ORIGINAL PAPER

Multi-objective factors optimization in fused deposition modelling with particle swarm optimization and differential evolution

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Abstract

The design of any system contemplates the elaboration of a prototype of the entire system or some parts, before the manufacturing phase. Nowadays, rapid prototyping (RP) is widely used by the designers. Achieving good manufacturing performances needs to handle various process parameters. Most works deal with single objective process parameters. The reality is quite different and the processes involve conflicting objectives. This paper addresses the multi-objective factors optimization of the fused deposition modelling (FDM) technology. The problem is converted into a single one using the weighted-sum method and then solved by resorting to two nature-inspired computing techniques, namely particle swarm optimization (PSO) and differential evolution (DE). The results obtained are compared.

Keywords Rapid prototyping · Fused deposition modelling · Multi-objective optimization · Weighted-sum method · Particle swarm optimization · Differential evolution

1 Introduction

For many years, the industry has been continuously evolving due to the increasingly great demand from consumers, and machining processes are widely used, including conventional and nonconventional processes [1–5]. One of the most important things in the industry is the prototype, which is a miniature or a scaled model of a product to be created. In previous years, the prototype was manually made by molding and it took a long time to manufacture; then with the rapid development of technology, rapid prototyping (RP) can make complex 3D shapes that are made using a Computer Aided Design (CAD) with different processes, to reduce time, minimize cost and achieve complex shapes that cannot be manufactured by machining. Nowadays, various techniques are used, such as 3D printing, or virtual and augmented reality [6, 7]. To obtain a high quality object, it is necessary to optimize the processes. The prototyping processes can be found in several fields, such as medicine, aerospace/aeronautics, and robotics.

Nowadays, the optimization of the prototyping processes remains a challenge for the researchers. Most of the optimization approaches used to solve engineering problems are nature-inspired due to their effectiveness [8]. This paper provides a nonexecutive review of the literature. Comprehensive reviews can found in Refs. [9–17]. Jandyal et al. [18] also provided a review published in 2022. Lee et al. [19] used the Taguchi method to optimize the fused deposition modeling (FDM) to produce the acrylonitrile butadiene styrene. The FDM has many parameters to be handled [20]. These parameters have an impact on the physical and mechanical properties of the designed products [21]. Naveed [22] stated that the raster angle is one of the most important parameters of the FDM. Udroiu and Nedelcu [23] investigated the inkjet printing and polymer jetting using CATIA software, but the results were not compared to those achieved by alternate methods. Wang et al. [24] used the Taguchi method with the Gray relational analysis to optimize the FDM. The results were compared to the prediction. Sood et al. [25] proposed empirical models for the FDM to improve the tensile, flexural and impact strength responses by considering

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five process parameters: layer thickness, orientation, raster angle, raster width, and air gap. Variance analysis was used to test the model. Rao and Rai [16] used the teaching–learning-based optimization (TLBO) and the non-dominated sorting TLBO algorithm to solve single and multi-objective prototyping processes, including the model developed by Sood et al. [25]. The Pareto was generated to find the set of optimal solutions. However, selecting one single solution from the Pareto set led to conflicting conclusions. Shirmohammadi et al. [26] implemented the artificial neural network (ANN) with the particle swarm optimization (PSO) to minimize the surface roughness of a 3D printing process. They concluded that the proposed hybrid approach reduced the error. Addressing multi-objective process parameters is a key element to achieve good performances and remains a challenge. Only a few works have investigated the latter.

In this paper, the multi-objective FDM process is addressed and optimized with the weighted-sum method and the optimal parameters are provided using the PSO and the differential evolution (DE). The remainder of the paper is organized as follows: Sect. 2 describes the problem. Sections 3 and 4 give the description of the implemented PSO and DE, respectively. Section 5 provides the results with a discussion. Finally, the last section concludes the paper with remarks and suggested directions for future work.

2 Multi-objective FDM process

The FDM is a RP process that uses a moving nozzle to extrude a polymeric material fiber [25, 27–30]. Based on empirical models, the multi-objective optimization problem of the FDM is given as follows [16, 25]:

Maximize Ts [MPa]

$$
\begin{aligned}
= {} & 13.5625 + 0.7156A - 1.3123B + 0.9760C + 0.5183E \\
& + 1.1671A^2 - 1.3014B^2 - 0.4363(A \times C) + 0.4364(A \times D) \\
& - 0.4364(A \times E) + 0.4364(B \times C) + 0.4898(B \times E) \\
& - 0.5389(C \times D) + 0.5389(C \times E) - 0.5389(D \times E) \quad (1)
\end{aligned}
$$

Maximize Fs [MPa]

$$
\begin{aligned}
= {} & 29.9178 + 0.8719A - 4.8741B + 2.4251C - 0.9096D \\
& + 1.6626E - 1.7199(A \times C) + 1.7412(A \times D) - 1.1275(A \times E) \\
& + 1.0621(B \times E) + 1.0621(C \times E) - 1.0408(D \times E) \quad (2)
\end{aligned}
$$

