

Energy Efficient Modeling and Optimization of Additive Manufacturing Processes

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Abstract

Additive manufacturing (AM) is a leading technology in various industries including medical and aerospace for prototype and functional part fabrication. Despite being environmentally conscious, avenues pertaining to further reducing the impact of AM on the environment exist. Material wastage and energy consumption are two major concerns of the process that requires immediate attention. In this research, a multi-step optimization enabling additive manufacturing process towards energy efficiency is developed. Process objectives such as material waste and energy consumption are minimized both in part and layer domain. Numerous examples are presented to demonstrate the applicability of the developed approach. The models formulated here for selective laser sintering (SLS) process can be easily extended to other additive manufacturing technologies.

1 Introduction

Additive manufacturing is a process of fabricating three-dimensional solid objects from a digital model such as CAD model. It is achieved using additive processes, where laying down successive layers of material creates an object. Additive manufacturing is distinct from traditional techniques (i.e. subtractive processes), which mostly rely on the removal of material by means of drilling, cutting etc. Over the last two decades, there have been tremendous technical advances in the field of additive manufacturing, including input file formats [1, 2, 3], materials selection [4], and process planning [5, 6].

Process sustainability is an important aspect which has received little attention in additive manufacturing. Despite the noticeable advances in the additive manufacturing technologies over traditional machining, relatively very few studies have focused on studying its potential effect on the environment and energy efficiency [7, 8, 9]. With the recent trend towards green economy, research in additive manufacturing should be complemented with the energy efficiency and sustainability. In additive manufacturing, process sustainability indicators such as material waste and energy consumption are always a concern.

For example, FDM processes generate waste in the form of support structure. Laser based processes such as SLA and SLS selectively sinters materials from a large material bed, leaving majority of un-sintered (56%) material as a waste [7, 10]. On the other hand, AM sub-processes such as laser scanning, raw material deposition, material extrusion, and bed heating and cooling processes are energy intensive [11, 12].

The research presented in the paper addressed the current research need towards sustainable additive manufacturing. More specifically, process energy and material waste in AM process are minimized using a multi-step optimization approach. The contribution of proposed paper is two-fold namely, (1) process sustainability modeling and optimization, (2) development of a novel heuristic optimization based adaptive slicing approach. Unlike other adaptive slicing approaches in the literature, the developed approach is generic and does not require pre-calculation of part geometry information such as complexity, curvature, and feature identification [13, 14, 15].

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The paper is organized as follows. In Section 2, numerous objectives and the concerned optimization models are formulated. The overall solution methodology is demonstrated in Section 3. Experimental results and findings from the present analysis are discussed in Section 4. Section 5 concludes the present work with some notes on future research directions.

2 Mathematical formulation of the process

The energy consumed by the selective laser sintering (SLS) machine during whole part build can be categorized into: (1) processing energy, and (2) non-processing energy (Figure 1). Non-processing energy consists of energy consumed by machine during recoater arm movement, build piston movement (upward/downward), and initial heating. On the other hand, processing energy consumption is largely determined by the amount of material which is required to be fused together to build the whole part. Experimental studies in the literature have found out the contribution of processing energy as much as 56% of the total energy consumption. In the present research, both processing and non-processing energy consumption is minimized by (1) reducing the number of recoater arm movement, build piston movement, and (3) optimizing the laser scan movement to sinter the part for each layer. A set of underlying objectives are formulated next.

