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Optimization Potentials of Laser Powder Bed Fusion: A Conceptual Approach

Additive manufacturing (AM), more specifically laser powder bed fusion (LPBF), has become increasingly important for the production of complex components. Despite recent improvements, issues with process parameter optimization, multi-material approaches, CAx chain, adaption for automated mass production, automated process planning, and quality control are still major concerns. So far, despite growing interest, the technology has not yet made the leap into everyday and large-scale use. The use of artificial intelligence offers opportunities to solve many of these problems and improve LPBF technology. In this paper, these topics are addressed to give the reader a holistic overview of the potential for optimization. The individual topics are not only explained and supported with example products from various industries but also evaluated in terms of cost-effectiveness and quality improvement. By evaluating the potentials, restrictions, and recommendations, a framework is created for further investigation and practical application of optimization approaches.

Keywords: *Additive manufacturing, laser powder bed fusion, artificial intelligence, automatization, process optimization, CAx process chain, CAD/CAM, CAQ.*

1. INTRODUCTION

Laser powder bed fusion (LPBF) [1] is a form of additive manufacturing (AM) [2, 3] that can create detailed and unique structural components. The development of artificial intelligence (AI), machine learning (ML), and deep learning (DL) has spurred advancements in a number of industries, including AM [4]. The increasing amount of research, as well as practical applications, show that AI, more specifically ML and DL, has made substantial improvements over the years. The industry's continued trend toward digitalization has helped to propel this expansion even more [5]. Enterprises acknowledge the immense potential inherent in the acquisition of knowledge from historical data, particularly considering the burgeoning quantities of information produced as a consequence of the pervasive process of digitalization.

The integration of AI into AM processes has led to significant improvements, from development to production planning and manufacturing to quality control. A prominent application is the utilization of topology optimization. This technique employs ML algorithms to refine a component's geometry according to its functional demands and limitations, ultimately reducing material consumption and weight but preserving performance [6]. AI has also been used to improve the reproducibility and reliability of AM processes through process monitoring and control [7]. For instance, convolutional neural networks (CNN) have been used for in-situ monitoring of the LPBF process, enabling the detection and classification of defects in real time.

Automatization has the potential to improve the productivity, quality, and consistency of the manufacturing process and minimize human error. Progress is already being made in the development and application of automatization technologies in LPBF, and future research and development is expected to lead to further improvements. To support the design and preparation process for LPBF, automatization can already be integrated into the CAD software. Automatic generation of layer data can save time and resources already at the beginning of the CAx chain [1]. The automatization approach is continued in the actual manufacturing process. This approach holds great potential, which is currently rarely exploited. In terms of the number of research projects, there is a great need to catch up here.

Based on the above, this paper covers topics such as AI-based process parameter optimization, multi-material approaches, automatization, and potential LPBF use cases. Overall, it highlights the benefits of combining LPBF, AI, and automatization for improved manufacturing outcomes in multiple aspects, including design and CAM optimization, process monitoring, and quality control.

2. APPROACH TO AI INTEGRATION AND MULTI-MATERIAL USE IN LPBF

The application of AI can significantly improve the quality of components by optimizing process parameters and predicting material properties, in-situ quality con–

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trol, and AI-assisted adaptive process control. This section discusses these aspects and their potential impact on LPBF technology as well as the use of multi-materials in LPBF.

2.1 AI-supported optimization techniques

Process parameters significantly affect the quality of AM components, but also the stability of dimensions and shape in different environments after a longer time of components application [8]. Among many parame– ters, in particular, laser power, scan speed, and layer thickness must all be precisely controlled to achieve the required quality [9]. To overcome this difficulty, AI-supported optimization techniques have been created, improving the effectiveness of the procedure.

Another optimization method in LPBF is the use of AI for material property prediction and in-situ quality control. By incorporating AI models, researchers can predict material properties, such as density, tensile strength, and fatigue life, based on process parameters and material compositions, such as minor deviations of the starting material composition [10, 11].

Lastly, AI-supported adaptive process control has emerged as a promising avenue for real-time adjust– ments to the LPBF process. By utilizing AI algorithms to analyze sensor data during the printing process, researchers can develop adaptive control strategies that modify process parameters on the fly in response to process variations or detected defects [12]. This appro– ach can lead to improved manufacturing outcomes and more effective processes.

In the following, these three AI-based optimization techniques are described in more detail.

Traditional optimization methods often rely on trial and error and extensive experimentation, which can be time-consuming, expensive, and highly dependent on the operator's expertise [13, 14]. To overcome these challenges, the application of AI, specifically ML, and DL techniques, has emerged as a promising approach for process parameter optimization in LPBF [15]. One such technique involves the implementation of surrogate models based on ML algorithms, which can provide a data-driven approach to optimize process parameters. These surrogate models can be trained on experimental data [16] or FEM-simulation results to approximate the relationship between process parameters and part quality. The smoothed particle hydrodynamics (SPH) method, known for its mesh-free numerical approach, exhibits notable capabilities in accurately replicating intricate geometries and the associated physics involved in the liquefaction, flow, and solidification phenomena of metallic materials [17]. In the study [18], 3D nume– rical modeling of selective laser melting (SLM) was performed using the discrete element method (DEM) and the finite volume method (FVM). The Marangoni effect and recoil pressure were incorporated into the model. The mechanism for the formation of defects such as balling, pores, and distortions in the melt trajectories was analyzed.

MeltpoolNet, a comprehensive framework for evaluating ML in the characterization of melt pools in additive metal manufacturing, was presented in [19]. An extensive dataset of experiments with different alloys and AM processes was collected to develop ML models for predicting melt pool geometry and defects. Various ML algorithms, such as random forest, gradient boos– ting trees, support vector machines, neural networks, etc., were used.

Additionally, AI-driven multi-objective optimization techniques, such as the non-dominated sorting genetic algorithm and particle swarm optimization, have been employed to optimize multiple conflicting objectives simultaneously, such as minimizing surface roughness and construction time in order to maximize mechanical properties [20, 21]. This study focuses on the appli– cation of multi-objective optimization and multi-criteria decision-making using evolutionary approaches. Evolu– tionary algorithms such as the non-dominated sorting genetic algorithm (NSGA-II) and multi-objective parti– cle swarm optimizer (MOPSO) were applied. The ana– lyzed solutions also reveal general trends for optimal positions as a function of geometric features.

