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Martin Brylowski, Lea-Sophie Schwieger, Ayman Nagi, and Wolfgang Kersten

# How to apply Artificial Intelligence in the Additive Value Chain: A Systematic Literature Review

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# How to apply Artificial Intelligence in the Additive Value Chain: A Systematic Literature Review

*Martin Brylowski[1], Lea-Sophie Schwieger[1], Ayman Nagi[1] and Wolfgang Kersten[1]*

1 – Hamburg University of Technology

***Purpose:*** *Additive manufacturing (AM) enables the manufacturing of metal parts and is therefore increasingly important for industry. Unfortunately, the manufactured parts exhibit many imperfections, such as faults or other quality defects. The use of artificial intelligence (AI) allows for the steady optimization of processes, making its potential implementation in AM interesting as it could help to improve processes for industrialization and serial production.*

***Methodology:*** *A systematic review was conducted of the literature on applications of AI in AM. A total of 741 articles published between 2008 and 2020 were scanned to determine whether they described an explicit application of AI in a metalworking process. A detailed analysis yielded 87 relevant sources.*

***Findings:*** *The articles were scanned for existing application areas of AI in AM, including application in the associated value chain phases of AM planning and AM execution. In AM planning, AI is frequently used to support the design process, while in AM execution, AI is mostly used for process monitoring and defect detection.*

***Originality:*** *The applications of AI in AM were investigated by means of a systematic literature review. The resultant findings should provide insights into existing and potential application areas for AI in AM.*

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# 1 Introduction

Additive manufacturing (AM) is characterized by the layer-by-layer building of a component based on a CAD model. This enables the production of many complex geometrical structures (e.g., topology-optimized structures), and reduces costs and waste. The value chain of AM consists mainly of design, material selection, manufacturing and quality assessment (Qi, et al., 2019). There are various reasons for the industrial use of AM, including design flexibility, the enabling of a high degree of product customization at relatively low cost, and shorter lead times (Stoyanov and Bailey, 2017).

Unfortunately performance, quality and reliability are all major challenges for AM (Stoyanov and Bailey, 2017). One problem is that defects – such as pores – occur frequently (Qi, et al., 2019). Moreover, residual stresses that influence stability and mechanical performance as well as shape accuracy also present critical problems. Particularly common processes include fused deposition modelling, selective laser sintering, inkjet printing and stereolithography (Stoyanov and Bailey, 2017).

Recently it has been recognized that the use of artificial intelligence (AI) techniques, and particularly the use of neural networks, accelerates the development of AM technologies and also allows for many new possible applications (Qi, et al., 2019). With AI, no analytical equations are necessary, since the algorithm used can learn relationships between input parameters and output performance and recognize patterns autonomously based on existing data (Hassanin, et al., 2020). Input parameters include design, material and process parameters, while "output performance" means microstructural and mechanical properties (Qi, et al., 2019). The training of neural networks is time-consuming, requiring significant computing power as well as a substantial number of training samples, but their subsequent use allows for the acceleration of processes (Aggarwal, 2018).

The aim of this work is to identify the possible application areas of AI in AM by examining previous works. Consequently, the research question has been formulated as follows: Where has artificial intelligence been applied in additive manufacturing?

The remaining paper is structured as follows. It proceeds with an explanation of the methodological approach of the literature review in Section 2. Section 3 then continues with the descriptive and qualitative content analysis of the use cases. This is followed by an explanation of the results of the research in Section 4. Finally, Section 5 summarizes the findings and provides an outlook on further possible research areas.

## 2 Methodology

The systematic literature review was carried out according to the methodology laid down by Tranfield, Denyer and Smart (2003). The research was thus first planned, and from the planned steps a review protocol was written to ensure objectivity. The research question was then formulated and, as a result, the two thematic contexts of AI and AM were identified. Based on these generic terms, suitable search terms could be determined by means of synonyms. Consequently, a search string could be formulated by means of Boolean operators, which can be seen in Figure 1.

The second step was to conduct the research. In the two selected meta-databases, Scopus and Web of Science, the search string was used to search within the abstract, title, and keywords of sources in order to identify suitable papers. This resulted in the identification of 758 potentially relevant papers on Scopus, and 293 on Web of Science (September 11th, 2020). After the removal of duplicate works, the result was 741 published works. Finally, a title and abstract screening was carried out to exclude works dealing with use cases in the context of medicine or the plastics processing industry. This resulted in a reduction to 190 potentially relevant literature sources. By means of a full-text screening, a final determination of thematic relevance followed, resulting in the selection of 87 relevant literature works, which are considered below. This procedure is outlined in Figure 1.

