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Title: The impact of the risk of build failure on energy consumption in additive manufacturing

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Abstract

Additive Manufacturing (AM), also known as 3D Printing, is associated with significant promise in the manufacturing sector. However, it has been shown that the risk of build failure has a substantial impact on the costs of AM and that this results from a relatively high level of process instability. Importantly, for such a promising technology, the effects of the risk of build failure on energy consumption have not yet been studied, which creates a significant gap in the knowledge of the real environmental performance of AM. This research addresses this gap by investigating the energy consumption of AM subject to the possibility of build failure. This is done by constructing a novel expected energy consumption model, integrating process energy consumption, the energy embedded in the raw material and the probability of build failure as a function of the number of layers deposited. Model parameters are obtained from a series of build experiments conducted on the AM technology variant polymeric laser sintering, also known as laser powder bed fusion of polymers. The energy consumption model shows that the risk of build failure accounts for a substantial share of overall expected energy consumption, amounting to up to approximately 31% at full capacity utilization. Additionally, this paper uncovers a complex relationship between the risk of build failure and efficiency gains in per-unit energy consumption resulting from increasing levels of capacity utilization.

1. Introduction

The World Resources Institute has recently estimated that energy generation and consumption contributed to 73% of Global Greenhouse Gas emissions in 2017 (Friedrich et al., 2020). Additionally, Taylor (2008) estimated that industrial users are the largest consumers of energy and that their consumption will continue to grow until 2050. In this context, it has been stressed that the energy consumption of manufacturing processes is a key determinant of sustainability for manufacturers (Le Bourhis et al., 2013; Baumers et al., 2013; Wang et al., 2017; Wang et al., 2018a; Wang et al., 2019; Peng et al., 2019a; Peng et al., 2019b; Cappucci et al., 2020).

To measure the ecological impact of manufacturing activities, Kellens et al. (2012) stressed that information relating to manufacturing energy consumption, process productivity, and emissions is essential. However, it has been noted that the long supply chains and complex distribution networks in manufacturing increase the challenge of registering the resource flows (Surana et al., 2005). In this context, an important role falls to the measurement of carbon emissions originating from electricity consumption (Jeswiet and Kara 2008). Building on such data, the main goal in "design for environment" methodologies is to minimize resource consumption during the manufacturing process (Telenko et al., 2008).

Additive Manufacturing (AM), also known as 3D Printing, is associated with significant promise in the manufacturing sector due to its freedom from many constraints on product geometry and its ability to deliver highly customized products (Tuck et al., 2008). AM equipment enables a digitally controlled manufacturing process in which material is added in a sequence of steps, usually in a layer-by-layer fashion. Compared to conventional manufacturing (e.g., machining, injection moulding), AM affords new possibilities in product design (Hague et al., 2004), digital supply chain deployment (Tuck et al., 2007), and the use of new build materials (Huang et al., 2013).

AM may enhance process sustainability through improving resource efficiency (Despeissse et al., 2017) and extending the lifecycle of products (Wang et al., 2018b; Verboeket and Krikke 2019; Jiang et al., 2019; Gong et al., 2019). To complement sustainable AM, there is a need to improve manufacturing efficiency via less impactful supply chains (Huang et al., 2013), efficient process and resource recycling (Kohtala 2015; Despeissse et al., 2017).

A body of literature has investigated the energy consumption of various AM technology variants. Several studies have investigated the energy consumption of metal AM (Mognol et al., 2006; Kellens et al., 2010; Baumers et al., 2010; Baumers et al., 2011; Raoufi et al., 2020a; Raoufi et al., 2020b; Giudice et al., 2021; Peng et al., 2021; Zakaria et al., 2022) and polymer-based AM (Luo et al., 1999; Sreenivasan and Bourell 2009; Sreenivasan and Bourell 2010; Baumers et al., 2010; Faludi et al., 2015; Wiese et al., 2021; Lopes et al., 2022). Sun et al. (2021) reported that the AM processes and printed products must be validated and qualified to satisfy the standards of critical parts in energy production (e.g., nuclear energy, oil and gas), conversion, and storage systems (e.g., battery and fuel cell). Di and Yang (2022) investigated the economic and environmental benefits of the integrate Production-Inventory-Transportation (PIT) supply chain structure and suggested that this structure enabled by AM allows a reduction of approximately 26% of greenhouse gas emissions.

Additionally, the energy embedded in the used raw materials and the process energy consumption are considered in some studies. Morrow and colleagues (2007) calculated the energy consumption of Direct Metal Deposition (DMD) in this way for virgin H13 steel powder. Baumers et al. (2017) measured the energy embedded in recycled Ti-6Al-4V cast material. Gao et al. (2021) analyzed the energy consumption of raw metal material extraction and subsequent AM processes. Liao and Cooper (2021) investigated the embedded energy of feedstock material (powder and any inert shielding gas) in metal powder bed processes. Van Sice and Faludi (2021) compared the environmental impacts of AM and conventional manufacturing, showing that metal AM has a significantly higher environmental footprint than some conventional process. Monteiro et al. (2022) undertook a literature review of metal AM and summarized four types of resource efficiency perspectives, including design, material, process and recycling perspectives.

Alongside the investigation of energy consumption, the financial cost of operating AM technology has received attention (Alexander et al., 1998; Hopkinson and Dickens 2003; Ruffo et al., 2006; Baumers et al., 2016; Raoufi et al., 2022). A significant insight from Baumers et al. (2017) is that the expected impact of build failure is absent in most investigations of the cost of AM. The existing literature investigating build failure in AM is divided into four categories, including software-based simulation (Bresson et al., 2022; Chakraborty et al., 2022; Ge and Flynn 2022), design optimization (Misiun et al., 2021; Prabhu et al., 2021; Xu et al., 2022), data-based estimation (Wang et al., 2021; Jirandhi et al., 2022) and mechanism exploration (Osswald et al., 2021; Roh et al., 2021). However, the impact of build failure for the environmental performance of AM, in terms of both process energy consumption and the energy embedded in the used raw materials, has not yet been investigated directly and in combination. This forms a significant omission in the currently available literature on AM.

