Additive Manufacturing in the Scope of Industry 4.0: A Review on Energy Consumption and Building Time Estimation for Laser Powder Bed-Fusion Processes

Mario Rupp[1,*], René Klink[1], Markus Merkel[1], David K. Harisson[2]
[1]Aalen University, Germany
[2]Glasgow Caledonian University, Scotland
[*]Corresponding Author: Mario.Rupp@hs-aalen.de

Abstract: The paradigm of Industry 4.0 pushes additive manufacturing (AM) from rapid prototyping towards the position of series production. Especially in metal 3D printing, increased attention is being paid to the topics of sustainability and resource efficiency. Energy demand during production and the calculation of building times play a decisive role here. Science has developed models for calculating energy consumption based on analytical and empirical approaches. Building time calculators have been introduced using a wide variety of analytical, analogical and parametric approaches. The present review summarizes the results and the state of the art, illustrates the results graphically and thus paves the way for further research approaches. The specific energy consumption per kilogram of processed material has risen over the last decades, which can be explained by higher technical requirements for production machines. Building time calculations continue to be subject to errors, depending on the type of calculation. The introduction of machine learning approaches has the potential to reduce this discrepancy.

Keywords*: DIRECT DIGITAL MANUFACTURING, ENERGY CONSUMPTION, BUILDING TIME ESTIMATION, SUSTAINABILITY*

1. Introduction

Industry 4.0 is shaping the manufacturing environment. Since its introduction in 2015, the buzzword is used to describe the paradigm of digitization, connection and interaction of machines, products and factories [1]. Authors distinguish between several aspects of Industry 4.0 when it comes to the influence of the production such as technology, organization and social aspects [2]. The main focus of the research was on the technical aspects including the development of so-called cyber-physical systems. These systems are the connection between the digital and physical world with one of the key systems of additive manufacturing (AM) [3]. Geometries are designed, simulated and optimized digitally and the technology allows the user to directly produce the object in a layer-wise process. The present research, therefore, focuses on metal AM with the main process of Laser Powder Bed-Fusion (LPB-F). Introduced as Direct Metal Laser Sintering (DMLS) in 1994, the process evolved over the last three decades towards increasing material availability, higher quality aspects as well as process developments. Metal powder is applied to the build platform in a build chamber. Typical coating thicknesses vary between 30 µm - 50 µm [4]. A laser unit then melts the corresponding areas locally. After solidification, the deformed material embodies the end geometry. This process is repeated until the component is completed in height. Production usually takes place in an inert gas atmosphere and is similar to the welding process. Due to its strong improvements, L-PBF is rolling from niche technology of rapid prototyping towards serial production [5]. Nevertheless, technology introduction in the production industry is highly challenging. Besides adjustments in supply chains and process design for factories, also the economical side is increasingly important for implementing and using the technology [6]. With existing subtractive and conventional manufacturing methods, highly developed, optimized and efficient processes are available. The comparison on the technical and economical side is one of the main aspects when it comes to decision making [7]. Initial cost models pave the way to an economic decision. Within the current technology, AM seems to be more expensive than conventional manufacturing, especially for high batch sizes [8]. However, there are major differences in the literature, also due to the main cost drivers. These include energy requirements and the calculation of building time, both directly related to the manufacturing machine itself.

Energy consumption plays a decisive role in new technology implementation. The trend towards more environmentally conscious processes, energy savings and emission reductions are necessary to achieve climate targets. Different authors have already studied the environmental benefits of L-PBF and identified advantages [6, 9]. Despite the higher input in the manufacturing process, the technology requires less energy overall due to the low buy-to-fly ratio, the ratio of primary material to waste, and therefore also emits fewer emissions [10]. Energy demand for the manufacturing process could be described by primary and secondary energy. Primary energy is defined as the energy required to convert the material from powder to solid metal and is also called “printing energy” [11]. This also includes process-relevant energies such as the consumption of the gas pump. Secondary energies are those which support the process before or after, e.g. for removal of the powder. As a decisive parameter for the comparison, the specific energy consumption (SEC) can be used. It is the quotient of the energy required per kilogram of material solidified (kWh/kg). When it comes to the analysis of the SEC, available studies are bound to multiple parameters such as material specifications, machines and required quality. In addition, the authors study different process chains and, in some cases, also consider the pre- and post-processing involved in the additive process. For example, Faludi et al. studied the life cycle assessment of the L-PBF process including the whole process chain. For manufacturing, the authors concluded, that electric energy is the key parameter for the environmental impact [12].

