on PETG material. The study focuses on minimizing dimensional error while maximizing tensile strength and ductility in the FDM process. The process parameters considered include layer thickness (Lt), build orientation (Bo), fill density (Fd), and fill pattern (Fp), which are investigated using the Taguchi L9 orthogonal array. The goal is to achieve an optimal balance between minimal dimensional error and maximum tensile strength and ductility. By analyzing the response characteristics with Grey Relational Grade (GRG) and Grey Fuzzy Relational Grade (GFRG), the best combination of input parameters is identified. Analysis of variance (ANOVA) reveals that Bo and Fd are the most significant factors influencing the mechanical properties.

Keywords: Fused Deposition Modelling, polymers, Grey Relational Analysis, Fuzzy Grey Relational Grade, tensile strength

1. Introduction

The primary goal of manufacturing industries is to reduce production costs while maintaining the required mechanical properties of parts. This has led many sectors to transition from traditional manufacturing methods to additive manufacturing (AM) processes. Introduced in the 1980s, AM is classified into four major categories based on the manufacturing method: Selective Laser Sintering (SLS), Laminated Object Manufacturing (LOM), Stereo lithography (SLA), and Fused Deposition Modelling (FDM) [1].

FDM, introduced by S. Scott Crump in the 1990s, co-founder of Stratasys Inc., has gained popularity due to its ability to create complex geometries, eliminate the need for dies and molds, and offer low system costs and maintenance compared to other methods [2]-[3]. Despite these advantages, FDM has some limitations, including lower dimensional accuracy and surface finish [4].

FDM-produced parts are typically anisotropic in nature and do not match the precision or surface quality of injection-molded parts [5-9]. Issues such as lower dimensional accuracy [10] and the staircase effect [11-19] are common. Additionally, FDM is a slower process than injection molding, often requiring more time and effort to reduce manufacturing defects [20-23].

Over the last decade, numerous studies have focused on improving the quality of FDM-produced parts. Due to the large number of process parameters involved, it is challenging to analyse their combined effects on material properties and dimensional accuracy. Design of Experiments (DOE) is widely used to streamline testing and analysis procedures. Other methods, including full factorial designs, ANOVA, bacteria forging techniques, and fuzzy logic, have also been explored to optimize the process. Some studies, such as the work by Jaya Christiyan et al. [25], focus on individual parameters like build orientation, layer thickness, and printing speed, which have been shown to influence mechanical properties such as tensile and flexural strength.

Other research has explored the effect of multiple process parameters. Godfrey et al. [26] examined the impact of five parameters—layer thickness (Lt), build orientation (Bo), raster angle (Ra), raster width (Rw), and air gap (Ag)—on tensile strength, while Tanoto et al. [27] demonstrated how print orientation affects tensile strength and processing time. Sahu et al. [28] focused on dimensional accuracy, analyzing changes in length, width, and thickness based on different parameter combinations. Raut et al. [29] investigated how build orientation impacts both cost and mechanical properties, identifying optimal orientations for minimizing cost and maximizing strength.

Venkatasubbareddy et al. [30] explored the effect of process parameters on surface roughness and dimensional accuracy using Taguchi Grey Relational Analysis, while Lui et al. [31] determined optimal process parameters for mechanical properties using a grey relational grade. Similarly, Shaikh et al. [32] identified key parameters such as layer thickness, raster width, and extrusion temperature, with the highest GRG value observed for specific flatness errors, build time, and surface roughness.

From the literature, it is evident that the Taguchi technique is one of the most commonly used methods in both industry and research to identify optimal parameters in FDM. Grey Relational Analysis (GRA), a multi-objective optimization method, has been widely applied for FDM optimization. However, GRA has limitations in processing uncertain or ambiguous factors in experimental data. To address this, the Grey-Fuzzy Relational Analysis (GFRA) approach is adopted, which provides more accurate results by incorporating fuzzy logic to derive the Grey Fuzzy Relational Grade (GFRG).

