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Research and application of machine learning for additive manufacturing

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A R T I C L E I N F O

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A B S T R A C T

Additive manufacturing (AM) is poised to bring a revolution due to its unique production paradigm. It offers the prospect of mass customization, flexible production, on-demand and decentralized manufacturing. However, a number of challenges stem from not only the complexity of manufacturing systems but the demand for increasingly complex and high-quality products, in terms of design principles, standardization and quality control. These challenges build up barriers to the widespread adoption of AM in the industry and the in-depth research of AM in academia. To tackle the challenges, machine learning (ML) technologies rise to play a critical role as they are able to provide effective ways to quality control, process optimization, modelling of complex systems, and energy management. Hence, this paper employs a systematic literature review method as it is a defined and methodical way of identifying, assessing, and analysing published literature. Then, a keyword co-occurrence and cluster analysis are employed for analysing relevant literature. Several aspects of AM, including Design for AM (DfAM), material analytics, in situ monitoring and defect detection, property prediction and sustainability, have been clustered and summarized to present state-of-the-art research in the scope of ML for AM. Finally, the challenges and opportunities of ML for AM are uncovered and discussed.

1. Introduction

Additive manufacturing (AM), also known as rapid prototyping, 3D printing, and freeform fabrication, is capable of depositing, joining or solidifying materials to construct physical objects from computer-aided design (CAD) models [1]. Compared with conventional manufacturing methodologies, such as subtractive manufacturing and formative manufacturing, AM systems show higher efficiency and flexibility within the high-yield production and offer a new perspective for the design and processing of both parts and materials. However, the AM process is well-known as a highly complex system including various technologies that combines material science, mechanics, optics, and electronics with computer science. As a result, the quality of produced parts is affected by numerous factors, such as material properties, processing parameters, process stability, and working conditions. This leads to the challenges that are summarized and highlighted as follows.

- It is generally difficult to model the mathematical relations of the underlying AM process because the correlated factors are from various heterogeneous perspectives and different process stages.
- High-fidelity physical-based models are generally too complicated considering the in-process uncertainties of the AM process, which demand significant computational resources.
- It is challenging to integrate AM digital models, pertinent to various phenomena, at multiple scales into one unified framework [2].

The applications of machine learning (ML) technologies have been proved effective in a wide range of fields, such as computer science,

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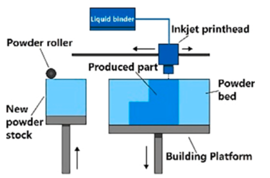
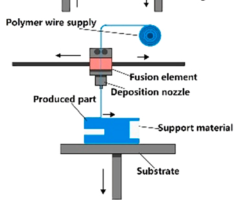
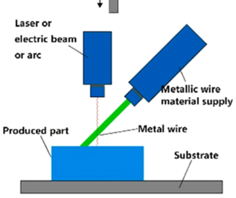
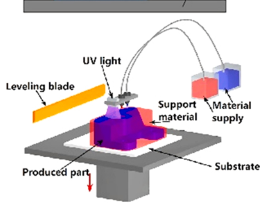
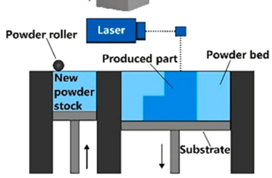
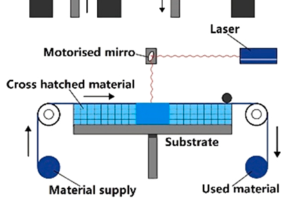
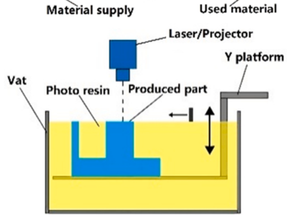
aviation, healthcare, and the manufacturing industry [3]. With the advancement of data acquisition and storage technologies, data-driven approaches based on ML technologies have been increasingly adopted to discover hidden knowledge and build highly complex relationships in digital manufacturing systems [4]. By using reliable datasets, ML models are capable of learning hidden patterns and uncovering latent knowledge to support decision-making, in terms of process optimization, quality control, and system improvement. As one of the most popular manufacturing systems in Industry 4.0, AM has been incorporated with digital systems and sensor networks where high-volume data can be obtained. Hence, a growing number of researchers have applied ML algorithms to tackle challenges in AM, such as design optimization, in situ monitoring, process modelling, and energy management. However, different researchers and organisations focus on various AM issues by using diverse ML technologies. To clarify the significant research challenges and future opportunities of ML for AM, a comprehensive review is necessarily crucial to summarise and analyse current research topics. There have been some existing review articles focusing on different perspectives of this topic [5], such as the ML for the material development of AM [6], and ML applications in laser powder bed fusion processes [7]. Additionally, the highlighted papers in these review articles were selected and reviewed based on authors' research and industry experience, which is valuable but subjective. In order to discover the exhaustive challenges and opportunities in this increasingly growing research field, a systematic and data-driven review method is needed.

This paper aims to review, summarise, analyse and present the latest research and applications of ML for AM. Section 2 introduces the state-of-the-art of the AM process, including seven main AM system categories

Table 1
AM process categories.

AM process	Working principle	Material	Material feedstock	Material distribution	State of fusion	Represented technology
Binder Jetting[15]		Polymer	Liquid	Print head	Chemical reaction bonding	Binder jetting
Material extrusion[16]		Polymer	Filament	Deposition nozzle	Thermal reaction bonding	Fused filament fabrication (FFF)
Directed energy deposition[17]		Metallic	Filament/ Powder	Deposition nozzle	Melted state: (electric beam/arc /laser)	Wire + arc additive manufacturing (WAAM)
Material jetting[20]		Polymer	Liquid	Print head	Chemical/Thermal reaction bonding	Drop on demand (DOD)
Powder bed fusion[19]		Polymer/ Metallic/ Ceramic	Powder	Powder bed	Melted state/Laser/ Solid-state	Selective laser melting (SLM)
Sheet lamination[21]		Polymer/ Metallic	Sheet	Sheet stack	Solid state: (Ultrasound)/ Chemical reaction bonding	Ultrasonic additive manufacturing (UAM)
Vat photopolymerization [22]		Polymer	Liquid	Vat	Chemical reaction bonding	Digital light processing (DLP)

and their characteristics. In Section 3, the methodology of systematic review is introduced. Based on the results of the systematic review, this paper also applies a data-driven method to analyse notable articles, a keyword co-occurrence and clustering method. Several aspects of AM issues are clustered based on these notable articles which are reviewed and summarised in Section 4. The challenges and opportunities are discovered and clarified in Section 5. Section 6 concludes.

2. AM: the state-of-the-art

The first commercial AM system was recognizably emerged in 1987 with stereolithography (SL) by 3D Systems [8]. Since then, AM has become one of the most crucial manufacturing solutions across various industries, such as automobile [9], aerospace [10], and construction [11]. According to the Wohlers Report 2020, the global market size of AM industry is over USD 11 billion in 2019 and will increase to over USD 35 billion by 2024 [12]. There are currently 7 AM process categories, published in the Standard Terminology for Additive Manufacturing Technologies, which are Binder Jetting, Directed Energy Deposition, Material Extrusion, Material Jetting, Powder Bed Fusion, Sheet Lamination and Vat Photopolymerization [13]. Table 1 shows the details of these AM process categories. These seven categories focus on the single-step process, and for the multi-step AM process, the system combines two or more AM processes [14].

- **Binder Jetting.** Binder jetting process is one of the earliest AM processes developed for polymer powder-based material. An inkjet print head is used to spray the liquid binder onto the polymer powder. The powder material is solidified crossing the section of produced part layer by layer by the chemical reaction bonding at a reasonable speed [15].
- **Material Extrusion.** Material extrusion (ME) AM process is currently the most prevailing AM process in the market. The materials of extrusion-based AM systems are normally forced out in a semisolid state via a nozzle where constant pressure is applied. Then the extruded materials solidify and bond to the previous extruded materials to form a solid structure [16].
- **Direct Energy Deposition**. Direct energy deposition (DED) processes utilize focused energy, such as a laser beam, electron beam, or plasma arc, to melt and fuse simultaneously the substrate and the material that is being deposited into the substrate's melt pool to construct parts [1]. Powder-based and wire-based materials can be used for DED processes [17].
- **Material Jetting.** Material jetting (MJ) is another fast AM process, which uses ultraviolet (UV) light as the main power to solid-liquid photopolymer droplets. The droplets are controlled by the voltage signal. Through the print head, the liquid or melted material is jetted onto the produced part surface [18].
- **Powder bed fusion.** The powder bed fusion (PBF) processes consist of thin layers of fine powders, which are spread and closely packed on a platform. One or two thermal sources are employed in the systems to melt and fuse material powder particles in each layer. Subsequent layers of powders are spread across the previous layers using a roller and then fused together until the entire product is built. Selective laser sintering (SLS), selective laser melting (SLM), and powder-based electron beam melting (EBM) are the commonly used PBF technologies [19].
- **Sheet lamination.** 2 AM technologies are commonly classified into the class of sheet lamination (SL) AM process, ultrasonic additive manufacturing (UAM) and laminated object manufacturing (LOM). The sheets of the material are bonded together as the part based on the fusion resource, like ultrasonic [21].
- **Vat Photopolymerization.** Vat photopolymerization (VP) processes mainly use ultraviolet (UV) to cure or harden materials such as photopolymers, liquids, resins for building products. These processes are capable of manufacturing large parts with submillimetre details and are widely applied in the coating and printing industry [22].

The processing characteristics of each AM process is specific and can be allocated into different production scenarios. For example, the WAAM, as a variation of DED technology normally uses an arc-based heat source, such as a plasma or Metal Inert Gas deposition [23], to melt and fuse metal materials for constructing parts layer by layer. It has recently attracted great attention in the industry, especially the aerospace industry, as it is capable of producing large metal parts with a high deposition rate, low equipment cost, high material utilization [24].

3. Research methodology

To investigate the research and application of ML for AM, a systematic literature review and text mining analysis are adopted for identifying, assessing, and analysing the literature published between 2000 and 2020. The overall methodology is illustrated in Fig. 1. In the first place, a systematic literature review is adopted to search, select, and assess relevant publications. The systematic literature review is defined as a systematic, explicit and reproducible method for identifying, evaluating, and synthesizing the existing body of completed and recorded work produced by researchers [25]. The review process typically involves several main steps [26], including specifying research questions, identification of research, selecting and assessing the collected publications. In the article selection and assessment processes, explicit exclusion and inclusion criteria are required to assess each potential primary study. After the systematic literature review is conducted, the keyword co-occurrence and clustering analysis for selected publications are applied to make a comprehensive overview of the main research topics and directions in the applications of ML for AM.

3.1. Research questions

The research questions for conducting the systematic literature review are set up and presented in Table 2 with its motivations.

3.2. Search strategy

3.2.1. Search terms identification

The search strategy designed in this work includes keyword identification, resources for the searching, searching process, and criteria for article selection, to collect available and qualified published articles relevant to the topic [26]. The search query using Boolean operators is shown in Fig. 2.

The search terms are modified by reducing synonyms while searching in some databases (e.g., IEEE Xplore) due to the search term limitation.

3.2.2. Resources for searching

The searching of relevant articles is conducted by inserting keywords (search terms) in five databases, including ACM digital library, IEEE Xplore digital library, Science Direct, Springer Link, and Scopus. These databases are the most representative databases of scientific research that is closely related to the topic of this review and contains a massive volume of literature, such as journal papers, conference proceedings, and books.

- ACM digital library (https://dl.acm.org)
- IEEE Xplore digital library (http://ieeexplore.ieee.org)
- ScienceDirect (http://www.sciencedirect.com)
- SpringerLink (https://link.springer.com)
- Scopus (https://www.scopus.com)

3.2.3. Inclusion and Exclusion Criteria for Article Selection

Based on the directions of exploration and motivations presented in

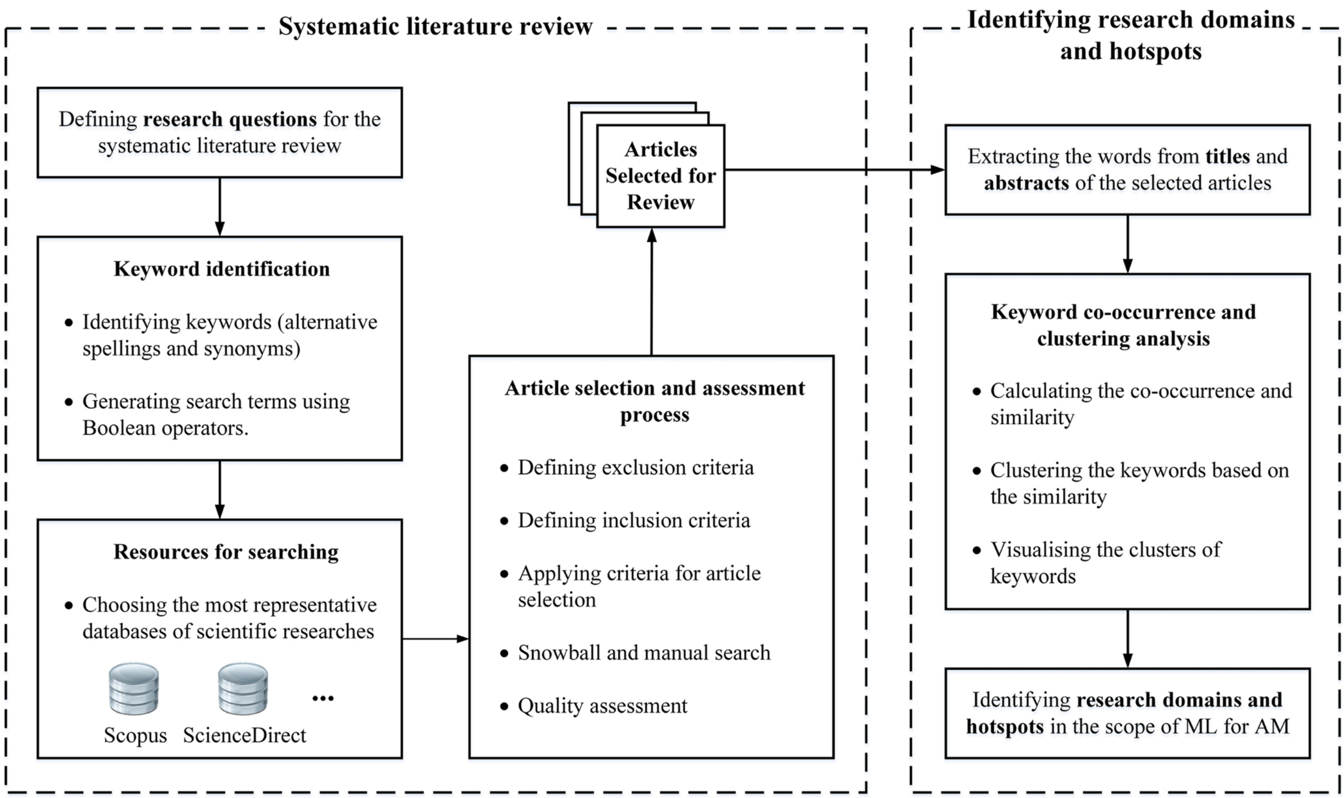


Fig. 1. The overview of the research methodology.