Maximize Is [MJ/m^2]

$$
\begin{aligned}
= {} & 0.401992 + 0.034198A + 0.008356B + 0.013673C \\
& + 0.02138A^2 + 0.008077(B \times D) \quad (3)
\end{aligned}
$$

Subject to the following design variables:

$$0.127 \text{ mm} \leq A \leq 0.254 \text{ mm} \quad (4)$$

$$0° \leq B \leq 30° \quad (5)$$

$$0° \leq C \leq 60° \quad (6)$$

$$0.4064 \text{ mm} \leq D \leq 0.5064 \text{ mm} \quad (7)$$

$$0 \text{ mm} \leq E \leq 0.008 \text{ mm} \quad (8)$$

where Ts [MPa] is the tensile strength, Fs [MPa] is the flexural strength, Is [MJ/m^2] is the impact strength, A [mm] is the layer thickness, B [degree] is the orientation, C [degree] is the raster angle, D [mm] is the raster width, and E [mm] is the air gap.

In this paper, the multi-objective problem described in Eqs. (1)-(3) is converted into a single objective problem using the weighted-sum method [31–34] as follows:

$$\text{Maximize } Z = w_1 Ts + w_2 Fs + w_3 Is \quad (9)$$

where Z is the one-scaled objective function and w_i ($i = 1, 2, 3; w_1 + w_2 + w_3 = 1$) are the weight factors for each objective function.

3 Particle swarm optimization

The particle swarm optimization (PSO) is a nature-inspired optimization algorithm inspired by the moving mechanism of swarms, such as flocks of birds and schools of fishes. It was initially developed by Kennedy and Eberhart [35]. It is based on the position and the velocity of the particles of the swarm. PSO is one of the strongest optimization algorithms which has proven its effectiveness to tackle various engineering problems, such as the design of system availability and cost [33, 36], trajectory planning of robots [37], the combined heat and power economic emission dispatch problem [38], and system reliability [34]. Details on the PSO can be found in Refs. [35, 39, 40]. The pseudo-code of the implemented PSO to solve the above problem is given in Algorithm 1.

Algorithm 1. Pseudo-code of the implemented PSO.

Input the parameters;

Generate random solutions;

While No. of iterations ≤ max No. of iterations Do

     Evaluate the one-scaled objective function and constraint handling using penalty functions;

     Move the particles;

     Update the position and the velocity;

     Find best position and velocity;

End while

Display the results: Z, Ts, Fs, Is, A, B, C, D, and E.

4 Differential evolution

The differential evolution (DE) is a nature-inspired optimization algorithm inspired by the population evolution mechanisms. It was developed by Storn and Price [41] and is based on the genetic algorithms [42] but is characterized by more perturbations during iterations. Many works used the DE due to its robustness, such as PID controller [43], maintenance planning [44], state of charge estimation of batteries [45], and system availability [46]. More details on the DE can be found in Refs. [41, 46–48]. The pseudo-code of the implemented DE to solve the above problem is given in Algorithm 2.

Algorithm 2. Pseudo-code of the implemented DE.

Input of the parameters;

Generate random solutions;

While No. of iterations ≤ max No. of iterations Do

     Evaluate the one-scaled objective function and constraint handling using penalty functions;

     Perform evolution mechanisms;

     Perturbations during iterations;

End while

Display the results: Z, Ts, Fs, Is, A, B, C, D, and E.

5 Results and discussion

The problem descried has been solved using the above two algorithms and implemented using MATLAB 2017 and run on a PC with the following characteristics: i5 of 2.50 GHz with 4 GB. Each algorithm has been run over ten independent runs. The population size is 20 and the maximum number of iterations is 100. These parameters have been fixed by trial-and-error and based on experience. The weight factors are considered equal, i.e. ($w_1 = w_2 = w_3 = 0.3333$).

Tables 1 and 2 report the results obtained by the PSO and the DE over the ten runs, respectively. The values of the one-scaled objective (Z), the three process performances (Ts, Fs and Is), design variables, number of function evaluations (NFE), CPU time, and standard deviation (σ) are included.

