



Machine learning in design for additive manufacturing: A state-of-the-art discussion for a support tool in product design lifecycle

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Abstract

Additive manufacturing represents one of the most significant improvements in Industry 4.0. Design for additive manufacturing is the discipline that studies integrated CAD/CAE tools with guidelines for optimizing 3D printing in terms of cost, process time, quality, and precision. In this context, machine learning is used to support control and decision-making activities in additive manufacturing. However, the use of machine learning methods is generally limited to one single process phase. No studies are proposing a machine learning approach focused on different phases of the product lifecycle, from the early design phase to manufactured parts. In the literature, machine learning applications for additive manufacturing regard only one specific phase of the production process. This paper describes current improvements in the integration of additive manufacturing and machine learning, highlighting limitations, and proposes to include different phases of the product lifecycle while designing with machine learning tools. The research provides a guide to develop a new design platform where machine learning supports the engineers in the definition of the product design and process parameters. Finally, the paper also introduces the informatics infrastructure and necessary capabilities to implement the proposed model.

Keywords Design for additive manufacturing · Machine learning · Product lifecycle · Laser-powder bed fusion

1 Introduction

Additive manufacturing (AM) is the production process of adding material to realize parts from 3D CAD models using a layer-by-layer approach [1]. This process is one of nine enabling technologies for Industry 4.0 and differs from conventional manufacturing techniques such as subtractive and formative ones [2]. The 3D printing processes can realize complex geometries that are impossible or difficult to create using traditional technologies [3]. The advantages of AM processes also include the ability to create hierarchical structures from the micro to

the macro scale, using advanced materials, and improving the part functionalities [4]. While in the past AM was only used for rapid prototyping, now AM can be used in small-medium batch production [5]. Therefore, there is an increasing need for tools and methods to support design and optimization in design projects, reducing the disadvantages of this technology. Some disadvantages concern the risk of failure related to deformation while printing, elevated surface roughness, the necessity of additional machining, printing time, and elevated cost. The complexity of the AM process requires tools to support different phases along the design workflow.

Thermal gradients and printing resolution contribute to geometrical deformation in the 3D printed part; therefore, it is challenging to ensure geometric and dimensional tolerances in AM, especially with metal powders. Another issue concerns the prediction of the fatigue behavior [6]. Focusing on metal AM, laser-powder bed fusion (L-PBF) is one of the reference processes to obtain 3D metal parts with high quality, resolution, and mechanical strength. The sectors in which AM has spread most are aerospace [7], automotive [8], dental and medical industry [9], oil and gas [10], architecture and design, etc.

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Design for additive manufacturing (DfAM) is the branch of the engineering design that considers every known problem of the AM process, from the early design phases to the quality inspection of the finished part. The use of DfAM tools and methods may decrease the risks of failure and defects on the 3D-printed parts [11]. The usage of AM in the industry, particularly for metal 3D printing, is slowed down by the high costs; the uncertainty of the results related to the large number of parameters involved and the inconsistency in part quality.

Nowadays, several studies describe machine learning (ML) as a tool used by designers and technicians to speed up and simplify the definition of parameters in AM. ML systems can be used in multi-objective problems with many parameters related to geometry, process, material properties, etc. In AM, the relationships between variables and mechanical performance, such as fatigue strength, density, residual stress, and surface finish, can be found using ML algorithms [12]. ML tools and methods are widely used in Industry 4.0, where a lot of data is produced from sensors, inspections, and control systems [13]. Data-driven methods are often used to monitor the process parameters, to recognize defects, and to support decision-making.

Current ML applications for AM and DfAM focus on a single phase of the complex production process. In literature, no studies use machine learning to analyze different phases of the product design lifecycle from the early design phase to 3D printed parts. Therefore, there is a lack of an overall look at the possible benefits of using ML to correlate different aspects of the product design, production process, and control systems that are not connected. Correlating and combining different application levels could identify hidden correlations before unknown to the designers.

The paper aims to provide a perspective on ML applications to support the integrated product-process design of AM components, proposing a product design lifecycle approach. The paper describes the opportunities and difficulties of applying ML in AM and DfAM, considering the L-PBF process. To support the implementation of the analyzed methods, the paper also describes the necessary informatics tools, infrastructure, and capabilities to implement an ML model in production.

This paper is organized into seven sections. Section 2 introduces the background research, considering additive manufacturing and machine learning. Section 3 reports the proposed approach as an answer to the critical overview. Section 4 describes the current use of ML in different phases of the AM process. Section 5 introduces the informatics infrastructure and tools to implement the ML model. Finally, Sect. 6 and Sect. 7 report the discussion and conclusions of the paper.

2 Background research

2.1 Additive manufacturing

Seven categories of AM processes are classified in ISO/ASTM 52900:2022 [1] for creating an object from a 3D CAD model, such as binder jetting (BJT), directed energy deposition (DED), material extrusion (MEX), material jetting (MJT), powder bed fusion (PBF), sheet lamination (SHL), and vat photopolymerization (VPP). The materials utilized in these processes are plastics [14, 15], composites, bio-based materials, ceramics [16], and various metal alloys [17] such as steel, aluminum, titanium-aluminum, copper, and more. Each AM technique enables the realization of complex geometries through different approaches. The main advantages of using AM solutions are achieving complex shapes, reducing the number of joints and parts [18], and being lightweight. The mass reduction of a component can be achieved by design practices such as topological optimization (TO), generative design (GD) [19], lattice structures, or multi graded approaches. TO and GD interact with finite element analysis (FEA) and CAD tools to define the material distribution suitable to minimize weight, compliance, or other objectives in accordance with specific structural, functional, and geometrical constraints. In many cases, this approach leads to innovative free-form geometries like organic shapes [20]. Lattice structures are multiscale patterns of elemental unit cells that allow a significant percentage of mass reduction to be achieved [21]. Moreover, auxetic cells can also improve structural and crashworthiness characteristics [22]. Another promising lightweight method is the development of graded components. Functionally graded components are characterized by multi-material and/or graded density lattice structures so that tailored properties such as stress-strain distribution can be achieved [23].

Even if AM was presented as a “complexity for free” process, giving the possibility of printing every kind of complex shape, technicians know that several manufacturing requirements, characteristics, and obviously, limits must be considered [24]. From the process point of view, there is a relevant link between the product’s final quality and the characteristics and the state of the input material (powders, liquid, extruded wire, and sheet) [25]. This link is often non-linear, and it involves both thermal and mechanical properties [26], not only at a macroscale but also at meso-scale and micro-scale [27]. One of the main limitations of the AM process is related to the available materials because they are most related to specific 3D printing technologies [28]. In industrial applications, only specific type of materials is directly certified by vendors in accordance with specific AM machines. This testifies the

relevant link between process variables and input material characteristics (such as granulometry and chemical composition for powders) to affect the final properties of the components.

This paper is specifically focused on L-PBF (Fig. 1a), also called selective laser melting (SLM). Compared with other metal 3D printing processes, L-PBF can provide metal 3D parts with medium-fine surface roughness and tolerances. This AM process is based on the fusion of thin layers of metal powders through the thermal energy provided by a laser source [29]. The mechanical properties of materials can be reduced by process defects related to non-homogeneity in thermal distribution, bad range of powder granulometry, porosity, and wrong energy source parameters set-up [30]. The thermal gradient generates a residual stress state that can lead to geometrical distortion, and part failure such as distortion, delamination, or cracking [31]. The thermal gradient can also compromise the fatigue assessment which is also affected by surface roughness, porosity, and residual stress [32]. To achieve a high density compared to parts fabricated by foundry, the metal powder particles should be completely melted [33, 34]. Defects related to porosity, residual stresses [35], dimensional tolerancing [36], balling [37], and roughness, are directly related to process control (temperature, environment measurements, and chemical analysis) and material property [38]. Compressive strength, elastic modulus, porosity, and surface roughness can be improved by heating treatments able to increase the microstructural performance of the materials reducing issues related to fusion porosity, balling effect, and entrapped gas pores and shrinkage [39, 40].

Due to the high cost of the L-PBF process, different simulation methods have been developed to predict the thermo-mechanical behavior of the metal 3D printing process [41]. As described in Fig. 1b, these simulation methods can be classified into micro-scale [42], hybrid micro-scale, meso-scale [27], thermo-mechanical, thermo-fluid dynamics, and inherent strain-based methods [43]. These methods investigate different aspects of the AM process, such as analysis of the melt-pool geometry, the induced porosity, and roughness, and the micro-structural formation [44]. Micro and meso-scale methods are suitable to analyze the behavior from micro-structure to molten pool; however, the elevated computational cost and time limit their application in the simulation of a full 3D component. The other methods are suitable to analyze the mechanical behavior of a full 3D part while printing; however, they are less precise.