Table 2
Research questions posed for the systematic literature review.

Research Question	Motivation
RQ1: What kind of issues in AM can be currently tackled by using ML technologies?	To explore state-of-the-art of AM challenges that can be tackled by using ML technologies.
RQ2: What ML algorithms have been adopted to tackle the challenges?	To present the ML algorithms adopted by previous studies to tackle challenges in AM. Answer this question will help researchers understand and select appropriate ML algorithms for dealing with similar issues in AM.
RQ3: What are the advantages and limitations of using ML algorithms to solve the issues in AM?	To study the reasons and limitations for adopting a certain ML algorithm to tackle a specific research challenge in AM. Answer this question will assist researchers to make the trade-off between ML-based methods and conventional methods, as well as exploring modified strategies.

(("additive manufacturing" OR "3D printing" OR "rapid prototyping" OR "layer manufacturing") AND ("artificial intelligence" OR "machine learning" OR "deep learning" OR "supervised learning" OR "semi-supervised learning" OR "unsupervised learning"))

Fig. 2. The search query for searching publications.

Table 2, the listed following are the exclusion and inclusion criteria for the article selection process. The exclusion criteria are applied in the title, abstract, and keyword list of a publication while inclusion criteria are applied in full text.

Exclusion Criteria, sources that met the constraints reported below were excluded from this study:

a) Articles that were focused on other technologies rather than machine learning for tackling issues in AM.
b) Articles that were focused on other manufacturing systems rather than AM systems by using ML technologies.
c) Articles that were not written in English.

Inclusion Criteria, sources that met the constraints reported below were included from our study:

a) All the articles, written in English, reporting machine learning technologies for tackling AM issues.
b) Articles that introduce new techniques to improve the performance of existing machine learning technologies used for AM.

3.3. *Article Selection and Assessment Process*

The framework for the article selection process is illustrated in Fig. 3. The searching process starts with searching publications from the pre-defined databases using the Boolean operator based on the identified keywords (10,054 publications were included). Then these publications were filtered through an initial selection process based on the proposed exclusion criteria where 4212 publications remained. The publications were selected by the proposed inclusion criteria and 277 papers were included. A manual search process is adopted to search for additional sources related to the review topic [27,28], where the exclusion and inclusion criteria were re-applied. Twenty-five publications were selected by the manual search process. In the quality assessment stage, the quality of the selected publications is assessed by the following criteria and 228 publications were finally obtained.

- In the paper, the focused issues in AM should be clearly defined.
- The motivations for employing the ML algorithm to tackle the issues should be clarified.

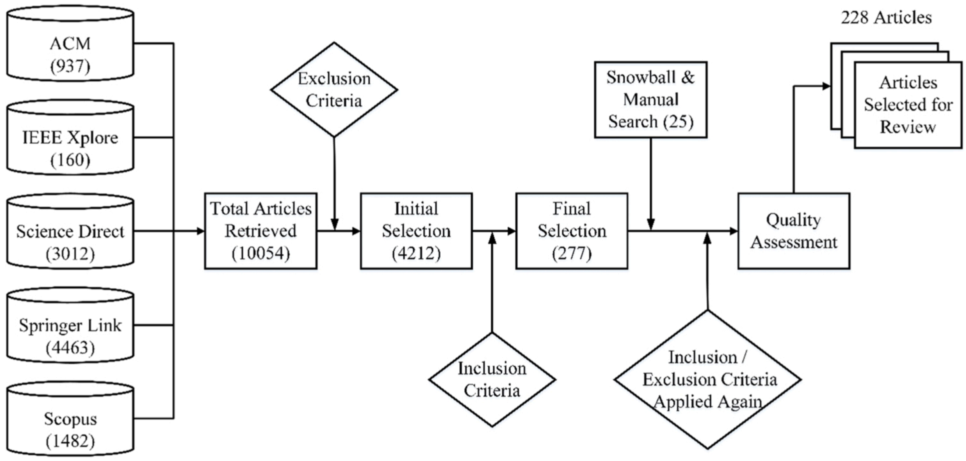


Fig. 3. The framework of the proposed article selection process.

- The evaluation or validation of the proposed methodology should be presented.

3.4. Keyword co-occurrence and clustering analysis for selected articles

The analysis of keyword co-occurrence can provide an effective way to reflect the research hotspots in the research fields through analysing the distribution of keywords [29]. In the keyword co-occurrence analysis, the keywords can be words or phrases that are extracted from the title, abstract, and keyword list in a publication for representing the core contents of a study. The two keywords are counted as one co-occurrence when they occur together in the publications. The clustering approach, introduced by Waltman et al. [30], is employed to group these keywords based on the co-occurrence matrix [31]. Considering a bibliometric network of n nodes, the main concept of this clustering approach is to assign the keywords into n nodes and group these n nodes into k clusters. Based on the co-occurrence matrix, the similarity s_{ij}, also known as the association strength [32], between keyword i and j can be calculated as:

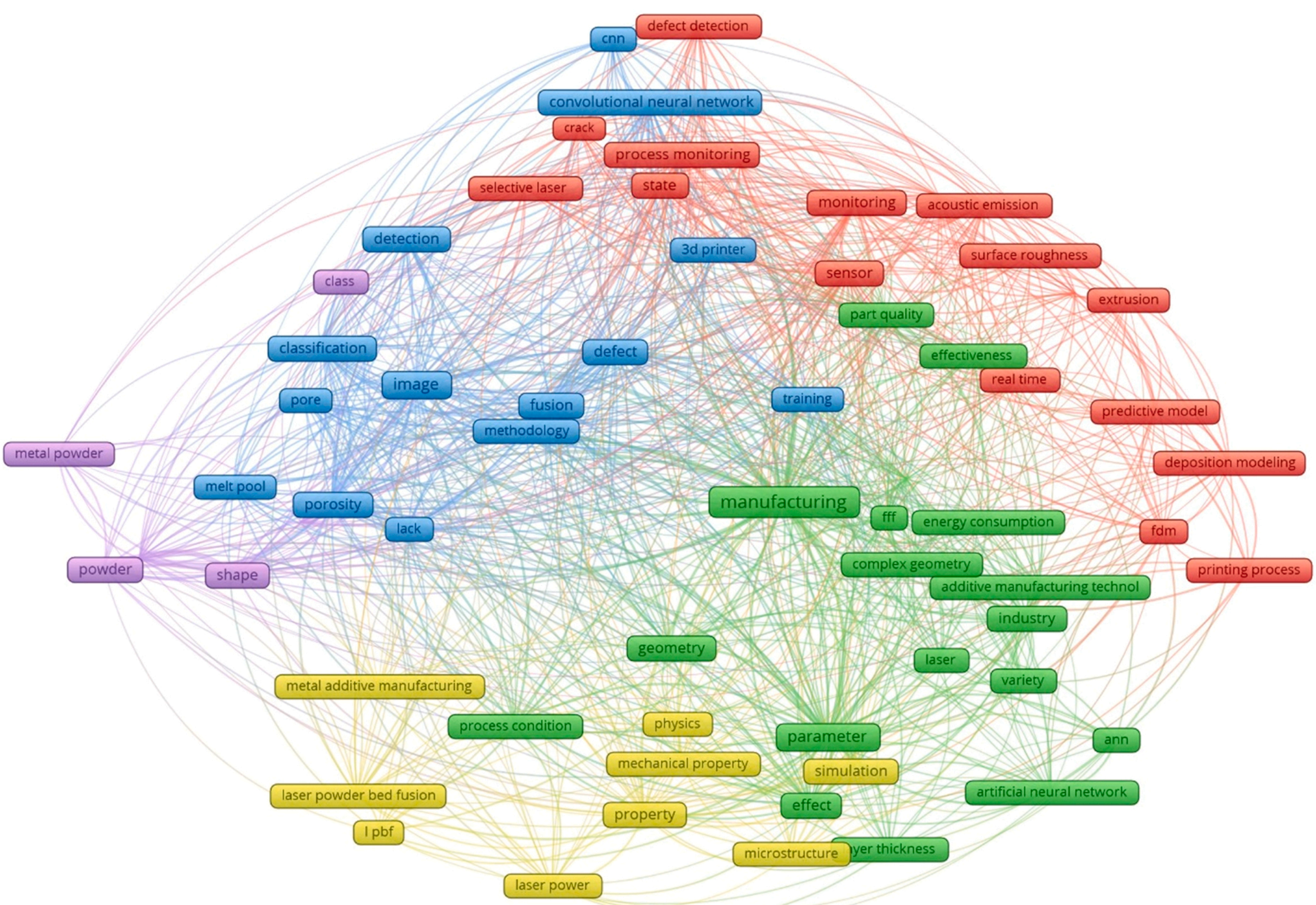


Fig. 4. The clustering results based on the keyword co-occurrence for the selected publications.

$$s_{ij} = \frac{c_{ij}}{w_i w_j} \tag{1}$$

where c_{ij} denotes the number of co-occurrences of keyword i and j, and where w_i and w_j denote the total number of occurrences of word i and j. The clustering method is to minimize $V(x_1, \ldots, x_n)$:

$$V(x_1, .., x_n) = \sum_{i<j} s_{ij} d_{ij}^2 - \sum_{i<j} d_{ij} \tag{2}$$

$$d_{ij} = \left\| x_i - x_j \right\| = \sqrt{(x_i - x_j)^2} \tag{3}$$

In Eqs. (2) and (3), x_i represents a positive integer that indicates a cluster to which node i belongs, and d_{ij} denotes the distance between node i and j. By minimizing the Eq. (2), this clustering method can be interpreted as that the higher the association strength of two nodes, the stronger the relatedness between the nodes. The results of applying the clustering algorithm [30] based on the keyword co-occurrence for the selected publications are obtained by using VOSviewer [31], professional software for bibliometric analysis.

In Fig. 4, the research hotspots are clustered into 5 main clusters that are represented by different colours (i.e., purple, blue, yellow, green, and red). According to the clustering algorithm described previously, the keywords close to each other indicates strong relatedness. Two keywords connected by a link represents the co-occurrence of them in the publications. For each cluster, the research domain is defined by the understanding of the clustered keywords. The keywords in the green cluster such as complex geometry, geometry, layer thickness, and parameter are related to the topics of DfAM. However, the keyword (i.e., energy consumption) relevant to the research of AM sustainability is also displayed in this cluster. This may be due to the increasing trend that researchers study AM sustainability from the design perspective.

The research domain of the cluster in blue is defined as image-based defect detection and monitoring, where the keywords are image, defect, detection, classification, porosity, pore, etc. Similarly, the cluster in red is defined as sensor signal-based monitoring, where the keywords are sensor, acoustic emission, process monitoring, defect detection, real-time, etc. The implementation of process monitoring is based on the success of detecting defects during the manufacturing processes. Hence, these two clusters (blue and red) can be merged into one cluster, representing the same research domain but with different strategies. The keywords displayed in the yellow cluster are physics, property, microstructure, simulation, mechanical property, laser power, etc. These keywords are closely related which indicates that the studies mainly focus on investigating and modelling the relationships between processing parameters and their resulting performances. For the cluster in purple, the keywords are powder, mental powder, shape, and class which can be defined as material analytics. To present the clustered keywords with their corresponding research domains more reasonably, the keywords in each cluster are polished and re-clustered manually based on domain understanding, shown in Table 3. The general terminologies in the clustered keywords (e.g., additive manufacturing, 3D printing, technology, model, etc.) are removed from each cluster and not displayed in the table.

Table 4 shows the link and total link strength information of the top 10 occurrence keywords (the general terminologies are removed). The occurrences represent the total number of a keyword that occurs in the selected publications and a link is counted when two keywords occur together in a publication. For a keyword, the total link strength is the sum of its association strengths, indicating the relatedness of the keyword with other keywords. In other words, the higher the total link strength, the stronger the relatedness.

According to Table 4, the quality issues (keywords: monitoring, defect, property, porosity) of the AM produced products is the biggest concerns that attract most researchers' attention. It is worth noting that the parameter is the most commonly considered attribute in AM research. In addition, most studies focus on process modelling and defect detection domain. Based on the keyword co-occurrence and clustering analysis, the articles under different research domains are reviewed and discussed in the next section.

Table 3
Clustering results for selected publications.

	Clustered Keywords	Research Domain
Cluster 1	Complex geometry, geometry, layer thickness, parameter	DfAM
Cluster 2	Powder, metal powder, shape, class	Material analytics
Cluster 3	Image, defect, detection, classification, convolutional neural network, porosity, pore, fusion	Image-based defect detection and monitoring
	Sensor, process monitoring, acoustic emission, real-time, surface roughness, predictive model, crack, defect detection	Sensor signal-based defect detection and monitoring
Cluster 4	Physics, property, microstructure, simulation, mechanical property, laser power	Process modelling and control
Cluster 5	Energy consumption	Sustainability

Table 4
The links and total link strength information of the top 10 occurrence keywords.

Keywords	Cluster Number	Occurrences	Links	Total Link Strength
Parameter	1	87	60	630
Image	3	58	46	619
Monitoring	3	43	52	434
Defect	3	41	52	415
Property	4	41	44	329
Porosity	3	39	53	547
Classification	3	34	47	324
Sensor	3	34	48	393
Simulation	4	32	32	178
Detection	3	27	34	187

4. ML for AM

4.1. ML for DfAM

AM has provided opportunities for innovative designs and advances in product performance, in terms of geometric freedom and highly integrated structures [33]. Due to its unique production paradigm, the AM processes may involve different batch sizes, production times, and cost drivers compared with conventional processes. It also requires different approaches to metrology and quality control. Therefore, DfAM has been proposed as a way to provide AM design professionals with a wide range of design and analysis tools for complex part structures and AM processes. Typically, DfAM includes two main research topics, part design and design optimization [34]. For part design, AM creates free forms and customized geometries, enabling the creation of complex internal features to increase functionality and improve performance of target parts, which provides designers with huge design space. For design optimization, AM part designers need to determine production path strategies, part locations, build orientations, and support structures for improving the quality of final printed products. Due to the advances of artificial intelligence and available data, ML technologies have been increasingly applied to DfAM in recent years [35].

4.1.1. Part design

At the conceptual design phase, most AM designers select appropriate design features based on their knowledge and experience. However, there is a lack of systematic and intelligent techniques to assist AM professionals to explore AM-enabled design space [36,37]. Hence, Yao, et al. [36] introduced a hybrid ML approach for design features recommendation at the conceptual design phase in AM. In the paper, the authors classified the functionality-centric design knowledge inherent in AM design features and target components into 'loadings', 'objectives' and 'properties', which were coded with numerical digits and saved in database files. Then hierarchical clustering was carried out on the coded design knowledge to reveal the relationships among design features and target components, resulting in a dendrogram. Previous industrial application examples with their design features implementation were simplified as a binary classification problem (implemented design features denote as '+1', otherwise '−1') and trained by a support vector machine (SVM) classifier. The trained SVM model was used to refine the hierarchical clustering results by an SVM-based progressive dendrogram cutting process, which aims at identifying the final sub-cluster containing the recommended AM design features. Through the case study results, the proposed hybrid ML approach was demonstrated useful in identifying appropriate AM design features for inexperienced designers. Neural network is another popular ML technology used to improve the part design in AM processes.

