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Optimisation of build orientation to achieve minimum environmental impact in Stereo-lithography

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Abstract

Additive Manufacturing includes a number of techniques that combine a specific equipment with certain materials but some common principles concerning the product design and aspects related to manufacturing optimisations can be identified. Amongst these principles, some process parameters are included that contribute to determining the environmental sustainability of engineering products and, in particular, that affect their Life Cycle Impact Assessment.
This paper aims to provide a method to find out build orientation for the additive stereo-lithography process by minimising the environmental impact. More precisely, environmental indicators related to product design, materials and machines are included and combined in order to estimate the process time and the volume of needed supports. Besides, Genetic Algorithms have been used to find out the product orientation that optimises the manufacturing process in terms of quantity and volume of used material, thus minimizing its environmental impact. The proposed method has been implemented by a new software application that is presented in a nutshell.

Keywords: Additive Manufacturing; Product Optimisation; Product Design; Environmental Impact; Genetic Algorithms

1. Introduction

The Additive Manufacturing (AM) technology has been evaluated as a possible opportunity to reduce cost, energy supply and CO_2 emissions related to manufacturing processes [5]. The development of additively manufactured products can theoretically lead to obtaining great environmental benefits during the use phase of the product through a weight reduction due to an optimised design [1]. Compared to traditional manufacturing approaches, AM can improve the sustainability of industrial products. The Life Cycle Assessment (LCA) is a key challenge in order to provide a reliable measurement of the environmental performances of additive manufactured products. In comparison with traditional processes, however, a lack of indicators dedicated to AM can be observed [8]. Nevertheless, attempts to

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quantify the whole sustainability of AM processes and products have been realised according to the Triple Bottom Line principle [3]. The quantification of the sustainability dimension for AM products is a challenging research topic [9] due to the tremendous speed of innovation in this field. In fact, paradigms of AM differ from the ones of conventional (and well-established) manufacturing technologies, thus imposing to continuously develop new methods to quantify the environmental impact of the production.

For example, in [6] a total life cycle analysis of AM products through the application of the Product Sustainability Index framework has been proposed.

Due to its recent development, the AM technology presents a lack of models to assess the sustainability of the manufacturing phase [10]. It can be observed that energy and material consumption are the main factors, which determine environmental performances of the manufacturing processes [14]. In scientific literature, some models based on the use of the Eco-indicator [17] have been proposed to estimate the Environmental Impact (EI) of AM parts [13, 19]. These methods estimate the EI due to energy consumption as in Equ. (1):

$$EI_{en} = fc_{electricity} \times ECR \tag{1}$$

where $fc_{electricity}$ is a factor issued from the database that is used in the Eco-Indicator 95 (usually assumed =0.57 milliPoints/kWh, mPts/kWh). ECR is an estimator of the energy consumption per mass unit (kWh/kg) during the part production, which is calculated as in Equ. (2):

$$ECR = P/PP \tag{2}$$

where P (W) is the consumed electric power by AM machines during production and PP is the process productivity per hour (kg/h).

In [11], Le Bourhis et al. introduced a more detailed model for the estimation of the EI for Direct Additive Laser Manufacturing (DALM). This model takes into account laser paths and fluid consumption (coolant and assistant gases) during the production.

In the present paper, a model to estimate the EI within comparative LCA studies is presented with the aim to determine the optimal orientation for additively manufactured layer-based products. The proposed model combines the effects of energy and material consumption by the use of the Eco-indicator and then by including the effects of the part orientation on the need of supporting structures and the building time. Then, through a Genetic Algorithm (GA) optimisation, the estimated EI is adopted to define the part orientation for the best performances. An example of the use of GAs to find out the best orientation for AM parts has been proposed in [16]. Unlike previous evolutionary techniques based on the energy consumption estimation [4], this approach aims to include the different environmental performances that result by the need of realising supporting structures under different orientations.

2. Environmental Impact estimation model

As aforementioned, the indicator of total EI of AM processes (EI_{Tot}) is performed by combining the EI of the material (EI_{Mat}) and to the one related to energy consumption (EI_{El}) as in eq. (5).

$$EI_{Tot} = EI_{Mat} + EI_{El} \tag{3}$$

The calculation procedure to obtain the two contribution factors EI_{Mat} and EI_{El} will be analysed in the next sections.

