Machine learning-based Additive Manufacturing: the state of the art and a proposed research agenda

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Abstract: Over the past decade, the advent of Industry 4.0 has brought the use of Additive Manufacturing (AM) to the forefront. AM is a technology born in 1987 but has been able to develop and adapt to today's needs, enabling flexible, multi-material and multi-functional manufacturing, which is essential across many sectors. However, the instability in the performance of AM and the constant exchange of heterogeneous data in the digital systems in which it is integrated present major challenges. Researchers have identified Machine Learning (ML) as a powerful tool for AM, capable of exploiting data to perform in-situ monitoring and design optimization, as well as process modelling and energy management, and much more. The subject, following technological developments and market demands, has been characterized by decisive changes over the years and is in continuous development. Therefore, this article aims to clarify the evolution of the topic, significant research characteristics, challenges, and future opportunities through a review based on bibliometric tools. In particular, the main findings identify anomaly detection, innovative ML algorithms and parameter optimization as pivotal topics and discuss their development.

Keywords: Machine Learning; Additive Manufacturing; SLNA; Bibliometric Review; Industry 4.0.

I. INTRODUCTION

The first commercial additive manufacturing (AM) system was launched in 1987 with 3D-based stereolithography (Wohlers and Gornet, 2014). Since then, AM has become one of the most important tools in many different industries, such as automotive, medical, construction, and aerospace (Abdulhameed et al., 2019). It deposits, solidifies, or joins materials to construct physical objects from computer-aided design (CAD) models. Compared to other traditional manufacturing methodologies, AM systems show greater flexibility and efficiency in production, enabling rapid prototyping and small batch production. This, combined with its ability to create multi-material, and multi-functional designs with complex shapes and structures (Qi et al., 2019), makes it an integral pillar of Industry 4.0 (Ciano et al., 2021; Haleem and Javaid, 2019). Moreover, AM can pave the way for ever-evolving topics, such as the development of new materials, and the reduction of waste, remanufacturing, and other central themes in sustainability (Qin et al., 2022). All of this makes AM an increasingly core agenda for industrial investment; in fact, the global market size of the AM industry is projected to grow from over USD 11 billion in 2019 to over USD 35 billion by 2024 (Wohlers, 2020). However, the AM process is a highly complex system involving various technologies and combining mechanics, materials science, computer science, optics and electronics (Qin et al., 2022). Multiple challenges are involved. Among the others, a major challenge for AM is to reduce the inconsistency in the quality of printed products. This depends on numerous parameters, such as layer thickness and printing speed, material properties, process stability, and working conditions. To solve this problem, experiments, simulations and in-situ monitoring using images to detect defects could be carried out. However, it is difficult to integrate digital AM models, relevant to various phenomena, on multiple scales into a cohesive framework and would require advanced computational and analytical tools (Qin et al., 2022; Razvi et al., 2019). Moreover, as one of the main pillars of the Industry 4.0 manufacturing systems, AM has been incorporated with sensor networks that incessantly exchange heterogeneous data in the so-called cyber-physical system. This leads to the statement by Razvi et al. (2019): "*AM has become a* *manufacturing domain that is data-rich but knowledge-sparse*". The AM needs to be supported by techniques and technologies capable of manipulating 'big data', which can be acquired by sensors. Many researchers identify the answer to this need in machine learning (ML), a branch of artificial intelligence (Jin et al., 2020; Meng et al., 2020; Qi et al., 2019; Qin et al., 2022; Razvi et al., 2019). Using reliable data sets, ML technologies can learn hidden patterns and discover latent knowledge to support decision-making. This allows various uses of ML in AM, including in-situ monitoring and design optimization, as well as process modelling and energy management, and many others (Qin et al., 2022). Technologies are constantly evolving, and the scientific community is continuously exploring new and innovative approaches to integrate ML methods in AM. To clarify the evolution of the topic, significant research characteristics and challenges, and future opportunities, this article aims to answer the following research questions through a literature review based on bibliometric tools:

RQ1: What are the main contributions and how have they affected the evolution trajectory of the topic?