Due to its relevant computational efficiency, the inherent strain-based method is one of the most used simulation methods for evaluating the 3D printing of metal parts with L-PBF. This method consists of two phases: the first one realizes a thermo-mechanical simulation on a micro-scale specimen to compute the plastic strain tensor (phase called calibration phase), the second one applies the resulting plastic strain tensor to an actual component and performs a linear elastic analysis [45]. However, the inherent strain-based method shows several limitations related to calibration required, no coupling with thermal simulations, and different simplifications related to fixed inherent strain values, time-dependent phenomena not considered, non-linear effect not considered, etc. This method can provide

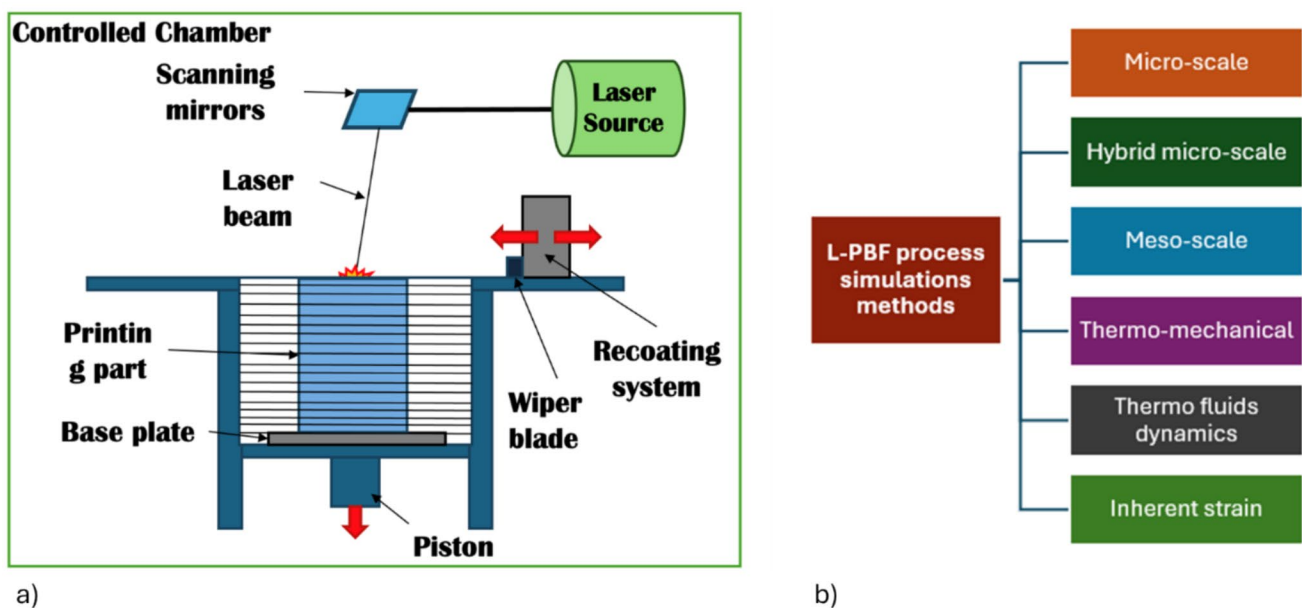


Fig. 1 a The operating scheme of the L-PBF process; b L-PBF process simulation methods classification

an average prediction of residual stress and deformations in metal AM with results mostly affected by the calibration data.

During the DfAM activity, many geometrical and process parameters are analyzed to achieve a feasible and optimized design solution. The final geometry of a 3D printed part can be the result of a long simulation phase. To reduce time in simulation and optimization and improve the efficiency in the design phase, machine learning methods can be used to predict the thermo-mechanical behavior of the AM process, reducing trial–error procedures. However, this workflow still requires the development of simulations to produce a dataset for training the machine learning models.

2.2 Machine learning

In 1959, Arthur Samuel described ML as the “field of study that gives computers the ability to learn without being explicitly programmed” [46]. ML is a discipline of AI that enables a system to learn by training from a dataset obtained from various sources rather than following a pre-programmed technique [2]. The algorithms used in ML are based on activation functions and the assignment of weight factors for each input variable to analyze data and find hidden connections among them. The final objective is the prediction of future events or scenarios that are unknown [47]. The approaches can be classified in supervised learning (SL), unsupervised learning (UL), and reinforcement learning (RL), as described in Fig. 2.

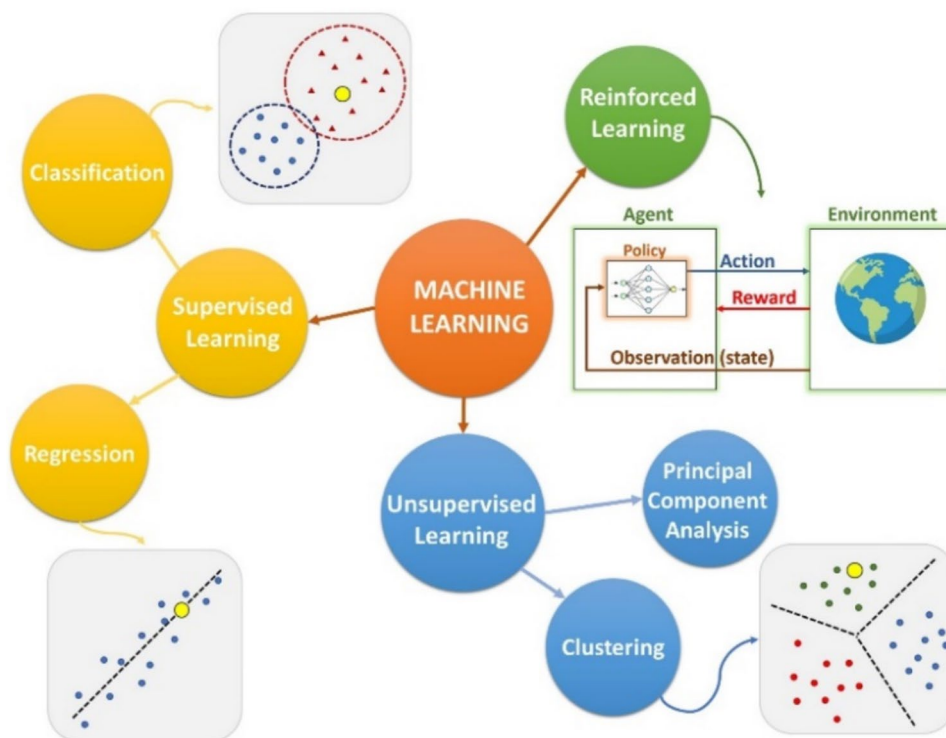
SL algorithms are trained using a dataset with known input and output pairs. In training, the algorithm extracts the associations between independent attributes and a designated dependent attribute to develop a prediction model [48]. Indeed, the model can make predictions of unknown output values from a new set of input data. The performance depends on the size and variance of the training dataset to achieve better generalization and greater predictive power for new datasets [47]. Decision trees, Naive Bayes, support vector machines (SVM), and artificial neural networks (ANNs) are some of the most widespread supervised ML algorithms.

On the other hand, UL algorithms are used to learn how to represent input patterns using statistical methods from a dataset [49], without using explicit target outputs associated with each input [50]. UL methods are classified as clustering and dimensionality reduction algorithms such as K-means clustering and principal component analysis.

RL algorithms are the third ML category. These methods are applied to find a solution to the challenge of learning from interaction with an environment to get a specific objective [51]. The RL approach is a closed-loop method because the learning system’s actions influence its later inputs [52]. In fact, these techniques are used in autonomous robotics and control systems.

In engineering design, SL methods are widely used due to their capacity to find unknown relationships between input and output. ANN is one of the most used ML methods, able to model non-linear relationships and conduct parallel processing [53]. ANNs can be trained with different learning processes such as SL or UL.

Fig. 2 The scheme of the ML classification. The ML approaches are classified in three macro-categories: supervised learning (SL), unsupervised learning (UL), and reinforcement learning (RL)



2.2.1 Artificial neural networks

ANNs take inspiration from the functioning of biological mechanisms in the human brain, made up of a very large number of interconnected neurons. Each neuron is a single cell that elaborates a single task such as the response to a specific input signal [54]. An ANN has three fundamental parts: node character, network topology, and learning rules. Node character defines how input signals are processed by the node, such as the activation function, the number of inputs and outputs associated with a single node, and the weight associated with each input and output. Network topology maps the connection and the organization between nodes. Learning rules determine how the weights are initialized and adjusted [53]. Figure 3a shows the structure of a basic node with inputs, weights, and outputs. The nodes are organized into *layers* and column vectors of the node. There are three types of layers such as the input layers, the hidden layers, and the output layers (Fig. 3b). Designing the network topology means defining the dimensions (number of nodes and layers) and the path of the connections among the node [53].

Each node elaborates multiple inputs x_i pre-multiplied by weights w_i . When the sum of the weighted inputs exceeds the threshold value T , the node computes the input signal through a transfer function f and sends the output signal y to the neighboring nodes (Eq. (1)). The transfer function f can be binary step function, linear, sigmoid, tanh, ReLU, leaky ReLU, parametrized ReLU, exponential linear unit, Swish, or SoftMax [55].

$$y = f\left(\sum_{i=0}^n w_i x_i - T\right) \tag{1}$$

During the training phase, the weights are optimized to obtain the output desired values. The weights are adjusted to minimize the error between the network and experimental outputs. Different types of networks require different learning processes. In each data-driven analysis, the dataset with the input data must be sufficiently numerous. Data sources

can be filled with both real experiments and virtual analysis. The use of simulations in data collection can reduce the time and cost in the training phase; however, the accuracy of the simulations can affect the ML result.

While the first sections have introduced the background research related to L-PBF process and ML methods, the following section describes the proposed approach for applying ML in the context of DfAM considering product design lifecycle. After that, the paper will continue describing the currently application of ML in the field of AM, and the implementation tasks.

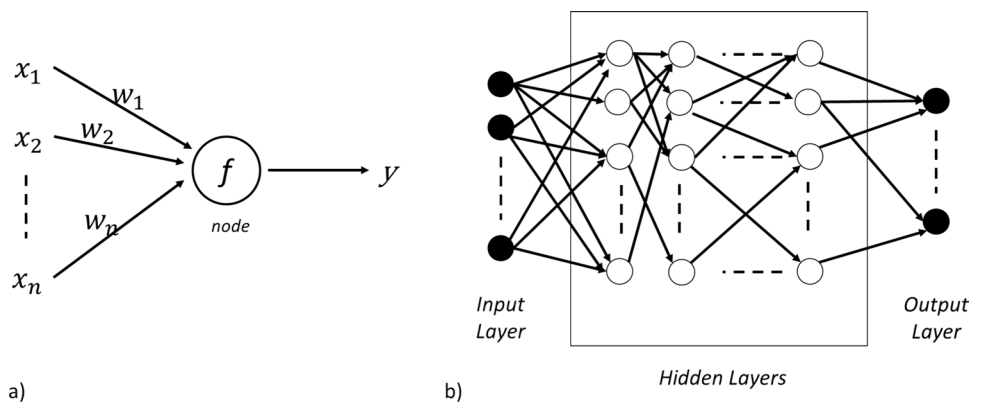
3 Approach

The state-of-the-art shows the use of ML in a single application level in AM. In the literature, these levels are generally classified such as geometrical design, process configuration, and process monitoring (in situ). The paper highlights this current limitation and aims at extending the use of ML to support different levels of applications. Four levels of applications are analyzed here, including the cost estimation level. Supporting different application levels means extending the ML actions over the product design lifecycle.

