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Review

Search for the Optimal Build Direction in Additive Manufacturing Technologies: A Review

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Abstract: By additive manufacturing technologies, an object is produced deposing material layer by layer. The piece grows along the build direction, which is one of the main manufacturing parameters of Additive Manufacturing (AM) technologies to be set-up. This process parameter affects the cost, quality, and other important properties of the manufactured object. In this paper, the Objective Functions (OFs), presented in the literature for the search of the optimal build direction, are considered and reviewed. The following OFs are discussed: part quality, surface quality, support structure, build time, manufacturing cost, and mechanical properties. All of them are distinguished factors that are affected by build direction. In the first part of the paper, a collection of the most significant published methods for the estimation of the factors that most influence the build direction is presented. In the second part, a summary of the optimization techniques adopted from the reviewed papers is presented. Finally, the advantages and disadvantages are briefly discussed and some possible new fields of exploration are proposed.

Keywords: build orientation factors; cost analysis; multi objective optimization; part build orientation

1. Introduction

ISO standards [1] define Additive Manufacturing (AM) as the *"process of joining materials to make parts from 3D model data, usually layer upon layer [...]"*. This definition evidences a characteristic element that is common to quite all of AM technologies. The object is manufactured deposing material layer by layer and grows itself along the build direction, which is one of the main technological parameters of AM technologies. This process parameter affects the cost, the quality, and other important properties of the manufactured object. Although AM are promising technologies that are changing the economic and production models, many aspects of it, such as the part accuracy, cost reduction, or the achievement of adequate mechanical properties remain challenging. Emblematic, for most of these topics, is the stair-stepping effect, a typical drawback of many AM processes. As evidenced in Figure 1, it generates, due to the layer thickness, a difference between the nominal and real surface. The stair-stepping effect decreases as the layer thickness decreases; it would disappear when the thickness is null, which is a technologically impossible condition. Although great efforts have been made in recent years to reduce the value of the thickness, to date, it still causes two kinds of error, both affecting the final quality of the manufactured object. First of all the real geometry and the nominal geometry are not coincident. This mismatch is generally evaluated in the related literature as Volumetric Error [2]. Moreover, the stair-stepping effect produces deterioration in surface quality. Both these reasons represent an obstacle to AM diffusion. For many applications, the part accuracy of the manufactured objects can not be accepted without additional post-processing, introducing new cost and delay. Furthermore, these post-processing operations are strictly related to the AM technology in use, and post-treatments compromise the repeatability of the entire process [3].

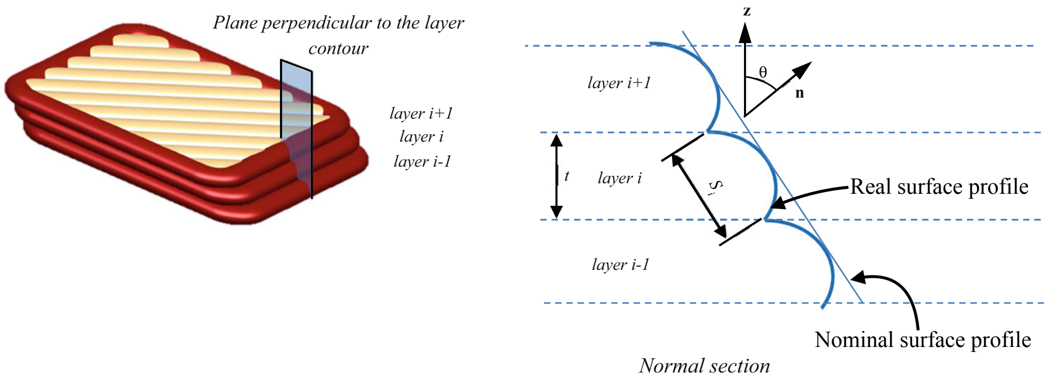


Figure 1. Stair-stepping effect: the nominal surface and the real surface are not coincident.

The stair-stepping effect is dependent on the build direction. As can be observed in Figure 2, two different build directions will determine different volumetric errors and surface quality. Differently from the subtractive process, in AM, the part material is deposited during the manufacturing process and, usually, the previously deposited layer represents the support against the gravity force for the layer in construction. For particular geometries, the laying layer may be overexposed with respect to the previous one. This introduces the concept of the overhang area, defined as those parts of surfaces whose normal vector is opposite to the build direction. These kinds of areas could be candidates to have support structures. The direct consequences of support generation are an increase in the material amount and build time, thence of cost. Not least, supports deteriorate the quality of those parts of surfaces with which they are in contact.

Build direction highly impacts on support generation. Different spatial orientation of the same object results in different overhang area with respect to the build platform and, consequently, different support structures must be adopted to manufacture the object (Figure 2).

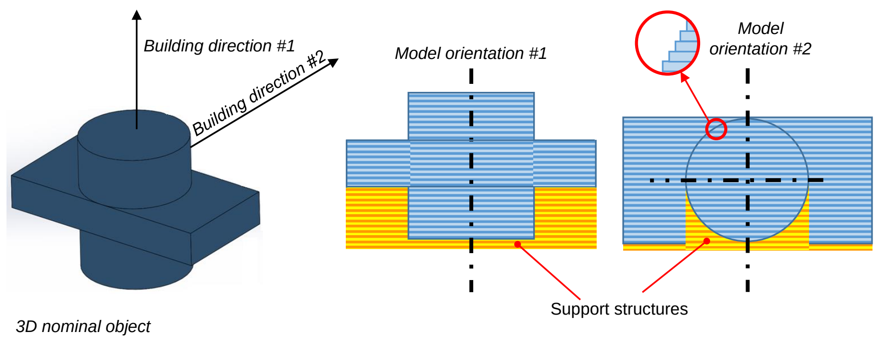


Figure 2. Stair-stepping effect and supports structure: effect of the build direction.

The mechanical properties of AM components are also dependent on the build direction. AM parts suffer from anisotropy, due to the object being realized along a preferential direction. This imposes important limitations on the strength of the manufactured piece [4]. Consequently, it is important to evaluate the optimal build direction which can maximize the mechanical properties of the component, taking into account the expected stress status.

These are only some of the reasons for which many kinds of research activities spent efforts on identifying a valid method to find the optimal build direction. A correct choice can maximize the object performances, ensuring accuracy and surface quality at the minimum manufacturing cost.

Despite the large number of methods to search for the best build direction published in the related literature, it remains an open issue. Build direction affects aspects of the manufacturing process that can be conflicting. Therefore, the research of the optimal build direction is a typical multi-optimization problem, whose solution is not trivial.

In this kind of problem, the outputs which need to be properly chosen are known as Objective Functions (OFs). The optimization process is generally reduced to a mathematical problem that requires an analytical formulation of the OFs. This introduces the first challenging aspect of optimization methods for searching the optimal build direction: the proper and analytic identification of the process features to be optimized is far from being easy, as demonstrated by the numerous proposals of the researchers during these years. The reasons which make this task so hard are several. Models used to predict the features to be optimized should be both accurate and computationally efficient. For example, the most efficient way to predict build time is to consider it to be directly proportional to the height of the object along the build direction. This hypothesis is widely used but, due to the drastic simplification of the problem, it is poorly accurate since many other factors afflict the build time. In the opposite, the most rigorous approach consists of analyzing the part program, which is the set of instructions provided as input to the AM machine during the manufacturing process, but, although this approach is very accurate, it is computationally so expansive [5] that it cannot be used in multi-objective optimization.

While solving an optimization problem, the model of the simulated feature must be evaluated recursively many times, but computation resources are limited. So it is necessary to use a prediction model that is both efficient and accurate. The optimal OF choice is depending on the kind of optimization to perform, the available computational resources, and their influence upon the final results. In some cases, features are evaluated by not valid models, since they are based on erroneous parameters or founded on incorrect hypothesis. It is the case of the measure of quality surfaces that is often evaluated using the R_a index, a not valid parameter to measure the stair-stepping effect [6].

This paper provides a critical review of the research activities concerning AM build direction optimization. In Section 2, from the related literature, the main OFs contributions, depending on the building orientation, were identified. Then, for each of the main factors, most important published mathematical formulations are described and critically analyzed. In the second part of the paper (Section 3), a summary of the optimization techniques adopted from the reviewed papers is presented. In conclusions (Section 4), advantages and disadvantages are briefly discussed and some possible new fields of exploration are proposed.