2.1. Material EI

Table 1 is an adaptation from [13] reporting the environmental impact in different phases of the life cycle for an epoxy resin to be used in a stereolithography apparatus (SLA 5170). All the quantities in 1 are expressed in mPts/kg. According to what stated in the previous paragraph, the contribution of electrical consumption has been removed, because a different approach is here adopted to estimate its impact.

Table 1. Environmental impact of material in different phases of the life cycle [mPts/kg]

Material preparation	
SLA 5170 Epoxy resin (EI_{MP})	10
Build process	
Process residues (EI_{BP})	negligible
Use	
Material toxicity (EI_{MT})	1.2
Disposal	
Landfill (EI_L) Incineration (EI_I)	0.035 1.8
Total	11.24/13.00

For an additively manufactured part produced by using SLA, the total volume of transformed material (V_{Tot}) can be assumed as the sum of both the material for the part (V_P) and the material for the supporting structures (V_S), as in equ. 4:

$$V_{Tot} = V_P + V_S \tag{4}$$

While the material of the part V_P contributes to EI in all the summarised phases in Tab. 1, the volume of supporting structures is not relevant to the use phase. Therefore, the total EI of the adopted material for part production (EI_{Mat}) can be estimated as it is showed in equ. 5 (where it is assumed a disposal through incineration):

$$EI_{Mat} = V_{Tot}(EI_{MP} + EI_{BP} + EI_I) + V_P \times EI_{MT} \tag{5}$$

The volume of the part is a constraint of the productive process that is not affected by the orientation of the part. The estimation of part volumes starts from the triangular mesh of the STL model by using different methods that have been proposed in the literature (e.g. [7]).
On the other hand, the volume of supporting structures depends on the orientation of the part in relation to the building direction (the ”Z” direction in the following sections). A method to estimate the volume of supporting structures in a SLA process has been proposed by [15].

2.2. Electricity EI

The EI due to electricity consumption EI_{El} can be estimated by the use of equ. (6):

$$EI_{El} = fc_{electricity} \times W_m \times t_b \tag{6}$$

Where $fc_{electricity}$ is the previously mentioned characterisation factor of EI for energy in mPts/kWh, W_m is the average power consumption of the machine during the process in kW and t_b is the estimated building time in hours. The value of $fc_{electricity}$ can be determined according to the Ecoinvent methodology for the specific geographical area (in the following we will assume $fc_{electricity}$ equal to 0.57 mPts/kg according to [13]). The average power consumption during the productive phase is a feature of the SLA machine that can be found in its technical documentation.
In order to estimate the building time (in hours) for the production of the component under a certain orientation, the formula in equ. (7) can be used:

$$t_b = k_1 + k_2 \times n_L + k_3 \times V_{tot} + k_4 \times S_p + k_5 \times \frac{V_{tot}}{S_p} \tag{7}$$

where $k_1, k_2, ..., k_5$ are experimentally determined coefficients,n_L is the number of layers used to build the part and S_p is the total projected area on the xy plane calculated as in equ. (8)

$$S_p = \frac{1}{2} \sum_{i=0}^{N} det \begin{vmatrix} 1 & 1 & 1 \\ x_{i,1} & x_{i,2} & x_{i,3} \\ y_{i,1} & y_{i,2} & y_{i,3} \end{vmatrix} \tag{8}$$

being N the total number of triangles in the mesh and ($x_{i,j}$,$y_{i,j}$) the x and y coordinates of the j-th vertex of the i-th triangular element.
Table 2 reports indicative values of the experimental coefficients in eq. (7) that can be adopted for stereolithography process.

Table 2. Approximate values for stereolithography of coefficients in eq.(7)

k_1	k_2	k_3	k_4	k_5
9.692	0.194	-0.006	0.016	11.892

It is worth to notice that the estimated building time depends on the orientation of parts during the building phase. Therefore, the orientation of the part in the building environment is a key parameter to determine the EI of manufacturing processes for both the material and the energy component.

3. Research procedure of the optimal orientation

The procedure to find out the part orientation that minimises the EI of the AM process is here described. A GA based approach is adopted to find out the part orientation minimising the environmental impact of the manufacturing process of the part [18].

