International Journal of Precision Engineering and Manufacturing (2024) 25:429–452
https://doi.org/10.1007/s12541-023-00905-5
Online ISSN 2005-4602
Print ISSN 2234-7593

REVIEW

A Critical Review of Machine Learning Methods Used in Metal Powder Bed Fusion Process to Predict Part Properties

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Received: 12 March 2023 / Revised: 10 September 2023 / Accepted: 12 September 2023 / Published online: 7 October 2023

Abstract

Metal Powder Bed Fusion (M-PBF) technique is one of the popular branches of Additive Manufacturing (AM). One of the biggest challenges in M-PBF is understanding relationship between processing parameters and produced part's mechanical properties. In this review paper, recent M-PBF and Machine Learning (ML) studies are comparatively investigated to guide the scientific community in selecting right ML algorithm to predict and optimize the mechanical properties of the parts produced by M-PBF technique. In this context, theoretical background of M-PBF techniques are discussed in terms of processing parameters and mechanical properties. Constraints on M-PBF processes are examined and possible solutions are studied. ML theory is briefly reviewed and various ML algorithms are investigated regarding their applicability and validity for M-PBF processes. Popular Design of Experiments (DOE) methods are reported. Future trends and suggestions on M-PBF techniques are discussed.

Keywords Additive manufacturing · Machine learning · Metal powder bed fusion · Design of experiment · Optimisation

Abbreviations

AM	Additive manufacturing
ANN	Artificial neural network
CNN	Convolutional neural network
ANFIS	Adaptive neuro fuzzy inference system
VED	Volumetric energy density
EBM	Electron beam melting
HD	Hatch distance
MIMO	Multi input multi output
ML	Machine learning
LP	Laser power
LT	Layer thickness
SISO	Single input single output
DMLS	Direct metal laser sintering
SIS	Selective inhibition sintering
DNN	Deep neural network
SVM	Support vector machines
RF	Random forest
FEA	Finite element analysis
CFD	Computational fluid dynamics
DEM	Discrete element method
M-PBF	Metal powder bed fusion
SLM	Selective laser melting
SS	Scanning speed
RD	Relative density

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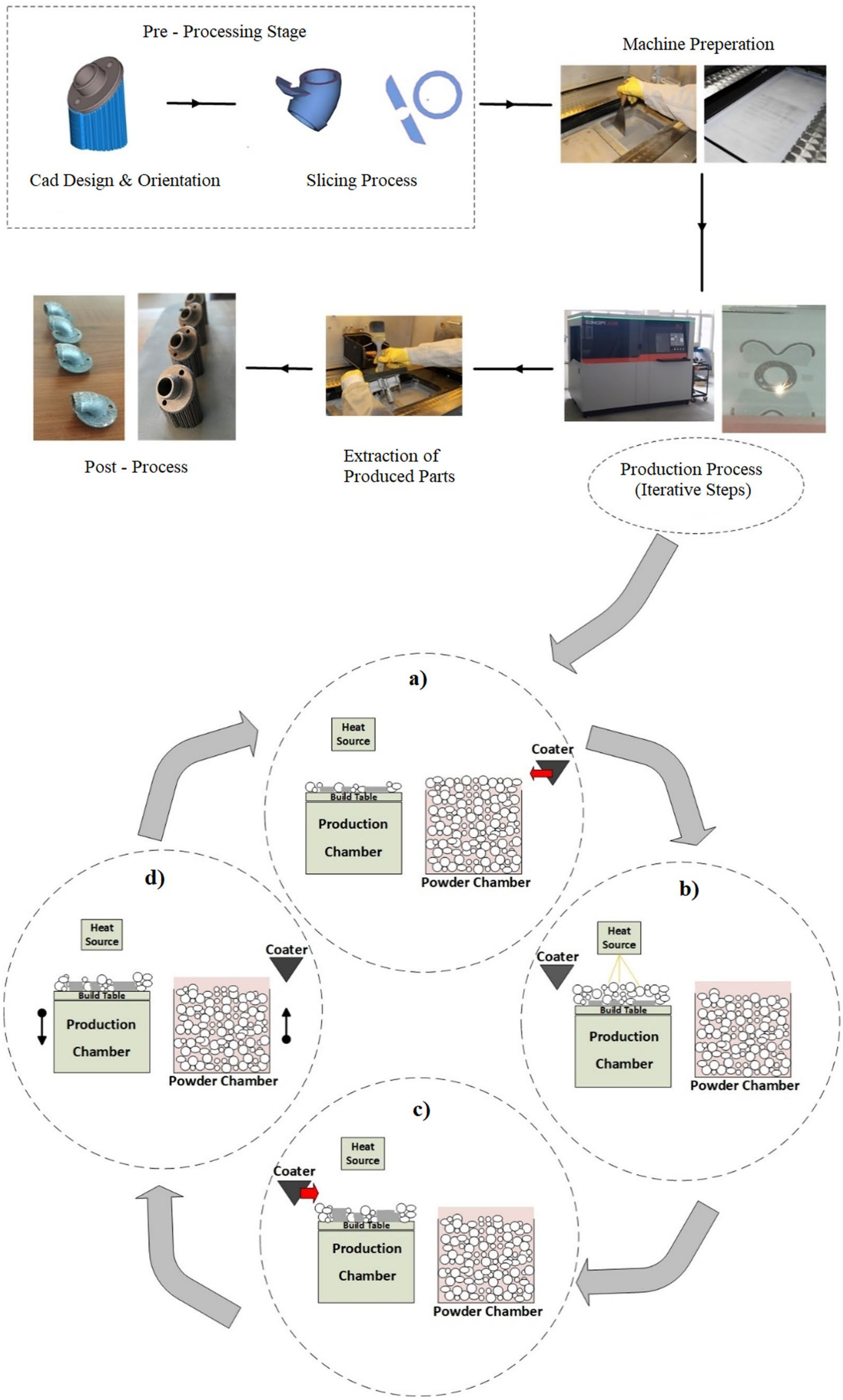
1 Introduction

Metal Powder Bed Fusion (M-PBF) is a specific kind of Additive Manufacturing (AM) production technique that utilizes metallic powders to build three-dimensional parts in layer upon layer process [1]. This process essentially has many components such as heat source (e.g. Laser, Electron beam etc.), powder chamber which stores the feedstock material, production chamber with a powder bed, powder coater mechanism and sensory equipment to monitor the process (Thermocouples, oxygen sensors, additional imaging cameras etc.).

The basic architecture of M-PBF that includes pre-processing, post-processing and production stage are illustrated in Fig. 1. In this process, parts are designed in digital CAD format and sliced into layers. For each layer, coater mechanism spreads powder onto the product ion chamber



Pre - Processing Stage
Cad Design & Orientation
Slicing Process
Machine Preperation
Production Process (Iterative Steps)
Extraction of Produced Parts
Post - Process
a)
b)
c)
d)
Heat Source
Coater
Build Table
Production Chamber
Powder Chamber

◂**Fig. 1** The process architecture of M-PBF and iterative production steps; **a** Coater mechanism spreads powder onto the production chamber **b** Heat source melts powder using the pre-defined coordinate region **c** Powder is exposed to heat in selected area and other powders are left as loose **d** Production chamber height is decreased with value of layer thickness, powder chamber height is increased at least the value of layer thickness

(Fig. 1a), then the heat source is interacted with powder using the pre-defined coordinate region (Fig. 1b). Powder is exposed to heat in selected area and other powders are left as loose (Fig. 1c). After that, production chamber height is decreased as much as the value of layer thickness, powder chamber height is increased at least the value of layer thickness (Fig. 1d). The next powder layer is spread by coater again. This process is repeated until the last layer is selectively exposed to heat. At the end of iterative steps, loose powder is removed from the process chamber and solid parts are extracted. The remaining powder is generally recycled for the next production. Then, produced parts are post-processed (Support structure cleaning, milling, sand-blasting, heat treatment etc.) in consideration of necessity.

M-PBF process has many advantages over conventional manufacturing methods. Lightweight and high-performance structural part production with minimum post-process, relatively small amount of lead time, less feedstock wastage are prominent properties of the M-PBF process. Design parameters allow producing complex parts which cannot be produced in other production methods [2–6]. Especially, layer thickness value (20–80 micron), powder properties (spherical shape, powder size distribution), processing parameters (Heat Source.

Power, Scanning speed, Scanning width etc.), environmental conditions (Inert gas flow rate, ambiance temperature etc.) are the main parameters that affect the quality of produced parts [7, 8].

Despite the unique advantages of the M-PBF, it has also several drawbacks which are related with part quality. There are significant disadvantages both in process and part scale [9–13]. These are simply:

- Porosity formation in parts due to the usage of non-optimized processing parameters,
- High surface roughness on parts due to the powder—heat source interactions,
- Anisotropic mechanical properties due to layer by layer production phenomena,
- Inadequate characterization of process modelling analysis and physics of M-PBF methods,
- Reproducibility constraint of produced parts that hurdles mass production in M-PBF.

There are diverse studies that aim to decrease the level of aforementioned drawbacks [14–25]. Yet, these studies mostly focus on time-dependent simulations and/or high–cost experiments. Recent studies show that eliminating those drawbacks might be possible by using a decent organized ML algorithm with relatively low cost process [22, 26–28].

On the other hand, ML is a conceptual data-driven learning method which is used for the purpose of optimizing specified performance criteria in a given problem. It is a sub-field of Artificial Intelligence (AI) that makes decisions relying on the experiences itself. ML was firstly proposed by Arthur Lee Samuel in 1959 [29]. According to that, there are commonly two ML types, which are defined as Supervised and Unsupervised Learning.