Figure 4 describes the approach proposed to support the product design lifecycle using ML while designing metal parts to be realized by the L-PBF technology. In the early design step, DfAM tools and methods are used to define the early 3D model of the product. After, ML methods are introduced into the design workflow to support DfAM tools and revise the early 3D models. The ML methods are trained considering data set from different application levels such as geometrical design, process configuration, cost estimation, and process monitoring. As a step beyond the state of the art, more application levels could be analyzed inside a design workflow.

The aim of using ML in DfAM is to support the definition of the CAD geometry, select the process parameters, and improve the process monitoring to avoid expensive failures. The approach should consider the entire product design

Fig. 3 **a** A single node of an ANN with input (x_i), weight (w_i), transfer function (f), and output (y); **b** the scheme of the general topology of an ANN



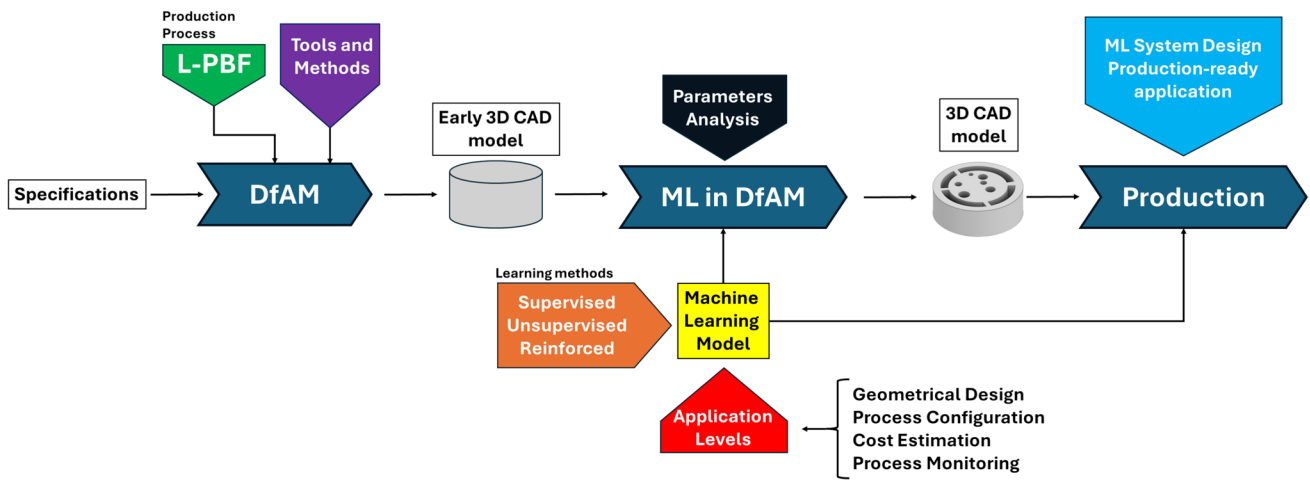


Fig. 4 A schematic approach for including ML in the product design lifecycle

lifecycle; however, the state-of-the-art shows that ML in AM is still applied considering a single process or design phase.

To use ML tools in DfAM, it is necessary to study the problem in depth to identify which parameters need to be controlled or optimized. However, the AM designer must define input and output parameters for training. In the case of the SL algorithms, where the ML models correlate the input parameters with the output ones, the data can be fed with real tests and/or simulations. In this context, virtual simulations can reduce time and cost related to experiments [56].

Developing an ML system means implementing an ML model inside a real production scenario where monitoring sensors and quality inspections could also provide data for validating and training the same ML models. Therefore, the last step considers deploying ML models in production-ready applications using specified informatics infrastructures.

Figure 5 shows the possible design workflow to help the designer in defining an ML system to be used in AM. The workflow can be divided into two phases: the preliminary study and preparation phase and the use phase. The first

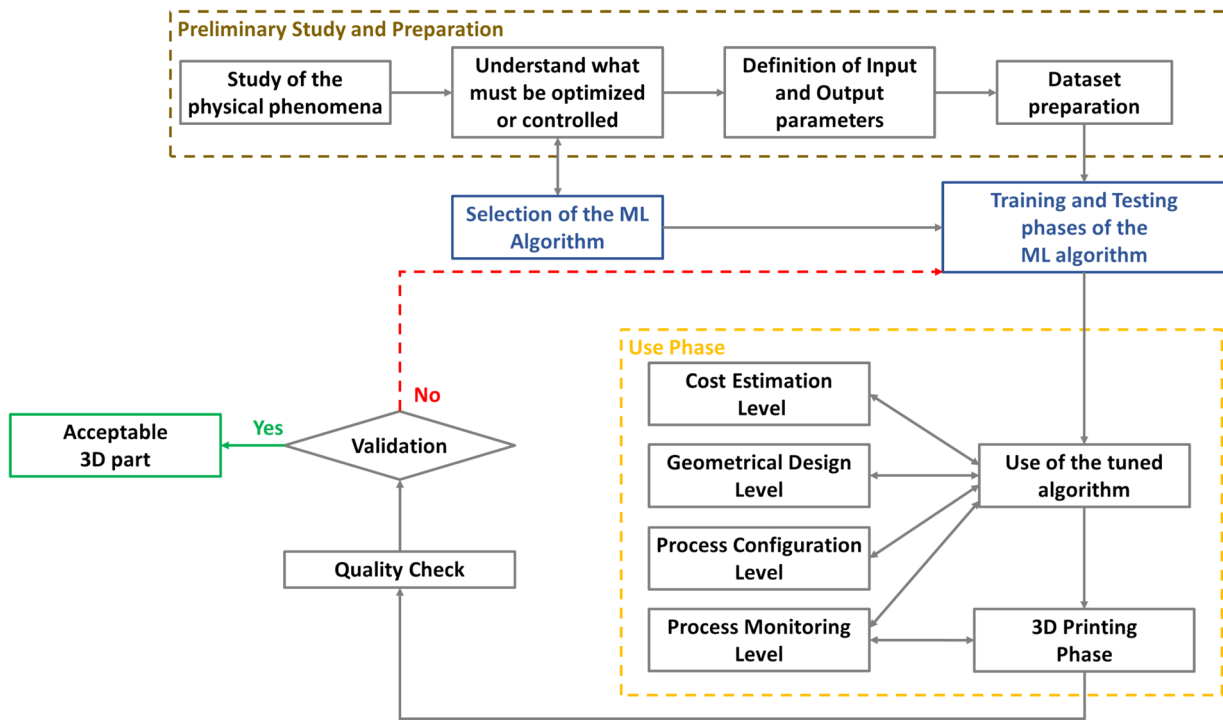


Fig. 5 An approach for designing a ML model for AM applications

phase concerns the necessary analysis of the physical phenomena, useful for understanding which parameters must be controlled or optimized, to help the selection of the correct ML algorithm, and to prepare the dataset for the training and testing phase properly. This phase requires a long work and a large amount of data in addition to the complete definition of the physical process of the problem studied by the designer. The second one concerns the tuned algorithm usage to achieve the chosen purpose, such as the design optimization, the process monitoring, or the process configuration. A final validation helps identify problems or errors and, if necessary, apply a further training and testing phase.

In the following section, the paper continues describing current ML applications in DfAM, defining the application levels, and analyzing parameters and algorithms. The reported state-of-the-art confirms that the current practices use ML to support single application levels.

4 Using machine learning in DfAM

4.1 Application levels

The ML methods are widely used to optimize the numerous parameters in the L-PBF process; however, in a more general approach, they may also support component design development, taking advantage of the AM capability of achieving complex topologies and performing integrated product-process optimization. The application levels that regard the usage of ML methods in AM can be classified as follows: geometrical design level, process configuration level, cost estimation level, and process monitoring level (often called “in situ” monitoring).

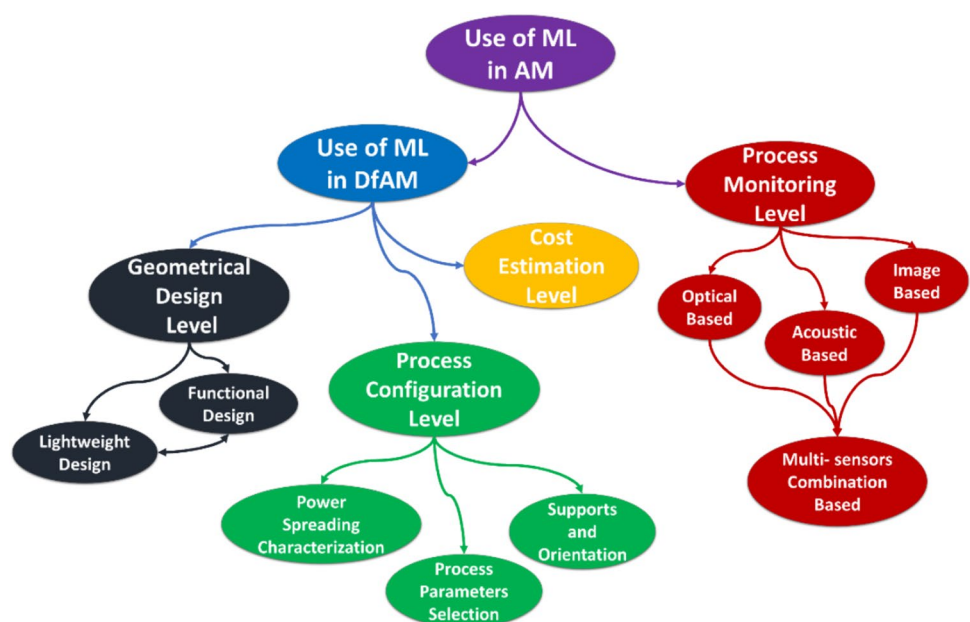
Figure 6 illustrates the four application levels and their respective specifications in the study of the L-PBF process. Geometrical design, process configuration, and cost estimation levels can be grouped into sub-classification related to using ML in DfAM. Process monitoring level refers to the in situ control.