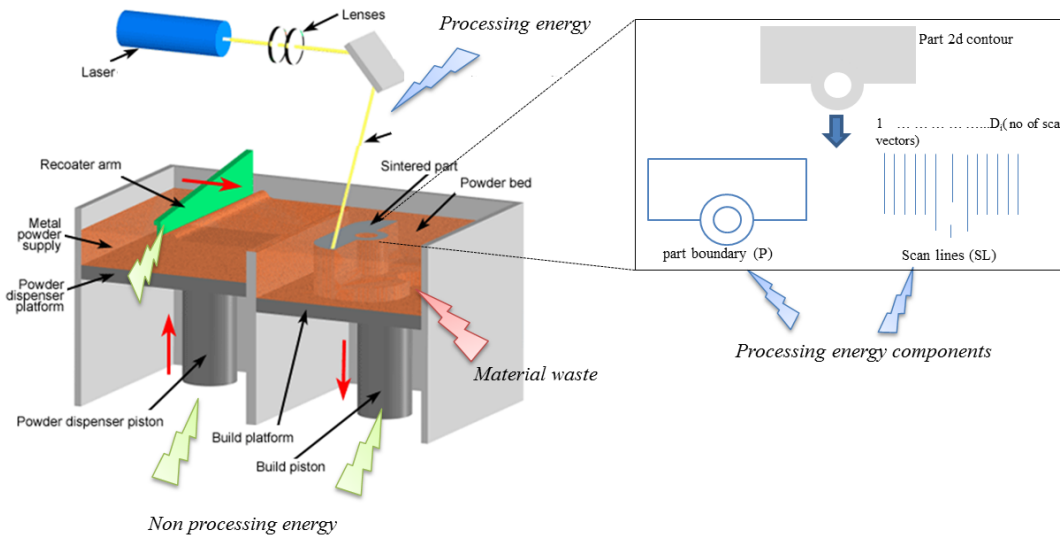


Figure 1: Schematic of selective laser sintering (SLS) with highlighted energy components

2.1 Laser processing energy

The material absorptivity (ω), laser average intensity (I_{avg}), laser scan speed (SS), and laser spot diameter (SD) are the factors contributing to the overall input energy requirement (e) for sintering the material powder [13]. Mathematically, it can be written as:

$$e = \frac{SD \times \omega \times I_{avg}}{SS} \quad (1)$$

Laser average intensity (I_{avg}) is the laser power per unit area, written as:

$$I_{avg} = LP/A_{SD} \quad (2)$$

In equation 2, LP is the laser power, and A_{SD} (equation 3) is the area covered by laser beam spot.

$$A_{SD} = \frac{\pi \times SD^2}{4} \quad (3)$$

The equation (1) can thus be written as:

$$e = \frac{4 \times \omega \times LP}{\pi \times SS \times SD} \quad (4)$$

The total energy required by the laser to sinter one slice of the part will be:

$$E_s = e \times A_s \quad (5)$$

In equation (5), A_s is the area of s^{th} slice of the part. A_s can be broken down to the actual number of scan lines and slice boundaries to sinter the power material. Figure 2 explains the effective slice area of a sample 2D profile. It consists of scanning the outer boundary and inside solid area through a series of parallel laser beams. The slice sintering area can be written as:

$$A_s = SD \times \sum_{i=1}^{I_s} SV_i + \sum_{j=1}^{C_s} P_j \quad (6)$$

In equation (6), A_s is the sintering area of s^{th} slice profile, SD is the beam spot diameter. SV is the length of scan vector, I_s being the total number of scan vectors in a slice s . P is the outside boundary of slice, and C_s is the number of contours in slice s . Hence, the total energy required to sinter the whole part will be:

$$\Xi = \sum_{s=1}^S E_s \triangleq \Xi = e \times \sum_{s=1}^S A_s \triangleq \Xi = \frac{4 \times \omega \times LP}{\pi \times SS \times SD} \times \sum_{s=1}^S \sum_{i=1}^{I_s} SV_{si} + \sum_{j=1}^{C_s} P_{sj} \quad (7)$$

In equation (7), S is the total number of slices in part (i.e. equivalent to $L-1$, where L is the number of layers).

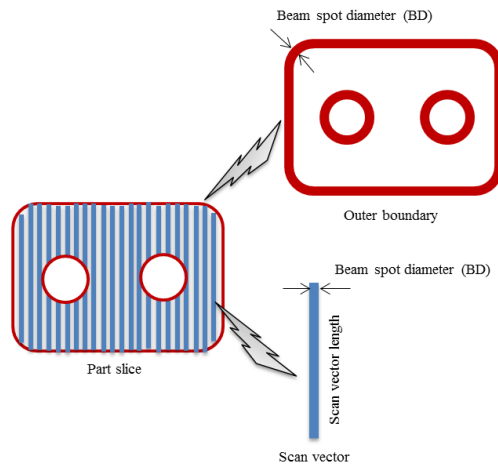


Figure 2: Part slice component determining effective sintering area

2.2 Material waste

In SLS, the un-sintered powder material is typically reused, however, at the expense of powder material strength. The powder binding strength deteriorates at each reuse run, making around 56% of un-sintered material as waste. In the present research, the material wastage (ξ) is calculated at part level, mathematically can be written as:

$$\xi = (SV_{bed} - V_{part}) \times \psi \quad (8)$$

In equation (8), V_{part} is the volume of the 3D part, ψ is the material waste fraction, and SV_{bed} is effective sintering volume of the bed. The powder material to be laid on sintering zone depends on the part height, thus the effective volume of the bed becomes $AR_{bed} \times H_{part}$. The above equation is reduced to:

$$\xi = ((AR_{bed} \times H_{part}) - V_{part}) \times \psi \quad (9)$$

2.3 Surface quality

The part surface finish is another important factor that needs to be considered while minimizing material waste. As mentioned in earlier sections, part height plays an important role in determining the energy consumption of the fabrication process. Maintaining an appropriate surface finish may increase the process energy consumption, but will minimize part post-processing. Here, the part surface roughness is used as an estimate to calculate surface finish of the part based on the orientation of triangular facets. Mathematically, the surface roughness of a facet can be calculated as [16]:

$$Ra_i = \begin{cases} (2\cos\phi\sin\phi \times 937 + 3.5\phi + 48) \times 0.0254, & \text{if } 0 \leq \phi \leq \pi/2 \\ (2\cos(\pi - \phi)\sin(\pi - \phi) \times 937 + 3.5\phi + 48) \times 0.0254, & \text{otherwise} \end{cases} \quad (10)$$

In equation (10), Ra_i is the surface roughness of i th facet, ϕ is the angle between facets surface normal and build direction. Comparison of surface roughness of various facets is shown in Figure 3. The inclined facets will contribute to the surface roughness of the parts. The average surface roughness is calculated as:

$$Ra_{avg} = \frac{\sum_{i=1}^F Ra_i \times A_i}{\sum_{i=1}^F A_i} \quad (11)$$

In equation (11), A_i is the Area of i^{th} facet and F is the total number of facets. In next section, the developed optimization models are discussed.

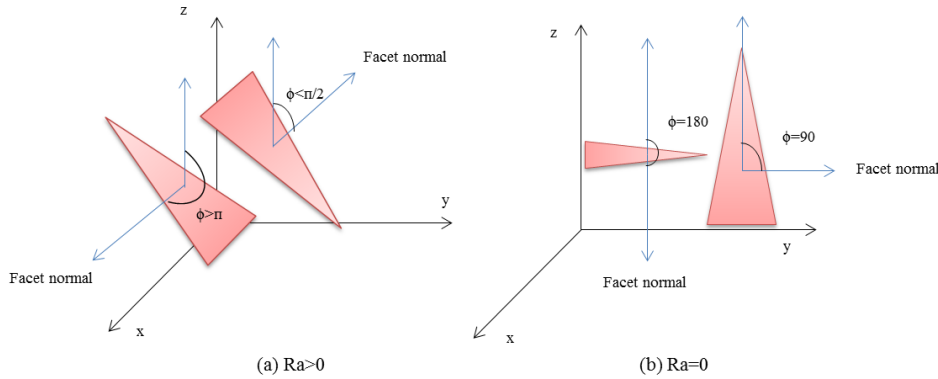


Figure 3: Comparison of surface roughness of facets. (a) Inclined facets will add to the surface roughness of the part. (b) Parallel and perpendicular facets will have 0 surface roughness.

2.4 Optimization models

In this sub-section, description of the optimization models is provided. Objectives such as part surface roughness, volumetric error are combined with material waste and energy related objectives respectively to ensure the surface accuracy of the part is not sacrificed while part processing energy and material waste are minimized. Considering the nature of additive manufacturing processes, the 3D models to be fabricated are optimized at two levels. In level 1, the 3D models as a whole is optimized by minimizing the material waste and surface roughness, whereas, in level 2, optimization is done for each slice of the part (to ensure minimum energy consumption) which is combined with the developed adaptive slicing approach.