Some existing work has touched upon such “ill-structured” aspects (Son 1991) in AM energy consumption, mostly emphasizing raw material losses occurring during the additive process (Kellens et al., 2010; Faludi et al., 2017). Investigating material losses, Ruffo and colleagues (2006) modelled material wastage by applying a waste factor, between 0 and 1, to unprocessed powder in a study of polymeric laser sintering. Similarly, Kellens et al. (2011) applied a refresh rate of around 45%, as suggested by Dotchev and Yussof (2009), to quantify the waste streams occurring in laser sintering. Baumers and Holweg (2019) found that approximately 90% of powder remains in the build space without being converted into parts, and approximately 10%

to 50% of this remaining powder is typically discarded.

Build failure poses a risk to product quality and further influences the energy and material flows in AM through the need for reprinting. This failure may change energy demand, material supply and the nature of production planning (Holmstrom et al., 2016). Although AM supply chains can consume significantly less energy, due to shorter transportation and less material use, the high energy needs of the AM process and material preparation should not be underestimated (Li et al., 2017).

Due to the risk of build failure, which can be substantial in AM (Baumers and Holweg 2019), it is likely that the available methodologies for measuring the energy impact of AM understate the actual levels of energy consumption. To address this issue, this paper offers the following contributions. First, it presents a novel model of the energy consumption of AM which incorporates the risk of build failure. This is done by attaching a layer-based build failure model to an AM energy consumption model. Second, this paper assesses both process energy consumption and the energy embedded in the raw material used during the additive process. To achieve this, a sub-model articulating an equilibrium between material inflows and outflows is employed. This is particularly relevant for AM technology variants that exhibit significant material waste streams, which generate an additional energy footprint. To demonstrate the application of this model, this paper explores the total energy consumption for the AM technology variant polymeric laser sintering.

The methodology adopted to investigate the energy consumption of AM subject to the risk of build failure is presented in Section 2. Following this, Section 3 specifies the energy consumption model and presents the results with a focus on the effects of capacity utilization, risk of build failure, and energy embedded in the raw material. Section 4 then reflects on the results, compares the obtained Specific Energy Consumption (SEC) values to those presented in the literature, and discusses the implications. Conclusions are drawn in Section 5.

2. Methodology

2.1 Process mapping

Understanding the consumption of resources, such as raw material, energy, time, and money plays a key role in any investigation of the commercial and environmental performance of AM. In the construction of such resource consumption models, the first step is usually to establish a process map representing the elements of the process under investigation. Process maps are specific to individual AM systems and this paper constructs a model for the EOSINT P 100 system, which is a widely used industrial polymeric AM machine. The technology variant, laser sintering, also known as laser powder bed fusion, was chosen because it is frequently adopted in the manufacture of end use products (Ruffo and Hague 2007). However, the model and methodology introduced in this paper can easily be extended to other machines and processes.

The general operating process in laser sintering is as follows. A layer of material is deposited on the build platform. Following this, the system selectively scans the surface of the powder bed with a laser, generating a thin, planar slice of solid part geometry surrounded by unfused powder. Once the sintering of a layer is finished, a fresh layer of powder is added, and this process repeats layer by layer until the part is completed. It is important to note that polymeric powder bed fusion systems of this kind allow the construction of multiple parts per build and do not require the deposition of auxiliary supporting structures (Gibson et al., 2010). Figure 1 summarizes the general activity flow of laser sintering, identifying the material, energy, and information flows investigated in this research.

As seen in Figure 1, the laser sintering process consists of a sequence of steps beyond the deposition operations described above. The initial steps cover file preparation, control system set up, machine preparation, and build release. Following this, the build process takes place, involving machine warm up, the actual material deposition cycle and machine cool down. The next steps are retrieval of the parts and machine cleaning. After this, should the build process have failed, the process re-initiates at the file preparation step; otherwise, the final step is post processing of the parts. Figure 1 also shows that energy inputs are modelled as flowing into the raw material, alongside the machine warm up, deposition process and machine cool down steps. The energy consumption during removal and post processing is not included in the scope of the modelling because it is related to the geometric complexity, and investigation of this is not an aim of the paper (Baumers et al., 2017). To this end, a single geometry was used in the build experiments and analysis.

2.2 Specification of the energy consumption model for laser sintering

A scheme of the conceptual model of energy consumption developed in this paper is presented in Figure 2.

As can be seen, the total energy consumption in megajoules (MJ), E_{build}, is composed of the energy embedded in the material, E_{embed}, and the process energy, $E_{process}$, which are both affected by the risk of build failure $P(N)$, and capacity utilization, q, expressing the number of parts in a build. The total energy embedded in the material depends on the material consumption during the process and the mean embedded energy of that material, m. The material consumption in grams includes the mass of the parts, M_{part}, waste material, M_{waste}, and material losses, M_{loss}. The process energy consists of build job energy, for example warm up, $E_{warm\ up}$ and cool down, $E_{cool\ down}$ as well as depositing process energy, $E_{deposition}$.

2.2.1 Process energy consumption estimation model

The sub-model used to estimate the process energy consumption of the AM system $E_{process}$ is shown in Eq. (1).

$$E_{process} = E_{warm\ up} + E_{deposition} + E_{cool\ down} \tag{1}$$

In this model, $E_{warm\ up}$ and $E_{cool\ down}$ reflect the fixed energy consumed during the warm up and cool down processes per build respectively. The values of 17.46 MJ and 7.77 MJ are taken for this, based on prior work (Baumers et al., 2015). $E_{deposition}$, represents energy consumption during the deposition process, which was measured using a digital power meter (Yokogawa CW240) in our build experiments.