Nevertheless, the authors argued that a lot of research was done but with a focus on the polyamide side and other processes [11]. Analysing literature, primary data collection on energy consumption in the L-PBF process also shows different main consumers during the construction process. Ma et al. illustrated that the auxiliary system consumes the most energy during manufacturing, followed by the cooling system and the laser [13]. In controversy, Liu et al. argued, that the laser is the most energy-intensive unit, accounting for more than 68% of the whole consumption [14]. In their research, Gao et al. showed that the system loss and the secondary energy of the manufacturing machine are the main energy drivers [15]. This different understanding might be stated because of the complexity of energy consumption and the many dependencies. Data collection in this area of research is highly individual and influenced by many parameters.

Building time calculations are of crucial importance in production [16]. For example, supply chains, production planning and scheduling depend on a correct prediction of the production time. While conventional methods such as turning, milling and drilling have relatively short production times, building times of several days can be state of the art for AM. Accordingly, errors in the time calculation are to be understood differently. Absolute errors of a few percent mean a massive relative delay of several hours in AM. Authors have recognized the importance of the topic and developed different approaches to solving the construction time calculation [17]. In principle, models of all powder bed-based processes, for metal or polyamide, can be applied and transferred to each other. Various other models for printing processes such as Fused Deposition Modelling (FDM), Layer Object Manufacturing (LOM) or Direct Deposit Manufacturing (DDM) can not be transferred. Due to the crucial role in AM, authors are trying to directly drive build time optimization in addition to developing a build time model [18]. Common optimizations increasingly include the packing of a building platform within the build chamber [19]. The time for coating or preheating and cooling afterwards is thus distributed over several components, while the fixed times per component do not change. In addition, algorithms have been developed to improve component orientation in the build chamber [20]. Ultimately, this again increases packing, but with a different approach. Minimizing the building height reduces the number of layers and thus reduces the building time.

However, in total, three different approaches can be distinguished in the time calculation. These are the parametric, the analytical and the analogical approach and were first classified by Zhang et al. [21]. The parametric approach requires only a few parameters to calculate a result [22]. Mainly object parameters like building volume, height, and surface roughness could be considered to estimate the build time [18]. However, the calculations are inaccurate compared to the other approaches and are no longer common due to the complexity of AM [17]. The analytical approach on the other hand requires a great deal of machine data, process data and construction data. These are then calculated in mathematical models and result in a building time. An example of this is software such as Prusa Slicer, which uses more than 200 parameters to predict the construction time [23]. The analytical approach is the most accurate but due to its complexity hard to implement and adapt for companies in the early production stage, for example, to calculate pricing for external part production. However, there is an influencing connection between the analytical and parametric approaches. Research and Industry as the applicator are looking for a simple, math-based model in the middle of both approaches in terms of numbers of variables and exact building time calculation [17]. The analogical approach must be viewed in a differentiated manner from the outset. While the first approaches are based on mathematical models, the analogical approach is based on the empirical collection and use of data [17]. For this purpose, experiments are designed, components are created and data is collected based on real building processes. Thus, the model is not only validated at the end but is based on these empirical data [22]. Within the analogical approach, the usage of machine learning and artificial intelligence leads to new improvements in time estimation. Authors are gaining knowledge and first results show, that artificial neural networks are able to estimate building times precisely by only including features like size and volume of the part [24]

If energy consumption is considered concerning the building time calculation, critical dependencies can be identified. On the one hand, the energy input of the laser is decisive for the construction rate and thus for the overall build time. On the other hand, the energy input can be reduced, which may have a negative effect on the mechanical properties, residual stresses and the surface of the component. This trade-off can be applied, for example, to components where surface finish is not important.