Overall framework of the two-level optimization approach is provided in Figure 4. The developed approach starts with part preprocessing, where, 3D models are first translated into positive x, y, and z axis for ease of calculation (step 1). Next, the part surface roughness and overall material waste is minimized (step2). It is achieved by optimally orienting the part along build direction (i.e. z axis). The output of the level 1 optimization provides optimal orientation of the part which is kept fixed. For level 2 optimization, both part slicing and the laser processing energy of individual slices is determined. Part slicing is based on developed adaptive slicing heuristic which starts with random slicing solutions and iteratively improves the overall slicing while minimizing the process energy, and volumetric error of the part. Detailed description of the developed heuristic algorithm is provided in Section 3.

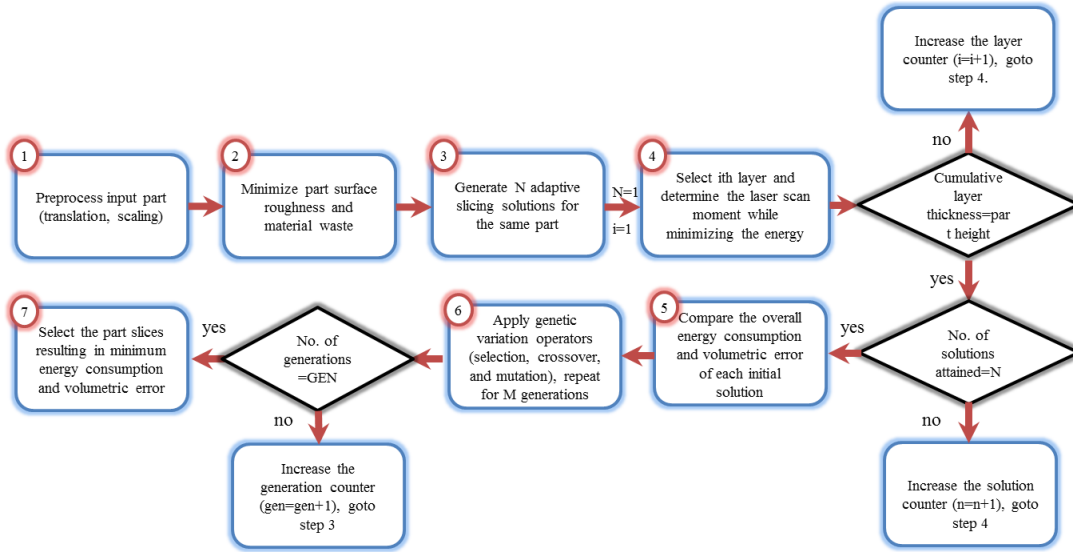


Figure 4: The developed optimization framework for adaptive slicing

2.4.1 Minimization of material waste and part surface roughness (level 1)

In the part level, both material wastage and surface roughness are optimized. The overall optimization model can be written as:

$$\text{Min. } f(\alpha, \beta) = \frac{w_1 \times \xi + w_2 \times Ra_{avg}}{w_1 + w_2}, \text{ s.t.}, 0 \leq \alpha, \beta \leq \pi \quad (12)$$

In equation (12), α, β , are the part rotation angles in x,y directions which are varied in the range $(0 - \pi)$, w_1 , and w_2 are the weights associated with the objective functions namely material waste and surface roughness. As the main objective of present study is to minimize material waste and energy consumption, higher weight is assigned to the material waste. In the research the weight associated with material waste criteria is set to 0.75 (i.e. $w_1=0.75$), whereas, weight value of 0.25 (i.e. $w_2=0.25$) is assigned to part surface roughness.

2.4.2 Minimization of laser processing energy (level 2)

The laser processing energy is optimized by varying the number of layers and scanning directions of the lasers for each layer. AM processes fabricate complex parts which often has varying cross sections. The number of scan lines to sinter the 2D layer contour will vary from one direction to another. By optimizing the laser scanning directions, the laser processing energy can be minimized. Mathematically, it can be written as:

$$\text{Min. } f(\gamma) = \frac{4 \times LP}{\pi \times SS \times SD} \times \sum_{i=1}^{I_s^\gamma} SV_{si} + \sum_{j=1}^{C_s} P_{sj}, \text{ s.t. } 0 \leq \gamma \leq \pi/2 \quad (13)$$

In equation (13), s is the indices used for slice, I_s^γ is the number of scan vectors required to be sintering for whole slice, γ being the laser scanning direction. The process energy consumption of each layer is minimized by optimizing the laser scanning movement.

