An overview of strategies for identifying manufacturing process window through design of experiments and machine learning techniques while considering the uncertainty associated with.

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Abstract. The industry sector has long been seeking methods to enhance its manufacturing system control, production, and monitoring, while maintaining the quality of its products and reducing costs and time. One method for achieving a more comprehensive understanding of the manufacturing processes is the identification of a corresponding process window (PW). However, there is no globally accepted definition of process window, which is principally used in different manufacturing processes. In some cases, it is combined with operating window or process map concepts. In light of the aforementioned consideration, this article puts forth a definition of process window, drawing upon the various notions and aspects related to the optimal process parameters selection as discussed in the literature. Furthermore, the identification of key controllable process parameters and the criteria to delimit boundaries of desired parts are described as aspects to identify the corresponding process window. Moreover, this paper provides an overview of the techniques used to establish a process window, principally through the application of machine learning techniques (ML) and design of experiments (DOE). Furthermore, the uncertainty intrinsic to the manufacturing process and the methodologies employed to identify the process window are examined. In conclusion, this article emphasises the necessity of transferring these models to new materials or machines, which will require further investigation in future research.

Keywords: Manufacturing Processes, Process Window, Design of Experiments, Machine Learning Techniques, Uncertainty.

1. Introduction

The industry sector has long been seeking methods to enhance its manufacturing system control, production, and monitoring, while simultaneously improving its manufacturing sustainability approach and ensuring the production of high-quality products in a cost and time-effective manner [1]– [3]. To address these challenges, many research studies has been conducted in different manufacturing processes. The objective has been to establish the relationship between process parameters and the quality of parts fabricated, as well as to identify methods for selecting or optimising these parameters.

Indeed, previous studies have underscored the significance of enhanced performance and quality in products through the understanding of effective modelling, control, and monitoring of process parameters across diverse manufacturing processes. However, there exists a complex relationship between manufacturing process parameters, material properties (mechanical, chemical, and thermal), and geometrical characteristics on parts fabricated, ensuring quality and repeatability. In order to address this complexity, different studies have been carried out to establish a systematic approach to determine the impact of process parameters [4]– [7].

A study whose objective is to analyse and evaluate the influence of various process parameters in different mechanical properties is referred to in the literature as a "parametric studies" [8]–[13]. The objective of research studies in this field is to establish a relationship between process parameters and part properties with a view to determine which parameter combinations are more effective. In order to achieve this, studies focus on how to model the interactions between the two. The modelling of the relationship between input workpiece material properties, output quality parts (geometric and material properties), and in-process parameter settings (machine and equipment) is regarded as an abstract representation [3], [14]. For example, [9], [15] emphasise the importance of establishing a quantitative process-structure-property-performance (PSPP) relationship in metal additive manufacturing to enhance comprehension of the physics associated with the process.

There also exists different reviews concerning the identification, selection, optimisation and so forth of manufacturing process parameters, in additive manufacturing [1], [16]–[30], in laser cutting process [31], metal spinning [32], in extrusion [33], in plastic injection moulding [34], hydroforming [35], single point incremental forming [36], friction stir welding [37], resistance spot welding [38], laser welding [39], heat treatment [40] to cite some of them. One method for a more comprehensive understanding of the manufacturing processes described in the aforementioned reviews, is to delineate the corresponding process window (PW), considering the diverse technical specifications of the parts being fabricated [41]. For instance, in the context of the moulding process, specifically in the case of vacuum assisted resin transfer moulding (VARTM), PW were derived from parametric studies that considered limits of processing parameters. This was done with the objective of reducing non-desirable effects on the resin rheology, using a simplified numerical simulation model [42]. Additionally, PW may offer valuable insight into the design and implementation of an active control system for monitoring the manufacturing process [43].

The present article therefore addresses the application of PW in manufacturing processes. The current article does not address the utilisation of PW in chemical industrial processes. However, it is worth noting that this concept is widely used across different industrial sectors with the same objective of selecting process parameters. It is therefore necessary to specify which type or family of manufacturing process is the focus of this article. Manufacturing processes have been classified by Todd et al. (1994) into two families: shaping and non-shaping processes [44]. The term 'shaping processes' was used to describe manufacturing processes that result in modification to the geometry of the part. These processes can be further classified into three categories based on the final mass of the manufactured part: mass reduction, mass conservation, and mass increase or joining. Non-shaping processes were classified into two principal types: heat treatment and surface finishing. Nevertheless, the term 'shaping' could be confused with the manufacturing shaping process, which is carried out in a shaper machine tool use to remove material from a workpiece [45].

Another manufacturing process classification is found in the DIN 8580 norm, which is a widely recognised standardisation. The DIN 8580 norm classifies manufacturing processes into six principal groups, which are identified by their original German names in parentheses. These groups are as follows: primary shaping (Urformen), forming (Umformen), dividing (Trennen), joining (Fügen), modifying material property (Stoffeigenschaft ändern), and coating (Beschichten) [46], [47]. The terms were translated from the original German text and taken from the 'Metal Forming Handbook' [47]. However, the term 'shaping' is reintroduced in this classification, accompanied by the term 'primary' in order to differentiate it from the aforementioned shaping process. However, to prevent any misunderstanding, it should be noted that, rather than employing the term 'shaping', the alternative term 'forming' is used. This results in the term 'primary forming' being applied in its place.

The primary forming processes are those which create an initial structure from raw materials. These processes include casting, injection moulding, powder metallurgy, and additive manufacturing (AM), amongst others. Material forming is the process of modifying the shape of a material through controlled geometry without the removal of material. This encompasses a range of techniques, including forging, rolling, extrusion, stamping, and drawing, among others. The term "dividing" refers to the local separation of material, which encompasses a range of processes including cutting, shearing, drilling, milling, turning, and so forth. The term "joining" is used to describe the process of assembling individual workpieces to create sub-assemblies. This encompasses a range of techniques, including welding, soldering, and brazing, among others. The term "coating" is used to describe the addition of thin layers to components. This process encompasses anodising, galvanising, painting and electroplating, among other techniques. The modification of material properties entails a change in the intrinsic characteristics of a given material, with the objective of enhancing its overall performance [46].

The manufacturing processes classification employed in this study is that set forth in the DIN 8580 norm. The processes that are the primary focus of this article are those related to primary forming, dividing, forming, and joining. It should be noted, however, that the term 'forming' can also be understood in the context of 'forming technology', which encompasses subtopics from other main groups, including dividing and joining [47]. The aforementioned confusion is not a factor in the present article, as the relevant processes are included within the scope of this paper. References related to the modification of material properties, coating manufacturing processes, and those used for semiconductor device fabrication are included briefly for the purpose of comparison with existing methodologies, given the relevance and evolution of the PW concept.

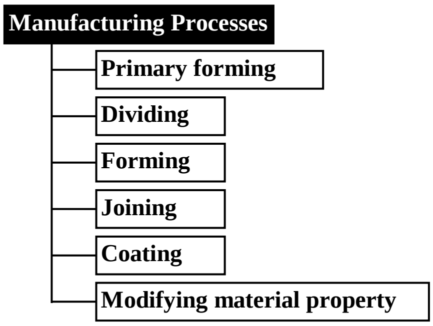

Fig. 1. Classification of manufacturing processes according to DIN 8580 norm [46].

PW has been effectively employed in the literature on lithography processes for semiconductor manufacturing production – as evidenced by the work of Van den Heuvel et al. [48]. This would facilitate comprehension of the physical phenomena involved and enable the identification of a robust manufacturing point. Furthermore, surrogate models include well-established methods such as linear regression and polynomial regression, as well as machine learning (ML) techniques employed to identify the corresponding PW. Indeed, there has been a notable increase in the utilisation of ML in the optimisation of diverse manufacturing process parameters, particularly in instances where a substantial volume of data is available, and statistical data-driven methodologies are being proposed [49], [50].

The objective of identifying PW is to establish a correlation between the processing parameters and the input workpiece material properties with the quality of the resulting parts. To illustrate, the identification of PW (in the casting process) could prove invaluable in understanding the critical parameters to be controlled during the process parameter specification, with the aim of avoiding solidification defects [51]. In an industrial context, the application of PW in the moulding process allows start-ups to fabricate products that meet acceptable standards. This is achieved by establishing the range of processing conditions for a particular process and highlighting that any variation made on the design and/or fabricating equipment of the product will result in a different PW [52]. In AM, the establishment of PW is essential to fabricate reliable and durable parts [53].

Similarly, manufacturers must generate their own sets of parameters for each material or machine when using aluminium alloys in friction stir welding (FSW) and AM selective laser melting (SLM) processes [54], [55]. This is because the optimal parameter values are not yet transferable between machines [56]. Furthermore, inconsistencies have been identified with regard to the properties of the raw material when utilising the same machine, which introduces an element of uncertainty regarding the final quality of parts produced [57]. This highlight the potential benefits of establishing PW, as it could streamline the process for manufacturers in determining an optimised parameter set [58].

Fig. 2 illustrates the shape modification of PW in relation to the material, employing the same machine and equipment for experimentation in the FSW process. This work clearly shows that and PW cannot be transposed from one material to another, because each material has its own combination of processing parameters. Therefore, requires a dedicated experimental campaign for each material. In fact, an FSW PW is only valid for a defined configuration such as: material, thickness, tool geometry, and machine.

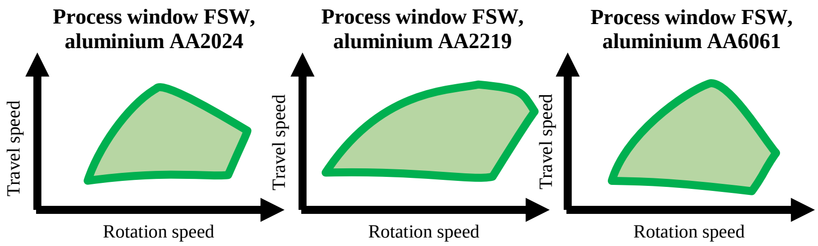

Fig. 2. Three different PW domain shape in FSW process using different material (aluminium alloys). Based on [55].

Nevertheless, PW identification is occasionally challenging. For instance, limitations in AM simulation tools including time-consuming and high computational costs (referred to as hardware characteristics) which can impede parameter calibration due to the coupling of complex thermal interactions in the manufactured parts as well as their geometry, clamping, and other factors. Similarly, in the hot metal gas forming process a complex relationship exists between heat transfer, deformation, and microstructure evolution. This necessitates a multidimensional mapping between the process parameters and the critical evaluation methods [59]. This results in a constrained process parameter space with relevant results [15], [59], [60].

Consequently, the absence of reliable simulation tools for certain processes [49] has prompted the implementation of empirical investigations, frequently based on a classical design of experiments (DOE) methodology incorporating expert input and a multitude of trials [58], [61]. Similarly, in the development of new materials, for example, for AM processes, it is necessary to conduct empirical studies with a limited number of parameters to be investigated in the characterisation of material properties. This requires a significant investment of time, effort, and human resources [62].