2. Objective Functions

From the analysis of the reviewed works, the following main contributes to OFs are identified: surface quality, part quality, support structure, build time, cost, mechanical properties, and multi-part job. For each of these, in the presented paper, the most important results described in the related literature are reported, evidencing the advantages and weaknesses of each one. In Table 1 a summary of later discussed features, formulas, and criteria are shown.

Table 1. Summary of methods discussed in this section.

Authors	Objective Functions (OFs)	Optimization Phase	Remarks
Weighted sum based methods			
Lan et al., 1997 [7]	AM features.	**Customized**	
McClurkin et al., 1998 [8]	Cost, Surface quality, Support volume, Supported area.	**Customized**	
Pham et al., 1999 [9]	AM features, Build time, Cost, Support volume, Supported area.	**Customized**	
Hur et. Al 2001 [10]	Build height, Cross-section length.	**Genetic Algorithm**	
Thrimurthulu et al., 2004 [11]	Build time, Surface roughness.	**Genetic Algorithm**	
Kim et al., 2005 [12]	Cost, Build height, Build time.	**Genetic Algorithm**	*Cost is an index of Surface roughness due to post-treatments.*
Byun et al., 2006 [13]	Build time, Cost, Surface roughness	**Customized**	
Canellidis et al., 2009 [14]	Build time, Surface roughness.	**Genetic Algorithm**	
Singhal et al., 2009 [15]	Build time, Supported area, Surface roughness	**Optimization toolbox of Matlab (FMINCON)**	*More efficient than classical GA-based methodologies.*
Phatak et al., 2012 [16]	Build height, Material utilizzation factor, Surface roughness, Support volume, Supported area	**Genetic Algorithm**	
Paul et al., 2015 [17]	Cylindricity error, Flatness error.	**Customized**	
Das et al., 2015 [18]	Angularity error, Cylindricity error, Flatness error, Parallelism error, Perpendiculary error, Support volume.	**Optimization toolbox of Matlab (FMINCON)**	*Valid for NURBS models.*
Moroni et al., 2015 [19]	Cylindrical features.	**Genetic Algorithm**	*Optimal orientation of cylindrical features to maximize assembly accuracy.*
Brika et al., 2017 [20]	Build time, Cost, Mechanical properties, Surface roughness, Support volume	**Genetic Algorithm**	*OFs weights are defined using a Fuzzy methodology ([21]).*
Chowdhury et al., 2018 [22]	Build height, Manufacturability features, Surface quality, Support volume, Supported area.	**Artificial Neural Network-based**	
Primary and secondary objectives based methods			
Cheng et al., 1995 [23]	Build time, Part accuracy, stability.	**Customized**	
Alexander et al., 1998 [24]	Build height, Surface quality, Support volume, Supported area.	**Customized**	*Direction choise is user-driven.*
Singhal et al., 2005 [25]	Surface quality.	**Trust Region Driven**	
Ahn et al., 2007 [26]	Surface roughness.	**Genetic Algorithm**	
Ezair et al., 2015 [27]	Support volume.	**Customized**	*A customized and high-efficient algorithm GPU-based for support evaluation is proposed.*

Table 1. *Cont.*

Authors	Objective Functions (OFs)	Optimization Phase	Remarks
Delfs et al., 2016 [28]	Build time, Surface quality.	**Optimization tool of Magics**	Very time-consuming.
Luo et al., 2016 [29]	Part accuracy.	**Principal components analysis**	
Pereira et al., 2018 [30]	Build time, Part accuracy, Supported area.	**Global Derivative-free Optimization (PSwarm)**	
Lovo et al., 2019 [4]	Mechanical properties.	**Sequential Quadratic Programming (SQP)**	
Mele et al., 2019 [31]	Environmental Impact.	**Genetic Algorithm**	
Pareto front based methods			
Nezhad et al., 2010 [32]	Build time, Surface quality, Support Volume.	**Genetic Algorithm**	
Padhye et al., 2011 [33]	Build time, Surface roughness.	**Genetic Algortithm; Particle Swarm Optimization**	*Two different optimization procedures are compared in this research, evidencing similar results.*
Strano et al., 2011 [34]	Energy consumption, Surface roughness.	**Customized**	*A self-defined procedure, more efficient than GA, is described.*
Huang et al., 2018 [35]	Build time, Surface roughness.	**Genetic Algorithm**	*A GA based on Compute Unified Device Architecture is used to increase solving speed.*
Khodaygan et al., 2018 [36]	Build time, Surface quality.	**Genetic Algorithm**	
Yazdi et al., 2018 [37]	Build time, Material utilizzation.	**Genetic Algorithm**	*Some technical requirements are defined as constrains.*
Cheng et al., 2019 [38]	Mechanical properties, Support volume.	**Particle Swarm Optimization**	
Raju et al., 2019 [39]	Mechanical properties, Surface quality.	**Genetic Algorithm**	
Di Angelo et al., 2020 [40]	Build cost, Surface quality.	**Genetic Algorithm**	*Implements an analytical an general-purpose formulation of surface quality.*

Table 1. *Cont.*

Authors	Objective Functions (OFs)	Optimization Phase	Remarks
Other methods			
Zhang et al., 2016 [41]	Part accuracy, Surface roughness, Support volume.	**Customized**	*Euclidian distance and shape analysis, derived from Grey System theory, are performed to make final decision.*
Zhang et al., 2016 [42]	Build time, Surface roughness.	**Customized**	*Multi-part two dimensional job optimization.*
Jaiswal et al 2018 [43]	Part accuracy.	**Surrogate model toolbox of Matlab (MATSuMoTo)**	*A surrogate model is applied to reduce computational burden.*
Ransikarbum et al., 2018 [44]	Cost, Build time, Mechanical properties, Part accuracy, Surface quality, Support volume.	**AHP-based**	*Analytic Hierarchy Process is adopted as decision criteria.*
Golmohammadi et al., 2019 [45].	Build time, Surface quality.	**Taguchi-based experiments**	*No need of calculating derivates, as required by gradient-based methods.*
Qin et al., 2019 [46]	AM features, Build time, Cost, Surface roughness, Support volume.	**Fuzzy-based**	
Qin et al., 2020 [47]	Mechanical properties, Surface roughness, Support volume.	**Facet-clustering**	

2.1. Part Quality

One of the main limitations of the AM parts is the lack of "quality" of final objects, characterizing most of the technologies. Cheng et al. [23] identified the main sources of errors, shown in Figure 3, characterizing the AM process.

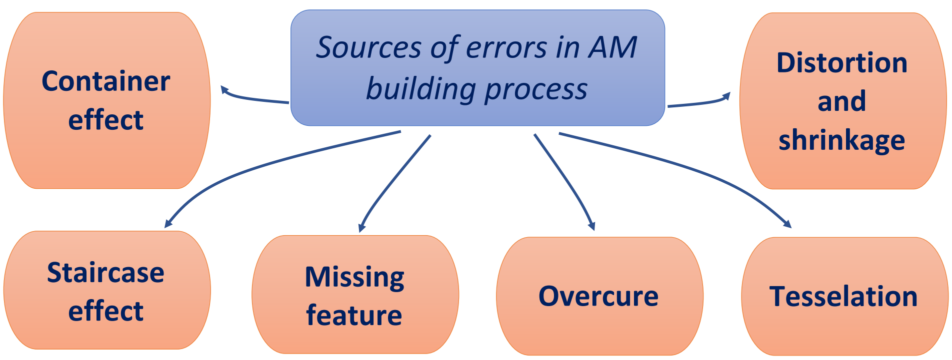


Figure 3. Sources of errors in Additive Manufacturing (AM) building process described in [23].

These errors, affecting the AM process and being difficult to be kept low, make the classical subtractive processes more attractive for those applications where strictly dimensional and geometrical tolerances are assigned to assembly parts. Although most of these errors cannot be eliminated due to technical limitations, many published research activities tried to propose solutions to minimize their effect on the final part.

In [9,23], part quality is optimized by minimizing bad features and maximizing good features. According to Zhang et al. [41]: *"an AM feature refers to an identified shape feature representing a certain shape pattern that has some significance or certain functions to a part and carries the information which is important for the pre-processing, processing or post-processing of AM"*. For each k-th feature, a certain weight factor ε_j is assigned, that is depending on build orientation and is maximum along a defined build direction. The optimal build direction $\mathbf{d}$ is obtained maximizing the total objective value of the K AM features defined for the part, according to the following OFs.

$$Q = \sum_{k=1}^{K} \mathbf{d} \cdot \varepsilon_k \quad (1)$$

Equation (1), although very powerful for its capability to maximize accuracy for "functional" portions of the manufactured part, is generally limited by the low availability of automated procedures for recognizing these features. The human interaction performed by an expert user is still the most efficient way to accomplish this task.