In Supervised Learning, pre-organized dataset and their relevance outputs are used to predict future events for the previously unobserved dataset. For unsupervised learning, the research needs to have dataset with some observations without the need of having labelled observations. Thus, hidden structures of data can be extracted to infer a function without output label information. ML type selection strongly depends on the problem requirements itself [30–32].

ML is directly connected to dataset preparation, which means collection of data affects the convergence performance of a ML type. ML have a broad range of application in data science. Prediction, classification, quality assessments are some major application fields of ML [33–37]. Since ML utilizes dataset to create a model, data related disciplines are tied closely to ML.

The main objective of this review paper is to make a comparative analysis of the recent works published in the literature in the last seven years to guide the scientific community in selecting right ML technique to predict the mechanical properties of the parts produced by M-PBF technique. Hence, the number of experimental work can be kept to a minimum that is required to understand the interaction of process parameters and their impact on mechanical properties of the manufactured parts. This paper also contributes in guiding the M-PBF practitioners to improve product quality, to optimize manufacturing process and to reduce costs.

Section four, ML theory was reviewed and various ML algorithms were defined and experimental design methods were presented and their relationship with ML algorithms were studied. In section five, ML algorithms were investigated in terms of their applicability and validity for M-PBF processes and recent literature findings on M-PBF manufacturing with ML algorithms were discussed and analysed comparatively. In the last section, conclusions and future trends were handled.

2 Metal Powder Bed Fusion (M-PBF)

M-PBF process consists of various methods which differs from each other by several aspects such as phase change of materials (sintering, melting phases), heat source type,

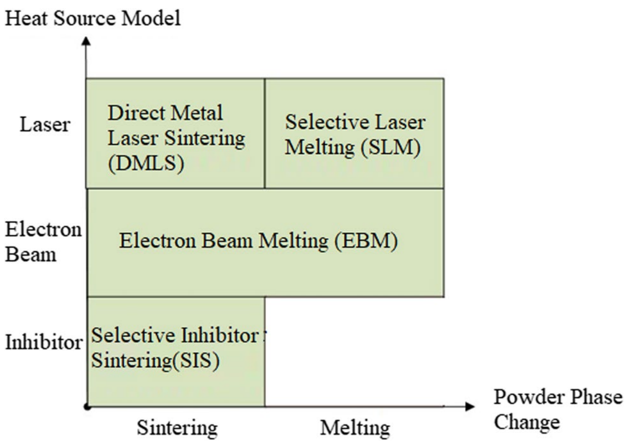


Fig. 2 Classification of M-PBF methods

material type, powder size and shape etc. [38]. The most popular methods are Selective Laser Melting (SLM), Electron Beam Melting (EBM), Direct Metal Laser Sintering (DMLS), and Selective Inhibition Sintering (SIS). Figure 2 simply represents M-PBF methods in terms of phase change and heat source model.

2.1 Selective Laser Melting (SLM)

In this production method, laser system is used as a heat source and melts the feedstock selectively in the pre-defined region. Various powder materials can be used as feedstock such as Steel alloys, Aluminum alloys, Titanium alloys, Nickel-based alloys etc. [39]

The process is carried out in a protective gas atmosphere (e.g. Argon, Nitrogen) due to the risk of fire or explosion of melted powder and as continuously ventilating process chamber to hold O_2 steady at approximately 0.2–0.4% level [40]. As it was mentioned in the previous section, iterative steps are repeated until the last layer is exposed. These steps include laser scanning (guided by galvanometric mirrors), powder recoating, feedstock and build chambers' moving respectively for each layer. Figure 3a represents the SLM process schematically.

Those produced parts are highly preferred in aerospace, automotive and medical fields owing to their unique design, mechanical strength and material properties. That parts can be produced as in desired quality is important so appropriate selection of processing parameters is vital. There are many studies that show the effects of parameters on various part criterions such as mechanical durability, distortion, surface properties etc. [41–43]. However, there are still significant challenges in SLM method in terms of process performance, part property assessments and productivity issues, which obstruct attractiveness of method itself [44]. Some specimen based SLM produced parts are illustrated in Fig. 3.b.

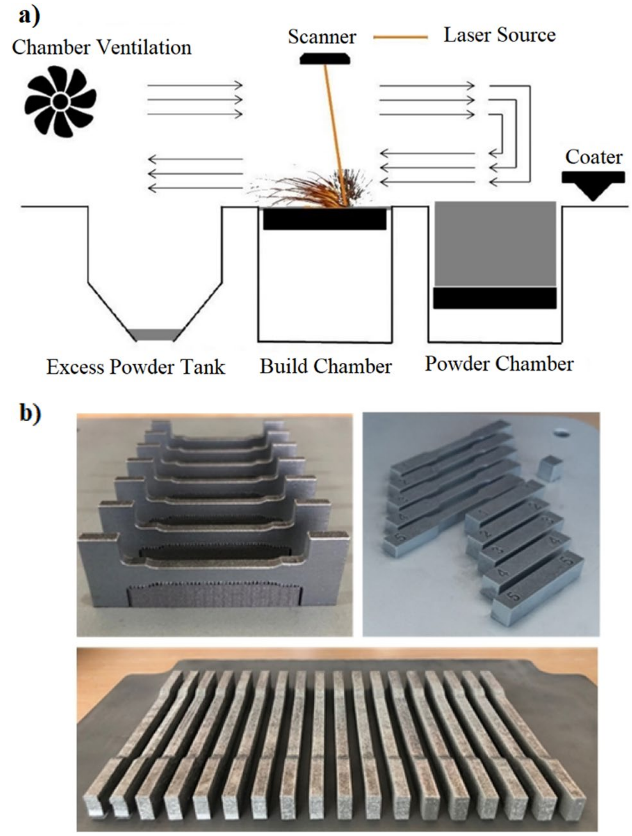


Fig. 3 **a** SLM Process scheme (Courtesy of [44]) **b** Cubic, Tensile and Charpy Impact specimens produced by SLM technique with AlSi10Mg alloy. (Courtesy of EKTAM)

2.2 Electron Beam Melting (EBM)

EBM method is another remarkable branch of M-PBF production. The key process strategy is similar with SLM method but there are distinguishing general factors of this method [45–47]; these factors are given as follows:

- Powder Size Distribution varies between 45 and 105 micron which is originated by process itself,
- Process is carried out in a vacuum environment instead of protective inert gas,
- Electron beam generator is mounted to the system which is used as a heat source,

EBM process have similar steps as in other M-PBF methods. After CAD data preparation, the process starts in a vacuuming the process chamber. Then, preheat process is initialized to heat the chamber temperature around 700–800 °C. Before each layer is exposed, the powder is preheated to a certain level to sinter the loose powder on the build table. This eventually makes the feedstock sintered around the produced part (Powder Cake) [48]. A simple schematic representation of EBM process can be seen in Fig. 4a [49]. Some specimen parts produced by EBM and sintered powder cake are illustrated in Fig. 4b.

2.3 Direct Metal Laser Sintering (DMLS)

In Direct Metal Laser Sintering (DMLS) method, parts are built in a metal powder bed. However, powder's temperature doesn't exceed the powder's melting phase. On the contrary, sintering phenomena occurred between powder particles. It involves neck formation between adjacent powder particles. The main driving force for sintering is lowering of the free energy when particles grow together. A gradient in vacancy concentration between the highly curved neck (high vacancy concentration) and the 'flat' surfaces (low vacancy concentration) causes a flux of vacancies from the neck [50]. The method has broad range of material types such as Steels, Titanium alloys, Bronze alloys etc.

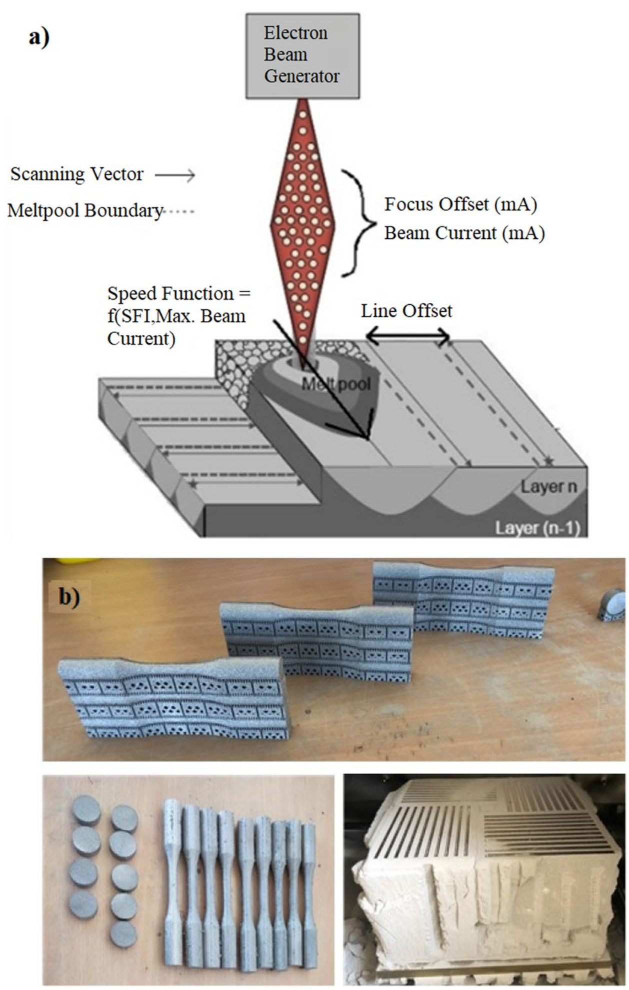


Fig. 4 **a** EBM Process scheme (Courtesy of [49]) **b** Disk and Cylindrical Tensile specimens produced by EBM technique from Ti6Al4V alloy. (Courtesy of EKTAM)

2.4 Selective Inhibitor Sintering (SIS)

SIS is another M-PBF method which has unique production process. SIS have also powder bed but instead of fusing powders by heat source in each layer, an inhibitor is applied to the periphery lines of sliced layers. Inhibitor is deposited at the part's boundary that impedes the sintering process and remainder of powder stay loose inside of the inhibited region. The inhibitor material is usually a liquid chemical solution and its main aim is to keep the contour region of powder from sintering. One example of sliced layer and produced Bronze alloy part can be seen in Fig. 5 [51]. Table 1 represents general advantages and disadvantages of M-PBF methods.