2. Experimental Procedure

2.1 Work material

The filament material used in this work is PETG. When compared with base form of PET it is less brittle and simpler to use. It doesn't absorb water and it also has a low level of shrinkage. Fig 1.a shows the tensile specimens produced using FDM process parameters. After the test is performed the broken specimens are shown in fig 1.b.

Fig.1. (a) shows the fabricated tensile specimens before a test. (b) Shows the fabricated tensile specimen after the test.

2.2 Test procedure

To estimate the tensile strength(TS) of the FDM printed specimens, first, the specimens dimensions are noted and the testing is done using INSTRON 8801 universal testing machine (UTM) as shown in Fig.3.The specimen testing's are done at room temperature and an extension speed of 2mm/min. While performing the experiments real-time data is recorded. With the help of recorded data only the mechanical properties such as tensile strength, ductility is noted. The mechanical properties are calculated with the actual dimensions of the fabricated specimen, not with the dimensions of the CAD model.

Fig.2. (a) shows the universal testing machine for testing tensile specimens.(b) shows the tensile specimen in the machine

2.3 Process parameter selection

The experimental design for four factors and three levels, presented in Table-1. Experimental plan for Taguchi's L9 orthogonal array is shown in Table-2.

Table: 1 Process parameters and their levels for FDM process

S.No	Factor	Parameter	Symbol	Level-1	Level-2	Level-3
1.	A	Layer Thickness(L_t)	mm	0.1	0.2	0.3
2.	B	Build Orientation(B_o)	Degrees	0	45	90
3.	C	Fill Density(F_d)	%	30	60	90

4.	D	Fill Pattern(F_p)	-	Line	Hexa	Tria

Table: 2 Experimental plans based on Taguchi's L9.

Expt. No	Layer Thickness[mm]	Build Orientation [°]	Fill Density [%]	Fill Pattern	No of specimens
1.	0.1	0°	30	Line	2
2.	0.1	45°	60	Hexa	2
3.	0.1	90°	90	Tria	2
4.	0.2	0°	60	Tria	2
5.	0.2	45°	90	Line	2
6.	0.2	90°	30	Hexa	2
7.	0.3	0°	90	Hexa	2
8.	0.3	45°	30	Tria	2
9.	0.3	90°	60	Line	2

3. Methodology

3.1 Error in the specimen dimensions.

The specimens are printed according to the ASTM standards. To evaluate the tensile strength of plastic material the specimen is designed with ASTM D638 and is shown in fig.3. The front views and top views of tensile specimen are shown below. The printing direction is shown by an arrow in the front view. Each run is repeated 2 times, with a total of 18 tensile samples were printed for this study.

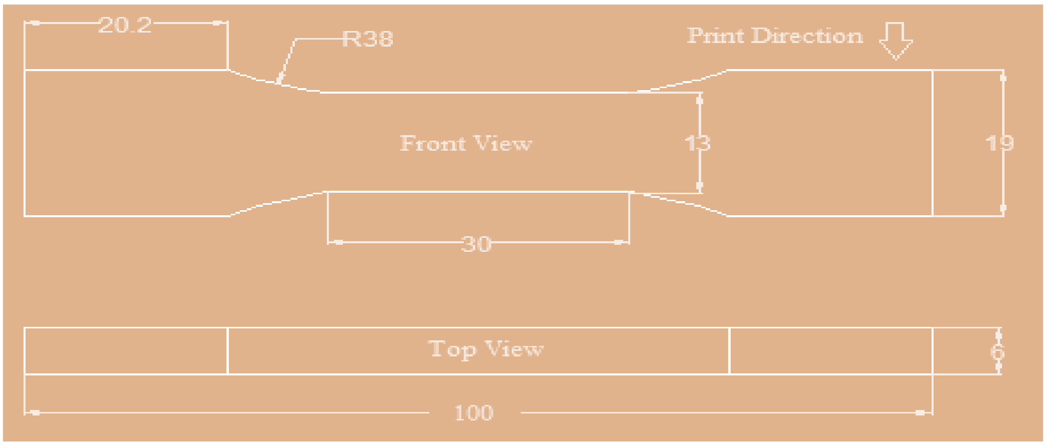

Fig.3.The CAD model dimensions of the tensile specimens.