Given the considerable number of articles that employ the PW concept, the various techniques that are available for its identification, and the relevance of the transferability of PW as a topic for future research, the objective of this paper is to provide an overview of the strategies developed in the currently literature to identify PW in different manufacturing processes, with a particular focus on the utilisation of

ML and DOE techniques, while also considering uncertainty quantification. Furthermore, this paper highlights potential directions for future research in this field.

Accordingly, this paper is structured as follows and the logic of the structure is illustrated in Fig. 3. Section 2 presents a review of the definitions of PW as they have been used in the literature with respect to different manufacturing processes. Furthermore, this section introduces the manufacturing process aspects that are used to identify the corresponding PW based on key process parameters and criteria that delimit boundaries. Section 3 presents a review of the evolution and limitations of PW identification techniques, including analytical models, numerical simulations, and physical experiments. It also introduces the use of ML and DOE techniques. Sections 4 and 5 describe the principal ML and DOE techniques used in PW identification, noting their advantages and limitations. Additionally, potential insights for future research are presented in both sections. Furthermore, the inherent uncertainty associated with manufacturing processes and identification techniques must be considered, this is addressed in sections 3, 4, and 5. Section 6 provides a summary and section 7 conclude the article.

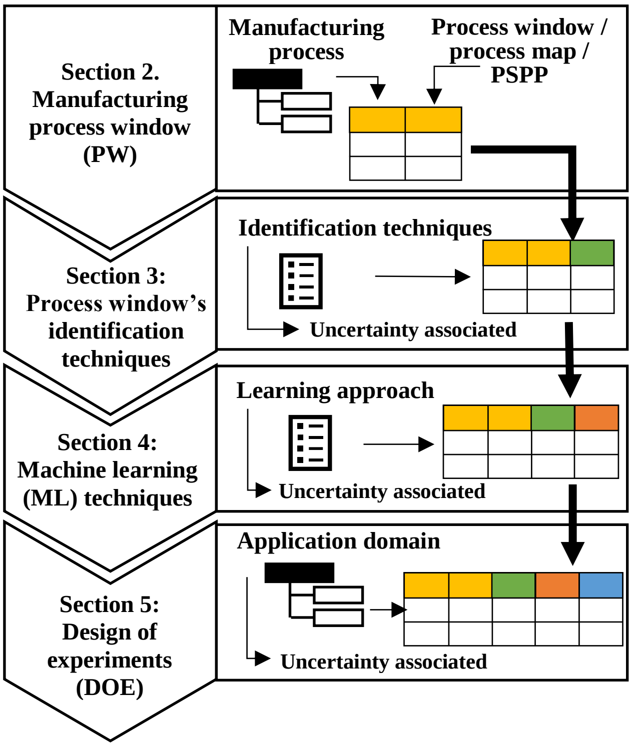

Fig. 3. Structure of the paper and mapping between sections.

2. Manufacturing process window

2.1. State-of-the-art methodology

A search on the Scopus database was conducted in order to identify the most frequently occurring keywords associated with the concept of PW. The preliminary search, utilising the terms “process window” and “processing window” (enclosed in parentheses and quotation marks to narrow the scope of the query) yielded 8,324 documents. Subsequently, a refined search was conducted focusing on subject areas such as: “Materials Science”, “Engineering”, “Computer Science”, and “Mathematics” returned 7,722 documents (status on 24th October 2023).

The subsequently phase entailed utilising the VOSViewer software. The author keywords yielded 13,623 keywords with a single occurrence. Additionally, typos and abbreviations were identified and rectified through the utilisation of a thesaurus file that was specifically created for this purpose. Next, the 100 words with the highest occurrence rates were selected (with a threshold of 23 occurrences), and five clusters were discerned as illustrated in Fig. 4. An initial interpretation of these clusters was conducted.

The first cluster (indicated by the red circle in Fig. 4), encompasses keywords pertaining to the utilisation of the PW concept across diverse domains. These include (1) manufacturing processes such as additive manufacturing (powder bed fusion, selective laser melting), friction stir welding, and injection moulding; and (2) materials such as composites, steels, titanium alloys, and aluminium alloys. (3) The third category encompasses the properties of parts, including mechanical and thermal properties, as well as microstructure. Finally, (4) the methods associated with identifying these properties include design of experiments, response surface methodology, numerical simulations, and finite element modelling. It is important to note that the objective of this article is to provide an overview of the techniques employed to identify a process window in manufacturing processes.

The second cluster (indicated by the green circle in Fig. 4) is focused on PW. However, in this case, the keywords that appear to be connected are more closely related to the application of lithography processes in semiconductor production. This involves the mention of various techniques, including optical proximity correction, resolution enhancement and so forth. The third cluster (indicated by the blue circle in Fig. 4) maintains a focus on lithography, albeit in a more general sense, encompassing process control and metrology aspects. Furthermore, the algorithm employed by VOSviewer positioned the machine learning concept within this cluster. The aforementioned clusters serve to illustrate the significance of the PW concept within the context of in semiconductor device fabrication.

The fourth cluster (in violet in Fig. 4) includes only two words, namely ‘block copolymer’ and ‘directed self-assembly’, which are not relevant in the context of this study. The fifth cluster (depicted in yellow in Fig. 4) includes only four keywords and is associated with the concept of “processing maps”. This concept is deemed relevant due to its connections with microstructures. The initial description of each cluster provides an overview of the primary connections between the most relevant keywords related to the PW concept.

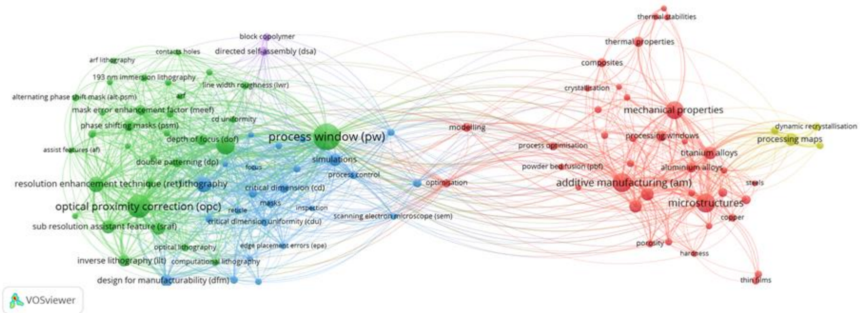

Fig. 4. The most recurrent keywords relationship with PW and concepts related. VOSviewer.

Accordingly, the selection of articles related to the PW concept and related concepts, including process map (PM) and process-structure-property-performance (PSPP) with a focus on identification, discovery, determination, estimation, or definition yielded 765 documents (last accessed on 7 November 2023). The precise research query is illustrated in Fig. 5. In order to focus on high-quality articles, the documents were filtered to include only journal articles, with any duplicate articles removed. Subsequently, a screening of the abstracts was conducted to restrict the articles to those related to manufacturing processes or semiconductor device production, resulting in 272 documents. Finally, a full-text article review was performed to identify the articles that proposed a methodology to identify PW, resulting in 94 articles. The methodology is illustrated in Fig. 5. Further research was conducted on July 19th, 2024, resulting in the addition of 13 new articles.

The terms “process or processing window”, “process or processing map”, “operating window”, and “parameter window” have been employed in various manufacturing and chemical processes since the 1970s to describe the selection of process control parameters. The terms “process window” and “processing window” were used interchangeably in a curing system (chemical reaction process) of polymers, where the notion of “range” describes the relation between key properties of polymers and curing reaction parameters [63]. The term “processing window” was employed in a chemical process (hydroliquefaction of coal) [64] to identify the optimal interaction between various processing parameters (i.e., optimum combinations – processing windows) by presenting them graphically with a contour plot. This paragraph illustrates the use of the PW concept in chemical processes, demonstrating its applicability at a large scale and introducing two fundamental characteristics: the notion of range and the graphical representation of the domain of required parts. The definition of PW in different manufacturing processes will be elaborated in the 2.2 subsection.

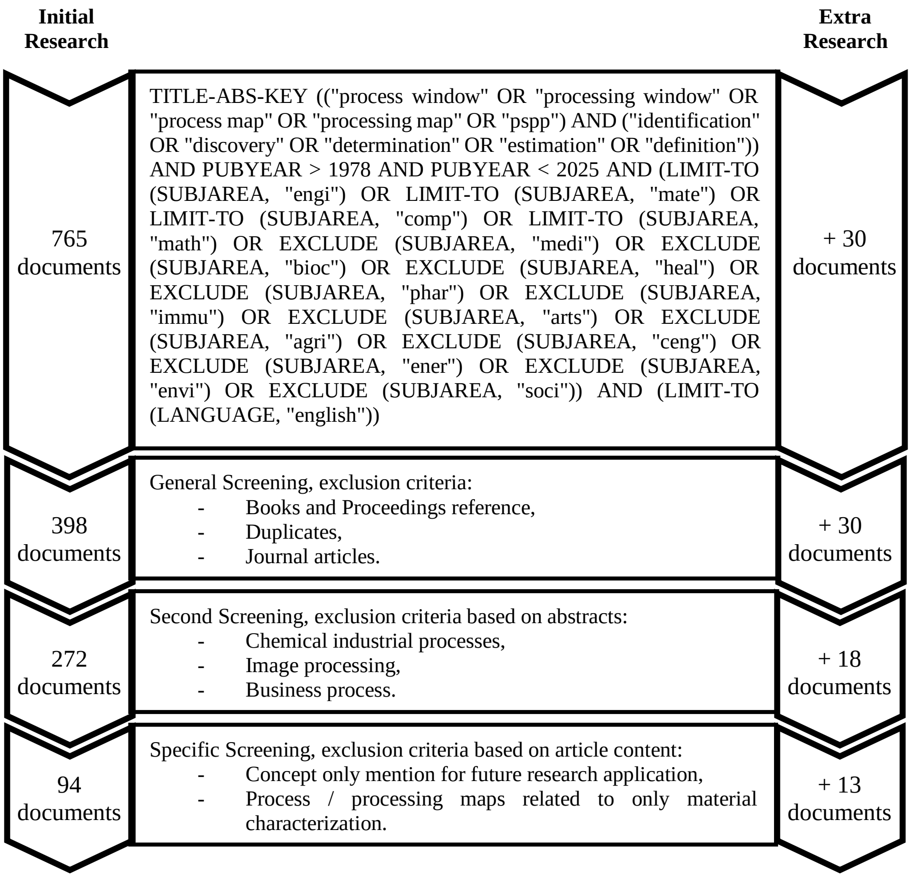

Fig. 5. Research methodology.

In light of the extensive range of manufacturing processes considered in this article, it is crucial to identify the principal process parameters and the various fundamental mechanisms that regulate the fabrication of the desired parts. The **Erreur ! Source du renvoi introuvable.** and 2.4 subsections present a comprehensive account of the key controllable process parameters and criteria for defining the boundaries of PW. The structure of these subsections is based on the classification of manufacturing processes presented in Fig. 1 based on the DIN 8580 norm. Indeed, the literature contains a variety of concepts that aim to identify manufacturing process parameters according to mechanical or geometrical criteria pertaining to the parts fabricated and the manufacturing process employed. To illustrate, the concept of a PM is primarily concerned with identifying process parameters, particularly in material forming processes based on thermal and mechanical properties including strain, strain ratio, and so forth. The concepts related to this topic will be elaborated upon in the 2.5 subsection.