2.4.3 Minimization of overall energy and part volumetric error (level 2)

The overall energy consumption (Ξ) of the process is the laser processing energy (given in equation 13), summed up for all the slices of the part. The adaptive slicing procedure selects the layer thickness so that the upper and lower contours of a slice have minimum difference. Volumetric error is used as an additional objective to ensure the parts required minimum post processing (another source of energy consumption). Volumetric error (VE) is defined as the volume difference between the actual part and the fabricated part. Mathematically, it can be written

as [8]:

$$VE = \sum_{l=1}^{L-1} lt_l \times |A_{l+1} - A_l| \quad (14)$$

In equation (14), VE is the volumetric error, which is calculated using the area difference between consecutive layers, and slice thickness (lt). The overall objective function is written as:

$$\text{Min. } f(lt, \gamma) = \frac{w_1 \times \Xi + w_2 \times VE}{w_1 + w_2}, \text{ s.t., } lt_{min} \leq lt \leq lt_{max} \quad (15)$$

In equation (15), It is the layer thickness which should be kept in the range $lt_{min} - lt_{max}$ (i.e. laser sintering capability), w_1 and w_2 are the weight associate with objective namely minimization of energy consumption and minimization of volumetric error. Higher weight is assigned to energy minimization objective (i.e. $w_1=0.75$, $w_2=0.25$). In next section, the methodology to solve the formulated objectives are discussed.

3 Solution approach

The models developed in previous section level are optimized in two-level. In level 1, material waste and average surface roughness of part is minimized by optimally orienting the part towards build direction. Being highly non-linear, the objectives are optimized using a heuristic approach. The developed heuristic comprises of a local search technique namely simulated annealing (SA), and a genetic algorithm (GA) based meta-heuristic. Both the SA, and GA are well-known algorithms to solve highly non-linear optimization problems as formulated in this paper. The developed heuristic uniquely combines the traits of both SA, and GA to solve the underlying problem. SA is a point based evolutionary local search technique that explores the search space iteratively based on a probability distribution proportion to the temperature. In the developed research, SA explores the search space until no change in the objective function is found for consecutive 100 iterations [17]. Adaptive slicing is performed using genetic algorithm (GAs). GA's belongs to a class of evolutionary search algorithms that works on population (also known as initial feasible solution) [18, 19]. GAs iteratively improves the search space by means of variation operators namely crossover, mutation, and selection mechanism. In the proposed research, individual refers to a set of layer thickness values constituting a part and a population consists of a set of distinct individuals. The cumulative layer thickness should be equal to the part height, which determines the number of layers. The process capability of the SLS machine is taken into consideration for population initialization and other processing steps. SA first iteratively improves the objective function given in equation 14 and provides the