Andrew and Markus [38] introduced a method that uses variational autoencoders (VAE) and ML techniques for the compliance optimization of cantilever design. In this work, the cantilever structures were encoded into a 2D latent space by VAE and the long short-term memory (LSTM) neural network was adopted to learn the latent space trajectories that correspond to the topology optimization process. The results showed that the VAE-LSTM model was capable of generating complex structures and evolving them. A framework of using neural networks for the analysis and design of micro-lattices architectures in AM was introduced by Nathaniel [39]. In this study, to obtain training datasets, the authors used a compact genetic algorithm (cGA) to generate micro-lattice structures of which the corresponding mechanical properties were obtained by finite-element analysis (FEA). The graph convolutional networks (GCN) with an asymmetric auto-encoder was adopted and trained by the graph representation of the generated micro-lattices. Specifically, through the training process, the encoder was able to learn the physical characteristics of micro-lattices and infer their mechanical properties. Then the decoder was used for generating the micro-lattices structures with specified mechanical properties. According to the empirical results, the encoder had an accuracy of 93.72% in predicting the mechanical properties of the given micro-lattices structures. The decoder was demonstrated to be capable of generating the micro-lattices from the specified mechanical properties. Another example of applying neural networks is that Jonnel et al., [40] used artificial neural networks (ANN) for geometry corrections of the designed lattice infill patterns in FDM systems. In this work, the 3D coordinates of the designed infill structures were used as the input of the ANN model, while the symmetrical deviation surface coordinates were the output. After training, the model was implemented to the STL file for geometric corrections., Considering the manufacturability of AM process, Tang et al., [41] proposed a strategy for lattice structure design and optimization to ensure products quality. To represent the design space of lattice structures, the concept "physical entity" was introduced to include the design information (geometrical information and material information) for each design stage. Then, the lattice unit cell model was defined and proposed to represent the topology of the elements inside lattice structures. The authors used the concept of "manufacturable element" to include the geometry, material, and process information of a lattice strut. ANN was used to bridge the relationship between manufacturability and geometrical data.

Integrating the physical and domain knowledge in ML algorithm has been proven which can improve the ML performance significantly [42]. Ko et al., [43] introduced a methodology for bridging the gap between multi-discipline designs and AM capabilities based on knowledge graph ML. In this work, the framework of the proposed method, shown in Fig. 5, consists of 4 main modules, including (1) AM prior knowledge structuration, (2) transformation of knowledge to DfAM ontology, (3) extraction of knowledge from AM data using ML, and (4) design rules transformation. The design fundamentals, principles, and rules were obtained by formalizing unstructured AM prior knowledge into structured knowledge and extracting knowledge from AM data based on ML algorithms. Then, these designs knowledge was encoded into ontologies with knowledge graphs. Finally, the design rules were constructed by reasoning with prior knowledge and newly discovered knowledge.

4.1.2. Design optimization

To obtain the required production quality, design optimization is a critical step before the AM process begins [44]. Many crucial elements and parameters are defined in this step. For instance, the determination of build orientation and direction significantly affects process and fabrication attributes [45]. In Ref [44], the authors applied K-means clustering with Davies–Bouldin Criterion cluster measuring on surface models to generate alternative build orientations in a computationally efficient way. The K-means clustering method was adopted to decompose stereolithography (STL) models into K facet clusters where the number of clusters was determined by Davies–Bouldin Criterion. The central normal vectors of each facet normal cluster were used as

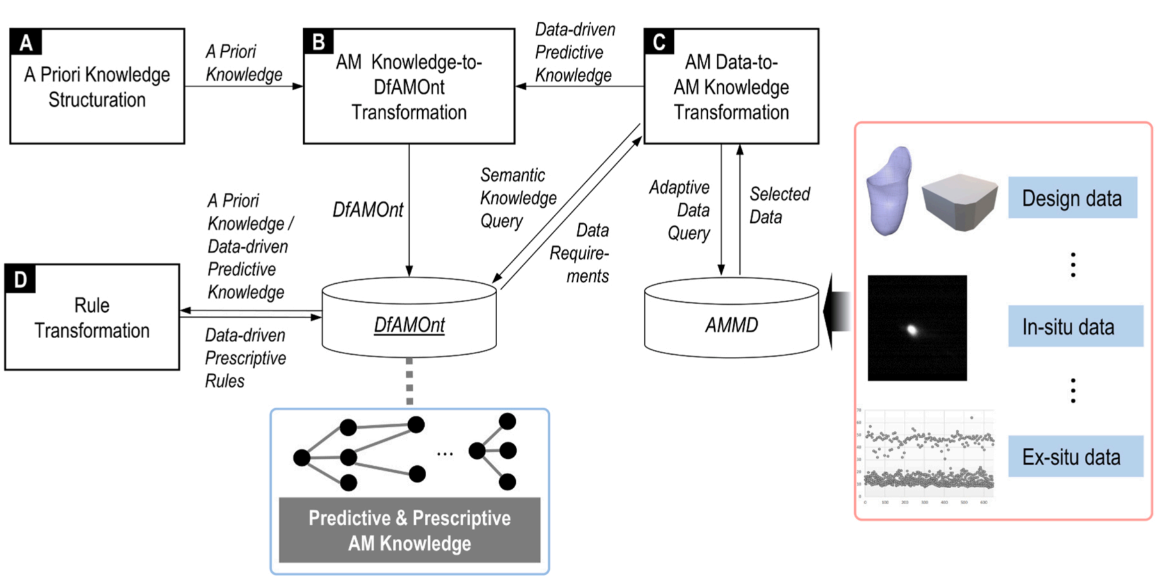


Fig. 5. The proposed data-knowledge-design rule framework. This framework consists of 4 main modules, including AM prior knowledge structuration, transformation of knowledge to DfAM ontology, extraction of knowledge from AM data using ML, design rules transformation, Ref [43].

alternative build orientations where the optimal orientation was ultimately obtained by a statistical evaluation process. To prevent unsightly surface artefacts or damages of fine surface details when removing support structures, a perceptual model of preference in the printing direction of AM was proposed by Zhang, et al. [46]. The authors developed a perceptual model to determine the preference of printing orientation in terms of area of support, visual saliency, preferred viewpoint, and smoothness preservation.

Support structures are also important and required in some AM processes if the designed models contain separated segments or overhang parts in a layer where does not exist solid material underneath. To find the minimum amount of support structures for successfully fabricating a model, Huang et al. [47] developed a support detection approach based on a surfel convolutional neural network (surface element - CNN) in AM. In this method, the surfel is the sampling point on the surface with normal information, defined through layered depth-normal image (LDNI) [48] sampling method. The LDNI stores array of rays that are shot to intersect with the CAD model, where the depth and normal values of intersection points on the rays are included. Based on LDNI sampling, local surfel images with ground-truth support regions were obtained and fed into the CNN model for classification. The experimental results indicated that the proposed methodology outperformed the normal-based method and image-based method in terms of support detection. It is highlighted in the paper that, due to the topology-preserving and salient feature extracting capability, the surfel CNN model is more robust for support detection on extreme features than the traditional image-based method.

AM has been increasingly employed for printing composite material parts. However, the fiber size, volume fraction and direction are important in determining the properties of the printed part. Kaushik et al. [49] introduced a method for reversing additive manufactured composite parts by toolpath reconstruction of the printing process using the LSTM network. In this method, the CT-scan images of fibre orientation at each layer were sequentially fed into the LSTM model for predicting the orientation angle of fibres. Then the G-code can be generated based on the fibre orientation and measured layer thickness. The method developed in this study showed the effectiveness of the ML model in identifying and tracking any given orientation of the fibres. It also demonstrated the possibility of reconstructing the G-code and reverse engineering any composite part for improving the properties of the printed parts.

4.1.3. Shape deviation

Due to the functionality and manufacturing requirements, shape accuracy measurement is essential and critical in DfAM, aiming to reduce the geometrical deviations of the final products [50]. In general, during an AM process, the geometries of final products are affected by various factors, such as material properties, thermal gradients, and build orientations, which lead to the low quality of printed parts. Hence, the geometrical inaccuracies of the produced products pose significant challenges to predictive modelling of shape deviations and developing error compensation strategies for AM. Several researchers have explored that ML models are used for tackling geometrical accuracy-relevant issues, such as shape deviation prediction [50–57], classifying and quantifying geometrical accuracy [58,59], and deviation compensation [60]. In the studies [53–56], ANN was adopted to model the relationship between process parameters and geometry-related errors in different AM processes.

Zhu et al. [50] proposed an ML-based method to model in-plane deviation and random local variant in AM. A mathematical relationship between the designed shape and the final shape was constructed from a transformation perspective, aiming at capturing the global trend of shape deviations. Due to unexplained variations with complex patterns, a multi-task Gaussian process (GP) learning algorithm was adopted to learn from the unexplained deviation data and model the local deviation. The experimental results demonstrated the effectiveness of the proposed methodology with prediction accuracies over 90%.

An automated geometric shape deviation modelling approach based on Bayesian neural networks (BNN) and transfer learning techniques for different shapes and AM processes was proposed by Ferreira et al. [52]. In this approach, the geometry shapes are defined under the polar coordinate representation, where each point on a product is identified by an angle θ. The in-plane and out-of-plane deviations of different shapes and processes are represented by statistical models. A baseline BNN for modelling shape deviation was firstly built by training on a small number of product samples under a specific AM process. Then transfer learning techniques were employed to transfer the baseline model to new shapes and processes. A case study was carried out under different SLA processes, where the proposed model yielded good performance in an automated manner. This study provides insights of automatically leveraging data and models from different processes, addressing the challenges of modelling for various shapes produced by distinct AM processes.

Tootooni et al., [59] introduced a method to classify the dimensional variation of AM produced products based on spectral graph theory and ML techniques. It is interesting that this work extracted the spectral graph Laplacian eigenvalues from the 3D point cloud data of the manufactured parts and used them as features in ML models for classification. This work provides a solution to reduce the measurement burden for post-process quality assurance. For shape deviation compensation, Shen et al. [60] introduced a framework for AM using a convolutional neural network (CNN). In this framework, the 3D model was encoded as a binary probabilistic distribution in 3D space and fed into the CNN model for capturing deformation features. An inverse function network was trained for obtaining the compensated model.

4.2. ML on material analytics for AM

A variety of materials, such as metals, ceramics, plastics, and their combinations are used for AM applications and the development of new materials is in progress [61]. Using different materials for producing products can result in different performances and properties. A significant amount of data can be generated from material property and conditions. It is essential to analyse and understand the relationships among material chemistry, material characteristics and final part performances based on the material data. The powder property is one of the key elements that affect the build process and final part quality in powder-based AM [62]. During the printing process, the interaction and consolidation between powder particles are complicated where high-quality powders are required to ensure the process reliability and final part property. Thus, qualifying powder materials is critical, and some researchers have made efforts in measuring and analysing powder materials by using ML technologies.

Powder characterization is important for evaluating the quality of powder materials in AM, where computer vision and ML technologies have been applied for autonomous characterization [63,64]. DeCost, et al. [64] introduced a method that used key-point based computer vision for quantitatively characterizing powder materials. In this study, eight powders that only differed in their particle size distribution were considered. The authors employed a computer graphics suite, called Blender, to generate synthetic powder micrographs. A bag of visual words (BOVW) image representation was adopted for characterizing the synthetic powder micrographs, where the images were represented by key-point features and organized into a visual dictionary. Then the difference of Gaussians (DoG) and Harris-LaPlace (HL) interest point detectors were used to select critical key-point features. The regions surrounding the key-point features were characterized by applying scale invariant feature transform (SIFT). Finally, the support vector machine (SVM) algorithm was used for the particle size classification of which the accuracy was 0.894. Compared with conventional characterizing methods, this study provided an alternative method to characterize feedstock powders based on ML.

Vrábel, et al. [65] also adopted SVM to classify Al alloy powder materials for the SLM process. In this work, the authors used the laser-induced breakdown spectroscopy (LIBS) technique to obtain spectra from the powder materials. Then the spectra were processed through unit vector normalization and principal component analysis (PCA). The PCA model was applied to reduce dimensionality and remove noise data, where four principal components (PCs) were obtained. These PCs were fed into the SVM model for material classification. Powder flows significantly affect the deposition behaviour of the layers on the substrate. Richard et al., [66] used the decision trees (DT) algorithm to classify powder flowability based on particle-level physical property measurements in cold spray AM, achieving an accuracy of 98.04% in classification.

Currently, ML technologies are generally used for classification tasks for powder material analysis. There still need further exploration and research to achieve the potential of leveraging ML for material analytics in AM, such as analysing material composition for alloy development and modelling the relationship among material chemistry, material properties and final part performances.

4.3. Defect detection and in situ monitoring for AM based on ML

Lack of quality assurance in AM produced parts is one of the key technological barriers that prevent manufacturers from adopting AM technologies, especially for high-value applications where component failure cannot be tolerated [67]. There still lacks effective and mature monitoring technologies in AM systems for detecting the onset of defects in real-time and keeping the stability of the process in control [68]. Due to different material supplies and working principles of different AM processes, the defects or quality issues can be various. For instance, the issues of porosity, lack-of-fusion, balling, crack are critical in the powder-based processes [67,69,70] and the geometry deviation [71], shape shrinkage [72], and surface roughness [73–75] in FDM processes have been focused by many relevant research groups. Only when these defect issues are detected synchronously and accurately during the AM process, the real-time control strategies can be realized. With the advancement of data acquisition, communication, and storage technologies, ML technologies have been increasingly used for in situ monitoring in AM systems [76,77]. The ML models are trained by different types of data which are classified into three categories, including one-dimensional 1D data (e.g., spectra), 2D data (e.g., images), and 3D data (e.g., tomography) [78]. Each strategy developed in existing studies has pros and cons. In general, two main types of strategies, image-based and sensor signal-based, are adopted for defect detection and in situ monitoring in AM. Strategies that leverage 3D point cloud data with ML models have also been explored in recent studies [79,80].

4.3.1. Image-based approach

Visual camera images can present the surface characteristics of every build layer to reflect the quality of the AM produced parts. Zhang et al. [81] developed a vision system with a high-speed camera to capture the sequential images for PBF process monitoring. Their research focused on detecting the information of melt pool, plume, and spatter. Features of these objects were extracted based on the understanding of the physical mechanisms. These features were then selected by PCA before being used as inputs for SVM classification. The performance of the SVM model showed an accuracy of 90.1% for quality level classification. This work also demonstrated that CNN is promising to achieve real-time monitoring as it has an accuracy of 92.7% without the feature selection process. CNN is capable of learning fairly representative features from the raw data automatically and is commonly used for image analysis. CNN-based defect detection and monitoring methods are developed in Ref [82–95]. As an extension of the CNN model, deep CNN (DCNN) with a hierarchical structure that allows multilevel image features to be extracted to achieve accurate pattern discovery was employed by Caggiano et al. [82] for online defect-recognition in the SLM process. Additionally, a modification of the CNN model developed by Scime and Beuth [83], called multi-scale CNN (MsCNN), improves the flexibility and overall classification accuracy of the conventional CNN model in autonomous anomaly detection. The proposed MsCNN methodology has been demonstrated to be robust when analysing builds that were manufactured by different materials, including AlSi10Mg, bronze, Inconel 625, Inconel 718, stainless steel 316 L, stainless steel 17–4 PH, and Ti-6Al-4 V, in the L-PBF systems. Lee et al. [96] adopted 3D-CNN and CNN-LSTM for the classification of different statuses, including damaged, cured, and uncured, in the two-photon lithography (TPL) process.