2.2. Definition of process window in manufacturing processes.

In the context of manufacturing processes, welding processes were identified as one of the earliest applications of this concept. As stated by Vivek et al., some of the earliest works on welding windows are from Wittman (1973) [65] and Deribas et al. (1975) [66], who were interested in relating welding parameters with the properties of the welds [67]. The welding PW represents, in a plot, the optimal ranges of different welding parameters, indicating the presence or absence of a good weld. It should be noted, however, that the plot does not represent any mechanical properties of the material that could be used to describe a good weld.

PW has been employed to define one or more optimal material properties (e.g., mechanical, thermal, etc.) and/or geometrical aspects of parts fabricated as a function of combinations of process parameter ranges, with the objective of avoiding the formation of defects that are undesirable [68], [69]. The region defined by the PW varies according to the configuration, including the raw material (thickness and heat treatments), tools, machine, and so on, which are employed due to changes in the operating window. The term ‘operating window’ is used to describe the range of process parameters that can be employed without any specific quality requirements being met, given the capabilities of the machines that are being used [43], [70]. The terms ‘operating window’ and ‘PW’ have been used interchangeably in the literature [71]. It is, however, important to note the distinction between the two, as the PW considers the ranges that respect the quality requirements in the machine process parameters ranges.

A definition of PW was provided in a PhD thesis that focused on lithography processes, the author [72] defined process windows as ‘*the description of process capability that must match the process requirements to guarantee an acceptable performance*’. In the semiconductor device fabrication, PW is referred to as parameter range in which the etching result is acceptable, although it may not represent the optimal outcome [73]. In FSW process, PW is defined as “*the parameters resulting in a successful material welding*”, principally without internal defects representing sound welds [74]. In AM processes, Barera et al., defined PW as a function of an upper and a lower limit [75]. In SLM processes, Evgenov et al., defined the PW as ‘*the values of the specific energy density at various principal parameters to obtain a material with a density close to the theoretical value*’ [61]. Aoyagi et al., defined PW ‘*as the region in which defect-free parts can be manufactured with the volume of region defined as the volume of the region with a probability exceeding 0.5 in the process map*’ [76].

However, given the differences in PW area application, a definition is required. Therefore, this paper proposes a definition based on an analysis of the relevant literature, which is as follows: PW is defined as the optimal region (set of optimum range combinations) of principal process parameters (operability conditions or process production settings) in the process parameter space that assures repeatability and reproducibility of quality and performance product material and geometric properties. To assist operators in controlling the process parameters, PW is represented graphically denoting the principal process parameters in axis (as Fig. 6 illustrates).

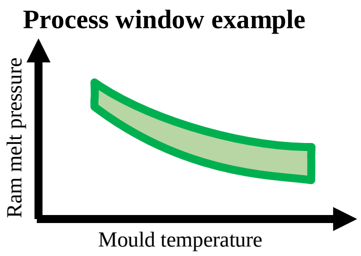

Fig. 6. PW graphical representation example in moulding process. Based on [52].

2.3. Key controllable process parameters

The number of parameters involved in each manufacturing process varies according to its inherent complexity. It is, therefore, essential to differentiate between key controllable process parameters and secondary controllable parameters [77]. In essence, key controllable process parameters are those that the operator controls, and the modification of their values results in a change in the quality of the parts that are fabricated. In contrast, secondary controllable parameters are fixed in accordance with two distinct scenarios. The first is based on the desired quality requirements, which are optimised to ensure they are respected (when sufficient knowledge about the process exists). The second is fixed arbitrarily.

In the following sections, the term 'key process parameter' will be used to refer to the key controllable process parameters and secondary controllable parameters will be referred to as 'secondary parameter'. Parameters that could be measure but not controllable are referred as 'non-controllable parameter'. To illustrate this distinction, in FSW, the key process parameters are the tool rotational speed (N), the tool traverse speed (v), and the axial (plunging) force (Fz), while secondary parameters include the tool geometry, the tool tilt angle, and so forth [78].

Primary forming processes. As observed by Chang et al., the quality of products manufactured in moulding processes is primarily influenced by three main categories of parameters: machine, control, and process [56]. Of these, the latter has the greatest impact on product quality, necessitating rigorous monitoring to ensure optimal outcomes. The process parameters in moulding encompass a range of variables, including temperature, uniformity, viscosity, flow speed, density, pressure, solidified layer, and internal stress of the polymer melt. The moulding parameters are related to the injection pressure, injection speed, holding pressure, holding time, and the timing of V/P (speed and pressure) switching.

Additive friction stir deposition (AFSD) is a process that combines friction stir deposition (FSD) with AM. The key process parameters include the tool rotating speed (ω), feed rate (F) or axial force (AF), tool traverse velocity (V), single layer height (H), and layer width (W) [12], [79].

In selective electron beam melting (SEBM), [80] observed that there is a lack of literature identifying the corresponding PW of titanium-aluminium alloys.

Consequently, the authors determined it by considering the energy density and scanning speed as principal parameters and their effects on surface defects, porosity, and Al loss. In the context of electron beam powder bed fusion process (PBF-EB), [81] highlighted that the process parameters are typically derived from material-specific PW, which are identified through the use of standardised cuboid specimens to delineate the boundaries of two principal process parameters (scan speed and beam power).

In the laser powder bed fusion (L-PBF) process, a number of different scan parameters were identified including the laser power (LP), laser speed (LS), laser focus (LF), point distance (PD), exposure time (ET), layer thickness (LT), and hatch distance (HD) [82]–[86]. Furthermore, Candela et al., outlined the process parameters that influence the surface quality (surface roughness) of additively manufactured parts, including layer thickness and particle size, sloping/overhang angle, surface parameters (cross-section perimeter and inner areas), and the use of support to attach the parts [83]. Furthermore, the present study examined the impact of scanning speed, laser power, and hatch spacing by selecting the ranges of parameters in accordance with the literature on volume energy density.

In the context of laser metal deposition (LMD), the key process parameters include laser power (P), scanning speed (S), and powder feeding rate (F) [58]. In wire arc additive manufacturing (WAAM), the key process parameters are wire feed rate (WFR), and travel speed (TS), and weave amplitude (WA), as demonstrated in the study conducted by Jadhav et al., [87]. In the case of AM using thermoplastic polymers, Barera et al., identified the deposition temperature as the principal parameter used to define the PW, noting that it can affect the processability and the adhesion between layers [75].

Dividing processes. As previously stated by Sommer et al., the high-speed milling key process parameters can be primary classified into two categories: geometrical and milling process [88]. In their study, the authors considered two geometric milling parameters: The Z-pitch in micrometres of the milling cutter and the infeed in micrometres, and two milling process parameters, including spindle speed n in rotations per minute and feed rate v_f in millimetres per minute. In the case of turning (machining) as outlined by Holmberg et al., the key process parameter are cutting speed (v_c), feed rate (f), and depth of cut (ap) [89].

Forming processes. In the case of the spin forming process (a mass conserving process), the component forming PW can be determined by considering the following parameters: roller nose radius (r_ρ), the roller feed ratio (f), the deviation ratio (Δ_{max}), and the roller oblique angle (β) [90].

The key process parameters in hot metal gas forming processes are plotted in consideration of the relationship between the tube temperature and gas pressure over time, as demonstrated by Ruan et al. in their research utilising boron steel tubes [59]. In the context of dieless laser drawing processes (for further insight into the process, see this article [91]), the primary parameters that exhibited variation were the extrusion temperature and the ram speed while other parameters were maintained at constant level.

Joining processes. In the context of resistance welding process, PW establishes the combination of two principal parameters (input power and heating time) that results in the generation of acceptable welds, while maintaining other secondary controllable parameters at a fixed level. In this instance, the welding pressure represents one such secondary controllable parameter [92].

In laser beam welding processes, a distinction can be made between two regimes: heat conduction welding (HCW), and deep penetration welding (DPW). The latter serves to define the PW, with the key process parameters being feed rate and laser power [93].

2.4. Criteria to delimit boundaries of PW.

The criteria used to define boundaries of PW are dependent on mechanical and geometrical aspects, including dimensional accuracy, surface integrity, and the presence of defects, among other factors. These criteria vary depending on the manufacturing process, the raw material, and the requirements of parts being fabricated.

Primary forming processes. In the context of moulding processes, an essential indicator of the quality of the moulding is the viscosity of the polymer during the melting process. A high value of this could potentially result in the formation of quality defects, such as under-filled and insufficiently sized parts. This criterion is influenced by a number of factors, including the parameters used to plasticise the material, the characteristics of the machine used, the characteristics of the raw material, and the parameters employed during the moulding process [56]. Roti [94] proposed a scientific moulding framework that considers four plastic factors such as heat energy, pressure, the flow state, and the cooling process. These factors are to be measured using sensors in order to ensure the quality of the moulded parts. Furthermore, the implementation of a PW in the moulding process can be regarded as a means of optimising the parameters associated with injection moulding. In this context, the melt temperature and holding pressure represent the primary process parameters, with the objective of producing finished products that adhere to a specified visual standard and ensure process stability.

In the context of AFSD process, the boundaries of PW are primarily delineated through the modulation of two principal process parameters, while the remaining parameters are maintained at a fixed value. For instance, in order to prevent the formation of surface defects, such as excess flash, voids, and galling, the primary parameters that must be regulated are the feed rate (F) and tool traverse velocity (V). In the event that the objective is to regulate the heat input and subsequently the peak temperature, along with other factors such as exposure time, heating rate and cooling rate, the parameters that must be controlled are the tool rotating speed (ω) and the tool traverse speed (V) [79]. Anderson-Wedge et al., identified the process parameter map of the AFSD process using aluminium alloy AA2219 [12]. They considered tool rotational speed and tool traverse velocity as principal parameters and microhardness and grain size as criteria to determine the local optimal process parameter set.

To illustrate in AM process, Juechter et al., proposed porosity (sound weld) as a mechanical criterion for determining the PW associated with the SEBM process, which represents the initial step in the development of a comprehensive processing chain [95]. In the context of laser dieless drawing (LDD), Milening et al., proposed a finite element method (FEM) model that was subsequently validated through experimentation [96]. This model was designed to identify a range of permissible technological process parameters via an inverse analysis, considering two distinct mechanisms of neck formation. In the context of electron beam melting (EBM), Kan et al., proposed that in order to identify the PW associated with the EBM process, it is essential to consider the physical aspects of thermal and fluid dynamics during the modelling process, with the aim of obtaining a respective microstructure [97].

In L-PBF process, Genç et al., identify the challenges associated with the fabrication of complex NdFeB magnets, including porosity/cracks, thermal stress, and defects in magnetic properties resulting from the rapid cooling rate and temperature differential between layers [82]. Similarly, in the L-PBF process utilising niobium, Candela et al., defined the PW based on surface roughness and defects, including dross formation and deformations [83]. Similarly, Koju et al., employed keyhole porosity as a criterion for defining the corresponding PW [84]. Conversely, Agricola et al., employed volume energy density (VED) or area energy density (AED) as a basis for selecting parameters [98]. In the context of LMD, Gao et al, used microhardness, surface roughness, and deposition rate as criteria to define PW limit boundaries [58].

