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Three levels of software applications for a digitalized additive manufacturing process chain

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Abstract

The further development of digital process-planning, -preparation and -analysis tools is crucial to increase efficiency and profitability of additive manufacturing (AM) systems. Therefore, we identified three distinct levels of software application along the AM process chain.
On the machine level (1), sensor data is analyzed to notify the user about problems during the print, machine state, or even part quality. In a conventional manufacturing plant, a digital workflow through the whole process chain is state of the art. The integration of a digital workflow in AM is not fully given but necessary to connect all the steps of the organizational level (2) efficiently. Simulations of parts, machines and the whole process chain in a digital twin (3) gather important feedback before printing, changing machine parameters or even ordering new machines. In this context, this contribution reports on current developments, challenges and future visions for implementing a fully digital additive manufacturing process chain.

Keywords: Additive Manufacturing, digital process chain, digitalization, digital workflow, laser powder bed fusion

1. Introduction

With approximately 6000 machines worldwide (Langefeld et al. (2018)), laser powder bed fusion of metals (LPBF M) is currently the most applied and researched additive manufacturing (AM) technology to produce high quality metal parts for prototyping, tooling and end parts (Schmidt et al. (2017)). A LPBF machine contains three main types of components: Mechanical components, electrical components and software components. Machine manufacturers focus on the optimization of the mechanical and electrical hardware of machines. With the goal to improve the process chain in all areas and rise the overall equipment efficiency, digitalization and the use of software tools can have a big effect (Bogner et al. (2016)). Although more machine manufacturers and software development companies are starting to introduce software to improve quality assurance, data preparation and digital workflow, the implementation is not state of the art in industry and further improvements are necessary. In other manufacturing processes, digitalization projects already reduce the downtime of machines (Jodlbauer et al. (2019)). This contribution will show the need, challenges and future visions on a digitalized AM process chain. To this end, we show the high potential for process improvement with a monetary calculation on process flaw cost estimation. Next, we introduce the three levels of software application, namely machine level, organizational level and simulation or cyber physical system level. We demonstrate ongoing work with a process monitoring analysis tool and present an estimation for the influence of different software approaches for support structure design on production cost.

2. Scrap cost estimation for LPBF M

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According to Hopkinson (2003) the cost structure of AM has three main components: Machine cost, material cost and labor cost. The machine costs consists of build cost due to the runtime of the machine and the consumption of energy and gas needed for the print. The material cost involve the printed part and the needed support structure, additional test parts for quality assurance, powder for quality control and lost powder, and build plates. Data preparation, machine set up, manual post processing are the main contributors for labor cost.

A simple approximation of the failure costs can show the possible impact of successful application of digitalization tools. The assumed failure rate in this calculation is 10% and the machine load factor for LPBF machines is 6800 hours per year in an industrial environment (Langefeld et al. (2019)). This calculation assumes that around 680 h of the machine time is lost due to failures. The machine costs per hour can be assumed with 50 €/h (Munsch et al. (2017)), which results in failure costs of around 34 000 € per year for a single machine (1).

$$\text{downtime per year} \cdot \textit{machine hourly rate} = 6800\frac{\text{h}}{a} \cdot 10\% \cdot 50\,€ = 34.000,-\,€ \tag{1}$$

Additionally, labor cost for cleaning, setting up the machine and data preparation are considered. Trained technicians cost up to 80€/h. Per failed job three hours of cleaning and setting up the machine and two hours for data preparation is estimated. With an average of 21,25 h per print, 32 jobs failed in the calculated time of 680 h.

$$\text{Labor cost} = 32 \text{ jobs } \cdot (3+2)h \cdot 80\frac{€}{h} = 12.800,-\,€ \tag{2}$$

The labor cost sums up to 12.800 € per year. Worldwide the failure cost sums up to 281 million € per year for the total of 6000 machines (Langefeld et al. (2018)). With a hypothetical improvement of 1 % in failure rate due to usage of software applications and digital process-planning, -preparation and –analysis tools, 2,8 million € can be saved. To investigate the potential of software and digitalization in different areas of the AM process, we identified three distinct levels for software application: 1) machine level, 2) organizational level, 3) simulation level and cyber physical systems (Figure 1a). Figure 1b visualizes the results of a scopus keyword search for word combinations in titles, keywords and abstracts of articles published during the last decade. The logarithmic scale shows nearly constant numbers for conventional manufacturing like die casting and drilling, but a strong increase for additive manufacturing and especially the combination software and LPBF.