Some researchers have also explored image-based monitoring approaches with their corresponding control strategies [97,98]. Wang et al. [98] presented a closed-loop control framework by seamlessly integrating vision-based techniques and neural networks (NN) to detect droplet phenomena and accordingly implement control strategies in liquid metal jet printing (LMJP) processes. In this work, a charge-coupled device (CCD) camera was employed in the monitoring system to capture jetting images. The key features were extracted from jet images by a flood-fill algorithm [99] and summarized to the properties of the droplet patterns (i.e., satellite, ligament, volume, and speed of droplets). The complex relationship between droplet features and voltage level was modelled by NN of which the architecture is shown in Fig. 6(a). This NN model enabled the conversion of real-time droplet features to voltage values and a proportional integral derivative (PID) process was used to adjust the drive voltage by comparing the output values of NN with target values for process control. Results from empirical tests indicated that more stable jetting processes can be realized in real-time through the proposed methodology. Fig. 6(b). shows the control processes for offset jetting stabilization.

Besides, Jin et al. [100] developed a real-time monitoring and autonomous correction system for FDM processes. A CNN classification model was used for detecting defects and a feedback loop was used to modify processing parameters. In their paper, three categories, including ‘Good-quality’, ‘Under-extrusion’, and ‘Over-extrusion’, were adopted to represent the quality of the printed parts and 120,000 images were used for training and testing. The adjusting commands were sent to the control system to modify the flow rate of the AM system when five successive over or under-extrusion judgments were made by the CNN model. Experimental results indicated that the proposed model achieved above 98% accuracy in predicting the part quality and the response rate of the system from defect-recognition to correction reaches or even surpasses the human reaction (9 s). However, the key parameters for the adjustment are selected based on the authors’ understanding of the processes in both Ref [98,100]. For instance, in Ref [100], the adjustment of flow rate was focused in this paper, while other parameters such as printing speed and nozzle height were not considered.

Apart from CNN-based models, SVM [101,102], Bayesian classification [103], deep belief networks (DBN) [104], deep neural networks (DNN) [105], *k*-means singular value decomposition (K-SVD) [106] have also been employed to analyse image data for quality inspection in AM systems. However, in Ref [101–103], key features of visual images need to be extracted before being fed into the ML models. In Ref [104], Ye et al. proposed an in situ monitoring method based on analysing plume and spatter signatures during the SLM process. The plume and spatter images were obtained by a high-speed near-infrared (NIR) camera and normalized by zero mean and unit variance to capture the pair-wise interactions between pixel values. These processed data were then fed into the DBN structure with four-level hidden restricted Boltzmann machines (RBMs) for classifying 5 distinct melted states (i.e., over-melted, middle-over melted, normal melted, middle-under melted, and under melted). The experimental results showed that the proposed method had a classification accuracy of 83.4%. The DBN structure developed in this study were demonstrated effective in learning features from original data with less prior knowledge.

Different ML models for image-based defect detection and

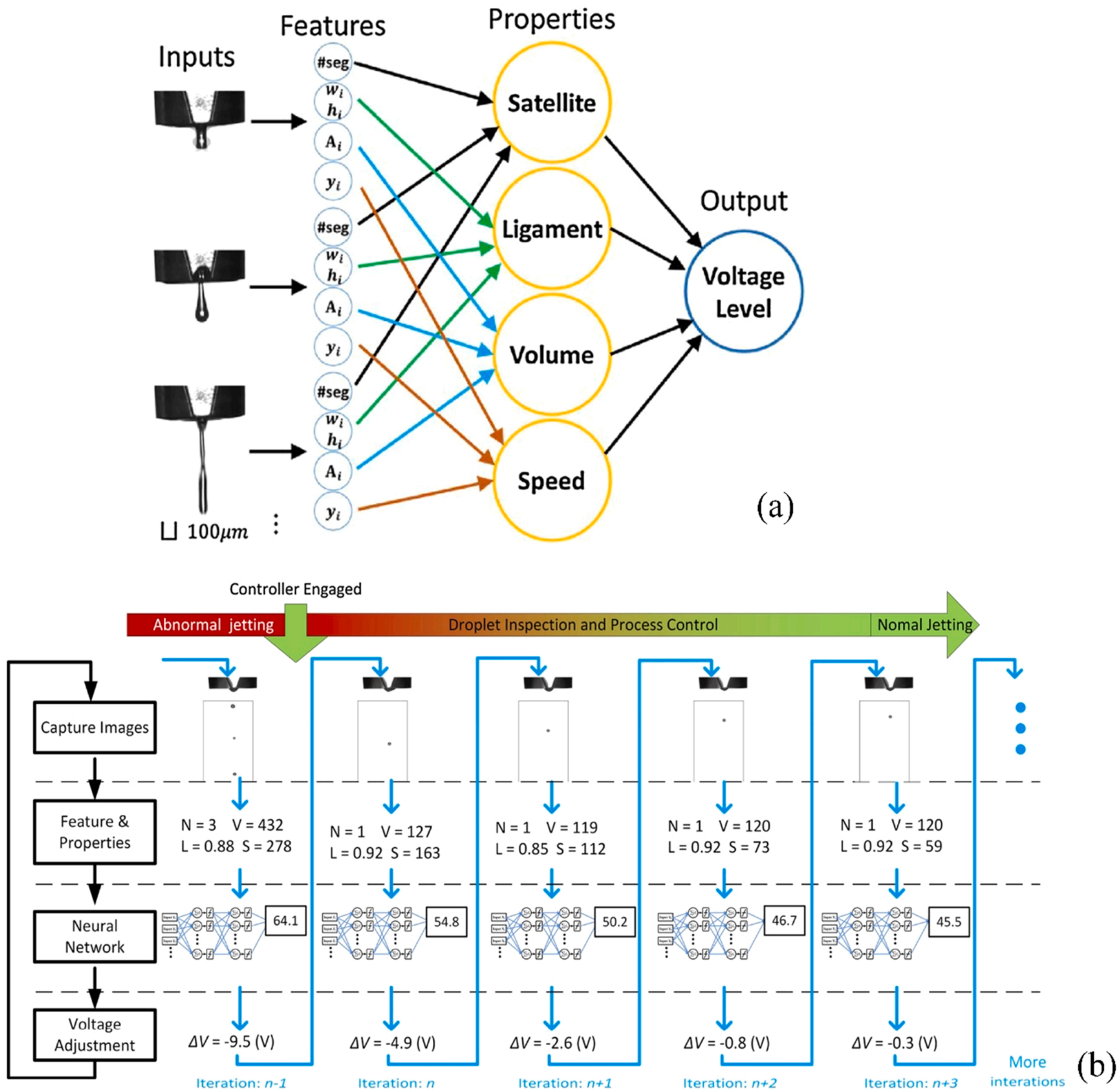


Fig. 6. (a) The developed NN for droplet defects detection based on key droplet patterns (i.e., satellite, ligament, volume, and speed) analysis from jet images; (b) The real-time control processes for offset jetting stabilization, Ref [98].

monitoring strategies have been developed in existing studies. However, it's worth noting that CNN-based models are prevailing in image-based methods and normally yield superior results than conventional ML models.

4.3.2. Sensor signal-based approach

Sensor signal-based approaches for system monitoring are widely applied in the manufacturing industry. In existing studies, different signals, including AE, optical emission, infrared signal, and multi-sensor signals are used for defect detection and monitoring in AM systems.

4.3.2.1. Acoustic Emission. Besides developing monitoring strategies based on image analysis, AE sensors have been applied in conventional manufacturing processes and are increasingly explored in AM. A quality monitoring approach based on AE for powder bed fusion (PBF) AM processes was proposed by S.A. Shevchik, et al. [107]. In this paper, the AM machine was equipped with a fiber Bragg grating (FBG) sensor to detect AE signals, shown in Fig. 7. The acoustic features, extracted from signals during the manufacturing process, were the relative energies of the narrow frequency bands of the wavelet packet transform. The spectrograms localized in the time-frequency domain were built from the acoustic features and used as input for spectral convolutional neural networks (SCNN) for classification. Based on the porosity measurement results of the printed workpieces, the qualities were categorized into poor, medium, and high. According to the empirical results, the classification accuracies of SCNN varied from 83% to 89%, indicating the feasibility of quality monitoring based on the proposed method. Similar methods using AE signals for quality monitoring on PBF processes can be found in Ref [108,109]. In Ref [109], where the reinforcement learning (LR) algorithm was adopted for training and classification. However, the corresponding control strategies have not been discussed in these studies [107–109].

In addition, some other researchers have also developed monitoring strategies by analysing acoustic emission data based on various ML models, such as SVM [110], hidden semi-Markov model (HSMM) [111], Clustering by fast search and find of density peaks (CFSFDP) [112], and LSTM [113] for FDM processes, DBN [114] for SLM processes and *k*-means [115] for laser metal deposition (LMD) processes. However, the studies [110–113] focus more on identifying and detecting the abnormal machine conditions, such as material run-out, filament breakage, extruder blockage or incorrect nozzle height, rather than the quality of manufactured products. For example, the methodology developed in Ref

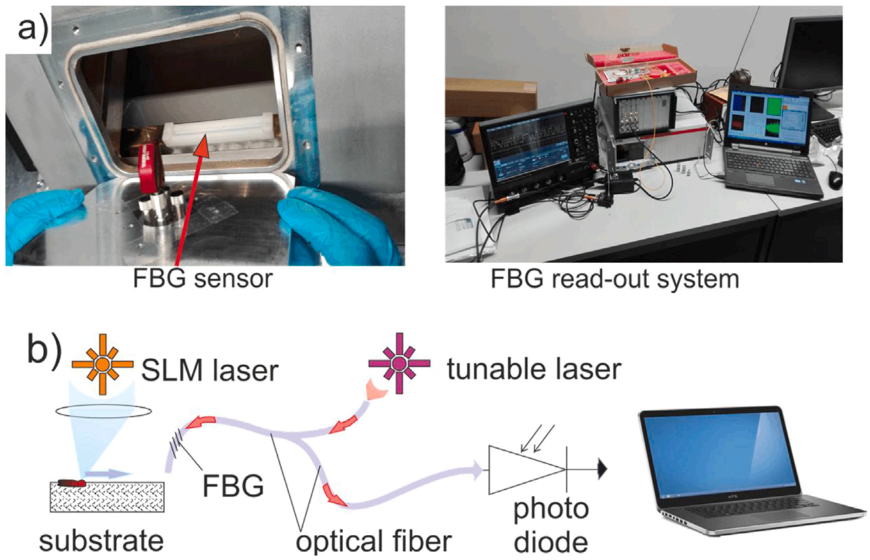


Fig. 7. The FBG system for collecting AE signals during the SLM process. The spectrograms localized in the time-frequency domain were built from the acoustic features and used as input for spectral convolutional neural networks (SCNN) for classification, Ref [107].

[114] is capable of identifying five melted states, including balling, slight balling, overheating, slight overheating, and normal phenomena for the SLM process. Compared with conventional ML models such as multilayer perceptron (MLP) and SVM, the DBN model is highlighted in this study to be capable of achieving a high defect detection rate without extracting features from raw signal data. Liu et al. [112] also developed a machine state monitoring platform based on AE sensors for FDM machine states identification using unsupervised learning. The monitoring platform (a) and procedure for machine condition fault diagnosis (b) are presented in Fig. 8 respectively.

4.3.2.2. Optical emission. Optical emission spectroscopy (OES) has long been used to better understand physical mechanisms and is also considered promising for real-time monitoring in AM systems [116–119]. Mohammad et al. [120] proposed an in-process porosity monitoring approach using optical emission signatures captured by the multispectral sensor during the LPBF process. In this study, the line-to-continuum ratio, a measurement of the emission spectrum to determine the defects, of chromium emission around 520 nm was monitored during L-PBF of nickel alloy 718 powder feedstock. Based on emission spectroscopy, Ren et al., [121] introduced a quality monitoring method for the DED process by applying LSTM-autoencoder and K-means clustering models. In their work, the LSTM-Autoencoder was adopted for extracting features from the spectra collected during the

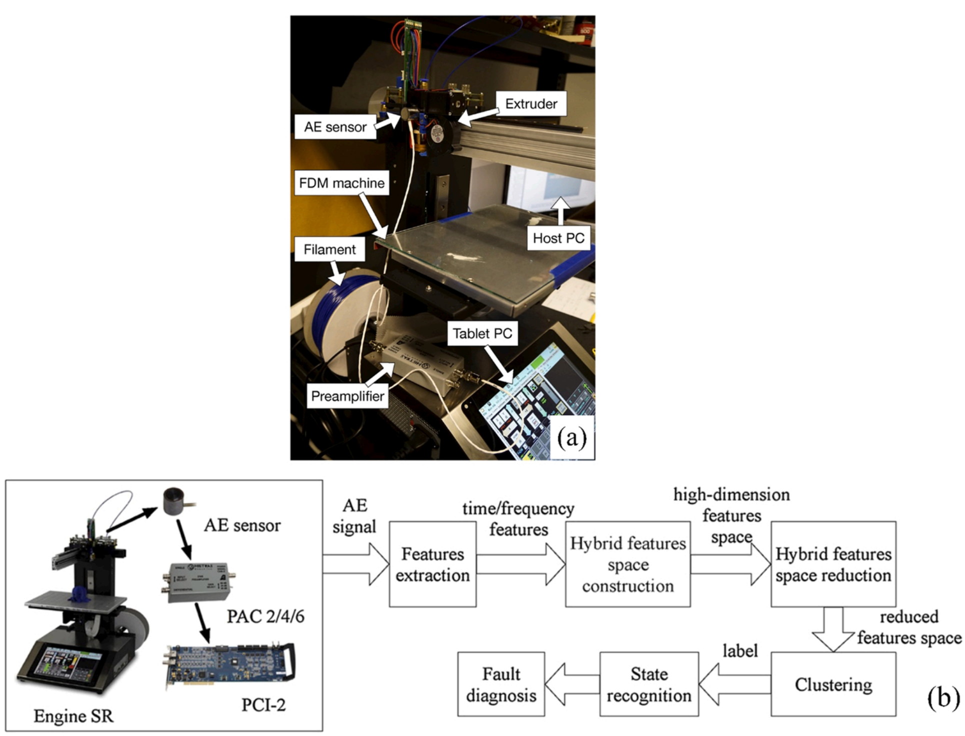


Fig. 8. (a) The AE sensor-based monitoring platform for the FDM machine; (b) the procedure of fault diagnosis for FDM machine states using unsupervised learning, Ref [112].

production, and the K-means clustering algorithm was used for the deposition quality classification.