All these algorithms can be integrated with surrogate models to provide an efficient and robust optimization framework for LPBF process parameter optimization.

Predicting material properties is a crucial aspect of LPBF technology as it allows for the optimization of processing conditions and the development of new materials [16].

One such approach involves using ML models to predict the optimal process parameters based on histo– rical data and simulations [22]. The method is based on predicting the temperature distribution of a component using a graph-theoretical computational heat model. By analyzing the model-based temperature trends, potential heat buildup in the layers was identified and corrected by adjusting the process parameters, which were opti– mized by iterative FEM simulations.

It can be shown that such AI models can effectively capture the complex relationships between process parameters and part quality, enabling more efficient parameter optimization and reducing defects [23, 24].

As manufactured, LPBF parts exhibit inhomoge– neous and anisotropic microstructure and poor surface quality. Post-treatments such as heat treatment shot peening and (electrochemical) polishing can help to improve these imperfections. The results from [25] show that post-processing methods have a significant effect on the residual surface stresses of AM stainless steel. In [26], the effects of post-treatments, both indi– vidually and in combination, on the microstructure, surface and mechanical properties, and fatigue behavior of AlSi10Mg specimens were investigated using DL networks. Roughness, surface modification factor, hard– ness, residual stresses, and void content were considered as input variables, and fatigue life as output variables. The sensitivity analyses were performed, showing the importance of surface-related properties and the remar– kable effect of surface post-treatments in improving fatigue performance.

Material property prediction models can be augmen– ted with process planning techniques to enable a more comprehensive approach to LPBF process optimization [27].

It's common knowledge that quality control plays a major role in most areas of a manufacturing company. Therefore, in-situ quality control is essential for detec–ting and mitigating defects during the LPBF process, ensuring the reliability and performance of the manuf–actured components [28, 29].

AI-driven in-situ quality control techniques can be employed to analyze sensor data and detect anomalies, such as porosity, residual stress, or surface roughness, in real-time [30, 31]. With this approach, which can already be integrated by machine manufacturers, small and medium-sized companies can already benefit from a significant improvement in quality.

The differentiation of these in-situ processes is made according to the detection sensor technology of defects.

Thermographic imaging is used in [32] to train a CNN architecture with depthwise-separable convolu–tions [33, 34], resulting in automatic defect detection with high accuracy during metal printing. The resear–chers preprocessed the thermographic images by resizing them to 64x64 pixels, converting them to grayscale, and normalizing their values. They manually labeled regions of interest (ROIs) around defects, which were areas with high-temperature gradients. The trained depthwise-separable CNN achieved an accuracy of 90,3 % on the test set for defect detection during the LPBF process.

Research paper [35] presents the utilization of a long-wave infrared (LWIR) camera for in-situ measu–rement of powder layer thickness during AM processes. Another possible approach to infrared thermography is shown in [36]. The findings in this paper establish that deviations in inter-layer cooling time (ILCT) exert a substantial influence on the quality attributes, manife–sting as variations in porosity, microstructure, and mec–hanical properties. An older approach from 2016 faci–litates close-range infrared camera observations [37].

Optical sensors such as complementary metal oxide semiconductor (CMOS), optical thermography, and optical topography are showing good results for in-situ observations, too. A good overview is shown in the review paper [38].

A well-known approach with a CMOS camera in this field is presented in [39]. The cameras were sync–hronized with the machine control system to ensure accurate data acquisition during the layer exposure and powder recoating process. Subsequently, the obtained data were processed and analyzed to monitor and detect defects. The concept of time over threshold (TOT) was effective in identifying lack-of-fusion void clusters. Another research explores the utilization of spatter-related information for rapid detection of defects and analysis of process stability with a high-speed CMOS camera outside the chamfer [40].

While the above-mentioned publications are mainly concerned with the detection of defects, the authors of [41] deal with the evaluation of geometry. They focused on using high-resolution imaging and image segmentation to detect errors and defects in 3D-printed layers. Various segmentation methods were compared, and the study examined the factors affecting measurement accuracy, such as repeatability, part-to-part variability, and build-to-build variability. The results demonstrated that active contours segmentation methods could achieve accurate contour identification in layerwise images but highlighted the importance of considering sources of variability.

As can be seen from the previous sections, there are many approaches using different sensors to monitor the process. An overview of these can be found in [41].

Conventional process control has been used since the beginning of LPBF manufacturing. These appro–aches have already been sufficiently highlighted in the review [23] in 2014 and improved in numerous further studies. AI-assisted adaptive process control, on the other hand, is a promising approach for real-time adjustments to the LPBF process, enabling improved manufacturing outcomes and more effective processes. Such closed-loop process control systems play a vital role in ensuring process stability and robustness [42]. The combination of AI-powered in-situ quality control and adaptive process control techniques can enhance the efficacy and efficiency of LPBF processes by allowing the system to modify process parameters when it detects flaws automatically. This can substantially decrease the occurrence of defective components and lead to a general improvement in quality [43]. AI-driven closed-loop control systems can leverage ML models to predict and control process variations in real time [44–46]. Such models are capable of capturing the intricate, non-linear connections between process parameters, sensor information, and part quality, facilitating the implemen–tation of more precise and adaptable control strategies [22]. By incorporating closed-loop control systems alongside in-situ quality control and adaptive process management, LPBF processes can become more efficient and resilient, ultimately leading to enhan–cements in component and material quality [47].

The study in [48] establishes the efficacy of ML models in detecting defects using in-process images. A CNN model was employed to predict porosity. The experiments reveal that X-ray computed tomography-assisted labeling provides more reliable and accurate results, achieving a 97 % accuracy in distinguishing porosity from non-porosity images. The findings contri–bute towards reducing post-processing costs and ena–bling real-time adjustments to printing parameters. By analyzing sensor data during the printing process, researchers can develop adaptive control strategies that modify process parameters on the fly in response to process variations or detected defects [49]. Reinfor–cement learning (RL) algorithms, such as Q-learning, Deep Q-Networks, and deep reinforcement learning, have been successfully employed in developing adaptive process control strategies for LPBF [50, 51].

