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# The energy performance assessment method to establish the best part build orientation in additive manufacturing

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**Abstract**

The growing use of additive manufacturing (AM) processes pushes research towards studying methods to reduce their environmental impact. The part build orientation is a significant process variable, which can be chosen through the Energy Performance Assessment (EPA), a straightforward method. The paper presents a method for identifying the best part build orientation considering energy consumption. The EPA has been adapted for this purpose, resulting in an approach based on four steps. The method was employed to determine the best printing direction for three parts and two AM technologies.

*Keywords: ecodesign, sustainable design, energy efficiency, 3D printing, additive manufacturing*

## 1. Introduction and literature review

Additive manufacturing (AM) technology has grown rapidly in recent decades due to its many advantages over conventional manufacturing techniques (Garzaniti *et al.*, 2018). The peculiarities and unique benefits of AM allow designers to realise components in their near-net shape and create customised goods with short lead times, contributing significantly to Industry 4.0.

Given the "non-subtractive" nature inherent in AM processes, they all appear environmentally sustainabile at a basic level, resulting in either no waste or at least a reduced amount of scraps. Various studies in the literature (Peng *et al.*, 2020) have delved into and compared the environmental impacts of additive techniques, such as Laser-Powder Bed Fusion (L-PBF), with traditional manufacturing methods. These studies have concluded that AM yields environmental benefits in specific applications, particularly concerning indicators associated with resource depletion. The advantages in terms of environmental sustainability become even more pronounced, especially in products with highly intricate geometries that require customisation. However, sustainability depends on process parameters. If correct printing parameters are not chosen, AM's energy consumption and environmental impacts could be higher than those of traditional manufacturing (Ngo *et al.*, 2018).

One of the main parameters to consider concerning the environmental sustainability of AM is the part-build orientation, on which this paper is focused. Establishing the part orientation holds significant importance in these processes as it directly influences various component properties, including surface quality (Wang *et al.*, 2016), the number of support structures required (Ezair *et al.*, 2015), the strength (Abdelrhman *et al.*, 2019) and fabrication cost (Solouki *et al.*, 2023), among other factors.

The best-known tool for environmental analysis is LCA (Life Cycle Assessment). LCA for additive manufacturing was used in different works, such as (Yang *et al.*, 2017), (Burkhart and Aurich, 2015) and (Bianchi *et al.*, 2022). LCA, however, has some limitations if used during the design phase. First, the

LCA implementation can be very complex. Obtaining the inventory data may be exceedingly challenging if the system scope is too broad. Furthermore, this type of analysis is carried out only very late in the design phases of a product, therefore when most of the decisions have already been made.
An alternative tool for environmental performance assessment, proposed by (Yi *et al.*, 2020), is the EPA (Energy Performance Assessment) model. EPA appears to be simpler to apply than LCA, as it is based exclusively on the study of the energy dimension of an object, not considering other aspects. Furthermore, unlike LCA, EPA can be applied in the early design phases when the object still needs to be created.
To demonstrate that the EPA, and therefore the energy assessment, is parallel to the LCA, (Yi et al., 2020) performed a complete environmental assessment, based on a cradle-to-gate LCA analysis of eight different object designs. Then, they compared LCA results with EPA. Primary energy (PE) and greenhouse gas (GHG) emissions were chosen as environmental impact indicators for the LCA. Instead, energy consumption (E) was selected as an indicator for the EPA. The comparative analysis led to determining the same solution using both methods. Therefore, it is possible to deduce that the EPA model is valid and comparable with the LCA method, which considers a broader environmental impact vision. For the reasons listed above and given that it has been proven useful, the paper presents a method to establish the best build part orientation in additive manufacturing by considering environmental sustainability through the EPA approach. The approach tackles the energy consumption as a driver to find the best print direction. Other criteria (e.g., strength, surface quality, cost, time) are not considered but can be integrated with this proposal. To the authors' knowledge, this is the first adoption of EPA within a method for selecting the part build direction.
After this introduction, Section 2 presents the overall EPA method, which is included in the approach for selecting the best part build orientation (Section 3). Section 4 uses the proposed procedure for three components and two additive manufacturing technologies.