3 Process Modelling of M-PBF

Process modelling allows to understand physical phenomena by using mathematical expressions. In this context, several interrelated steps are taken into consideration. After constructing a mathematical model which is based on physical theory, a numerical model can be developed

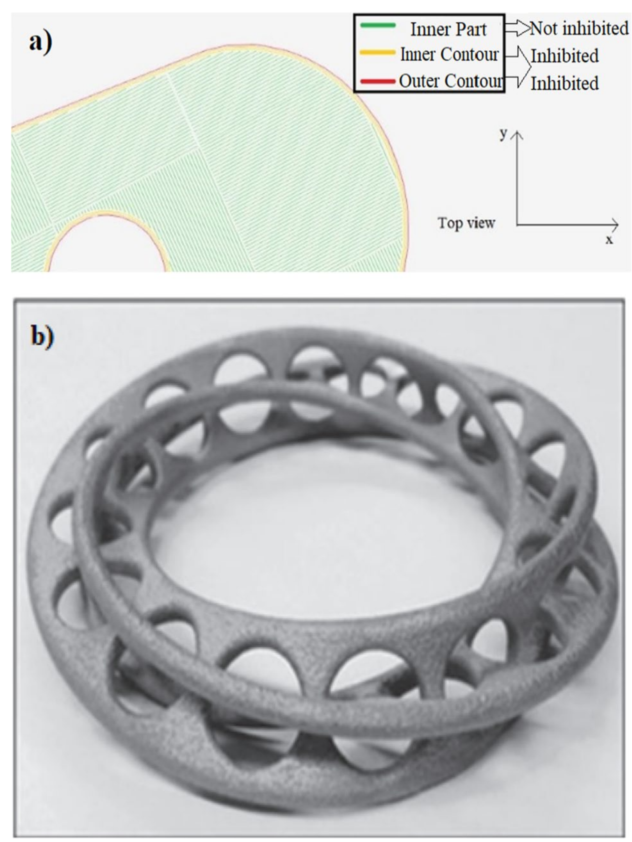


Fig. 5 **a** Slice representation of a CAD data with vectors **b** Modified Möbius Strip part produced by SIS technique from Bronze alloy. (Courtesy of [51])

Table 1 Advantages & Disadvantages of M-PBF methods (Comparatively)

M-PBF method	Advantages	Disadvantages
Selective laser melting	Super fine surface finish and relatively smaller parts (e.g. 0.4–0.6 mm thin walls) are printed [42] Broad range of material types are applicable in this method	Scanning is handled by galvanometric mirrors that obstructs reaching high speeds which leads to relatively slow process, Thermal gradients are heavily effects the process and cause residual stresses in the parts Inert gas ventilation effects part surface quality in case of having fully scanned layers during process
Electron beam melting	A preheat process is applied for each layer, which causes sintered feedstock around the melted part and highly reduces residual stresses due to lower thermal gradients, Scanning is handled by deflection and focus coils which eliminates the physical inertia of parts to reach high speeds, Stacking the parts without deformation is possible which allows mass production	Using high range of powder size distribution and correspondingly high layer thickness values make the surface quality of the produced parts coarser than those parts produced with other M-PBF method Sensitive to be affected from peripheral electromagnetic fields due to the generation of electrons
Direct metal laser sintering	Owing to comparatively lower power necessity, this process doesn't require high energy consumptions as it is required in other M-PBF methods	Because of sintering powder, lack of homogenous melt pool lead to produce porous structures which causes high surface roughness and lower durability in parts [52]
Selective inhibition sintering	The machine is cost effective because of using print head instead of expensive laser or electron beam generator The process is faster since only the boundary (contours) of the part is treated, whereas in other methods, the entire part cross section is scanned or treated (see Fig. 7a) [53] Complex supports are not needed in the SIS process because overhang features are supported by powder volumes underneath [51]	Poor surface finishing of parts and porous structures because of sintering process Narrow range of material types due to selection of proper inhibitor for each material that must be carefully selected Difficult removal process after sintering of inhibited sections due to the inhibitor chemical compound. [54]

to visualize the mathematical model in the way of understanding complex physical interactions. The numerical model eventually used for verification of real process in terms of compatibility. Finite Element Analysis (FEA), Computational Fluid Dynamics (CFD), Discrete Element method (DEM) are primary methods in numerical simulations [55].

From this point of view, M-PBF process can be modelled and compared with experiments. M-PBF is an inherently multiscale process: material transformations (e.g. melting, evaporation and solidification of powder) take place locally (e.g. (10–200 μm)) over short times (e.g. 10 ms), but parts are big (e.g.10 cm)^3 and take different scales of time (e.g. hours-days) to build [56]. Therefore, to be able to understand the process in every aspect, an accurate mathematical/physical modelling is needed. Several studies yielded results in M-PBF process modelling. Related examples are illustrated in Fig. 6.

3.1 Processing Parameters

Each M-PBF method have crucial processing parameters that influence the produced parts in terms of various quality assessments. For instance, dimensional accuracy, reliable mechanical properties, high productivity rates and surface finish are severely depending on the selection values of processing parameters [61]. Main effective parameters in M-PBF methods and effected part properties can be seen in Table 2.

Determination of optimal processing parameters is still an obstacle for producing desired part quality for researchers. From this point of view, ML algorithms will be a good

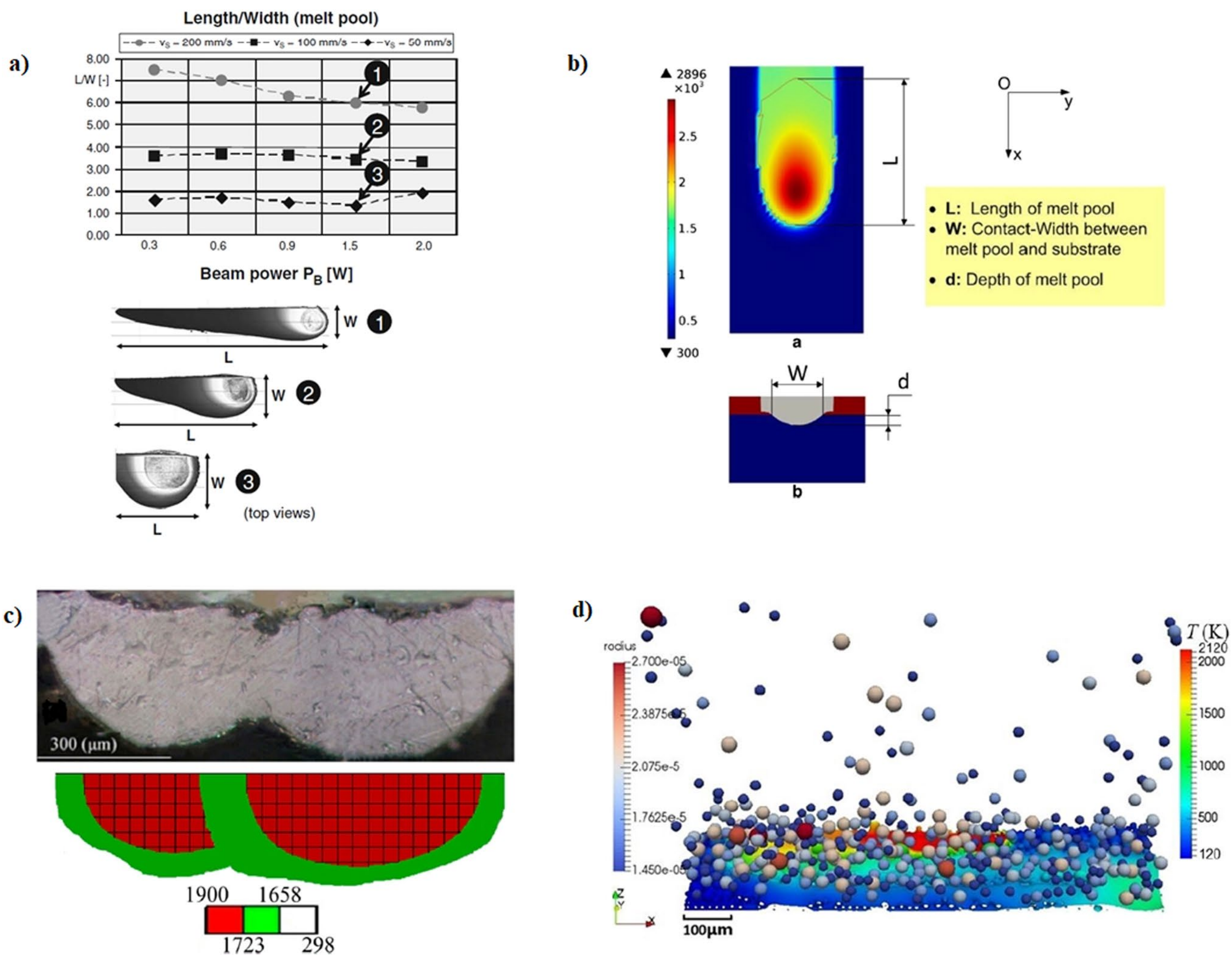


Fig. 6 **a** M. F. Zah et al. modelled FEA of Length/ Width ratio of meltpool geometry in EBM method with varying beam power and scanning speed (Courtesy of [57]). **b** Tran et al. modelled meltpool geometry in SLM method through given processing parameters (Courtesy of [58]). **c** Khan et al. numerically computed meltpool cross section geometry in SLM method and compared corresponding experimental results (Courtesy of [59]). **d** Le et al.proposed CFD–DEM modelling of powder deposition onto melted and solidified part in SLM method in his thesis (Courtesy of [60])

solution for creating accurate process spaces and predicting corresponding processing parameters [62].