4.1.1 Geometrical design level

The goal of the first application level, the geometrical design, is the design optimization with respect to the product’s functionalities considering that geometry has a relevant effect not only on the final weight but also on the achievement of the design requirements. According to the most recent literature analysis, AI may support the geometrical design level in many ways that, in agreement with Fig. 6, pertain to TO and generative design (GD). To satisfy the project’s requirements, custom micro and meso-structures can be realized using ML algorithms [2]. AM technologies, supported by ML algorithms, can print complex and free-form geometries. However, ML algorithms are applied where geometrical optimizations are necessary, not just in additive design [57, 58].

TO optimizes geometry removing unnecessary volume from the design space that must be connected to the non-design space, definable as the geometrical space where the design boundary conditions are applied or where functional volumes and/or surfaces have to be present. Through methods such as SIMP [59] or level set methods [60], the optimal volume distribution is found according to a FEA-based minimization problem. In [61], the actual limits of TO are discussed, and ML applications to overcome them are reviewed; machine learning TO is presented as a set of

Fig. 6 Classification of the ML applications in AM



strategies to enhance TO, with respect to its high computational efforts. Computational efforts are due to the huge number of variables that are related to the FEA mesh and the iterations necessary to converge. Other efforts may be related to the computation time to evaluate objective functions. GAN-based solutions are reported to bypass iterations [62, 63], other approaches use CNN to achieve a one-step TO through objective function and sensitivity metamodelling, so that FEA may be bypassed [64–66]. Unfortunately, this kind of approach reduces the result accuracy, due to a lack of physical soundness and case sensitiveness. By combining TO and long short-term memory networks, Kallioras et al. [67] created a GD framework that incorporates ML into the GD process. The use of TO can also involve the existing mechanical component redesign, focusing on the innovation of old parts to achieve better performances and lightweight. A workflow is proposed in [68], starting from reverse engineering (RE) and arriving at the quality check of the printed part, it passes through the intermediate phases of TO and printing. In [69], the TO is integrated with an AM knowledge base that considers AM constraints, supports, and orientation to redesign an automotive connecting rod. In [70], a CAD-based workflow has been proposed to achieve a lightweight design with lattice structures, considering the phases from RE to design optimization. In [71], researchers use a TO approach as a concept design tool for modeling the inner frame of an ancient bronze statue.

ML applications for generating meta-materials based on lattice structures seem a more mature field of applications in terms of accuracy and validation of the results. In this case, geometric variables describe the unit cell via CAD parametrization at a mesoscale level. Design requirements and constraints are the mechanical properties that are requested at the macroscale (such as stress–strain law, energy absorption, and deformation/compliance) [72]. These provide specific limits to the design space, which is often related to 2D cells, so that ML may be successfully applied without the limitation derived from complex TO, which is confined to a single cell. The macroscale evaluation of the mechanical behavior is usually investigated by homogenization or FEA. In [73], GAN is applied to optimize lattice geometry with respect to mechanical properties. AM components have been tested to validate the results. Researchers in [74] optimized and tested multi-material gyroid structures developed by ML adopting a data-driven design model. Mechanical properties can be described with good accuracy to determine the optimal relative density and PLA/TPU ratio by interpolation, so that ML may be accurately trained. From the trained NN, new design solutions were explored and validated. Després et al. [75] supported the creation of optimized micro-lattice structures for AM applications using a NN approach. To create new microstructures, they used genetic algorithms and used FEM tools to assess the relative mechanical properties.

A similar strategy was adopted by Alejandrino et al. [76], they realized a supervised NN trained with FEM simulations. They also studied an NN method for designing lattice structures that produce optimized patterns [77–84]; they also confirm the achievement of good results for this kind of application.

Generally speaking, GD aims to provide design alternatives autonomously in order to optimize a design problem according to its requirements and constraints. Some authors study GD approaches to develop a general procedure in agreement with design science theory [85–87]. Proper parametric CAD approaches or TO may explore design variants according to a modular approach that reflects the functional analysis of the part/assembly. Model updates from concept to executive design may be performed, including new details and evaluation criteria as demonstrated through the case study of the crank, in which three different manufacturing processes, including AM, are investigated.

In [58] and [88], the GD via RL is defined as a sequential process suitable to propose different alternatives starting from TO. The wheel design test case demonstrated how the GAN-based approach may guarantee diversity in the topology variant definition, taking into account also computational efforts through NN modeling. A review of the generative product design systems created since 1998 is provided in [89] to identify important methodologies and trends. Systems are examined based on their main objectives, requirements, generative methods, design phase, type of generation (automatic or interactive), and the number of design options. After the variant generations, CAE simulations may be adopted to move towards product-process design with the help of multicriteria analysis that can be assisted by ML. Many examples of this are present in the literature [90–94], supported by the adoption of TO and AM pre-processing tools in many CAD-CAE software (e.g., Altair Hyperworks, CREO PTC, Autodesk FUSION 360, and N-Topology). Examples and case studies are devoted to demonstrating the capability of variant generation and the aid provided by the automation of the multicriteria assessment of the peculiar problem. Unfortunately, the selection of the proper ML approach and the peculiarity of the physical description of the design problems do not allow a proper evaluation of the maturity of the solutions yet.

Table 1 reports some papers that show the use of ML in the geometrical design level. They are classified by algorithm, application, and methodology description and main features.

4.1.2 Process configuration level

The second level, process configuration, involves the selection of the process parameters and the powder spreading characterization with its optimization. Due to the numerous and complex parameters, this level is

Table 1 Examples of papers that use ML in the geometrical design level

Ref	Algorithms	Application	Methodology description and main features
[57]	Fuzzy NN; GA	TO	A system to provide automatic design and rapidly obtain a product form and its corresponding image; using NN to correlate input form parameters and a series of adjectival image words, and GA is to search for a near-optimal design
[58]	PPO; NN	TO	RL-based GD process, with reward functions for maximizing the diversity of TO designs
[62]	WGAN; CNN	TO	GAN generates an optimal topology for a given boundary condition and optimization settings. CNN provides the corresponding design variables and optimization conditions
[63]	cGAN; U-SE-ResNet	TO	Definition of a data-driven topology optimization model called TopologyGAN
[64]	CNN	TO	Using a 48×16 pixel resolution dataset, CNN substitutes the FEM process to calculate compliances
[65]	SOLO; DNN	TO	SOLO integrates DNN with FEM calculations. A DNN substitutes the objective as a function of design variables
[66]	SCA, FFNN, and CNN	TO	SCA is used to develop a material behavior database. FFNN makes predictions of mechanical responses. CNN is used to identify if damage has occurred on the micro-scale and penalize the design accordingly
[67]	SIMP; LSTM	TO	GD framework, called MLGen, integrates several methods to deliver automatically generated shape using TO (SIMP), LSTM, image filtering, and metaheuristics
[73]	GAN	Lattice opt	GAN model to create lattice structures with high strength-to-weight ratio
[74]	NN	Lattice opt	A data-driven inverse design model developed for multi-material gyroid structures. Starting from the fabrication of multi-material gyroid structures, an NN was trained to find the relationship between mechanical properties and design parameters
[75]	GA; encoder; decoder	Lattice opt	ML framework for analysis and design of microlattices. An encoder and decoder are responsible for analysis and design of microlattices, generated by a GA. The Mechanical properties are evaluated by FEA
[76]	NN; SCG	Lattice opt	The 3D coordinates of the infill pattern are extracted as the input of the NN model. The optimization technique of SCG is the algorithm used to train the FFNN
[77]	ANN-LM; k-fold	Lattice opt	ANN-LM used to predict the energy absorption of the lattice structure with parameters such as overlapping area, wall thickness, and size of the unit cell. The k-fold cross-validation technique was applied in the training phase to get the best training results
[78]	ML	Lattice opt	ML approach to predict the mechanical properties of G-Lattices under defined loading conditions. Training data is generated through a sampling technique. Voxeled data is employed as ML feature vectors for predicting properties determined by FEA
[79]	GD method	Lattice opt	GD method is used to investigate the structural topology of the original geometry under tensile loading conditions
[80]	NN-GO	Lattice opt	The shape of the lattice beam is investigated using a deep learning approach with high-order Bézier curves. This is then combined with NN-GO adaptive method for the generation of superior lattice structures
[81]	CNN, QSGS, RGGM, and LBM	Lattice opt	The thermal conductivity of composite materials is predicted using a CNN. Digital images are generated using the QSGS method and the RGGM to model the microstructure of the composites. LBM is used to predict the thermal conductivities
[82]	Bayesian optimization	Lattice opt	Computational framework that leverages Bayesian optimization to identify configurations with increased uniaxial effective elastic stiffness and plastic or buckling strength
[83]	LR, PR, DT, RF, and ANN	Lattice opt	The mechanical stiffness of lattice structure-based polymer foam is predicted using various ML algorithms. ML results are analyzed to identify the more efficient ML method
[84]	DT, LR, RF, and GBR	Lattice opt	ML approach to optimize the design of honeycomb, lattice, and gyroid infill structures in 316L steel fabricated L-PBF technology. ML is used to predict maximum stress while defining the infill parameters such as wall thickness, orientation, and shape
[58]	RL; PPO	GD	This study proposes an RL-based GD process, with reward functions maximizing the diversity of topology designs; GD as a sequential problem of finding optimal design parameter. PPO is used as the learning framework
[88]	GAN	GD	The proposed framework integrates TO and generative models (GANs) in an iterative manner to explore new design options. Anomaly detection can evaluate the novelty of generated designs, thus helping designers choose among design options
[90]	GAN; convolutional autoencoder	GD	A deep learning-based CAD/CAE framework is used in the conceptual design phase for generating 3D CAD models to be evaluated
[91]	Autodesk Fusion 360® algorithm	GD	GD method is used for optimizing customized structures used in cultural heritage applications

Table 1 (continued)

Ref	Algorithms	Application	Methodology description and main features
[92]	TO (SIMP)	GD	Iterative and automated GD method, based on Python scripts, to optimize the multi-material distribution of components. Possibility to change the target volume and the space distribution related to each material during the optimization workflow
[93]	Autodesk Fusion 360® algorithm	GD	A generative approach for the optimization of a static structural design problem
[94]	MATLAB PDE, FEA iteratively	GD	A forceflow based TO process explained in detail and extended with a PDE function to use as a GD tool

crucial for metal AM processes [95]. The selected AM technique and the specific 3D printer affect and sometimes determine the process parameters such as laser power, layer thickness, powder size and distribution, and scanning schemes. These process parameters hugely impact the mechanical properties of the component, such as surface roughness, porosity, density, and fatigue strength. [96]. The quality of the finished part is influenced by the uniformity of powder spreading [97]. Inadequate powder spreading can introduce defects or lead to issues like warping or swelling [98]. The AM printing phase's success depends on the component's final mechanical properties.

