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Parametric Optimization of Fused Deposition Modeling Using Multi-Objective Techniques

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Abstract

The Fused Deposition Modeling is one of the additive manufacturing used for the prototyping, production, modeling. This is one of the easy, flexible and economical methods for materials like ABS, PLA, PC, Rubber, and Linen. In this work optimization has been carried out for surface roughness, the length of workpiece using fused deposition modeling with different parameters using the Taguchi Method. A rectangular workpiece is produced using FDM. The process parameters were chosen as fill density, shell thickness, layer height, and speed. An orthogonal array L27 was performed to perform the experiments. Work piece (ABS) surface roughness is calculated using the metrological device called Talysurf. Multiple Regression analysis is performed to examine the out-turn of process parameters on Surface roughness, length of the workpiece. Then using the equations obtained from multiple regression analysis, Multi-Objective optimization to be carried out using Genetic, Goal programming.

Keywords: Fused Deposition Modeling; Taguchi Method; Regression Analysis; Surface Roughness; Multi-Objective; Genetic; Goal Programming

List of abbreviations: GA: Genetic Algorithm; MATLAB: Matrix Laboratory; GP: Goal Programming; DOE: Design of Experiments SR: Surface Roughness; RPM:Revolution per Minute; mm: Millimeter mm/sec: Millimeter per Second; μm: Microns: X1: Fill density(mm/sec): X2: Shell thickness(mm): X3: Layer height(mm): X4: Speed(mm/sec): Ra: Surface Roughness: DOE: Design of Experiments

Introduction

3D printing technology was introduced in 1980's by Scott Crump, chairman, and co-founder of Stratasys Ltd. This is one of the companies producing a large volume of 3D printers. The linear programming technique is a tool for the management decisions. The difficulty with the linear programming is that the objective function measured in only one dimension such as profit or loss or production capacity. It is impossible to measure the multiple objectives until or unless they are in the same units. Goal Programming developed by Charnes and Cooper gives a technique for solving such multi-objective models. The idea is to convert the multiple objectives into a single goal. Goal programming is an optimization technique used for analysis to find out necessary resources to get an expected set of objectives, to calculate the amount of achievement of goals with the required or available resources, providing the optimized solution under a varying degree of necessary resources and its priorities of the goals.

Rao et al., [1] presented dimensional accuracy, cost of production, product quality, and build time, energy consumed to the mechanical and tribological parameters of models. Here the multi-objective technique is used. The optimization technique used is a teaching-learning- based optimization algorithm and non-dominated sorting (NSTLBO) TLBO algorithm.

Anoop K Sood et al., [2] studied the effectiveness of process parameters like part build orientation, layer thickness, raster width, air gap, raster angle on the compression stress of sample. Presented mathematically validated predictive equation and the compressive stress on the process parameters. Quantum-behaved particle swarm optimization (QPSO) is used to know optimal parameter setting.

Sandeep Raut et al., [3] studied the effectiveness of the process parameter like build-up orientation and the total cost of the FDM parts. Here ABS is used as a material, CATALYST is

Figure 1: Fused deposition modeling machine (Courtesy: Vasavi College of Engineering)

the software, and Stratasys FDM is the machine. As per ASTM standards, the flexural, tensile samples prepared with the various build-up orientation in three-dimensional axes. The built orientation is a similar to the effect of tensile and flexural with total cost on processed parts. At minimum manufacturing cost, the FDM parts manufactured with high mechanical properties.

Alhubail et al., [4] evaluated the influence of the process parameters like an air gap, contour width, layer thickness, raster orientation, raster width and the quality of tensile strength and surface roughness. Produced FDM parts had weak tensile strength and surface error. The Composite ABS-M30i material is used to work on build parts. The Mathematical process like Signal to Noise ratio (S\N), Analysis of Variance (ANOVA), regression analysis is used to find the process parameters. Surface roughness and Tensile strength are mostly affected by an air gap. SEM is used to analyze the results.

Venkatasubba Reddy et al. [5], studied the fused deposition modeling on the ABS material of layer by layer process is done. The process parameters like an air gap, raster angle, raster width, layer thickness affect the surface roughness. The novel ABS-M30 has used build parts. Taguchi technique is preferred to modify the process parameters with length, width diameter, and surface finish. This method provides excellent dimensional accuracy and surface finish.