3.2 Pre-processing in M-PBF

M-PBF production is bounded with not only the process itself but also pre-processing is a vital stage to get better outcome from produced parts. Pre-processing consist of digital phases such as file preparation, part design, build orientation, support structure organization etc. [63] Part's positioning, support type selection, powder shape and quality highly effects produced parts in terms of production repeatability and mechanical properties [64, 65]. From this point of view, Günaydın et al. studied effects of pre-processing steps (build orientation, support structure density etc.) on mechanical strength of produced parts [66]. Anstaett et al. investigated pre-processing strategies for multi-material models in PBF [67]. Some pre-processing parameters were given with effected part properties at the end of Table 2 as well.

3.3 Post-processing in M-PBF

Another major topic in M-PBF is post-processing. One cannot say that, as built parts will always have adequate mechanical properties for the end use of productions. Furthermore, produced parts may have unsatisfactory performance in terms of their mechanical properties such as surface quality, fatigue strength, geometric tolerances. These lacks can be eliminated by implementing different post-processing methods [68–70] (e.g. machining, heat treatment, grinding, chemical polishing etc.)

Khan et al. combined post-processing studies in different M-PBF methods and showed the effects on mechanical properties [71]. Afkhami and Kaletsch et al. studied M-PBF produced parts in terms of distinct post-processing strategies such as hot isostatic pressing and machining to understand influence on tensile strength, fatigue behavior and microhardness of parts [68, 69]. Schematic representation of post-processing operations can be further seen in Fig. 7 below. According to that, as-built parts have lower performances than post-processed parts in terms of different mechanical strengths such as surface roughnness, porosity, wear, hardness etc.

3.4 Material Types in M-PBF

One of unique advantages of M-PBF process is to have vast range of material types. Different type of metal-based materials is used as feedstock in M-PBF process [80]. Since materials have different properties in terms of their characteristics, there is a great need of investigation of compatibility between M-PBF methods and material properties.

Material properties are effective on mechanical strength of part. Therefore, enhancement of part properties such as mechanical strength, elongation, ductility etc. are significantly related with the determination of material properties and understanding microstructure features accurately [81]. Since M-PBF process have high melting and cooling rates (in msec levels) and mechanical strength highly depends on microstructures of parts, material properties of M-PBF manufactured parts shouldn't be considered as identical with bulk state.

of the same material [82]. Due to the fact that M-PBF process is a layer by layer process, identical part production in different orientation will yield different material properties (anisotropic material properties). Figure 8 shows SLM parts with three different orientations (XY, XZ and ZX) and their corresponding Tensile Stress–Strain curves, which proofs anisotropic properties in M-PBF parts [83]. Table 3 classifies several studies in terms of material types and corresponding properties.

4 Machine Learning Concept

Recent developments in technology show the importance of information gathering with computer based learning methods to minimize cost expenses. One of the possible ways emerged as Machine Learning (ML) technology, which solves field-based problems. ML is a subject of both studying self-improvement methods to get new skills and ability of understanding by experience and classifying existed knowledge, continuously develop performance and achievements [97]. Modelling ML algorithms depend on existed knowledge and inferencing improvements from this source. Data prediction, object recognition, classification, sorting, optimization are the popular tasks of ML methods [98]. There are a lot of method which uses ML technology to get effective results such as Neural Networks, Fuzzy-Logic based methods, Support Vector Machines etc. Each method uses different mathematical processing to be able to achieve goals. Popular ML algorithms were explained with details in Table 4. According to that, methods were used in different fields for several purposes. Figure 9 shows general structures of selected ML Algorithms.

To be able to create accurate ML algorithms, there are some points to be considered [99, 100]:

- Since ML directly depends on problem itself, carefully modelling of problem and creation of dataset is crucial.
- Insufficient experience in labelling data may result in wrong relationship between model and problem.
- Lack of knowledge in selecting good features, overfitting or underfitting of trained model can be regarded as main points in ML.

Table 2 Main process parameters of M-PBF methods

Parameter name	Unit	M-PBF method	Parameter definition	Most effected part properties
Laser power	Watt	SLM-DMLS	It defines the heat source of process which mostly have Gaussian distribution shape [72]	Density [4], Fatigue life [145], Hardness [158]
Scanning speed	mm/sec	All	It defines the heat source's spatial motion in the build surface	Density[15, 175]
Hatch distance	µm	SLM-DMLS-SIS	It defines the distance between two adjacent scanning vectors [73]	Tensile strength [161], Elongation [170]
Beam diameter	µm	SLM-DMLS	It defines effective diameter of the heat source's right on the build surface	Microstructure and temperature history [179]
Layer thickness	µm	All	It defines the positional distance of two successive layers in build direction	Density—hardness [162]
Inert gas flow rate	liter/min	SLM-DMLS	It defines the rate of inert gas inside of process chamber, this parameter helps both stabilize O_2 value in a certain level and evacuate the soot from process chamber which is generated by the powder—laser interaction	Tensile strength [159], Surface roughness [160]
Beam current	mA	EBM	It defines the electron beam source's current value. This parameter determines power intensity that interacts with the powder bed [74]	Relative density [164], Tensile strength [165]
Line offset	mm	EBM	This parameter is similar to Hatch Distance parameter in SLM method which defines the distance between two adjacent vectors	Density [180]
Focus offset	mA	EBM	This parameter is similar to beam diameter parameter in SLM method and it defines effective diameter of the heat source's right on the build surface [75]	Microstructure [179]
Speed function	N/A	EBM	This parameter is used to achieve correct meltpool size by dynamically controlling both beam's maximum current value and Speed Function Index(SFI) value [76]	Tensile strength–Elongation [166], Density [180]
Build orientation	(Angle)	All	This is one of major pre-processing parameters. It defines part's positioning onto the substrate and it concerns with part's surface angle between horizontal surface axis [77]	Elongation [157], Tensile strength [159], Toughness [163]
Scanning strategy	N/A	All	It explains in what way the scanning vectors expose the area of layers. Continuous and chess type are the most popular scanning strategies in M-PBF [78]	Hardness [158], Residual stress [167], Density [168]
Support type	N/A	All	It describes the selection of non-solid and deformable printing samples which is used for heat dissipation, build part integrity etc. It is a pre-processing parameter and highly dependent with Build Orientation parameter	Surface roughness [160] Printability [169] Residual stress [167] Energy consumption [184]
Re-coater geometry	N/A	All	It defines the coater mechanism's geometry which can be polymer or metal based materials. Coater material's resistance to high temperatures, rigidness during coating, powder interactions with coater material are key factors in this parameter [79]	Printability-density[169]
Powder shape and size distribution	N/A	All	This is a powder related pre-processing parameter and key factors are flowability and packing ratio of feedstock. That is used to show whether powder is spread homogenous to build table or not	Density[181]

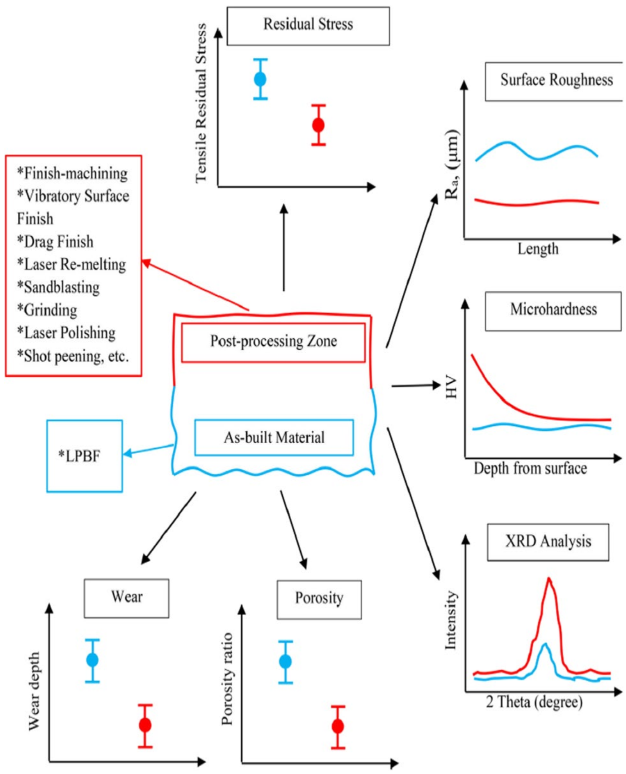


Fig. 7 Schematic representation of the effect of post-processing operations (Courtesy of [71])

4.1 Dataset Preparation Strategies

Dataset is utilized as the source of ML algorithms. Therefore, performance of an ML algorithm will be connected either how well the dataset is organized or the amount of dataset used. As long as the data, which is prepared by high-fidelity resources, is adequate for modelling and spread through the entire process window, ML algorithm fits with established mathematical problem [115].