The definition of the support structures and selecting the part's best orientation also concerns the process configuration level. The support structures allow the surfaces with critical overhang angles to be printed [99]. Against the high thermal gradients, the supports can reduce deformation and residual stress while optimizing the thermal dissipation. The supports must be lightweight and easily removable to minimize the scraps. The quantity and extension of the overhang surfaces to be supported are influenced by the part orientation. Moreover, 3D printing cost and time are highly affected by the choice of part orientation and supports. In this context, ML can support the definition of the parameters related to supports and part orientation. A genetic algorithm has been used in [100] to find the optimum of different conflicting objective functions among the solutions belonging to the Pareto front; the objective functions regard the minimization of the support structure volume and the building time. Estimation methods are developed for computing the amount of support structure and the build time.

Regression methods are well used in the literature to study the process parameters for metal AM processes. For example, a back propagation neural network (BPNN) with one hidden level was used in [97] to optimize the spreading parameters. The main objective of this study focuses on the part porosity and roughness. In this study, simulations were proposed to feed the training phase. Tapia et al. also investigated porosity prediction for SLM processes [101]. To correlate porosity with

process parameters, they first created a Gaussian regression model, followed by the implementation of a Bayesian inference framework to estimate statistical model parameters. Finally, the porosity of the printed part was predicted using the Kriging method. Ren et al. used a Gaussian regression model to select the optimal laser power value to maintain a constant melt-pool size [102]. While keeping the other process parameters constant, they used two input variables: laser power and thermal history. Baldi et al. [103] used regression methods to predict the melt pool morphology for Inconel 718, constructing a printability map for this material as a function of layer thickness and building platform temperature.

Focusing on the prediction of the part density, Gor et al. [104] investigated ML methods like ANN, K-nearest neighbor, support vector machine, and linear regression for objects printed in 316L stainless steel. The parameters examined in this study have to do with the build chamber, laser system, hatch spacing, layer thickness, and scanning speed. Porosity, defects, roughness, and density all have an impact on the fatigue response. Zhang et al. [105] studied the high cycle fatigue life of 3D printed materials. The method chosen for processing and post-processing can alter this mechanical property. To predict the high cycle fatigue life of stainless steel 316L parts, they used a neuro-fuzzy-based machine learning method.

Regression and classification methods were also combined in the literature. Kappes et al. proposed a regression and classification approach, using a random forest network (an SL method), to link the process variables to the part's final microstructure [106]. They studied parameters such as part orientation, the amount of recycled powder, heat treatment, laser power, laser speed, laser spot, and contour overlap. The objective of this study was to predict defects in L-PBF processes. These studies highlight that the most popular algorithms for predicting the parameters involved in AM processes are SL methods. The literature demonstrates various regression techniques with fruitful outcomes.

Table 2 reports some papers that show the use of ML in the process configuration level. They are classified by algorithm, input, output, and material.

Table 2 Examples of papers that use ML in the process configuration level

Ref	Process	Material	Algorithm	Input	Output
[97]	L-PBF	Ti-6Al-4 V	BPNN	Diameter, length, translation speed, rotation speed of spreader	Roughness, porosity
[100]	L-PBF	/	GA	Orientation; support volume	Orientation to optimize amount of support structures and building time
[101]	L-PBF	SS 17–4 PH	Spatial GPR; Bayesian	Laser power; scanning speed	Porosity
[102]	L-PBF	Inconel 625	GPR; CFHOC	Laser power	Melt-pool size
[103]	L-PBF	Inconel 718	Regression methods	Laser power; scanning Speed, Layer thickness; building platform temperature	Printability map of the material
[104]	L-PBF	SS 316L	ANN; KNN; SVM; LR	Laser power, scanning speed, hatch spacing, and layer thickness	Density
[105]	L-PBF	SS 316L	ANFIS	Processing/post-processing parameters and tensile properties	High cycle fatigue life prediction
[106]	L-PBF	Inconel 718	RFN	Part location, orientation, and recycled powder	Porosity (keyhole and lack of fusion)
[107]	L-PBF	SS 316L	Surface GP	Laser power, scanning speed, and laser beam size	Depth of the melt pool
[108]	L-PBF	Ti-6Al-4 V	SVM	Lack of fusion population, size, location, and morphology of defects	Fatigue life
[109]	L-PBF	SS 316L	ANN; RFN; SVM	Laser power, scan speed, hatch space, and powder layer thickness	CDM-based fatigue life prediction
[110]	L-PBF	Inconel 718	PR; SVR; DT; EGB	Post-processing parameters	Corrosion behavior

4.1.3 Cost estimation level

Most of the cost of a mechanical product depends on the design phase. The cost analysis considers the entire production cycle of the component, including the material cost, the process cost, and, sometimes, the disposal cost. While the cost related to traditional processes is well known in the literature, the cost analysis of metal AM parts is still a challenging topic. In the metal AM context, the analytical approach for the cost analysis could be replaced by ML methods due to the complexity of the process and the number of parameters involved. However, a few of the papers deal with ML for the cost estimation in SLM processes.

The approach developed in analytical tools provides the calculation of material cost, machine cost, operator cost, and cost related to energy consumption (Eq. (2)). Maintenance and administrative costs can be also considered [111].

$$C_{TOT} = C_{Equipment} + C_{Material} + C_{Labor} + C_{Energy} \quad (2)$$

In (2), $C_{Equipment}$ is the equipment investment cost; $C_{Material}$ is the material cost; C_{Labor} is the operator's cost; and C_{Energy} is the energy cost.

Analyzing the ML cost estimation methods for mechanical components, Manuguerra et al. [112] defined an ML approach for parametric cost estimation of axisymmetric components. Through performance indicators, they compared and evaluated five algorithms: generalized linear model, deep learning, decision tree, random forest, and gradient boosted trees. They identified many independent parameters necessary for a prediction model.

For 3D printed parts, Rudolph et al. [113] analyzed different statistical-based methods for an automated and self-learning calculation for SLM given a part's CAD data, using the prediction of capacity utilization and the prediction of part build height as input in the regression model. Chan et al. [114] used the similarities of the 3D geometry of parts and printing processes to identify relevant features. They used different ML algorithms for dynamic clustering, LASSO, and elastic net regressions to predict the cost based on historical data. Another example of ML applications for cost estimation in AM has been proposed by Sharma et al. [115], realizing a fuzzy set-based cost model. Initially, they developed a deterministic cost model, and then they converted it to a fuzzy set-based model by considering uncertainty in building time estimation and cost components.

This review analysis confirms that few ML studies focus on the cost estimation for metal 3D printing. One of the reasons could be the difficulty of achieving a cost dataset. However, there is a high interest in this topic because the high 3D printing cost is one of the main factors that limit the use of AM in the industry.

4.1.4 Process monitoring level

The process monitoring level is also called the in situ monitoring phase. This level concerns the real-time control of the 3D printing process through sensors [116]. The process monitoring and possible parameter corrections can significantly cut down the time and cost of the printed parts. Cracks, delamination, distortion, rough surfaces, lack of

fusion, porosity, foreign inclusions, and process instability (keyhole, balling) are just a few of the processing-related errors that afflict the metal AM process. These defects are typically caused by the layer-by-layer material deposition process [117]. They are related to a high number of internal or external factors. Sensors can recognize potential critical situations, and ML can reduce faults in 3D printing. On the other hand, the traditional approach uses the operators' experience to detect and avoid fabrication defects.

There are numerous ways to control the 3D printing process, monitoring the construction of each layer. The most common ML approaches used in the literature include the image-based approach, the acoustic emission, the optical emission, and the sensor signal-based approach. The image-based approach analyzes the layer-wise surface using photos from cameras to spot defects and lacks. Utilizing spectral convolutional neural networks, the acoustic emissions approach is based on the energies of the narrow frequency bands. The analysis of spectroscopy emissions during the process is called optical emission. This approach has been used for a long time to comprehend physical mechanisms

[118]. The signals consist of melt pool profiles, intensity, plume, and spatter signatures. The fourth method for process monitoring is the sensor signal-based approach, which combines acoustic, optical, infrared, and multi-sensor signals [98]. All these techniques are used to train ML algorithms for process monitoring.

SL algorithms are frequently used in image-based monitoring methods for classification and recognition issues, using high-speed cameras and algorithms such as deep convolutional neural networks [119] and SVM [120]. UL methods can be also used for image-based applications. In [121], images from near-infrared (NIR) cameras are used to monitor processes in real-time and identify melted states during the SLM process.