Pavan Kumar Gurrala et al., [6] considered the part accuracy of fused deposition modeling. Volumetric change and inaccuracy of the ABS material are known. Design of experiments is done to determine out the minimum number of operations. The models are done by taking effect of curl volumetric is found. The Parametric equation used for modeling of multi-objective optimization.

R.H. Philipson et al., [7] presented the application of goal programming to the single point turning operation with the objective to minimize cost.

Nurullah Umarusman et al., [8] suggested, De Novo Programming model which includes De Novo Programming and Min-max Goal Programming approaches and uses positive and negative ideas.

Fahraz Ali et al., [9] described work on the FDM for optimizing the parameters like slice height, raster angle ,raster width

number of contours, STL angle, STL deviation, air gap. Surface roughness, material consumption, build time are the decision variables.

Zulkarnain Abdul Latiff et al.[10], evaluated the process to decide the optimal post process parameters to get best outcome for hardness, compressive parts and good tensile strength.

Materials and Methods

Material used

Here Fused Deposition Modelling technique is used for producing rectangular components. Material used here is ABS (Acrylonitrile butadiene styrene and its chemical formula $(C_8H_8)_x\cdot(C_4H_6)_y\cdot(C_3H_3N)_z$ which is very commonly used thermoplastic polymer. glass transition temperature of ABS is nearly (105 °C) 221 °F.

Selection of orthogonal array

Figure 1 shows the 3D printing system (Fused Deposition Modelling) which is an available resource to do experiments. For this FDM the available or measurable parameters are fill density, shell thickness, layer height, and speed. Therefore these parameters are considered as process parameters for the Taguchi technique.

Selection of number of experiments are calculated based on the number of process parameters (factors) , levels of process parameters (factors) and orthogonal array was selected using Taguchi technique. L27 Orthogonal Array was selected.

Considered process parameters = 4

Considered levels for process parameters = 3

Required experiments to be conducted = 27

Experimental Procedure

Based on the Design of Experiments 27 workpieces were made which are shown in Figure 2. Table 1 presents the DOE along with length (the amount of wire consumed for making one workpiece) and surface roughness which is measured using the Talysurf instrument.

Regression analysis

Figure 2: Rectangular workpieces after fabrication on FDM machine

A regression analysis has been carried out for variables of experimental data and for the outputs i.e. surface roughness and length using Microsoft Excel.

Surface roughness. is one of the objective functions considered and the optimization is to minimize. The regression equation calculated is shown in Figure 3.

Length. is one more objective function considered and its optimization is to minimize. The regression equation calculated is shown in Figure 4.

Table 2 shows the experimental results and excels results of the workpiece when the fabrication is done. The result gives the length, surface roughness.

Multi-Objective Optimization (Genetic and Goal Programming). Regression equation is calculated for the Length and Surface roughness and validated. Then Multi-Objective optimization is carried out for minimizing the length and surface roughness. The techniques used for optimization is Goal Programming and Genetic algorithm. Objective function and their constraints are presented below.

Minimize (LENGTH)=2.6525 + (0.0065*X1) + (0.078056*X2) + (0.75*X3) + (0.001306*X4)

Subjected to constraints 20m/sec ≤ X1 ≤ 40m/sec
3 mm ≤ X2 ≤ 7 mm
0.06 m ≤ X3 ≤ 0.2 m 20rpm ≤ X4 ≤ 60rpm
Minimize (Surface Roughness) =25.49926+ (-0.08441X1) + (0.040294X2) + (-11.6414X3) + (-0.04084X4)