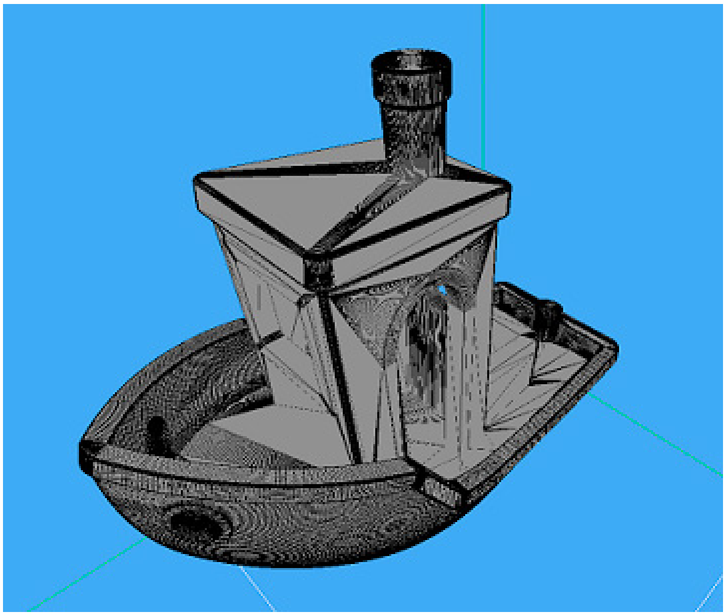

Fig. 1. The 3DBenchy torture test STL model [2]

A description of the adopted GA is provided in subsection 3.1.
The method is applied to determine the optimal orientation for the same part in two different SLA machines in subsection 3.2.

3.1. Genetic algorithm

From the previous sections it is possible to realise that, by naming ”Z” the building direction of the SLA process, any rotation around this axis has no effect onto the total EI of the product EI_{Tot}. Therefore, the phenotype of individuals of GA includes only the rotations around x and y-axes: 64 bits are used to represent each of these rotations, thus leading to a 128-bit chromosome.
Several parameters need to be set to determinate the effectiveness of a GA [12]. A uniform crossover strategy with a 50% mix probability has been here adopted for offspring generation. Flip bit mutation is performed during the offspring generation with a 10% probability rate for each chromosome. The number of individuals in each generation of the GA is limited to be between 50 and 100 individuals
The fitness value of each individual consists in the opposite of EI_{Tot} as defined in the previous sections. Elitist selection is used to determine the best individuals of the population to be used as parents of the next generation. The algorithm ends when the fitness of the best individual of the generation does not improve after 10 generations.
In the present section, the optimisation method is applied to define the orientation that minimises the EI for the 3DBenchy torture test part in Fig. 1 [2] in two different size SLA machines. The Form2 Formlabs and the ProJet 6000 HD by 3DSystems have been considered. Tab. 3 reports the power consumption of the two machines.
A layer thickness of 0.025 mm has been considered for part production, with a minimum height of the parts from the building plate of 20 mm.

Table 3. Electrical power consumption of the machines that have been used in the present study

SLA Machine	Electrical power consumption [W]
Form2	65
ProJet 6000 HD	750

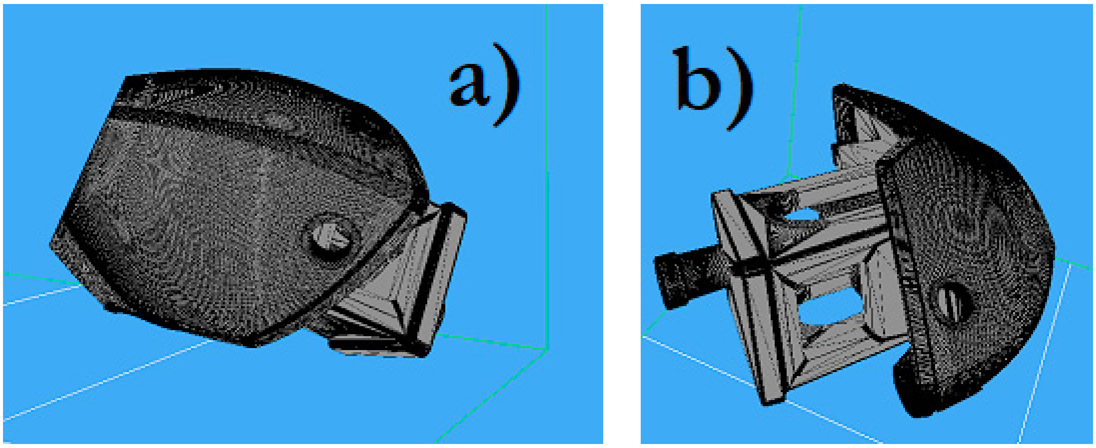

Fig. 2. Resulting optimal orientation for (a) Form2 and (b) ProJet 6000 HD

3.2. Results and discussion

Tab. 4 and 5 display the most significant iterations of the GA for the Form2 and ProJet HD 6000, respectively. The final optimal results for the two machines are shown in Fig. 2.