SL and UL methods are also used to analyze and interpret the dataset of acoustic emission methods. Mohammadi et al. proposed an approach using various ML techniques [122]. To match the acoustic signal with the defect type, a supervised deep-learning neural network was used after a hierarchical K-means clustering to label the data. The dataset was decreased using a principal component analysis (PCA). To facilitate the detection of defects, the Gaussian mixture

Table 3 Examples of papers that use ML in the process monitoring level

Ref	Process	Material	Algorithm	Sensors and input features	Output
[119]	L-PBF	Inconel 718	Bi-stream DCNN	Image feature learning and feature fusion	Pattern defective condition
[120]	L-PBF	SS 316 L	CNN; SVM	Images of melt pool, plume, and spatter	Quality anomalies identification
[121]	L-PBF	SS 304 L	DBN	NIR camera	Plume and spatter signatures
[122]	L-PBF	H13 tool steel	Hierarchical K-means, DNN, PCA, GMM, and VAE	AE sensor; elastic waves	Anomaly detection
[123]	L-PBF	SS 316 L	Spectral CNN	FBG sensor to detect the airborne AE signals	Quality monitoring
[124]	L-PBF	Hastelloy-X	K-means; SOM	Co-axial photodiode; melt pool light intensity	Porosity detection (LoF)
[125]	L-PBF	AlSi10Mg	Mapping algorithm	High-speed camera; melt pool light	Melt pool variations linked to pores
[126]	L-PBF	SS 316 L	CNN; LSTM	AE sensor, photodiode detectors: BR, Visible, and IR	Keyhole, conduction mode; LoF monitoring
[127]	L-PBF	SS 316L, CuSn8, and Inconel 718	CNN (1 model for 3 materials)	AE features	Keyhole, conduction mode, and LoF monitoring
[128]	L-PBF	SS 304	DBN	AE signals	Quality monitoring
[129]	L-PBF	Ti-6Al-4 V	LENSP realized with MLP, SOM, SOEDNN, and FGA	Melt pool images	Costs of the spatial distribution of defects
[130]	L-PBF	Inconel 718	GMM	Data from photodiode, UTS	Certification of AM builds
[131]	L-PBF	Inconel 625	SGTA for multidimensional signals	SWITC, HSVC, and photodetector	Different thermal signatures during overhang melting
[132]	L-PBF	SS GP-1	SVM	DSLR; high-resolution 3D CT scan data	Defect detection strategy
[133]	L-PBF	Inconel 718	SIFT, HOG, SS, and SVM	High-speed camera	Monitor melt pool geometry
[134]	L-PBF	SUS316L	DNN	Dichroic mirror, galvanometer scanner, F-theta lens, and a high-speed camera	Relations between melt-pool images and laser powers

model (GMM) was used. They also used a variational auto-encoder (VAE) approach to obtain a general feature of the signal that could be an input for the classifier. In [123], a sensitive acoustic emission sensor is used to differentiate acoustic features of different quality using an ML algorithm called spectral convolutional NN.

Table 3 reports some papers that show the use of ML in the process monitoring level. They are classified by algorithm, sensors and input features, output, and material.

4.2 Parameter analysis

As highlighted in the previous paragraphs, many various parameters can affect the 3D printing results. The parameters can be classified into many categories such as design, manufacturing, and monitoring parameters. Figure 7 highlights some of the most applied configuration set-ups used in literature to build, train, tune, and use an ML method to optimize the DfAM process. Starting from the printing set-up, relevant parameters for the success of metal 3D printing are the type of supports, the orientation of the part, and the limit overhang angle selection. Analyzing the manufacturing parameters, the most used are the scan speed, the laser power, the powder morphology and dimension, the layer thickness, the path pattern, and the overlapping rate. The most practiced ML methods are supervised methods such as the ANN, the CNN, the SVM, and the GPR. Finally, considering the monitoring phase, some of the main parameters

are the melt pool morphology, the porosity, the high cycle fatigue life, the roughness, and the tensile test.

For example, Giorgetti et al. [135] characterize the printability of the Inconel 718 alloy through the melt pool morphology realizing the alloy printability map as a function of printing process parameters. The printability map guarantees a dense and defect-free material by locating the ideal melting point of the powder. In [136], Magana-Carranza et al. analyze the effects of process parameters such as scan strategies, laser power, point distance, and materials on the residual forces due to thermal gradient during the L-PBF process.

Applying an ML method gives the possibility to extend the process analysis and improve the decision-making process; it allows the study of complex multi-parameter and multi-objective systems that are not possible to study with traditional techniques. Di Angelo et al. in [137] describe which parameters influence the search of the optimal build direction that affects part quality, surface quality, support structure, build time, manufacturing cost, and mechanical properties. The paper also analyzes the optimization techniques adopted to identify the optimal solution to the problem. In [138], Jayapal et al. realize a multi-criterion decision-making process to correlate geometric complexity, cost–benefit, and the additional cost associated with support structures using a fuzzy power Maclaurin symmetric mean operator for metric aggregation. The build orientations are also studied in [139], the paper applies a hierarchical

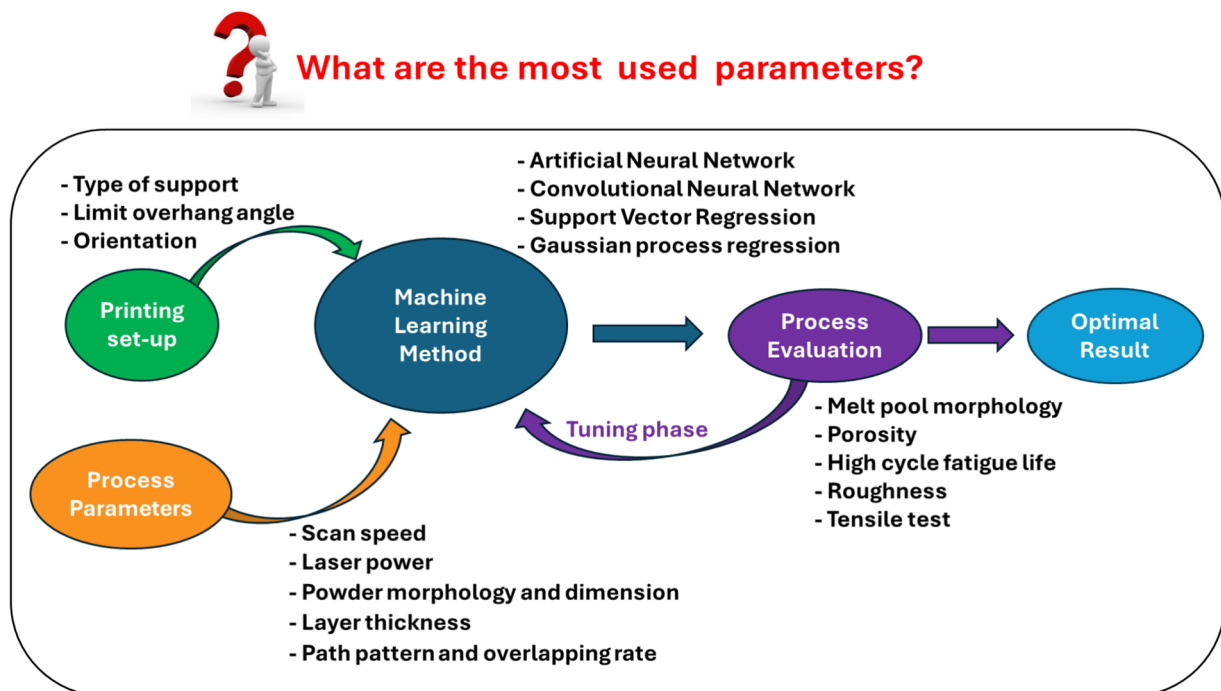


Fig. 7 Most used parameters for applying ML in the DfAM field

clustering algorithm to divide facets of the design model in standard tessellation language format into different clusters. The final set of alternative build orientations is generated by combining and refining the alternatives from all clusters.

Analyzing the current state of the art, it is possible to deduce that ML applications for AM and DfAM are focused on a single level of applications, without interactions between different levels (these levels are formerly known as geometrical design, process configuration, cost estimation, and process monitoring). These interactions could improve the results on using ML models by considering parameters from different levels in a single analysis. It would be possible to obtain a ML model able to help the designers from the early design phase of the product to the control of the manufacturing process, arriving at the quality check of the part.

5 Machine learning system design for production-ready application

As analyzed in previous sections, the literature shows different applications of ML models in the context of AM and DfAM. They are focused on analyzing, controlling, and optimizing the design and process parameters. However, these studies do not explore the necessary tools and infrastructures for enabling the use of ML in an industrial environment. ML in the industry requires a vast and complex infrastructure to execute the defined logic and successfully undertake the outlined decisions. Constructing a functional ML model is a small part of a big task, even if the common perception is that the definition of the ML code is the greater task in industrial applications. However, the reality shows that the code development is just the beginning of the implementation activity. A critical issue regards the infrastructure design to manage data, resources, and monitoring, as analyzed by Scully [140]. Figure 8 describes the comparison between ML perception and ML reality. Therefore, the ML learning and prediction phase are

just a part of the complete ML system. The real complexity is related to the design and maintenance of the infrastructure, which consists of hardware and software.

Developing an ML code requires a series of activities such as data collection, validation, analysis, feature extraction, preparing computational resources, and model training. At this point, the hurdle arises during the transition from the developed software to production. This phase requires the definition of a robust serving infrastructure to provide constant and continuous monitoring of the model. Ongoing management is necessary to ensure optimal performance and reliability. To manage the complexity, the definition of an automatic or manual pipeline could support all the design steps from the feature extraction to production tests. The following sections introduce the main concepts related to architecture, tools, and platforms for implementing ML in the AM industry.

5.1 Developing an ML system

The ML system implementation is always an iterative workflow because, after the system deployment, cycles of monitoring and update are necessary. This cyclical nature of the process involves frequent iteration and back-and-forth movement among distinct stages, as shown in Fig. 9. The main components of the iterative process, excluding the first and the last steps, can be summarized as data preparation, model development, model deployment, and testing.

5.1.1 Project scoping

Project scoping is the phase that defines the objectives, constraints, and type of the prediction problem (for example, regression or classification) [141]. In general, the objectives are related to the desired outputs that can be affected by the business needs [142]. However, there are also technical objectives related to the ML performance.