The main factor in dataset preparing is creation of a process mapping. A process map represents the model with using inputs and output(s). Data will be used as guide points in ML which then converges other points in the map. A visual example of process mapping with 2 inputs and 1 output of a M-PBF problem can be seen in the Fig. 10. According to that, ML creates the process map by using data points as reference and fill the voids by interpolation—extrapolation process that visualize entire window to use for the new data. It can also be visualized as in 3D planes as well.

It is possible to combine dataset preparation under the title of Design of Experiments (DOE). Following principles are implemented in the basis of DOE [116, 121]:

- Identification of factors which effects process performance,
- Selection of reasonable levels for each of these factors,
- Organization of a set of combinations of factor levels,
- Execution of experiments according to the defined experimental design

DOE methods are usually implemented to create dataset for ML problems owing to its systematic principle and cost & time effective features. There are various methods in DOE. Some popular methods are shown in Table 5, namely Full–Factorial, Orthogonal, Box Behnken Design(BBD), Central Composite Design(CCD).

Full–Factorial design shows that large amount of factor and level numbers will increase experimental work exponentially which eventually will be unfeasible. Orthogonal DOE has been utilized in several PBF studies to prepare the training and testing datasets. Orthogonal property gives advantages to be able to get cost-effective dataset [17, 27].

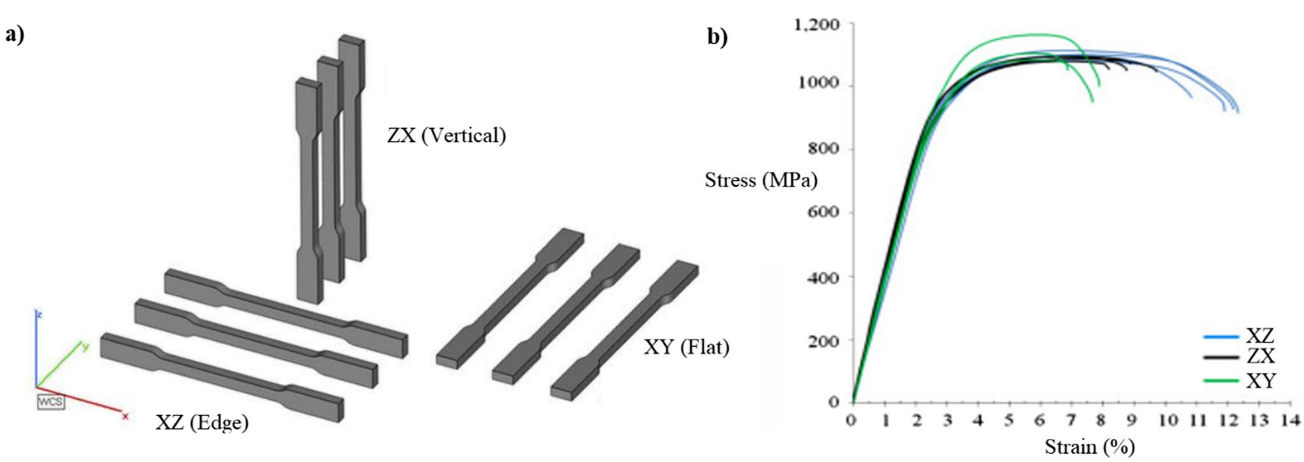


Fig. 8 **a** CAD model of pre-produced tensile specimen parts with different orientations **b** Stress – Strain Curve of produced SLM as-built parts (Courtesy of [83])

Table 3 Material types and properties in M-PBF

Material types	M-PBF methods	Material properties	Application fields	Example materials
Steel iron-based alloys [84–87]	SLM EBM DMLS	High corrosion resistance Surface roughness Relative density (> 93%)	Medical and biomedical (i.e., implants) Aerospace (i.e., Heat exchangers) Lightweight structures	304L stainless steel 316L stainless steel H13 tool steel Maraging steel
Titanium based alloys [88–90]	SLM EBM DMLS	High relative density (> 98%) Superior shear strength	Lightweight structures (i.e., scaffolds) Medical and dental (i.e., body prosthesis, dental implants)	Ti–6Al–4V Ti–6Al–7Nb Ti–13Zr–Nb
Nickel based alloys [91, 92]	SLM EBM	High-temperature resistance Fatigue strength Corrosion resistance	Aerospace (Aircraft engines, Combustion chambers) Die models for automotive parts Porous filtration media	Inconel 625 Inconel 718 Hastelloy X Nimonic 263
Other metals (aluminum, copper, cobalt-chrome, tungsten, gold, silver, bronze) [93–96]	SLM EBM SIS	High relative density of aluminium and cobalt-chrome (> 96%) and other metals (82–85%) High strength	Biomedical applications (i.e., crowns and bridges) Automotive parts Jewellery	Al6061 AlSi10Mg CoCr

Table 4 Popular ML algorithms

Algorithm	Definition
Neural networks	Neural Network is one of the popular supervised ML methods which is mostly preferred to simulate a physical process through utilizing the neural network logic which is inspired by human neural system [101]. It has layers, nodes and biases which are interconnected by snaps having weights. Most promising examples of this algorithm are Artificial Neural Networks (ANN)-Convolutional Neural Network(CNN)-Deep Neural Network (DNN). The main goal of neural networks is to obtain the desired output according to variations in the input. To do so, weights are adjusted iteratively in a process called "training" by using the datasets that include inputs and outputs [102]. ANN is the fundamental neural network model which is used for predictions and optimizations, it has generally one hidden layer. CNN is a neural network algorithm which uses mathematical terms called "convolution" [181]. It is generally used for object classification, image or sound recognitions [103]. DNN is an extended version of an ANN because it has more than one hidden layers. It has more advantageous on large size dataset applications in terms of performance and time
ANFIS	This ML type is a combination of neural networks and fuzzy inference systems (FIS). FIS has linguistic rules that constructs the model with fuzzy reasoning method. ANFIS topology consists of layers, nodes and interconnections as well. This method uses linguistic rules with membership functions (MF) in the training stage instead of crisp values [104]
Support vector machines (SVM)	SVM is one of classification based supervised learning method. The objective of the support vector machine algorithm is to find a hyperplane that has the maximum margin, i.e. the maximum distance between data points of both classes, in an N-dimensional space that distinctly classifies the data points. One of the advantages of SVM in classification is that method is effective in higher dimensional spaces [105]
Gaussian	The Gaussian Algorithm uses Gaussian probability distribution and can be used for non-parametric machine learning algorithms for classification and regression problems. The method is efficient in statistical analyses [106]
Naïve Bayes	This ML algorithm is originated by Bayes theorem and it uses probability theory in classification of dataset [107]. The method calls Naïve itself for the reason of using independent input features. Since it does not fit with real world problems, this is one of the main drawbacks of the algorithm
Decision tree	Decision Tree algorithm is a non-parametric ML algorithm which is used for regression and classification problems. It can have discrete/categorical dataset to perform the task. Boolean logic is used during training which makes the model simply visualized and interpreted [108]
Random forest	Random forest is an ensemble classifier which includes multiple Decision Tree architecture. Training samples are selected randomly from database and decision trees are randomly constructed for each input [109]
K-means	K-means is one of the simplest and popular unsupervised machine learning algorithms. This algorithm aims to classify the dataset by only using own data with given the number of clusters "k". Each cluster's dataset has the most similarities in itself compared to other clusters. Similarity criteria are generally used as Euclidian distance between dataset and pre-selected centroid of clusters [110, 111]
Apriori	Apriori algorithm is one of the classic unsupervised methods in terms of uncovering association properties in dataset. The objective of this algorithm is to identify frequently used items in dataset and extend the boundaries of transactions as long as those items appear sufficiently at the end of the process [112]