2.2.2 Material consumption estimation sub-model

In polymeric laser sintering, the powder that is not fused during the printing process can be, in principle, recycled for use in future builds. However, the recycled powder may be thermally degraded due to continuous exposure to the high temperature environment during the printing process. Therefore, virgin powder is normally added and mixed with the used powder, both to replace the consumed powder and to improve the powder's processability (Ruffo et al., 2006).

To simplify the estimation of material consumption, this model assumes that the AM system operates in a steady state in which, on average, the mass of the virgin powder introduced into the system is in equilibrium with the mass of the material exiting the system. Therefore, the amount of fresh powder material introduced into system, M_{input}, equates to the mass of powder fused as parts, M_{part}, the powder waste due to degradation, M_{waste}, and any other unaccounted-for powder losses, M_{loss}, for example due to powder evaporation during the sintering process or powder losses during machine cleaning. Figure 3 and Equation (2) summarize this model. All subsequent material-specific values in this research refer to PA2200, which is a nylon 12 polymer powder.

$$M_{input} = M_{part} + M_{waste} + M_{loss} \tag{2}$$

Equation (3) can be used to determine the mass of material fused, where ρ_1 is the density of the material as fused (0.93 g/cm^3, (EOS GmbH 2021), V_{part} is the volume of single geometry fused, and q is the number of parts contained in a build.

$$M_{part} = \rho_1 \times V_{part} \times q \tag{3}$$

Equation (4) specifies the waste streams resulting from the printing process, where ρ_2 is the density of the virgin powder (0.45 g/cm^3, (EOS GmbH 2021), V_{bed} is the volume of the available build space of the machine and α is the waste factor, as suggested by Ruffo et al. (2006). As suggested by Kellens et al. (2011), Baumers and Holweg (2019), the waste factor is equal to the refresh rate. This value is typically between 10% and 50% for polymer laser sintering, dependent on the operator's discretion and material used.

$$M_{waste} = \rho_2 \times \left(V_{bed} - V_{part} \times q\right) \times \alpha \tag{4}$$

2.2.3 Model of the energy embedded in the material

The energy embedded in the material (measured in megajoule, MJ), E_{embed}, reflects the total energy required to produce the raw material (Morrow et al., 2007), and is specified in Eq. (5).

$$E_{embed} = m \times M_{input} \tag{5}$$

In this model, m is the mean embedded energy of the raw material processed, (148 MJ/kg, according to Ashby (2011) and M_{input} is the overall mass of raw material consumed by the build operation, according to the steady state assumption shown in Eq. (2).

2.3 Expected energy consumption with build failure

As shown in the process map (Fig. 1), the process and, by extension, consumption of material and energy repeats if build failure occurs. So, the next step is to extend the energy consumption model to include build failure. In this research, any unrecoverable disturbance during the build process is treated as build failure. It is assumed that failure events emerge with a given probability in a way that reflects the layer-by-layer deposition process. To keep this model as simple as possible, it is assumed that the probability of build failure occurring with the processing of each layer is a constant, entering the model as the probability of failure per layer, $p_{constant}$. Baumers and Holweg (2019) investigated a similar build failure model and estimated that the constant probability of failure per layer is 0.016% for the AM machine investigated in this research. To obtain the overall probability of successfully finishing a build, a discrete probability tree model is established (Fig. 4).

Following the approach by Baumers and Holweg (2016), the probability of successfully completing a build can be specified as a function of the total number of layers, N:

$$P(N) = (1 - p_{constant})^N \tag{6}$$

This probability can then be attached to the estimators, $E_{process}$ and E_{embed}, to form a model of total expected energy consumption of the build with failure, E_{build}:

$$E_{build} = \frac{E_{process} + E_{embed}}{P(N)} \tag{7}$$

2.4 Test specimen and experiment methodology

To test the total expected energy consumption model, this study estimates the energy consumption during the manufacture of test specimens, shown in Figure 5. The "spider" shape of the test specimen restricts the attainable overall packing density, resulting in a realistic level of build volume utilization (Baumers et al., 2011).

This allows an assessment of the effect of capacity utilization on the energy consumption, which was shown to be significant (Baumers et al., 2017). To do this, the energy consumption data were collected from different build configurations successively adding test specimens to reflect an increasing utilization of the available build space. In this process, additional parts were added to fill a horizontal band of build space with up to five test specimens. The model developed in the remainder of this paper then uses the experimental data to estimate energy consumption as the full build space is utilised, starting from the floor of the build volume. This procedure allows the generation of build configurations containing 1 part (denoted "single part build") to 55 parts (denoted "full capacity build").

3. Results

3.1 Breakdown of total expected energy consumption

Figure 6 (a) and (b) show the energy consumption for the single part (q=1) and full capacity build (q=40) configurations at the risk of build failure. The total expected energy consumption is broken down into the model components. Comparing both pie charts, it is evident that the composition of the energy consumption changes with the build capacity utilization. The energy embedded in the material is the largest contributor in both the single part build (57.40% in Fig. 6 (a)) and the full capacity build (47.93% in Fig. 6 (b)). This emphasizes that a significant share of the overall energy consumption in laser sintering is due to the energy embedded in the raw material and will be explored further in Section 3.2.

The risk-related energy consumption is obtained for both levels of capacity utilization by subtracting $E_{process}$ and E_{embed} from E_{build}. The results suggest that the energy associated with risk of build failure is substantial at high levels of capacity utilization, at 31.06% of the total expected energy consumption. However, this is decreased when the available capacity is not fully utilized. For the single part build, the share of the total energy consumption falls to 22.75%. The reason for this pattern is the increase in the number of deposited layers in line with higher levels of capacity utilization, which leads to an accumulating risk of build failure.