In order to evaluate the material shrinkage, Senthilkumaran et al. [48], Aslani et al. [49] analyzed, through a series of experiments, the effect of build orientation and other process-related parameters. Due to complex interactions between process parameters and final geometrical and dimensional accuracy of the part, they suggest proceeding with an empirical characterization. Anyway, as previously discussed, proceeding this way limits the real usefulness of an optimization task.

Masood et al. [50] minimized the stair-stepping effect through minimization of Volumetric Error VE, defined in the following expression:

$$VE = \left| \sum_{i} \frac{1}{2} (S_{i+1} - S_i) T \right| \quad (2)$$

S_i identifies the contour area of i-th layer, while T is the layer thickness. The volumetric error is a representation of the orange volume shown in Figure 4. S_i identifies the contour area of i-th layer, while T is the layer thickness. The volumetric error is a representation of the orange volume shown in Figure 4. The greater the thickness of the layer used by the AM process in use, the greater will be this error, causing a mismatch between the manufactured and the nominal geometry. Paul and Anand [17] introduced an analytic model for optimizing cylindricity and flatness as a function of the part orientation. According to the trend of cylindricity and flatness errors with respect to build direction, shown in Figure 5a,b, two critical allowed values for cylindricity and flatness errors, respectively ε_{cyl_cr} and ε_{f_cr}, could exist, which should not be exceeded for quality reasons. This leads to defining, for each error, two intervals of build angle, called the feasible region and the infeasible region. Here, the build angle is representative of the angle between the build orientation and the feature orientation: the axis, for a cylinder, or the external normal, for a planar surface.

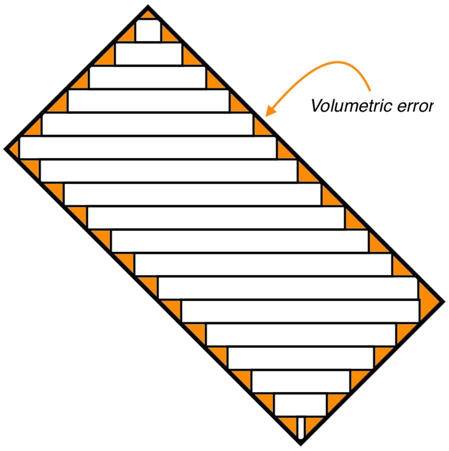
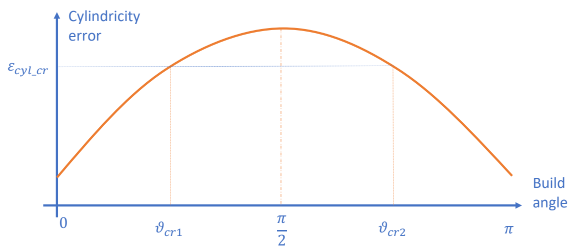
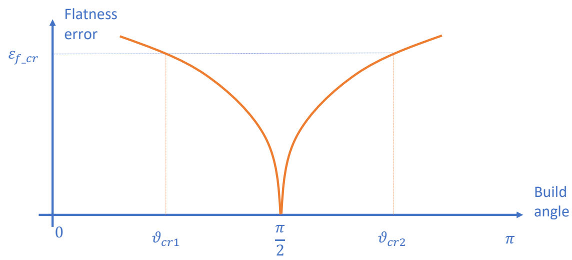


Figure 4. Graphical visualization of volumetric error.



(**a**) Cylindricity error.



(**b**) Flatness error.

Figure 5. Qualitative trend of cylindricity and flatness errors with respect to build orientation.

Keep both cylindricity and flatness error under acceptable value is a complex task, due to the evident conflict between the two error trends. The flatness error is minimum when cylindricity error is maximum and vice-versa. A penalty mechanism is so introduced, which is representative of the deviation away from optimal orientation. Thus, defined the build orientation, for each cylindrical or flatness feature j, a penalty value p_j and weight ω_j are assigned. The optimal build orientation the one where is the minimum value of the following summation:

$$OFA = \sum_j p_j \omega_j \tag{3}$$

Das et al. [18] extended this methodology also for other errors described by Geometric Dimensioning and Tolerancing (GD&T). In their paper a penalty system, similar to that previously discussed, is also provided for Perpendicularity, Parallelism, Angularity, Conicity, Circular Runout and Total Runout errors, which are quantified analytically given the build orientation.

Chowdhury et al. [22] proposed to maximize part quality considering the best practices of Design For Additive Manufacturing (DFAM). In particular, the authors identified, by analyzing the related literature, eight factors for DFAM, shown in Figure 6. Then they described a numerical procedure for optimizing most of them.

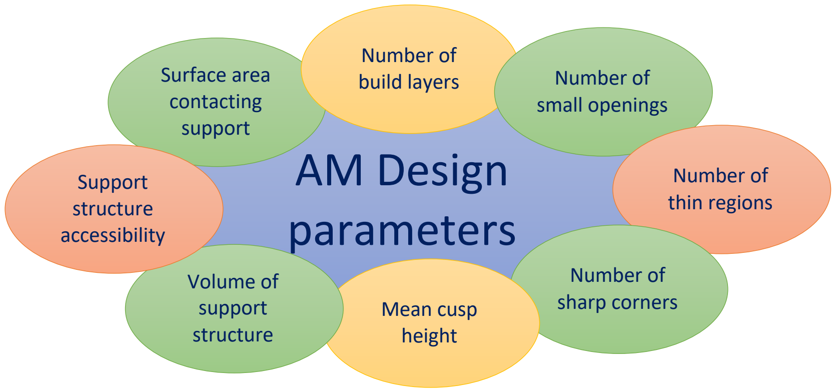


Figure 6. Design parameters considered in the optimization model for build orientation used in [22].

Particularly interesting is the presented procedure for determining thin features and small openings. These are highly critical in most AM processes due to the difficulty of manufacturing them according to design specs. They describe a ray-tracing based algorithm able to identify them on tessellated models, allowing us to predict critical manufacturing orientations.

2.2. Surface Quality

In this paragraph, several results obtained in the prediction of the surface quality of AM manufactured objects are presented. The methods can be grouped in four different main types: qualitative, theoretical, empirical, and semi-empirical.

The first, generally, is a feature-based approach consisting of maximizing the surface area or the part features that are oriented, according to user expertise, in a strategical direction. For example, the horizontal and vertical surfaces are not subjected to stair-stepping effect, while the down-faced surfaces generally require the generation of supports which causes a quality deterioration of surface texture. To this purpose, Xu et al. [51] suggested to use, as surface quality measure, the following parameter:

$$overhang\ area = \frac{number\ of\ z\, negative\ normals}{number\ of\ normals}\, a_p \tag{4}$$

The Equation (4) evaluates the percentage of the total area of the part a_p that is an overhang, assuming the build direction coincident with the z-axis; the greater the area of the overhang and the more supports structures are in contact with the surface of the part, deteriorating its quality. Anyway, no numerical information about the final surface quality of the object is provided by this criterion. An improved version was described in [9], whose authors, observing that not every down-oriented surface requires support generation, suggest to consider only the downward facets inclined of a certain angle value with respect to the horizontal plane. They also introduced an interesting feature-based procedure that allows selecting a set of critical features, such as user-specified surfaces, holes, cuts, shafts, and others, whose surface quality should be maximized.

Other authors spent efforts to implement theoretical models that perform a quantitative evaluation of the surface quality, by the mathematical integration of the approximated geometry of the section of the deposed layer. This solution is worthy of interest due to its applicability to a large set of problems, providing a reliable result for every orientation of the model in the space. The first OF, based on a theoretical approach, was introduced in [24], proposing the cusp average height as an index of surface quality. The cusp height, whose geometrical significance is shown in Figure 7, is an intuitive and suited geometrical property of AM components subjected to stair-stepping effect. It can be easily evaluated knowing layer thickness, build direction, and inclination of triangular facets.