Research [52] presents a layerwise imaging appro–ach for monitoring. The method entails capturing and analyzing images of fused and pre-placed powder layers under oblique illuminations to detect possible defects and enhance the quality of the produced parts. With advancements in sensing techniques, real-time control for adjusting parameters and addressing process anoma–lies reduce defects in the deposited builds.

A possible way of the above-mentioned techniques is used in [53]. Supervised ML is applied to detect defects using high-resolution imaging. Video monito–

ring with a high-frame-rate camera allows for cost-effective detection of changes in the melt pool and its surroundings. Statistical process control (SPC) charts were used to analyze the processed video volumes, revealing under-melting, over-melting, material spatter, and their correlation to defects.

Another emerging approach involves the use of RL for adaptive process parameter optimization in LPBF [51]. RL algorithms can learn optimal control policies by interacting with the environment, exploring the para–meter space, and adapting to variations in the process conditions.

A novel Deep Reinforcement Learning (DRL) fra–mework was developed in [51] aimed at optimizing the LPBF process to mitigate defects in fabricated components. The framework leverages computationally efficient simulations of temperature distribution and employs neural networks trained using the Proximal Policy Optimization algorithm to regulate process para–meters. The resultant control policies demonstrate remarkable efficacy in defect reduction while ensuring a consistent melt pool. Another RL approach introduces a new methodology that leverages high dynamic range optical imaging and CNNs to predict surface roughness [54]. The methodology incorporates spatially resolved and layerwise feedback signals, effectively addressing the shortcomings of prior methods. The predicted roug–hness maps act as feedback for reinforcement learning techniques, enabling the determination of optimal process parameters across varying conditions.

To further minimize latency and enable a new in-situ process, it requires new hardware. Previous research has focused on sensor data acquisition and real-time control strategies based on conventional methods that can only handle much-reduced metamodels. The reason for this state of research is the previous use of CPU-based computation units. Analogously, field-programmable gate arrays (FPGA) are used in control engineering for dynamic applications, but they are only suitable for AI-based metamodels to a limited extent.

In contrast, the computation can be performed using a neural processor unit (NPU) specifically designed for computing artificial intelligence algorithms (e. g. Akida BrainChip). The advantage of using such a processor unit is the fast response time of the control loop, which makes it possible to influence the dynamic process at an early stage specifically. A possible detection can be done by an event camera, which offers various advantages for the process analysis. This camera system works on the prin–ciple of the human eye instead of a shutter system (Figure 1). A charged-coupled device (CCD) camera captures a complete image after a fixed defined time, which increases the needed computing power. Thus, changes in the event camera are recorded separately for each pixel and only sent to the evaluation system when a change of state occurs. As a result of the change, heavily over–exposed and dark areas can be displayed particularly well - and at a speed similar to that of a high-speed camera. In summary, this methodology offers a state of the art that has not been explored before.

Currently, there are no publications using an event camera or an NPU-based evaluation unit in the field of LPBF manufacturing; however, this would be in promi–sing improvement proposal.

2.2 Multi-material approaches

The use of multi-materials in LPBF opens up new possibilities. Unlike single-material modeling, different physical properties are assigned to different material particles on the same powder layer. This requires a precise assignment of parameters for each material [55]. These systems typically use a combination of multiple powder feed options, such as hoppers and traditional powder application [56]. There are three main strategies for printing multi-material structures with LPBF [57]:

1. The process is performed directly on a substrate, and the multi-component part consists of the substrate and printed layers [58, 59]
2. The multi-material part is printed by depositing different materials layer by layer [60]
3. Multiple materials are mixed and deposited together [61–65].

The study of the authors in [58] presents a comprehensive assessment of additively-manufactured maraging tool steels, encompassing the entire process from powder production to hybrid builds. It investigates the effect of powder recycling on powder charac–teristics, highlighting the similarities in size distribution and chemical homogeneity between virgin and re-used powder while noting the lack of flow capability in the reused powder. Hybrid builds demonstrate a cohesive interface, exhibiting no signs of de-bonding during tensile deformation. Additionally, a heat treatment approach is proposed for the maraging steel powder /H13 tool steel substrate.

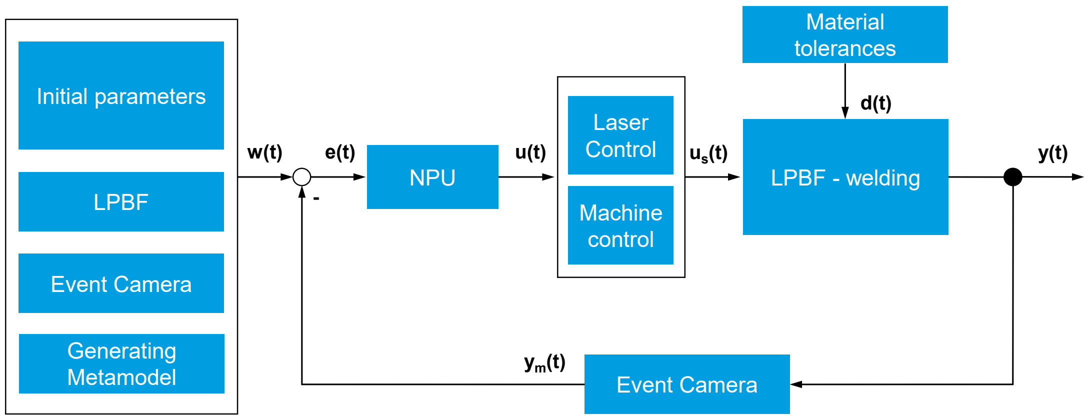

Figure 1. Working principle of an in-situ parameter adjustment based on metamodels and an event camera