RQ2: What are the main research areas about the link between AM and ML?

RQ3: What is a possible research agenda about the topic?

II. Materials and Methodology

A. Materials

The main source used to collect data in this research is Scopus, which is considered one of the most complete sources for scientific journal coverage (Pozzi et al., 2021). To ensure that the largest possible number of articles on the subject are included in the data set, the research query has been developed using the TITLE, KEYWORDS, and ABSTRACT fields. To enhance the generality of the study, the keywords selected have been 'Additive Manufacturing' and 'Machine Learning'. In doing so, the first output of the research led to 816 documents detected. The papers in this field have been published between 2015 and 2022. The studies of machine learning implemented in additive manufacturing began in 2015. Moreover, the research was filtered by subject area to include only articles belonging to 'Engineering', 'Computer Science', and 'Business, Management, and Accounting'. This led to a total number of 675 papers detected. The area of study has been limited to focus mainly on the business environment. Finally, to consider only the papers that presented a clear level of relevance, only journals and English-written papers have been considered. This led to a final number of 447 papers considered in the study (data extracted in October 2022).

B. Methodology

To provide an overview of the relationship between Machine Learning and Manufacturing, a bibliometric literature review has been conducted, based on the Systematic Literature Network Analysis (SLNA) methodology. With the combination of the use of the SLNA and the aspects related to keywords analysis and citation, a wide range of relevant contributions can be analysed based on a reliable and rigorous method (Strozzi et al., 2017).

To answer the first research question, a co-citation analysis has been conducted. In doing so, the main path of papers about research in machine learning has been developed. In addition, an analysis of the top cited papers that have not been included in the main path has been carried out (Saporiti et al., 2021). To perform the analysis, VOSViewer and Pajek have been used as the main tools. In particular, VOSViewer has been exploited to create the co-occurrence network from the bibliometric data, while Pajek was used to perform the analysis. In doing so, a key-route global search algorithm on the largest weak connected component has been conducted, which leads to the determination of the main path.

The second research question has been answered via the exploitation of a co-occurrence analysis concerning authors' keywords (Waltman et al., 2010). The analysis was committed to the determination of clusters of the keywords that can be detected in the extracted papers (Ciano et al., 2019). VOSViewer has been exploited to carry out the analysis. In particular, a set of clusters have been determined via the use of a VOS Clustering algorithm. In doing so, the threshold for a keyword to be considered relevant for the co-occurrence network has been set to 5. Finally, a thesaurus has been used to ensure avoid duplication of keywords.

The third research question focuses on analyzing the results of the methods applied for RQ1 and RQ2.

III. Paper Citation Networks

To improve the definition of the connections between papers, a partition related to the weak components was developed. In doing so, only the largest connected component was considered, as it represents the strongest and most stable elements of literature. The largest connected component detected included a total number of 323 papers, 72% of the initial sample of 447. Exploiting the main path analysis, trajectory is composed of 17 papers has been detected. The papers that compose the main path can be in a time frame that spreads from 2017 to 2022. In Figure 1, the main path is depicted.