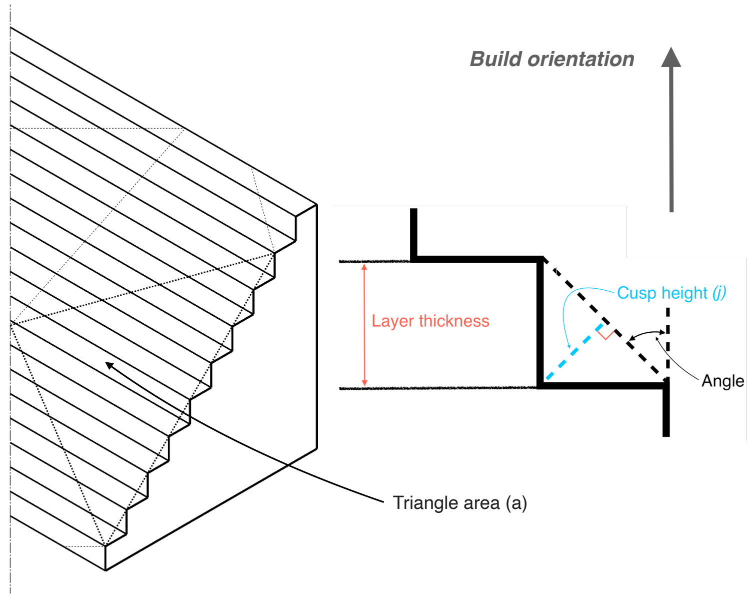


Figure 7. Cusp height, generated by difference between the nominal and real model, as simple and analytic evaluation of surface quality.

So, naming j_i and a_i the cusp height and area associated with the i-th triangle, the authors suggest minimizing the following OF to identify the best build direction in terms of surface quality.

$$\bar{j} = \frac{\sum_i J_i}{\sum_i a_i} \qquad J_i = \begin{cases} j_i & \textit{not supported triangle} \\ j_i + R & \textit{supported triangle} \\ R & \textit{horizontal supported triangle} \end{cases} \tag{5}$$

For the supported triangular facets, a constant term R is summed to cusp height j. This contribution represents the negative effect on the surface quality generated by supports. The Equation (5) is a powerful, simple, and efficient index to measure the surface quality but it is also characterized by several limits. The first is the hypothesis of a perfectly planar profile of the deposed layer. Later studies suggested a more accurate approximation with the B-spline curve [52] or elliptical profiles [53,54].

Empirical models [26,55,56] are based on data interpolations resulting from experimental investigations (based on DoE techniques) when certain process parameters, such as layer thickness, build orientation, and surface angle, change. Raju et al. [39] proposed an experiment, conformed to Taguchi methodology, for identifying the relationship between process inputs like layer thickness, support material, model interior, and, obviously, build orientation, on the quality surface. The results of the regression analysis demonstrate the validity of the approach. The main limitation of these prediction models is that they do not guarantee to operate their validity outside the investigated conditions.

The semi-empirical models proposed an approximation of the deposited profile according to specific curves but, unlike theoretical models, need to be adjusted using data resulting from experimental measurements. Byun and Lee [13] determined experimentally the values of the fillet and corner radii added to the shape of the profile proposed by Reeves et al. [57]. Pandey et al. [58] introduced a semi-empirical model based on the approximation of the layer contour with a parabola, whereas Boschetto and Bottini [59] with a circle.

The published implementations of theoretical, empirical and semi-empirical methods suffer from the confusion between the surface quality, that is a macro-geometric property of the surface texture (related to the presence of geometric pattern on it, such as the stair-stepping effect), with the roughness that is, instead, a micro-geometric property of the surface. This confusion comes from the application of the surface quality ISO standards, typically used for traditional subtractive manufacturing technologies, to AM ones. Often methods optimize surface quality using the roughness index $\overline{R_a}$, as defined by ISO 4287 [60]; the typical OF to be minimized is

$$\overline{R_a} = \frac{\sum_i R_{ai} a_i}{\sum_i a_i}, \tag{6}$$

where R_{ai} is the roughness estimated at the i-th triangle with area a_i. As evidenced in [6], the index R_a intrinsically filters the stair-stepping effect, which is the most significant component of the surface texture of AM manufactured objects. Consequently, surface quality evaluation based on R_a does not give inferences useful to finding the build direction that minimizes the stair-stepping effect (the main component of the surface defectiveness) (Figure 1). To this purpose, in [53], the authors suggest to use the index P_a [60], that evaluates quality surface better than R_a in those cases where the stair-stepping effect is significant, as for the case of Figure 8.

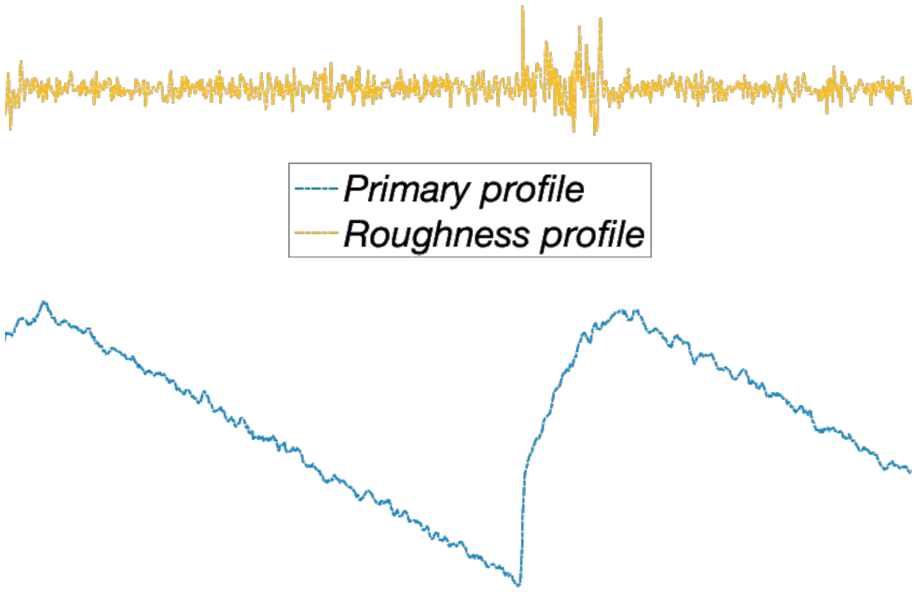


Figure 8. Qualitative plots describing the primary profile and roughness profiles, as defined by ISO 4287 [60], of the real profile of an AM component characterized by a significant stair-stepping effect.

The optimization criterion to find the best build direction in terms of surface quality is defined by the following expression:

$$\overline{P_a} = \frac{\sum_i P_{ai}\, a_i}{\sum_i a_i}. \tag{7}$$

Most optimization methods aim to maximize the quality of the surface but, as observed by Asadollahi-Yazdi et al. [37], the user should obtain the surface quality in accordance to design specifications. In other words, at the end of the optimization process, the manufactured object should show that the surface quality requirements are satisfied.

2.3. Support Structure

The amount of support structures is another optimization target and it is generally considered by most of the papers here analyzed. A high correlation can be evidenced among support amount and the build time, the total cost, the surface quality of the part, and wastage of material. Although it is impossible to guarantee the total independence among these parameters, it should be verified that the simultaneous use of all of them does not introduce high redundancy into the optimization work-flow; this could result in some OFs being more impacting than others to the final build orientation.

The volume of the support structures is, typically, considered to affect the build time and total cost of the manufactured part, whereas the overhanging area is associated with the surface quality. The calculation of the real value of the support volume involves a complete simulation of the manufacturing process by a very time-consuming analysis that, in practice, is not suitable for optimization methods. For these reasons, several researchers proposed simplified approaches, where the volume of support structures is approximated with mono-dimensional, two-dimensional or three-dimensional features.

One of the simplest and most used criteria for evaluating the support amount is based on the supported area. This evaluation is quite simple to be determined when a tessellated model is available and it can be performed by evaluating the area of triangles whose normals satisfy a certain angle inclination with respect to the build direction. Zhang et al. [61], being $\mathbf{x_i}$ the normal of i-th triangle, defined the supported area OF as follows:

$$a_{supported} = \sum_i a_i \left|\mathbf{d} \cdot \mathbf{x_i}\right| \delta_i \qquad \delta_i = \begin{cases} 0 & \mathbf{d} \cdot \mathbf{x_i} \geq \Delta \\ 1 & \mathbf{d} \cdot \mathbf{x_i} < \Delta \end{cases} \tag{8}$$

Ga et al. [62] proposed a two-dimensional feature to approximate the amount of support volume: the sum of the projection, onto the built platform, of each mesh triangle for which the angle between the normal of the triangle and the deposition direction is greater than 135°. Similar approaches were described in [15,63]. Anyway, although very simple to evaluate, the two-dimensional approaches for support structure volume estimation do not consider their effective amount.