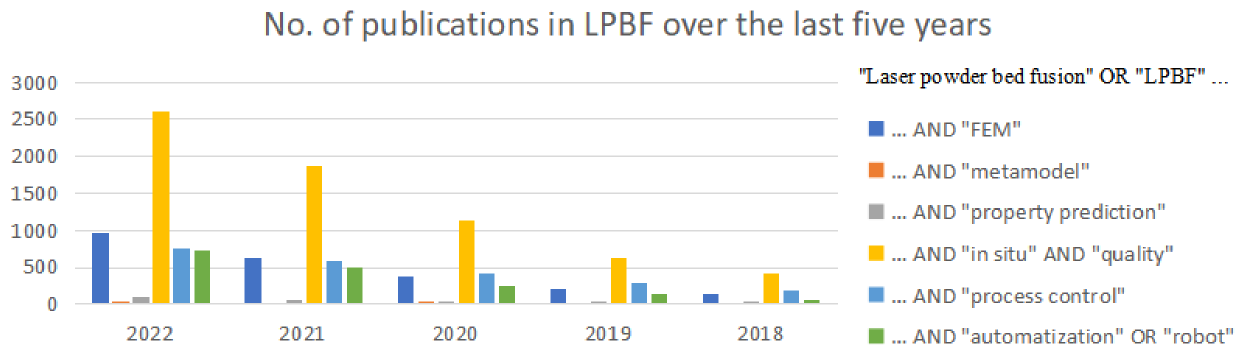

Figure 2. Number of publications with the prompts in the legend over the last five years, according to Google Scholar

The study [60] investigates the interfacial properties of dissimilar materials, namely 316L stainless steel and C52400 copper alloy. The interfaces exhibit robust metallurgical bonding, characterized by the inter–diffusion of elements and the presence of fine grains. Both interfaces feature isolated alloy islands with diverse shapes and morphologies. Cracking predomi–nantly initiates at the interface and propagates towards the stainless steel side, although no material separation occurs in the contact region. The thickness of the inter–face depends on the printing sequence, and a small amount of CuNi alloy is formed at the interface. These findings enhance the comprehension of interfacial pro–perties in dissimilar materials manufactured via SLM.

The authors of [65] conducted three experiments using different steel powders and an Aurora Labs S-Titanium Pro LPBF system. They achieved in-situ mixing and adaptive process control at different levels, as evi–denced by elemental maps, EDS line scans, microhar–dness, and microstructure analyses. The results show the successful implementation of multi-material processing with controlled spatial deployment of materials.

A completely new approach is taken by the authors in [66]. They successfully demonstrated the utilization of LPBF for the fabrication of multi-material parts by integrating metal foil within the LPBF process. The issue of powder contamination is effectively mitigated. An optimal laser power range of 120-140 W is iden–tified, striking a balance between attachment stability and minimizing thermal distortion. The contour cutting quality of the applied foil is contingent upon foil leveling and laser process parameters, with laser poli–shing proving effective in reducing burr heights. Achi–eving metallurgical bonding between IN625 foil and 316L substrate validates the feasibility of multi-material applications with customizable properties by applying individual foils.

3. APPROACH TO AUTOMATIZATION INTEGRATION IN LPBF

As mentioned earlier, LPBF has received a lot of attention recently. The number of citations in the various categories indicates the growing importance of this process in industry and research, see Figure 2. Figure 2 also shows that the number of researches dea–ling with the integration of automatization in LPBF is increasing. This increased interest is not surprising because, as can be seen in Figure 3, AM has high eco–nomic potential for the industry. However, complexity is also at the core of this figure because the more complex the components, the more economical AM becomes.

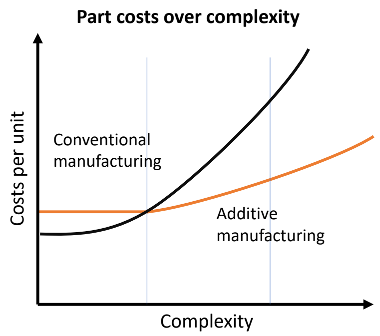

Figure 3. Advantages of AM in terms of cost and design

Sub-areas of automatization discussed in this section are the automatization of processes from engineering to production planning and manufacturing to quality assurance.

3.1 Optimizing CAx process-chain

Digital twins have gained attention for bridging the physical and digital worlds by collecting and analyzing data [67]. In AM, digital twins can improve the 3D printing of objects with desired mechanical properties. However, their development faces challenges, including the need for a better understanding of the concept, methods, and system integration.

Digital twins fulfill process requirements, including FE simulation, process parameter optimization, and sustainability evaluations [68]. In the context of additive LPBF manufacturing, the focus is on the CAx chain. The CAD to CAM system transition in LPBF introduces media discontinuity, especially in CAM programming. Neutral formats used for CAD (Step, Iges, ...) import lack the transfer of attributes, model-based definition (MBD), and process manufacturing information (PMIs), requiring manual processes and preventing the appli–cation of pre-calculated metamodels and feedback on CAD file formats. Consequently, a poor digital twin (automatic bidirectional data flow from the digital to the physical world) becomes a digital model (manual bidi–rectional data flow from the digital to the physical world) [69], hindering automatic data flow to the physical model.

Modern CAD/CAM systems like Siemens NX avoid media breaks and the use of neutral file formats and offer add-ons for LPBF functions. These systems enable direct implementation of adjustments in the CAD file based on deformation, such as modeling oval holes that become circular after printing. Linking these models to the product lifecycle management system (PLM) is necessary, but machine-related CAM systems often lack complete connectivity. The absence of this link prevents the availability of manufacturing information to the ERP system for production control. Post-processors convert CAx system models into machine-readable code for manufacturing. Siemens NX stands out as it offers machine-specific post-processors directly, eliminating the need for third-party suppliers. Machine manufacturers typically do not provide post-processors due to offering CAM software.

In summary, it can be concluded that a consistent data flow between engineering and ERP can only be achieved if media breaks are avoided.