The main goal of the present research is the systematic literature review of available publications. As shown before, the calculation of energy consumption and building time are crucial for the implementation of AM. Current research mostly focuses on polyamide materials with processes of FDM, Selective Laser Sintering (SLS) and comparable. To close this research gap in terms of available data for the LPB-F process, the first step towards a research agenda is a methodical literature research, to gain an up-to-date understanding of the current research status of energy consumption in L-PBF. Therefore, it is expected to identify decreasing energy consumption of the machines because of the technological developments and the increasing resource efficiency over time. For the building time calculators, a systematic review and classification of available time estimators are targeted. It is expected, that classified models get increasingly precise with the help of AI. This process of the specification should even go further.

The following sections are structured as followed. In chapter two, the methodology is introduced to approach the goals of the research. The results are discussed separately in chapters three and four. At the end of the present paper, the results are discussed and a conclusion of the current state is drawn.

2. Methodology

The methodology for the present research consists of a systematic literature review as shown in Figure 1. As a holistic database, Google Scholar connects the largest and best-known databases, including Elsevier and EbscoHost.

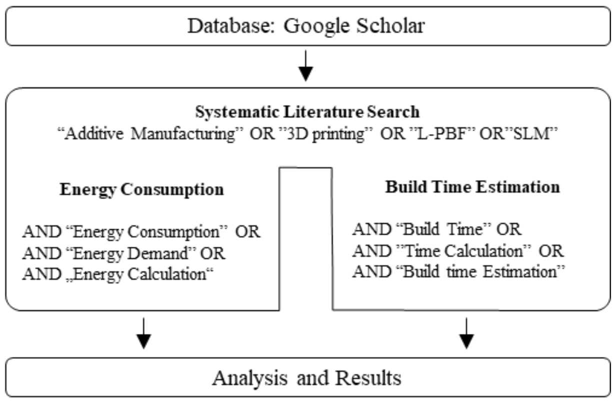

Fig. 1 *Methodology of the present systematic literature search*

As synonyms are required to address all relevant literature, the additive process is defined by the keywords additive manufacturing, 3d printing and L-PBF. Additionally, SLM as the main provider of L-PBF machines is added. Connected to those keywords addressing the additive process, the energy consumption and building time are addressed. Out of these keywords, the search matrix and its results provide a deep and holistic insight into the topics. As illustrated in Figure 1, the identified literature was scanned, analysed and results are formed.

3. Energy Consumption in L-PBF

As introduced in Chapter two, the systematic literature review identifies the main contributions to the topic. Those are divided into two stages. The first stage consists of secondary data interpretation. The authors use existing and published primary data related to the energy consumption of LPB-F and analyse these data from their perspective [12, 25–27]. Additionally, authors develop models for energy consumption forecasts and use those available primary data to validate. Majeed et al. collected and analyzed existing data in a small literature search. Metal and plastic processes were examined and presented. The specific energy consumption for LPB-F was found to be between 251 MJ/cm^3 and 463 MJ/cm^3 [11]. The study focused on the whole process chain which includes the wire erosion process to separate the object from the building platform. Also, Lui et al showed power consumption in relation to the building time. Based on a primary data collection of Kellens et al [28] and Faludi et al [12] they showed the ratio of different energy consumers using a Concept Laser M3 Linear machine. The laser unit including the cooling system had the highest energy demand with an average load of 2,2 kW [14]. Overall, SEC was between 85,3 and 157,2 MJ/kg. In a major comparison of energy requirements in AM, Gutowski et al published an interdisciplinary analysis. In their study, the authors compare a wide variety of additive processes such as Fused Deposition Modelling (FDM), Directed Metal Deposition (DMD), Selective Laser Sintering (SLS) and also LPB-F. Additionally, conventional technologies such as injection moulding and CNC Machining were compared [27]. Energy requirements vary between 1.200 MJ/kg (process rate of 0,04 kg/hr) in a single bed building down to 110 MJ/kg (process rate of 0,056 kg/hr) in a full bed building [27]. A single bed is defined as producing one object per building job, a full bed is the maximum of objects per building job.

The second stage focuses on primary data collection. For this purpose, specific building geometries were developed by the authors, placed on the building platform and the energy consumption was measured empirically. Often, this primary data collection is coupled with the development of a simulation tool to predict the energy demand. To group the data, several differentiations have been made. To gain a better understanding of the measured specific energies, the publication date and respectively the machine type is important. As mentioned earlier, huge technological leaps forward have been made to increase the efficiency of AM machines. Moreover, single builds and full builds need a controversial analysis because of the distribution of the energy values. Whereas gas flow and cooling of the laser unit is required unrelated to the number of parts in the building chamber, researchers have started to consider the energy distribution in their experiments. Also, the material of the produced object is important because of the different energies required to melt the material. In Table 1, all considered literature is shown. It can be seen, that steel and aluminium are the materials of focus. Many authors have done their experiments with single bed as well as with full bed constellations.