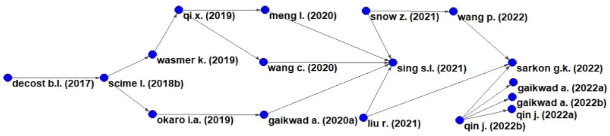

Figure 1. Main Path Network

The first paper in the main path is the work by DeCost et al. (2017). The study is focused on a computer vision system that evaluates powder raw materials for metal additive manufacturing and classifies powder according to its features. The first web encountered in the main path focuses on the defects and quality of the production process. Scime and Beuth, (2018) study a computer vision system that detects and classifies anomalies. The system has been developed for Laser Powder Bed Fusion (LPBS) process, focusing on the techniques known as bag-of-keypoints. The first successor of this paper is represented by the work developed by Okaro et al. (2019). This study presents a method for fault detection that exploits semi-supervised algorithms and photodiodes. The difference from the previous article is related to the algorithm described, as the techniques presented can classify the labeled and unlabeled images simultaneously. The successor of this work is represented by Gaikwad et al. (2020). In this document, a Sequential Decision Analysis Neural Network (SeDANN) model has been developed to control anomalies during the production process. The algorithm described in this context presents a direct evolution with respect to the predecessor's one. A second successor of the work by Scime and Beuth, (2018) is represented by the study of Wasmer et al. (2019) which encompasses a method that combines acoustic emission and reinforcement learning for quality monitoring. The successor of this paper, Qi et al. (2019) presents an application of Neural Networks and several other deep learning algorithms. These algorithms are developed and applied to pursue the optimization of several processes, such as design, on situ monitoring, and quality control. Another topic generally studied is related to parameter optimization and anomaly detection. Indeed, in their paper, Meng et al. (2020) propose an analysis about anomaly detection that encompasses the exploitation of ML methods such as classification, regression, and clustering. This study presents a compilation of the previously analyzed algorithms. The paper by Wang et al. (2020) describes the state of the art of machine learning applications in various fields of additive manufacturing. The main difference point of the paper is the focus on design for additive manufacturing (DfAM). The closing node of the first network is represented by the work of Sing et al. (2021), who comment on the use of machine learning applied at different stages of the manufacturing process (i.e., DfAM, file preparation, on situ monitoring and post-processing). Improving the quality in all the stages of the process will be reflected in increased consistency of the printed product. This paper presents an important summary of the method and techniques described in the last few years. Moreover, the authors highlight the lack of in-depth analysis of the process-structure-property relationship and the need to develop new data collection models and ML applications to improve quality in the field of additive manufacturing. Anomaly detection is one of the main topics detected in the main path. Indeed, Snow et al. (2021) compare neural networks and convolutional neural networks (CNN) to detect defects, meanwhile P. Wang et al. (2022) discuss about the topic considering supervised and unsupervised ML algorithms. Porosity study is another important topic. In their work, Liu et al. (2021) propose a physics-informed model (PIM) that can be exploited to predict the porosity levels of printed parts, while being independent from the 3D printer and technology used in the process. Qin et al. (2022) and Sarkon et al. (2022) describe the past application of ML. The first paper is a review, which describes the application of ML in AM doing a co-occurrence and cluster analysis. The second author describes the application of ML in AM, focusing on the understanding and prediction of the process. The two papers previously described mainly focus on the technical aspects of AM and ML, while in this paper the main focus is on the production aspects. Moreover, it is underlined that additive manufacturing is still an emerging technology, with limited material choice and small datasets for training of ML algorithms. In the last period, the work by Qin et al. (2022) is detected as a starting point for three different papers. Two of these studies focus on droplet transfer mode using ML techniques. Qin, Wang, et al. (2022) study a deep learning method apply to wire arc additive manufacturing (WAAM), this algorithm is the link between the two papers. Moreover, these techniques can be applied to different WAAM techniques. Gaikwad, Chang, et al. (2022) use the ML for process monitoring and quality assurance analysed the droplet characteristic, underlying the need for an expansion of data used in terms of dimensions and variables. The last paper of the main path is the one by Gaikwad, Williams, et al. (2022). In this study, a data fusion approach that captures multiple process phenomena is adopted to enhance defect detection performance. Referring to Qin et al. (2022), effective process monitoring is hindered by materials, machines and geometries.

IV. CO-OCCURRENCE NETWORK ANALYSIS

The co-occurrence network analysis has been exploited to propose the main topics in the field of machine learning and additive manufacturing. VoSViewer was used to carry out this analysis, a clusterization of keywords has been proposed. In doing so, the study identified 31 keywords. To avoid duplication of keywords, a thesaurus was used to replace the words. In Table 2, the set of keywords and detected clusters is depicted. This analysis resulted in the identification of 5 clusters.

The first detected cluster includes 9 keywords, mainly referred to the topics of Industry 4.0. Industry 4.0 and porosity can be linked in a data management and supervised machine learning to improve a quality system with the aim to find defects in a Low-pressure Die process (Uyan et al., 2022). Furthermore, Industry 4.0 use technologies, which are associated with smart manufacturing systems, like data analytics, artificial intelligence, augmented reality, virtual reality, mixed reality, internet of things, and additive manufacturing (Sahoo and Lo, 2022). The reduction of material waste, also advantage cost, is possible using precisely additive manufacturing. The powder bed fusion is a type of 3D printing process that melt layer of powder for create an object (Dogu et al., 2022).