Conclusion

Table 1: Experimental data for surface roughness and the length

S.N O	X1	X2	X3	X4	Surface Roughness (µm)	Length(m)
1	20	3	0.06	20	26.5624	2.28
2	20	3	0.1	40	25.05	2.96
3	20	3	0.2	60	17.0742	3.04
4	20	5	0.06	40	20.6803	4.05
5	20	5	0.1	60	19.707	3.44
6	20	5	0.2	20	19.6453	3.49
7	20	7	0.06	60	22.715	3.45
8	20	7	0.1	20	22.2216	3.47
9	20	7	0.2	40	21.141	3.48
10	30	3	0.06	40	17.2513	3.21
11	30	3	0.1	60	19.402	3.33
12	30	3	0.2	20	17.5803	3.49
13	30	5	0.06	60	19.7496	3.4
14	30	5	0.1	20	19.1703	3.45
15	30	5	0.2	40	20.3823	3.49
16	30	7	0.06	20	17.7786	3.45
17	30	7	0.1	40	20.1396	3.47
18	30	7	0.2	60	17.8646	3.48
19	40	3	0.06	60	19.0826	3.24
20	40	3	0.1	20	18.9223	3.35
21	40	3	0.2	40	21.6203	3.49
22	40	5	0.06	20	23.0316	3.41
23	40	5	0.1	40	17.8516	3.45
24	40	5	0.2	60	16.9586	3.49
25	40	7	0.06	40	22.132	3.45
26	40	7	0.1	60	18.8296	3.47
27	40	7	0.2	20	21.174	3.48

	A	B	C	D	E	F	G	H	I
1	SUMMARY OUTPUT								
2									
3	*Regression Statistics*								
4	Multiple F	0.500823							
5	R Square	0.250824							
6	Adjusted I	0.11461							
7	Standard I	2.260518							
8	Observati	27							
9									
10	ANOVA								
11		*df*	*SS*	*MS*	*F*	*gnificance F*			
12	Regressio	4	37.63779	9.409448	1.8414	0.156856			
13	Residual	22	112.4187	5.109941					
14	Total	26	150.0565						
15									
16		*Coefficient*	*andard Err*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*ower 95.0%*	*pper 95.0%*
17	Intercept	25.49926	2.537755	10.04796	1.11E-09	20.23627	30.76224	20.23627	30.76224
18	x1	-0.08441	0.053281	-1.58429	0.127399	-0.19491	0.026086	-0.19491	0.026086
19	x2	0.040294	0.266405	0.151253	0.881155	-0.51219	0.592784	-0.51219	0.592784
20	x3	-11.6414	7.388734	-1.57556	0.129399	-26.9647	3.681886	-26.9647	3.681886
21	x4	-0.04084	0.02664	-1.53309	0.139509	-0.09609	0.014407	-0.09609	0.014407
22									
23	SR=25.49926+(-0.08441X1)+(0.040294X2)+(-11.6414X3)+(-0.04084X4)								
24									

Figure 3: Summary Report and Regression equation for surface roughness

	A	B	C	D	E	F	G	H	I
1	SUMMARY OUTPUT								
2									
3	*Regression Statistics*								
4	Multiple F	0.519595							
5	R Square	0.269979							
6	Adjusted I	0.137248							
7	Standard I	0.266915							
8	Observati	27							
9									
10	ANOVA								
11		*df*	*SS*	*MS*	*F*	*gnificance F*			
12	Regressio	4	0.579644	0.144911	2.034028	0.124582			
13	Residual	22	1.567356	0.071243					
14	Total	26	2.147						
15									
16		*Coefficient*	*andard Err*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*ower 95.0%*	*pper 95.0%*
17	Intercept	2.6525	0.29965	8.851997	1.06E-08	2.031064	3.273936	2.031064	3.273936
18	X1	0.0065	0.006291	1.033183	0.312743	-0.00655	0.019547	-0.00655	0.019547
19	X2	0.078056	0.031456	2.481405	0.02121	0.012819	0.143292	0.012819	0.143292
20	X3	0.75	0.872438	0.85966	0.399247	-1.05933	2.559325	-1.05933	2.559325
21	X4	0.001306	0.003146	0.415039	0.682133	-0.00522	0.007829	-0.00522	0.007829
22									
23		LENGTH=2.6525+(0.0065*X1)+(0.078056*X2)+(0.75*X3)+(0.001306*X4)							
24									