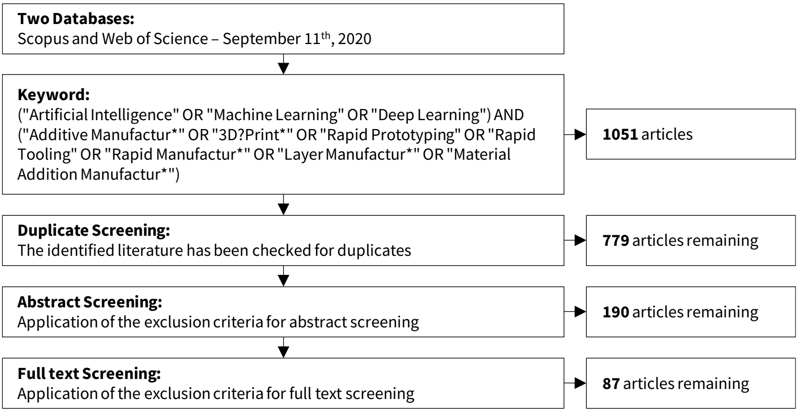


Figure 1. Methodological Approach of Exclusion to Determine Relevant Articles

# 3 Artificial Intelligence in Additive Manufacturing

In this section the descriptive analysis of the identified literature works is carried out first. This is followed by the results of the qualitative content analysis, wherein different application areas of AI in AM – divided between AM planning and AM execution – are presented.

## 3.1 Descriptive Analysis

One way is to examine the literature is to look at papers in terms of their frequency distributions by year and document type. Strikingly, over 95% of the selected sources were from the last six years (2016 to 2021; see Figure 2). This reflects recent advances in AI, including increased computing power and storage capacity, and highlights the novelty of AI in AM. Furthermore, the increasing number of use cases shows the growing relevance of AI in AM. The flattening number of use cases in 2020 can be explained by the fact that the databases were accessed on the 11th of September, meaning that the use cases ranging from mid-September to the end of December were not recorded.

Of the selected literary works, 31% were conference papers and 69% were journal articles. The high number of journal articles, which are often of higher quality than conference papers, illustrates the scientific importance of the topic. The increasing number of conference papers also indicates that research interest in this topic is continuing to grow.

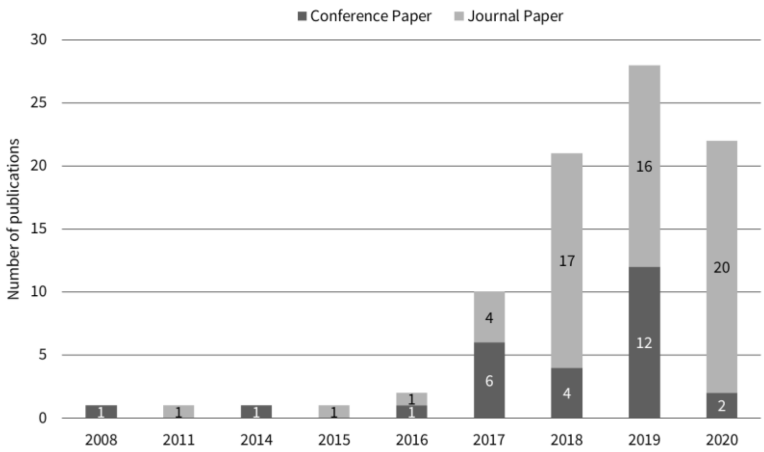


Figure 2. Frequency Distribution of the Relevant Articles

In the distribution of used algorithms, which can be seen in Figure 3, an accumulation can also be observed in the use of deep and supervised learning algorithms.

The use of supervised learning algorithms can be explained by the fact that many internal data sources were used, such as machine and sensor data from researchers' own experiments. It was to this data that AI was applied, rather than, for example, text data from the internet. In addition, the sensor technology and structured storage must have been defined before the data was recorded so that the data was available in a structured form. Among the supervised learning algorithms, slightly more classification algorithms than regression algorithms were used; this would result in the making of more categorical decisions as opposed to predicting continuous evolution. Regression algorithms do, in fact, also try to take into account the development of the data and to approximate future developments on this basis. In some use cases, a combination of both types of algorithms was used, so that future developments were predicted alongside the making of categorical decisions. In some use cases, researchers went a step further, with a combination of clustering, unsupervised learning algorithms and classification algorithms. This was done, for instance, when external data was evaluated in addition to the internally collected data, or when criteria for structuring the data were not yet known.

The frequent use of deep learning algorithms suggests how current this topic of AI in AM is in research. These are very new and innovative algorithms that are themselves capable of recognizing patterns, although it is not entirely clear how they actually work. However, this loss of control is accepted due to their established use in the industry and hopes surrounding their ability to add value.

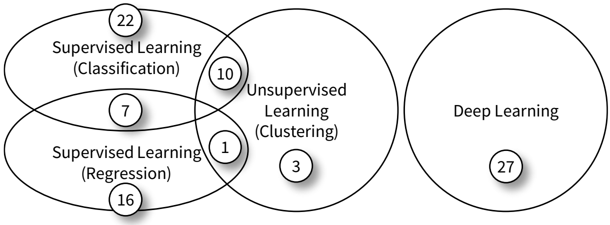


Figure 3. Distribution of Used Algorithms in the Relevant Articles

## 3.2 Qualitative Analysis

In the qualitative analysis of the identified use cases, different application areas of AI in AM could be identified on the basis of the areas defined by Razvi, et al. (2019), which were extended with some additional application areas. These areas of application can be divided roughly into the use of AI in AM planning, and its use in AM execution. Most of the use cases – 62 of 87 – took place in AM execution. Particularly high numbers of use cases were observed in process monitoring and in the monitoring of defects. Further information can be seen in Figure 4.