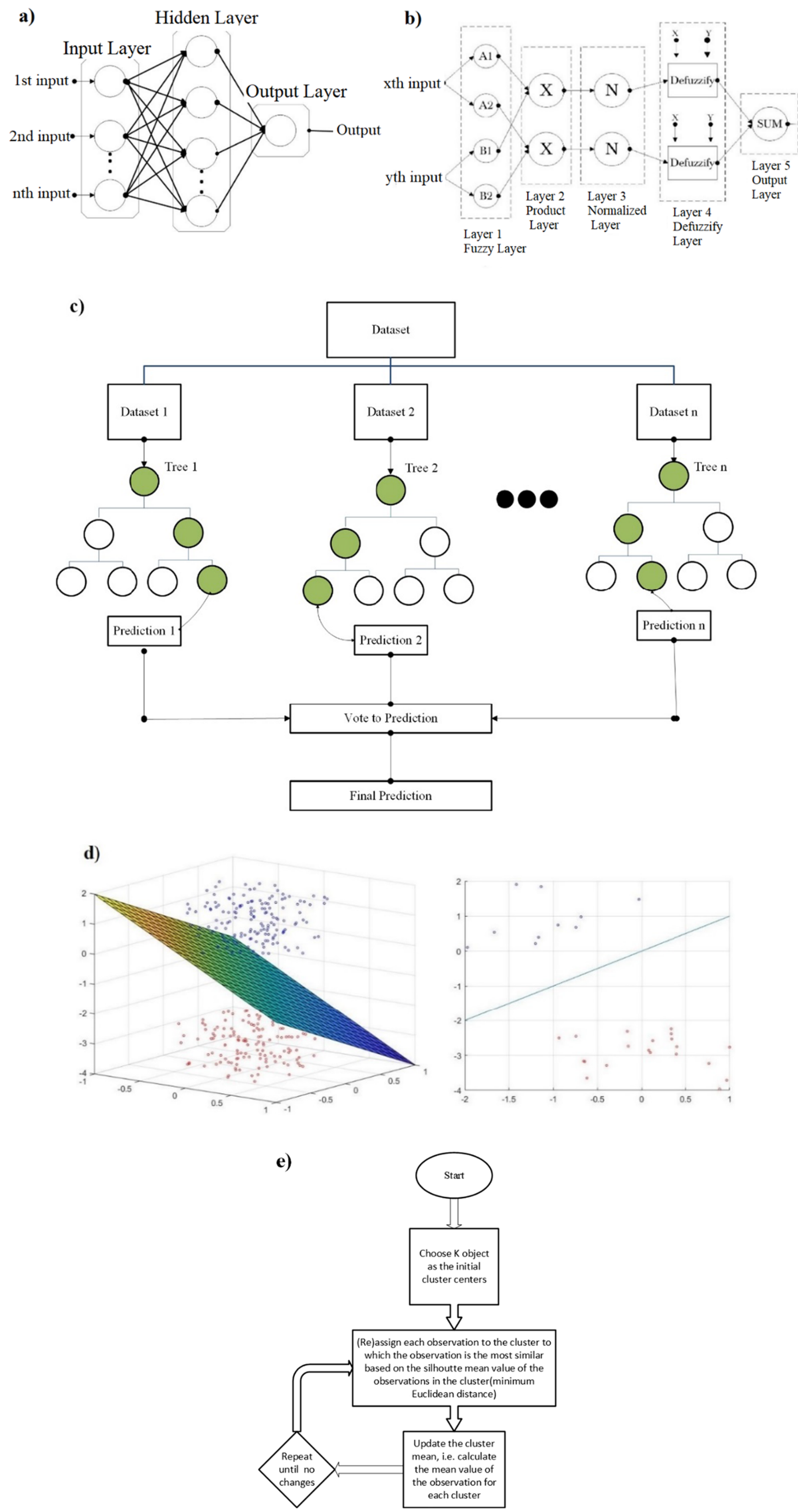


Fig. 9 **a** Simple representation of Artificial Neural Networks(ANN) including layers, inputs and output (Courtesy of [117]), **b** General Structure of ANFIS model(Courtesy of [118), **c** General flow chart of Random Forest algorithm (Courtesy of [113]), **d** Classification charts of SVM algorithm by using an 2D & 3D hyperplane **e** Flowchart of K-means algorithm (Courtesy of [114])

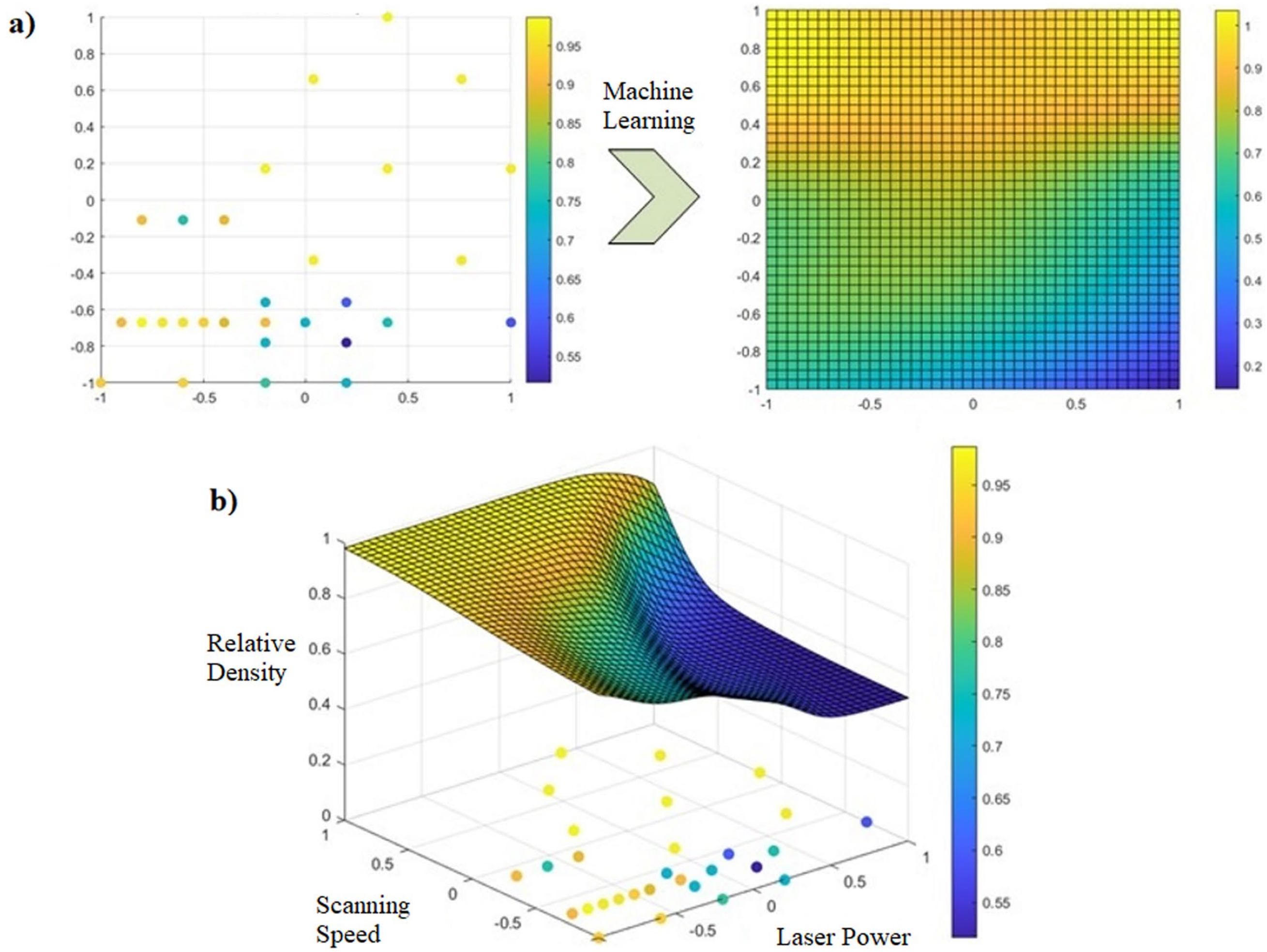


Fig. 10 **a** Guide points in process map and visualization of entire window in 2D **b** ML algorithm convergence in 3D

BBD Design is highly preferred in PBF studies to get effective results as well [18, 24]. In CCD, the biggest advantage is the model doesn't need for a three-level factorial experiments for building a second-order quadratic model [21, 22].

5 ML in M-PBF Methods

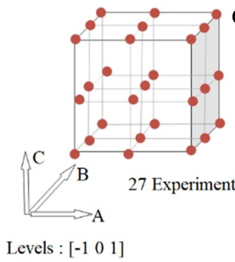
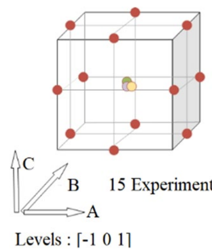
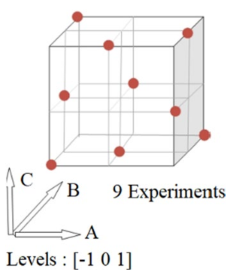
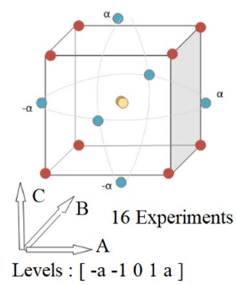
M-PBF part quality are evaluated in terms of various mechanical properties such as density, dimensional accuracy, fatigue life, surface roughness hardness, etc. Even though, design freedom leads to produce complex parts such as lattice structures and sandwich types, M-PBF still has significant drawbacks related with the part quality [154, 186]. Especially, high specific strength parts are yet to be designed and produced [117].

In previous section, it was explained that M-PBF methods use different variants of process parameters (PP). Procedures for optimal parameter selection are generally based on experimental works or high-fidelity simulations. Most of the time, either of them is time-consuming and expensive, owing to the trial and error principle. Therefore, one of the efficient ways in order to predict part properties is developing a mathematical model for the process, which is a sub-domain of ML study. In this manner, ML algorithms and platforms helps to improve product quality, optimize manufacturing process, and reduce costs [118].

Figure 11 illustrates a simple taxonomy of machine learning studies in M-PBF method in terms of general objectives and related fields. According to that, supervised learning is relevant ML type for M-PBF process, which includes prediction, optimization and control problems. Besides the classification methods, which is related with produced parts, powder and material, is applicable with Supervised learning [119]. Unsupervised learning is generally used for monitoring of process, cost estimation and quality management problems [120, 121].