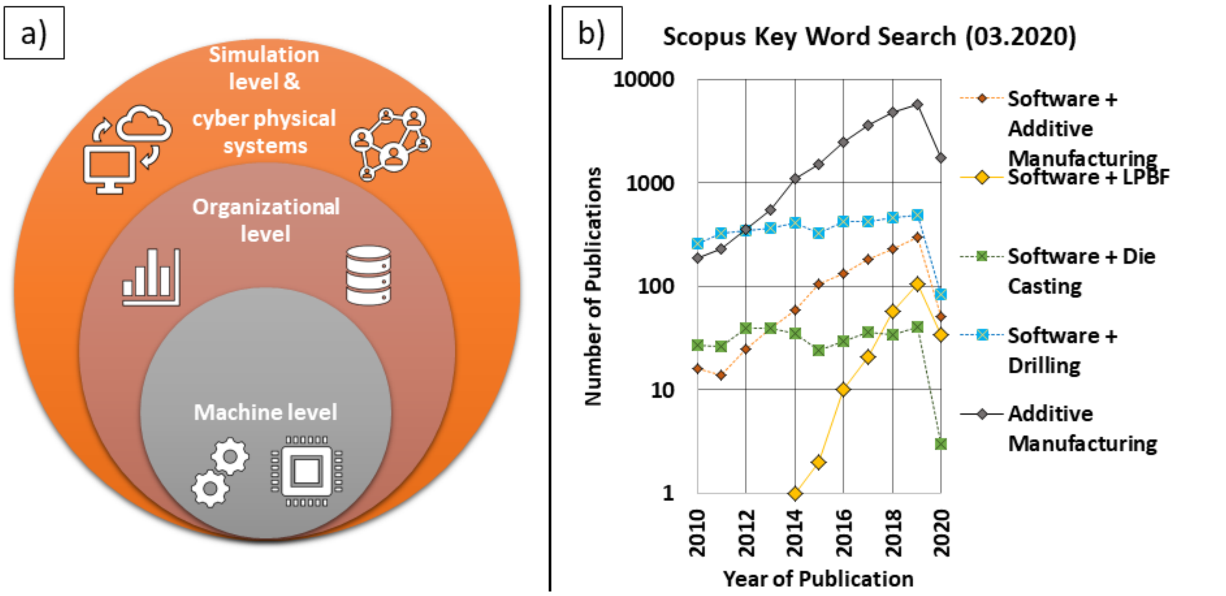

Fig. 1: a) Three levels of software application and digitalization visualized in a shell model. b) Scopus Key Word Search with software related word pairs found in titles, abstracts and keywords of peer reviewed articles from 2010 to 2020 on a logarithmic scale showing a strong increase for the pair Software & LPBF (yellow/black).

3. Potentials of digitalization and software applications

3.1. Machine level

Commercially available LPBF machines are equipped with sensors, which are delivering, if accessible, valuable data about the state of the machine and the process. Sensors include process monitoring and machine sensors. Process monitoring generate an insight of the current state of the printing job by utilizing the signature of the laser, the powder bed and melt pool radiation with the goal to detect process flaws and to find relationships to the final part quality. Commonly used monitoring systems contain photodiodes, high-speed camera systems and pyrometers (Everton et al. (2016)). Machine manufacturer software cover basic functionalities without evaluation of the generated data. Further development of evaluation software for data based and unused data can accelerate process development, reduce scrap and improve the detection of quality issues within the produced parts (Kolb 2020). Machine sensors monitor the state of the machine and are necessary for basic functionalities of the system. Status reports of single components of LPBF machinery are available to the operator.

3.2. Organizational level

To increase the overall efficiency and to reduce costs of printed parts, it's crucial to develop and integrate digital planning and preparation tools in the AM process chain, since physical constraints limit the output speed of machines. With the future vision of intelligent and automated planning tools, software can estimate the build time and calculate the price with the information of the CAD model. Intelligent clustering of different parts of same material to one job reduces the setup time for machines and structure the print orders efficiently. The implementation of manufacturing executive system (MES) software has the potential to generate an interface between the production and the planning level and generate a digital workflow. Operators are scheduled directly to the different steps of the process chain to reduce the latency between process steps. A MES is capable to increase the transparency and traceability of the produced part by collecting relevant data in a database (Kletti 2007). Evaluation of data can identify inefficient process steps for a further optimization of the whole process. The traceability of parts becomes ever more crucial for quality control and certification of the AM process (Thomas 2018).