Guepner et al., stated that the PW is defined based on two process limits considering constant aspects of parts fabricated and the lower or the higher values of the parameters according to defined criteria to respect quality requirements [99]. Indeed, the initial process limit in the LMD process is found to be associated with power, specifically in relation to the penetration zone. The subsequent process limit is identified based on the impact of varying the initial influential process limit on the efficiency of the process, which in turn affects the feed rates.

In the context of SLM process, as previously discussed by Ahn, the single-track test (STT) is a widely employed methodology for identifying the corresponding PW of the SLM process [100]. However, there is a considerable divergence of opinion in the literature regarding the laser melting conditions that should be applied from the results of top and section view analysis of varied materials. Nevertheless, given the intrinsic nature of AM, the identification of the PW must be based on the analysis of multi-layered parts. Moreover, they proposed a methodology for the construction of a stable PW, which provides more detailed information about the geometrical and surface qualities of parts. This methodology involves the consideration of the layer thickness as a criterion for evaluation.

A different article in the SLM process highlighted that the simulation and physical experimentation, which are typically based on trial and error, require a significant investment of time and resource to gain a comprehensive understanding of the relationship between process parameters and defects [101]. This is why Promoppatum and Yao proposed an analytical model based on defect generation in the melt [101]. Ghasemi-Tabasi et al. developed a rule for translating optimal parameters from one material to another, which was justified using FEM simulations and validated experimentally on red gold and 316L steel [102]. This rule was based on one measurement of powder absorptivity at room temperature, which respected the same material conditions. Moreover, monitoring the geometry of the molten pool is a common approach for controlling the in-situ quality of AM parts. However, not all the information is captured by sensors, therefore models to predict it are necessary.

Liu et al., developed a novel analytical model to predict molten pool cross-section geometry which was validated on experimental and numerical simulation of single-track SLM parts [103]. This model has the potential to be used to determine the PW, which in turn allows processing parameters to be optimised in a quick and efficient manner. Another criterion that is used to quantify the quality of the print parts is to measure the width and the depth of the molten pool using numerical simulation.

In WAAM process to delimit the PW, the bead cross-section measurement could be used to determine the microstructure, surface roughness, mechanical properties (e.g., tensile, microhardness, and so forth) of walls or single-track layer fabricated [87].

In the context of screw extrusion AM of thermoplastic polymers, Barera et al., observed that defects in tools, such as voids, cracks, and porosity, can affect the quality of the surface finish [75]. It is therefore essential to implement an appropriate printing strategy, utilising PW with suitable parameters, in order to ascertain the requisite quality criteria, including thermal stability, predictable expansion, minimal residual stresses and reduced warpage.

Dividing processes. In the context of high-speed milling work coupled with AM [88], the criteria employed to delineate the PW were based on the surface roughness of the Ni superalloy IN718. In the study conducted by Holmberg et al., which was applied in the turning (machining) process, the criteria used to define process parameters were based on three key factors: surface integrity (roughness), microstructure, and microhardness [89].

Forming processes. In the context of spin forming, the objective is to establish a forming PW in a manner that avoids the occurrence of fracture damage on the forming parts. In order to achieve this, the distribution of damage is quantified by varying one parameter at a time, as demonstrated by the work of Li et al. [90], which employed the use of aluminium alloy AA2219 on the multi-pass spinning damage in the ellipsoidal segment of the component.

In the metal gas forming process, the criteria for defining the PW in the corner zone in tubes are based on microstructural results that demonstrate the complete transformation of martensite [59]. In the case of dieless laser drawing processes [91], the criteria for delineating the boundaries of PW are the changes in wire diameter and the tensile force acting upon the wire. These are used to measure the length of the forming zone, which serves as a quality indicator for the process.

Joining processes. As previously stated in the context of collision welding processes (see reference [67]), the welding window represents the regions (comprising a range of principal parameters) where superior quality welds are typically observed. It should be noted, however, that any mechanical characteristic is given. In contrast, to the findings of [67], [92] indicated that PW are typically delineated through mechanical testing of the joints welded. This leads to the following consideration: while material or, in this case, welded tests are conducted, the PW is limited to microstructure and/or the initial outcomes of the visual inspection in order to maintain a straightforward visualisation tool. In addition, destructive tests are employed to determine the macroscopic characteristics of parts fabricated to detect potential issues such as porosity, hot cracking, elemental segregation, and dilution associated with rapid solidification, particularly in the context of welding processes [79]. In the study conducted by Kaufmann et al., the authors defined the target criteria for identifying optimal welds based on penetration depth and the minimum number of weld imperfections [93].

Modifying material property processes. Rajnovic et al., put forth a novel, more encompassing concept, designated as the "standard" PW in austempering process, which is ascertained through an evaluation of mechanical properties (tensile strength, elongation, etc.) in accordance with a specified standard (ASTM, EN, ISO, or an alternative standard), in contrast to the "microstructure PW", which is determined based solely on the quantitative metallographic outcomes [104]. One point that authors have highlighted is that the "standard" PW does not disregard the microstructure, but rather supplements it by incorporating standard mechanical properties.

2.5. Concepts related

The concept of PSPP, illustrated in Fig. 4 as the initial insight, is a method of mapping processes. Another related concept is the PM, which is used in conjunction with PSPP in the context of PW.

Process-structure-property-performance (PSSP). In 1997, Olson proposed a new approach to understanding the relationship between process, structure, property and performance in manufacturing process design [105]. This involved breaking down the interaction into two distinct paths: inductive and deductive. This approach was late adapted to the field of material design, where modelling is decomposed into forward and backward/inverse modelling. By way of an analogy with PW, the material design space is able to identify regions that respect the requirements, objectives, and constraints of the intended application [106], [107].

Process Map (PM). PM has been employed used in two distinct ways. The first is in the characterisation of material properties, which has resulted in the generation of limit diagrams that are predominantly utilised in material forming processes. The second is in general manufacturing processes, where it is used as a synonym for PW [70].

In the field of material characterisation, PM, also known as P-map, is a key tool in the development of metals and new alloys for hot deformation processes. These processes are typically validated through microstructure studies with the aim of improving their industrial production [108]. As previously stated by Rashkeev et al., the objective of constructing or calculating limit diagrams is to map a region in the parameter space that can be safely executed, taking into account processing operations and the complexities of the process [109]. PM has been extensively employed to ascertain the optimal processing conditions for evaluating the workability and microstructure of the deformed materials in hot working processes, as well as for developing processing routes for diverse materials [110]–[114].

To illustrate, Vaidya et al., decomposed the quantification of the coating properties through two process maps: first–order and second-order process map [115]. The first-order interconnect process parameters, process hardware, and feedstock characteristics (that is to say, the raw material characteristics) are introduced in conjunction with the spray stream characteristics (that is to say, the process) in order to facilitate the introduction of terms of process monitoring and control. A second-order process map establishes a link between spray stream characteristics derived from first-order process maps, and microstructure, along with the observed coating properties. In order to extend second-order maps, PW could be established by superimposing contour maps representing a desired combination of coating properties. Furthermore, PMs were defined as "*an integrated set of relationships that link materials and processes to microstructures, ultimately to properties and performance*" [115]. Thus, PMs aim to understand the influence of "key processing parameters" on the material thermal history and enable the establishment of a PW representing a desired combination of principal properties, which can be represented by a contour map. This map can then be used to construct comprehensive process-microstructure–property relationships [116]. For example, Mokdad et al., stated that the identification of material PM and the utilisation of constitutive equations, enables the establishment of PW in the manufacture of high-performance of carbon nanotubes (CNTs) reinforced aluminium matrix composites (AMCs) [117]. Furthermore, PM have been employed in the context of AM processes. For instance, Aoyagi et al., observed that PM facilitate the correlation of parts properties with process parameters, thereby assisting operators in the control of AM machines and the establishment of an optimal PW [118]. It can be argued that a PM represents a preliminary stage in the establishment of a PW.

Additionally, PM serves as a reference for operators and process engineers in selecting suitable controllable manufacturing process parameters based on the specification of the parts to be fabricated. It can also incorporate operating costs, thereby facilitating the design of robust processes [70], [119], [120]. A significant element of PM is the region that is established, which may be narrower than the extensive operating window. This is due to the fact that superior quality is sought [70]. As a synonym of PW, Ning et al., employed the concept of PM in the forging process to evaluate the efficiency of power dissipation and identify the instability regimes which depend on the microstructures [121].

2.6. Principal characteristics of process window

A significant attribute of PW is that parts fabricated in accordance with a set of specified parameters can be classified into two distinct categories: those that meet quality standards (within PW) and those that do not (outside PW). Another crucial attribute to consider in PW identification is the convexity of the surface (illustrated in Fig. 7), which could assist in reducing the number of experiments required to accurately delineate its boundaries. For this reason, a taxonomy that takes domain properties into account is proposed in Fig. 8.

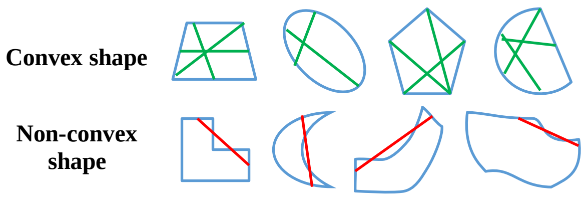

Fig. 7. Examples of convex and non-convex shapes.

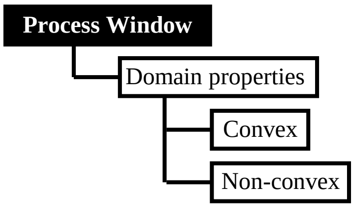

Fig. 8. Taxonomy of domain properties of PW.

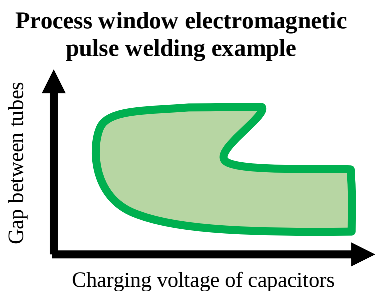

Fig. 9. PW with non-convex shape. Based on [122].

Nevertheless, this convex domain is not always observed. To illustrate, Raoelison et al., identified the weldability window of aluminium alloy 6060T6 in tubular assemblies welded by magnetic pulse welding process, where two convex curves delineated the welding window through the utilisation of destructive testing to characterise the weld quality [122], as shown in Fig. 9.

Tsai and Tang highlighted the aspect of PW related to concave surfaces [106]. In the event that this condition is not respected with the RSM model, a central composite design is carried out to address the issue. Once this is validated, the PW is constructed and then confirmation experiments are carried out to validate it.

3. Process window's identification techniques.

Following the introduction of the PW concept in the previous section, this section presents the identification techniques of PW. Initially the experimental and numerical approaches to identifying PW are described. This is followed by a comparison with approaches to identifying concepts associated. Subsequently, the sources of uncertainty and how they are considered in the identification of PW are presented. Finally, the section concludes with an overview of potential research directions.