In the second cluster, the focus is centered on additive manufacturing techniques. Quality control in real-time during the AM process can be useful for determining high quality. One of these process monitoring is acoustic emission, a method that acquires and analyses acoustic signals (AbouelNour & Gupta, 2022). The authors highlights that a possible future approach can be represented by the application of a the low-pass filter during the registration of the acoustic signal. Fused deposition modeling and Fused filament fabrication are additive manufacturing methods (Tao et al., 2021).

The third agglomeration addresses the topic of Machine Learning algorithms. The keywords Wire additive manufacturing and neural network are linked by a prediction model which has the aim to improve the deposition accuracy. The neural network studies parameters like laser power, travel speed and wire-feed rate (Mbodj et al., 2021), these parameters influence the bead geometry. In the paper, a future development is also described: a feedback control system which can be able improve the surface quality adjusting automatically the parameter. Meanwhile, Gaussian process and random forest are models used to optimize the material in additive manufacturing processes (Liang et al., 2021).

The fourth group is related to 3D printers and optimization methods. The thermoset composites need optimal parameter to stabilize the 3D printer process. The calibration of this composite can be optimized through the process using computer vision (Wright et al., 2022). Moreover, Kim and Zohdi, (2022) study an optimal tool path for the selective laser sintering process using a numerical simulation. A question that the author poses is when to use using machine learning algorithms, as it becomes necessary to find a trade-off between computational cost and the accuracy, that one wants to achieve.

The fifth and last cluster concerns Deep learning. Deep learning is a subgroup of Neural Networks, which uses multilayer computation. This type of neural network has different architecture, deep learning has more numbers of layer, different layer types and shape and at the same way change the connections between the layers. As a result, the deep learning is more complicated than neural network (Nguyen et al., 2019). Anomaly detection is usually performed in conjunction with a vision system and deep learning. CNN, a deep learning algorithm, is used to elaborate images. With the aim to reduce scrap production, Tayeh et al. (2020) discuss surface anomaly detection using CNN algorithm. In the future, the batch normalization in the CNN can be used to improve the result of ML.

TABLE 2. KEYWORDS CLUSTER

Industry 4.0 related	**Additive manufacturing techniques**	**Machine Learning algorithms**

Artificial intelligence	Acoustic emission	Gaussian process
Data analytics	Additive manufacturing	Machine Learning
Defects	Fused deposition modeling	Neural network
Digital Twin	Fused filament fabrication	Random Forest
Directed energy deposition	Mechanical proprieties	Selective laser melting
Industry 4.0	Predictive modeling	Surface roughness
Porosity	Quality control	Wire additive manufacturing
Powder bed fusion		
Process monitoring		

3d printed and optimization methods	**Deep Learning related**
3d printing	Anomaly detection
Computer vision	Convolutional neural network
Microstructure	Deep learning
Optimization	
Simulation	

V. Discussion

Based on the analyses of the citations and keywords used to characterise the research works, answers to research questions can be provided.

RQ1: What are the main contributions and how have they affected the evolution trajectory of the topic?

The development of the main path suggests a great initial attention of the literature on the development of ML algorithms aimed at optimizing different AM techniques. This issue is addressed by the works of DeCost et al. (2017), Scime and Beuth, (2018), Okaro et al. (2019), Gaikwad et al. (2020), Wasmer et al. (2019) and Qi et al. (2019). In the following years, a greater attention to the theme of anomaly detection and AM parameter optimization can be noticed. This trend can be detected in the papers by Meng et al. (2020), Snow et al. (2021) and P. Wang et al. (2022). However, the same interest of the literature about ML algorithms for AM applications is still consistent, as described in the works by Sing et al. (2021), Liu et al. (2021), Qin, Wang, et al. (2022), Gaikwad, Chang, et al. (2022) and Gaikwad, Williams, et al. (2022). Finally, in the last years a growing presence of literature reviews can be noticed, which could represent a rise in the maturity level of the topic. This trend is suggested by the literature reviews by Wang et al. (2020) and Qin et al. (2022).