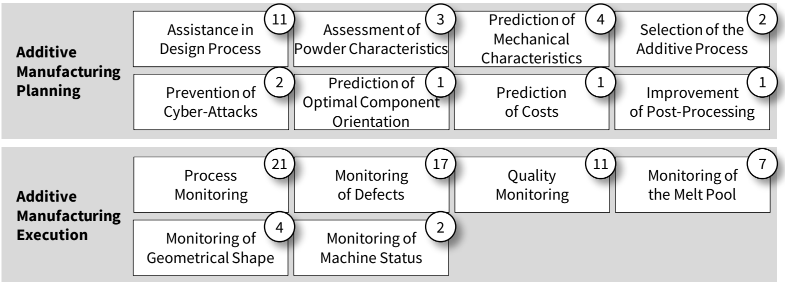


Figure 4. Observed Application Areas in AM Planning and AM Execution

### 3.2.1 Artificial Intelligence in Additive Manufacturing Planning

**Assistance in Design Process**

One major problem is often lack of experience on the part of engineers with additive processes, which can lead to errors. This was highlighted by eleven of the identified literature items. In such cases, AI can support the engineer in the design of additive products, which should lead to an increase in efficiency (Murphy, et al., 2018).

The identified use cases are very diverse, ranging from the development of design rules to the optimization and manufacturability testing of design ideas. For instance, design rules for thin-walled features were developed by Gaikwad, et al. (2019). A paper by Mycroft, et al. (2020), on the other hand, is concerned with exploring the limits of manufacturability in additive processes by identifying problematic regions, while in the work of Yang, et al. (2020) a decision system was developed for the identification of part candidates for AM applications.

AI can also be used to predict AM attributes, such as mass, required support structures and build times, as was done in the work of Murphy, et al.(2018). The work of Yao, Moon and Bi (2017), on the other hand, deals directly with a system that can suggest design solutions based on certain construction features.

**Prediction of Mechanical Characteristics**

The prediction of mechanical characteristics with AI is very relevant due to the high location dependency caused by many heating and cooling cycles. Since the layer-by-layer build-up process is often subject to strong process fluctuations, a prediction is much more difficult than it would be in conventional processes. Here, AI can help to predict mechanical properties on the basis of various data inputs (Yan, et al., 2018).

Since such predictions can be based on the choice of process parameters and geometry, as well as on the recording of the process, the use cases are partly also applied in AM execution.

The work of Garg and Tai (2014) focuses on the prediction of wear resistance, while the work of Yan, et al. (2018) uses AI for the prediction of varying tensile strength based on selected manufacturing parameters.

**Assessment of Powder Characteristics**

In many additive processes, powder is used as a raw material that is successively bonded in layers by an energetic jet. For successful production, the powder must be distributed as evenly as possible in the powder bed beforehand. Often, anomalies or irregularities that negatively influence process reliability and stability occur. Since it is practically impossible to detect such anomalies with the naked eye, a combination of AI and computer vision is usually used for this purpose (Scime and Beuth, 2018a).

The use cases make use of AI in the planning process, during production, and in powder management, by testing the powder material.

Using AI, powder distribution can be predicted in order to control scatter defects, as was done in the work of Desai and Higgs (2019); the detection of the development of component defects from the observed powder distribution is also possible, as was done in the work of Scime and Beuth (2018a). In addition, in the work of DeCost, et al. (2016), AI was used for the evaluation of microsections for the classification of powder material.

**Selection of the Additive Process**

The choice of the AM process has a lasting influence on component behavior. AI can help to select a suitable AM process based on various selection factors (Munguia and Riba, 2008).

Munguia, Bernard and Erdal (2011) developed as system that uses AI to assist in the selection of a suitable AM process based on initial product design specifications. In another work by Munguia and Riba (2008), a computer-aided system was used to compare the additive processes with each other and with conventional manufacturing processes, and also to aid in the selection of suitable production parameters.

**Prevention of Cyber-Attacks**

Cyber-attacks are playing an increasingly important role in cyber-physical production systems, even though only two use cases with respect to prevention of cyber-attacks in AM could be identified here. The attackers' motives range from theft of intellectual property to sabotage of safety-critical systems, both of which can cause massive financial damage (Yeboah-Ofori, Abdulai and Katsriku, 2018).

While the use case developed by Al Faruque, et al. (2016) deals with the possibilities of component reconstruction based on noise emissions, the work of Wu, Song and Moon (2017) dealt with the use of Machine Learning (ML) methods to detect cyber-physical attacks .

Since both use cases also examine the ongoing process of production, this application area is also used in AM execution.