Table 4. GA iterations for Form2

Iteration	X axis rot [degree]	Y axis rot [degree]	Impact energy [mPts]	Impact material [mPts]	Fitness Value
1	315	210	0.224542924693597	0.212255942821462	-0.430938944709162
2	229	50	0.212865306944648	0.218878104689034	-0.430938944709162
6	49	228	0.211558901357786	0.216731936524329	-0.428249529558869
11	226	43	0.21687986257664	0.210635263867283	-0.427516730399456
17	310	214	0.212514022522202	0.21449264118386	-0.427219384096009
28	307	214	0.207864492851287	0.217892599750405	-0.426072759559373
42	307	212	0.207963144405221	0.218054904271008	-0.425945892557975

Table 5. GA iterations for ProJet 6000 HD

Iteration	X axis rot [degree]	Y axis rot [degree]	Impact energy [mPts]	Impact material [mPts]	Fitness Value
1	76	42	1.76204874814783	0.401846864106925	-2.16255469771145
5	260	44	1.76317771920829	0.402763166962327	-2.16165793855784
7	103	44	1.75616815087397	0.403870550201607	-2.15771479576076
15	103	45	1.75389879659424	0.40375790187045	-2.15543144786841
25	102	45	1.75455405823332	0.403736546767845	-2.15371169663844

Tables 4 and 5 show that in both cases the variation of orientation angles is high during the first generations and tends to reduce by converging to the optimum value.

In the Form2 machine, the individual contributes to energy and material EI show a fluctuating behaviour while minimising their summation (i.e. maximising the value of the fitness function).
The effect of the GA optimisation applied to the ProJet 6000 HD results in a more evident trend through a reduction of the EI of energy consumption.
As a result, the optimal orientation in Fig. 2 (a) (Form2) is a compromise solution between building time and support material that is necessary to the production. On the other hand, in Fig. 2 (b) (ProJet 6000 HD) the proposed solution

aims to minimise the building time of the part, even if more material is required for support structures.
These results reflect the different characteristics in terms of sizes and energy consumption of the two SLA machines adopted for the study.

4. Conclusions

Additive Manufacturing is an innovative technology that is transforming the manufacturing approach to industrial products. Possibly, it allows cost reduction, energy saving and CO_2 emissions decrease. Therefore, AM can be considered a sustainable technology, but the quantification methods of the degree of sustainability for additively manufactured products are still not as much developed as the ones for traditional processes.
In the present paper a methodology to estimate the EI of Additively Manufactured parts for a comparison through a LCA has been presented. The proposed approach takes into account two of the main contributions to product impact that are the consumption of material and energy during the process. Both the EIs are modelled to reflect the effect of part orientation.
The calculation strategies adopted allow obtaining a quick estimation of EI, thus enabling the choice of an optimisation technique involving a high amount of iterations. An example of GA optimisation is presented to prove the effectiveness of the method in a comparative LCA for the optimal orientation of a sample model for two machines of different size. The results show how the adoption of a certain SLA machine (as well as a change of manufacturing parameters) leads to a different part orientation minimising the EI of the process.
In conclusion, the proposed method allows automating a decision-making process about part orientation to reduce the impact of AM according to the specific geometry of the part to be produced and the specific machine. This approach allows to find out the optimal orientation in a short time compared to a manual approach, where the final result and the time for orienting the part are deeply connected to personal skills of the operator. The adoption of LC indicators also lead to a repeatability of the results, avoiding the uncertainty related to personal interpretations.
General outlines of the method here applied to SLA can be extended to other AM layer-based technologies. As an example, when dealing with powder-bed AM processes, a first estimation of support structure volume can still be made on the basis of overhang angle; nevertheless, in that case further effects need to be considered (such as shield gas flow) and an accurate analysis of the powder impact is needed [9]. In general, the main current limit consists of the lack of impact indicators for raw materials that are typically adopted in AM. Further research to define these indicators in order to increase the soundness of this methodology are needed.