Table 1 Results obtained by the PSO

Run #	T_s [MPa]	F_s [MPa]	I_s [MJ/m^2]	Z	A [mm]	B [°]	C [°]	D [mm]	E [mm]	NFE	CPU [s]	σ
1	170.2548	125.3745	1.3162	**98.8849**	0.1270	7.6880	60	0.4064	0.008	1660	17.28	2.8E−04
2	170.4601	125.1358	1.3167	**98.8849**	0.1270	7.7105	59.9944	0.4064	0.008	1960	20.23	
3	170.5864	125.0318	1.3170	98.8845	0.127	7.7331	60	0.4064	0.007	1980	12.18	
4	170.3061	124.9912	1.3161	**98.8849**	0.127	7.7191	59.9466	0.4064	0.008	1840	11.90	
5	170.2408	125.3889	1.3162	**98.8849**	0.1270	7.6609	60	0.4064	0.008	**1220**	12.23	
6	170.2634	125.3570	1.3162	98.884	0.1270	7.6671	59.9989	0.4065	0.008	2000	12.38	
7	170.3064	125.3283	1.3163	98.8848	0.127	7.6741	60	0.4064	0.008	1720	11.57	
8	170.3662	125.1776	13,165	**98.8849**	0.1274	7.6934	59.9956	0.4065	0.008	2000	11.81	
9	170.4134	125.2184	1.3166	**98.8849**	0.127	7.6967	60	0.4064	0.008	1980	11.74	
10	170.3698	125.2216	1.3165	**98.8849**	0.127	7.6931	59.9936	0.4065	0.008	1680	11.95	

Bold values represent the best results

Table 2 Results obtained by the DE

Run #	T_s [MPa]	F_s [MPa]	I_s [MJ/m^2]	Z	A [mm]	B [°]	C [°]	D [mm]	E [mm]	NFE	CPU[s]	σ
1	170.3954	125.2397	1.3166	**98.8849**	0.1270	7.6923	60	0.4064	0.008	600	15.37	0
2	170.3954	125.2397	1.3166	**98.8849**	0.1270	7.6923	60	0.4064	0.008	500	9.90	
3	170.3954	125.2397	1.3166	**98.8849**	0.1270	7.6923	60	0.4064	0.008	620	9.78	
4	170.3954	125.2397	1.3166	**98.8849**	0.1270	7.6923	60	0.4064	0.008	640	9.38	
5	170.3954	125.2397	1.3166	**98.8849**	0.1270	7.6923	60	0.4064	0.008	500	9.52	
6	170.3954	125.2397	1.3166	**98.8849**	0.1270	7.6923	60	0.4064	0.008	620	9.43	
7	170.3954	125.2398	1.3166	**98.8849**	0.1270	7.6923	60	0.4064	0.008	660	9.83	
8	170.3954	125.2397	1.3166	**98.8849**	0.1270	7.6923	60	0.4064	0.008	560	9.18	
9	170.3954	125.2397	1.3166	**98.8849**	0.1270	7.6923	60	0.4064	0.008	**440**	9.89	
10	170.3954	125.2398	1.3166	**98.8849**	0.1270	7.6923	60	0.4064	0.008	660	9.58	

Bold values represent the best results

Table 3 Comparison of PSO vs DE

	Z	NFE	CPU[s]	σ
PSO	**98.8849**	1980	12.23	2.8E−04
DE	**98.8849**	**440**	**9.89**	**0**

Bold values represent the best results

From Table 1, it can be observed that the best value of Z obtained by the PSO is 98.8849 for all runs, except #3, #6 and #7. The fewer NFE corresponds to #5 (1,220) with 12.23 s of CPU time. The optimal values are TS = 170.2408 MPa, Fs = 125.3889 MPa, Is = 1.3162 MJ/m^2, whereas the decision variables are A = 0.1270 mm, B = 7.6880°, C = 60°, D = 0.4064 mm, and E = 0.008 mm. The standard deviation of the ten runs is 2.8E−04.

From Table 2, it can be observed that the best value of Z obtained by the DE is 98.8849 for all runs. The lower NFE corresponds to #9 (440) with 9.89 s of CPU time. The optimal values are TS = 170.3954 MPa, Fs = 125.2397 MPa, Is = 1.3166 MJ/m^2, whereas the decision variables are A = 0.1270 mm, B = 7.6923°, C = 60°, D = 0.4064 mm, and E = 0.008 mm. The standard deviation of the ten runs is 0.

Table 3 summarizes the best results obtained by the PSO and the DE. It can be observed that both algorithms obtained the same value of the one-scale objective (Z = 98.8849). However, the performances of the DE have outperformed those of the PSO in terms of number of function evaluations, CPU time, and standard deviation.

6 Conclusions

The goal of this paper was to investigate the multi-objective fused deposition modelling (FDM) optimization problem which is a rapid prototyping process (RP). The considered objectives were the tensile strength, the flexural strength, and the impact strength. The multi-objective problem was converted to a single one using the weighted-sum method in order to avoid the disadvantages of the Pareto set. The particle swarm optimization (PSO) and differential evolution (DE) were implemented with constraint handling to solve the problem. It was shown that both algorithms provides the same value of the one-scaled objective, but the performances of the DE were better. The latter means that the DE required fewer function evaluations, required less CPU time, and has a lower standard deviation. Therefore, the present work contributes to the machinability of the FDM process by providing the optimal process parameters when considering both objectives, i.e., the tensile strength, the flexural strength, and the impact strength. Future work will be devoted to the development of a hybrid approach to improve the results and solve other rapid prototyping processes.

Declarations

Conflict of interest The authors declare no competing interests.

Consent for publication All authors agree to transfer copyright of this article to the Publisher.

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