3.1. Approaches for process window identification

PW identification is achieved through a process of experimentation, employing a combination of trial-and-error, statistical techniques, analytical models, and numerical simulations. These methods are illustrated in the following paragraphs.

Experimental. To illustrate, Du et al., emphasised the significance of experimental techniques, which serve as the foundation for numerical simulations [123]. Another pertinent consideration is the extensive number of tests that are required to identify the PW, which in part explains why other parameters are being researched and why they are relatively straightforward to measure. In the literature, the use of mechanical tests to determine the PW is occasionally observed to be shorter than the predicted PW in the welding process [92].

For instance, experimental methodologies were developed to qualify means of production by selecting the processing parameters to produce a sound weld, i.e., a weld that is free from any internal or external defects, thus facilitating the implementation of the FSW process [124], [125]. In order to identify the PW, an experimental procedure was carried out in which three principal welding processing parameters were varied until the corresponding PW was found. However, many experiments were carried out to identify the experimental points in accordance with the requirements, and these points did not yield any information about the localisation in the PW.

Furthermore, the FSW parameters were initially identified through a trial-and-error approach [126], [127]. However, this method is inherently time-consuming, necessitates significant computational resources, and requires substantial physical resources. Consequently, developing the PW in FSW could facilitate the identification of an optimal range of process parameters through the analysis of mechanical properties, including tensile properties, the lowest hardness distribution profile, and microstructural analysis.

In their article, Barera et al., set forth four criteria for identifying the PW based on experimental tests conducted on AM of thermoplastic polymers [75]. These criteria include the following: an easy geometry, consistent mechanical test results in both the longitudinal and transverse directions, the ability to vary a single parameter, and the generation of data that is useful for the industry. Similarly, Günaydın et al., developed a method utilising the Non-dominated Sorting Genetic Algorithm (NSGA-II) to ascertain the optimal direction for the fabrication of parts produced by the PBF-L process [128].

Analytical models and numerical simulations. As previously stated by Bur et al., the utilisation of conventional simulation methodologies is inherently limited in its capacity to effectively explore the design space during the optimisation of the automated fibre placement process and the determination of the PW [129]. The development of simulation in AM has been rapid, reflecting growing interest across a range of industrial sectors. Andreotta et al., proposed that accurate simulation could assist in reducing the costly and time-consuming experiments required to identify the corresponding PW in powdered metal AM [130]. It is therefore necessary to develop methodologies to achieve this. Kim et al., proposed a methodology to predict hardness in thermomechanical treatment for hot stamping processes thanks to PW [131]. This method uses FEM simulation coupled with a widely used model (quench factor analysis - QFA) to combine different parameter value combinations and predict hardness in order to train an artificial neural network (ANN) responsible for PW construction. The results were verified with experiments, resulting in an error prediction of 3.1%.

An additional illustration of this approach can be found in reference [132], which employs numerical simulations. A FEM model was developed to simulate the interactions between resistance spot welding process parameters and weld properties. The model was constructed using DOE approach to determine the main effects and interactions of process parameters. This was done with the aim of defining an operating PW for future research. Furthermore, Tsai and Luo, indicated that reverse modelling was used to determine operating parameters in the injection moulding process to obtain a PW at a minimum cost in keeping with the quality specifications of the products, resulting in relevant outcomes within defined limits [133]. The results of the studies demonstrated that numerical simulations could predict the molten pool geometry without the necessity for experimental procedures. However, the models in question require a significant investment of computational resources and time to achieve the desired results. PW offers some flexibility in selecting processing parameters for laminate consolidation by means of a numerical simulation method [103], [134].

As previously stated by Wei et al., further development is required in metal AM numerical models due to the intrinsic nature of forward models [49]. These models take process parameters as inputs and calculate outputs, such as fusion zone geometry, cooling rate, temperature fields, and so forth. However, in many instances, the inverse is required. This is why multiple trial-and-error runs are conducted to identify process variables, given the existence of numerous process parameter combinations that can satisfy a given target attribute (zone geometry, cooling rate, etc.).

In fact, the determination of the optimal PW in AM demands the development of computationally cheap, fast, and connected models to accurate predict thermal histories and melt pool characteristics. This is why, different research groups have created models based on these principles and applied them to welding. To illustrate, Honarmandi et al., adapt the Eagar-Tsai (E-T) model to predict melt pool characteristics from a perspective of uncertainty quantification and propagation [15]. Model parameters are calibrated using single-track experimental data, which are then combined with a physics-based correction to achieve significantly enhanced accuracy. Nevertheless, one of the principal limitations of these models is the oversimplification of complex physical phenomena in the SLM process and the interactions between all the process parameters [103].

When the objective is to identify the optimal process parameter (centred in the zone identified), the problem can be formulated as an optimisation problem. For instance, Guo et al., denoted research studies classification of process parameter optimisation between static (based on a surrogate model that once the model is trained, the model is not updated anymore) and dynamic (based on knowledge or historical cases due to feeding data overtime), as Fig. 10 shows [135]. To illustrate, research following this reasoning for process parameter optimisation can be found in AM processes such as L-PBF [136], SLM [137], and other manufacturing processes including laser welding [138], and moulding [135]. In the automotive industry application, Aslan and Yildiz developed a methodology to optimise the topology by using lattice structures to reduce the weight on a suspension arm [139]. This was conducted using AM to achieve the complex structures and FEM to validate the model improvement.

In a pioneering study, Yıldız et al., employed a novel hybrid Harris Hawks optimisation with Nelder-Mead algorithm (H-HHONM) for optimising process parameters in milling [140]. The approach was benchmarked against a range of metaheuristics, yielding promising outcomes for design and manufacturing optimisation problems. Similarly, Yıldız et al., used the Harris Hawks optimisation algorithm (HHO), the grasshopper optimisation algorithm (GOA), and the multi-verse optimisation algorithm (MVO) [141], while Yildiz, developed an hybrid whale optimisation algorithm based on the Nelder-Mead local search algorithm [142]. The objective of both works is the optimisation of grinding process parameters and other manufacturing design applications.

3.2. Approaches for concepts related identification

Process-structure-property-performance (PSPP). The number of approaches available for exploring the material design space is limited, which has encouraged researchers to focus their attention on different performance-driven design approaches with the aim of establishing links between PSPP relations. Robust design methods following the inductive design exploration method (IDEM), considering the uncertainty associated with design parameters and their propagation in order to mitigate them in design space exploration were developed [107], [143].

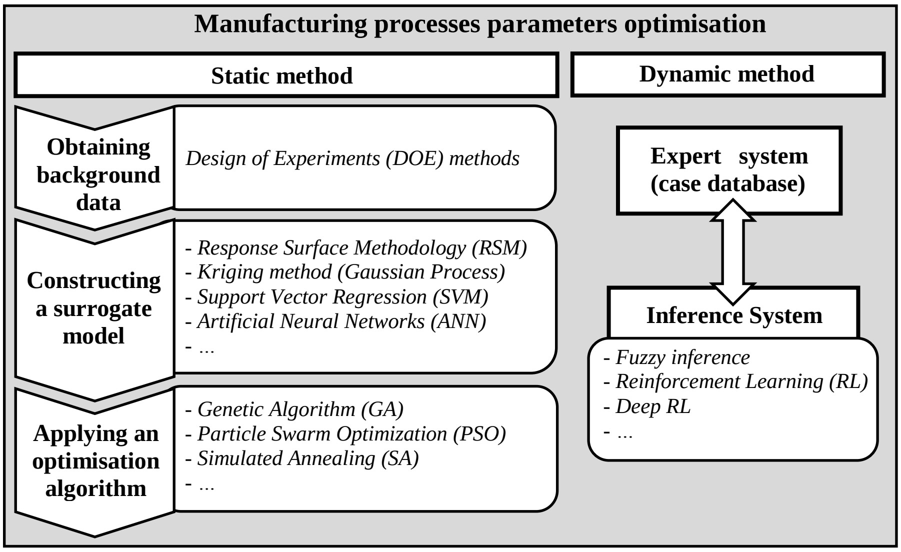

Fig. 10. Manufacturing process parameters optimisation. Based on [135].

Process Map (PM). The optimal working parameters are principally dependent on the characteristics of dynamic restoration mechanisms, namely globularization or dynamic recrystallisation (DRX), superplasticity, and dynamic recovery (DRV), which result in the "safe" domain of the PM [111], [144]. In order to identify the range of appropriate parameters for SLM in the first instance, a PM is constructed using a substantial quantity of raw data based on the energy density criterion, which is not universally applicable to all materials and equipment [103].

The PM for material characterisation objectives, were developed initially with only two variables, namely temperature and strain rate. This resulted in a 2D PM, which was extended from the concept of Ashby's maps to include limiting conditions [145]. A significant advancement in PM was the incorporation of strain into the temperature and strain rate space, leading to the development of 3D PM. These have become a primary tool for investigating deformation mechanisms in the presence of microstructure defects, enabling the visualisation of continuous changes in power dissipation in metal forming processes [117], [146].

PM are typically developed using a dynamic material model (DMM) which combines efficiency and stability maps through a procedure outlined in detail by Prasad et al. in 1984 [108], [112], [147]–[150]. DMM employs two supplementary functions: one that characterise power dissipation and another that delineates the corresponding metallurgical (microstructure) alterations [151]. PM is constructed by superimposing an instability map over power dissipation map, thereby enabling the delineating of flow instability domains and the demarcation of various deterministic domains for the hot working of the alloy [152]–[157].

New methods for identifying PM were proposed, for example, by using the Arrhenius model to quantify the impact of material parameters and calculating the strain-compensated Arrhenius model. This was compared with a genetic algorithm-optimised Arrhenius model, which obtained better results than strain-compensated Arrhenius model [108]. Rieiro and Ruano modified the stability criterion of the DMM framework by introducing a Garofalo equation in the expression of power dissipation and adding a new parameter obtained from experimental data [158]. In order to implement simulation techniques, such as FEM, in the identification of the PM, numerous studies have combined DMM with material parameters modes, for instance, the Arrhenius constitutive model [147], [149], [159].

3.3. Sources of uncertainty in manufacturing process

The term 'measurement uncertainty' is defined in the Guide to the Expression of Uncertainty in Measurement (GUM) as 'a parameter associated with the result of a measurement that characterises the dispersion of the values that could be attributed to the measurand' [160]. The GUM provides a widely accepted framework for static measurement, however, it does not extend to the domain of dynamic measurement [161]. The GUM classifies measurement uncertainty into two categories: Type A and Type B. In order to quantify the uncertainty associated with the output responses, a number of different robustness types have been proposed. Ellis and McDowell employed three robustness types in an effort to identify the optimal performance level while simultaneously reducing the variation in the output response [107]. These included type I (noise variables to manage aleatory uncertainty), type II (control factors to manage two sources of aleatoric uncertainty), and type III (uncertainty effects in the response function to deal with aleatoric and epistemic uncertainty).