The X-ray computed tomography (CT) techniques were employed to quantify the pore severity in each layer of a test part. The pore severity was classified into four levels, Disc A (160 J/mm^3), Disc B (80 J/mm^3), Disc C (53 J/mm^3), Disc D (107 J/mm^3). The graph-theoretic approach was adopted to extract features, called graph Fourier transform coefficients, from the line-to-continuum signatures. These features were used as input in various ML models, such as *k*-nearest neighbours (*k*-NN), NN and SVM, for predicting the porosity level in each layer with the CT data taken as ground truth. The results demonstrated that the proposed methodology had an accuracy of 90% (F-score) of classification in a computation time of less than 0.5 s.

4.3.2.3. Infrared signal. Outputs from the visual and simulation-based porosity detection methods are possibly far from actual yields in some cases since they are often incapable of taking into account the uncertainty that results from material or process parameters [122]. Characteristics of a melt pool have been demonstrated to have a strong link with the formation of defects through existing studies[123–125]. Therefore, some researchers have explored methods for detecting and predicting porosity by capturing in situ melt pool morphologies using infrared sensors [122,126]. The information of the melt pool can be obtained by using various instruments such as infrared sensors, pyrometers or high-speed cameras. Khanzadeh et al. [127] adopted self-organizing maps (SOMs) to analyse 2D melt pool images for detecting anomalies in additively manufactured thin walls in the DED process. As an extension of the work in Ref [127], a real-time porosity prediction method based on morphological characteristics of melt pool boundaries was proposed by Khanzadeh et al. [122]. In this paper, the time-varying melt pool signals were captured by a dual-wavelength pyrometer and categorized as either pores or normal melt pools by X-ray tomography. In the proposed method, shown in Fig. 9, features from melt pool boundaries were obtained through functional principal component analysis (FPCA) and used as input in different supervised ML models, including *k*-NN, SVM, decision tree (DT), and linear discriminant analysis (DA), for predicting porosity. It was reported from the experimental results that the *k*-NN model obtained the best performance for correctly predicting an abnormal melt pool with an accuracy of 98.44%, while the DT model achieved the best result for false-negative value of only 0.033%.

4.3.2.4. Multisensor signal. Recently, researchers have begun to fuse data acquired from multiple in-process sensors for analysing and developing defect detection strategies as it is unusual that the data collected from a single source can cover all information of different phenomena. Kim et al. [128] proposed a data-driven method for monitoring and fault diagnosis of the FDM process states using two types of sensors, an accelerometer and an AE sensor. The root mean square (RMS) values were extracted as critical features from time-domain signals under healthy and faulty process states. The faulty FDM process state was realized by considering the loosened bolt which would be resulted in shifting layers in the printed specimen due to a feed motion of the extruder head. The extracted features were fed into the SVM model which had an accuracy of 87.5% for classification according to the experiment results.

A heterogeneous sensor-based in situ monitoring approach was developed by Montazeri et al. [129] to detect the occurrence of lack-of-fusion defects in titanium alloy (Ti-6Al-4 V) parts manufactured in the DED process. In this study, the data was collected from an optical emissions spectrometer and a CCD camera with a near-infrared (NIR) filter, aiming at capturing the dynamic phenomena around the melt pool region. The authors fused the data into a weighted network graph developed in Ref [130] and employed the graph Kronecker product

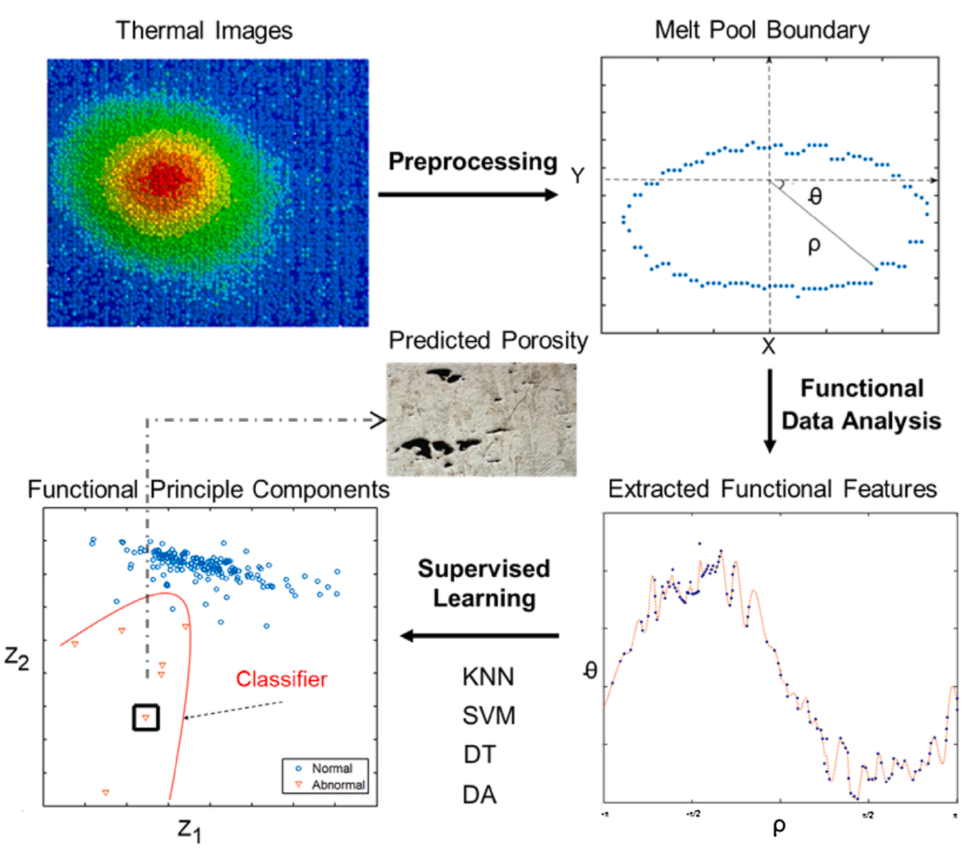


Fig. 9. Illustration of using ML techniques for porosity prediction based on melt pool boundary features that are extracted from thermal images by using FPCA, Ref [122].

approach to building a dictionary of graph-theoretic features related to the severity level of lack-of-fusion defects. These features were used as inputs to the SVM model for classification which achieved F-scores close to 85% and 70% for a two-level and three-level classification scenario respectively. Compared with traditional statistical signal processing approaches, the merits of the graph Kronecker product method was demonstrated in the paper. Similarly, strategies of using multi-sensor data for quality monitoring in AM systems are developed in [131–133]. It is worth noting that, in Ref [131], Bastani et al. proposed a novel supervised classification approach, called online sparse estimation-based classification (OSEC), which aimed to improve the classification accuracy and reduce the computational burden for real-time monitoring. In this study, the OSEC method was demonstrated to be capable of processing raw sensor data directly with F-score performances between 89% and 95% and being successfully applied to multiple sensor monitoring scenarios with a 685 Hz sampling rate.

Photodiode data is considered closely correlated to the properties of the melt pool by Okaro [134]. In this paper, the authors used a semi-supervised ML model, Gaussian mixture model (GMM), trained by the key features extracted from photodiode data to classify 'acceptable' and 'faulty' AM builds regarding the tensile strength in the L-PBF process. randomized singular value decomposition (SVD) was employed as a feature extraction method to handle large datasets (approximately 400 G per build) collected from photodiode sensors. The experiment results indicated that the GMM model achieved a 77% success rate in identifying faulty specimens. Additionally, the proposed semi-supervised approach was demonstrated to be able to use data from both builds where the resulting components were certified and build where the quality of the resulting components is unknown, which is cost-efficient especially in cases where part certification is costly and time-consuming. Monitoring methods for AM systems based on vibration data and ML models were also developed by several researchers [135,136].

Various monitoring and defect detection methodologies have been developed, such as using pyrometer, AE, optical emission, infrared camera, and high-speed visual camera, to detect macroscale or mesoscale defects based on ML models. Typically, the 1D (sensing signal-based) data can be processed faster but is normally less informative while the 2D (image-based) or 3D data is often incapable of taking into account the process and material uncertainties.

4.4. ML for process modelling and control in AM

The properties and performances of additively manufactured parts have long been major concerns of the AM industry as a high degree of quality, performance, reliability, and repeatability is required in aerospace, automobile, defence, etc. [137]. This urges the development of robust predicting tools to feedback specific properties and performances under different AM conditions. ML technologies have been increasingly adopted for bridging the process conditions to final product performances due to their ability of learning and modelling highly complex relationships. In general, the in-process performances, such as the melt pool geometry or line morphology, are significantly related to the quality of the final products. Therefore, some researchers focus on modelling in-process performance by adopting various combinations of process parameters for understanding the physical phenomena and identifying optimal parameter settings. However, with the development of in-process sensing systems and IoT technologies, researchers tend to model the process-structure (PS) [138–143], process-structure-property (PSP) [144–147], and process-property-performance (PPP) [2] relationships directly by exploring the data and information acquired from the printing processes. This information includes processing parameters and processing resultant data during the printing process. By building these models, further studies such as material design, process optimization, and quality improvement, can be explored. For instance, Gan et al. [144] introduced a data-driven method for modelling the PSP relationship in the DED process, illustrated in Fig. 10, where multi-physics modelling, experimental measurements, and data mining were integrated. In this method, simulations were carried out based on a computational thermal-fluid dynamics (CFD) model to obtain structure and property results (e.g., melt pool geometry, cooling rate, dilution, microhardness, etc.). These results were then validated by actual experiments and fed into the SOM (self-organizing map) model with process parameters (i.e., laser power, mass flow rate, and energy density) for investigating the PSP relationships. It was stated in the paper that helping researchers visually identify underlying relations among the features is the main advantage of using the SOM technique.

The following paragraph reviews and concludes the main areas that researchers apply ML technologies for process modelling and control in AM, including the prediction for mechanical property, shape deviation, and in-process signature.

4.4.1. Mechanical property

Masahiro et al. [148] introduced a prediction model for tensile properties based on analysing the microstructural features of the fabricated parts with post-heat treatments. In this study, the specimens were fabricated by the SLM process using Ti-6Al-4 V alloy powder. The microstructures on the cross-section of the specimens were observed using scanning electron microscopy (SEM), while the parallel-length part of the specimens was observed by using a micro-focus X-ray CT. The averaged maximum and minimum Feret diameters and aspect ratios of each α and prior-β grains were extracted by using ML-based image analysis tools. In addition, the defect features (e.g., the volume fraction of pore) were also taken into consideration. Finally, these features were used for the prediction of tensile properties by multiple linear regression analysis with leave-one-out cross-validation. According to the experimental results, the models showed good performances in predicting the yield strength and the ultimate tensile strength by using the selected microstructural features.

Process parameters are considered significant to determine the properties of the printed parts. Therefore, finding optimal combinations of process parameters for producing products with desired mechanical properties is crucial. ANN is frequently adopted by researchers for modelling the complex relationships between process parameters and part properties such as the strain recovery rates and transformation temperatures [149] and compressive strength [150]. Besides ANN, Nathan et al. [151] introduced a method that bridged the links between process parameters and part properties by using a Bayesian network (BN). In this study, laser power, scan speed, hatch spacing, and layer thickness were selected as the parent nodes with different parameter settings to govern the casual relationships with child nodes. The yield strength, ultimate tensile strength, surface roughness, hardness, and density were used as child nodes. The authors used the data collected from the publications where the parts were manufactured by SLM processes using 316 L to train the BN. By using this BN model, the users can be provided with the probability distribution predictions of the remaining nodes when they enter a known value for one or more nodes. For a specific machine, the developed BN model can be continually re-trained to improve the accuracy.

Compared with previous studies that investigated the relationships between static factors and part properties, Zhang et al. [152] presented a method taking into account the in-process layer-wise information. The authors proposed a predictive model based on deep learning to improve the quality control regarding the tensile strength of printed parts in the FDM process. In this model, a merged structure that combines a fully-connected neural network with a long short-term memory (LSTM) network was constructed for tensile strength predictions. The LSTM network was employed to process sensing signals, temperature, and vibration, which aimed at capturing the process variations and sequential inter-layer interactions of the FDM process. Other relevant factors, such as printing speed, layer height, extruder temperature, and material property, were combined with the output of the LSTM network

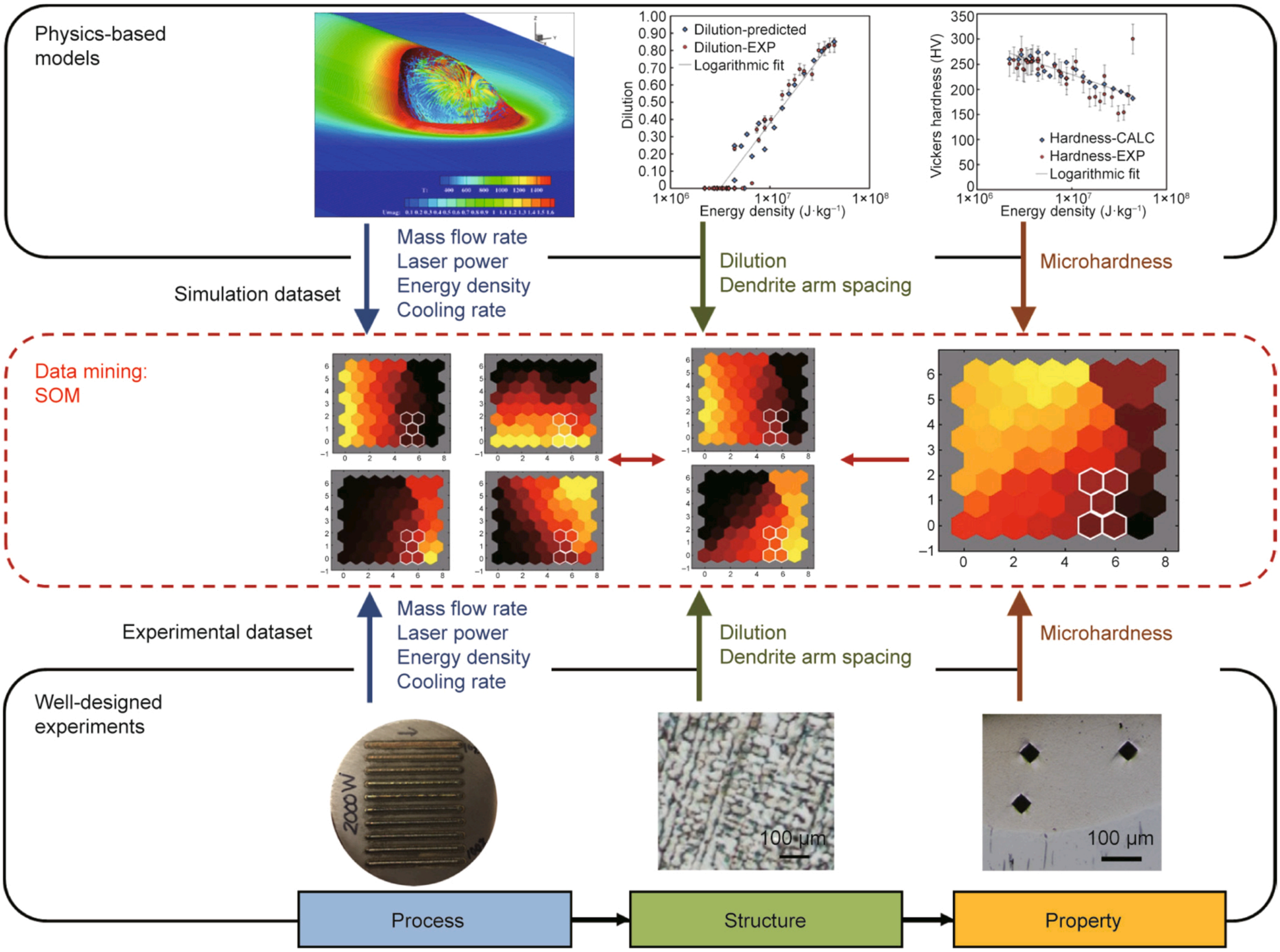


Fig. 10. The structure and property results (e.g., melt pool geometry, cooling rate, dilution, microhardness, etc.) of DED processed parts are obtained from simulations and validated by actual experiments. These results are fed into the SOM (self-organizing map) model with process parameters (i.e., laser power, mass flow rate, and energy density) for PSP (process-structure-property) relationship modelling, Ref [144].