Excluding the risk-related energy consumption and the energy embedded in the material, the energy for warm up is the major contributor in the process energy consumption (51.08%) in the single part build configuration, followed by the deposition process energy (26.19%) and energy for cool down (22.73%). However, in the full capacity build scenario, the deposition process consumes the most energy (84.67%) during the printing process, and warm up and cool down processes use smaller amounts of energy, at 10.61% and 4.72% respectively.

3.2 Energy consumption per unit

To further investigate the effects of capacity utilization on the energy consumption, a unit-based model of total expected energy consumption is established, as shown in Eq. (8). The capacity utilization, q, is represented by the quantity of parts in the build and ranges from 1 to 55.

$$E_{part} = \frac{E_{build}}{q} \tag{8}$$

In addition, the specification of the total expected energy consumption model, E_{build}, is adjusted to separate the contributions of embedded energy and risk-related energy consumption. Four model specifications arise: model ***a*** as in Eq. (8) originally, model ***b*** with embedded energy but excluding build failure, model ***c*** with build failure but excluding embedded energy, and model ***d*** covering process energy consumption with no embedded energy and build failure. The unit-based model allows these energy consumption behaviours to be explored across the entire range of build capacity utilization, depicted in Figure 7.

As can be seen in Figure 7, the unit energy consumption follows a non-monotonously decreasing saw-tooth pattern across all four model specifications, which is a result of packing five parts in each band of build space. This effect is caused by the layer-wise filling of the available build capacity, as documented for laser sintering production costs by Baumers and Holweg (2019) and Ruffo and Hague (2007).

Figure 7 also shows that increasing the capacity utilization generally results in decreasing per-unit energy consumption in sparsely filled builds. Interestingly, though, the model specifications that include failure (models ***a*** and ***c***), show that an accumulating risk of build failure begins to overwhelm aforementioned efficiency gains at higher levels of capacity utilization. This results in a U-shaped pattern of energy consumption in which the minimal per-unit energy consumption occurs at q=40 in the full model (model ***a***). At this level of capacity utilization, the total energy consumed for the manufacture of a sample part is 15.05 MJ.

Pairwise comparison of models ***a*** to ***c***, and ***b*** to ***d***, shows that the energy embedded in the material leads to a dramatic increase in the per-unit energy consumption as the quantity increases. The increase in total energy consumption is from approximately 210% to 390% across the entire range of capacity utilization.

4. Discussion

The results presented in Section 3 demonstrate a realistic and practical way to model the energy footprint of AM, extending previous work on AM energy consumption by studying the energy embedded in the material, the effect of capacity utilization, and the expected impact of the risk of build failure.

The results can be compared to the literature by assessing the Specific Energy Consumption (SEC), which is the energy consumed by the AM process per unit mass of product geometry deposited (mostly measured in or convertible to MJ per kg). Note that this omits the energy embedded in raw materials. Incorporating the risk of build failure, the following specification for SEC is constructed:

$$SEC_{build} = \frac{E_{process}}{P(N) \times M_{part}} \tag{9}$$

In terms of energy consumption, this research also explored the effects of embedded energy on SEC of AM through adding the energy embedded in the material E_{embed} into the numerator of Eq. (9). Table 1 provides an overview of SEC results.

Table 1 Specific energy consumption comparison for AM processes

Literature	Luo et al. (1999)	Kellens et al. (2010)	Baumers et al. (2010)	Baumers et al. (2015)	This research: Excl. embedded energy	This research: Incl. embedded energy
AM variant	Laser sintering	Laser sintering	Selective laser melting	Laser sintering	Laser sintering	Laser sintering
Material used	Polymer	PA2200	SAE 316L	PA2200	PA2200	PA2200
SEC (Single part build) (MJ/kg)	N/A	N/A	139.50	1122.09	1304.10	6203.96
SEC (Full capacity build) (MJ/kg)	107.39; 144.32	130.12	111.60	113.66	161.42	542.45

The comparison in Table 1 shows that the energy consumption levels estimated in this research are higher than the available literature, suggesting that previous work has understated the energy consumption of AM. The results confirm, as expected, that the degree of capacity utilization has a significant effect on the energy consumption of the process (Baumers et al., 2017), highlighting its importance for operating the process efficiently. However, the relationship between capacity utilization and efficiency gains in per-unit energy consumption is non-linear, the U-shaped pattern (models ***a*** and ***c***) in Fig. 7, with the most energy-efficient builds occurring at intermediate levels of capacity utilization. This is due to the accumulating risk of build failure as the Z-height in the builds becomes large. Increasing the capacity utilization further, improved amortization of fixed job energy consumption but this was insufficient to offset the increased risk of build failure and waste in embedded energy. Therefore, in practice, the risk of build failure and energy embedded in the material should not be overlooked when assessing the environmental performance of AM systems. This argument is analogous to existing research on the financial cost of AM (Baumers and Holweg 2019).

It is also important to note that accounting for embedded energy is paramount for improving the degree of transparency in understanding the total energy consumption of the manufacturing process. AM already has an inherent advantage in this regard as it is possible to produce complex geometries in a single manufacturing step; this contrasts to conventional manufacturing, which often requires multiple operations spread across different sites (Baumers et al., 2013). This research expands the scope of the energy consumption analysis, using well-documented methods to offer an even more realistic picture of the true energy footprint of AM.

Moreover, the results of this work underline the considerable impact of material waste streams on the environmental footprint of AM. Against the popular narrative, many AM processes create significant waste streams that need to be taken into account when evaluating the environmental performance of AM, for instance via life cycle assessment (Kellens et al., 2012; Faludi et al., 2015; Kellens et al., 2017a; Kellens et al., 2017b). Excluding the risk of build failure, the SEC values for the single part build (5859.50 MJ/kg) and full capacity build (337.25 MJ/kg) are significantly different from the situation excluding waste streams (1231.69 MJ/kg vs. 107.80 MJ/kg, respectively). The comparison of the SEC values in Table 1 suggests that waste streams have a bigger impact on the environmental performance than the risk of build failure.