In the ultrasonic consolidation process, a peel test and microstructural analysis were conducted to identify an exact PW, which proved to be unfeasible [162]. Consequently, a general PW was identified instead. The findings of this study provide insight into the potential for establishing an exact or general PW based on the experimental results. In the context of welding application, there are still limitations to ensuring the repeatability of welded joints due to the inability to fully control the input process parameters, which are subject to a certain degree of uncertainty. In light of these consideration, Mansour et al., put forth a probabilistic model to guarantee the desired reliability in manufacturing, considering two types of uncertainties: aleatory uncertainty associated with process parameters and the epistemic measurement uncertainty in the criterion (penetration depth) for identifying process parameters [163].

In AM manufacturing processes, Kumar et al. highlight the variation in the quality of the manufactured parts are affected by different sources of uncertainties [57]. To illustrate in melting pool models in AM, model assumptions, unknown simulation parameters, numerical approximations, and measurement error were identified as sources of uncertainty [57]. Furthermore, three types of uncertainty quantification (UQ) in current research studies in AM were classified in the literature: (1) UQ of AM using experiments, UQ of melting pool model, and (3) UQ of solidification (microstructure) model. For instance, statistical methods such as analysis of variance (ANOVA) and Taguchi DOE were utilised to evaluate the effects and variability of parameters in the quality of parts fabricated by conducting repeatedly experiments using different defined process parameter settings [57].

3.4. Perspectives in PW identification and transferability.

When process production is to be transferred using new materials or new machines on a different manufacturing process, an optimum process operation window is a fundamental prerequisite [164]. However, this PW determination requires a substantial empirical testing procedure that is sequential and time-consuming, comprising fabrication, metallographic preparation, and all analysis and testing to verify the quality of the part [6], [7], [165]–[167]. Indeed, as Holmberg et al., has highlighted, there is a significant challenge in developing novel and innovative methods for identifying the PW for the machining process of the commercially available AM alloys [89].

As Liu et al., have observed, the results of a single research study lay not be conclusive when applied to a different material or SLM machine [103]. Moreover, in their article on welding processes, Groche et al., asserted that "*the process window presented in this paper is only valid for this specific material combination in this specific condition*" [168]. In light of these considerations, the aforementioned limitation in PW transferability is also relevant in the context of AM, given the inherent variation in thermal cycles (specific conditions) across different machines, materials, and manufacturing processes [169]. This underscores the need for a methodology capable of identifying PW, considering the variability introduced by these factors. The proposed methodology should be able to reduce the number of experiments required to create a database, which is a crucial advantage in the context of manufacturing processes, where controlled conditions like heat transfer are not always feasible.

Moreover, as previously stated, two primary process parameters are identified in PBF-EB as essential for the construction of the corresponding PW. However, other parameters such as scan length, may impose limitations on the fabrication of complex geometries due to alterations in the dimensions of the melt pool. This underscores the necessity for the transfer of process parameters identified from standardised PW. Consequently, Breuning et al., employed a semi-analytical heat conduction model to assess the stability of the melt pool geometry and to determine the optimal process parameters for complex geometries, establishing an analytical relationship between the two [81]. Silvestri et al., denoted in FSW process that the combination of process parameters identified in PW should be selected according to the reduction of energy consumption in order to integrate sustainability into the decision-making process [170]. Gao et al. proposed a multi-objective optimization of process parameters for laser metal deposition based on neural network and genetic algorithm to improve the deposition quality and deposition efficiency of NiTi shape memory[58].

4. Machine learning techniques to identify process window.

This section presents an overview of research using ML techniques to identify PW. It begins by examining the initial application of these techniques in surrogate models and then proceeds to explore other techniques for identifying PW. Table 1 located at the end of this section, provides a comprehensive summary of the articles discussed.

ML methods could be classified into diverse types depending on their principal interest, ML techniques are classified according to the learning approach (as Fig. 11 shows), i.e., supervised (trained using labelled historical data), unsupervised (developed without previous labelled data), or reinforcement learning (an agent that learns how to interact with its environment) [171]. In supervised learning, the objective is to establish relationships (mapping) between empirical data as an input (training dataset) and an output (prediction). Supervised learning is subdivided into two categories: regression, which is used for continuous outputs, and classification, which is employed when the outputs are discrete class labels [172]. In fact, studies highlighted the relevance of research topics in ML techniques in the context of AM processes, where supervised learning is primary employed when developing mechanistic models [49], [173].

As stated in the no free lunch theorem, "*there is not a single best model that works optimally for all kinds of problems*" [171], therefore domain knowledge and/or trial-and-error (e.g., using cross-validation or Bayesian methods) are required to select which ML model or models are used to identify PW. The subsequent stage is to train the models and select the optimal model(s) for the specific problem, in this case PW identification, using experimental or numerical data as the training, validation, and testing data. It is, however, important to consider how the models are fitting in terms of balancing the bias-variance trade-off (in the case of regression models, this means minimising the mean squared error (MSE) of the models) and avoiding underfitting (poor fitting from training data) or overfitting (perfect fitting from training data, which creates a complex model) problems, as these affect the generalisation of results.

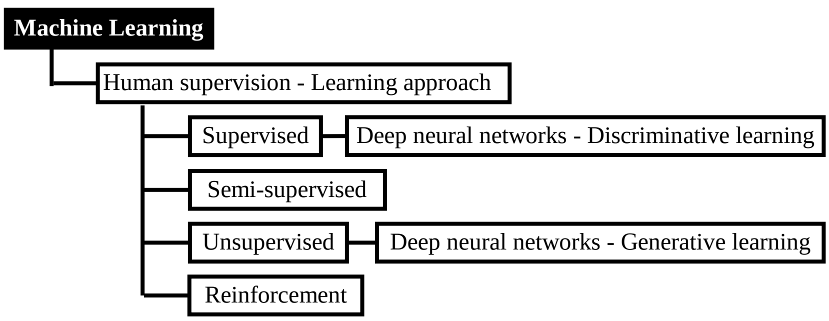

Fig. 11. Machine Learning taxonomy based on human supervision or learning approach placing deep learning techniques. For further information about deep learning classification, see [174].

4.1. Surrogate models

A surrogate model (also known as a metamodel or response surface approximation) is a statistical technique that aims to reduce the amount of experimental data required to approximate the input/output relation of a black-box function [175]. In this case, the objective is to identify the PW between process parameters and product properties.

In the surrogate model step of Fig. 10, the most common approaches to determining it are supervised regression ML techniques, such as Kriging or Gaussian process regression (GPR), which provide uncertainty quantification [136], [138]. Kriging is regarded as an exact interpolation model [175]. To illustrate, [137] proposed an ensemble approach with three models such as Kriging, radial basis function (RBF), and support vector regression (SVR), with the objective of reducing the number of experiments to be carried out. However, it should be noted that this approach does not account for the numerous process parameters and product performance characteristics inherent to the SLM manufacturing process. Furthermore, the methodology was not tested in a real-time scenario. In the context of the turning process, an ANN model was developed by Denkena et al., for the purpose of robust material classification during machining [176]. This model was principally based on the corner points of the PW and included three parameters. The aim of using corner points was to reduce the required number of trainings points due to the limitations of using a single position within the PW with a restricted range, while maintaining or improving performance.

4.2. Other machine learning approaches

Other ML approaches proposed in the literature include ANN or the combination of different ML techniques to define PW. For example, classification methods may be used in place of regression. For instance, Feenstra et al., identified PW by employing ANN (created on JMP15® software) in directed energy deposition (DED) AM processes by using 297 images as data for the principal parameters of three materials to ensure the reliability of the ANN model [165]. However, this methodology has not yet to be tested in a real-time scenario. Similarly, Xing et al., screens PW in the SLM process using a computer vision approach with image feature classification using deep neural network models to generate stable melt pools [7]. However, 1129 experiments were conducted following a high-throughput DOE.

In the case of using numerical experiments, Jafari-Marandi et al., proposed a decision-making approach that employs a cost-driven self-organising error-driven neural network (SOEDNN) to address misclassification issues in process control of AM processes [177]. However, the data employed in the training phase considered only one type of product, which constrained the generalisation for other types of products. Moreover, the employed methods are computationally expensive and time-consuming. On the other hand, Liu et al., developed a hierarchical multi-property approach to enhance the PW of wire laser AM, integrating Naïve Bayes (NB) networks for classification and GPR, which reduced the searching space from 47,970 candidates to

1,100 candidates [178]. However, the approach was trained exclusively for single-layer printed parts, whereas multi-layer is preferred option for AM processes.

In the context of physical experimental approaches, [118] proposed a methodology for determining PW in metal AM particularly in powder-bed fusion types. This methodology was demonstrated through a case study of a medical CoCr alloy, employing support vector machine (SVM) classification and providing a physical interpretation of the decision function, specifically in terms of defect difficulty identification. The methodology was tested using a uniform experimental design, in which 11 data points were obtained by uniform experimental design varying two principal parameters. However, the ranges or zones of the PW were not fully defined, without consideration of the uncertainty associated with the classification prediction. This is despite the inclusion of a cost parameter that accounts for the number of misclassified data points is compared at each iteration.

Recently, Wang et al., developed a hybrid ML method applied to femtosecond laser-induced nanostructure processes [179]. This method used 150 samples, which were fabricated and selected through a uniform sampling method. This method considered four principal laser parameters. Its combined dimensionality reduction, data clustering with a convolutional neural network for transfer learning, and classification methods (decision trees – DT, ANN, and SVM). These classification methods were trained on an imbalanced data set. They predicted the decision boundary of the PW. However, this method considered only one type of principal process parameters and did not considered a real-time scenario.

Up until this point, the primary application of classification techniques has been the use of image data to identify PW. In fact, classification algorithms can be employed for the purpose of identifying, bounding, or mapping the feasible design space in engineering design optimisation problems, as evidenced by Sharpe et al. [180]. In the context of engineering design optimisation, surrogate models are frequently employed as a forward mapping tool. In this approach, unique design variable values are input and their performance is then predicted. In contrast, inverse mapping is used to identify a set of design variable values that satisfy specified criteria. This is achieved by, for instance, utilising classification techniques [180].

As previously stated by [180], the objective of classifier is to identify pertinent design variables that satisfy specified constraints by mapping the feasible design space to predict whether candidate designs belongs to a particular class. As stated by Fuhg and Fau, "*surrogate classification can be based on continuous function outputs, which can be either numerical or experimental results or post-processed quantities*" [181].

4.3. Uncertainty in machine learning techniques in process window identification

Two sources of uncertainty in ML methods exist: aleatoric (statistical – variability due to inherently random effects – irreducible part) and epistemic (systematic – caused by a lack of knowledge – reducible part) uncertainty. In the context of ML classification methods, two distinct sources of noise have been identified by Wickramasinghe [182]. These are attribute (also referred to as feature or factor) noise and class noise. Attribute noise is associated with erroneous values of attributes, the absence of attributes, an inconsistent data distribution, and redundancies in the data. Class noise could be divided into two distinct sources. The first source arises when different labels are assigned to the same examples that occur with high frequency. This phenomenon can occur, for instance, when bootstrap methods are employed in an imbalanced dataset. The second source encompasses instances where a sample is incorrectly labelled. This can be classified as misclassification. [183].