Figure 4: Summary Report and Regression equation for the length

Table 2: Experimental data and excel data for the surface roughness

S.NO	X1	X2	X3	X4	Surface Roughness(μm)	Length(m)	SR in Excel Data	Length in Excel data
1	20	3	0.06	20	26.5624	2.28	26.564	3.08778
2	20	3	0.1	40	25.05	2.96	25.05	3.14398
3	20	3	0.2	60	17.0742	3.04	17.072	3.24508
4	20	5	0.06	40	20.6803	4.05	20.683	3.27002
5	20	5	0.1	60	19.707	3.44	19.707	3.32614
6	20	5	0.2	20	19.6453	3.49	19.643	3.3489
7	20	7	0.06	60	22.715	3.45	22.715	3.45222
8	20	7	0.1	20	22.2216	3.47	22.226	3.43002
9	20	7	0.2	40	21.141	3.48	21.141	3.53112
10	30	3	0.06	40	17.2513	3.21	17.253	3.17898
11	30	3	0.1	60	19.402	3.33	19.402	3.23508
12	30	3	0.2	20	17.5803	3.49	17.583	3.25778
13	30	5	0.06	60	19.7496	3.4	19.746	3.36114
14	30	5	0.1	20	19.1703	3.45	19.173	3.3389
15	30	5	0.2	40	20.3823	3.49	20.383	3.44002
16	30	7	0.06	20	17.7786	3.45	17.776	3.46502
17	30	7	0.1	40	20.1396	3.47	20.136	3.52112
18	30	7	0.2	60	17.8646	3.48	17.866	3.62222
19	40	3	0.06	60	19.0826	3.24	19.086	3.27008
20	40	3	0.1	20	18.9223	3.35	18.923	3.24778
21	40	3	0.2	40	21.6203	3.49	21.623	3.34898
22	40	5	0.06	20	23.0316	3.41	23.036	3.3739
23	40	5	0.1	40	17.8516	3.45	17.856	3.43002
24	40	5	0.2	60	16.9586	3.49	16.956	3.53114
25	40	7	0.06	40	22.132	3.45	22.132	3.55612
26	40	7	0.1	60	18.8296	3.47	18.826	3.61222
27	40	7	0.2	20	21.174	3.48	21.174	3.63502

Results and Discussions

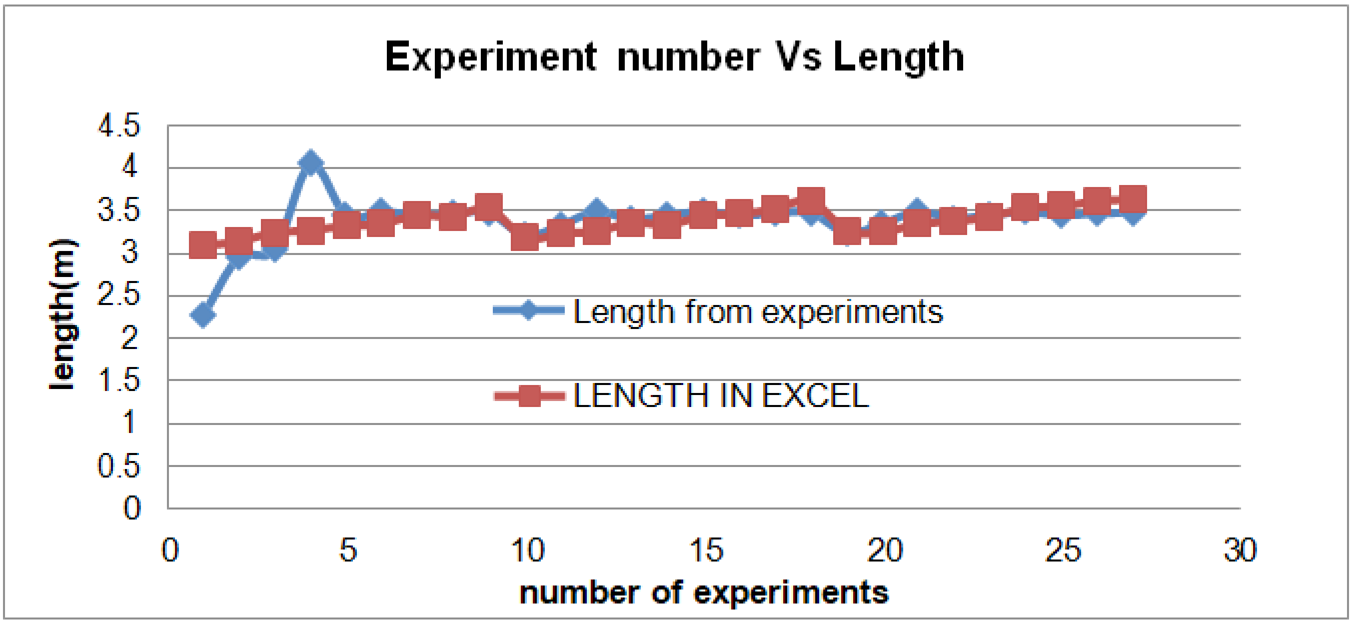


Figure 5: Experiment number Vs length.