## 2. The Energy Performance Assessment method

The EPA method is based on EnPIs (energy performance indicators), a quantitative evaluation of energy performance (ISO - International Organization for Standardization, 2023) linked to design or process parameters. EnPIs are classified in measured energy value (e.g., energy consumption per build task), the ratio of calculated value (e.g., energy consumption per volume), statistical model (e.g., the relation between mean power and mean temperature), and engineering model (e.g., the ratio between safety factor and energy consumption).
During the design process, an engineer generally has multiple requirements, thus, various EnPIs. Since EnPIs have different units of measurement (e.g., J, J/cm$^3$, MPa/J), normalisation is first required to subsequently sum their scores (Yi *et al.*, 2020). During the normalisation, it is essential to consider if the EnPIs must be maximised (the higher the EnPI, the better the solution). For example, the ratio between safety factor and energy consumption is an EnPI to maximise. On the other side, the energy consumption per volume must be minimised. For this reason, the value for each EnPI, obtained for each analysis (i.e., part build orientation in this study), is obtained by dividing the upper or lower difference (i.e., the difference between the EnPI and the maximum or minimum value) by the range of values.
Second, weighting EnPIs allows engineers to set different importance to each EnPI (so, to each design requirement). Pairwise comparison can be employed to establish relative weights. Factors depend on weights assigned to design requirements and specifications.
Third, EnPIs are aggregated by summing the relative value of each one. At last, a single and final indicator is obtained. The best part build orientation is that with the higher aggregated EnPI.

## 3. The EPA method for part build orientation

This section explains a systematic and comprehensive methodology to identify the optimal part build orientation of 3D printed components that minimises energy consumption. It does not consider other criteria (e.g., mechanical strength, surface quality, time, cost) that are outside of this research paper's scope. Overall, the methodology is independent of the AM process. On the contrary, the life cycle inventory (LCI) depends on the technology used. The LCI can be defined by directly measuring the 3D printing process or by taking data from the literature, which is becoming vast and covers the most relevant technologies.



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The proposed methodology precedes the nesting phase and is applied to each component of the print job individually. The parts can then be positioned on the build plate with optimal orientations. In detail, the first step defines the necessary input information for applying the method (§3.1). Then, the primary data needed to build the LCI and required for energy assessments are determined and collected into a database (§3.2). Subsequently, there is the selection of the energy indicators (§3.3) and the calculation of the optimal printing direction (§3.4).

## 3.1. Setting of product and process parameters

The first phase of the methodology starts with providing input data, which are:

1. *Component 3D model*: the virtual model prototype is employed to analyse and identify its geometric attributes and distinctive features (e.g., volume, bounding box, print height, projected area).
2. *AM technology and related printing machine*: energy assessments are directly related to the printing technology and the printer. For example, selective laser processes use more energy than extrusion. Furthermore, different machines can be used with their respective energy consumption within the same process.
3. *Component material*: information on the material influences energy consumption. The energy required for feedstock generation and part manufacturing depends on the material.
4. *Number of orientations analysed*: within the printing chamber, the part may be placed on a limitless number of orientations. This parameter allows the engineer to limit the number of options. A high value allows a low processing load, but the optimal orientation can only be found with limited precision. While a large number increases the computational load, it provides a more accurate evaluation. The approach might be applied several times around the first sub-optimal directions detected to speed up the process.
5. *Post-processing operations*: depending on the technology and the engineer's needs, it is possible to define which post-processing operations will be performed on the component.

## 3.2. Set the Life Cycle Inventory

The second phase consists of collecting the data necessary for the energy assessment. This phase can be divided into two activities. The first aims to create the LCI, which contains the energy information related to the feedstock (a), printing phase (b) and post-processing operations (c). The second activity aims to collect the geometric data for each orientation.