In the context of PW identification, the contiguity aspect may be considered as a means of determining the points that could be regarded as “ambiguous”. To illustrate this, Liang et al., developed a relative classification uncertainty measure by using the K-nearest neighbour (KNN) algorithm and Bayes theory to detect and eliminate the side effects of the initial noisy information existing in the circular range of the nearest object to the target object [184]. Headley et al., incorporate uncertainty in the classification process by integrating the associated measurement uncertainties into the ML regression training model [185]. To this end, they employ a bootstrapped data set to derive the mean values of 50 trained models.

Probability calibration. As Feng has observed, probability theory provide a means of interpreting the uncertainty inherent in any prediction and of evaluating the capability of the learning model itself [186]. However, the predicted probability is susceptible to bias due to the nature of the metrics employed in classification algorithms. It is therefore necessary to employ calibration methods in order to obtain calibrated probabilities that will ensure a superior quality of prediction. Probability calibration can be conceptualised as a scaling operation that takes the output probability of classification and transforms it by means of regression methods. In the context of binary classification problems, there are two principal approaches to calibration of predictions: Platt scaling [187] and isotonic regression [188].

Classification performance metrics. Performance metrics are a fundamental component of ML techniques, serving to quantify the quality of the prediction presented in Table 1. In the context of ML-supervised regression techniques, the most commonly employed performance metric is accuracy. Nevertheless, accuracy is not the optimal metric for classification problems due to the underlying assumption of a constant and relatively balanced class distribution across examples. Additionally, the accuracy evaluation considers “equal error costs”, whereby a false positive error is considered equivalent to a false negative error [189]. Hence, the necessity arises for the utilisation of alternative performance metrics, such as the confusion matrix, the receiver operating characteristic (ROC) curve, and the area under the curve (AUC), amongst others.

4.4. Perspective of machine learning techniques in PW identification

Semi-supervised learning is a relevant research area due to the potential for reducing the number of labelled data points required for training a classifier model [171]. This is particularly pertinent in the context of experimental campaigns, where the number of labelled data points may be limited. One example of a semi-supervised learning approach is self-training, also known as “pseudo-labelling”. In this method, the model created is used to infer “pseudo-correct” predictions on unlabelled data. These predictions are then used as labels, combining with labelled data for the next training cycle. However, a significant challenge associated with self-training is the confirmation bias. This occurs when the model’s predictions, which could be generated incorrectly, are repeatedly used as labels, leading to a gradual decline in model performance [171].

As defined by Hosna et al., transfer learning involves the reuse of pre-existing models that have been trained on previous tasks with similar characteristics in order to train the current model [190]. The topic of transfer learning is of interest due to the reduction in the number of experiments or simulations that must be carried out, which is made possible by the reuse of data from other product configuration in the training step of ML algorithms [191].

In addition, transfer learning could bridge various data sources, as Tang et al., stated in their article on AM manufacturing processes [192]. However, the data must be “relevant” to be reusable for similar manufacturing processes considering different conditions, such as the product, machines, equipment, and raw materials involved. For instance, Maier et al., compared various approaches to incorporating expert knowledge and transferring knowledge using GP, with a focus on determining hyperparameters a priori in turning processes [193]. Future work in this area will focus on developing methods for incorporating a priori knowledge to select the initial experiments. Moreover, there is a need for further research into the use of real-time online data in the selection and optimisation of process parameters. One potential approach is the utilisation of reinforcement learning algorithms and deep learning algorithms [194].

A further avenue for investigation is the application of metaheuristics to explore and exploit results in the design space and the operating window, considering a range of factors including economic and environmental impact. For example, Gürses et al., proposed the use of a novel prairie dog optimisation algorithm (PDOA) in the optimal economic design of heat exchangers, with the objective of incorporating cost optimisation [195]. The algorithm is combined with Gaussian mutation and chaotic local search (MSPDOA). Similarly, Shu-Chuan Chu et al., developed a ship rescue optimisation method for use in search space exploration and exploitation processes, which could be employed in PW identification [196]. Moreover, Meng et al., presented a comprehensive and comparative article on the subject of different multi-objective reliability-based design optimisation (RBDO) techniques, outlining the various types of multi-objective algorithms that can be employed in manufacturing processes, particularly for PW identification [197]. The article addressed the challenges associated with conflicting design objectives and probabilistic constraints.

Table 1. Articles proposing the use of machine learning techniques to identify the PW in which the aim of using PW is denoted, the type of learning approach, the algorithms used, metrics to evaluate the performance and if any optimisation algorithm is used. The next abbreviations are employed in the columns name: construction (C), optimisation (O), reference (Ref.), regression (Reg), classification (Clf), clustering (Cls), optimisation algorithm (OA).

Manufacturing Process Group	Manufacturing Process	Ref.	PW use		Machine Learning					
			C	O	Learning approach			Algorithm(s)	Performance Metric(s)	OA
					Reg.	Clf.	Cls.			
Primary Forming	Injection Moulding	[56]	✓	✓	✓			Multilayer Perceptron (MLP)	Root Mean Square Error (RMSE)	
	Moulding	[198]	✓		✓			XGBoost	RMSE, Mean Absolute Error (MAE), and R-squared	✓
	DED process	[199]	✓		✓			KNN, DT, random forest (RF), extreme gradient boosting (XGB) regression	Not specified	✓
		[200]	✓	✓	✓			GP, XGB, and SVM	R-square, RMSE, MAE, mean bias error (MBE)	✓
		[201]	✓	✓		✓		RF, XGB, Logistic Regression, SVM, NN, and KNN	MAE, R-square, F1 score, ROC, and AUC	✓
	LMD process	[58]	✓	✓	✓			Response Surface Methodology (RSM), Back Propagation NN, and RF	Maximum relative error and average prediction error	✓
	L-PBF process	[202]	✓		✓			GP	RMSE and Mean Absolute Percentage Error (MAPE)	✓

Manufacturing Process Group	Manufacturing Process	Ref.	PW use		Machine Learning					
			C	O	Learning approach			Algorithm(s)	Performance Metric(s)	OA
					Reg.	Clf.	Cls.			
		[203]	✓	✓	✓			SVR, MLP, Regression Tree, RF, Adaptive Boosting, Gradient Boosting, and XGB	MAE and MAPE	
		[204]	✓		✓			ANN	MSE	
		[205]	✓		✓			Least Square SVM	RMSE	✓
		[206]	✓		✓			DT Regression, Extra Tree Regression	R-squared, MAE MSE, RMSE	
		[207]	✓	✓	✓			Multiple Linear Regression, RF, KNN, Gradient Boosting Regression, and Bagging	R-square and MSE	
		[185]	✓		✓			SVR	Not specified	
		[208]	✓	✓	✓			GPR	RMSE	✓
	PBF-EB process	[76]	✓	✓		✓		RF, SVM with linear, polynomial and RBF kernels	Accuracy	✓
	SLM process	[209]	✓		✓			GP	MAPE	✓
		[7]	✓			✓		Deep Neural Network	MAPE	
Dividing	Machining	[210]	✓			✓		GP	Not specified	
	Turning	[176]	✓			✓		ANN	F1 score and confusion matrix	
Coating	Aerosol Jet 3D printing	[211]	✓	✓		✓	✓	K-Means and SVM	Not specified	
Modifying material property	Thermomechanical Treatment	[131]	✓		✓			ANN	Not specified	

5. Design of Experiments in process window identification

The previous section shows how to model and identify the corresponding PW. However, techniques to recover data were introduced in some cases, for example, using an experimental design approach. This section outlines the design of experiments (DOE) to identify and establish PW in the literature of different manufacturing processes is outlined. Response surface methodology (RSM) is applied with DOE to create a model with the results obtained from this combined with ML models to identify the corresponding PW. Table 2 provides a summary of the articles reviewed denoting the type of DOE, the method(s) used, and the number of experiments resulting from their application.

5.1. Physical experimental design to identify process parameters.

The process of obtaining background data with the aim of identifying optimal process parameters and subsequently verifying the corresponding PW is a common one. This is typically carried out and verified by means of physical experimental measures. The conventional physical experimental approach employs a trial-and-error methodology or varying only one factor at a time, which is both time-consuming and expensive. In fact, Engelhardt et al., pointed out that relying solely on experimental data may prove inadequate for comprehensively exploring the design space [205]. However, integrating experimental techniques with mathematical modelling can offer a more efficient approach.

In the absence of a reliable mathematical model is not available, a statistical methodology approach is necessary to conduct an experiment campaign while reducing the number of experiments to be carried out. To illustrate, DOE and ANOVA methods are frequently employed in conjunction in the context of manufacturing process parameter optimisation. Therefore, experimental design is required to specify all necessary aspects of carrying out an experiment. A priori knowledge of the experiment conditions is a crucial element in the experimental campaign, as it enables the identification of key aspects for analysis and the allocation of resources in a manner that optimises the campaign's objectives [212].

The rationale for employing the DOE methodology is rooted in its ability to establish a systematic and rigorous plan for selecting a collection of sample points while obtaining the maximum amount of information within a given domain. This is achieved by controlling the variables and factors that may influence the outcome, ensuring a comprehensive and accurate representation of the data. Furthermore, the DOE methodology considers the potential sources of variability (uncertainty) in the factors under investigation, while simultaneously aiming to reduce the number of experiments that need to be conducted [59]– [63].

In order to establish the most optimal conditions, it is recommended that a statistical experimental design be employed. One such design might be a Taguchi experiment. Zhuang et al., implemented two quality criteria based on molten pool dimensions (width and depth) to identify the appropriate processing parameters ranges by applying DOE and RSM techniques in conjunction with an existing PW, thereby increasing the accuracy of the predictions for melt pool dimensions [218].

5.2. DOE techniques classification.

The classification of DOE techniques proposed by Garud et al. and Lee et al., is employed in this paper and is illustrated in Fig. 12 [213], [219]. DOE methods are classified into two principal categories: classical (or traditional) methods, which are principally used for physical experiments, and modern methods, which are principally used for simulation experiments.

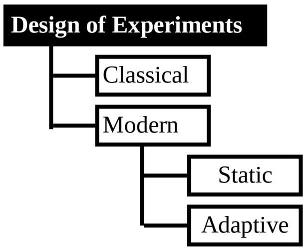

Fig. 12. Taxonomy of Design of Experiments according to historical development and application domain. Based on [213], [219].

Classical DOE techniques. The applications of the classical DOE method can be categorised into three principal areas: variable interaction studies, screening studies, and optimisation studies [219]. In fact, the DOE method has been used in three principal ways in the PW identification literature. Firstly, it has been used to identify the principal parameters that exert influence on the manufacturing process (variable interaction studies). Secondly, it has been used to generate sample points for execution in physical or simulation experiments. This is achieved by creating different combinations of the process parameters space (screening studies). Thirdly, it has been used to select sample points for optimisation of the surrogate model (optimisation studies).