Table 6 represents ML algorithms specifically with related M-PBF applications. Literature studies generally focus on predicting single mechanical property but

Table 5 Popular DOE methods

Design of experiment (DOE) method	Symbolic representation	Definition	Design of experiment (DOE) method	Symbolic representation	Definition
Full-factorial design		Given *k* factors and *l* *levels* for each factor, l^k experiments will be needed in this design to extract necessary information in process map	Box Behnken Design (BBD)		In this design, mid-points of the edges and 3 center points are positioned for process space. Each factor has three levels and one of the factor always remains in the middle point in every experiment [152]
Orthogonal design		This design method utilizes the orthogonality property of vectors which tells that each vector interacts independently. Unlike the Full-factorial design	Central Composite Design (CCD)		This experimental design is a combination of two—level factorial design (each factor includes 2 levels), 2**k* additional axial points and 2 center points [153]

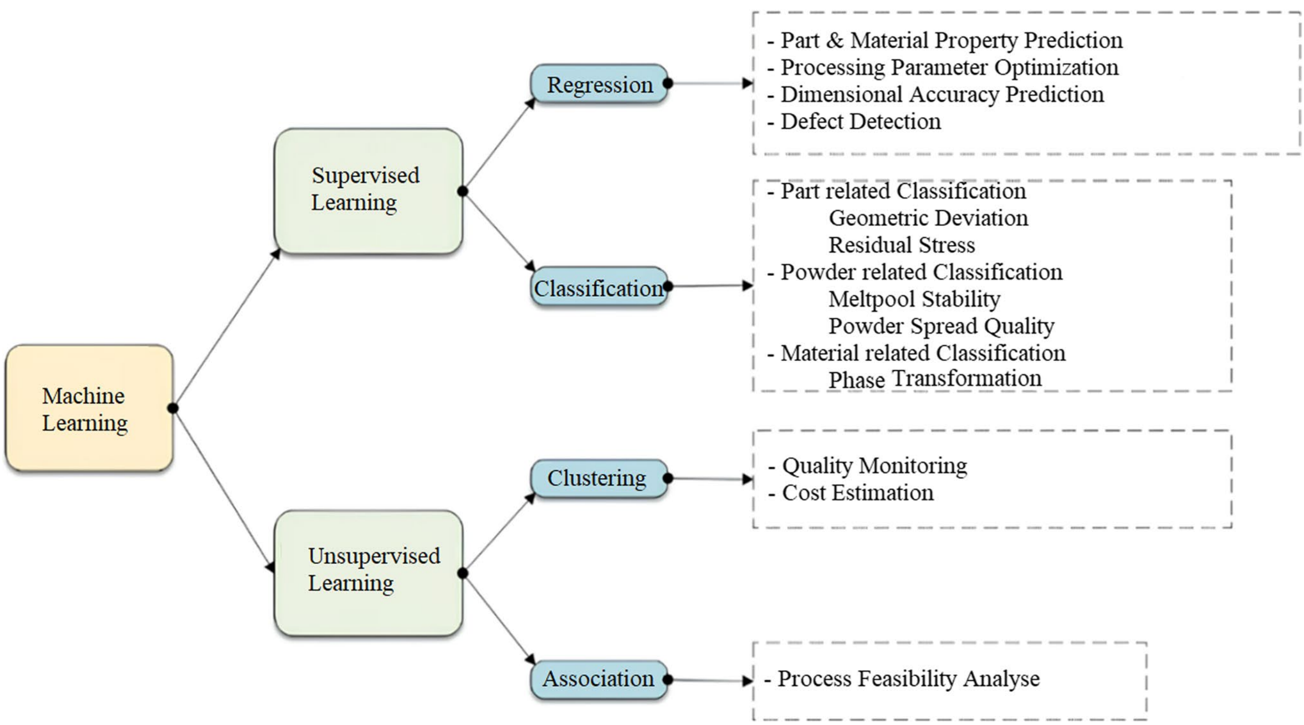


Fig. 11 Application fields of machine learning types in M-PBF methods

there are only a few studies, which combines the multiple outputs in ML model [58, 122]. Shen et al. and Wang et al. have utilized ML models to predict DMLS parts in their studies which confirms that prediction and experimental results fits well [14, 15]. Though many DMLS studies use different material than metals, it is worth to show those studies due to their remarkable results [19, 22, 185]. Fotovvati et al. studied the effects of most influential PPs on SLM manufactured Ti6Al4V parts in terms of their density, hardness and, surface roughness. ML model

Table 6 ML algorithms with M-PBF applications

ML type	Algorithm	Method	M-PBF applications
Supervised	Regression	Neural Networks	Property prediction [58] Process parameter optimization [27] Topology optimization [141] Defect classification [173]
	Regression	ANFIS	Property prediction [21, 174, 178] Process parameter optimization [24]
	Classification	SVM	Defect detection [171, 176, 187]
	Classification	CNN	Meltpool monitoring [183]
	Classification	Naïve Bayes	Defect detection [172]
	Classification	Gaussian	Dimensional accuracy [144]
	Regression & Classification	Decision tree	Defect classification [109]
	Regression & Classification	Random forest	Surface roughness prediction [172] Hardness prediction [113]
Unsupervised	Clustering	K-means	In-situ Monitoring & process quality control [114, 155, 156]
	Clustering	K-means	Cost estimation [177]
	Association	Apriori	N/A

was trained based on these experiments and accurately predict the response of various properties of SLM parts [123]. Neural Network – based ML methods such as Deep Neural Network (DNN), Convolutional Neural Network (CNN) were generally preferred to obtain process space and understand the process interactions [23, 28, 124, 125]. Researchers mainly focus on developing ML models for SLM production technique with different mechanical property prediction [126–131, 141–147], and yet there are a few studies with other M-PBF methods.

Scanning strategy is playing a key role in describing residual stress, porosity etc. Demir et al. proposed a well-established four-layer DNN model to predict defects and residual stresses of SLM manufactured parts with laser scanning strategy input [131].

On the other hand, there are several studies that connects ML with pre&post-processing stages of M-PBF. Liu, Jia, et al. and Wang, Peng et al. investigated ML applications of laser based PBF technique with comprehensive process modelling and controllability of process [118, 132]. Jiang et al. presented a comprehensive study of ML with many kind of Additive Manufacturing methods including polymer and resin based methods [182]. Li et al. evaluated a comprehensive review of ML assisted pre & post-processing stages M-PBF production method. It shows that prediction and optimization of those stages are as significant as production stage [70]. Mythreyi et al. studied machine-learning-assisted prediction of the corrosion behavior of post-processed Inconel 718 [133]. Günaydın et al. and Zhang et al. studied multi-objective optimization techniques to optimize pre-processing parameters such as build orientation, build time and support structure volume. The study yielded visualization possibilities to allow researchers to choose the optimum orientation between the support structure volumes and build time [66, 134].

Structural Optimization is another vital issue of AM processes. Since MPBF opens new doors in terms of part design; intricate and innovative parts can be produced. One of the effective ways for this manner, is to optimize part in terms of its geometrical constraints. FEM based residual stress or thermal models guide to create new generation designs for traditionally produced parts [135, 136]. It aims to minimize lead-time of M-PBF process and consumption rate of feedstock, maximize mechanical strength with lightweight design. In this way, ML is also used for geometrical optimization in MPBF production [137, 138]. In the literature, Iver et al. proposed a structural optimization method called Producibility-Aware Topology Optimization (PATO) to ensure the performance of PBF parts in terms of cracks and warpages due to the method's prone to thermal stress based fails [139]. Garbrecht et al. investigated post hoc analysis of AM parts to enhance mechanical strength by using a novel ML method called Genetic programming-based symbolic regression (GPSR). A topology optimization example was then conducted using the GPSR results that constitutes application of the automated framework and post hoc analyses [140].

Hong et al. investigated geometry deformations of circle cross section lattice parts produced in SLM technique. An ANN model is designed for compensation of lattice structures which have different angles with horizontal axis. Results show that ANN compensated parts achieve higher printing dimensional accuracy compared to the uncompensated structures [141].

AI is a quicker way to identify of the optimum set of processing parameters. Chi Hun et al. proposed an ANN model

Table 7 Literature studies in chronological order

Year	Research paper	Material type	M-PBF method	ML method	Target outputs
2016	Chowdhury et al	Ti6Al4V	DMLS	ANN	Geometry compensation
2017	Ahmet et al	Ti6Al4V	EBM	ANN	Surface roughness
2018	Rajamani et al	HDPE	SIS	FIS	Wear rate
2018	Baturynska et al	Polyamide 2200	DMLS	ANN	Dimensional accuracy
2018	Zhang et al	Ti6Al4V	EBM	ANN	Powder spreading layer roughness
2018	Derahman et al	Glass filled polyamide	SLM	ANFIS	Surface roughness
2018	Sohrabpoor et al	Glass filled polyamide	DMLS	ANFIS	Elongation, tensile strength
2018	Yuan, Bodi, et al	SS 316 L	SLM	ANN	Track width prediction
2019	Gajera et al	CL50WS Steel	SLM	FIS	PP optimization
2019	Zhang et al	SS 316L	SLM	ANFIS	Fatigue life
2019	Marrey et al	Ti–6Al–4V	SLM	ANN	PP optimization
2019	Tran et al	SS 316 L	SLM	ANN	Meltpool depth, peak temperature
2019	Khorasani et al	Ti–6Al–4V	SLM	ANN	Surface roughness
2019	Scime et al	Inconel 718	SLM	K-means	Meltpool quality
2020	Nguyen et al	Ti6Al4V	SLM	ANN	PP optimization
2020	Chen et al	AlSi10Mg	SLM	ANN	Printability, track defect
2020	Hassanin et al	Ti6Al4V	SLM	ANN	Mechanical strength
2020	Fotovvati et al	Ti6Al4V	SLM	ANN	Hardness, relative density, surface roughness
2021	Barrionuevo et al	SS 316L	SLM	SVM	Relative density
2021	Demir et al	N/A	SLM	ANN	Residual stress
2021	Hong et al	Maraging steel	SLM	ANN	Geometry compensation
2021	Chi Hun et al	Ti–5Al–5V–5Mo–3Cr	SLM	ANN	Relative density
2021	Sanchez et al	Inconel 718	SLM	ANN	Creep rate
2021	Park et al	Pure titanium	SLM	ANN	Relative density
2021	Mehrpouya et al	NiTiHf	SLM	ANN	Phase transformation temperature
2021	Cao et al	SS 316L	SLM	Gaussian	Dimensional accuracy, surface roughness
2021	Zhan et al	SS 316L	SLM	ANN, SVM	Fatigue life
2021	Perdomo et al	SS 316L	SLM	ANN, ANFIS	Surface roughness
2022	Elangeswaran et al	N/A	SLM	Gaussian	Fatigue Life
2022	Park et al	Ti6Al4V	SLM	ANN	Relative density, surface roughness, PP optimization
2022	Kumar et al	Inconel 718	SLM	ANN, RF, Naïve Bayes	Relative density
2023	Z. Yao et al	Ti6Al4V	SLM	SVM, decision tree, RF	Tensile ductility