**Prediction of Optimal Component Orientation**

Optimal build orientation is an important parameter in AM, as it has a significant impact on accuracy, cost and build time. A good orientation can only be achieved by sufficiently experienced engineers, and even then such orientations are usually not optimal (Canellidis, Giannatsis and Dedoussis, 2009).

It is possible for AI to help with determination of an optimal build orientation, thus automating this process step. The only identified use case, which was developed by

Zhang, et al. (2018), deals with the determination, using ML methods, of an optimal component orientation based on the features of the component.

**Prediction of Costs**

The use of AI can also help with estimation of the costs incurred in the course of development and during the process of AM. Only one literature work, authored by Chan, Lu and Wang (2017), could be identified; it deals with cost estimation by means of ML, taking into account historical cost data on components that have already been manufactured.

**Improvement of Post-Processing**

Many additive processes still require post-processing of the surface and porosity (Richter and Wischmann, 2016). Using AI, the influence of this post-processing can be determined and also improved, as was the objective of Hatamleh, et al. (2019). Here, prediction of the influence of laser shock peening on varying residual stresses was investigated. Since post-processing data is also collected for this purpose, this application area also takes place in AM execution.

### 3.2.2 Artificial Intelligence in Additive Manufacturing Execution

**Process Monitoring**

Monitoring manufacturing processes by means of AI is an elementary application field in AM, a fact made clear by the presence of 21 identified use cases in our sample. AI helps to cope with the particularly high levels of complexity of additive processes. In AM, AI is used to identify and quantify process parameters that significantly influence process repeatability and product quality (Everton, et al., 2016).

For the most part, the use cases occurred in AM planning (when setting up the printer) and in AM execution (when printing the component), and involved recording data using imaging techniques. Often the use cases dealt with an optimization loop, so that in the future machines can adjust process parameters based on the observations they made of the process.

Many studies in the literature have worked to determine the influence of process parameters. The influence of process parameters on surface roughness was determined using AI in the work of Akhil, et al. (2020), while their influence on porosity was determined by Imani, et al. (2018), and their influence on tensile properties was determined by Marmarelis and Ghanem (2020). Some works only examined individual process parameters. For example, Douard, et al. (2018) investigated the influence of support structures on geometric quality. Raitanen and Ylander (2020) applied AI to detect faulty machine conditions and part porosity and to determine the correlation between these factors.

In other use cases, the focus was more on improving the process parameters. For this purpose, detection of errors by the machine itself was specifically used to improve process parameters in the work of Razaviarab, Sharifi and Banadaki (2019). A study by Mondal, et al. (2020) focused on control of the melt pool for improvements. In the work of Uhlmann, et al. (2017), targets of improvement included the reduction of energy consumption and emissions.

Other sources were more concerned with monitoring the process system as a whole. For example, the probability of a successful print can be predicted, as was done in the work of Amini and Chang (2018). In a use case by Wang, et al. (2018) system monitoring was used to stabilize the printing process by inspecting droplet behavior, while, Rafajlowicz (2017) developed a control system that examines images to make control decisions regarding laser power.

**Monitoring of Defects**

Due to their layered structure, additively manufactured components often tend to show anomalies and defects within their structure (Gobert, et al., 2018). Consequently, the detection of component defects during the additive manufacturing process is an elementary application area of AI, a fact made clear by the presence of 17 identified use cases in our sample. Input data were mostly collected by means of imaging techniques.

Many use cases were mainly concerned with the detection of component defects through the layer-by-layer recording of images using cameras, as in the work of Gobert, et al. (2018) . In the papers by Eschner, et al. (2019) and Okaro, et al. (2019), on the other hand, acoustic and photodiode data were used. By evaluating thermographic images, it is also possible to detect delamination and splatter, as Baumgartl et al. demonstrated (2020).

Other authors, in addition to detection, also dealt with the classification of defects and pores, such as Angelone, et al. (2020) and Williams, et al. (2018).

Some sources dealt specifically with the monitoring of porosity, for which, among other methods, pyrometric data (Mitchell, et al., 2019) and micro x-ray computed tomography data (Zhu, et al., 2020) have been used.

**Quality Monitoring**

The quality of a component can often only be determined after the manufacturing process has been completed, which can result in a waste of time and material. Consequently, AI can help to reduce waste by processing process data and providing early warning of poor component quality, enabling corrective measures to be initiated (Delli and Chang, 2018).

For the monitoring of component quality, image data (Yuan, et al., 2019) as well as noise emissions (Wasmer, et al., 2019) and optical thermography of the melt pool (Yadav, et al., 2020) can be used. In a paper by Li, Yan and Zhang (2019), quality monitoring was used specifically to evaluate material behavior based on the detection of the material's microstructure. AI can also be used to predict and optimize quality (Stoyanov and Bailey, 2017).

**Monitoring of the Melt Pool**

Monitoring the melt pool is a significant area of application of AI, as the melt pool in particular is responsible for many defects in additive components (Scime and Beuth, 2018b).