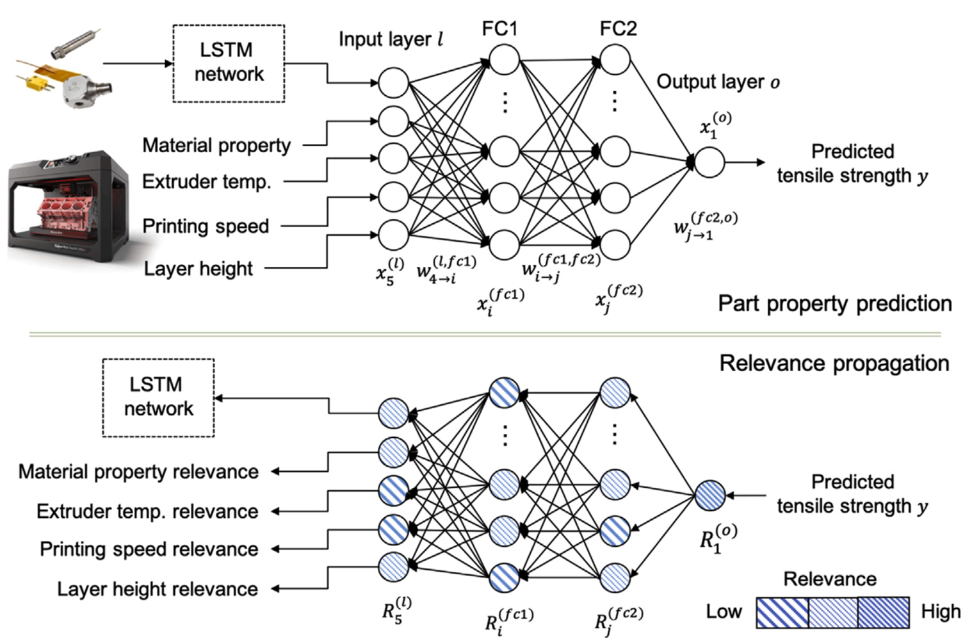


Fig. 11. The neural network schematic of tensile strength prediction including two full connection layers and relevance propagation methods, Ref [152].

and fed into the fully-connected neural network for the final part property prediction. A case study was carried out which demonstrated the effectiveness of the proposed sequential layer-by-layer modelling. In addition, a layer-wise relevance propagation (LRP) algorithm was adopted in this work to identify the contributions of each input to output based on the LSTM network. The proposed methodology of this study is illustrated in Fig. 11.

Researchers have also made effort to investigate and study the mechanical properties of fabricated parts in AM processes using ML technologies [145,146,153–162]. For exploring substitute model for traditional numerical simulation methods, Koeppe et al. [153] introduced a strategy, combining experiments, finite element (FE) simulations, and deep learning (DL) model, to predict the maximum von Mises and equivalent principal stresses of printed lattice-cell structures in AM. In this study, the FE simulations were validated by empirical experiments, and the datasets obtained from simulations were used to train the LSTM model for prediction. By taking design-related information into account, Baturynska, et al. [156] developed ML-based models for part property (e.g., tensile modulus, nominal stress, and elongation) prediction, where part location, orientation, and STL model properties were considered as the inputs. Using ANN for fatigue life predictions for aerospace alloy parts have been investigated by Zhan et al., [157,158].

4.4.2. *In-process signature*

Many researchers have done many efforts on computational models to simulate AM processes [2,154,163,164]. However, with the emergence of advanced data mining techniques, ML is considered promising for modelling and uncovering the complex correlations among process conditions and resultant signatures. Meng and Zhang [165] proposed a process modelling method for laser powder bed fusion (LPBF) of stainless steel. In this work, a processing map of the re-melted depth of single tracks in terms of laser power and laser scan speed was developed by using the GP-based ML model. The GP regression model was trained using the datasets obtained from simulations of the computational fluid dynamics (CFD) model and the predictions were then compared against experimental data for validation. For 316 L and 17–4 PH stainless steel, the preferred conduction mode regions of laser power and laser scan speed were predicted by the GP model to assist the process optimization. Based on the process maps, the normalized enthalpy criterion of identifying keyhole modes was modified for these two metals respectively. Tapia et al. [166] also adopted the GP model for process modelling in LPBF of 316 L stainless steel. A GP-based surrogate modelling framework was proposed in the paper, which was then used to predict melt pool depth of single tracks in terms of laser power, scan speed, and laser beam size combination. The operators can benefit from the applications of process maps which can provide predictions to reduce the demand for experimental or computational studies and obtain optimal process parameter combinations. ML models have also been applied to predict in-process signatures such as geometries of deposited metal trace using ANN [167] in laser metal deposition (LMD), the stress distribution of cured layers using CNN [168] in SLA, product magnetic characteristics using XGboost in SLM [169], connection status between printed lines using DNN in FDM [170], and printed line morphology using ANN [171] in SLM and using GP [172] and SVM [173] in aerosol jet printing (AJP).

Melt-pool geometries or characteristics have closely related to the quality of the produced products in metal AM processes. The control and minimization of the melt-pool variation are crucial to the stability and reliability of the AM processes. Therefore, several studies have been conducted on the investigation of melt-pool characteristics. A data-driven approach to predict melt-pool area for scan strategy improvement in the PBF process was developed by Yeung et al. [174]. The build time, laser power, scan speed, and neighbouring effect factors were considered as the input to the polynomial regression model for melt-pool area prediction. Then, the laser power was adopted as the design variable for controlling melt pool size and reducing its variation. The optimized laser power distributions (a–c) and the resultant melt pool image areas (d-f) are presented in Fig. 12.

In addition, Mondal et al. [175] also used the predictive melt-pool dimensions to obtain optimal scan strategy based on GP surrogate model. Other studies on the prediction of the characteristics of the melt-pool using ML models can be found in Ref [176–179]. Thermal profiles are able to reflect the interaction between layers, resulting in residual stress and distortion distribution during the printing processes. This drives researchers to investigate the thermal profiles for the improvement of product quality. Mriganka and Olga [180] introduced a data-driven method for the modelling of thermal history based on ANN in FDM. The authors proposed a unique geometry representation method that translated G-Code into a set of features. There were three types of features, including features related to the deposition time, features related to the distances from the cool surfaces and heat sources, that were used for predicting the thermal profile. A heat influence zone that determined the area significantly affected by the heat source was defined for feature selection. These selected features were fed into ANN, also called the surrogate model (SM) in the paper, to predict the temperature profiles. In the case study, the training data was obtained by FE simulations based on a physical model, and the prediction from the SM had an accuracy higher than 95%. The comparison of the temperature distributions obtained from the FE model (a-d) and SM (e-h) is shown in Fig. 13.

Other studies on the prediction of thermal histories in different AM processes can be found in Ref [181–186], where ML-based models were applied. For instance, Ren et al. [182] introduced a combined model called RNN-DNN (recurrent neural networks and deep neural networks) to model the relationship between laser scanning strategies and their corresponding thermal history distributions in the DED process. From the studies above, it's apparent that ML technologies have made significant contributions to modelling complex AM processes, largely facilitating the development of control strategies and improving the reliability of the manufacturing processes.

Lack of physical insights and normally requiring a considerable volume of training data samples are the main drawbacks of most ML models. Integrating physical knowledge with ML models has great potential to provide more explainable results and reduce training samples. Hence, physical-informed ML techniques have risen in recent studies [187–190]. The bond formation and mesostructure have strong influences on the final mechanical properties of the FDM produced products. Different from the studies that purely rely on data-driven or physical models, Berkcan et al., [188] introduced a physical-informed ML approach to predict bond quality and porosity of the parts manufactured by the FDM process. In their study, two coupled multi-physics models, thermal model and polymer sintering model, were first constructed to predict the temperature evolution, bond formation, and mesostructure evolution. As the multi-physics models were built within certain assumptions that cannot fully represent the highly complex physical phenomenon, a DNN was adopted to improve the prediction performance. There were three strategies, (1) embed physics constraints in the loss function of the DNN, (2) the outputs of physical models are used as extra inputs in the DNN, and (3) the DNN is firstly trained by the data generated from physical models and updated by real-world experiments data, for integrating physics knowledge with ML algorithms. The experimental results indicated that incorporating physics knowledge with ML models was able to enhance the prediction accuracy even with a small amount of data.

4.5. *ML on AM sustainability*

Over the past couple of decades, AM technologies have attracted extensive attention across the world. Compared with conventional manufacturing, AM shows higher efficiency and flexibility, leading to its increasing adoption in the industry. However, according to the life-cycle analysis (LCA), the energy consumption of AM systems tends to have a significant effect on the environment [191]. This drives AM

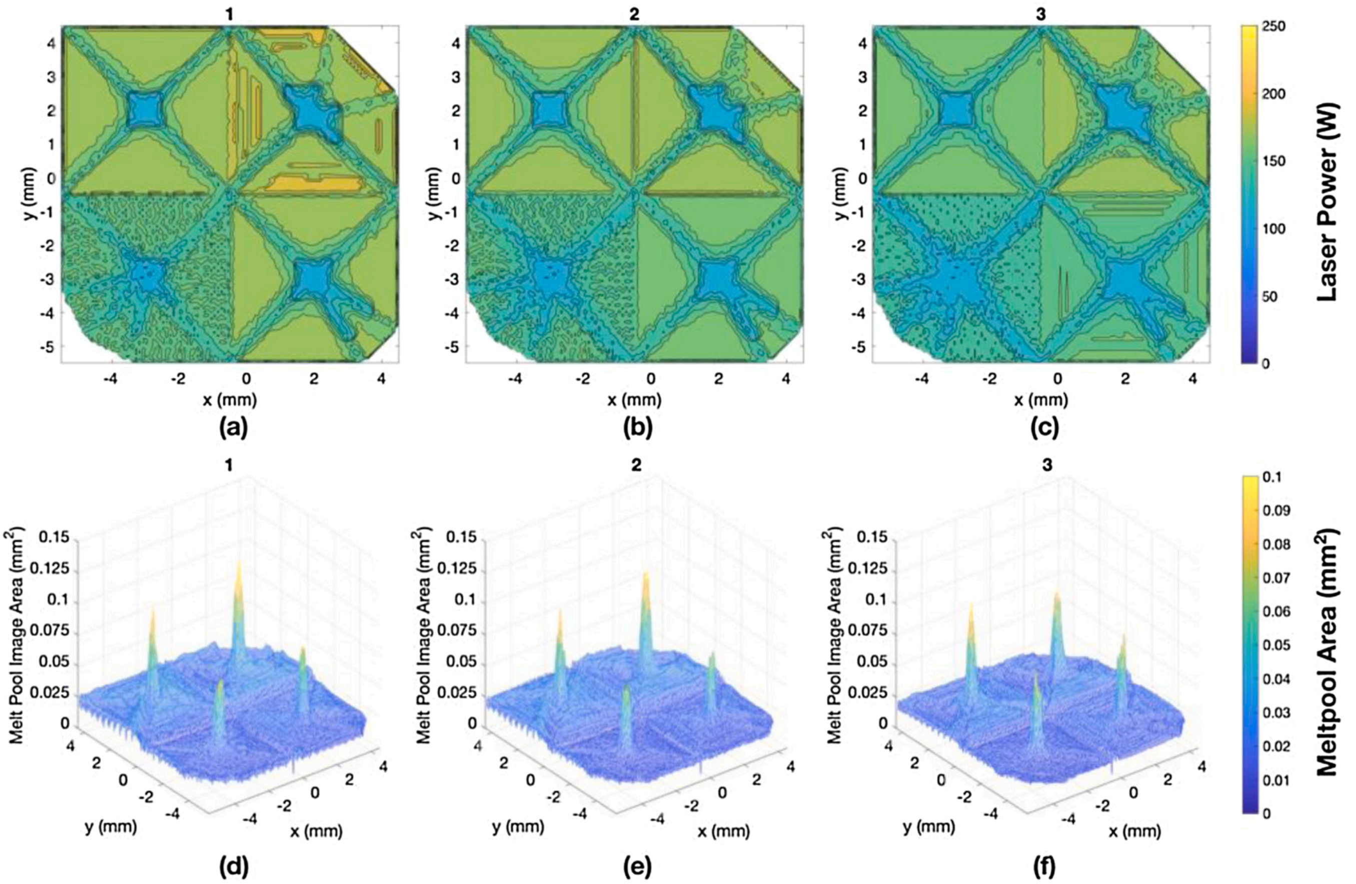


Fig. 12. The optimized laser power with corresponding melt pool image areas is predicted by the proposed ML approach. The melt pool area is allocated in high power density areas as predicted Ref [174].

sustainability to a crucial research topic as the number of AM systems being employed keeps growing. More specifically, cost and energy consumption are considered the key indicators to measure the sustainability of AM [192].

4.5.1. *Cost estimation*

Cost estimation is a crucial task before the manufacturing processes start. Reduction of costs (e.g. material and build time costs) is significant to AM sustainability in the industry. A data-driven cost estimation framework, shown in Fig. 14, was introduced by Chan et al. [193] for AM systems based on big data analytics tools, aiming at reducing the subjectivity of the cost estimation process. In the framework, the automated cost estimation system is an online service provider where manufacturing jobs with 3D models and relevant information, such as material types, surface textures, and tolerances, were uploaded. Feature vectors of the submitted jobs were extracted and clustered which were then fed in ML models with their costs as output for training. A simulation-based cost prediction function was also presented in the framework to simulate the whole manufacturing process for cost estimation when there was a small number of relevant jobs in the database. The final cost prediction from the ML model was combining the costs of similar jobs in the database and the prediction from the simulation. When a new 3D model in STL file format was uploaded, g-code was generated automatically where feature vectors were able to be extracted to represent geometry information. These feature vectors were used as the input for the ML models that were built from the closest cluster to predict the cost. However, cost elements such as post-processing and labour cost are not included in the model, and obtaining sufficient data with high quality in the database is also challenging.