3.2 Slicing Software

Flash print is the software used to slice the CAD model. Fig 4.shows the CAD model parts on the flash print screen and the specimens on the platform. The parameters namely layer thickness (L_t), build orientation (B_o), fill density (F_d) and fill pattern (F_p) are changed according to the contents in Table-2, while the other parameters were kept constant.

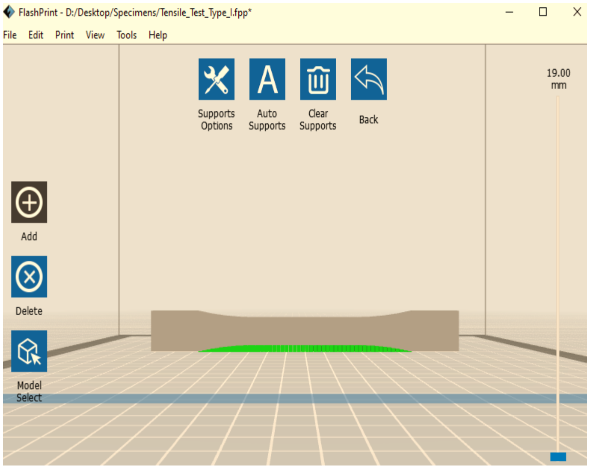

Fig.4.The specimens on the platform in flash forge software to fix process parameters.

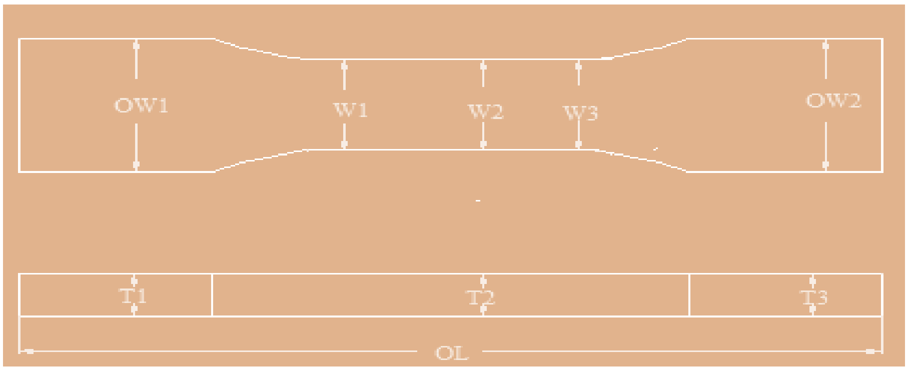

Fig.5.The measured locations of the printed tensile specimen.

To find the accuracy in the dimensions, all the specimens printed were measured and compared with the CAD model dimensions. A total, of nine measurements are taken for each tensile specimen in which the overall length (OL)-[mm] of the specimen, the overall width (OW)-(mm), the width (W)-(mm), and the thickness (T)-(mm) is shown in fig.4. The dimensions of the printed specimens were measured using venire callipers. The overall width (OW) can be found by averaging OW1 and OW2. The width (W) and the thickness (T) can be found by averaging W1, W2, W3, and T1, T2, T3 respectively.

Table-3 shows the measured dimensions of set-1 printed specimens. Measured dimensions of Set-2 printed specimens are shown in Table-4.

Table-3: Measured dimensions of set-1:

Expt.No/ CAD model	**OL (100.0)-mm**	**OW (19.0)-mm**	**W (13.0)-mm**	**T (6.0)-mm**
1.	100.14	19.15	13.18	6.17
2.	100.27	19.32	13.29	6.16

3.	100.23	19.37	13.35	6.54
4.	100.19	19.30	13.18	6.19
5.	100.38	19.41	13.28	6.26
6.	100.30	19.25	13.24	6.25
7.	100.25	19.42	13.29	6.39
8.	100.39	19.37	13.27	6.30
9.	100.65	19.17	13.22	6.35

Shows the measured dimensions of the printed tensile specimens. It is observed that every dimension measured is higher than the CAD model dimension. For each specimen, the error values are found using Equations (1) and (2).

$$E_{specimen} = ¿ D_{CAD} - D_{specimen} \vee ¿ \quad (1)$$

$$E_{\sum ¿^{P} = \sum_{P} E_{specimen} ¿} \quad (2)$$

Where E $_{specimen}$ error in the dimension of the specimen.