In order to overcome these limitations, many papers evaluate the support volume as a 3D feature. This analysis is more complex and, generally, leads to an approximation of the effective quantity of supports, whose accuracy is directly related to the computational cost of the method. The first related criterion, proposed by Pham et al. [9], consists of evaluating the z-coordinate of barycenter for each triangle that requires support. Then the volume of supports is calculated as the sum of areas of each supported facet multiplied for its z-height. The proposed method, considering two typical process features of the AM process, beamwidth, and hatch distance, avoids the overestimation of the support volume.

$$v_s = \frac{\sum_i z_i^{barycenter} a_i \left|\mathbf{d} \cdot \mathbf{x_i}\right| \delta_i \times beam\ width}{hatch\ space} \qquad \delta_i = \begin{cases} 0 & \mathbf{d} \cdot \mathbf{x_i} \geq \Delta \\ 1 & \mathbf{d} \cdot \mathbf{x_i} < \Delta \end{cases} \tag{9}$$

Khodaygan and Golmohammadi [36] approximated the amount of support material with a linear dimension (S), defined as the sum of the average vertical coordinates of the barycenter of downward facets (Z_{down_i}), weighted on areas (a_{down_i}), and multiplied for the deviation of downward faces from the deposition direction:

$$S = \frac{\sum_{i=1}^{m} Z_{down_i}\, a_{down_i}}{\sum_{i=1}^{m} a_{down_i}} \cdot \left(1 + \sum_{i=1}^{m} \left|\mathbf{x}_i \cdot \mathbf{d}\right|\right). \tag{10}$$

In [64], support volume is evaluated as the sum of all volumes delimited by the triangles needing support. All these analyzed methods do not take into account when supports rest directly on the object surface instead of the build platform.

A more accurate support volume evaluation, based on the voxelization, is introduced in [17]; the object to be manufactured is firstly voxelized, then the support volume is calculated as the sum of volumes of trapped empty voxels. In order to take into account also the complexity of the support structures, Chowdhury et al. [22] completed the previously considering method by adding the supports contact area and the Support Structure Accessibility (SSA):

$$SSA = \frac{v_s - v_s^{inaccessible}}{v_s} \tag{11}$$

SSA evaluates the percentage of the voxel of supports that are inaccessible; $v_s^{inaccessible}$ is the sum of the volumes of all trapped empty voxels, for which the six vectors along the orthogonal Cartesian axes from the barycenter have intersections with the object surface. In this way, the build orientations that don't allow support removal can be avoided.

The main limitation of the methods based on the voxelization of tessellated models is the high computational cost [65], that is not compatible with any optimization method requiring many iterations. For this reason , Di Angelo et al. [40] introduced an innovative algorithm without voxelization (Figure 9), which is particularly suitable for an optimization task, due to its accuracy and efficiency.

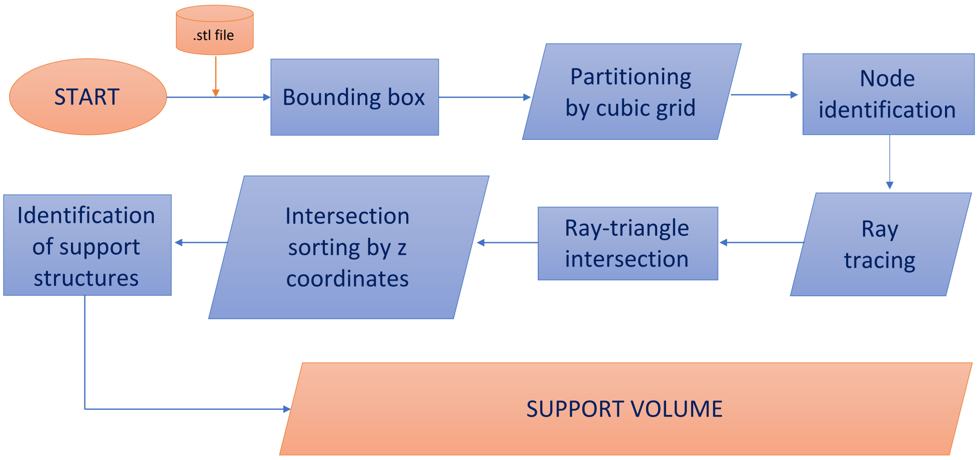


Figure 9. Flowchart of the voxelization algorithm proposed by [40].

Whereas all the previously analyzed methods require tessellated geometries as input, Das et al. [18] dealt with an optimization task for NURBS models. The proposed method is based on the following main steps:

- discretization of the NURBS surface into fine points and extraction of the normal at these points;
- identification of points requiring supports by means of the dot product between normal and build direction;
- projection of identified points onto the X–Y plane;
- iterative Quadtree decomposition of X–Y plane until a pre-defined threshold value is met.

The volume of support structures is the sum of the areas of these quadtree decomposed multiplied by their corresponding heights.

Karim et al. [66] suggested an expert algorithm for identifying Externally Supported Features (ESFs). They realized an algorithm which, through intersection operations between adjacent layers, can punctually identify and quantify the ESFs. The optimal orientation is determined by an ANN, whose inputs are data calculated by the algorithm for different part orientation. Although not discussed in the paper, the computation cost of this methodology is evident; moreover, since it is not clearly described how to realize the numerical implementation, this procedure appears limited for now.

2.4. Build Time

A first intuition about the relationship between build time and build direction was presented in [7]. Analyzing the manufacturing process of an SLA apparatus, they noticed that a significant amount of time was taken up by the dip-delay phase, which represents the time required to allow the liquid to flow over the newly formed layer. This delay is introduced during the construction of each layer. This evidences that build time is directly proportional to the height of h of the manufactured object with with respect to the build direction:

$$t_{build} \propto h \tag{12}$$

Equation (12) has the great limit to be basically qualitative. A more accurate model describing this phenomenon, was introduced by Xu et al. [51]. The build time t_{build} in the SLA process can be expressed as the sum of two contributes:

$$t_{build} = t_w n + K_1 \sum_{i=1}^{n} S_i L_i \tag{13}$$

where t_w is the recoating time and n the number of layers. The second term on the right member of Equation (13) is a representation of the volume of the part, being S_i and L_i, respectively, the contour area and layer thickness of i-*th* layer. Equation (13) takes into account variable slicing strategies that can be performed for different build directions. This method, firstly formulated for the SLA technology, was then extended, with necessary modifies, to other AM technologies in later works, such as [11]. Due to its simple implementation and application, most optimization problems use this formulation for evaluating build time. One of the main weaknesses of this model is that the time for support generation is not considered.

Thrimurthulu et al. [11] tried to take into account the effects of support generation on build time introducing in their model the F term, identifying the ratio between support-facet triangles and the total area of the component:

$$t_{build} = K_2 h (1 + F\rho), \tag{14}$$

where ρ is the density of supports and varies between 0 and 1. A limit of the model remains the poor evaluation of the build time due to supports: the height of supports is not distinguished from the height of the part. A new version of this solution was presented in [36]. Unlike the previous version of the model, it identifies a correction functional relation between build time and geometric parameters. Due to a dimensional incompatibility between the used parameters, the modified one appears to be not properly defined.

Griffiths et al. [67] proposed a build time estimator based on a linear combination of part height h, part volume v_p, and support volume v_s of the object:

$$t_{build} = K_{3a} + K_{3b} h + K_{3c} v_p + K_{3d} v_s. \tag{15}$$

In this expression two novelty contributions are considered: the part volume v_p and the support volume v_s. This last is evaluated according to procedure described in [68] and it is based on rays intersection (more details are reported in Section 2.3).

All the analyzed methodologies do not take into account the complexity of the object to be manufactured; this is due to it not being trivial to translate the complexity into easily-calculable parameters of the model. For this purpose, Di Angelo et al. [40] presented a parametric model which, although very specific for FDM technology, considers a large set of factors afflicting the build time:

$$t_{build} = K_{4a}\, l_{ext} + K_{4b} \left(\frac{v_p - l_{ext} T^2}{Q_p} \right) d_p + K_{4c} l_s + K_{4d} \left(v_s - l_s T^2 \right) + K_{4e} N \tag{16}$$

The Equation (16) introduces three new contributes: the external layers perimeter l_{ext}, external support perimeter l_s and number of repositioning of deposition tool N. Moreover, it considers, other than the classical factors related to the geometry and process parameters, an innovative term, Q_p, allowing us to adapt the method to object slenderness, which is critical for parametric estimation of the build time. An innovative and efficient method, already described in Section 2.3 by Figure 9, is proposed for support evaluation. The results in [40] show the proposed method for the build time evaluation is most robust and accurate than the state-of-the-art above all for complex objects (with both squat and thin structures, and different values of thickness due to the presence of holes or ribs).