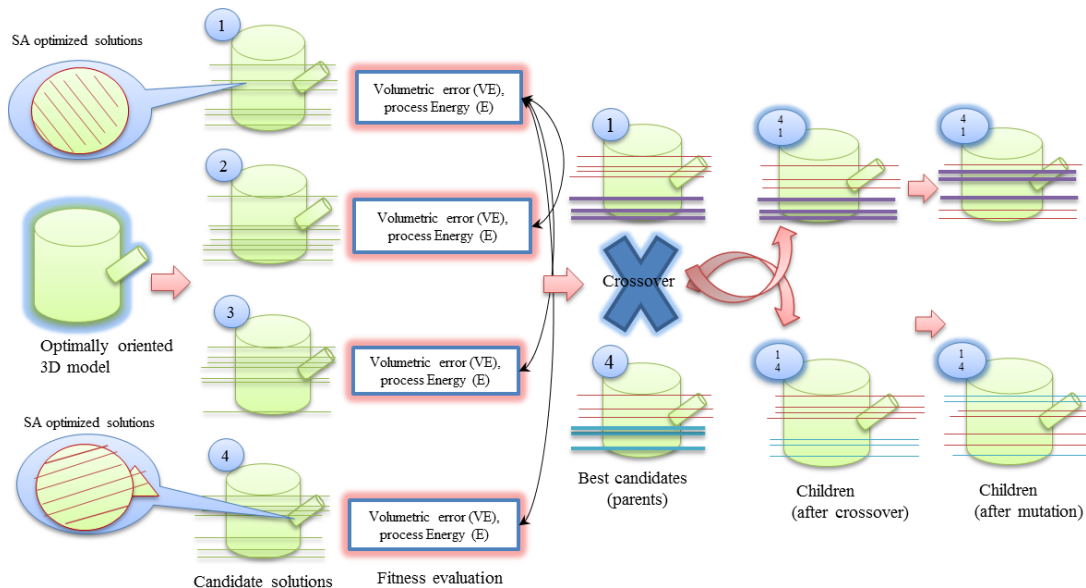


Figure 5: Candidate solution generation and variation operators on sample 3D part

Table 1: GA specific parameters used in the study

No.	Parameter	Value/range
1	Population size	10
2	Crossover type	single point
3	Mutation type	swap
4	Crossover probability	0.8
5	Mutation probability	0.01
6	Termination criteria	Max. generation (50)

Table 2: Machine specific data (SLS Vanguard™ HiQ Sinterstation)

No.	Parameter (symbol)	Value/range
1	Machine build volume ($AR_{bed} \times H_{bed}$)	$(380 \times 330) \times 457 \text{ mm}^3$
2	Laser power (LP)	70 W
3	Part orientation angle (α, β)	$0^\circ - 180^\circ$
4	Laser scanning movement (γ)	$0^\circ - 90^\circ$
5	Laser sintering capability ($lt_{min} - lt_{max}$)	0.03-0.1 mm
6	Laser scan speed (SS)	1000 mm/sec
7	Laser beam spot diameter (SD)	1.75e-2
8	Input material	Polycarbonate powder (PC)
9	Material absorptivity (ω)	0.95%
10	Material waste fraction (ψ)	56%
11	Laser scan spacing	1.75e-2
12	Fixed energy usage	16000 W

best part orientation. Both SA, and GA are then applied in tandem to perform slice level energy minimization and adaptive slicing respectively. The quick convergence properties of SA provides faster solution, whereas, unique encoding schema of GA facilitates efficient adaptive slicing. Figure 5 display the schamatic of GA encoding schema once the part is optimally oriented. The contribution of SA based search technique is also highlighted for random part slices. The developed developed candidate solution generation scheme ensures only feasible solutions are generated by: (1) generating part slice thickness within the range of machine capability, i.e. $lt_{min} - lt_{max}$, and (2) making the cumlative layer thickness of individual solution equal to the part height. Feasibility is also ensures after variation operators namely crossover and mutation is applied. The process shown in Figure 5 is repeated for each generation until the termination criteria is reached. Here the termination criterion is maximum number of generations which is fixed to 50. Genetic Algorithms (GA) is explore the search space to get the best solution in terms of slice thickness values and minimum energy consumption [20]. The GA specific parameters used in the study are shown in Table 1.

In next section, details of experiment results is presented.

4 Experimental results

In this section, numerous example parts are optimized using the solution methodology discussed in Section 3. The analysis shown here is based on SLS vanguard HiQ Sinterstation machine with polycarbonate (PC) as input material powder. Table 2 describes the machine specific parameters used in the present study¹. In the present study, the laser processing energy is minimized, whereas, the non-processing energy used during piston, recoater arm movement, and bed heating is kept fixed. An interface is developed in MATLAB (2012a) for the analysis. Based on the formulated optimization models, the interface consists of two major components, i.e. part level optimizer, and slice level optimizer, discussed below. All example parts‘ used in the study are in mm.

¹<http://www.3dsystems.com/products/datafiles/>

4.1 Part level optimizer

Part level optimizer provides quick optimal solution to the material waste and surface roughness by appropriately orienting the part along build direction. An example 3D part of dimension $(0.3mm \times 0.3mm \times 0.6mm)$ as shown in Figure 6 (a) is used for the analysis. The part level optimizer recommends the input part to be oriented $90^\circ, 0^\circ$ along x and y axis respectively. The resultant surface roughness is 8.39 Ra, whereas, material wastage is $22.77 cm^3$ (Figure 6 (b)). Material wastage reduced from $44.93 cm^3$ to $22.77cm^3$ (an improvement of 50.67%) (Figure 6 (c)).