D_{CAD} is the dimension of the CAD model.

D $_{specimen}$ is the dimension of the printed specimen.

$E_{\sum ¿^{P} ¿}$ Is the sum of errors in the dimensions of all the specimens.

The errors in the set-A and set-B are shown in Table-5 and Table-6. The sum of dimensional errors of set-A and set-B is shown in Table-7.

Table-4: Error in the dimensions of set-A

Expt.No/ CAD model	OL	OW	W	T	Sum of dimensional errors
1.	0.14	0.15	0.18	0.17	0.64
2.	0.27	0.32	0.29	0.16	1.04
3.	0.23	0.37	0.32	0.54	0.46
4.	0.19	0.30	0.18	0.19	0.86
5.	0.38	0.41	0.28	0.26	1.33
6.	0.30	0.25	0.24	0.25	1.05
7.	0.25	0.42	0.29	0.39	1.35
8.	0.39	0.37	0.27	0.30	1.33
9.	0.65	0.17	0.22	0.35	1.39

Table-5: Error in the dimensions of set-B

Expt.No/ CAD model	OL	OW	W	T	Sum of dimensional errors
1.	0.44	0.13	0.25	0.19	0.97
2.	0.24	0.25	0.23	0.06	0.78
3.	0.28	0.52	0.52	0.48	1.81
4.	0.16	0.27	0.16	0.23	0.82
5.	0.33	0.21	0.24	0.22	1.01
6.	0.32	0.21	0.25	0.48	1.26
7.	0.10	0.55	0.23	0.31	1.19
8.	0.19	0.38	0.37	0.35	1.29
9.	0.69	0.25	0.15	0.27	1.38

Table-6 :Average dimensions of both the sets:

Expt.No/ CAD model	Sum of dimensional errors in set-1	Sum of dimensional errors in set-2	Error in the dimensions (Average of Set 1&2)
1.	0.64	0.97	0.80
2.	1.04	0.78	0.91
3.	1.46	1.81	1.63
4.	0.86	0.82	0.84
5.	1.33	1.01	1.17
6.	1.05	1.26	1.15
7.	1.35	1.19	1.27
8.	1.33	1.29	1.31
9.	1.39	1.38	1.38

3.3 Grey Relational Analysis

Grey Relational Analysis (GRA), also called Deng's Grey Incidence Analysis model was developed by Julong Deng a Chinese professor. In GRG, the entire information is represented by black and white colours. If there is no information then it is represented by black, and processing all information is represented by white. In this concept, the experimental data is first normalized within the range of 0 to 1. The procedure of converting the experimental data within the range of

0 to 1 is known as normalization. Based on the normalized data the grey relational coefficient is calculated by correlating the desired and actual experimental data. By averaging the grey relational coefficients the grey relational grade is obtained. The overall quality characteristics of the multi-response process depend on the calculated grey relational grade.

The data to be used in grey relational analysis must be pre-processed into quantitative indices for normalizing raw data for another analysis. The process of converting the original sequence into a decimal sequence between 0 to 1 is known as pre-processing. Depending on the requirement the Equation (3) for larger the-better (LB) and Equation (4) for smaller-the-better (SB) are used for data pre-processing.

$$.x_i^{¿}=\frac{x_i(k)-min\,x_i(k)}{max\,x_i(k)-min\,x_i(k)} \quad \text{i=1,2,.........m and K=1,2,........,n} \qquad (3)$$

$$x_i^{¿}=max\,¿¿ \qquad (4)$$

Where $x_i(k)$ and $x_i^{¿}(k)$ are the observed and normalized data, for ith alternative and kth criterion. After data normalization, the GRC is computed to express the relationship between the ideal and the normalized data.

$$\xi_i(k)=\frac{\Delta_{min}+\zeta\,\Delta_{max}}{\Delta_{0i}(k)+\zeta\,\Delta_{max}}(5)$$