3.3. Simulation level and cyber physical systems

The process simulation can take place in different areas of the AM environment. Starting at the part scale, simulation of orientation and support design can reduce print time, manual preparation effort and the risk of failed prints. A virtual copy of the physical processes and the machine in a digital twin can gather important information about the print and the whole process chain and connects the physical and the virtual world. With further improvement of simulation software, the part can get optimized and printed virtually before printing the real metal part. This future vision can be extended to a one-click to print application without the need of human resources. With connected sensors, actuators and software of cyber physical systems, information can be delivered to a network and distributed to improve the automation level. The state of specific components like electric engines, laser pump diodes or filters can be used to develop predictive maintenance algorithms to avoid sudden and unplanned downtime of the machines.

4. Examples, overview and future vision:

4.1. Evaluation of coating images with a convolutional neural network

The M2 Cusing LPBF machines from the Concept Laser GmbH are equipped with a powder bed monitoring system, which is recording images of the building platform before and after recoating. The collection of image data for each layer enables an online assessment of the process and bed quality. Defects can lead to a damaged silicon coating lip, which can decrease the part quality or even the abort of the whole job. A classification algorithm based on convolutional neural network (CNN) is applied to detect the occurrence of such defects after training. Figure 2a shows the basic architecture of the used CNN. Further information about the structure of the CNN and the used terminology can be found in Brownlee (2016). Images are classified as OK when there is now visible defect on the powder bed (Figure 2b). The error classes involve the classes: 1) detachment, when delamination and distortion are present lifting parts out of the powder bed (Figure 2c). 2) surface roughness and waviness, if such shape deviations exceed the applied layer thickness and make them visible after recoating (Figure 2d). Missing powder occurs if the powder chamber delivery is insufficient to cover the whole platform (Figure 2e). Formation of stripes due to recoater damage or wear (Figure 2f). The classification algorithm currently only triggers a notification at the occurrence of failures due to machine guarantee restrictions and the operator can decide whether to continue or cancel the process.

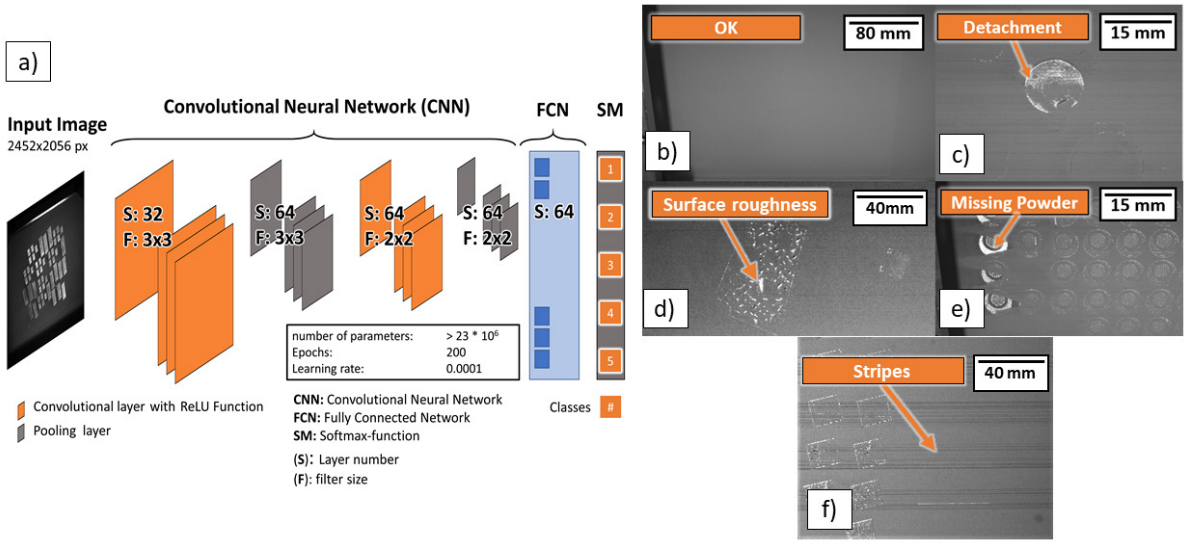

Fig. 2: Architecture of the classification convolutional neural network; b) Good powder layer; c) visible detachment of a part; d) high surface roughness; e) Missing powder; f) Strips in powder layer

The bar diagram in Figure 3a shows an analysis of a small series build job that run 28 times. The build height of 6880 layers was not constant due to test part columns printed besides the two end parts present on each platform (see Figure 3b for an unrecognizable version of the end part). A total of 172992 layer images with a data volume of approximately 1,5 TB was analyzed. One build job failed after inconsistent bonding during the first layers leading to 164 detachment events in a row. Besides that, it is obvious that surface roughness and recoater damage with resulting stripes contribute decisively to the process and end part quality.