From Figure 5. and Figure 6. It is observed that the results obtained from Microsoft Excel and Experimental Values are more or less the same. Therefore, for further MS Excel analysis, the equation resulted from Microsoft Excel is considered for optimization. Figure 7 presents the goal programming solution calculated using Microsoft Excel and Table 3: presents the results obtained using goal programming.

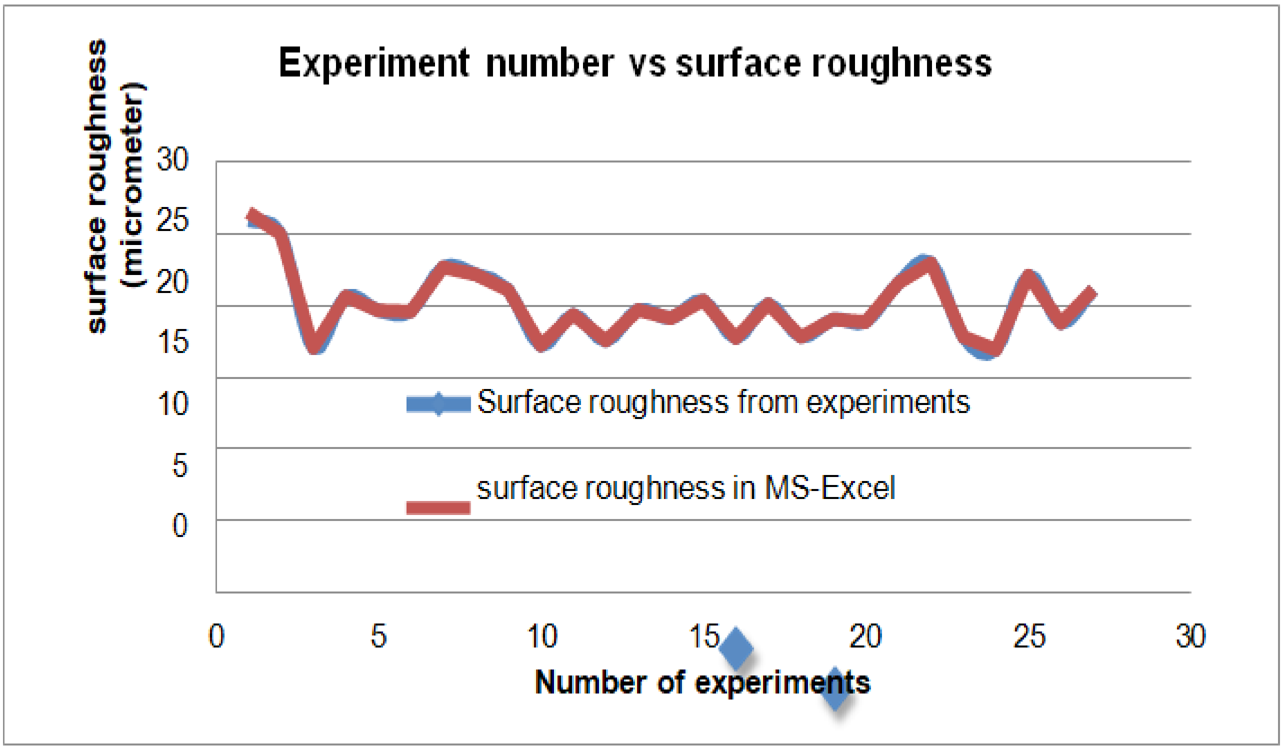
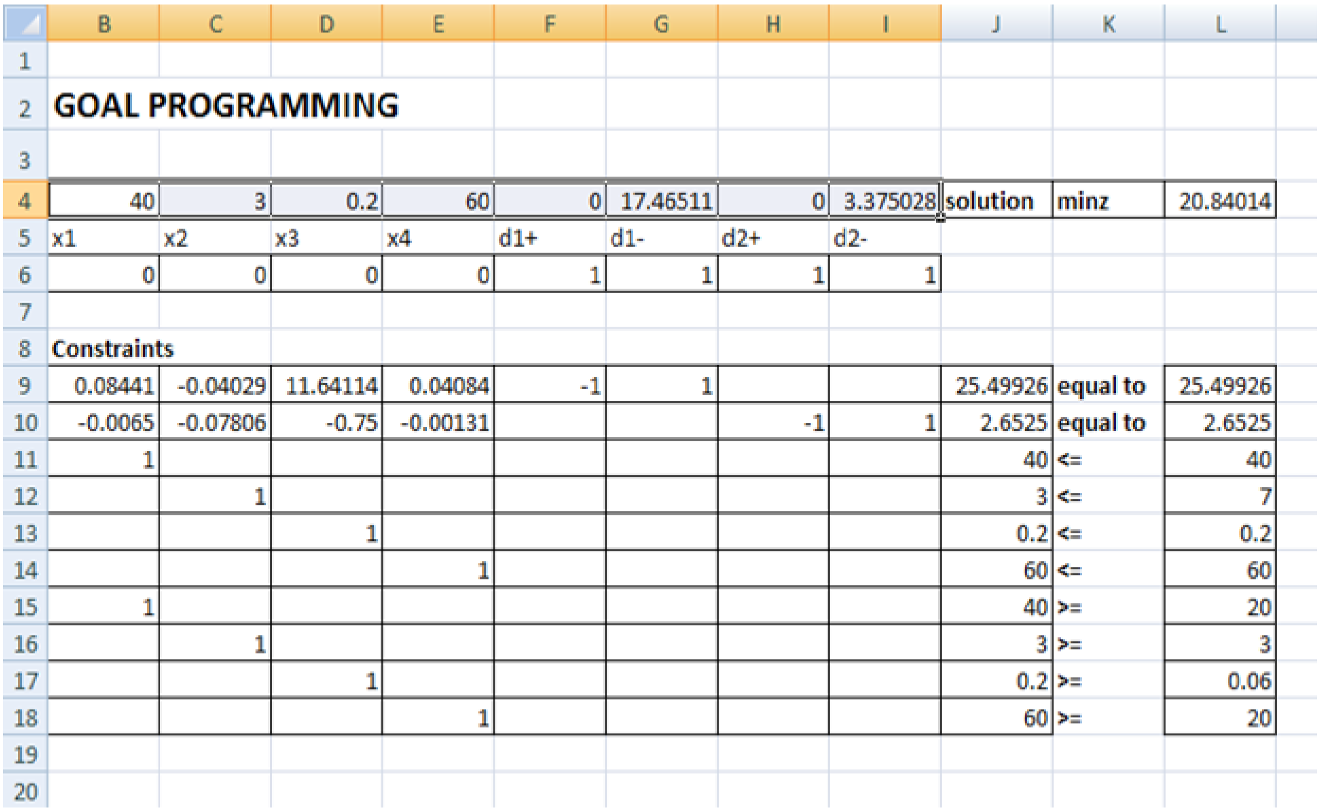