3.2 Adaption for automated processes

Automatization plays a vital role in enhancing the efficiency, consistency, and repeatability of LPBF processes. The optimization and automatization heavily rely on data-driven decision-making, which allows valuable information and insights to be extracted from the vast amounts of generated data [70]. AI-powered techniques such as principal component analysis and cluster analysis can be employed to identify patterns, trends, and correlations within the data, enabling the development of informed process optimization strategies [71, 72]. AI-driven decision support systems can also be integrated with automated process planning and closed-loop control systems to provide real-time feedback and suggestions for process modifications, further enhancing efficiency and quality [73, 74].

Automatization and increased efficiency in AM require a holistic approach. Furthermore, the automatization of component feeding using robots and other specialized solutions plays a key role. Article [75] presents a methodology for designing handling systems that automate the handling of LPBF components, including the selection of gripping and clamping devices, robots, and peripheral systems. It provides insights into the potential benefits of automated gripping and clamping in AM, as well as the integration of post-processing into the overall process chain.

Another aspect explored in the research paper [76] is the application of multiple lasers in AM machines to increase productivity. While multi-laser machines can significantly reduce processing time, their use on a single workpiece can be complex and impact material properties. The paper investigates the influence of multi-laser scan strategies on the creep characteristics of LPBF alloy 718. The findings demonstrate that employing multi-laser scan strategies does not adversely affect creep behavior and enables a reduction in build time while maintaining mechanical integrity. These results support the application of LPBF for complex geometries and improved operational efficacy.

Figure 4 provides a summary of the most important improvements, considering both cost-effectiveness and quality improvement. The figure illustrates a trade-off between these two aspects, with quality being crucial in the long run to establish brands [77]. The highest potential for economic efficiency lies in multi-laser machines, although using multiple lasers on one component can lead to distortion issues. In terms of quality, in-situ quality measures, such as automatic parameter adjustment, show significant potential and cost-effectiveness. Combining these measures with a multi-laser application can further increase economic potential by reducing scrap and associated costs.

The research recommendation aims to stimulate new areas in the automatization of LPBF processes. Multi-laser applications and automated part handling is highlighted as offering high economic potential, as AM operations are time-intensive and do not require constant personnel supervision. The use of personnel is only necessary for unloading finished parts, removing remaining powder, and sawing the printed parts from the base plate. An automatic part handling system, combined with the zero-point clamping system, can automate these tasks fully. However, the automatic removal of powder residues remains a challenge. Interchangeable work areas for machines [78], allowing parallel cleaning and unloading with production (like matrix production [79, 80]), can be a potential solution, like those used at the BMW group [81, 82]. Due to the short operating times of the robot, a multi-machine configuration with a robot should be considered. Whether a closed industrial robot with large payloads and an automated guided vehicle (AGV) is used or a collaborative robot on an AGV depends largely on the base plate and, thus, the size of the component.

3.3 Automated process planning

Automated process planning is an essential aspect of LPBF, as it allows for the generation of optimized build plans and process parameters based on the geometry and material requirements of the components [83, 84].

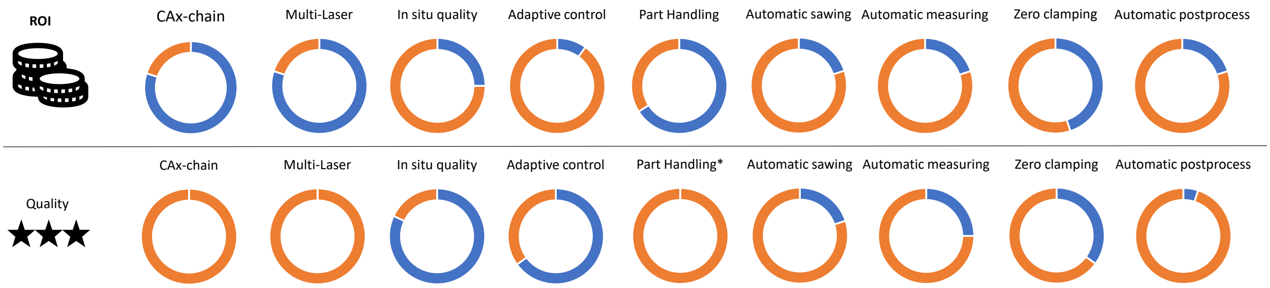

Figure 4. Quantitative return on invest (ROI) and quality increase of different automatization aspects

AI-driven algorithms, such as genetic algorithms and simulated annealing, have been employed to optimize the build orientation, support structures, and scan strategies in LPBF [85, 86]. By integrating these algorithms with surrogate models for process parameter optimization, researchers can develop comprehensive, automated process planning frameworks that minimize build time, material usage, and defects while maxi–mizing component quality [87, 88].

The scientific article [89] proposes the utilization of ontology as a means to enhance knowledge repre–sentation in the domain of process planning for LPBF. The ontology captures relevant concepts, relationships, and constraints, facilitating knowledge sharing and decision-making. A schematic diagram illustrates the ontology's development process, highlighting its poten–tial benefits in improving process planning.

A major challenge in planning is the auto ID process of components in manufacturing. The publication [90] deals with the use of combined auto-ID systems in additive process chains. It shows that a lack of auto–matization and digitalization limits the economic suc–cess of additive production. The systematic selection and combination of suitable systems can provide a ne–cessary database for effective production control. Here, ultrawideband (UWB) for tracking and indoor loca–lization of the batch is used, while data matrix codes (DMC’s) are printed directly on the parts and used for identification of every single part. The procedures mentioned refer to production control, which is essen–tially a part of the supply chain. Consequently, however, the consideration of (factory) standards and attributes in the CAD/CAM chain is missing in this context of LPBF process planning.

In the study [91], modified data in AM is introduced using the Standard for the Exchange of product model data Numerical Control (STEP-NC). The existing STEP-NC lacks the necessary definitions for process parameters and scan strategies. The proposed data rep–resentation establishes clear definitions for interlayer relationships, technology controls, and scan strategies. This research underscores the importance of information models in AM, advocating data representations as vital enablers of AM technology and ensuring seamless data exchange among systems.