Since monitoring with the naked eye is practically impossible, in the use cases AI was often used in combination with computer-vision-based approaches. These use cases took place in AM execution by monitoring the printing process, as well as by changing process parameters within an improvement loop.

Monitoring of the melt pool can enable the detection of anomalies and also determine the influence of the melt pool on porosity, as was examined in the work of Scime and

Beuth (2018b). In addition, in the work of Yeung, Yang and Yan (2020), AI was used to control the melt pool by regulating laser energy.

**Monitoring of the Geometrical Shape of Components**

Investigation of geometric shape is mostly carried out in AM execution when monitoring the printing process, but also allows conclusions to be drawn on how to improve geometry and the printing process.

Examination of the component's geometric shape can be used to control quality by avoiding geometric deviations. The variance in geometry should be within predefined tolerance limits. In addition, process parameters can be inferred by examining component shapes. In this way, AI can help provide a better understanding of the morphological formation of additive components, and thus also enable the prediction of systematic shape deviations to enable correct intervention if necessary (Francis and Bian, 2019).

For example, AI was used by Korneev, et al. (2020) to predict a component's "printed" shape, and by Francis and Bian (2019) to predict deviations due to heat-induced distortions.

**Monitoring of the Machine Status**

Condition monitoring of AM machines is an AI application area in which the main objective is to increase the productivity of the AM process. Work in this area mainly impacts product quality and manufacturing costs, which are significantly influenced by the reliability and performance of AM machines (Liu, et al., 2018). In this context, scientists believe that improved monitoring of machine conditions can lead to reduced waste as well as increased product quality (Wu, Wang and Yu, 2017).

Liu, et al. (2018) used AI to determine faulty machine conditions on the basis of acoustic emissions, while Wu, Wang and Yu (2017) applied AI to improve machine monitoring, which also enables machine maintenance predictions.

# 4 Conclusion

To answer the research question ("Where has artificial intelligence been applied in additive manufacturing?"), it is apparent that there are many different areas of application of AI in both AM planning and AM execution. AI is often combined with imaging and computer vision techniques that can automatically detect and process features. One of the main motives behind the use of AI seems to be ensuring and improving quality and preventing defects during design and production.

Investigation of the algorithms used also made it possible to ascertain further information. Supervised and deep learning algorithms were used especially frequently in the use cases investigated. The accumulation of supervised algorithms suggests that much of the data was collected in a structured manner based on classification criteria known by the researchers themselves, since these algorithms are particularly suitable if structuring criteria are already known. The fact that regression algorithms were less used makes it apparent that the focus of research was less on predicting the continuous evolution of data and more on classifying states. The combination of unsupervised and supervised learning algorithms was also used more frequently when classification criteria were not yet known in a use case, or when these criteria were first collected from external data. New and novel deep learning algorithms are capable of recognizing patterns on their own; the fact that many use cases made use of these algorithms highlights the important of such functionality with respect to AI's application in AM.

The number of use cases in AM planning was significantly lower than the number of cases in AM execution. In the cases that did involve AM planning, AI was most frequently used for assistance in the design process. Cases in the area of process selection were observed much less frequently. Also rare were use cases in which AI was used to predict optimal component orientation or to perform cost estimation. This suggests that these areas are either not very error-prone or not complex enough to require the use of AI. Another rarely occurring application of AI is for the prevention of cyber-attacks, which can probably be explained by the fact that AI is often applied to manufacturing systems in general, and not specifically to AM systems. Furthermore, AI has also been comparatively infrequently used in the prediction of mechanical properties, although problems relating to mechanical properties are still common.

The application areas in which use cases appeared particularly frequently in AM execution were process and quality monitoring and the monitoring of defects. This can be explained by the fact that monitoring can prevent defects that still occur frequently, which in turn can improve quality. In particularly rare cases AI was used to assess powder properties – the lower frequency of such cases suggests that such monitoring may not be as critical as the aforementioned factors to final quality. Only one use case involving the use of AI to improve post-processing could be identified, which can probably be explained by the fact that it is more valuable to avoid post-processing than to improve it. It has also been rare for AI to be applied to machine monitoring in AM. This does not necessarily imply that AI is rarely used to monitor machines, but simply that studies have been more generalized, and have not looked specifically at machine monitoring in AM.

It should be stated that some use cases may not have been detected because they were not identified by the search string, or may have been excluded because they deal with plastic processing AM.

# 5 Implications and Further Research

Several things became clear as a result of this literature review. In general, the review showed that AI can significantly increase the added value of AM, as well added value in tangential areas, such as predictive maintenance.

**Practical Implications**

For the practical implementation of AI in AM, some implications can be inferred from this research. On the one hand, based on the distribution of algorithms, a need for data can be recognized – a need of which users of AI should be aware. In addition, knowledge of the algorithms used provides the means to infer the respective need for structured or unstructured data for the application in question.

Furthermore, analysis of the use cases made it clear what is possible through the use of AI in the area of AM planning, as well as in the operational implementation of AM, and what different application areas result from this, such as quality monitoring and the determination of machine parameters. In addition, various possible use cases in the respective application areas were shown, including quality monitoring by means of various forms of data, such as images, acoustic measurements, and pyrometry.