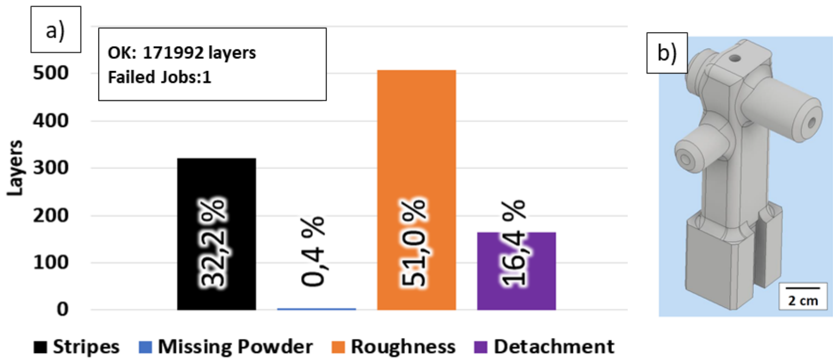

Fig. 3: a) Resulting error occurrence after analyzing a small series build job with the convolutional neural network b) unrecognizable representation of the manufactured parts

4.2. Automated generation of support structures

The efficient design of support structures is a crucial part of the LPBF process chain. Especially for prototyping the process time is key, besides the need for a quality standard in support structure design. Software companies have invented automated and simulation based support design methods. Here we want to analyze how different ways of support design contribute to build time and part pricing. In order to estimate the influence of support design we compare three support designs for one imaginative part and calculate a mean time for a unit cell of block support. The cases include an automatically designed support structure (Figure 4A) (Magics - Materialise NV), a version that mimics simulation based designs (Figure 4B) and a hybrid structure (Figure 4C). Therefor we start with the calculation of the path length per layer of the support unit cell p_{luc}:

$$p_{luc} = 10\text{ mm} * 10\text{ hatches} * 2\text{ additional } 10\text{ mm contour lines} = 120\text{ mm} \quad (3)$$

Here we used a fully connected lattice / block support structure and a hatch distance of 1 mm for simplification. Next, the layer height of 50 µm is applied to the cubic centimeter volume height of 1000 µm and all layers are cumulating to a path length for the unit cell p_{uc}:

$$p_{uc} = 120 \text{ mm} * 1000 \text{ µm} / 50 \text{ µm} = 2400 \text{ mm} \tag{4}$$

Further we can assume a fast scan speed of 1000 mm/s that is reduced by an artificial factor of 2 that accounts for frequent jumps in between scan trajectories, irregular shapes along contours and extra start and stop movements due to perforations among others like delay times and skywriting. The estimated total irradiation time for the unit cell t_{irruc}, and estimated irradiation times for the block support structures of the examples above $t_{irr,A\text{-}C}$

$$t_{irruc} = 2400 \text{ mm} * 2 / 1000 \text{ mm/s} = 4{,}8 \text{ s} \tag{5}$$

$$t_{irr,A} = 3{,}5 * 4{,}8 \text{ s} = 16{,}8 \text{ s}; \; t_{irr,B} = 45{,}12 \text{ s}; \; t_{irr,C} = 5{,}28 \text{ s} \tag{6}$$

This simple calculation made clear that automated support design differences might influence the total machine run time. Especially for small series it is necessary to prepare parts without intensive labor costs, without the risk of job fails and iterations, but with efficient machines usage time.