Table 1: Overview of the literature for primary energy consumption data

Authors	Machine	Material	SEC (kWh/kg)	Build Rate (kg/hr)	Config
[29]	EOSINT M270	Steel	70,6	0,0386	full bed
[13]	BLT S200	Steel	112,7	0,0035	single bed
[30]	EOS M 290	Steel	27,2	0,0763	single bed
[25]	SLM250	Steel	31,0	-	full bed
[12]	Renishaw AM250	Alum.	166,7	0,0075	single bed
[12]	Renishaw AM250	Alum.	101,1	0,0125	full bed
[31]	-	Steel	93,1	0.0164	single bed
[32]	SLM 280 HL	Alum.	142,2	-	full bed
[32]	SLM 280 HL	Alum.	102,6	-	full bed
[26]	M3 Linear	Steel	163,3	-	single bed
[26]	M3 Linear	Steel	117,5	-	full bed
[26]	SLM 250	Steel	29,4	-	single bed
[26]	SLM 250	Steel	23,1	-	full bed
[26]	EOSINT M270	Steel	94,2	-	single bed
[26]	EOSINT M270	Steel	66,9	-	full bed
[28]	Concept Laser	Alum.	85,9	-	full bed
[28]	Concept Laser	Alum.	148,1	-	full bed
[33]	M3 Linear	Steel	26,9	0.1023	single bed

Main contributions and data are provided by Baumers and colleagues [12, 25, 26, 29]. Also, Ma et al., as well as Ochs et al., did some data collection on relatively new machines (BLT S200 and EOS M 290) [13, 30]. Peng et al. focused on the relation between energy consumption and mechanical parameters such as tensile and flexural strength as well as density [34]. It was shown, that there is a direct positive influence on the energy input and the mechanical properties.

In a second study, Peng et al. analysed the relation between laser power, scan speed and overlap rate in terms of SEC input. As shown in Figure 2. The specific energy increases with an increased overlap rate and decreased scan speed [32].

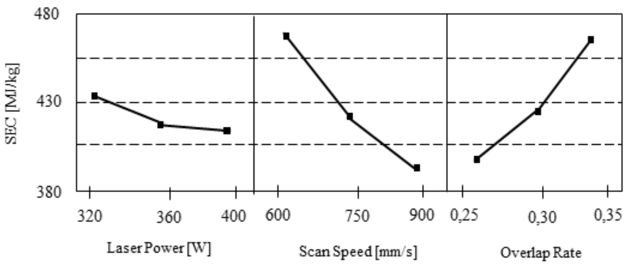

Fig. 2 *Influence of Laser Power, Scan Speed and Overlap Rate on SEC, adapted from [32]*

In the following, the data of Table 1 are analysed and illustrated. Figure 3 shows the relation of the SEC and the publication date of the study. It is clearly shown, that there is a trend towards increasing SEC in relation to the publication of data.

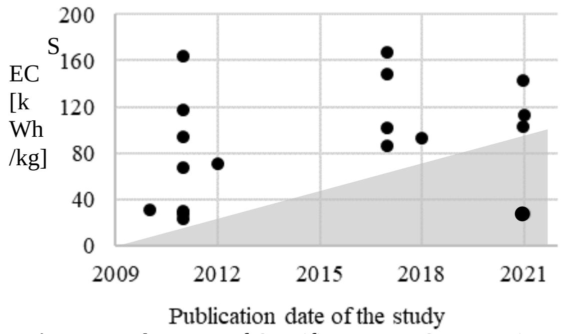

Fig. 3 *Development of Specific Energy Consumption (SEC) in relation to the publication date of the primary data study*

As argued by Gutowski et al, a proper way to compare existing energy consumption data is the comparison of specific energy and building rate. This was chosen to illustrate the results in Figure 4. Despite available data sets, some authors use their measurements for other aspects of energy demand on AM and do not provide all data to calculate the building rate.