The difference in energy consumption behaviour between additive and conventional manufacturing processes, such as injection moulding, requires acknowledgement. In AM, since the build volume is fully packed at q=55, there is no improvement in the unit energy consumption in choosing to build a marginally higher quantity of parts. This is because producing one more part would need a new build cycle, resulting in a repeat of the full, fixed job energy consumption. Moreover, the minimum achievable energy consumption in AM is subject to the most energy-efficient operation for one build. Whereas the energy consumption curve in conventional manufacturing decreases asymptotically as the volume increases, continually improving the per-unit energy consumption.

Finally, sustainable AM requires greener supply chains, more efficient manufacturing process and high-quality resource recycling (Huang et al., 2013; Kohtala 2015; Despeissse et al., 2017; Allwood 2022). Additionally, the impacts of build failure on the complexity of supply chain structure should not be underestimated (Holmstrom et al., 2016; Li et al., 2017). Moreover, the recycling and reuse of wasted material have a key role to play in improving resource efficiency in AM (Huang et al., 2013), while the combination of digitalization, interconnection and automation is likely to facilitate resilient and efficient AM implementation.

5. Conclusions

This paper has investigated the effects of the risk of build failure on the energy consumption of AM. This has been achieved by modelling the expected energy consumption per unit across the entire range of build capacity utilization. Embedded energy is also considered as part of the total energy consumption to assess the overall energy footprint of AM.

In many existing AM studies, the effects of the risk of build failure on AM energy consumption are ignored. The model proposed in this paper allows researchers and manufacturers to obtain expected energy and material consumption information for the investigated system and shows how more realistic models can be constructed. It can thus facilitate further research to mitigate the environmental impacts of AM, in terms of total energy consumption, relevant to specific design methodologies (Baumers et al., 2013). Without consideration of build failure, process energy consumption estimates may not be realistic and resource consumption may be underestimated, leading to overly optimistic assessments of energy demands and the environmental impacts of AM.

The results also show that, for the investigated laser sintering system, the energy embedded in the material has a greater impact on the total energy consumption than the AM process itself. Moreover, the impacts of waste streams have an outsized effect on the ecological impact of AM compared to the risk of build failure.

A limiting factor in this investigation of the effects of build failure is that it investigated the single machine case only. When considering mass production using AM, process failure on individual AM machines is likely to affect the operation of other machines and the overall resource consumption. Operating multiple AM machines allows further optimization. For example, when operating two machines, the production time of splitting jobs equally into two builds tends to be shorter than filling one and running another at lower capacity, therefore, influencing appropriate job scheduling. In addition, in this paper build failure is explored in the context of build configurations containing identical parts in the form of a fixed probabilistic value for each layer. This might not be reflective of common practice for the technology as mixed-part builds are often used (Ruffo and Hague 2007; Baumers et al., 2017). The effect of shape complexity, design complexity, process parameters and parts orientation may in reality affect the probability of build failure. To address these limitations, further research could expand the presented model. One important consideration would be to systematically consider the role of product geometry and other layer-based characteristics. Such an investigation could be done in the context of part design, multiple machines, mixed part geometries, build volume packing and production scheduling.

Although the energy accounts for only a small portion of total production costs (Ruffo et al., 2006; Baumers et al., 2013), energy-efficient operation of AM is crucial to improve its environmental friendliness. It is shown that the total expected energy consumption of AM is reduced by operating AM at intermediate levels of capacity utilization. Monitoring manufacturing processes are conducive to reducing parts scrappage (Wuest et al., 2014; Rao et al., 2015). Moreover, this paper suggests that processes and product designs should be leveraged to minimize the Z-height of builds, in order to decrease the possibility of build failure and its adverse impact on the environmental performance of the AM process.