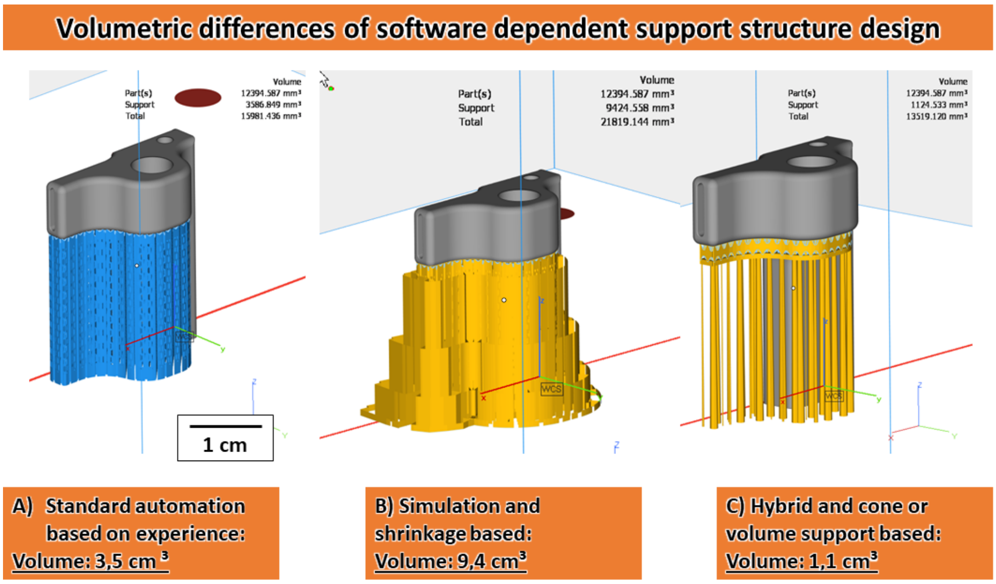

Fig. 4: Visualization of the automated support structure of an imaginative part with an overhang and different support strucure volumes.

4.3. Meltpool monitoring software

Meltpool monitoring in LPBF-M got increasing attention by machine manufacturers and the scientific community (Eschner 2019), because of three main benefits: Process understanding, machine efficiency and part quality. As shown in previous publications it is possible to monitor part layer roughness and powder bed quality (Kolb 2018 a) and support parameter and process development (Kolb 2018 b). Future software developments have the potential to detect process flaws accurately and control counter measures with high resolution at a meltpool size scale. This will ultimately affect the acceptance of new customers and economically accelerate certification processes.

4.4. Automated quotation tool

Additive manufacturing is most valuable in prototyping and sample phases if customers benefit from a lean process. An automated quotation tool with fast and reliable information for customers will create benefits for both, the customer decision process and the print-shop workflow, since trained personnel can focus on development and organizational tasks. Software capable of such a task has to include process insights and economic calculations from powder to high-end machining finishes.

4.5. Overview on examples along the three levels

An overview of the shown examples with the resulting improvements in the areas of process, economy and part quality is shown in Table 1. It shows that the inclusion of digitalization along the additive manufacturing process chain can increase the overall efficiency throughout the mentioned areas.

Table 1: Overview of influences of software-improvements

Influences of software-improvements			
Example	**Process**	**Economy**	**Part quality**
Coating image evaluation	Stability and output improvement	Reduction of scrap, machine downtime and personnel cost	Improved overall part quality, process control applications
Efficient simulated support generation	Stability, efficiency, personnel-independency, speed, post-processing optimization	Reduction of scrap, machine downtime and personnel cost, powder losses	Better surface quality, less distortion
Meltpool Monitoring	Process stability monitoring, process development & parameter improvement	Support for clearance and certification, reduction of scrap and machine downtime, and post process qualification	Improved overall part quality, process control applications
Quote Tool	-	Less personnel cost, faster quotes and communications, customer satisfaction	-

4.6. Future vison of the digital process chain

The combination and extension of the mentioned examples results in a future vision of the digitalized process chain. With the customer's request, the digital workflow starts by an automated generation of the quotation in a software tool which gathers the necessary information, like part and support volume, from the 3d model and simulations with no need to start additional software (e.g. CAD Software). The 3d model is simultaneously prepared with a nesting algorithm to combine different parts based on the material, priority and estimated print time to one build job. Those jobs are automatically planned to reduce the downtime of machines due to overlapping completion of different machines or finishing outside the working period of the technicians. This results in an efficient utilization of the working hours. To monitor the state of the process and the machine, intelligent (e.g. AI based) monitoring software will detect process flaws and machine problems and notify the personal or even adjust the used parameters to prevent the failure of jobs. The integration of the whole machine park in a manufacturing executive system gives an overview of the current state of every machine in the process chain and increase the traceability and transparency of the production. With the transformation of the physical parts, processes and machines to digital twins, the whole process chain can be represented virtually. This digital representation can be used investigate future scenarios like the scaling of the machine park based on an assumed order quantity.

5. Summary

The integration of digital process-planning, -preparation and -analysis tools in the additive manufacturing process chain yields potential to increase the overall efficiency and profitability. With a scopus keyword search, we showed the strong increase in software related research in additive manufacturing. We presented an approach for software tools that operate on different levels of the process. On the machine level, sensor data identifies flaws during the print process and report the current state of the machine to the operator. Improved digital planning tools in the organizational level can reduce the latency between steps of the process chain and increase the transparency and traceability of the produced part. Cyber physical systems and process simulation connect the physical and the virtual world reducing unplanned machine-downtime. Examples for potentials of software application on process, economic and part properties were presented and a future vision of the digital process chain was given.

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