Where $\Delta_{Oi}(k)$ is the absolute value of the difference between $x_i^0(k) \wedge x_i^{¿}(k)$. The distinguishing sequence (ζ ¿ lies between o and 1 and is mainly responsible to expand or compress the range of GRC values. Generally, ζ=0.5 is preferred. On the other hand, $\Delta_{min}=\forall j^{min}\epsilon i \forall k^{min} \vee ¿ x_0(k)-x_j(k) \vee ¿$is the smallest value of$\Delta_{0i}$, $\Delta_{max}=\forall j^{max}\epsilon i \forall k^{max} \vee ¿ x_0(k)-x_j(k) \vee ¿$ is the largest value of Δ_{0i}. A higher GRC value for an alternative indicates that it is closer to the optimal solutions concerning a particular criterion. By averaging the GRC values GRG value is determined.

$$\gamma_i=\frac{1}{n}\sum_{k=1}^{n}\xi_i(k)(6)$$

Where n is the number of criteria/attributes.

3.4 Fuzzy logic

The fuzzy logic technique is used when there is any degree of uncertainty in making the decision. The decision is partially true in some cases. In those cases, the membership function of range from 0 to 1 is assigned for the trueness. 1 is assigned for completely true, and 0 is represented for completely false. The partially true statements lie between 0 and 1 [11]. The fuzzy logic technique can be implemented by developing a Fuzzy Logic Controller (FLC). The layout of fuzzy logic control is shown in fig.5.

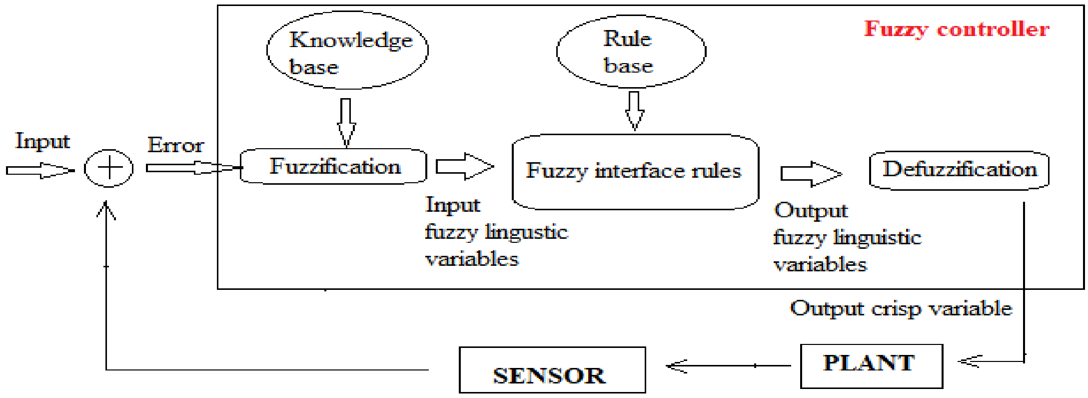

Fig.5. The architecture of fuzzy logic control

In the grey fuzzy logic approach, to have the interference between input and output a set of fuzzy rules is developed. A set of such fuzzy rules is shown below:

Rule 1: if $y_1$is A_1 and $y_2$is B_1 and $y_3$is C_1 and y_4 is D_1, then output(G) is E_1, else
Rule 2: if $y_1$is A_2 and $y_2$is B_2 and $y_3$is C_2 and y_4 is D_2, then output(G) is E_1, else

Rule n: if $y_1$is A_n and $y_2$is B_n and $y_3$is C_n and y_4 is D_n, then output(G) is E_1, else