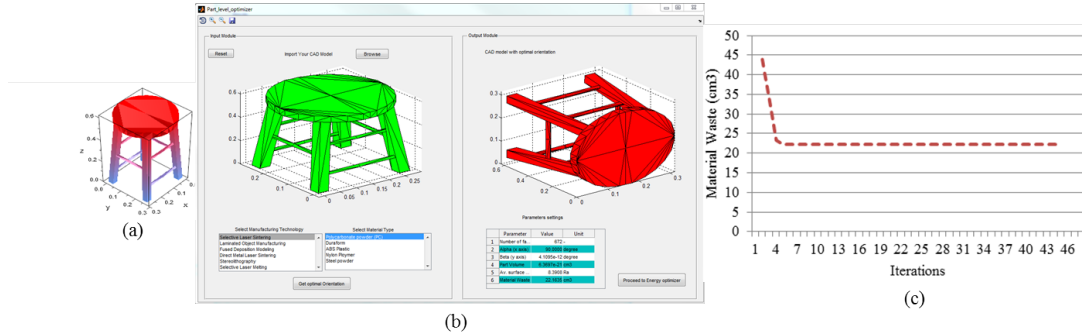


Figure 6: (a) an example 3D model, (b) the corresponding part level optimizer with initial and optimal part orientation using SA, and (c) iterative improvement in the material waste.

4.2 Slice level optimizer

The slice level optimizer performs optimization on part slices and provides optimal/near-optimal laser scan movement of each slice, slice thickness, the process build time, process energy consumption, and volumetric error. An input 3D part of dimension $2 mm \times 2 mm \times 4 mm$ (Figure 7(a)). The part level optimizer recommends the input part to be oriented as it is, i.e. $0^\circ, 0^\circ$ along x and y axis respectively (Figure 7(b)-top right). The resultant surface roughness is 0.1438 Ra, whereas, material wastage is $299.87 cm^3$. A majority of material waste is attributed to the part profile. The process energy consumption is 0.79 W, whereas the process would take just 46 sec to build the part. Part volumetric error is $0.0635 mm^3$, suggesting high accuracy of the part. Figure 7 (b) also display the laser scanning movement of 6 random slices. Figure 7 (c) shows the energy consumption and build time of each slice, which follows similar trend, suggesting high correlation.

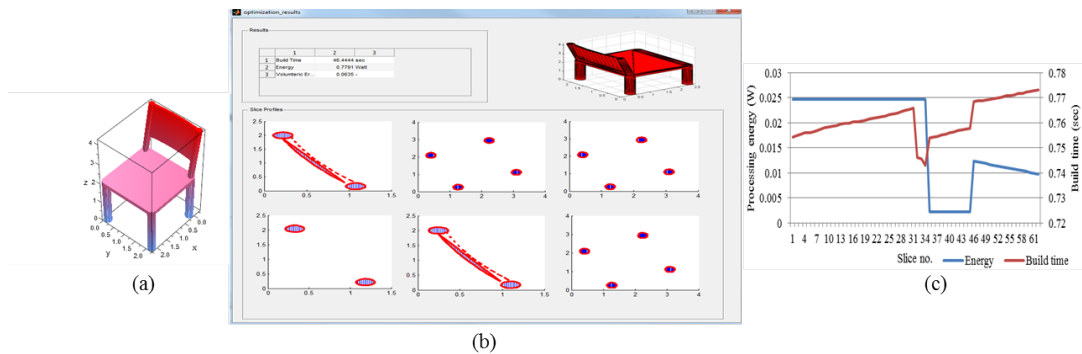


Figure 7: (a) an example 3D model, (b) the corresponding slice level optimizer with 6 random laser slices, and (c) the optimized energy consumption of each slice and corresponding build time.