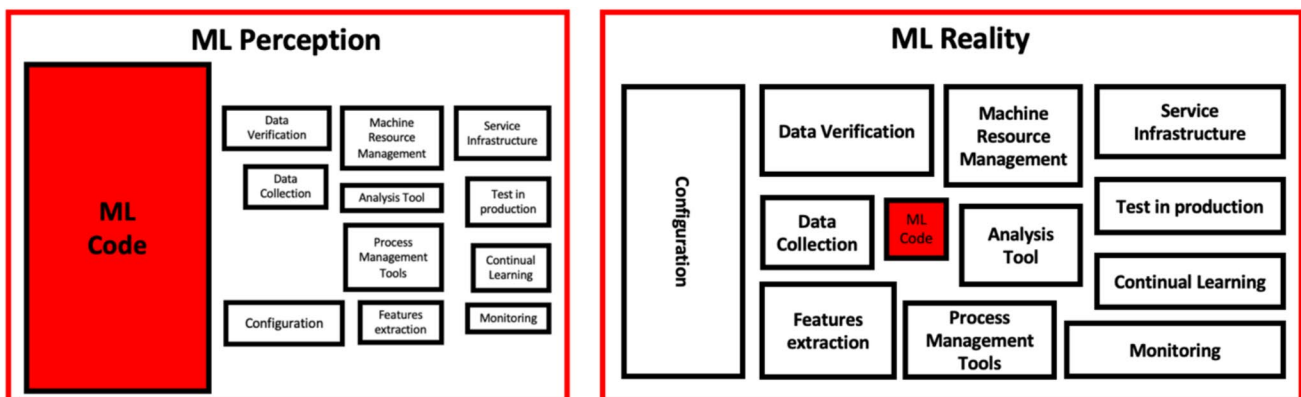


Fig. 8 ML perception vs. ML reality in the industry

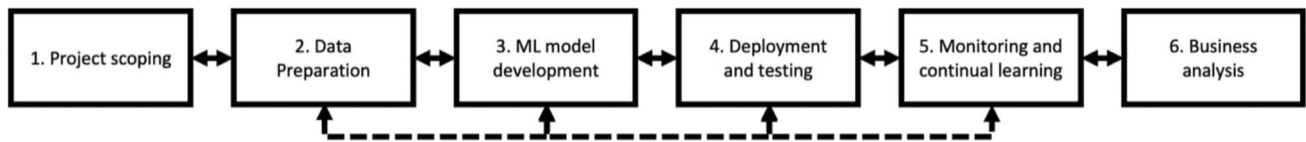


Fig. 9 Process of developing an ML system

5.1.2 Data preparation

Data preparation regards the data collected from heterogeneous sources such as databases, tables, spreadsheets, and other files. Then, the data is combined and organized in a suitable structure. This process involves different sub-phases such as data profiling (review of the source data), data cleaning to remove any errors or inaccurate records, data validation (to ensure that data are clean, correct, and useful), and data transforming (data is converted in a format or structure suitable for the further analysis) [143]. The scope of these phases is to ensure that the data is properly labeled and annotated [144]. After that, data can be used to train ML models, elaborate statistical analyses, or generate reports [145]. Therefore, data preparation is a crucial step in the data analysis process because all the processed data are the input in the ML model. Moreover, the input data affects the model training and the ML results.

5.1.3 ML model development

The model development regards the employment of learning algorithms that use designated datasets for training. In other terms, an ML model can be seen as a bounding box that stores the learned weight values from a neural network. During training, the model learns to map input data to appropriate output predictions through continuous adjustments of its weights. The dataset used for training should be “labeled”; therefore, input and output columns should be defined in the source data. The output values are the target of the ML model. Under the training phase, the model can adjust its internal parameters in response to the patterns and relationships present within the data. This training process involves iterative computations that aim to minimize a predefined loss function, effectively guiding the model to make accurate predictions or classifications. The objective of this fine-tuning is to adapt the model to predict output values from unseen data. This adaptability enables the model to make accurate predictions on fresh data encountered during its deployment in real-world scenarios [146].

Several algorithms are discussed in the literature. Thus, many possible ML models can be implemented for each test case in production. However, the industrial context requires reliable tools and fast analysis; therefore, the evaluation of the best candidate model for production can be achieved

using different techniques like perturbation test, invariants test, direct expectation test, model calibration test, confident measurement test, and slide-based evaluation test [147].

Concerning the ML model development, some of the issues to be considered are overtraining [148, 149], overfitting, underfitting [150, 151], and imbalanced data [152, 153]. Researchers are still working on these issues, defining models to evaluate the performance of ML methods [154, 155].

5.1.4 Deployment and testing

After a model meets the production requirements, it is deployed and tested. The deployment means hosting the model on the internet, allowing other services to invoke it for making predictions. This can occur either through an online API for real-time usage or in batches by providing a set of data to predict from. The model can be hosted either on a physical on-premises device or a cloud-based machine. Maintaining an online model involves a significant infrastructure. Monitoring the system’s behavior and promptly addressing any issues to prevent service disruptions are critical aspects of the deployment phase. These aspects are necessary to ensure the system uptime [156].

After the model deployment, a testing activity in production is necessary for the validation. Typically, multiple ML models are deployed for domain experts to explore and perform different techniques like shadow deployment, A/B testing, or Canary release. When a model is in production, new data emerges, necessitating the testing of the production model against the most current dataset. Consequently, deployment encompasses a series of iterative experiments, and the oversight of diverse artifacts amassed during these experiments, encompassing both the model and the data [157].

5.1.5 Monitoring and continual learning

Monitoring and continual learning are necessary because the model’s performance tends to fade over time. Once a machine learning model is deployed into production, its performance inevitably starts to decline. This degradation is intrinsic, owing to the model’s sensitivity to real-world shifts and user actions. Therefore, continuous training serves as a mechanism to alleviate challenges stemming from alterations in input data by flexibly adapting to them [158].

The need for initiating a model reconstruction can arise from alterations in data, modifications to the model itself, or updates in the underlying code. In this context, monitoring is essential to detect early signs of potential model deterioration.

Monitoring concerns the practice of observing, measuring, and recording diverse metrics that aid in detecting the issues related to the model degradation. As machine learning systems are a subset of software, the foremost set of metrics falls under operational metrics. Typically, they are categorized into three tiers: the network hosting the system (for example, the throughput, which denotes the count of prediction requests your model receives within the last minute), the machine executing the system (for example, the CPU/GPU usage and memory utilization), and the application that the system operates within (for example, the proportion of requests yielding error codes). Another set of metrics to track involves those specific to machine learning like accuracy, precision, recall, etc. These metrics provide insight into the well-being of ML models and assess four key aspects: accuracy-related metrics, predictions, features, and raw input. These artifacts are produced at various stages within the pipeline of an ML system.

Continual learning ensures that the ML system is updated over time. Continuous integration empowers organizations to maintain rapid and frequent software release cycles [159]. In the context of ML, the objective of continual integration is to enhance software quality and efficiency by ensuring regular integration and merging of new code, often multiple times within a day [160]. Therefore, the continual learning requires a continuous deployment after the release update. The deployment immediately begins once a new version successfully traverses the continuous integration pipelines [161].

5.1.6 Business analysis

The phase of business analysis concerns the automatic elaboration of the data collected by the ML model. This elaboration should be accurate and fast. The scope is to support the data-driven decision process using the business objectives defined in the first phase. These objectives should be well-defined, measurable, and aligned with the broader business strategy.

Key performance indicators (KPIs) are the metrics used to measure the success of the ML prediction [162]. These metrics should directly reflect the business goals. Common KPIs include revenue, customer retention, conversion rates, cost savings, cost–benefit analysis, and

risk assessment. A cost–benefit study assesses the cost-effectiveness of the ML system, comparing the costs for maintaining the whole system in terms of data collection, model maintenance, computational resources, and the benefits derived from improved business outcomes. On the other hand, risk assessment identifies the potential risks associated with the ML system, including ethical considerations, regulatory compliance, and potential biases in the model’s predictions.

5.2 Tools and platforms

An ML model’s development needs a specific infrastructure to be used in industrial applications. Working with ML systems requires a different set of skills and capabilities if compared with simple code writing. These capabilities refer to tools for data processing and model management. Without them, it is not possible to implement an ML system in production use cases. Generally, data processing and management tools are commercial platforms.

5.2.1 Data processing tools

The data processing tools can be classified as data labeling and data extraction. Data labeling tools include extensive plans for labeling data such as text, images, and audio. They are used within big data and sometimes are referred to as annotation, tagging, and sorting tools. Data extraction tools, also known as data versioning, supervise diverse iterations of datasets, structuring them in an easily accessible and orderly manner [163]. This capability empowers data science teams to derive insights by pinpointing the impact of changes on model performance and comprehending the evolution of datasets over time.

Some of the most used commercial tools used for data processing are:

- *Amazon SageMaker Ground Truth*: tools for automatic data labeling.
- *Label Studio*: a data labeling service and exploration for multiple data types based on a web application platform.
- *Sloth*: an open-source software for computer vision research used for labeling image and video data.
- *LabelBox*: a popular data labeling tool for creating optimized datasets.
- *Tagtog*: a data labeling tool for text-based labeling.
- *Playment*: a multi-featured data labeling platform.
- *iMerit*: an end-to-end data labeling platform with purpose-built applications and experts in the loop to deliver high quality at scale.

- *Pachyderm* is cost-effective at scale, enabling data engineering teams to automate complex pipelines with sophisticated data transformations.
- *Prodogy* is a scriptable annotation tool enabling a new level of rapid iteration.
- *Comet* provides a standardized process for better visibility and collaboration; easily save, store, version, and link datasets to models in training and production.

5.2.2 Model management

Model management consists of tools for developing, training, versioning, deploying, and monitoring ML models. The tracking of experiments is another specific property of these tools. The user can iterate many experiments and evaluate the quality of different models by defined metrics.

Several commercial tools are available for the model management. They can be classified into six groups, as reported in Table 4. The sixth category (all-inclusive tools) concerns software with full management features. On the other hand, the other tools are focused on some specific phases, from deployment to testing.

6 Discussions

ML can be used in AM due to its ability to manage vast amounts of data and find input–output relationships. One of the advantages is the possibility of improving the design workflow. In particular, the early design phase can be driven by the results of ML models that include the input–output correlations. Some of the issues regard the availability and quality of datasets, the appropriate selection of the ML methods, and the implementation of the ML system into a real industrial scenario. The paper shows how ML can improve and accelerate the design phase and the decision-making process in AM, reducing the overall lead time. The literature shows how ML methods can support the correlation between the mechanical properties to be achieved and the parameters related to part orientation, supports definition, and monitoring phases. This input–output correlation can be reversed in both ways. Therefore, ML can realize multi-parameter and multi-objective correlations that are difficult or impossible to obtain with analytical and simulation methods. However, there is a lack of ML studies that consider parameters from different application levels.