for determining optimal PPs of newly used metal powder (Ti–5Al–5V–5Mo–3Cr) in terms of part density. Negligible error rates were achieved in prediction of density, and also determining optimal PPs from pre-defined density values [142]. Sanchez et al. applied ML techniques in order to understand the effect of PPs on the creep rate of parts. The creep rate was predicted with a percentage error of 1.40%. The most important material descriptors were found to be part density, number of pores, build orientation and scan strategy, in order [124]. Table 7 shows overall literature studies chronologically.

In Fig. 12, ML performances are compared for prediction of mechanical properties such as surface roughness, relative density, dimensional accuracy and fatigue life. Different ML performance metrics (R^2 and Root-Mean Square Error (RMSE)) are used. Results show that, ANN algorithms are capable of predicting most significant properties of additively manufactured parts. Fuzzy logic based algorithms are often implemented in prediction problems. Different ML algorithms such as Random Forest, Gaussian algorithm give sufficient performance in Fatigue Life prediction.

6 Conclusions

In this review article, recent ML studies on part property improvements of M-PBF parts are comparatively investigated. Furthermore, M-PBF production techniques were studied in terms of their processing stages (pre-processing, post-processing), parameters and material types. Recent

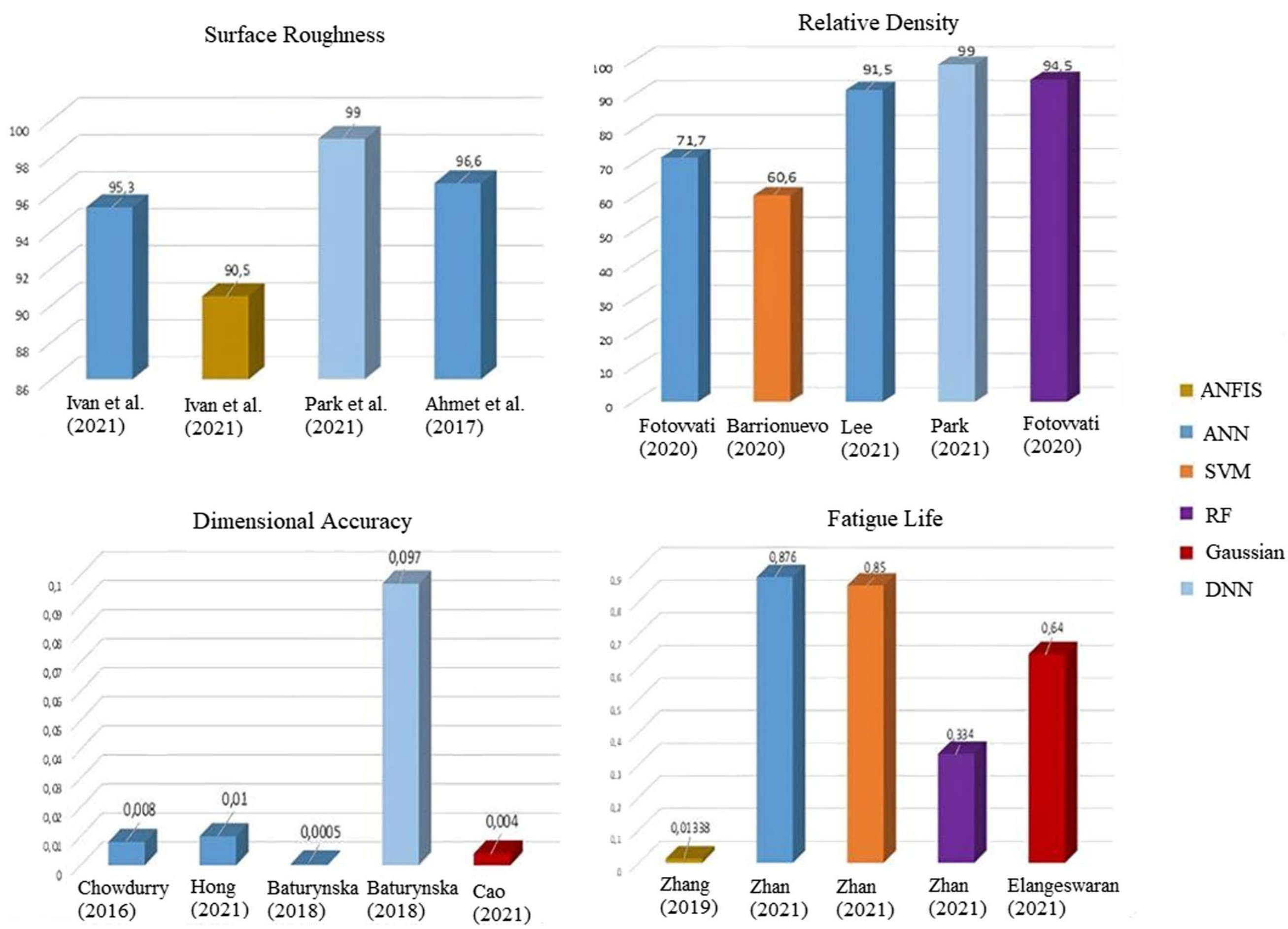


Fig. 12 ML performance metrics of different studies in terms of mechanical part properties

studies show that, time and cost dependent factors were pushed research strategies to search novel methods such as AI, ML algorithms etc. Process modelling and experimental design improvements yielded sufficient results in prediction, classification problems. Accurate M-PBF process modelling was a vital resource in ML construction. Since process modelling in M-PBF is still in progress, research trends should focus more onto this field.

Especially, powder particle attractions during thermochemical process, spreading of powder particles, heat transfer between particles and substrate, process parameters effect on production should be investigated thoroughly. Exploiting some of the high-fidelity simulations which are developed lately, would be a possible solution for those factors.

State of the art indicates that ML modelling can predict mechanical properties of produced parts with a negligible error and optimization techniques are applied efficiently to maximize/minimize the given target output. Literature studies also showed that SLM process is the most preferred method, which is combined with ML algorithms. There are only a few studies with other M-PBF methods possibly because of insufficiency in process modelling ability. Due to fact that the experimental process of M-PBF is expensive, DOE methods are guiding researchers to evaluate the process space with an affordable way. Research trends show that, orthogonal DOE is the most preferred method among the DOE methods. For instance, CCD and BBD design methods have systematic approach in creating process space of problem and they were often implemented in M-PBF for the reason of creating input & output relations more clear and independent.

The frequently studied materials on ML are SS 316L, Ti6Al4V, Inconel alloys etc. Literature studies also indicated that most of ML algorithms in M-PBF were used as supervised ML algorithms which mainly yield adequate solutions in the cases such as; prediction of mechanical properties, process parameter optimization regard to specific part property, classification of process anomalies and geometric deviations in parts etc.

Since M-PBF method covers wide range of material types, different unique materials such as Al alloy series, Cr-Co, Copper should be chosen for the future ML studies which will further expose the relationship between novel material properties and AM methods. Furthermore, a generalized ML model that predicts mechanical responses for a given input, which is independent of material selection, could be another future direction.

Most of the study reveal that experimental strategy doesn't include DOE methods. It is proven that systematically gathered data gives effective results on ML models [149, 150]. Therefore, ML modelling shall be organized with systemic data collection (DOE methods) to be able to get results with minimized cost and high performance.

On the other hand, produced parts were investigated in terms of their mechanical properties, however there are only a few study which uses ML models to predict and optimize dynamic characteristics of parts(e.g. natural frequencies, mode shapes). So, one of the future perspectives should be regarding the investigation of dynamic behavior of produced M-PBF parts by using ML technology.

Finally, despite the fact that there are several challenges, M-PBF methods have remarkable advantages in terms of complex structural part production with minimum post-process need, relatively small amount of lead time, less feedstock wastage etc. Therefore, ML modelling will be one of the appropriate technique to be able to implement those advantages into the industrial practices in the near future with a cost-effective way.

Acknowledgements The authors would like to acknowledge that this paper is submitted in partial fulfilment of the requirements for Ph.D. degree at Hacettepe University. It is supported by the Hacettepe University Scientific Research Projects unit under BAP Project ID-20225. The authors would also like to thank the Additive Manufacturing Technologies Application and Research Center (EKTAM) team, Gazi University, Ankara, Türkiye for their technical support.

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