It is usually time-consuming to build a patient-customized model that is used for surgical preparation. Huff et al. [194] demonstrated and discussed the feasibility of using ML models to reduce the time and cost of AM for surgical planning. In this work, ML models are applied for patient selection, optimizing the scanning process of CT scans, and automated segmentation of medical images. ML technologies can potentially improve the process of 3D anatomical modelling and contribute to the sustainability of applying AM in medical practice.

4.5.2. *Energy consumption*

Mathematical models for estimating energy consumption have been explored and investigated in existing studies [192,195] of various AM systems. For instance, Verma and Rai [192], developed mathematical models for estimating energy consumption and material waste in the SLS system and optimized the AM processes. However, AM systems are complex of which the energy consumption is correlated with various subsystems and factors, showing a large difference in terms of different working principles and main material supplies. It is difficult to take into account various factors based on conventional methods (e.g., mathematical formulas) for energy modelling. Hence, ML models have been increasingly adopted for analysing and modelling the energy consumption of AM systems.

A linear regression (LR) model was adopted by Tian et al. [196] to capture the relationships between process parameters, part quality and energy consumption respectively in the fused filament fabrication (FFF) process. In this paper, the printing resolution, printing speed, and nozzle temperature were considered as the process parameters. The geometry accuracy features, including thickness deviation and average out-of-tolerance percentage, were selected as the indicators of part quality. Based on the linear regression models, the optimal solution for acquiring energy-efficient process parameters under the specific quality

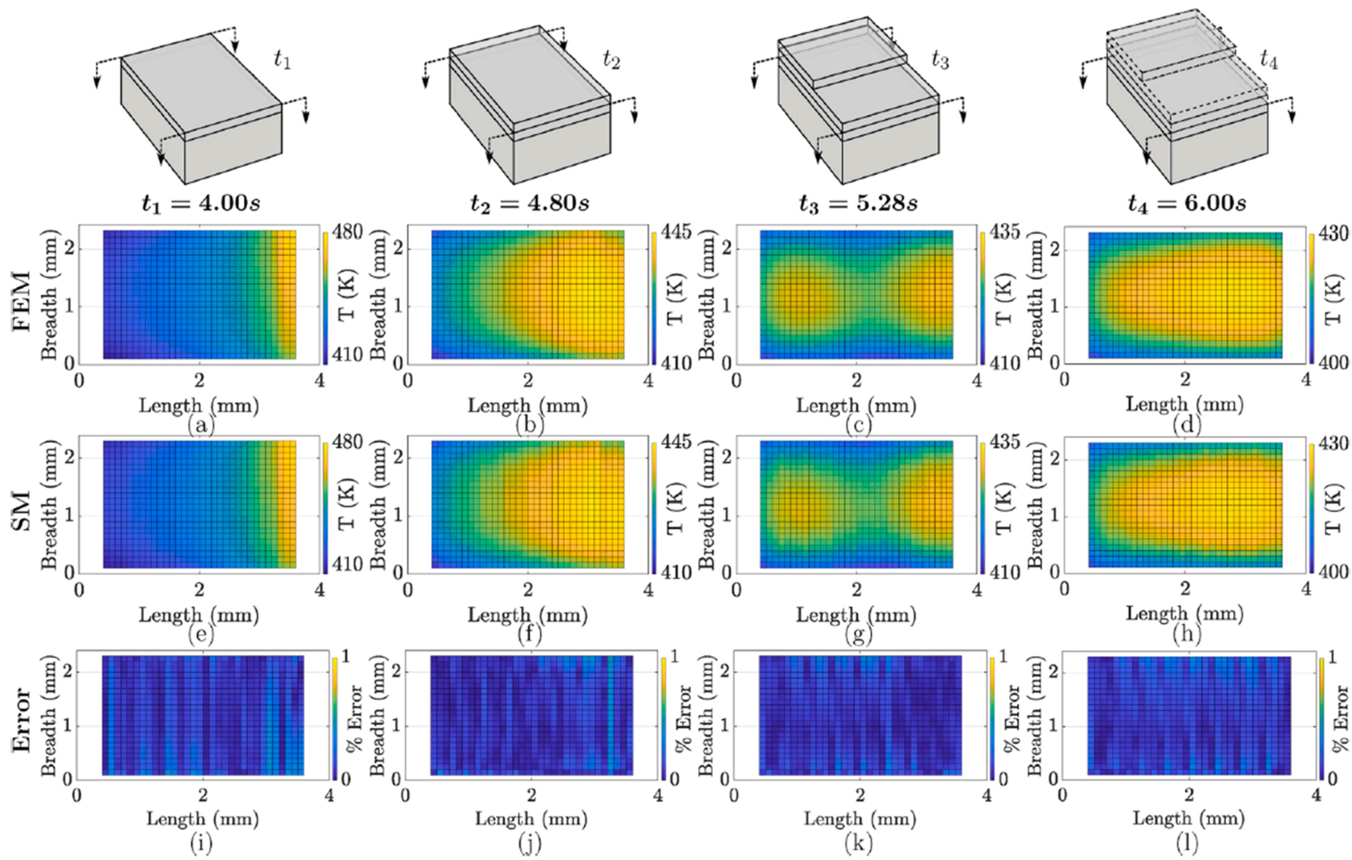


Fig. 13. The comparison of the FEM (finite element model) and SM (surrogate model) for temperature distribution, Ref [180].

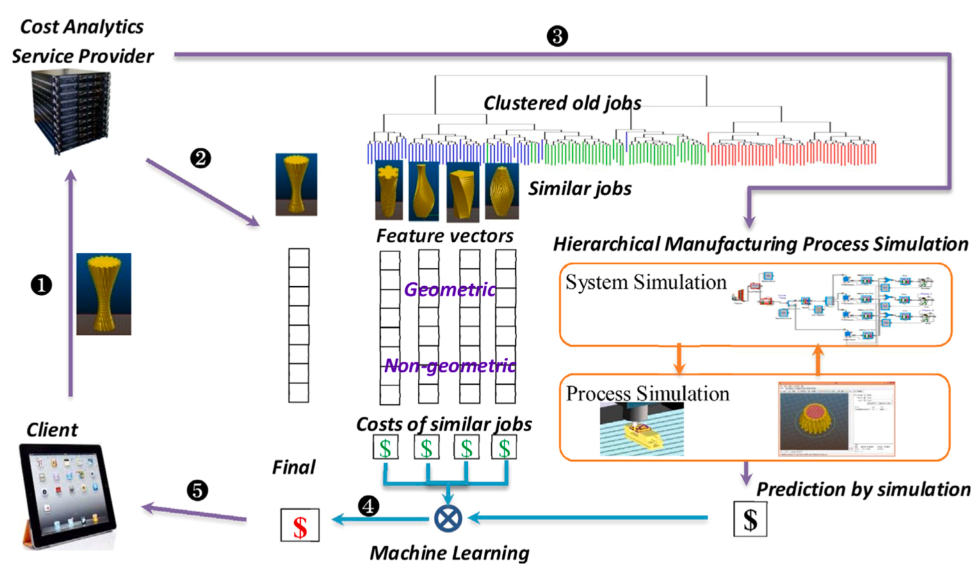


Fig. 14. The automated cost estimation framework for AM systems, Ref [193].

requirements was developed. This work provided a strategy for minimizing the energy consumption of the AM system while simultaneously ensuring the geometry-related quality of the manufactured parts.

Qin et al. [197] proposed a multi-source data analytics method for AM energy consumption modelling based on ANN. In this method, the data generation of an AM process was categorized into four sources, including design, process operation, working environment, and material condition, which tended to cover the entire production phases during an AM process. This multi-source data was heterogeneous and classified as layer-level and build-level which were hard to integrate in a direct way for modelling. Hence, a clustering method was carried out on the layer-level data and then integrated with build-level data in the ANN model. A case study was implemented on an SLS system. The empirical experiment results indicated that the ANN model had an accuracy of 80.3% for energy consumption prediction when the number of clusters was four. Furthermore, as an extension of the study, the authors [198] found out that the design-relevant features, including part design and design optimization, had significant impacts on AM energy consumption based on the weights of neurons in the ANN model. Thus, a design-relevant feature-based energy consumption prediction model was established and a particle swarm optimization (PSO) method was adopted to optimize the design-relevant features for reducing the energy consumption of the target AM system. Hu et al. [199] also analysed the impacts of design and working environment attributes on AM energy consumption based on the gradient boosting decision tree (GBDT) algorithm. In this work, information gain was used to evaluate the contribution of each attribute to the unit energy consumption in the SLS process.

Geometry feature-based energy consumption estimation methods for mask image projection SLA systems using ML technologies are developed by Yang et al. [200,201]. In the Ref [201], three methods, including sensitivity analysis based on Pearson correlation coefficient (PCC) and Laplacian score, PCA, and stacked autoencoders (SAE), were applied to feature extraction and selection of layer-wise geometry-related indexes. These extracted features were fed into different ML models for predicting energy consumption. According to the experimental results, the neural network has the lowest averaged root mean square error (RMSE) of 0.75% regarding both training and testing while the SAE structure has the best testing performance with an RMSE of 0.85%. The main contribution of these studies [197–201] is presenting a design-based method to better manage the energy consumption of the target systems before the AM processes start for AM designers, which is a significant improvement for AM sustainability. However, still, the feature extraction method that best represents the characteristics of geometry models remains an open challenge.

Several existing studies have demonstrated the effectiveness and superiority of using ML technologies for cost estimation, reducing cost, improving energy management in different AM systems. However, the potential of applying ML for AM sustainability have not been fully achieved, where further studies of using ML for energy saving, reducing material waste, and improving manufacturing process efficiency need to be explored.

4.6. Classification of recent research work

In the previous section, the recent research of ML for AM is reviewed including different AM processes of manufacturing various types of material, like powder bed fusion (PBF), direct energy deposition (DED), material extrusion (ME), vat photopolymerization (VP) and material jetting (MJ), which have been introduced in Section 2. It is obvious that ML technologies have played a critical role in these AM processes. Table 5 has classified the recent research work of ML technologies for AM processes during the last five years.

In the table, the eight most representative ML technologies are included, SVM (I), deep learning (II), decision tree (III), *k*-NN (IV), Bayesian (V), linear regression (VI), Gaussian process (VII), Markov model (VIII), clustering algorithms (IX) which are the most often used ML technologies for the AM research perspective. Generally, researchers choose ML technologies based on the research or project target, in which the most applicable technology is selected. These ML technologies are used in 5 AM research domains, in terms of DfAM (RD1), material analytics (RD2), defect detection and in-situ monitoring (RD3), process modelling and control (RD4), and sustainability (RD5). Interestingly, over 70% of research focus on RD3 (defect detection and in-situ monitoring), and RD4 (process modelling and control) which data-driven methods are more intuitive in these two research domains, and ML technologies highly reply to the data. However, data is also available and important for other research domains which are lack-of-attention. There are huge potential research opportunities in these domains compared to RD3 and RD4. Furthermore, many potential research ideas in RD1 (DfAM), RD2 (material analytics) and RD5 (sustainability) can be inspired by ML approaches in the RD3 and RD4.

The most used ML technology is deep learning which was applied for over half of the reviewed research and in all five research domains. It has been implemented as one of the most popular ML technologies for AM issues. Benefiting from its high compatibility of input data, various types of data is collected and used for deep learning models, such as image, video, acoustic data, process parameters, CAD model, and other sensor data. Also, comparing ML technologies between deep learning and others, deep learning has generally shown merit. Deep learning technologies, such as artificial neural networks, convolutional neural networks and Long-short term memory neural networks, have been studied and applied to many industrial fields as one type of the latest ML algorithms. Many researchers tend to compare deep learning with conventional ML algorithms which deep learning generally shows its merits, in terms of, high prediction accuracy, data adaptability and the capability of processing big data [202].

However, deep learning algorithms are required a huge amount of training data to build the model. For many real issues, collecting high quality and big size data is challenging. Additionally, the majority of deep learning technologies require a high-performance computational platform to train the model which increases the research or development budget. The necessity of using deep learning as a solution for the issues should be considered [203]. Many factors should be discussed before selecting an ML algorithm which depends on the complexity and nature of the issues. Another issue of both deep learning and conventional ML is the rational interpretations. Many researchers have realised this issue which 'black box' solutions are hard to use for revealing the basic mechanisms of many research fields [204]. ML technologies are increasingly required a reasonable explanation and domain knowledge-based structure. The fundamental knowledge and corrections of AM processes largely obey the law of physics and material. Knowledge-based ML technologies can integrate the known theory to discover the potential information from the multi-source datasets [108]. Many researchers have started to tackle this issue by using physical-informed and knowledge graph neural networks [43,187,188].

To present the performance of the ML algorithms, evaluation metrics are the most important element which use for measuring the quality of the proposed ML model in the case studies. Many different metrics can be applied depending on the purposes of the research [210]. However, for AM issues, the focuses of the majority of research are on the solution of the critical issues in which the evaluation metrics theoretically influence the proposed methods less than other factors of ML technologies, such as the prior parameters, data format, and data variables. Although the evaluation metrics are not included in Table 5, many more details are reported in the ML literature [211,212].

In addition, about half of the reviewed research applied ML technologies to solve the issues in the research domain of defect detection and in-situ monitoring. However, for the work on defect detection and in-situ monitoring, multiple data processing and modelling are still crucial problems. While ML is a powerful tool for empirical modelling but it still highly depends on data. From the studies reviewed, various types of data are considered as the input of ML technologies, such as image data, video data, sensing data and design data. How to integrate multi-source data for ML is still an important research topic. Furthermore, increasingly researchers have moved their concentration from process to design and sustainability which ML technologies can also play a critical role.

5. Challenges and opportunities

Although ML technologies have been increasingly employed in digital manufacturing systems, there are still several challenges that remain to be tackled, as well as opportunities to be seized. In this section, four aspects of challenges are summarized based on the previous literature review. In addition, three directions of opportunities are presented to herald the future research and development of ML for AM.

Table 5
The classification of research work of ML for AM.