Figure 6: Experiment number Vs surface roughness.

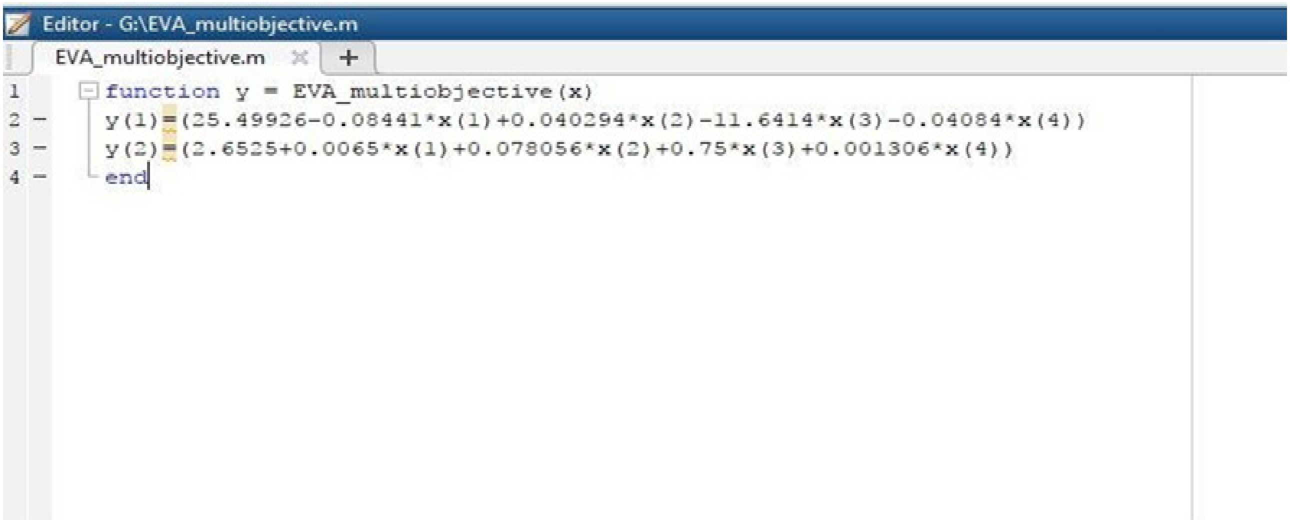


	B	C	D	E	F	G	H	I	J	K	L
1											
2	GOAL PROGRAMMING										
3											
4	40	3	0.2	60	0	17.46511	0	3.375028	solution	minz	20.84014
5	x1	x2	x3	x4	d1+	d1-	d2+	d2-			
6	0	0	0	0	1	1	1	1			
7											
8	Constraints										
9	0.08441	-0.04029	11.64114	0.04084	-1	1			25.49926	equal to	25.49926
10	-0.0065	-0.07806	-0.75	-0.00131			-1	1	2.6525	equal to	2.6525
11	1								40	<=	40
12		1							3	<=	7
13			1						0.2	<=	0.2
14				1					60	<=	60
15	1								40	>=	20
16		1							3	>=	3
17			1						0.2	>=	0.06
18				1					60	>=	20
19											
20											

Figure 7: Goal programming solution in Microsoft Excel

Table 3: Results obtained from Goal Programming

Fill density(mm/s)	40
Shell thickness(mm)	3
Layer height(mm)	0.2
Speed(mm/s)	60




```
function y = EVA_multiobjective(x)
y(1)=(25.49926-0.08441*x(1)+0.040294*x(2)-11.6414*x(3)-0.04084*x(4))
y(2)=(2.6525+0.0065*x(1)+0.078056*x(2)+0.75*x(3)+0.001306*x(4))
end
```

Figure 8: MATLAB code for GA

Figure 8 presents the MATLAB code used for Genetic Algorithm and Fig.9. presents the allotment of variables in Genetic algorithm optimization tool. Table 4: shows results obtained from genetic algorithm. Table 5: presents comparison results obtained from goal programming and genetic algorithm.