Optimizing the part build orientation is critical for achieving high-quality and efficient manufacturing. The orientation of a part impacts its mechanical properties, surface quality, and the time it takes to build. By automatically determining the optimal orientation, the LPBF process can be fine-tuned to reduce support volume, minimize volumetric error, enhance surface roughness, lower build time and cost, and ultimately produce parts with the desired properties [92]. Therefore an XML Schema of the author of [93] is used to construct a moderately complex information model of LPBF process plans, achieving the goal of polymor–phism despite challenges in defining data structures.

3.4 The 3D scanner as a measuring instrument

3D scanners have the potential for reverse engineering and quality monitoring. The scanners based on laser triangulation have an increasing accuracy and therefore increasing interest. In the field of reverse engineering, mainly 3D scans of spare parts that are no longer avai-lable are created and reprinted. Among other fields, the authors in [94] present a 3D-printed protective cover for a micro automatization device for cutting silicon wafers. Commercial systems like Zeiss's T-Hawk 2 handheld scanner can scan large objects and be operated manually without a tripod. These devices meet the ISO 10360 stan-dard for coordinate measuring machines and have an accuracy of 0,035 mm.

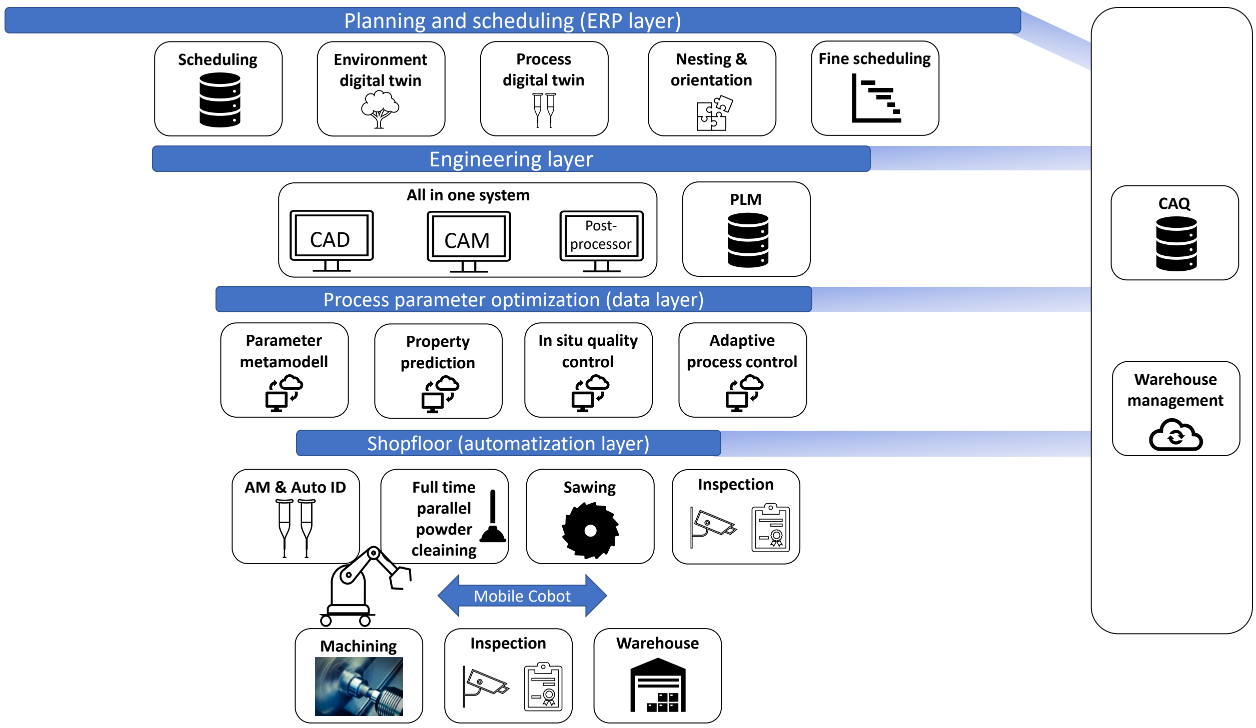

Figure 5. General view of a perfect LPBF process chain with four different layers

Accuracy can be further improved by robot guidance or rotating devices with tripods. However, coordinate mea–suring machines have significantly higher accuracy in an ideal measuring room environment. Compared to tradi–tional coordinate measuring machines, 3D scanners are faster, do not require explicit programming, and obtain the whole part.

Complex models, such as those used in LPBF, can be effectively inspected externally. This process plays a crucial role in the digitalization chain. By utilizing PMIs and MBD in CAD models, data can be directly transferred to the laser scanner. This enables automated evaluation of part quality based on defined tolerances. The data is also automatically integrated into the quality management system (QMS) and enterprise resource planning (ERP) system, connecting the design, quality control, and production processes.

Automatization offers additional potential in this context. Components can be measured fully automa–tically on the printing plate or afterward, with the scanner positioned by a robot or vice versa. For comp–lex geometries requiring scanning from all sides, two robots can collaborate, similar to car body welding app–lications. One robot positions the component, while the other positions the scanner. After quality control, down–stream production can proceed. This approach helps detect defects early, reducing costs and minimizing the ecological footprint by reducing scrap. Nevertheless, this actually isn't evaluated. Figure 5 shows the optimal structure of an LPBF process chain holistically.

4. POTENTIAL USE CASES FOR AI-BASED IMPROVEMENTS OF AN LPBF PROCESS

4.1 Personalized medical implants

The production of personalized medical implants is a promising application for LPBF processes [95]. It can be utilized to develop customized implants tailored to individual patient needs, optimizing mechanical proper–ties and biocompatibility [96]. In-situ quality control and adaptive process control can further enhance the production process by ensuring high-quality implants with minimal defects [97]. This can ultimately lead to improved patient outcomes and more efficient health-care systems [98, 99].

A study [100] found that LPBF-produced porous implants with pore sizes of 500-700 μm and porosity of 60% ÷ 70 % exhibited the best bone integration. Such implants have a structure and performance similar to human cancellous bone. Possible corrosion does not pose a risk for implants, as shown by the results in [101]. After 28 days of exposure to a 0.9 wt% NaCl solution, improved corrosion resistance was shown due to the formation of an oxide layer.