### *3.2.1. Life Cycle Inventory*

a) *Feedstock*: energy required to transform the raw material (e.g., billet) and produce the feedstock (e.g., powder, filament or resin) through specific processes (e.g., atomisation).

b) *Printing phase:* machine energy consumption to print a certain amount of material. For example, the unitary 3D printing energy consumptions for AISI 316L and Inconel 718 (considering L-PBF - technology and the SLM® 280 machine) are 383.13 [MJ/kg] (Guarino et al., 2020) and 427.47 [MJ/kg] (Torres-Carrillo et al., 2020) respectively.

c) *Post-processing operation*: the energy consumption for post-processing operation (e.g., part separation, support removal). These technologies may differ according to the printing technology and material. For example, part separation from baseplate (in L-PBF or L-DED - Laser-Directed Energy Deposition) can be done through a band saw or wire EDM.

### *3.2.2. Geometric information*

The part-related information includes mass [kg], height along the printing direction [mm], smallest dimension on the printing plate [mm], largest dimension on the printing plate [mm] and projected area on the printing plate [$mm^2$]. Combining the geometric parameters extracted for each orientation and the energy consumption information related to the selected input makes it possible to obtain the overall energy consumption associated with each printing direction.



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## 3.3. Select EnPIs

The EPA model uses EnPI indicators that provide quantitative information to choose the best alternatives corresponding to the printing directions. Depending on the information available and the need for which the best orientation is sought, various EnPI indicators can be used (Table 1).

**Table 1. EnPIs overview (Yi et al., 2020)**

| EnPI Group | Typology |
|---|---|
| *Measured energy value* | Energy consumption per build [J, kWh] |
| | Daily or weekly energy consumption [J, kWh] |
| | Energy waste per build [J, kWh] |
| | Peak power consumption [W] |
| *Measured value ratio* | Specific energy consumption [J/cm$^3$ or J/kg] |
| | Energy consumption per layer [E/layer] |
| | Ratio of energy required to total energy consumed [%] |
| | Ratio of heat dissipated to energy consumption [%] |
| | Relationship between energy consumption and value creation [J/€] or energy cost [€] |
| *Statistical model* | Relationship between average power and average temperature [W - °C] |
| | Relationship between energy consumption and laser beam energy density [J - J/m$^3$] |
| *Engineering model* | Relationship between safety factor and energy consumption [1/J] |
| | Relationship between residual voltage and energy consumption [MPa/J] |
| | Relationship between energy consumption and thermal deformation [J/mm] |
| | Ratio of energy consumption to material density [J/%] |

## 3.4. Calculate orientations

Once the EnPIs are chosen, it is possible to apply the method and identify the best printing direction. The section includes three stages: normalisation of the indicators (§3.4.1), assignment of weights (§3.4.2) and definition of the best orientation (§3.4.3).

### *3.4.1. Normalisation of the indicators*

The engineer can choose different indicators with which to select the best printing direction. This step makes it possible to summarise and consider various indicators under a single value.
Considering many rows, $i$, as the number of identified indicators and many columns, $j$, as the number of selected indicators, the first operation involves calculating $R^j$. It represents the difference between the maximum and the minimum value of the same indicator $j$.

$$R^j = \max(EnPI_i^j) - \min(EnPI_i^j) \tag{1}$$

Normalisation is then carried out. Two approaches can be used: Upper Difference (UD) and Lower Difference (LD). For example, for indicators in which energy is calculated directly [e.g., J/kg], UD is used; LD is used for indicators in which energy is related [e.g., 1/J].

$$UD_i^j = \max(EnPI_i^j) - EnPI_i^j \tag{2}$$

$$LD_i^j = EnPI_i^j - \min(EnPI_i^j) \tag{3}$$

So, the normalised indicators:

$$EnPI_i^{j\,'} = \frac{UD_i^j}{R^j} = \frac{\max(EnPI_i^j) - EnPI_i^j}{\max(EnPI_i^j) - \min(EnPI_i^j)} \tag{4}$$

$$EnPI_i^{j\,'} = \frac{LD_i^j}{R^j} = \frac{EnPI_i^j - \min(EnPI_i^j)}{\max(EnPI_i^j) - \min(EnPI_i^j)} \tag{5}$$