WhereA_i, B_i,C_i and D_i are the fuzzy subsets defined by the corresponding membership functions, ie, μ_{Ai}, μ_{Bi}, μ_{Ci} and μ_{Di} respectively. The fuzzy inference engine is the kernel of a fuzzy system. The inference engine performs fuzzy reasoning of fuzzy rules while taking max-min inference for generating a fuzzy value, μ_{Co}(G):$\mu_{Co}(G)$=($\mu_{A1}(y_1) \wedge \mu_{B1}(y_2) \wedge \mu_{C1}(y_3) \wedge \mu_{D1}(y_4) \wedge \mu_{E1}(G)$¿

$$\vee(\mu ¿¿ A2(y_1) \wedge \mu_{B2}(y_2) \wedge \mu_{C2}(y_3) \wedge \mu_{D2}(y_4) \wedge \mu_{E2}(G))¿$$

$$\vee(\mu ¿¿ An(y_1) \wedge \mu_{Bn}(y_2) \wedge \mu_{Cn}(y_3) \wedge \mu_{Dn}(y_4) \wedge \mu_{En}(G))¿$$

Where $\wedge$ is the minimum operation and $\vee$ is the maximum operation. Acentric fuzzification method is utilized to transform the fuzzy multi-response output, $\mu_{Co}(G)$ into a crisp value of GFR :(G_0)

$$G_o = \frac{\sum G\,\mu_{CO}(G)}{\sum \mu_{Co}(G)} \quad (7)$$

4. Results and Discussion

The results of error in the dimensions, tensile strength (TS) and ductility (D) are tabulated in table -8. Based on the values obtained in table-8, Grey Relational Grade (GRG) is calculated from Grey Relational Analysis (GRA). Experiment number seven gives the highest grey relational grade, whereas experiment number nine gives the lowest grey relational grade. The control parameters for FDM process are layer thickness, build orientation, fill density and fill pattern.

Three levels, each were set for the above four parameters. Error in the dimensions (mm), tensile strength (N/mm^2), and ductility (mm/mm) are the multi-performance characteristics of FDM process. Based on three replicates in each experiment, the response was measured. Larger-the-better type of quality characteristic (beneficial attributes) and is shown by equation (4). Based on the equation normalized values are developed and is shown in table-9. The normalized values lie within the range 0-1.With the help of normalized data, the corresponding Grey Relational Coefficient (GRC) and Grey Relational Grade (GRG) values are then computed and is shown in table-10. It is observed that experiment number seven gives the optimal value out of nine experiments. To reduce the uncertainty involved in the data and to derive a more realistic and improved data fuzzy logic approach is used.

Table-7: Design of Experimentation with L9 orthogonal array and experimental results

Expt.No	Layer Thickness - mm	Build Orientation	Fill Density - %	Fill Pattern	Error in the dimensions - mm	Tensile strength - Mpa	Ductility - mm/mm
1	0.1	0°	30	Line	0.80	19.12	0.06848
2	0.1	45°	60	Hexa	0.91	12.86	0.04734
3	0.1	90°	90	Tria	1.63	32.18	0.04821
4	0.2	0°	60	Tria	0.84	27.50	0.05811
5	0.2	45°	90	Line	1.17	29.21	0.0492
6	0.2	90°	30	Hexa	1.15	10.45	0.03361
7	0.3	0°	90	Hexa	1.27	39.47	0.08104
8	0.3	45°	30	Tria	1.31	14.21	0.04258
9	0.3	90°	60	Line	1.38	8.00	0.02989

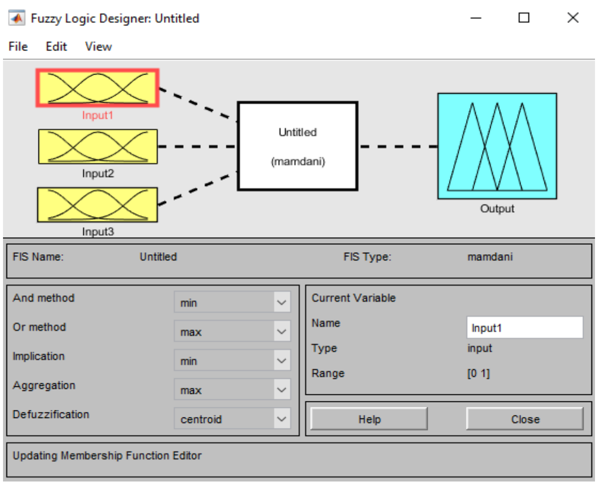

Fig .6. Shows the fuzzy logic designer.