Table 4 Classification and description of some commercial ML tools that include management functionalities

Classification	Some commercial tools
ML model optimization	- <i>Optuna</i> : an automatic hyperparameter optimization framework, particularly designed for ML - <i>SigOpt</i> : a model development platform that makes it easy to track runs, visualize training, and scale hyperparameter optimization for any type of model built with any library on any infrastructure
Versioning and tracking ML models	- <i>Neptune</i> is an ML metadata store used for experiment tracking and model registry - <i>Data Version Control (DVC)</i> is essentially an experiment management tool for ML projects - <i>Pachyderm</i> : data versioning and pipelines for ML operational - <i>MLflow</i> : a platform to streamline ML development, including tracking experiments, packaging code into reproducible runs, and sharing and deploying models
ML model evaluation and testing	- <i>Kolena</i> : an ML testing and debugging platform to surface hidden model behaviors and take the mystery out of model development - <i>Deepchecks</i> : a tool for testing and validating ML models and data
ML model deployment and serving	- <i>Amazon Web Services (AWS)</i> : a cloud service provider with over 200 fully featured services from data centers to infrastructure technologies such as computing, storage, and databases - <i>Cortex</i> : an open-source platform designed for deploying trained ML models directly as a web service in production
ML model monitoring	- <i>AWS Sagemaker</i> : it is part of the AWS platform. Data scientists and developers can prepare, build, train, and deploy high-quality ML models - <i>Fiddler</i> : a model performance management platform that offers model monitoring, observability, and explainability fairness - <i>Arize</i> : an ML platform for ML practitioners to monitor, troubleshoot, and explain models - <i>WhyLabs</i> : an AI platform designed to prevent data quality or model performance degradation by allowing you to monitor your data pipelines and ML models in production
All-inclusive tools	- <i>Amazon SageMaker</i> : a fully managed ML service - <i>Azure machine learning</i> : a cloud service for managing the ML project lifecycle - <i>Vertex AI</i> : a managed ML platform that provides you with all of Google’s cloud services in one place to deploy and maintain ML models

This lack of correlation between the application levels is called process-structural-property (PSP) and it is known in the literature [164]. The paper proposes including different product lifecycle phases while designing AM parts with ML tools. This approach could guide the development of a new design platform in which ML supports engineers in defining the product design and process parameters.

As a possible solution, the geometric design and process configuration level could be analyzed into the same design framework, using models such as ANNs. The integration between geometric and process parameters could improve the early design phases in the DfAM workflow.

Generally, ML can accelerate the iterative design process in AM, managing multiple parameters, improving part performance, reducing waste and time, and preventing possible failures. Even if there are several advantages to using ML methods, these algorithms require a long training and tuning phase. These operations need large amounts of data that must be organized and arranged before being used. Industry 4.0, with the digitalization of the manufacturing processes and the high number of involved sensors, supplies a large amount of data that can be used to train and tune the AI algorithms. However, data gathering can be an expensive process. To overcome this limit, different papers propose the use of simulations or surrogate models to generate the input data and labels for training and validation.

In Sect. 4.2, the paper proposes a description and analysis of the parameters involved in the application levels. The selection of the proper parameter combinations can significantly affect the final quality of the 3D-printed parts. For the L-PBF process, various process parameters must be considered, such as laser power, layer thickness, laser speed, build chamber temperature, and metal powder dimensions. In addition, configuration parameters such as orientation and support type must be considered. In the literature, ML methods in AM and DfAM are only related at a single level of application, without any correlations between different levels. Establishing these connections could be crucial in helping designers understand the entire L-PBF process, from the early design phase to quality checks after printing monitoring.

As described in Sect. 5, the implementation of ML models in production also shows several issues related to the integration between sensors, data, learning tools, deployment, testing, etc. Therefore, within the study of the ML model, it is necessary to define the hardware and software platform used to implement the code in production. Developing a functional ML model is a small part of a big task that requires a vast and complex infrastructure to execute the defined logic and undertake the outlined decisions. Focusing on future possible development, tools, and methods in AM should support all implementation phases, from modeling to deploying, and managing parameters from different application levels.

7 Conclusion

The paper analyzes the use of ML in AM, describing algorithms, methods, and steps for production-ready applications with L-PBF. The study shows that ML is a tool that can assist designers in defining 3D printing projects while considering geometries, process parameters, cost, and monitoring phases. Different examples are reported to analyze methods, algorithms, parameters, output, and materials involved in the literature. Focusing on the application levels, ML algorithms are used at the geometrical design level to create lightweight and functional components by generative and topological optimization methods. At the process configuration level, the combination of process parameters is optimized by ML tools to achieve the desired mechanical properties. The list of parameters also considers the powder distribution and characterization, the definition of part orientation, and supports. At the cost estimation level, a few ML approaches are described in the literature. The objective of this level is to predict the final printing cost of a component from the parameters of the CAD model. Finally, in the fourth level, called process monitoring, ML tools are useful for monitoring the 3D printing process to avoid failures that might compromise the outcome. The quality of the AM-produced parts depends on the proper execution of the 3D printing processes, and many factors have an impact on the outcomes, such as the optimization of the part geometry to implement lightweight and functionality; the choice of suitable process parameters correlated to the obtained mechanical properties; the selection of the proper orientation and support combination to reduce deformation and residual stress due to the high thermal gradients; and the choice of the appropriate process parameters to the obtained mechanical properties.

While current ML applications for AM and DfAM regard some specific aspects of the complex production process, this paper provides an overall look at the possible benefits of using ML by correlating different aspects of the production process and control systems. The paper provides a perspective on ML applications to support the product-process design of AM components, proposing a product design lifecycle approach that considers all discussed application levels.

The paper also introduces how to tackle the problem of implementing the ML model in production. While Sect. 4 describes the ML algorithms and their applications in the L-PBF context, Sect. 5 analyzes the necessary tools and infrastructures for enabling the use of ML in an industrial environment. In conclusion, it can be stated that ML may provide valuable support in all the DfAM activities despite the required implementation effort. ML can speed

up the product-process development phase, supporting the decisions in new challenging projects. However, the approach should consider different levels of the product design workflow.

In conclusion, the paper shows the necessity of introducing ML from the early design phases, considering the correlations related to each application level, which are defined as geometrical design, process configuration, cost estimation, and process monitoring (also called in situ monitoring). While ML methods are most applied in process configuration and process monitoring levels, there is a lack of ML methods that correlate all levels in the early design phase, which is the phase more impacting on production cost, 3D printing time, and product behavior.

Nomenclatures *AE*: Acoustic emission; *AI*: Artificial intelligence; *ANN*: Artificial neural network (ANNs: artificial neural networks); *ANN-LM*: Artificial neural network with Levenberg–Marquardt algorithm; *ANFIS*: Adaptive neuro-fuzzy inference system; *AM*: Additive manufacturing; *BJT*: Binder jetting; *BPNN*: Back propagation neural networks; *BR*: Back reflection; *CAD*: Computer aided design; *CAE*: Computer aided engineering; *CDM*: Continuum damage mechanics; *CFHOC*: Constrained finite-horizon optimal control; *cGAN*: Conditional generative adversarial network; *CNN*: Convolutional neural network; *DBN*: Deep belief network; *DCNN*: Deep convolutional neural network; *DNN*: Deep neural network; *DED*: Directed energy deposition; *DfAM*: Design for additive manufacturing; *DSLR*: Digital single-lens reflex; *DT*: Decision tree; *EGB*: Extreme gradient boosting; *FBG*: Fiber Bragg grating; *FFNN*: Feed forward neural networks; *FEA*: Finite element analysis; *FEM*: Finite element method; *FGA*: Fluid genetic algorithm; *GA*: Genetic algorithm; *GBR*: Gradient boosting regression; *GD*: Generative design; *GAN*: Generative adversarial network; *GMM*: Gaussian mixture model; *GP*: Gaussian process; *GPR*: Gaussian process regression; *HOG*: Histogram of oriented gradients; *HSVC*: High-speed visible camera; *IR*: Infra-red; *KB*: Knowledge base; *KNN*: K-nearest neighbor; *LBM*: Lattice Boltzmann method; *LENSP*: Laser engineered net shaping process; *L-PBF*: Laser-powder bed fusion; *LoF*: Lack of fusion; *LR*: Linear regression; *LSTM*: Long short-term memory network; *MEX*: Material extrusion; *MJT*: Material jetting; *ML*: Machine learning; *MLP*: Multi-layered perceptron; *NIR*: Near-infrared; *NN*: Neural network; *NN-GO*: Hybrid neural network and genetic optimization; *PBF*: Powder bed fusion; *PCA*: Principal component analysis; *PDE*: Partial differential equation; *PLA*: Polylactic acid; *PPO*: Proximal policy optimization; *PSP*: Process-structural-property; *PR*: Polynomial regression; *RE*: Reverse engineering; *RFN*: Random forest network; *RGGM*: Random generation-growth method; *QSGS*: Quartet structure generation set; *RS*: Random seeding; *SCA*: Self-consistent clustering analysis; *SCG*: Scaled conjugate gradient; *SGTA*: Spectral graph theoretic approach; *SHL*: Sheet lamination; *SIFT*: Scale invariant feature transform (SIFT); *SIMP*: Solid isotropic material with penalization; *SL*: Supervised learning; *SLM*: Selective laser melting; *SLS*: Selective laser sintering; *SOLO*: Self-directed online learning optimization; *SOM*: Self-organizing map; *SOEDNN*: Self-organizing error-driven neural networks; *SS*: Stainless steel; *SVM*: Support vector machines; *SVR*: Support vector regression; *SWITC*: Short wave infrared thermal camera; *TO*: Topological optimization; *TPU*: Thermoplastic polyurethane; *RL*: Reinforced learning; *U-SE-ResNet*: Hybrid network U-SE(squeeze-and-excitation)-ResNet; *UL*: Unsupervised learning; *UTS*: Ultimate tensile strength; *VAE*: Variational auto-encoder; *VPP*: Vat photopolymerization; *WGAN*: Wasserstein generative adversarial networks; *XGBoost*: Extreme gradient boosting

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Declarations

Conflict of interest The authors declare no competing interests.

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