**Scientific Implications**

This research also has some implications for research, meaning that scientists can also benefit from this review. The overview of the frequency of journal articles shows how established this topic is, and how high the level of scientific inquiry already is in this area. With the increase in conference papers, it is clear that a great deal of research is currently being conducted, which is also made evident by the use of advanced deep learning algorithms. In addition, the distribution of algorithms shows which algorithms are considered to be capable of solving previously identified problems. Additionally, it has also been shown that value can be added by combining algorithms.

The analysis of the application areas and the distribution of use cases in this review shows in which areas and how (i.e., with which data and algorithms) research has already been carried out. This has also highlighted particularly innovative use cases, as well as previously underrepresented application areas. In addition, the bridge to other research areas, such as economics, was also shown, which illustrates the importance of interdisciplinary research. Thus, among other things, this research shows that it is also worth looking at the value chain into which AM is integrated in order to improve the final AM product.

**Further Research**

From a research methodology perspective, all the identified articles were dedicated to the topic from a conceptual or experimental perspective. So far, none of the use cases studied have dealt with industrialization or implementation into a corporate structure, which could be one possible future research area.

Furthermore, the distribution of the use cases in the application areas also made clear in which application areas there is a need for further research. Consequently, it has become apparent that the greatest need still exists in AM planning. For example, there is still a need for application of AI in the assessment of raw material in powder form, as well as in the improvement of post-processing (where post-processing cannot be avoided). Furthermore, there is room for additional important applications of AI in the prediction of mechanical properties, process selection and the estimation of costs.

# Appendix

## A.1 AM Planning Use Cases

Table 1: Assistance in Design Process

| Authors | Title |
|---|---|
| Després et al. (2020) | Deep Learning and Design for Additive Manufacturing: A Framework for Microlattice Architecture |
| Gaikwad et al. (2019) | Design Rules and In-Situ Quality Monitoring of Thin-Wall Features Made Using Laser Powder Bed Fusion |
| Garrelts et al. (2019) | A Straightforward Approach to the Derivation of Topologies |
| Guo et al. (2020) | Semi-Supervised Deep Learning Based Framework for Assessing Manufacturability of Cellular Structures in Direct Metal Laser Sintering Process |
| Mahmoudi et al. (2018) | On the Printability and Transformation Behavior of Nickel-Titanium Shape Memory Alloys Fabricated Using Laser Powder-Bed Fusion Additive Manufacturing |
| Murphy et al. (2018) | Using Autoencoded Voxel Patterns to Predict Part Mass, Required Support Material, and Build Time |
| Mycroft et al. (2020) | A Data-Driven Approach for Predicting Printability in Metal Additive Manufacturing Processes |
| Page et al. (2019) | Automated Candidate Detection for Additive Manufacturing: A Framework Proposal |

| Authors | Title |
|---|---|
| Yang et al. (2020) | Towards an Automated Decision Support System for the Identification of Additive Manufacturing Part Candidates |
| Yao et al. (2017) | A Hybrid Machine Learning Approach for Additive Manufacturing Design Feature Recommendation |
| Zhang et al. (2019) | Machine Learning Assisted Prediction of the Manufacturability of Laser-Based Powder Bed Fusion Process |

Table 2: Prediction of Mechanical Characteristics

| Authors | Title |
|---|---|
| Garg, Tai (2014) | An Ensemble Approach of Machine Learning in Evaluation of Mechanical Property of the Rapid Prototyping Fabricated Prototype |
| Hassanin et al. (2020) | Controlling the Properties of Additively Manufactured Cellular Structures Using Machine Learning Approaches |
| Seifi et al. (2019) | In-Situ Fatigue Prediction of Direct Laser Deposition Parts Based on Thermal Profile |
| Yan et al. (2018) | Data-Driven Prediction of Mechanical Properties in Support of Rapid Certification of Additively Manufactured Alloys |

Table 3: Assessment of Powder Characteristics

| Authors | Title |
|---|---|
| DeCost et al. (2016) | Computer Vision and Machine Learning for Autonomous Characterization of AM Powder Feedstocks |
| Desai, Higgs (2019) | Spreading Process Maps for Powder-Bed Additive Manufacturing Derived from Physics Model-Based Machine Learning |
| Scime, Beuth (2018) | A Multi-Scale Convolutional Neural Network for Autonomous Anomaly Detection and Classification in a Laser Powder Bed Fusion Additive Manufacturing Process |

Table 4: Selection of the Additive Process

| Authors | Title |
|---|---|
| Munguia et al. (2011) | Proposal and Evaluation of a KBE-RM Selection System |
| Munguia, Riba (2008) | A Concurrent Rapid Manufacturing Advice System |

Table 5: Prevention of Cyber Attacks

| Authors | Title |
|---|---|
| Al Faruque et al. (2016) | Acoustic Side-Channel Attacks on Additive Manufacturing Systems |

| Authors | Title |
| --- | --- |
| Wu et al. (2017) | Detecting Cyber-Physical Attacks in CyberManufacturing Systems with Machine Learning Methods |