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### 3.4.2. Weights assignment

Among the chosen indicators, it is possible to decide which is more important and which is less critical through the definition of weights ($WF^j$). The weights are calculated through a pairwise comparison. Three values can be defined for each comparison (i.e., 1, 3, 6). After that, for each indicator in the row, the values expressed by the comparison with each indicator in the column are added up ($S^j$). The resulting sum is compared to the total score of all scores ($\sum_{j=1}^{n} S^j$).

$$WF^j = \frac{S^j}{\sum_{j=1}^{n} S^j} \tag{7}$$

Finally, the weighted indicator is obtained by multiplying the normalised indicator value with the respective weight:

$$EnPI_i^{j''} = EnPI_i^{j'} \times WF^j \tag{8}$$

### 3.4.3. Selection of the best orientation

The last step is to add all the values obtained for each indicator with the same orientation.

$$Sum = \sum_{j=1}^{m} EnPI_i^{j''} \tag{9}$$

Then, comparing all the various sums of each orientation, the one with the highest value will be the best.

## 4. Case study and results discussion

The case study involves the application of the methodology on three different components, processed with two different technologies and materials. For the present case study, the energy consumption information (LCI) for feedstock, printing, and post-processing operations was retrieved from the literature.

### 4.1. Component and inventory data

From an energy point of view, each process is characterised by the AM technology and related printer, material and post-processing operation. With Specific Energy Consumption [kWh/kg], it is possible to represent the energy consumption of the printer and feedstock, respectively (Table 2). In the first case, it means the printer's energy consumption to print a mass unit of the associated material. The printer's energy consumption can also be expressed with the Energy per Layer parameter [kWh/layer]. In the second case, the Specific Energy Consumption represents the energy spent to extract and produce the feedstock used for printing.

Table 2. Life Cycle Inventory. *Values elaborated from (Faludi et al., 2017)

| | **L-PBF: Laser-Powder Bed Fusion** | | | **L-DED: Laser-Directed Energy Deposition** | | |
|---|---|---|---|---|---|---|
| | **Feedstock** | **Printing** | **Post-Proc.** | **Feedstock** | **Printing** | **Post-Proc.** |
| **Specific energy consumption [kWh/kg]** | *Inconel 718* 100.4 (Fredriksson, 2019) (Böckin and Tillman, 2019) | 29.4 (Baumers et al., 2011) | - | *AISI 316* 7.8 (Guarino et al., 2020) | 67.0 (Baumers et al., 2011) | - |
| **Energy per Layer [kWh/layer]** | - | 0.066 (Baumers et al., 2011) | - | - | 0.059 (Baumers et al., 2011) | - |
| **Energy per Cutting Dimension [kWh/mm]** | - | - | *Wire EDM* 0.16894 (Faludi et al., 2017)* | - | - | - |
| **Energy per Cutting Surface [kWh/mm²]** | - | - | | - | - | *Cutting* 0.000000758 (Faludi et al., 2017)* |



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Regarding post-processing, the wire EDM (Electrical Discharge Machining) process was evaluated for components A and C. Its energy consumption is related to the Energy per Cutting Dimension [kWh/mm]. The cutting machine (band saw) was considered for component B. In this case, it is considered the Energy per Cutting Surface [kWh/mm$^2$].

Table 3 represents the three components used for the case study, used by the authors in a previous study about build part orientation (Sartini *et al.*, 2023). Geometrical information on the components is given for each printing direction in Chapter 4.3. The parts are illustrated in the starting configuration. From this case study, 14 printing directions were analysed through the proposed method.