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Figures

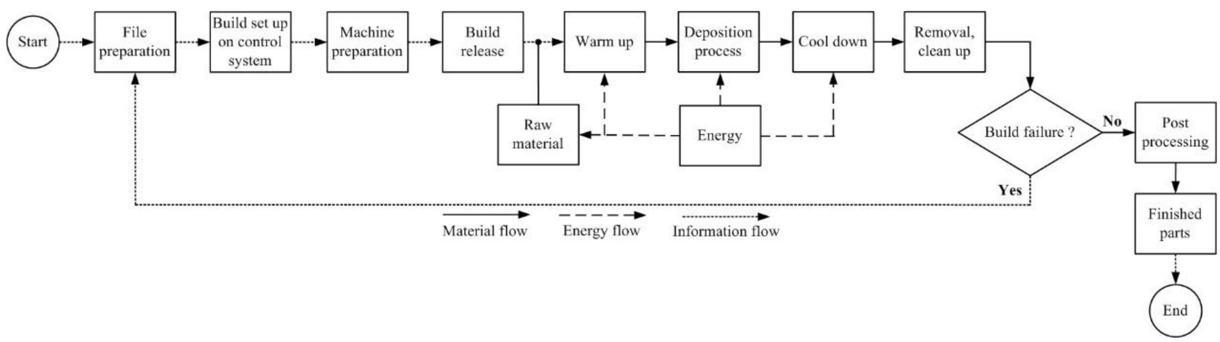


Figure 1 Process map of polymeric laser sintering

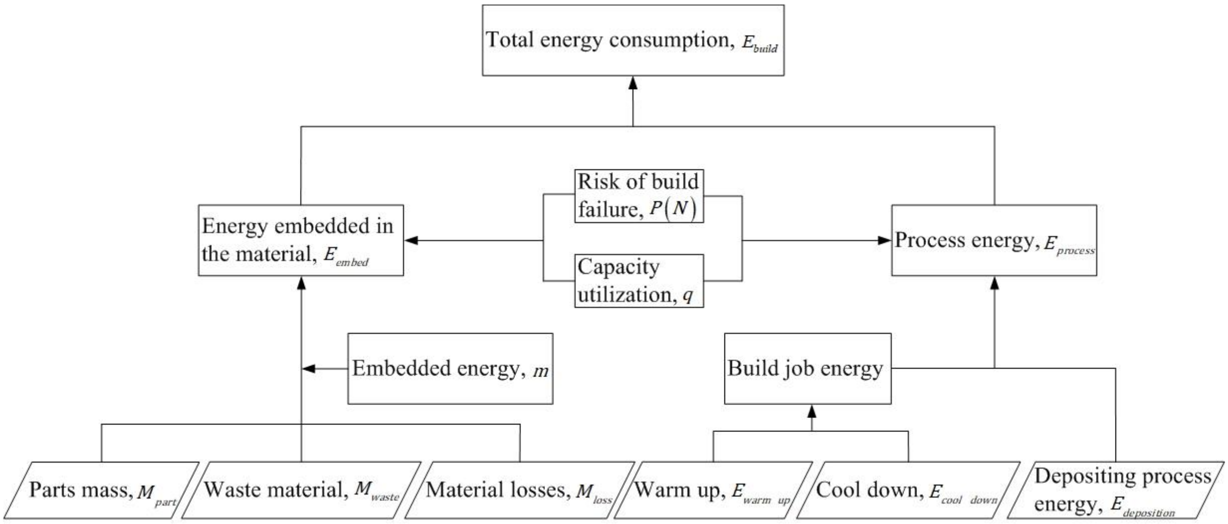


Figure 2 Scheme of the energy model

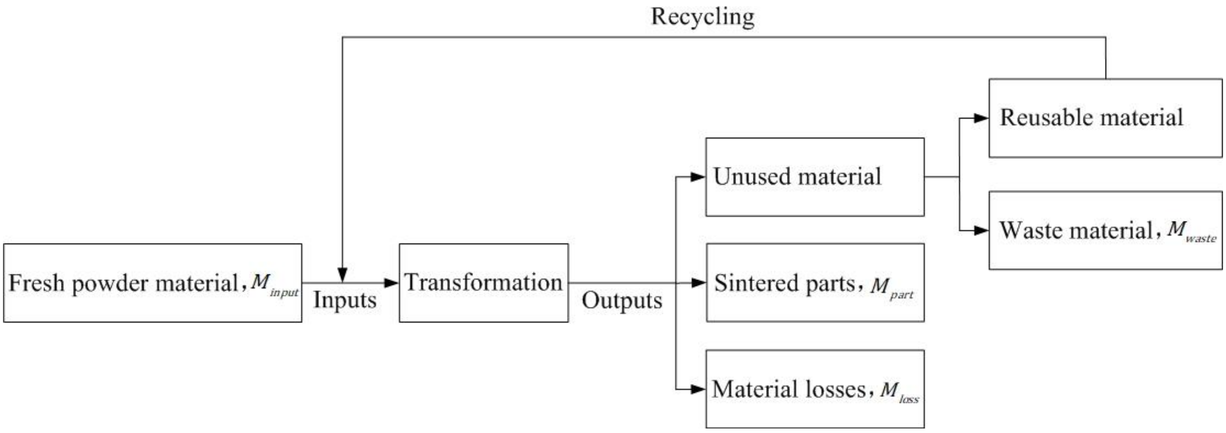