Table 6: Prediction of the Optimal Component Orientation

| Authors | Title |
| --- | --- |
| Zhang et al. (2018) | A Statistical Method for Build Orientation Determination in Additive Manufacturing |

Table 7: Prediction of Costs

| Authors | Title |
| --- | --- |
| Chan et al. (2017) | Data-Driven Cost Estimation for Additive Manufacturing in Cybermanufacturing |

Table 8: Improvement of Post-Processing

| Authors | Title |
| --- | --- |
| Hatamleh et al. (2019) | Prediction of Residual Stress Random Fields for Selective Laser Melted A357 Aluminum Alloy Subjected to Laser Shock Peening |

## A.2 AM Execution Use Cases

Table 9: Process Monitoring

| Authors | Title |
|---|---|
| Akhil et al. (2020) | Image Data-Based Surface Texture Characterization and Prediction Using Machine Learning Approaches for Additive Manufacturing |
| Amini, Chang (2018) | MLCPM: A Process Monitoring Framework for 3D Metal Printing in Industrial Scale |
| Amini, Chang (2018) | Process Monitoring of 3D Metal Printing in Industrial Scale |
| Caiazzo, Caggiano (2018) | Laser Direct Metal Deposition of 2024 Al Alloy: Trace Geometry Prediction via Machine Learning |
| Douard et al. (2018) | An Example of Machine Learning Applied in Additive Manufacturing |
| Han et al. (2020) | Quantitative Microstructure Analysis for Solid-State Metal Additive Manufacturing via Deep Learning |
| Imani et al. (2018) | Process Mapping and In-Process Monitoring of Porosity in Laser Powder Bed Fusion Using Layerwise Optical Imaging |
| Kappes et al. (2018) | Machine Learning to Optimize Additive Manufacturing Parameters for Laser Powder Bed Fusion of Inconel 718 |

| Authors | Title |
|---|---|
| Marmarelis, Ghanem (2020) | Data-Driven Stochastic Optimization on Manifolds for Additive Manufacturing |
| Mondal et al. (2020) | Investigation of Melt Pool Geometry Control in Additive Manufacturing Using Hybrid Modeling |
| Mozaffar et al. (2018) | Data-Driven Prediction of the High-Dimensional Thermal History in Directed Energy Deposition Processes via Recurrent Neural Networks |
| Olleak, Xi (2020) | Calibration and Validation Framework for Selective Laser Melting Process Based on Multi-Fidelity Models and Limited Experiment Data |
| Özel et al. (2019) | Focus Variation Measurement and Prediction of Surface Texture Parameters Using Machine Learning in Laser Powder Bed Fusion |
| Rafajłowicz (2017) | Image-Driven, Model-Free Control of Repetitive Processes Based on Machine Learning |
| Raitanen et al. (2020) | A Data-Driven Approach Based on Statistical Learning Modeling for Process Monitoring and Quality Assurance of Metal Powder Additive Manufacturing |
| Razaviarab et al. (2019) | Smart Additive Manufacturing Empowered by a Closed-Loop Machine Learning Algorithm |
| Silbernagel et al. (2019) | Using Machine Learning to Aid in the Parameter Optimisation Process for Metal-Based Additive Manufacturing |
| Uhlmann et al. (2017) | Intelligent Pattern Recognition of SLM Machine Energy Data |

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|---|---|
| Wang et al. (2018) | In-Situ Droplet Inspection and Closed-Loop Control System Using Machine Learning for Liquid Metal Jet Printing |
| Zhang et al. (2017) | Machine Learning Enabled Powder Spearding Process Map for Metal Additive Manufacturing |
| Zohdi (2018) | Electrodynamic Machine-Learning-Enhanced Fault-Tolerance of Robotic Free-Form Printing of Complex Mixtures |

Table 10: Monitoring of Defects

| Authors | Title |
|---|---|
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| Baumgartl et al. (2020) | A Deep Learning-Based Model for Defect Detection in Laser-Powder Bed Fusion Using In-Situ Thermographic Monitoring |
| Caggiano et al. (2019) | Machine Learning-Based Image Processing for On-Line Defect Recognition in Additive Manufacturing |
| Cui et al. (2020) | Metal Additive Manufacturing Parts Inspection Using Convolutional Neural Network |
| Eschner et al. (2019) | Acoustic Process Monitoring for Selective Laser Melting (SLM) with Neural Networks: A Proof of Concept |
| Gobert et al. (2018) | Application of Supervised Machine Learning for Defect Detection during Metallic Powder Bed Fusion Additive Manufacturing Using High Resolution Imaging |