**Table 3. Case study components**

| Component A | Component B | Component C |
|---|---|---|
|  |  |  |

## 4.2. nPIs selection

For the present case study, four indicators were considered:

1. *TEC* (Total Energy Consumption) [kWh]: obtained by multiplying the Specific Energy Consumption (kWh/kg) by the mass (kg) of the object considered as the sum of the mass of the piece itself and the mass of the supports, if any. The total mass will vary according to orientation because the mass of the supports varies.
2. *EL* (Energy Layer) [kWh]: obtained by multiplying the Energy per Layer (kWh/layer) by the number of layers. The latter is calculated by dividing the height of the part along the printing direction by the thickness of the layer considering each technology. The height of the part varies according to orientation. In particular, a layer thickness of 0.03 mm for L-PBF and 0.46 mm for L-DED were chosen.
3. *ED* (Energy Dimension) [kWh]: represents the energy per mm of machined size. It is obtained by multiplying the consumption of the post-process wire EDM - Energy per Cutting Dimenson (kWh/mm) by the smaller size of the part in contact with the printing plate. This smaller dimension varies depending on the orientation of the part.
4. *ES* (Energy Surface) [kWh]: represents the energy per mm$^2$ of the machined surface and is obtained by multiplying the post-process band saw consumption - Energy per Cutting Surface (kWh/mm$^2$) by the projected area in the printing plate.

The ED and ES indicators were appropriately created to consider the energy consumption of post-processing operations.

## 4.3. Optimal printing direction calculation

The first step is the definition of weights. For this study, TEC was considered the most important indicator. EL and ED (or ES, depending on the component analysed) were considered less important than the TEC indicator and of equal importance, respectively. Therefore, giving a score of 6 to the indicator TEC and a score of 3 to the indicators EL and ED (or ES) results in weighting factors of 0.6 and 0.2, respectively [equation (7)]. It is to be noted that the weights chosen are arbitrary and for illustrative purposes. As L-PBF technology is the most common and widely used technology for printing metal components, an example of the calculation procedure considering component B is shown in Table 4. The method remains the same for the other combinations.

Table 4 shows the results of the different calculation steps. Starting from the data collected during the inventory phase and the geometric information at each orientation step, the selected EnPI values are obtained. Then, through equation (1), the difference between each indicator's maximum and minimum value is calculated. A normalisation phase is then applied by equations (2) and (4) at each orientation value and indicator. Based on these values and considering previously defined weighting factors, new weighted values are obtained through equations (8). Once the weighted values have been prescribed, the optimal orientation is evaluated using equation (9). The last column shows that the best printing direction is the one with orientation (135°, 45°, 135°).