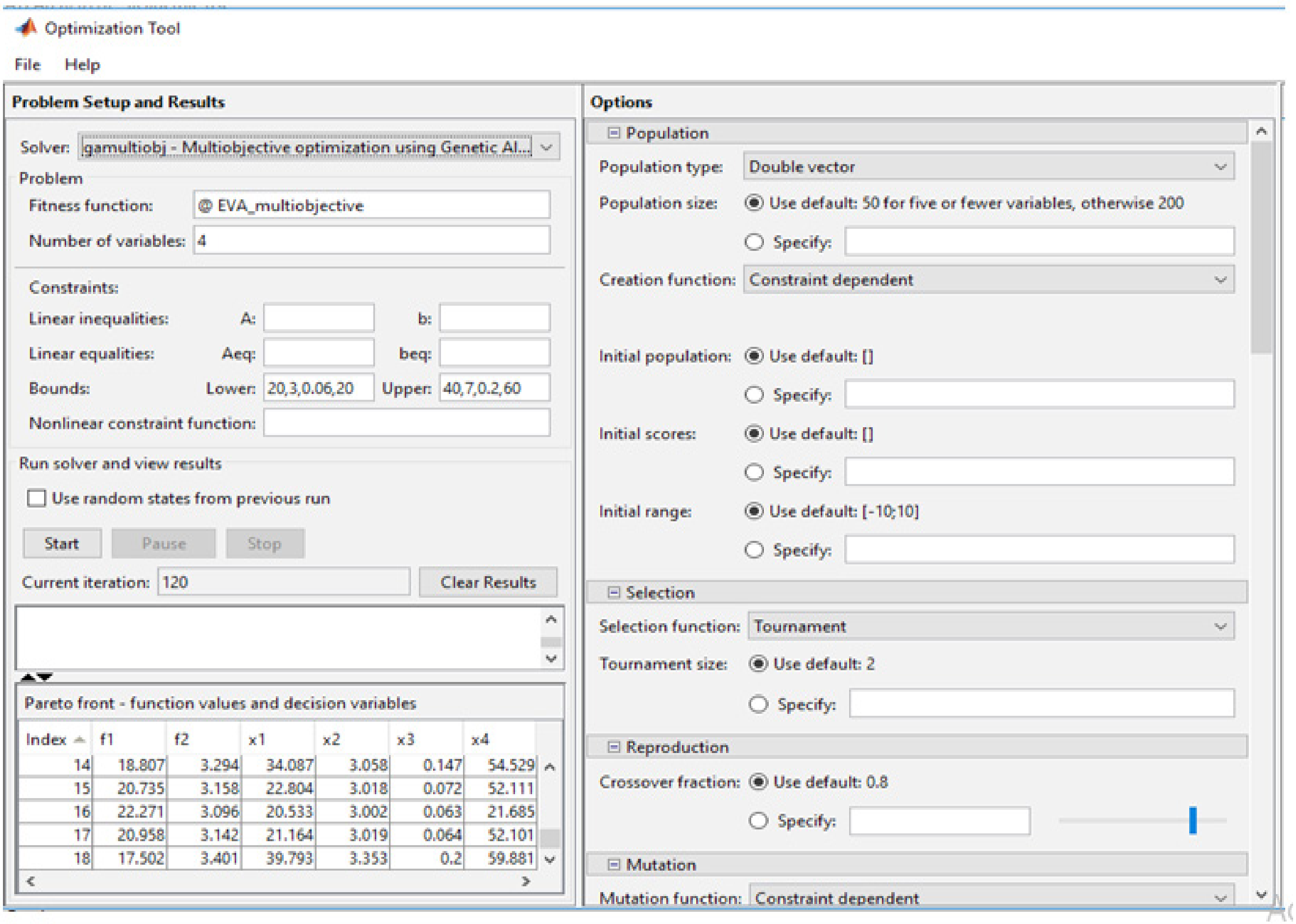


Figure 9: GA function values and decision variables

Table 4: Results obtained from the Genetic algorithm

Fill density(mm\s)	39.793
Shell thickness(mm)	3.353
Layer height(mm)	0.2
Speed(mm\s)	59.881

Table 5: Comparison between the Genetic algorithm and Goal Programming

Parameters	Genetic Algorithm	Goal programming
Fill density(mm/s)	39.793	40
Shell thickness(mm)	3.353	3
Layer height(mm)	0.2	0.2
Speed(mm/s)	59.881	60

From Table 5: presents the optimized results obtained from Genetic Algorithm and Goal Programming. From this, it is observed that rounding the decimals, both the algorithms are yielding the same results, i.e., fill density =40mm/s, shell thickness=3mm, layer height=0.2mm, speed=60mm/s.

Parametric optimization of surface roughness, the length of the rectangular workpiece (ABS) using fused deposition modeling for various parameters has been performed. The process parameters considered are fill density, shell thickness, layer height, and speed. An orthogonal array L27 was used to perform the experiments. Workpiece surface roughness is calculated using the metrological device called Talysurf. Multiple Regression analysis is performed to get the relationship between process parameters and Surface roughness, the length of the workpiece. Then using the equations obtained from multiple regression analysis, a multi-objective optimization is carried out using Genetic, Goal programming. It is observed that both the optimization techniques are yielding the same results. The obtained results are x1=40m/s, x2= 3mm, x3= 0.2mm, x4= 60mm/s.

Future Scope

This work can be extended on FDM for other materials like PLA (Polylactic acid), by researching other variables which impact on surface roughness and length, by considering other optimization techniques which are easy to use.

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