Even more complex strategies can be pursued to build time evaluation. Di Angelo et al. [40] use into their work a detailed linear parametric method, defined for a specific technology (FDM).

This constrain is overcome in [53], where the parametric model is implemented by an Artificial Neural Network, demonstrating that accuracy and stability are improved. Since a similar solution is proposed by none of the analyzed papers related to the optimization task, it could be interesting to spend efforts, in the future, for integrating a similar approach into OF defining build time.

2.5. Cost

In [24], one of the most accurate cost models for AM components is defined. It analyzes every single aspect which determines the total cost. One of the most significant results is to not consider only the build cost c_{build}, but also the pre-processing c_{pre} and post-processing c_{post} cost, that in most cases can not be neglected. So the total cost c_{tot} is defined by the contributions of three elements:

$$c_{tot} = c_{pre} + c_{build} + c_{post} \tag{17}$$

Each one of the three terms is punctually described in the paper. Even a different formulation for FDM and SLA is proposed. The validity of this formulation was confirmed by several published types of research that use this definition of cost in their optimization functions, even the most recent. Someone, like Brika et al. [20], tried to extend the formulation to the new emerging technologies like PBF. Others, such as Byun and Lee [13], Canellidis et al. [14], proposed a simplification of it, observing that in most practical cases the pre-processing cost c_{pre} is negligible compared to the others. These papers put in evidence the main downside of this model, represented by its complexity. Despite this, it is the most appropriate for determining accurately each one of the contributions affecting the total cost, many terms need to be evaluated and it may be difficult for the user to estimate all of them simultaneously, due to lack of information or uncertainty about the manufacturing process. Therefore, in industrial applications, their use is neglected where a fast and efficient evaluation needs to be performed.

The formulation of cost introduced in [13] is particularly suitable to be used into optimization methods:

$$c_{tot} = (t_{pre} + t_{post})c_{labuor} + c_{operative}t_{build} + c_{material}, \tag{18}$$

where:

$c_{material}$	material cost
$c_{operative}$	operative cost
c_{labour}	labour cost
t_{build}	build time
t_{pre}	pre-processing time
t_{post}	post-processing time

With the aim to implement more reliable methods, Asadollahi-Yazdi et al. [37] suggested evaluating build time and material directly from the set of command instructions given to the AM machine to realize the part. This approach, whose computation cost is enormous, cannot be based on simply reading the G-Code, but must take into account all that information, such as the jerk and acceleration laws, related to the specific machine [5]. On the other side, the computation cost is enormous. Although their the optimization method is based on this technique, its use is limited to a scientific contest.

Griffiths et al. [67] suggested an interesting remark, sustaining that each objective to optimize can be led back to a cost element. This is undoubtedly true and a similar approach to an optimization task brings to several advantages: for example, the multi-objective problem comes back to a single optimization task whose only function is represented by the cost. This makes the optimization job amazingly easy to perform. Moreover, it returns a result more significant for the industrial world. Anyway, the intuition of Griffiths et al. [67] looks more like a proposal. No methods of concretely applying this solution are provided. Therefore, it may be interesting for further researchers to explore this field. An example, in this sense, is represented by Mele et al. [31]. They describe a procedure allowing us to obtain the optimal build direction in relationship to an Environmental Impact (EI) index, which is evaluated considering the energy and material consumption of the building process. The EI is a reflex of Life Cycle Impact Assessment of engineering products, which cannot be neglected any longer from the industries during product design and, therefore, it is an additional cost element to evaluate in the budget phase. Another interesting work concerning this topic is [12]. In their research, the authors describe a numerical model for translating all the issues related to surface quality in the AM process as an element cost.

In Table 2 a summary of the most relevant models for cost evaluation proposed by literature is reported. It should be noticed that, although about forty papers were analyzed for this review, only a limited number introduce new references points about this topic. Most of them use already-known formulations, with limited and negligible novelties. Some models are too generalist and, therefore, difficult to adapt to the specific use case. Others, on the other side, are more punctual, but they require a large set of input information and can be used for a limited number of occurrences. It would be desirable to work on new proposes which, considering the common points and differences between the different AM technologies, would be able to provide an immediate, more or less approximate, evaluation of the total cost depending on the process in use. This would be a great result, especially for those AM makers who have to optimize, other than the build direction, also the machine park utilization.

Table 2. Summary of the most relevance cost models proposed in optimization methods.

Authors	Considered Cost Components	Technology
Lan et al., 1997 [7]	Build time (number of layers)	
Xu et al., 1997 [51]	Build time (number of layers)	
Alexander et al., 1998 [24]	Prebuild cost (positioning, defining process parameters, generating supports, slicing, computer and operator cost), Build cost (manufacturing time, idle time, machine cost, material cost), Postprocessing cost (remove supports, finish surface, post-processing treatments, extra materials, operator cost).	FDM, SLA
Thrimurthulu et al., 2004 [11]	Build time (number of layers, supported area).	FDM
Kim et al., 2005 [12]	Postprocessing cost (polishing, postcure, support removal, washing)	
Byun et al., 2006 [13]	Pre and postprocessing time (operator cost), build cost (drawing exterior contour, filling interior area, generate supports, unproductive time, material cost).	
Nezhad et al., 2010 [32]	Build time (path length determined after slicing).	
Strano et al., 2011 [34]	Energy cost (preheating and part sintering).	SLS
Phatak et al., 2012 [16]	Build time (number of layers), material utilizzation factor.	
Brika et al., 2017 [20]	Build time (number of layers, part volume, part support), energy cost, indirect cost (portion of build-plate).	PBF
Yazdi et al., 2018 [37]	Build time (Gcode), material cost (GCode).	
Khodaygan et al., 2018 [36]	Build time (number of layers, supported area).	
Garzaniti et al., 2018 [69]	Recurring cost (hourly machine cost, energy, material), Non recurring cost (capital expediture, operating expediture, non recurring cost related to manufacturing phase).	
Di Angelo et al., 2020 [40]	Energy cost, Fixed Cost, Post-processing cost, Support material's cost.	FDM

2.6. Mechanical Properties

Mechanical properties have been considered as a secondary aspect of AM components, being well-known the structural limitations given by their anisotropic properties. Due to the adopted technology, anisotropy can be more or less evident, but it is always observable and, although depending on a significant amount of factors like the process in use, materials or process parameters, mechanical properties, were demonstrated to be highly influenced from build orientation [70,71]. Nowadays, new and promising AM processes allow realizing structural components that can operate even in critical conditions and, therefore, optimization of mechanical properties is become subject of scientific investigation.

Brika et al. [20] treated the mechanical properties of AM components in a multi-optimization problem. They investigate the influence of process parameters on mechanical properties through stochastic models. A full factorial experiment was designed to identify a relationship between build orientation, mechanical properties, and heat treatments, which contribute decisively towards defining the response of powder-based components.

A further advantage of the AM process is its capability to make components with a non-homogeneous distribution of material. For example, different structures, materials, and density could be obtained for functional regions of the components, making a significant advantage in terms of cost and weight. Since the build direction affects the way the different materials can be deposed into the object, its definition can be the object of an optimization problem where the independent variable is the structural behavior. Jaiswal et al. [43] analyzed the factors affecting the mechanical properties of components produced by Functionally Graded Materials (FGM) technology. This problem is analytically evaluated performing a voxelization of the geometry. The optimal build direction is chosen to minimize a OF called "average Material Composition Error".

Cheng and To [38] proposed an optimization algorithm for minimizing the residual stress on finished components, whose independent variable is the build direction. This issue is particularly critical in AM laser-based processes where it is not rare to observe cracks, delaminations, and large deformations. The typical solutions for studying residual stress are based on finite element techniques, which, especially for complex geometry, are very computationally expensive. In order to analyze FE models computationally lighter, a voxel-based methodology is proposed. Computational weight is further reduced, making use of asymptotic homogenization and multi-scale model.

Lovo et al. [4] described an analytic procedure to optimize build orientation on truss-like structures, such as the case shown in Figure 10.