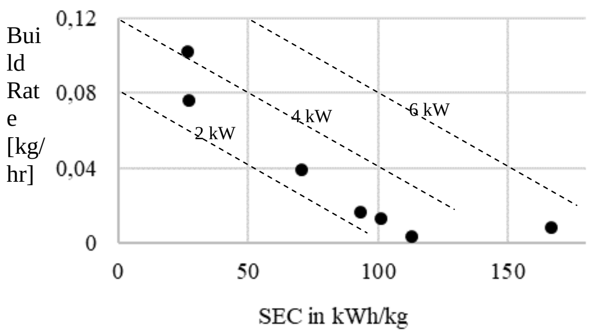

Fig. 4 *Correlation of Build Rate and Specific Energy Consumption (SEC)*

It can be seen, that both building rate and SEC vary a lot from a minimum SEC of 27,2 kWh/kg (build rate of 0,0763 kg/hr) to a maximum of 166,1 kWh/kg (build rate of 0,0075 kg/hr). The building rate is decreasing when SEC is rising. This typical correlation is in line with Gutowski et al. findings [27]. The limiting factor is the maximum laser power. Once the scan speed is increased, the building rate is rising and the SEC is falling to a minimum.

Despite the energy savings, mechanical properties are changing as stated by Peng et al. [32]. It must be considered that energy optimization also influences the component quality in terms of mechanical properties and can change the surface of the parts. Based on the data, the literature also suggests improvements. One main factor for energy optimization during the building time is to use the maximum capacity of the building chamber. Thus this is not a direct influence, power consumption for heating up and cooling down the building chamber is distinguished to all parts in the chamber [14].

4. Building Time Estimation Models for L-PBF

Analysing literature including building time estimators showed a clear focus of the researcher which is on developing models for polyamides. Only a few stand-alone publications handle LPB-F respectively SLS processes such as [16, 17, 22] (Figure 5).

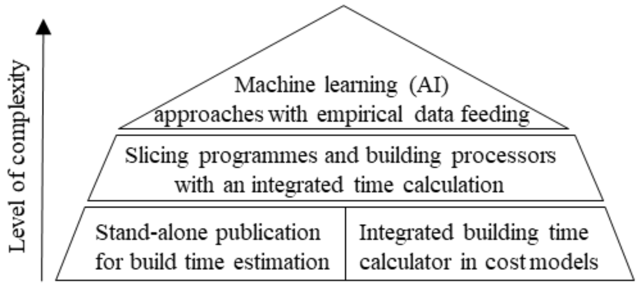

Fig. 5 *Types of Publications Including Building Time Estimators*

Most estimators are introduced in combination with cost accounting models. As a key part of the machine costs, authors mostly developed simple ways to roughly calculate the building time [35]. Also, complex models within their cost calculation are introduced [36]. Building upon those stand-alone publications and the integrated estimators in cost models, the next level of complexity are algorithms implemented in programmes for STL files preparation and build processors for AM machines. Those programs calculate the building time based on data sets provided by their company as well as on experiences of the user and completed jobs. Mostly machine data such as hatch distance, layer thickness, scan power, scan velocity and coating time are used. This method is close to machine learning approaches when empirical data are used for improvements. One of the biggest providers of those programs is Magics Materialise. Nevertheless, there are rarely scientific publications including Software for improving building time calculations. As shown in Figure 5, the most complex type of building time estimators are machine learning and artificial intelligence (AI) approaches. There is an increasing number of authors suggesting and developing those algorithms. Even though this approach could be classified as an analogical approach, there is a huge potential to increase the accuracy of estimation by using very few parameters (Figure 6).

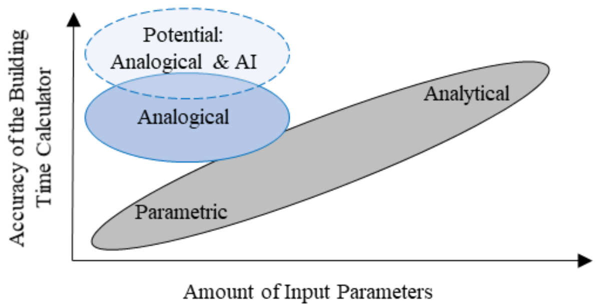

Fig. 6 *Classification and Potential of Different Building Time Estimator Approaches for LPB-F processes, aligned to [17]*

The relation between non-machine-parameters (geometry, volume of the part, box volume) and building time is very attractive for fast calculation. As stated by Oh et al., parametric estimators are the most inaccurate method even though there are just a few parameters necessary. Analytical approaches on the one hand require a high number of input parameters, on the other hand, the accuracy is among the most precise [23].