Figure 3 Material process model of AM

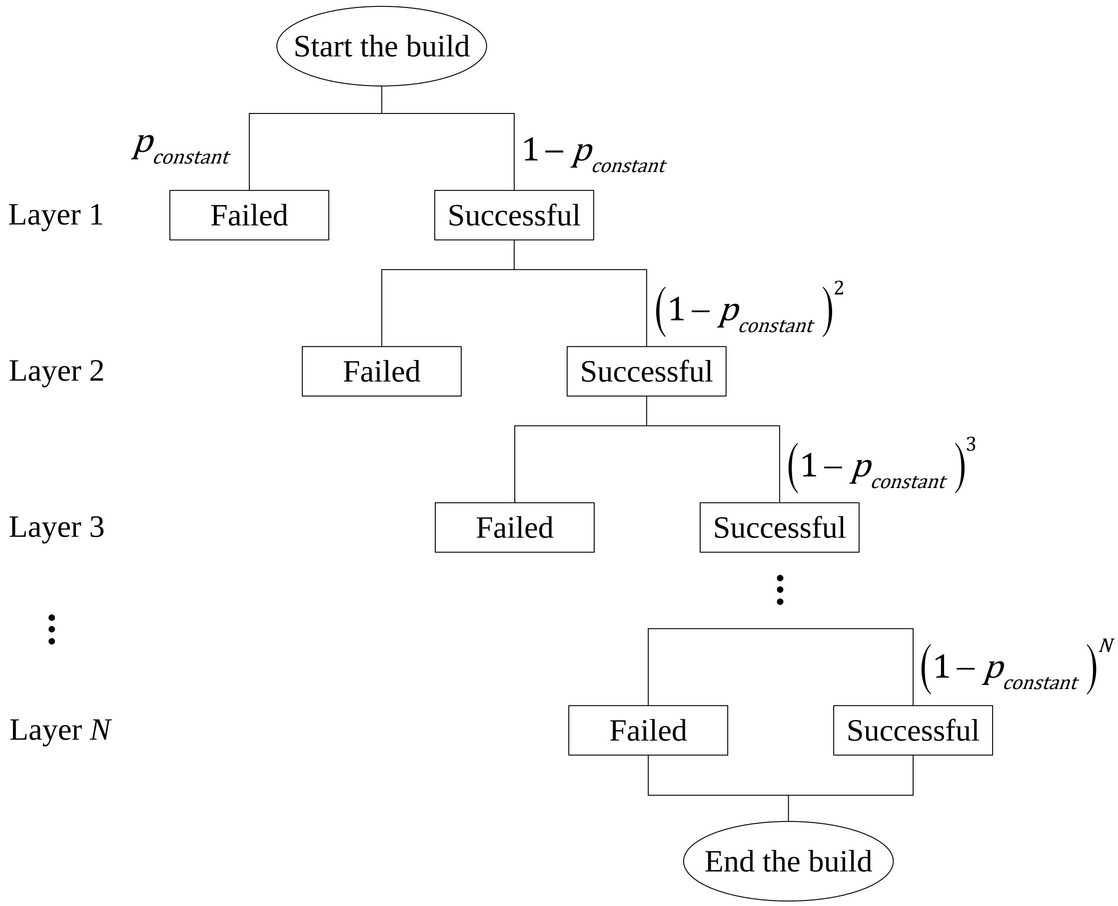


Figure 4 Probability tree model (Baumers et al., 2017)

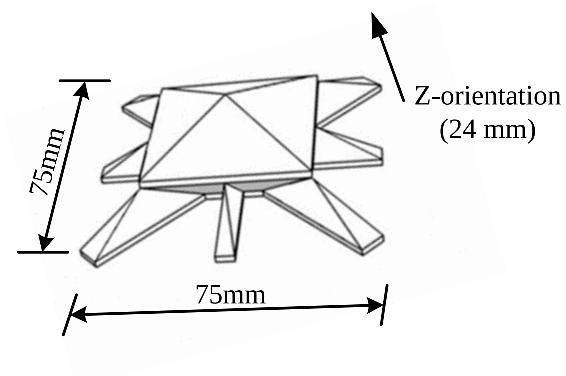
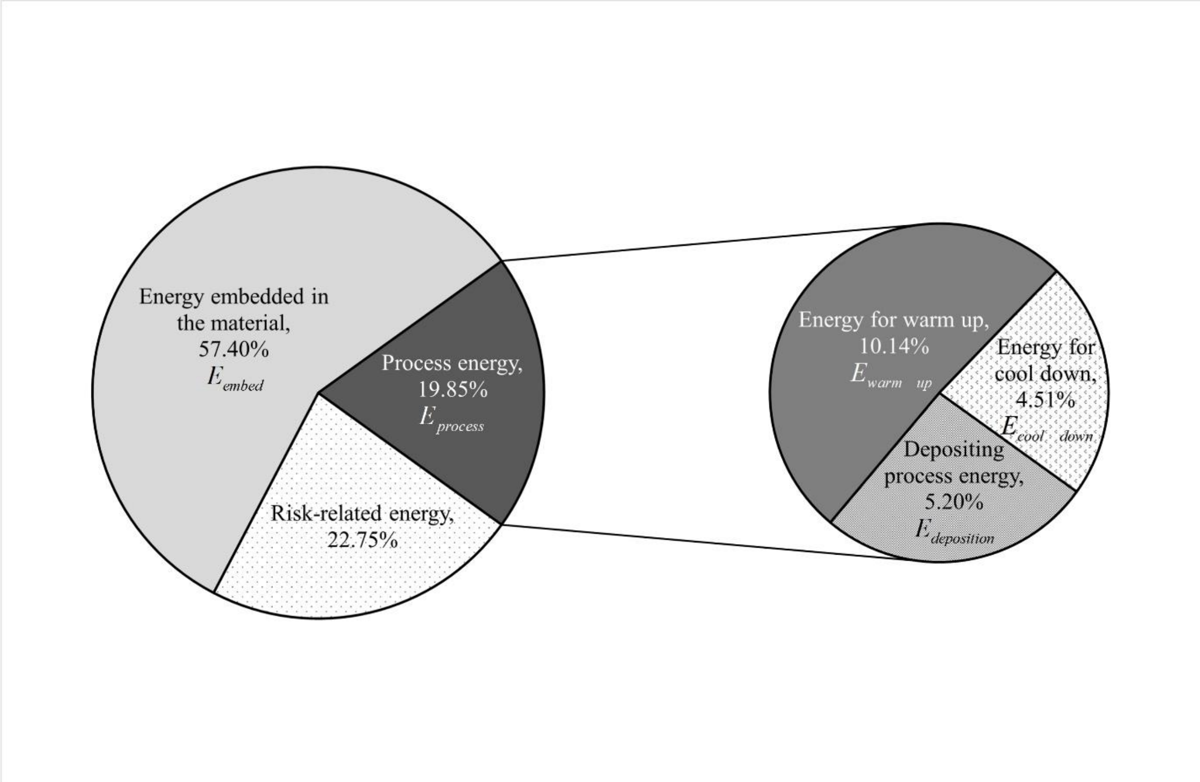


Figure 5 The standardized test part (Baumers et al., 2011)