4.3 Results comparison

In this section, the results obtained from the developed approach are compared against the state-of-the-art (i.e. uniform slicing). The models used for the comparison are actual models developed using additive manufacturing

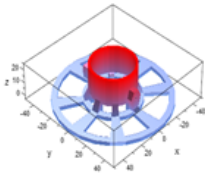
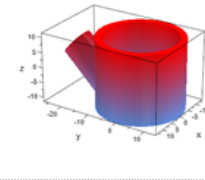
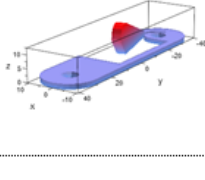
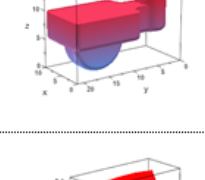
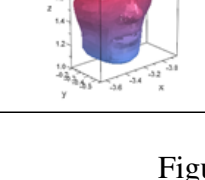
Input model	No. facets /scaling	Criteria	Uniform slicing (min. layer thickness)	Uniform slicing (mean. layer thickness)	Uniform slicing (max layer thickness)	Proposed
	3138/0.25	Material waste (mm ³) Avg. surface roughness (Ra) Build time (sec) Energy (W) Volumetric Error (mm ³)	4929.4e3 19.57 984.82 1.328e6 10.49	4929.4e3 19.57 447.38 6.087e5 15.40	4929.4e3 19.57 287.81 3.875e5 35.03	4929.4e3 19.57 518.26 7.952e5 2.85
	1332/0.25	Material waste (mm ³) Avg. surface roughness (Ra) Build time (sec) Energy (W) Volumetric Error (mm ³)	404.81e3 7.5685 312.97 1.008e4 2.470	404.81e3 7.5685 141.596 4.523e3 5.168	404.81e3 7.5685 91.476 2.938e3 7.814	404.81e3 7.5685 130.21 3.621e3 1.362
	1368/0.25	Material waste (mm ³) Avg. surface roughness (Ra) Build time (sec) Energy (W) Volumetric Error (mm ³)	220.01e3 21.05 96.504 228.577 0.9632	220.01e3 21.05 44.204 112.403 2.0743	220.01e3 21.05 28.017 52.390 3.170	220.01e3 21.05 42.3318 99.850 0.3210
	21900 /0.25	Material waste (mm ³) Avg. surface roughness (Ra) Build time (sec) Energy (W) Volumetric Error (mm ³)	269.32e3 10.45 99.436 66.130 0.3356	269.32e3 10.45 45.398 32.428 0.6364	269.32e2 10.45 29.116 19.106 1.1025	176.01e3 4.831 40.657 19.906 0.2535
	12795/4.0	Material waste (mm ³) Avg. surface roughness (Ra) Build time (sec) Energy (W) Volumetric Error (mm ³)	292.61e3 17.87 97.84 0.066 0.0304	292.61e3 17.87 41.498 0.0272 0.0348	292.61e3 17.87 26.7064 0.0312 0.0388	98.59e3 21.52 35.576 0.032 0.024

Figure 8: Comparison of proposed approach with state-of-the-art

techniques². The parts includes here comprises of a variety of application areas with varying complexity, estimated by number of facets. Irrespective of the size, parts with large number of facets are considered to be more complex than parts with small number of facets. Depending on SLS process compatibility, the example parts are compared against uniform slicing with maximum layer thickness (0.1 mm), uniform slicing with minimum layer thickness (0.03 mm), and uniform slicing with mean layer thickness (0.065 mm).

Figure 8 describes the list of 3D parts used in the analysis and the obtained results. Parts fabricated with maximum layer thickness are always quicker to build, and consumes least process energy. However, parts build using maximum layer thickness always yields poor surface quality (i.e. higher volumetric error), resultantly, more energy consumption during post-processing. Compared with uniform slicing (with minimum, and mean layer thickness), proposed approach always provides the best results. In terms of material savings and surface roughness, proposed approach always provides best results. The savings in the material is larger for complex parts (i.e. parts with larger facets).

²<http://www.thingiverse.com/>

5 Conclusions and future research

The experimental analyses demonstrate the applicability of optimization in additive manufacturing industry in achieving optimal process plan. The proposed approach outperforms state-of-the-art slicing approaches both in terms of material waste and energy consumption. With an aim towards sustainability, the developed optimization models are most applicable as compared with state-of-the-art additive manufacturing.

Considering the computational effort, only small-scale parts are analyzed for process optimization. Future research will aim towards minimizing the computational cost of optimization algorithms by developing process plans based on shape similarity. Modifying the developed approach to incorporate the process planning of other additive manufacturing technologies such as fused deposition modeling (FDM), selective laser melting (SLM), laminated object manufacturing (LOM) is also a topic for future research.

Acknowledgements

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