RQ2: What are the main research areas about the link between AM and ML?

Regarding RQ2, the interest of literature in the applications of ML algorithms to AM techniques is focused on the topics of Industry 4.0, AM techniques, ML algorithms, optimization methods and deep learning applications. In particular, it is possible to notice the heavy presence of Industry 4.0 technologies linked to the topics of AM techniques as well as ML algorithms. While the connection between Industry 4.0 and AM is quite evident, since AM represents one of the pillars of Industry 4.0, the connection with ML algorithms is more sophisticated. Indeed, Industry 4.0 could be identified as the connection link between AM and ML. Moreover, ML could be considered as a boost to greatly improve the performance and the quality of AM production and products. A particular attention is deserved by the theme of Digital Twins (DT). Indeed, since the interest in the literature about DT applications presented a remarkable rise in the last years (Saporiti et al., 2023), the use of this technology combined with AM can be considered a way to bring a considerable improvement in the quality of products as well as in the analysis of the manufacturing process. Moreover, even if the theme of data analytics is consistent in the co-occurrence analysis, the topic related to cybersecurity is not addressed. Thus, this Industry 4.0 pillar seems to be underrated by the analysis, as the connection between a large flow of data and the topic of data protection has to be considered, especially when considering potentially sensitive data as innovative manufacturing techniques as well as specific products computer-aided designs.

RQ3: What is a possible research agenda about the topic?

In order to answer RQ3, a possible research agenda about ML in AM applications has been developed. In doing so, several main directions have been detected. First, as claimed by Gaikwad, Chang, et al. (2022), the development of the use of ML for process monitoring and quality assurance via the analysis of the droplet characteristic data could be a potential future research direction. In doing so, future studies could enhance comprehension of this topic by providing further information about physical elements such as geometric integrity, factional behavior and microstructure. Second, studies focused on the topic of the development of materials for AM with the use of ML algorithms could represent interesting future research directions. Indeed, as claimed by Qin et al. (2022), AM is still a quite innovative technology, and its development is far from concluded. Moreover, the variety of materials that have been specifically developed for AM applications is still very limited. Therefore, the training datasets for ML algorithms are still limited to the existing materials used in AM applications. Third, the paper by Sing et al. (2021) sustains the lack of a precise analysis of the relationships between process, structure, and properties in AM. Therefore, a promising research direction could be represented by the developing of innovative data connection models and ML applications, aiming at improving the overall product quality in the AM field. Finally, the theme of cybersecurity is not detected in this bibliometric review. However, the centrality of the topic when considering processes with large data exchange or sensitive data exchange is remarkable. Therefore, a further research direction for the agenda is detected in the development of research streams that considers the need of cybersecurity models when exploiting the functionalities of ML algorithms for AM applications.

VI. Conclusion

In this paper three research questions have been discussed. First concerning the identification of the main contributions areas on ML application in AM, the paper proposed a paper citation analysis. The results show an important interest of the literature in the field of development of new ML algorithms in order to cope with the needs of innovative AM techniques. Moreover, a certain interest in the topics of anomaly detection and AM parameter optimization can be detected. Second, a co-occurrence analysis has been exploited in order to identify the main research areas in the field of ML applied to AM. In doing so, this paper identified five keywords clusters. In particular, a great attention to the connection between Industry 4.0, AM and ML can be detected, with interesting considerations about some brand-new technologies such as the DTs. Finally, based on the paper citation network as well as on the co-occurrence analysis a research agenda has been proposed. In doing so, future research directions that concern the topics of process monitoring, quality assurance, materials development, and cybersecurity needs have been identified. This paper presents several drawbacks. First, only Scopus has been used as database. Second, only journal papers that belong to the research areas 'Engineering', 'Computer Science', and 'Business, Management, and Accounting' have been considered. Third, only authors keywords have been considered in the co-occurrence analysis.

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