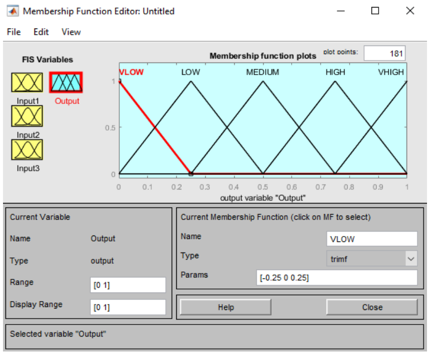 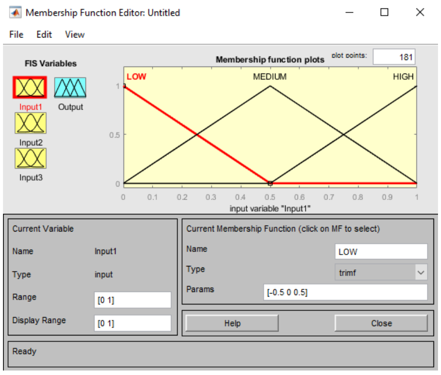 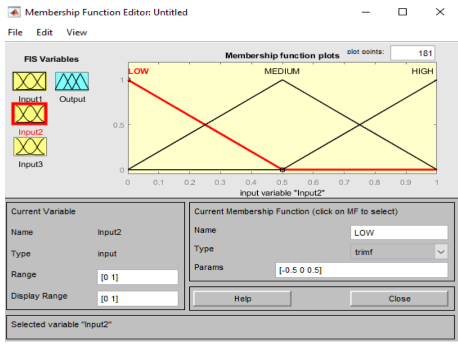

Fig.7. (a) Membership function for error in dimensions
(b)Membership function for tensile strength (c) Membership function for ductility

If we want to add the rule, change the rule and delete the rule, the rule editor can be used which is shown in fig.8. In the rule viewer, graphical representation of fuzzy logic reasoning is seen. The number of rows in the rule viewer represents the fuzzy rules. In this work a total of 27 rules are formulated. The inputs and outputs are represented in columns. Here, in the fig. 7, it is seen that a total of four columns out of which three are input parameters and one is output parameter.

Table-8. : Results of the conformation test.

		Setting level	Error in dimensions - mm	Tensile strength - Mpa	Ductility - mm/mm	GFRG	Improvement in GFRG
Initial parameters		A1B1C1D1	0.80	19.12	0.06848	0.72	_
Optimal parameters	Predicted	A1B1C3D2	-	-	-	0.83	_
	Experiment	A1B1C3D2	0.90	42.5	0.09204	0.84	0.12

Conclusions

In this study, the process parameters influencing multiple performance characteristics of FDM were optimized using Taguchi's design of experiments. The optimal process parameters for improving layer thickness, build orientation, fill density, and fill pattern were determined using Grey Relational Analysis (GRA). The Grey relational coefficients were utilized as inputs in the fuzzy logic designer (MATLAB R2018a) to obtain the Grey Fuzzy Relational Grade (GFRG). This approach effectively enhanced performance characteristics such as dimensional accuracy, tensile strength, and ductility. The following conclusions are drawn based on the experimental results and confirmation tests:

- The GFRG response table shows that higher GFRG values correspond to better multiple performance characteristics. The optimal parameter combination for the FDM process was identified as A1B1C3D2, which minimizes dimensional errors and maximizes tensile strength and ductility.
- ANOVA analysis reveals that fill density has the most significant impact on improving tensile strength, while build orientation plays a crucial role in enhancing ductility.
- This optimization technique is economical and convenient for predicting optimal process parameters in FDM.
- The Taguchi method, combined with fuzzy logic using Fuzzy-GRG, simplifies the optimization process by converting multiple performance characteristics into a single performance metric.