**Table 4. Optimal build part orientation calculation for L-PBF process and Inconel 718 material**

| Orientations | | | L-PBF technology - Inconel 718 | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | | | | EnPI Calculation | | | Normalized EnPI $EnPI_i^{j\prime} = \frac{UD_i^j}{R^j}$ | | | Weighted EnPI $EnPI_i^{j\prime\prime} = EnPI_i^{j\prime} \times WF^j$ | | | Sum $\sum_{j=1}^{m} EnPI_i^{j\prime\prime}$ |
| X | Y | Z | Mass (kg) | N° Layer | Projected Area (mm$^2$) | TEC (kWh) | EL (kWh) | ES (kWh) | TEC | EL | ES | TEC | EL | ES | Optimal |
| 0 | 0 | 0 | 1.31 | 4333 | 4295.4 | 169.56 | 286.00 | 0.0033 | 0.450 | 0.083 | 1.000 | 0.270 | 0.017 | 0.200 | 0.487 |
| 90 | 0 | 0 | 1.40 | 2000 | 11332.0 | 181.50 | 132.00 | 0.0086 | 0.253 | 1 | 0 | 0.152 | 0.2 | 0 | 0.352 |
| 180 | 0 | 0 | 1.45 | 4333 | 4295.4 | 188.15 | 286.00 | 0.0033 | 0.144 | 0.083 | 1 | 0.086 | 0.017 | 0.2 | 0.303 |
| 0 | 90 | 0 | 1.52 | 3000 | 5457.7 | 196.91 | 198.00 | 0.0041 | 0 | 0.607 | 0.835 | 0 | 0.121 | 0.167 | 0.288 |
| 0 | 180 | 0 | 1.45 | 4333 | 4295.4 | 188.15 | 286.00 | 0.0033 | 0.144 | 0.083 | 1.000 | 0.086 | 0.017 | 0.200 | 0.303 |
| 0 | 0 | 90 | 1.31 | 4333 | 4295.4 | 169.56 | 286.00 | 0.0033 | 0.450 | 0.083 | 1.000 | 0.270 | 0.017 | 0.200 | 0.487 |
| 0 | 0 | 180 | 1.31 | 4333 | 4295.4 | 169.56 | 286.00 | 0.0033 | 0.450 | 0.083 | 1.000 | 0.270 | 0.017 | 0.200 | 0.487 |
| 45 | 45 | 45 | 1.31 | 4189 | 10292.0 | 169.56 | 276.50 | 0.0078 | 0.450 | 0.139 | 0.148 | 0.270 | 0.028 | 0.030 | 0.327 |
| 45 | 45 | 135 | 1.06 | 4189 | 10292.0 | 137.75 | 276.50 | 0.0078 | 0.973 | 0.139 | 0.148 | 0.584 | 0.028 | 0.030 | 0.641 |
| 45 | 135 | 45 | 1.06 | 4189 | 10292.7 | 137.75 | 276.50 | 0.0078 | 0.973 | 0.139 | 0.148 | 0.584 | 0.028 | 0.030 | 0.641 |
| 135 | 45 | 45 | 1.06 | 4543 | 9208.2 | 137.75 | 299.86 | 0.0070 | 0.973 | 0 | 0.302 | 0.584 | 0 | 0.060 | 0.644 |
| 45 | 135 | 135 | 1.06 | 4189 | 10292.7 | 137.75 | 276.50 | 0.0078 | 0.973 | 0.139 | 0.148 | 0.584 | 0.028 | 0.030 | 0.641 |
| 135 | 45 | 135 | 1.05 | 4543 | 9208.3 | 136.13 | 299.86 | 0.0070 | 1 | 0 | 0.302 | 0.6 | 0 | 0.060 | 0.660 |
| 135 | 135 | 45 | 1.05 | 4543 | 9211.0 | 136.15 | 299.86 | 0.0070 | 1.000 | 0 | 0.301 | 0.600 | 0 | 0.060 | 0.660 |
| 135 | 135 | 135 | 1.06 | 4543 | 9211.0 | 137.75 | 299.86 | 0.0070 | 0.973 | 0 | 0.301 | 0.584 | 0 | 0.060 | 0.644 |
| | | | | | $R^j$ | 60.79 | 167.86 | 0.01 | | | | | | | |

Table 5 and Table 6 show the best printing directions for the remaining components and technologies analysed and their total consumption, split into the various energy contributions.

The approach could be repeated around the obtained optimal orientations by increasing the number of orientations analysed. Results highlight that energy consumed during the printing phase is always higher than energy for feedstock or post-processing operations. However, post-processing is not negligible for some orientations (e.g., component C, L-DED technology) because the energy consumption is almost the same as for printing. Furthermore, the part build orientation selection cannot be carried out considering only the energy consumed during printing. Indeed, the energy related to feedstock and post-processing is sometimes up to around 30% of the printing energy (e.g., components A and B for the L-PBF process).

The part build orientation is carried out considering only one part at a time. The best direction calculated for a part does not consider the other parts that could be printed in the same job. Thus, optimising the direction for each part of the job does not guarantee minimising the energy consumption for the entire build. Indeed, energy consumption depends on the packing density, which is not considered in this study.