5. Discussion

Primary data collected within the literature review was done with the database of Google Scholar. This assumed that the gathered data was reviewed on a scientific level. This boundary leads to a low level of data amount. By the use of other literature such as data available on the internet besides scientific background, a wider perspective could be drawn. On the other side, the quality of data and methodology could decrease.

For energy consumption, metal production is very power-intensive manufacturing compared to other materials and machines such as FDM and SLS. Over the years, the minimum SEC was increasing due to higher requirements on mechanical properties, surface quality and secondary energy efforts such as heating the building platform and cooling. This was also shown by Gutowski et al in their review and also accounts for polyamide AM [27]. Going one step further, high differences in primary energy data lead also to high differences for cost calculation. Given the estimated electricity price in Germany for 2022 of roughly 40 ct./kWh, this leads to a range of about 10 € to 60 € power costs for one kilogram metal objects. Nevertheless, energy is a small amount of overall costs, this has to be taken into account as well.

Also, building rates and quality standards of LPB-F processes have risen over the decades [32]. More laser power, preheating and cooling is required to fulfil the properties which also lead to a higher SEC demand. However, the SEC is limited by the number of lasers and the maximum laser power.

Nevertheless, primary data was mostly generated using older AM machines with older hardware. Since the developments of software and hardware in the technology sector are rapid, the authors suggest new experimental data collection using the newest machine generations. As the relatively new machine EOS M 290 (release year 2016) indicated by Ochs et al, the result showed a decrease of SEC to about 27 kWh/kg [30].

For the calculation of the building time, authors have introduced different models with different scopes. Most models can be found within a cost accounting approach using analogical methods. As production planning and calculation is important, the inclusion of the models is a logical way to present the building time models. As classified by Oh et al, the accuracy of the models depends on their methods [17]. Whereas currently, the most precise method is the analytical way, the authors assume that artificial intelligence has a great influence on precision and input parameter reduction at the same time. This was confirmed with results using the method [17, 24]. Additionally, AI approaches are easy to apply and variable for the user. However, the requirement here should be an appealing graphical user interface that enables the end-user to perform a quick and simple calculation.

6. Conclusion

Energy consumption and building time calculation are key elements for AM implementation in productions. Nevertheless, it is not possible to exactly calculate both energy and time demand as forecast. This is shown by the present research. Further priorities can therefore be placed on the development of simulation models based on Artificial Intelligence. Whereas for building time estimation this trend can be observed increasingly, structures and algorithms, as well as proper data sets, have to be developed for energy demand.