References

1. D. T. Pham and R. S. Gault (1998), "A comparison of rapid prototyping technologies," *International Journal of Machine Tools and Manufacture*, vol. 38, no. 10-11, pp. 1257-1287.
2. S. Scott Crump (1992), “Apparatus and Method for Creating Three-Dimensional Objects,” U.S. Patent 5,121,329.
3. G. N. Levy, R. Schindel, and J. P. Kruth,(2003) "Rapid manufacturing and rapid tooling with layer manufacturing (LM) technologies, state of the art and future perspectives," *CIRP Annals*, vol. 52, no. 2, pp. 589-609.
4. E. Sachs, M. Cima, J. Cornie, (1990) "Three-dimensional printing: rapid tooling and prototypes directly from a CAD model," *CIRP Annals*, vol. 39, no. 1, pp. 201-204.
5. A. Gebhardt, (2011)"Understanding Additive Manufacturing: Rapid Prototyping, Rapid Tooling, Rapid Manufacturing," *Hanser Publishers*, Munich.
6. R. Ahuja and J. S. Kharay, (2016) "Analysis of Mechanical Properties of FDM Parts by Considering Build Parameters: A Review," *Journal of Mechanical Engineering and Automation*, vol. 6, no. 5, pp. 112-119.
7. M. L. Shofner, K. Lozano, F. J. Rodríguez-Macías, and E. V. Barrera, (2003) "Nanofiber-reinforced polymers prepared by fused deposition modeling," *Journal of Applied Polymer Science*, vol. 89, no. 11, pp. 3081-3090.
8. J. P. Kruth, M. C. Leu, and T. Nakagawa, (1998)"Progress in additive manufacturing and rapid prototyping," *CIRP Annals*, vol. 47, no. 2, pp. 525-540.
9. D. Espalin, D. W. Muse, E. MacDonald, and R. B. Wicker, (2014) "3D Printing multifunctionality: structures with electronics," *International Journal of Advanced Manufacturing Technology*, vol. 72, pp. 963-978.
10. K. K. Sahu, S. K. Sood, and A. Verma, (2018) "Improving Dimensional Accuracy of Fused Deposition Modelling Parts Using Grey Taguchi Method," *Materials Today: Proceedings*, vol. 5, no. 9, pp. 19112-19122.
11. Y. Zhang, J. Chai, L. Jin, and J. Tian, (2019)"Optimization of Process Parameters of Fused Deposition Modeling Using a Fuzzy Logic Approach," *Materials*, vol. 12, no. 3, p. 253.
12. V. Venkatasubbareddy, S. Sundaram, and S. Sahu, (2019) "Optimization of Process Parameters in Fused Deposition Modelling Using Grey Relational Analysis," *Journal of The Institution of Engineers (India): Series C*, vol. 100, no. 4, pp. 617-623.
13. S. Jaya Christiyan, S. Chandrasekaran, and P. Venkatesh, (2018) "A study on the influence of process parameters on the Mechanical Properties of FDM parts," *Materials Today: Proceedings*, vol. 5, no. 5, pp. 11219-11224,.

14. R. K. Raut, V. S. Jatti, N. K. Khedkar, and V. P. Singh, (2014) "Investigation of the effect of built orientation on mechanical properties and total cost of FDM parts," *Procedia Materials Science*, vol. 6, pp. 1625-1630.
15. B. Shaikh, P. M. Pandey, and A. Garg, (2019 "Multi-objective optimization of fused deposition modelling process parameters using fuzzy logic," *Proceedings of the Institution of Mechanical Engineers, Part B: Journal of Engineering Manufacture*, vol. 233, no. 2, pp. 403-417.
16. D. S. Godfrey, P. K. Ray, and A. Kumar (2018), "Fused Deposition Modelling: A Methodology for Improving Mechanical Strength Using a Hybrid Approach," *Journal of Manufacturing Processes*, vol. 34, pp. 697-707.
17. K. Lui, S. Li, Z. Jin, and L. Xiong (2020), "Optimization of FDM Parameters Using Taguchi Method with Grey Relational Analysis and Fuzzy Logic," *Journal of Manufacturing Systems*, vol. 58, pp. 202-215.
18. H. Tanoto, Y. Zhu, X. Zhao, and S. Wei,(2021) "Multi-objective Optimization of Process Parameters in FDM for Fabrication of PETG Parts," *International Journal of Advanced Manufacturing Technology*, vol. 89, no. 5, pp. 1875-1885.