Although the LPBF process offers flexibility and precision in the production of complex implants, there are some limitations, as already discussed and sufficiently stated in this paper, but they also affect the production of medical implants [102]. The use of lattice structures allows the stiffness of individualized implants to be adjusted, which can lead to faster bone healing [103].

4.2 Aerospace components

AM has the potential to revolutionize the aerospace industry by enabling the production of lightweight, optimized metallic components suitable for space flight. However, industry leaders still harbor concerns about the readiness of AM for flight parts, given the high stakes in terms of safety and cost.

The aerospace industry can benefit significantly from improvements in LPBF processes [104]. Topology optimization and generative design techniques can be employed to minimize weight while maintaining perfor–mance, leading to reduced fuel consumption and emis–sions [105, 106]. High-speed X-ray imaging quantifies pore formation and further enhances the production process by ensuring high-quality titanium components with optimized mechanical properties [107] – which are often used in aerospace. In-situ quality control and adaptive process control can contribute to more reliable and repeatable manufacturing processes, meeting the stringent requirements of the aerospace industry [108].

In the aerospace industry, various components are manufactured using the LPBF method, including support and landing gears, servo-hydraulic control elements, hydraulic and electromechanical actuators for flap drives, gyro systems for guided missiles, and drive elements for land vehicles in extraterrestrial use [109, 110].

The study [111] discusses the benefits of AM, add–resses reliability and safety concerns, and presents successful case studies in the aerospace industry.

One example is engine components such as blade-integrated discs (blisks), which were previously made from nickel-based superalloys that were difficult to machine. The Fraunhofer Institute for Production Tech–nology (IPT) is conducting a new process chain [112]. The researchers aim to manufacture blisks close to the final contour to minimize material waste and machining. This can reduce material consumption, which brings both economic and ecological benefits.

The research paper [113] is a valuable resource for individuals who wish to expand their knowledge of AM applications in aerospace.

4.3 Automotive industry

The scientific research results on LPBF-manufactured automotive components show that the LPBF process is widely used in the automotive industry. The limitations of the process lie in its scalability for mass production, which is typically strong in the automotive industry. This section is, therefore, inevitably dominated by automatization solutions. Research in LPBF has also led to the development of methods for removing support structures from LPBF-manufactured parts. A promising approach for the removal of support structures is to chemically dissolve them [114]. This application is the result of the IDAM project, which was essentially led by the ILT and has a project duration of three years.

Article [115] examines the use of Inconel 718 turbine blades in the pre-design phase for turbochargers. The study demonstrates that by optimizing the processing parameters, the fusion can be uniform and match the intended geometry. Areal and point EDS inspections were conducted on the virgin powder and samples, yielding favorable results. However, production in the automotive industry does not only require turbine blades, but other components around the mixture charging of the exhaust side are also under high-temperature stress and require flow-optimized structures [116]. This type of application is also suitable for self-fluxing Ni-based alloy coatings as they are widely used under conditions of wear, corrosion, and high temperatures [117].

Another area is the repair and customizing of vehi–cles. Especially for oldtimers and other rare vehicles, there is no high demand for spare parts; in consequence, original equipment manufacturer parts are lacking. The publication of [118] shows a Knowledge-Based Assis–tance System for part preparation in additive repair on a wheel carrier. To increase the fatigue strength of the wheel carrier, particle-filled cavities are introduced in the area near the tie rod connection. The designer can select which evaluation criterion is prioritized, either volume cut-off or surfaces requiring support structures. As the authors show here, the component is not only replicated but its strength is also improved. In addition, new, modern materials specially tailored to the applic–ation can be used for components from old vehicles.

4.4 Tooling

Tool manufacturing in conjunction with LPBF enables the production of wear-resistant and high-hardness components such as cutting, punching, and other tools or fixtures. Cutting tools with a steel base body benefit from this to a large extent, as the ultra-hard cutting materials, such as carbide, PCD, etc., are brazed or screwed on. This technology enables the use of intel–ligent cooling strategies that are not possible in con–ventional cutting production. This can be particularly advantageous for small tools where it is difficult to fit cooling channels into the limited space [119, 120].

Another approach is to improve cooling by intro–ducing cooling channels in the back of the insert seats. This cools the internally cooled tool not only from above in the area of the rake face but also from the rear side in the area of the clearance face. Such a modification of the pocket of the insert, in combination with an optimized in–sert, enables effective cooling and, thus, a longer tool life.

Additively manufactured forming tools and hybrid welding fixtures enable resource savings, as mentioned in a research paper in collaboration with Ford [121]. Further–more, stamping and forming tools can be lighter than con–ventionally manufactured tools. This leads to improved handling and efficiency during the production process. These 3D-printed tools were tested by forming U-bends and trimming/cutting/blanking 2 mm thick hot-dip galva–nized DP600. The approval criteria required 50.000 U-bends without surface scratches and 100.000 trimming strokes with a maximum burr height of less than 0,2 mm (lower than 10 % of the sheet thickness). Tool life could be further improved with the use of Ni-based self-fluxing alloy coatings [122], as this can be applied to LPBF comp–onents. With this coating, LPBF tools can also be used for hot forming, as the temperature resistance is improved [123]. Another application is mold making, e.g., for the production of plastic products, like explained in [124].

The core (inserts) of an injection mold is 3D-printed from 1.2709 steel, optimizing conformal cooling and compared to a conventionally manufactured core made from Uddeholm AM Corrax. Cooling and cycle time can be improved when the injection mold core is optimized. Another approach [125] is to coat AM plastic cores from small-batch production to increase service life.

The study [126] demonstrates the rapid prototyping procedure of casting core production and compares it. The paper describes different approaches to the deve–lopment of casting cores: direct, indirect, and direct production of molds, and the main factors in deciding on the application of this technology.