Reference	AM Process	Research Domain	ML Technologies I	II	III	IV	V	VI	VII	VIII	IX	Data Type	Research Target	Material Used in Studies
Zhang, et al.[81]	**PBF**	RD3	√	√								Image	Quality level	Steel
Ye, et al.[104]		RD3		√								Image	Melt pool state	
Shevchik, et al. [107]		RD3		√								Acoustic data	Quality level	
Ye, et al.[114]		RD3		√								Acoustic data	Melt pool state	
Tapia, et al.[166]		RD4							√			Process parameters	Melt pool state	
Meng and Zhang [165]		RD4							√			Process parameters	Melt pool state	
Chandrika and Ya [179]		RD4			√	√		√				Process parameters	Melt pool state	
Nathan, et al.[151]		RD4					√					Process parameters	Quality level	
Germán, et al.[205]		RD4	√	√	√	√			√			Process parameters	Quality level	
Aniruddha, et al. [187]		RD4		√								Sensor data and image	Quality level	
Xin, et al.[106]		RD3									√	Thermal imaging	Porosity detection	
Bugatti, et al.[77]		RD3	√	√							√	Video	Defect detection	
Montazeri, et al. [120]		RD3	√		√	√						Optical data	Porosity detection	Nickel alloy
Aminzadeh and Kurfess[103]		RD3					√					Image	Quality level	
Caggiano, et al.[82]		RD3		√								Image	Defect detection	
Seulbi, et al.[178]		RD4	√		√			√				Process parameters	Melt pool state	
Mehrshad, et al. [149]		RD4		√								Process parameters	Quality level	
Scime and Beuth [83]		RD3		√								Image	Defect detection	
Fathizadan, et al. [93]		RD3		√							√	Image	Defect detection	
Okaro, et al.[134]		RD3							√			Photodiode data	Quality level	
Yeung, et al.[174]		RD4						√				Process parameters	Melt pool state	
Mondal, et al.[175]		RD4							√			Process parameters	Melt pool state	
Vrábel, et al.[65]		RD2	√									Radiation data	Material classification	Aluminium alloy
Yao, et al.[36]		RD1	√									CAD model	Feature selection	
Chen, et al.[171]		RD4		√								Process parameters	Line morphology	
Zhang, et al.[206]		RD4		√								Production information	Manufacturability	
Ertay, et al.[95]		RD3		√								Image	Pore prediction	
Masahiro, et al. [148]		RD4						√				Image	Tensile property	Titanium alloy
Shin, et al.[141]		RD4		√								Process parameters	Density prediction	
Zackary, et al.[90]		RD3		√								Image	Defect detection	
Li, et al.[91]		RD3		√								Image	Quality level	Cobalt alloy
Baturynska[156]		RD4			√		√	√				Design information	Nominal stress	Polymer
Qin, et al.[198]		RD5		√								CAD model	Energy consumption	
Hu, et al.[199]		RD5			√							CAD model	Energy consumption	
DeCost, et al.[63]		RD2	√									Image	Material classification	Multiple materials
Ko, et al.[43]		RD1			√							Production information	Design rule construction	
Montazeri, et al. [129]	**DED**	RD3	√									Optical data and image	Quality level	Titanium alloy
Khanzadeh, et al. [122]		RD3	√		√	√						Thermal imaging	Porosity detection	
Zhang, et al.[84]		RD3		√								Acoustic data	Porosity detection	
Li, et al.[56]		RD4	√									Process parameters	Offset distance	Copper alloy
Ren, et al.[121]		RD3		√							√	Emission spectroscopy	Quality level	Aluminium alloy
Ding, et al.[207]		RD4	√									Process parameters	Bead modelling	
Ren, et al.[182]		RD4		√								Scanning patterns	Thermal history	Steel
Chen, et al.[80]		RD3	√	√	√	√	√		√		√	3D point cloud	Defect detection	
Lam, et al.[142]		RD4		√								Tool paths	Void-filling strategy	
Ren, et al.[183]		RD4		√								Process parameters	Temperature field	
Richard, et al.[66]		RD2			√							Particle-level features	Flowability classification	Multiple materials
Jonnel et al.[40]	**ME**	RD1		√								3D coordinates	Geometry correction	Polymers
Wu, et al.[111]		RD3								√		Acoustic data	Material condition	
Zhang, et al.[152]		RD4		√								Process parameter	Tensile strength	
Wu, et al.[132]		RD4	√					√				Sensor data	Surface roughness	
Jin, et al.[100]		RD3		√								Image	Quality level	
Kim, et al.[128]		RD3	√									Sensor signals	Defect detection	
Koeppe, et al.[153]		RD4		√								CAD model	Stress prediction	
Zhu, et al.[50]		RD4							√			Shape variation	Geometric deviation	
		RD4		√								G-Code	Thermal history	

(*continued on next page*)

Table 5 (*continued*)

Reference	AM Process	Research Domain	ML Technologies									Data Type	Research Target	Material Used in Studies
			I	II	III	IV	V	VI	VII	VIII	IX			
Mriganka and Olga [180]														
Jiang, et al.[170]		RD4		√								Process parameters	Quality level	
Kapusuzoglu, et al. [188]		RD4		√								Process parameters	Porosity prediction	
Mohammad, et al. [88]		RD3		√								Image	Defect detection	
Li, et al.[79]		RD3	√		√	√						3D point cloud	Defect detection	
Roach, et al.[208]		RD4		√								Image	Compression response	Silicone
Aditya, et al.[168]	**VP**	RD4		√								Image	Stress distribution	Liquid resin
Yang, et al.[201]		RD5		√				√				CAD model	Energy consumption	
Lee, et al.[96]		RD3		√								Video	Quality level	
Ferreira, et al.[52]		RD4					√					CAD model	Geometric deviation	
Shen, et al.[60]		RD4		√								CAD model	Geometric deviation	
Wang, et al.[98]	**MJ**	RD3		√								Image	Droplet behaviour	Polymers
Zhang, et al.[173]		RD4							√			Process parameters	Line morphology	Silver
Després, et al.[39]	**General**	RD1		√								CAD model	mechanical properties	Software-based
Huang, et al.[47]		RD1		√								CAD model	Structure design	
Nathan, et al.[209]		RD1		√								Image	Design optimization	
Zhan et al.[158]		RD4	√	√	√							Process parameters and fatigue loadings	Fatigue life	Steel

5.1. Challenges

5.1.1. Data fusion

AM is considered a complex system, where several subsystems and the manufacturing processes are affected by various correlated factors. Therefore, it is necessary and significant to integrate or fuse the data from multiple sources or modalities to jointly analyse for enhancing knowledge discovery, as well as improving the modelling accuracy. But it is difficult to fuse the heterogeneous data generated from AM systems as it normally has different types, dimensions, and structures (e.g., images, 3D models, and signals). Several methods have been adopted by researchers to tackle the issues, such as extracting features from raw data to reduce data dimensions or using decomposition and factorization techniques for data concatenation. There is still significant latent or useful information from raw data which is lost through feature extraction processes. Moreover, the data from different modalities or sources may yield conflicting results in ML models. Hence, in what way and how to fuse the heterogeneous data for modelling and analysing becomes a critical challenge when applying ML for AM. Data registration techniques play an important role in aligning multi-sensory data to ground truth data properly before the data is fused or integrated into ML models. Some researchers have explored tackling data alignment issues, such as [213–216], that effectively pave the way for data fusion in AM.

5.1.2. Training with limited amount of data

According to the selected articles reviewed in the previous section of the paper, ML algorithms play an important role in classification and regression tasks for AM. However, the performances of ML algorithms are influenced by the data available for training. For instance, in the topic of process monitoring, CNN is the prevailing algorithm to process image data for defect detection. It is capable of learning useful information from raw images directly and automatically. The convolutional layers and pooling layers in the CNN architecture can extract representative features and lower feature dimensions. In the meantime, its performances suffer from the data volume. The CNN model often requires a sufficient amount of data for training processes and fine-tuning the parameters to yield high accuracy results. Using X-ray computed tomography to detect defects (e.g., porosity, cracks, and lack of fusion) of the produced products for labelling data is typically costly and time-consuming. Additionally, when using ML for mechanical property predictions, researchers need to conduct a number of experiments where different processing parameter combinations are considered. Testing the properties of the manufactured parts also requires considerable labour. Thus, it is always expensive and impractical to collect a large amount of training data from experiments. Some researchers are investigating the use of process simulations for training, in addition to experimental results. Furthermore, the ML models are consequently applied to the real AM process and collaborate with some control algorithm, such as adaptive control. The limited data may lead to a high possibility of failure due to the lack of training. Even if a well-trained ML model is obtained, it is difficult to be robust and widely applied in the same AM process but for different machines where the uncertainties affect the model performance. Therefore, it is challenging to obtain a robust and reliable ML model with a limited amount of training data.

5.1.3. Interpretability

Since ML technologies have been increasingly adopted for modelling and decision making in several crucial scenarios (e.g. medical use, defence, and precision machining), people have to make a trade-off between transparency and accuracy [217]. The results yielded by ML models need to be interpretable and tractable to assist decision-makers to understand the results and their rationale. Some conventional ML algorithms such as LR and DT are capable of generating explainable results. However, it requires profound domain knowledge for variable selections and is normally hard to yield better results than DNN-based models. In AM systems, an interpretable ML model can help engineers improve the understanding of manufacturing processes and develop corresponding control strategies. Hence, still, the explanation of the inference from black-box ML models remains challenging and require further effort. One possible strategy moving forward is to integrate ML results with high fidelity simulations of relevant parts, processes, or process conditions to help manufacturing personnel understand the outcomes yielded by ML.

5.1.4. Spatial and temporal scales

AM processes occur over a wide range of size and time scales. Build volumes can be measured in meters, while grains in metal alloys may be micrometres in size. Similarly, a build may require dozens of hours, while heating and cooling of feedstock occurs over microseconds. These wide ranges of spatial and temporal scales lead to significant challenges in AM process monitoring and control and, from an ML perspective, relate to the data fusion and latency issues raised earlier. Data fusion must occur at the appropriate size and time scales. Furthermore, consistency across size and time scales is necessary to help ensure results are meaningful. It seems that networks of ML models will likely need to be developed to model relationships at the relevant size and time scales and additional relationships across these scales. It is not clear if similar ML network models have been developed for other domains which could perhaps inform the AM research community of promising technical directions.

5.1.5. Latency

Using ML technologies for modelling and data analytics based on cloud computing often requires considerable computing power and are not ideal where low latency is a major concern (e.g., real-time monitoring and control). For instance, DNN is a prevailing ML algorithm and DNN-based models are capable of performing high accuracy or generating reliable inferences in many different tasks. It has been widely applied in natural language processing, target recognition, and fault diagnosis. However, training a DNN-based model normally requires considerable time and computing resources. This is unlikely to be supported by local or edge devices due to the limited computing power. Thus, in the real-time monitoring and control scenario, the collected data normally need to be sent to the Cloud for processing and analysing. Then the control instructions are sent back from the Cloud to the local system. This whole process normally causes latency for real-time defect detection and control. Moreover, the uncertainties of the network connection and the limitation of the network bandwidth also affect the reaction time. Therefore, it is challenging to apply ML models to practice where low latency is required.

5.2. Opportunities

5.2.1. Transfer learning

A major assumption in most ML models is that the training and future data must be in the same feature space with the same distribution [218]. However, in real-world industry applications, it is impractical and costly to retrain a model for each machine or system. Therefore, knowledge transfer becomes critical in this scenario. Transfer learning can transfer prior knowledge or information from a domain to a related domain, improving ML models [219]. For example, for process modelling in AM, transfer learning techniques can be used to transfer a pre-trained model for different machines with similar working principles, which requires less amount of training data than training a new model. Hence, transfer learning can enable the rapid development of ML models for different AM machines, materials, and part designs. In the future, more studies on transfer learning techniques for AM can be explored to achieve its potential.

5.2.2. Light-weight computing model

As described previously, low latency is the major concern in real-time monitoring and control. Most studies of applying ML for defect detection or anomaly correction are implemented at the Cloud level where latency is not a major concern. In real-world applications, applying analytical models on the local or edge devices is important to attain low latency. Due to the limited computing power of edge devices, it is crucial and significant to develop lightweight computing models for implementing artificial intelligence on the edge. Data fusion techniques are one of the promising approaches as they can reduce data dimensionality in raw data. Additionally, designing and adopting ML algorithms with fast data sampling or sorting strategies such as light gradient boosting machines (LGBM) [220] also reduce the computing load.

5.2.3. Learning by cloud-edge synergy

The current state-of-the-art applications of ML in AM are mostly performed by centralized services on the Cloud. The information and data are transmitted between Cloud servers and local devices which is unavoidably increase network burden if tremendous data is collected and transmitted. Consequently, unexpected latency will occur and affect the decision making during the manufacturing process. However, it is also challenging to train ML models directly on the edge devices with local datasets. Therefore, collaborative learning between the Cloud and edge is a possible and promising solution that leverages the knowledge from the Cloud to improve the model developed by edge devices. Knowledge transfer is applied in the Cloud-Edge learning paradigm.

5.2.4. Other opportunities

Apart from the above three potential research topics of ML for AM, there are still some research opportunities in many relevant research areas. Although many research pioneers have started to discover these topics, the lack of research is still obvious. One of these opportunities is on the topic of sustainability. In this paper, the research of the ML on AM sustainability is reviewed in the last section. However, these papers mainly focused on the cost and energy consumption where the research of AM sustainability involves more perspectives, in terms of remanufacturing, waste recycling and process and life-cycle emission [221,222]. These research issues are generally complex and affected by many different variables that ML has the strong advantage of overcoming. Moreover, according to the studies reviewed, another research opportunity, AM researchers pay less attention to, is the physics informed ML approach. With the rapid development of AM, the current unsolved research issues tend to be increasingly fundamental. The typical ML algorithms including deep learning technologies are hard to discover the hidden fundamental knowledge without the assistance of domain knowledge. The knowledge-based ML methods become more and more critical and essential for solving challenging AM issues. Additionally, the interpretability of ML for engineering problems is always discussed. The research of physics informed, and knowledge-based ML models are effectively explained.

6. Conclusions

ML has made a significant contribution in many AM aspects, such as DfAM, defect detection, process monitoring, modelling and control, and also has the great potential to become a type of critical solution for the entire field of AM. The focus of this paper has been on the research and application of various ML technologies for AM systems. The paper was inspired by the current popularity of machine learning for solving AM issues. After reviewing seven categories of AM processes this paper has then followed a systemic literature review method which aims to target the state-of-the-art relevant research articles. There are over hundreds of research articles selected for further detailed reviewing and analysis. Based on these research articles, this paper has also applied the keyword co-occurrence and clustering analysis aiming to identify the hotspots in the research field. Five aspects of AM issues were clustered by the proposed method. Then, the selected research articles were arranged, presented and reviewed following these clusters. These articles are also summarised based on the targeted AM processes, applied ML algorithms, research domains, and utilised data. Finally, research challenges and opportunities of ML for AM are highlighted and discussed focusing on various perspectives.

CRediT authorship contribution statement

Qian Tang : Writing – review & editing. **Charlie C.L. Wang:** Writing – review & editing, Methodology, Formal analysis. **David W. Rosen:** Formal analysis, Methodology, Writing – review & editing. **Timothy W. Simpson:** Writing – review & editing. **Lu Yan:** Writing – review & editing. **Jian Qin:** Writing – original draft, Formal analysis, Conceptualization, Methodology. **Fu Hu:** Conceptualization, Formal analysis, Methodology, Writing – original draft. **Ying Liu:** Writing – original draft, review & editing, Supervision, Methodology, Formal analysis, Conceptualization. **Paul Witherell:** Formal analysis, Methodology, Writing – review & editing.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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