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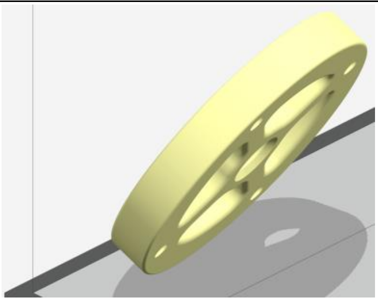
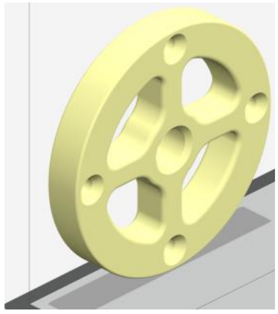
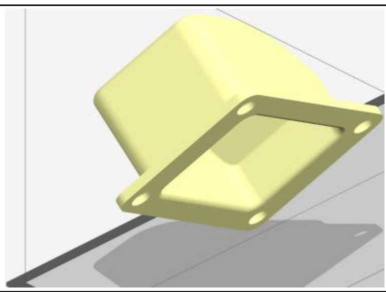
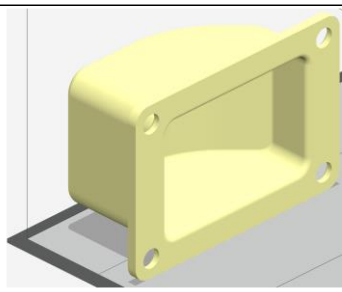
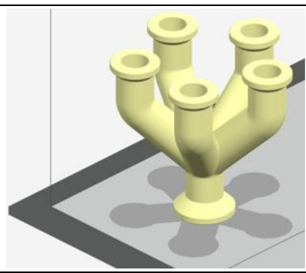
**Table 5. Optimal orientations for each component and technology**

| Component | Technology | X | Y | Z | Feedstock production [kWh] | Printing process [kWh] | Post-processing [kWh] | Total energy consumed [kWh] |
|---|---|---|---|---|---|---|---|---|
| **A** | L-PBF | 45 | 45 | 45 | 66.079 | 224.756 | 10.838 | 301.67 |
| | L-DED | 0 | 0 | 180 | 5.000 | 55.873 | 2.534 | 63.41 |
| **B** | L-PBF | 135 | 45 | 135 | 105.30 | 330.683 | 0.007 | 435.99 |
| | L-DED | 0 | 90 | 0 | 8.072 | 81.136 | 0.004 | 89.21 |
| **C** | L-PBF | 90 | 0 | 0 | 3.415 | 84.599 | 6.410 | 94.42 |
| | L-DED | 90 | 0 | 0 | 0.255 | 7.023 | 6.410 | 13.69 |

**Table 6. Optimal orientations representation**

<table>
<tr><td rowspan="2">A</td><td>45°,45°,45°</td><td>0°,0°,180°</td></tr>
<tr><td></td><td></td></tr>
<tr><td rowspan="2">B</td><td>135°,45°,135°</td><td>0°,90°,0°</td></tr>
<tr><td></td><td></td></tr>
<tr><td rowspan="2">C</td><td colspan="2">90°,0°,0°</td></tr>
<tr><td colspan="2"></td></tr>
</table>

## 5. Conclusions

The paper proposed an approach to calculate the optimal build part orientation considering the energy consumption. This method is for product and process engineers who want to evaluate and improve environmental sustainability for additive manufacturing processes. The methodology, independent of process type, considers energy related to feedstock, printing and post-processing operations. This study lays the basis for creating a software tool capable of assisting engineers in evaluating the optimal orientation from an environmental point of view. The tool has to interact with a 3D geometry (directly through a graphic engine or indirectly by employing APIs of commercial CAD systems tools) to extract



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the information (e.g., print height, projected area, overhang area) required to evaluate the EnPIs for each part build orientation. Moreover, the tool must manage a database containing the LCI for the requested printing and post-processing technologies.

The energy indicators selected do not consider product design (e.g., material density, safety factors) and process (e.g., productivity) parameters because, in this study, the part and its characteristics (e.g., shape, dimensions, material) are predetermined. Nevertheless, considering engineering indicators, the method can be extended to select the best design solutions, such as those resulting from generative design and topology optimisation. The process should be applied by considering an entire printing job rather than a part at a time. Indeed, by considering the packing density and optimising the build part directions of all the parts within the build box of a machine, it will be possible to guarantee the minimum energy consumption for the entire job.

The approach can be further developed by considering, for example, social indicators (e.g., powder released during post-processing operations). This study can also be included within a broader method (Sartini *et al.*, 2023) for the build part optimisation based on other criteria (e.g., cost, productivity, surface quality, strength). Since the rapid growth of innovative post-processing operations, the life cycle inventory needs to be extended to include such processes.

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