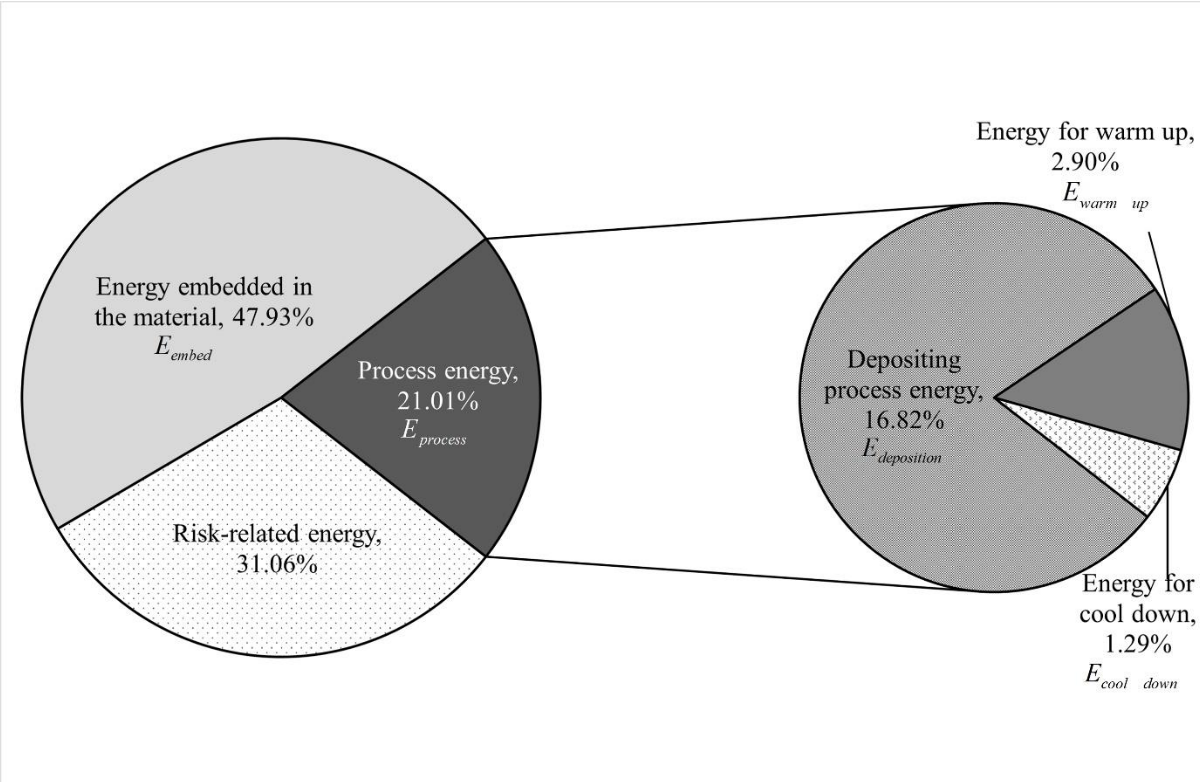


Figure 6 (a) Breakdown of total expected energy consumption (MJ) in the single part build configuration (*q*=1) and (b) breakdown of total expected energy consumption (MJ) in the full capacity build configuration (*q*=40)

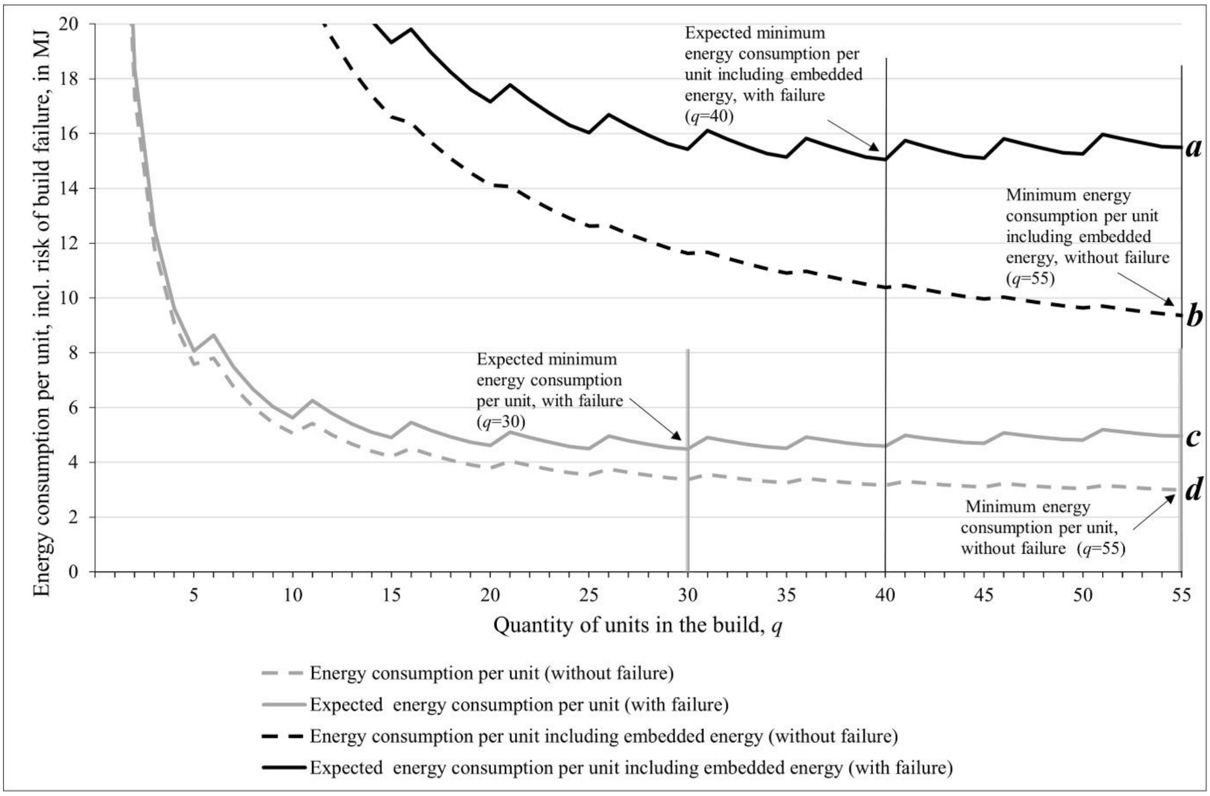


Figure 7 Relationship between energy consumption per unit (MJ) and quantity