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References

[1] Burkhart, M., Aurich, J.C., 2015. Framework to predict the environmental impact of additive manufacturing in the life cycle of a commercial vehicle. Procedia CIRP 29, 408–413.
[2] Creative-Tools.com, . 3dbenchy – The jolly 3d printing torture-test. URL: http://www.3dbenchy.com. accessed: 2018-04-22.
[3] Elkington, J., 1998. Partnerships from cannibals with forks: The triple bottom line of 21st-century business. Environmental Quality Management 8, 37–51.
[4] Garg, A., Lam, J.S.L., Savalani, M.M., 2016. A New Variant of Genetic Programming in Formulation of Laser Energy Consumption Model of 3d Printing Process, in: Handbook of Sustainability in Additive Manufacturing. Springer, pp. 31–50.
[5] Gebler, M., Schoot Uiterkamp, A.J.M., Visser, C., 2014. A global sustainability perspective on 3d printing technologies. Energy Policy 74, 158–167. URL: http://www.sciencedirect.com/science/article/pii/S0301421514004868, doi:10.1016/j.enpol.2014.08.033.
[6] Hapuwatte, B., Seevers, K.D., Badurdeen, F., Jawahir, I.S., 2016. Total Life Cycle Sustainability Analysis of Additively Manufactured Products. Procedia CIRP 48, 376–381. URL: http://www.sciencedirect.com/science/article/pii/S2212827116006533, doi:10.1016/j.procir.2016.03.016.
[7] Jones, M.W., 1996. The Production of Volume Data from Triangular Meshes Using Voxelisation. Computer Graphics Forum 15, 311–318. URL: https://onlinelibrary.wiley.com/doi/abs/10.1111/1467-8659.1550311, doi:10.1111/1467-8659.1550311.

[8] Kellens, K., Baumers, M., Gutowski, T.G., Flanagan, W., Lifset, R., Duflou, J.R., 2017a. Environmental dimensions of additive manufacturing: Mapping application domains and their environmental implications. Journal of Industrial Ecology 21.

[9] Kellens, K., Mertens, R., Paraskevas, D., Dewulf, W., Duflou, J.R., 2017b. Environmental Impact of Additive Manufacturing Processes: Does AM contribute to a more sustainable way of part manufacturing? Procedia CIRP 61, 582–587.

[10] Le Bourhis, F., Kerbrat, O., Dembinski, L., Hascoet, J.Y., Mognol, P., 2014. Predictive model for environmental assessment in additive manufacturing process. Procedia CiRP 15, 26–31.

[11] Le Bourhis, F., Kerbrat, O., Hascoët, J.Y., Mognol, P., 2013. Sustainable manufacturing: evaluation and modeling of environmental impacts in additive manufacturing. The International Journal of Advanced Manufacturing Technology 69, 1927–1939.

[12] Lobo, F.J., Lima, C.F., Michalewicz, Z., 2007. Parameter setting in evolutionary algorithms. volume 54. Springer Science & Business Media.

[13] Luo, Y., Ji, Z., Leu, M.C., Caudill, R., 1999. Environmental performance analysis of solid freedom fabrication processes, in: Electronics and the Environment, 1999. ISEE-1999. Proceedings of the 1999 IEEE International Symposium on, IEEE. pp. 1–6.

[14] Nopparat, N., Kianian, B., 2012. Resource Consumption of Additive Manufacturing Technology.

[15] Pham, D.T., Dimov, S.S., Gault, R.S., 1999. Part orientation in stereolithography. The International Journal of Advanced Manufacturing Technology 15, 674–682.

[16] Phatak, A.M., Pande, S.S., 2012. Optimum part orientation in Rapid Prototyping using genetic algorithm. Journal of Manufacturing Systems 31, 395–402. URL: http://www.sciencedirect.com/science/article/pii/S0278612512000428, doi:10.1016/j.jmsy.2012.07.001.

[17] Singh, R.K., Murty, H.R., Gupta, S.K., Dikshit, A.K., 2009. An overview of sustainability assessment methodologies. Ecological indicators 9, 189–212.

[18] Sivanandam, S.N., Deepa, S.N., 2007. Introduction to genetic algorithms. Springer Science & Business Media.

[19] Sreenivasan, R., Goel, A., Bourell, D.L., 2010. Sustainability issues in laser-based additive manufacturing. Physics Procedia 5, 81–90.