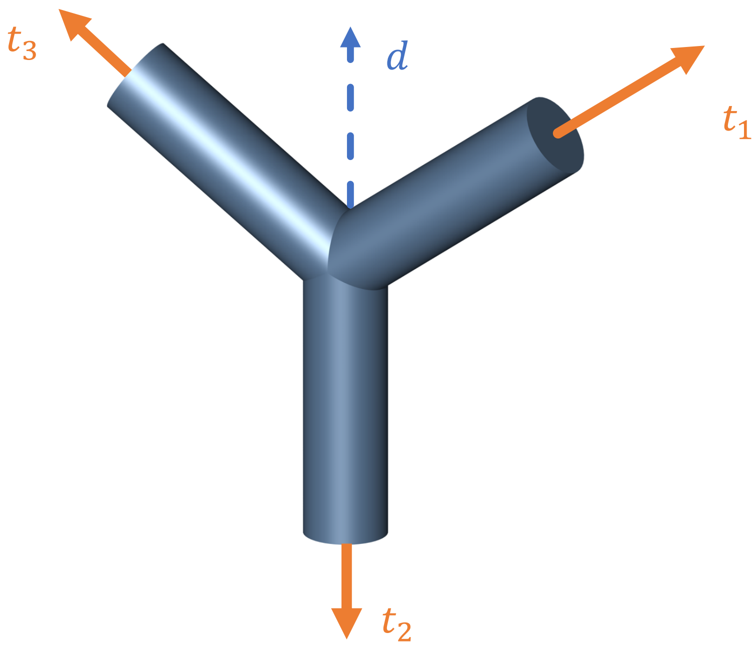


Figure 10. An example of truss-like structure.

It is known that a fiber structure guarantees the maximum resistance on forces along the filament direction. In AM components, generally, filament direction is perpendicular to build orientation. Then, assuming that structure is mainly subjected to tensile stress, defined B the number of beams composing the structure, the optimal build orientation is obtained by minimizing the following of β:

$$\beta = \sum_{b=1}^{B} \omega_b (\mathbf{t_b} \cdot \mathbf{d})^2 \tag{19}$$

where $\mathbf{t_b}$ and ω_b define the spatial orientation and the assigned weight to b-*th* beam.

2.7. Multi-Part Job

AM is showing promise also for the production of large-scale components. Hence, a growing interest is dedicated to optimally distributing the different components into the build volume for maximizing the productivity of each job task. The optimal placement of several parts into a build platform, with respect to user-defined objectives, is a complex non-deterministic polynomial-time (NP) hard problem [41,67].

In order to solve it, Zhang et al. [41] proposed a two-dimensional procedure, based on two main steps, which is an improvement of a previous research [72]. The authors considered a multi-step procedure, described by the flowchart in Figure 11. The initial phase determines the optimal build orientation of each component, according to some AM based-feature criteria. Then, after evaluating the projected area of each component upon the build plate, a "parallel nesting" algorithm is applied for maximizing compactness. The authors considered a two-dimensional optimization task in their work, avoiding overlapping of objects into the build volume (see [10]) due to its negative impact on surface quality. This constraint makes the optimization task lighter than a three-dimensional problem but, at the same time, introduces limitations. For example, the procedure is not able to solve satisfyingly those situations where parts, being characterized from a different height or a particular shape, could be build so that their 2D projection partially overlapped into the build platform. In this way, unnecessary waste of material for support generation would be avoided.

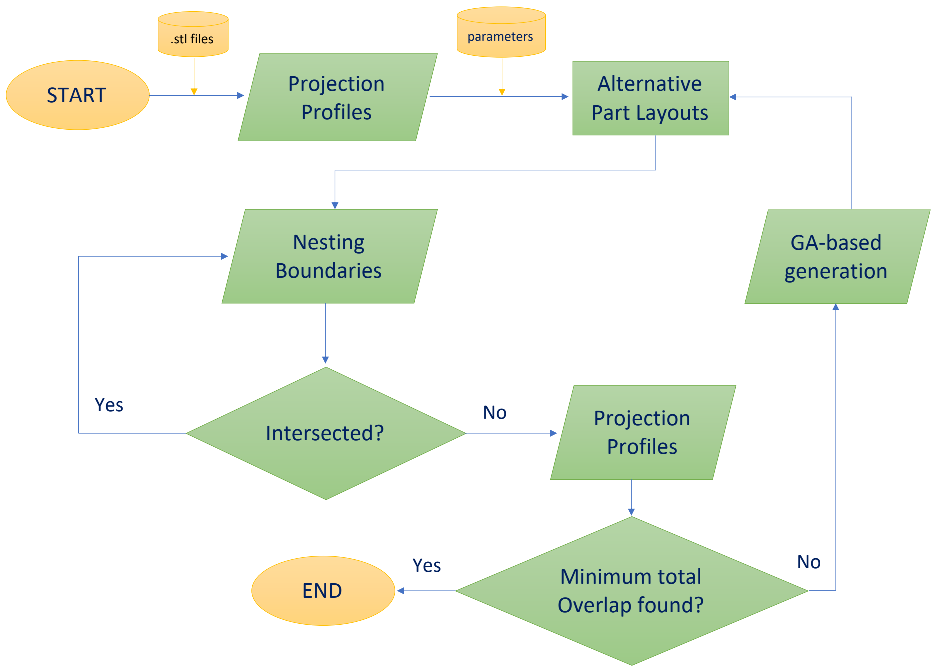


Figure 11. Flowchart of two-dimensional optimization used in [41].

Since any exhaustive approach to a hard NP problem could be not solved in a reasonable time, Ref. [67] suggested a properly designed heuristic approach to reduce the solution space of the problem, based on Iterative Tabu Search Procedure (ITSP). This is defined by six main stages: first, an initial solution based on the minimum number of bins is searched. The second and third phases minimize the height and support structures of every single object and these steps are replied in the fourth and fifth stages for the pairwise objects. In the last step, an additional bin is created and some random pieces assigned to it. The build orientation of parts is determined using a tabu search, while the two-dimensional irregular bin packing problem is solved by applying the methodology described in [73].

Although both presented methods introduce solutions for optimizing the use of computation resources, they still appear too expensive computationally.

3. Optimization Methods and Decision Criteria

The earlier conducted analysis allows us to observe that several independent factors concur in an optimization task and, moreover, some of them are even in conflict. This makes it very challenging to define decision criteria to adopt when several OFs have to be optimized. Three main strategies are presented in the literature to absolve this task. The first consists of defining a primary OF to optimize, representing the most important goal to reach in the final part. Other OFs can later be considered, but they concur in the final result only if not penalizing the primary function. This way of proceeding cannot be considered a real multi-optimization job.

An alternative is to reduce the analyzed OFs into a single optimization function, defined as a weighted sum of considered OFs. Thence, defined ω_j the weight of j-*th* OF, the optimal build direction **d** minimizes (or maximizes) the following summation:

$$\sum_{j=1}^{J} \omega_j OF_j \tag{20}$$

The weighted sum is a powerful instrument for solving multi-objective problems due to its simplicity and efficiency. This is even more true when analytical definitions of the implemented OFs are used. On the other side, it is not always easy to assign a correct weight for the different OFs. This would require a deep knowledge of how the considered criteria take effect on the final product. A similar knowledge, especially during the design, it's not generally available. Moreover, it should be observed that several OFs criteria are quite conflicting with each other. This makes attribution of weights even more complex, considering that even a small variation of them can significantly affect the final solution. In this sense, an interesting proposition is given in [20], which evaluates the weights of OFs adopting a fuzzy-based approach. Last but not least, weighted sum-based optimization leads to a single result instead of a set of solutions to be later compared. This is, especially for numerical methodologies, a critical aspect to consider is the to not remote possibility of these not converging to a globally optimal solution.

All these reasons bring several authors to choose a Pareto optimal solutions approach. A Pareto optimal set is a series of solutions that are not dominated by one another [32]. Let us consider a minimization problem with J objectives that should be optimized with respect to build direction **d**; a set of P non-dominated solutions **OFs** will be identified by the algorithm:

$$\mathbf{OFs}_i(\mathbf{d}_i) = [OF_{1i}(\mathbf{d}_i), OF_{2i}(\mathbf{d}_i), ..., OF_{Ji}(\mathbf{d}_i)] \tag{21}$$

where $i = 1, 2, ..., P$.