4.5 Building smart components

Smart components manufactured using the LPBF pro–cess offer innovative functions and expanded possibi–lities for AM. New applications can be realized by inte–grating sensors and other electronic components. For example, components made of SS316 with embedded fiber optic sensors for temperature monitoring up to 1000 °C were produced [127]. By integrating printed ele–ctronics, such as strain gauges, additional functions can be introduced into additively manufactured components [128]. Intelligent components manufactured with LPBF find application in various fields. These include the space industry, where additively manufactured, optimized metallic components can be used for satellites [129]. However, when sensors are integrated during the LPBF process, then process downtimes usually occur [130]. This article highlights the increasing demand for sensor-monitored components to minimize maintenance and proactively replace parts before failure. Comparing manual and automated sensor integration, automated methods are 32 times faster with improved part quality. Future challenges include implementing multi-material mechanisms and demonstrating the value of LPBF in comparison to conventional sensor integration [130]. In study [131] the integration of IoT, automatization, and AI to improve the reliability and scalability of AM processes for the mass production of smart materials was explored.

Another approach deals with quality. The chosen material for this investigation was 316 L stainless steel, which has a range of applications, such as injection molds and continuous flow reactors. A temperature SAW sensor has been chosen for this process. To assess the internal integrity of the cover plate and the SAW sensor, three-dimensional non-destructive characteri–zation was carried out using an X-ray computed tomo–graphy (CT) scan [132].

5. CONCLUSION & OUTLOOK

This article titled "Optimization Potentials of Laser Powder Bed Fusion: A Conceptual Approach" explores the integration of artificial intelligence and automa–tization approaches into LPBF technology. The study outlines the potential benefits and challenges of this manufacturing process and focuses on the complete process chain from engineering to quality management to optimize the LPBF process. Therefore, the most significant publications are considered.

One of the main challenges in LPBF is achieving high component and material quality, which requires precise control over laser power, scan speed, and layer thickness. The main focus for further research should be on in-situ quality and adaptive control but in combination with multi-laser applications. In fact, multi-laser applications have the greatest economic potential, attracting the interest of influential big companies. In addition, various multi-material approaches are summarized to show the potential of tailored material properties.

The aim is also to optimize the CAx process chain and improve the efficiency, quality, and reliability of LPBF processes. Digital twins are highlighted as a means to bridge the physical and digital worlds in AM, offering the potential for improved fabrication and environmental impact evaluation. There is further potential here in research and development for integ–rated CAD/CAM systems in the LPBF area and the closed-loop approach to connect more machines to manufacturer-independent programs and make them open for customer-specific and research applications through integrated interfaces.

Automatization plays a crucial role in enhancing LPBF processes. Robotics, AI technologies, and auto–mated process planning can optimize fine scheduling, build plans, process parameters, and support structures. Further attention in the area of automatization should be paid to automated gripping and clamping systems and interchangeable substrate units. Here, the maximum potential for efficiency, economy, and improvement of the environmental footprint of manufacturing exists.

The seamless data exchange in the complete LPBF processes enables new dimensions of process planning. However, the integration of special LPBF functions in the ERP system is only slightly developed. This subject area must be developed by large ERP system manu–facturers in cooperation with machine manufacturers in order to make it interesting for widespread use.

Furthermore, the use of 3D scanners in the LPBF process is explained, as they are increasingly used as measuring instruments in quality control. They enable reverse engineering and process quality monitoring. High accuracy, based on laser triangulation, makes them faster and easier to use than conventional coordinate measuring machines. Further research in the area of the stages model in the CAD system in relation to LPBF components and the automatization of in-situ scanners for product control will fully exploit the potential of a closed process loop.

In addition, further research should address automatic defect assessment and decision-making for the repair, further processing, or recycling of LPBF components.

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NOMENCLATURE

AM	Additive Manufacturing
LPBF	Laser Powder Bed Fusion
AI	Artificial Intelligence
ML	Machine Learning
DL	Deep Learning
CNN	Convolution Neural Network
SPH	Smoothed Particle Hydrodynamics
SLM	Selective Laser Melting
DEM	Discrete Element Method
FVM	Finite Volume Method
NSGA-II	Non-dominated sorting genetic algorithm
MOPSO	Multi-objective swarm optimizer
ROI	Region of Interest
LWIR	Long wave Infrared
ILCT	Inter-layer Cooling Time
CMOS	Complem. Metal Oxide Semiconductor
TOT	Time over Threshold
RL	Reinforcement Learning
SPC	Statistical Process Control
DRL	Deep Reinforcement Learning
FPGA	Field-programmable Gate Arrays
NPU	Neural Processor Unit
CCD	Charged Couple Device
MBD	Model-Based Definition
PMI	Product Manufacturing Information
PLM	Product Lifecycle Management
ROI	Return on Invest
AGV	Automated Guided Vehicle
UWB	Ultrawideband
CT	Computer Tomography

ПОТЕНЦИЈАЛИ ЗА ОПТИМИЗАЦИЈУ ПРОЦЕСА ЛАСЕРСКЕ ФУЗИЈЕ ПРАХА У КОМОРИ: КОНЦЕПТУАЛНИ ПРИСТУП

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Адитивна производња (additive manufacturing, AM), тачније ласерска фузија праха у комори (laser powder bed fusion, ЛПБФ), постаје све важнија за производњу сложених компоненти. Упркос сталним побољшањима, проблеми са оптимизацијом пара–метара процеса, приступима са више материјала, ЦАх (computer aided) ланцем, прилагодбом за ауто–матизовану масовну производњу, аутоматизованим планирањем процеса и контролом квалитета, и даље постоје. До сада, упркос растућем интересовању, ова технологија још није направила значајан скок у свакодневну и широку употребу. Употреба вештачке интелигенције нуди могућности за решавање мно–гих од ових проблема и побољшање ЛПБФ техно–логије. У овом раду, ове теме су обрађене да би читаоцу дале холистички преглед потенцијала за оптимизацију. Појединачне теме нису само објаш–њене и подржане примерима производа из разли–читих индустрија, већ су и оцењене у смислу испла–тивости и побољшања квалитета. Проценом потен–цијала, ограничења и препорука, ствара се оквир за даље истраживање и практичну примену опти–мизацијских приступа.