7. References

1. R. Y. Zhong, X. Xu, E. Klotz, S. T. Newman, Engineering 3, 616 - 630 (2017)
2. G. Beier, A. Ullrich, S. Niehoff, M. Reißig, M. Habich, J. Clean. Prod. 259, 120856 (2020)
3. M. Rupp, M. Schneckenburger, M. Merkel, R. Börret, D. Harrison, J. Open Innov. Technol. Mark. Complex. 7, 68 (2021)
4. L. Hitzler, M. Merkel, W. Hall, A. Öchsner, Adv. Eng. Mater. 20, 1700658 (2018)
5. Z. Bi, G. Wang, J. Thompson, D. Ruiz, J. Rosswurm, S. Roof, C. Guandique, Enterp. Inf. Syst. 14, 1 - 24 (2021)
6. M. Gebler, A. J. M. Schoot Uiterkamp, C. Visser, Energy Policy 74, 158 - 167 (2014)
7. S. Yang, T. Page, Y. Zhang, Y. F. Zhao, J. Intell. Manuf. 31, 1917 - 1933 (2020)
8. P. C. Priarone, V. Lunetto, E. Atzeni, A. Salmi, *Procedia CIRP* 78, 85 - 90 (2018)
9. M. Mani, K. W. Lyons, S. K. Gupta: J. Res. Natl. Inst. Stand. Technol. 119, 419 - 428 (2014)
10. M. Rupp, M. Buck, R. Klink, M. Merkel, D. K. Harrison, Clean. Environ. Syst. 4, 100069 (2022)
11. A. Majeed, A. Ahmed, J. Lv, T. Peng, M. Muzamil, J. Braz. Soc. Mech. Sci. Eng. 42, 694 (2020)
12. J. Faludi, M. Baumers, M. Maskery, I. Hague, J. Ind. Ecol. 21, 30, (2017)
13. Z. Ma, M. Gao, Q. Wang, N. Wang, L. Lei, C. Liu, Z. Liu, Int. J. Adv. Manuf. 116, 3377 - 3390, (2021)
14. Z. Y. Liu, C. Li, X. Y. Fang, Y. B. Guo, Procedia Manuf. 26, 834 - 845 (2018)
15. C. Gao, S. Wolff, S. Wang, J. Manuf. Syst. 60, 459 - 472 (2021)
16. M. Ruffo, C. Tuck, R. Hague, Int. J. Prod. Res. 5131 - 5146 (2006)
17. Y. Oh, M. Sharp, T. Sprock, S. Kwon, J. Comput. Des. Eng. 8, 243 - 1256 (2021)
18. S. H. Choi, S. Samavedam, Comput. Ind. 47, 39 - 53 (2002)
19. Y. Oh, P. Witherell, Y. Lu, Addit. Manuf. 36, 101492, (2020)
20. C. Wang, X. Qian, Addit. Manuf. 34, 101246, (2020)
21. Y. Zhang, A. Bernard, J. M. Valenzuela, K. P. Karunakaran, CIRP J. Manuf. Sci. Technol. 10, 49 - 60 (2015)
22. G. Medina-Sanchez, R. Dorado-Vincente, E. Torres-Jimenéz, R. López-García, Mater. 12, 23 (2019)
23. Y. Zhang, S. K. Moon, J. Comput. Des. Eng. 8, 489 -509 (2021)
24. J. Munguía, J. Ciurana, J. Riba, Manuf. Eng. 223, 995 -1003 (2009)
25. M. Baumers, C. Tuck, R. Hague, I. Ashcroft, *A comparative study of metallic additive manufacturing power consumption* (2010)
26. M. Baumers, C. Tuck, I. Ashcroft, R. Hague, *Energy inputs to additive manufacturing: does capacity utilization matter?* (2011)
27. T. Gutowski, S. Jiang, D. Cooper, G. Corman, M. Hausmann, J.-A. Manson, T. Schudeleit, K. Wegener, M. Sabelle, J. Ramos-Gerez, D. P. Sekulic, J. Ind. Ecol. 21, 69 - 79 (2017)
28. K. Kellens, E. Yasa, W. Dewulf, J. R. Duflou, *Environmental Assessment of Selective Laser Melting and Selective Laser Sintering* (2015)
29. M. Baumers, C. tuck, R. Wildmann, I. Ashcroft, E. Rosamond, R. Hague, *Combined Build-Time, Energy Consumption and Cost Estimation for Direct Metal Laser Sintering* (2012)
30. D. Ochs, K. K. Wehnert, J. Hartmann, A. Schiffler, J. Schmitt, *Procedia CIRP* 98, 613 - 618 (2021)
31. L. Yi, N. Krenkel, J. C. Aurich, *Procedia CIRP* 78, 67 - 72 (2018)
32. T. Peng, J. Lv, A. Majeed, X. Liang, J. Clean. Prod. 279, S. 123609 (2021)
33. K. Kellens, E. Yasa, W. Dewulf, J. P. Kruth, J. R. Duflou, *Energy and Resource efficiency of SLS/SLM processes* (2011)
34. T. Peng, S. Xu, H. Zhan, Y. Zhu, Rapid Prototyp. J. 24, S. 1428–1435 (2018)
35. M. Baumers, C. Tuck, R. Wildmann, I. Ashcroft, E. Rosamond, R. Hague, *Combined build-time, energy consumption and cost estimation for direct metal laser sintering* (2012)
36. L. Rickenbacher, A. Spierings, K. Wegener, Rapid Prototyp. J. 19, S. 208–214 (2013)