Being **A** and **B** two generic elements of the space solution, a solution **A** is dominant on solution **B** if:

$$OF_j(\mathbf{A}) \leq OF_j(\mathbf{B}) \quad j = 1, 2, ..., J \quad \wedge \quad \exists j \ / \ OF_j(\mathbf{A}) < OF_j(\mathbf{B}) \tag{22}$$

A solution is called Pareto optimal when it is not dominated by any other element of solution space: a Pareto optimal solution cannot be improved further without penalizing at least one OF.

Pareto optimal solutions define the so-called Pareto front. In Figure 12, a representative example of a Pareto front for a two-dimensional problem is depicted.

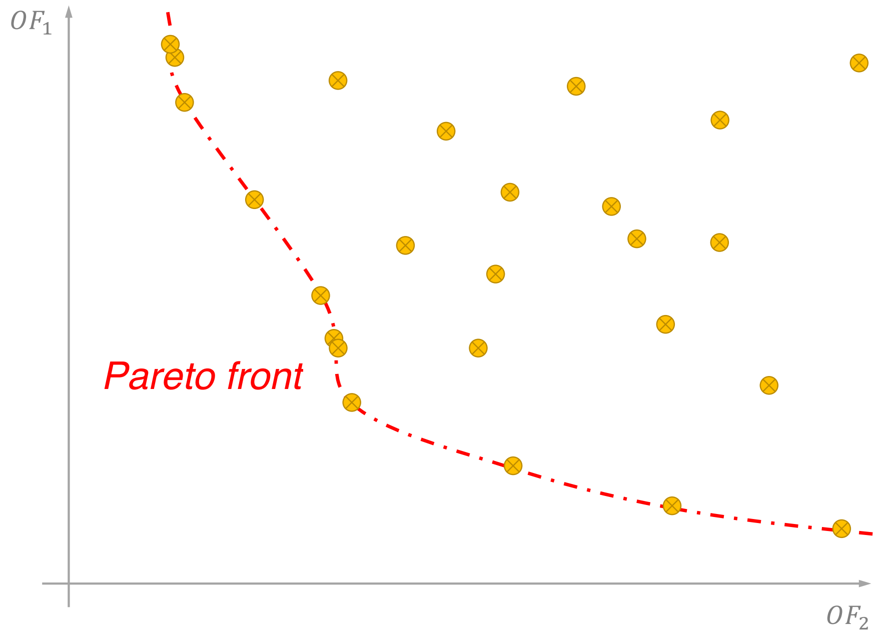


Figure 12. A representative example of a Pareto front for a two-dimensional optimization problem.

Having assigned a multi-objective optimization problem, evaluating a Pareto front is quite a complex computational task. Therefore, it is not only important to correctly define the mathematical problem, but also to adopt the right methodologies to solve it into a reasonable time, a very important requirement for any optimization task. Most of the analyzed papers perform this task by genetic-based algorithms, like Non-Dominate Sorting Genetic Algorithm-II (NSGA-II), or Particle Swarm-based Optimizers (PSOs).

NSGA-II is a very popular Genetic Algorithm (GA) employed for solving multi-objective optimization [74]. GAs are very suitable for large-scale optimization problems, in particular for those where the sought global extreme is hidden among many poor, local extreme [14]. GAs, such as NSGA-II, are based on genetic operators like crossover, mutation, and selection. Starting from an initial population of N elements, randomly generated, a child population is created using genetic operators. Then the population is sorted in a set of solutions (front), according to a non-domination strategy. These operations are cyclically repeated for improving the population features. The fronts are compared to each other, assigning to each population element a determined ranking defined by a fitness value. This allows to determine a Pareto set of solutions. Another powerful GA algorithm, SMS-EMOA, was described in [75]. It uses the hyper-volume indicator as a selection measure during the solution process. This method was implemented in [40].

PSO shares many mechanisms of GA, but instead of evolving the population into the solution space, the candidate solutions, here called particles, move into it, simulating the behavior of electrically charged particles. A charge is assigned to each element, whose magnitude and the sign is determined by the values assumed by OFs in that point. Regions having higher attraction will pull other region points in, while low attracting regions repulse other elements to allow exploration of new solution space elements.

Padhye and Deb [33] solved their multi-objective optimization task both with NSGA-II and PSO, evidencing similar results from the two methodologies.

A Pareto front, differently from a weighted-sum single-objective, is defined by a set of candidate solutions. Hence, decision-making criteria need to be adopted for choosing a final solution to use. This evaluation could be demanded for a user expert, but a similar way of proceeding introduces subjectivity into the decisional process. Moreover, a graphical representation of the Pareto front can be obtained until a three-dimensional problem, making very hard a critical analysis of results for tasks in larger spaces. In [33] three different possibilities are described for automatizing this process. The first is called Aspiration point method and assumes some pre-decided preferences from the designer, which permit us to define an operating point to reach. The goal of the method is to identify a solution that is better than the aspiration point imposed by the designer.

Another way of proceeding is defined by the marginal utility methods that, differently from the previous described, doesn't require any user information and identifies the solution showing the least affinity with respect its neighbors in solution space.

Another user-less method is known as the L_2-metric. It requires a normalization of implemented OFs. A reference point is assigned to the origin of normalized space and the Euclidean distance L_2 of each element of the Pareto front is evaluated, choosing as a solution the point with the smallest value of it. Very similar to this is the Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) [13], which determines the optimal solution having the smallest distance from an ideal point and largest from the "nadir point", defined as a point with worst OFs values in the Pareto front.

4. Conclusions

The optimal part deposition orientation definition is a complex task in which many different conflicting OFs must be considered at the same time. The OFs discussed in this paper, to date, are those used to set up the build direction. As the AM technologies evolve, these OFs are subject to evolution. Furthermore, new ones could be identified in the future and add to the old ones. If for one hand, the optimization of the construction direction follows the improvement of the functional performance of the object, the growing particularity of each AM technology makes the manufacturing requirements on which to optimize the build direction more and more specific. It is the case of the stair-case effect, that is substantially negligible in modern AM processes, based on powder metallurgy. In the future, the traditional layer manufacturing paradigm could be overcome, and new performance of additive technologies introduced, for which some of the OFs used at present could not be used anymore.

It cannot be excluded that, in the future, the concept of build direction could also evolve, depending on the development of new technologies, which could give the capability to build an object in many different directions. In this futuristic scenario, the optimization of the build direction will be a strategic factor whose multiplicity must be optimized considering all the single parts in which the object can be decomposed.

Build time is considered by almost all literature concerning AM optimization. Despite the large effort profuse in this investigation, the methods for predicting it remains an important aspect to be improved: the predictions performed are not accurate and, often, the methods are devoted to specific classes of objects.

Mechanical properties are an emerging factor of multi-objective optimization, strictly linked to adopted material and how it is deposed. This objective could be, more properly, priority constraints that must be pursued, so that new criteria for multi-objective optimization problems should be defined to take into account other factors, such as cost or surface quality.

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Abbreviations

The following abbreviations are used in this manuscript:

$.stl$	stereolitography file format
AM	additive manufacturing
ANN	artificial neural network
a	area of triangle
a_{part}	external surface area of the part
$a_{supported}$	supported area of the part
CAD	computer-aided design
CAM	computer-aided manufacturing
$c_{material}$	material cost
$c_{operative}$	operative cost
c_{build}	build cost
c_{labour}	labour cost
c_{post}	post-processing cost
c_{pre}	pre-processing cost
$\mathbf{d}$	build direction
ESF	externally supported feature
FGM	functionally graded materials
FDM	fused deposition modeling
h	height of the part with respect to the build direction
$ITSB$	iterative tabu search procedure
j	cusp height
l	layer path length
l_{ext}	layer external path length
l_s	layer supports path length
N	number of repositioning of deposition tool during the building process
$NSGA-II$	non-dominate sorting genetic algorithm-II
$NURBS$	non-uniform rational basis spline
n	number of layers
OF	objective function
P_a	arithmetic mean of the primary profile
PBF	powder bed fusion
PBO	part build orientation
PBO	particle swarm-based optimizer
S	contour area
SLA	stereolitography apparatus
SSA	support structure accessibility
s	scanning speed
R_a	roughness index
T	layer thickness
$TOPSIS$	technique for order of preference by similarity to ideal solution
t_{build}	build time
t_{pre}	pre-processing time
t_{post}	post-processing time
t_w	recoating time for each layer
V	number of voxel
v_p	volume of part
v_s	volume of supports
$\mathbf{x}$	triangle normal
z	z-component of triangle

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