| Authors | Title |
|---|---|
| Imani et al. (2019) | Deep Learning of Variant Geometry in Layerwise Imaging Profiles for Additive Manufacturing Quality Control |
| Mitchell et al. (2019) | Linking Pyrometry to Porosity in Additively Manufactured Metals |
| Okaro et al. (2019) | Automatic Fault Detection for Laser Powder-Bed Fusion Using Semi-Supervised Machine Learning |
| Petrich et al. (2017) | Machine Learning for Defect Detection for PBFAM Using High Resolution Layerwise Imaging Coupled with Post-Build CT Scans |
| Scime et al. (2020) | Layer-Wise Anomaly Detection and Classification for Powder Bed Additive Manufacturing Processes: A Machine-agnostic Algorithm for Real-Time Pixel-Wise Semantic Segmentation |
| Snell et al. (2019) | Methods for Rapid Pore Classification in Metal Additive Manufacturing |
| Tang et al. (2017) | An Online Surface Defects Detection System for AWAM Based on Deep Learning |
| Williams et al. (2018) | Defect Detection and Monitoring in Metal Additive Manufactured Parts through Deep Learning of Spatially Resolved Acoustic Spectroscopy Signals |
| Wu et al. (2016) | Detecting Malicious Defects in 3D Printing Process Using Machine Learning and Image Classification |
| Zhang et al. (2019) | In-Process Monitoring of Porosity during Laser Additive Manufacturing Process |

| Authors | Title |
|---|---|
| Zhu et al. (2020) | Unraveling Pore Evolution in Post-Processing of Binder Jetting Materials: X-Ray Computed Tomography, Computer Vision, and Machine learning |

Table 11: Quality Monitoring

| Authors | Title |
|---|---|
| Han et al. (2019) | Image Classification and Analysis during the Additive Manufacturing Process Based on Deep Convolutional Neural Networks |
| Li et al. (2020) | Quality Analysis in Metal Additive Manufacturing with Deep Learning |
| Li et al. (2019) | A Deep Learning Method for Material Performance Recognition in Laser Additive Manufacturing |
| Özel et al. (2017) | Surface Topography Investigations on Nickel Alloy 625 Fabricated via Laser Powder Bed Fusion |
| Patel et al. (2019) | Using Machine Learning to Analyze Image Data from Advanced Manufacturing Processes |
| Ren et al. (2020) | Computational Fluid Dynamics-Based In-Situ Sensor Analytics of Direct Metal Laser Solidification Process Using Machine Learning |
| Shevchik et al. (2019) | Deep Learning for In Situ and Real-Time Quality Monitoring in Additive Manufacturing Using Acoustic Emission |
| Stoyanov, Bailey (2017) | Machine Learning for Additive Manufacturing of Electronics |

| Authors | Title |
|---|---|
| Wasmer et al. (2019) | In Situ Quality Monitoring in AM Using Acoustic Emission: A Reinforcement Learning Approach |
| Yadav et al. (2020) | Inline Drift Detection Using Monitoring Systems and Machine Learning in Selective Laser Melting |
| Yuan et al. (2019) | Semi-Supervised Convolutional Neural Networks for In-Situ Video Monitoring of Selective Laser Melting |

Table 12: Monitoring of the Melt Pool

| Authors | Title |
|---|---|
| Guo et al. (2020) | A Physics-Driven Deep Learning Model for Process-Porosity Causal Relationship and Porosity Prediction with Interpretability in Laser Metal Deposition |
| Khanzadeh et al. (2018) | Porosity Prediction: Supervised-Learning of Thermal History for Direct Laser Deposition |
| Lee et al. (2019) | Data Analytics Approach for Melt-Pool Geometries in Metal Additive Manufacturing |
| Scime, Beuth (2018) | Using Machine Learning to Identify In-Situ Melt Pool Signatures Indicative of Flaw Formation in a Laser Powder Bed Fusion Additive Manufacturing Process |
| Yang et al. (2019) | Investigation of Deep Learning for Real-Time Melt Pool Classification in Additive Manufacturing |

| Authors | Title |
|---|---|
| Yeung et al. (2020) | A Meltpool Prediction Based Scan Strategy for Powder Bed Fusion Additive Manufacturing |
| Yuan et al. (2018) | Machine-Learning-Based Monitoring of Laser Powder Bed Fusion |

Table 13: Monitoring of the Geometrical Shape

| Authors | Title |
|---|---|
| Elwarfalli et al. (2019) | In Situ Process Monitoring for Laser-Powder Bed Fusion using Convolutional Neural Networks and Infrared Tomography |
| Francis, Bian (2019) | Deep Learning for Distortion Prediction in Laser-Based Additive Manufacturing using Big Data |
| Korneev et al. (2020) | Fabricated Shape Estimation for Additive Manufacturing Processes with Uncertainty |
| Zhu et al. (2018) | Machine Learning in Tolerancing for Additive Manufacturing |

Table 14: Monitoring of the Machine Status

| Authors | Title |
|---|---|
| Liu et al. (2018) | An Improved Fault Diagnosis Approach for FDM Process with Acoustic Emission |

| Authors | Title |
| --- | --- |
| Wu et al. (2017) | In Situ Monitoring of FDM Machine Condition via Acoustic Emission |

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