In order to implement the DOE methodology, the research integrates two or three-stage DOE. For instance, one kind of DOE is used for an initial screening step in the parameter space, another is employed to establish the process parameter influence, and a third is used to relate product properties and optimise them [220]. Similarly, the objective of utilising two or more DOE is to delineate the PW identified according to different criteria. For instance, one may commence with the porosity and subsequently consider microstructural and mechanical properties [221].

Examples of the application of DOE approaches for the identification of optimal process parameters include full factorial matrix design, fractional factorial design, the Taguchi method [136], [137], [222], central composite design [138], [223]–[225], and D-optimal design [226]. Fig. 13 illustrates the principal DOE techniques employed in the PW literature.

In the moulding process, [106] constructed PW in accordance with the specified quality requirements for the products in order to achieve the lowest possible operating costs. This was done by employing an inverse modelling technique using Taguchi, full factorial, and central composite design DOE techniques. In the thermal spray process, [227] selected the predominant factors based on their influence on the coating characteristic, thereby reducing the number of factors to be considered. They proposed a methodology to identify PM using DOE to establish an empirical relationship through an RSM second-order quadratic model, which was validated using ANOVA.

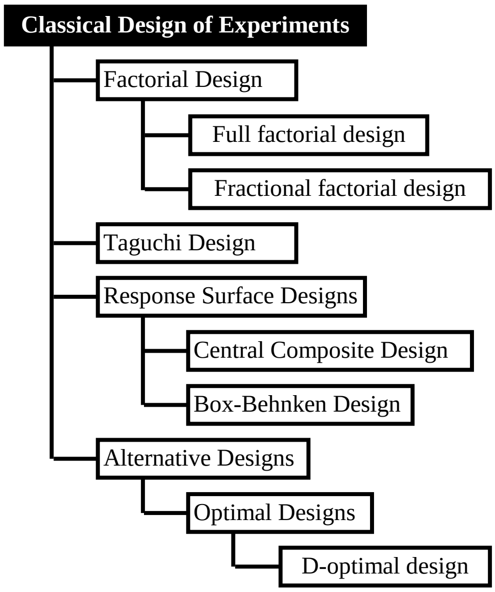

Fig. 13. Taxonomy of principal classical DOE applied in PW identification. Based on [219]

Modern DOE techniques. To illustrate the process of identifying manufacturing parameters, Guo et al., proposed a methodology for identifying the corresponding PW in the extrusion process [4]. This methodology was developed using RSM, which was created through orthogonal regression based on FEM simulations. Furthermore, Karandikar et al., devised an entropy-sigma acquisition function that requires the minimum number of tests (either time-domain simulations or data from the literature), active learning based on LHS and grid-based methods, and a GP surrogate model for use in machining processes to identify stability process maps (PWs in machining processes) [210]. It is important to note that the selection of the subsequent set of tests should be made with the objective of obtaining the most information regarding the PW boundaries. However, the acquisition function was developed and validated using a defined function (a mathematical model) that mimics the PW. Moreover, the validation was conducted exclusively using numerical tests, and no experimental measures were carried out to verify and/or validate the procedure in a physical real-time scenario.

Furthermore, Ranaiefar et al., proposed an integrated computational framework to model the effect of evaporation on material properties in metal AM [9]. This was achieved by combining thermal models solved by numerical simulation with adaptive Markov Chain Monte Carlo and the Metropolis-Hasting criterion, which were used to calibrate the numerical parameter in order to consider the data uncertainty. Subsequently, the solutions were validated through experimental campaigns. However, future research must focus on validating or verifying the computational framework through experimental results.

5.3. Uncertainty associated.

In the Laser Beam Welding process, Abioye et al., employed a full factorial design with three parameters and two levels, and incorporated additional centre points to illustrate the linearity between factors and responses [228]. Subsequently, ANOVA test was performed to ascertain the significance of the factors and their interactions. The present study considers uncertainty only in the context of tensile strength values, without delving into the related aspects of the process parameters.

To illustrate, uncertainty has been quantified in some research seeking to optimise process parameters. To illustrate, Zhang et al., developed a multi-objective optimisation framework in the aerosol jet printing (AJP) process using a small data set obtained using the LHS method combined with a noisy input GP for prediction uncertainty [229]. Subsequently, the non-dominated sorting genetic algorithm (NSGA-III) optimisation method was employed to reduce contradictions in the AJP processes, however, the impact on the overall performance within the specified design space was not quantified.

Similarly, Zhang et al., developed a framework for L-PBF AM processes that integrates the static design of experiments (sixty processing parameter combinations were suggested with grid sampling and the LHS method), statistical calibration in an iterative way using GP surrogate model to fit on physics-based thermal simulation for uncertainty analysis, and fabrication characterisation in order to determine the processing parameter window of a given alloy [230].

5.4. Perspective of DOE in PW identification

Another technique related to the semi-supervised learning approach, which was discussed in the previous section, is active learning. In the case of DOE literature, active learning is referred as adaptive DOE. In the context of active learning, the learner has the ability to select iteratively unlabelled samples that could be the most "informative" by querying as few $(\boldsymbol{x}, y)$ points as possible when labels are expensive to collect, then being classified by experts. Furthermore, these samples can be added to the training set, thus creating a more accurate model [171], [231]–[233]. Consequently, the most crucial and important step is how to define and design the rules for selecting the most valuable samples [234].

Active learning in experiment design can be conceptualised as an unsupervised, or generalised, form of active learning where the principal goal is to infer a parameter vector of some model using carefully chosen data samples [171]. This is exemplified by the estimation of conditional probability using as little data as possible. In the case of PW identification, the adaptive DOE exploration and exploitation trade-off could be satisfied by letting exploration investigate and detect regions of particular interest (i.e., those that are uncertain), while exploitation defines sample points in those regions to reduce prediction error. To accomplish this task, enrichment or learning criteria are needed that are based on both physical or experimental criteria and also numerical criteria.

Table 2: DOE methods to identify PW by denoting the reason to use PW concept, if it was combined with ML algorithm, what type of design was used (classical or modern approach), the purpose use of DOE technique, the number of samples that are mentioned in the article and the response analysis employed with. The following abbreviations are used in the table: generation (G), definition (D), optimisation (O), machine learning (ML), classical (C), modern (M), interaction (I), screening (S), number of samples points (NP), and references (Ref.)

Manufacturing Process Group	Manufacturing Process	Ref.	PW use			ML	Design of Experiments							
			G	D	O		Type		Technique	Purpose			NP	Response Analysis
							C	M		I	S	O		
Primary Forming	Moulding	[198]	✓			✓	✓		Taguchi		✓		100	Not used
		[106]	✓		✓		✓		Taguchi	✓			18	ANOVA
							✓		Full Factorial Design		✓		27	Quadratic model
							✓		Central Composite Design			✓	45	Quadratic model
		[235]	✓				✓		Full Factorial Design	✓			16	ANOVA
	DED process	[200]	✓		✓	✓	✓		Full Factorial Design		✓		343	ML model
	Direct Laser Deposition	[236]	✓		✓		✓		Full Factorial Design	✓			27	Not used
	LMD process	[237]	✓				✓		Full Factorial Design	✓	✓		20	Linear Regression
		[58]	✓			✓	✓		Central Composite Design		✓		30	Linear Regression and ML model
	L-PBF process	[205]	✓			✓		✓	Latin Hypercube Sampling		✓		144	ML model
		[206]	✓			✓	✓		Box-Behnken Design		✓		108	Linear Regression and RSM
		[238]	✓				✓		Full Factorial Design		✓		54	ANOVA
		[84]	✓				✓		Full Factorial Design		✓		135	Not used
		[239]	✓		✓		✓		Taguchi		✓		36	Not used
		[208]	✓		✓	✓	✓		Central Composite Design		✓	✓	42	ML model
	PBF-EB process	[76]	✓	✓	✓	✓		✓	Latin Hypercube Sampling		✓	✓	64	ML model

Manufacturing Process Group	Manufacturing Process	Ref.	PW use			ML	Design of Experiments							
			G	D	O		Type C	M	Technique	Purpose I	S	O	NP	Response Analysis
	SLM process	[209]	✓			✓		✓	High-throughput DOE		✓		81	Not used
		[7]	✓			✓		✓	High-throughput DOE		✓		1129	Not used
		[218]	✓	✓			✓		Central Composite Design		✓		49	Second order polynomial function
		[240]	✓		✓		✓		Central Composite Design		✓	✓	20	ANOVA
	WAAM process	[87]	✓				✓		Box-Behnken	✓	✓		15	ANOVA
Dividing	Drilling	[119]	✓		✓		✓		Taguchi			✓	25	S/N ratio
	Grinding	[241]	✓				✓		Full Factorial Design	✓			36	ANOVA
	Milling	[88]			✓		✓		Taguchi	✓		✓	9	Signal-to-Noise (S/N) ratio and ANOVA
	Micro-EDM	[242]	✓				✓		Taguchi		✓		36	Not used
Forming	Extrusion	[4]	✓					✓	Virtual orthogonal design		✓		25	Second order polynomial function
	Sheeting Forming	[243]			✓		✓		Box-Behnken Design		✓	✓	67	RSM and ANOVA
Joining	FSW	[74]	✓	✓			✓		Full Factorial Design		✓		15	Not used
	Laser beam welding	[228]	✓				✓		Full Factorial Design	✓			11	ANOVA
		[93]	✓				✓		Full Factorial Design	✓			120	Not used
	Mini-wave soldering	[244]	✓				✓		Full Factorial Design	✓	✓		Not mention	Not used

Manufacturing Process Group	Manufacturing Process	Ref.	PW use			ML	Design of Experiments						NP	Response Analysis
			G	D	O		Type C	Type M	Technique	Purpose I	Purpose S	Purpose O		
	Hot Gas Welding	[245]			✓		✓		Taguchi			✓	9	S/N ratio
Coating	Aerosol Jet 3D printing	[211]	✓		✓	✓		✓	Latin Hypercube Sampling	✓	✓		Not mention	Not used
	Cladding	[246]	✓				✓		Full Factorial Design	✓	✓		45	ANOVA
		[247]			✓		✓		Taguchi			✓	18	S/N ratio and ANOVA
	Plasma-sprayed YSZ	[115]	✓	✓			✓		Central Composite Design		✓		30	Not used
		[227]	✓				✓		Central Composite Design		✓		20	Second order polynomial and ANOVA
Semiconductor device fabrication	Etching	[73]	✓		✓		✓		Taguchi	✓			9	Signal-to-Noise (S/N) ratio
							✓		Taguchi	✓	✓		9	
	Self-aligned Silicide	[248]	✓				✓		Full Factorial Design	✓			8	ANOVA

6. Summary

This paper presents and analyses a variety of articles on the topic of process parameter identification, with a particular focus on PW identification. It examines the methods employed to define these parameters, exploring the use of physical and numerical DOE, combined with statistical and ML techniques to create a surrogate model. The inherent uncertainty of ML techniques and measurement is also considered.

The concept of PW was introduced as a means of identifying optimal process parameters in a range of manufacturing processes. The definition of PW was provided as the optimal region of principal process parameters within the process parameter space that ensures the repeatability and reproducibility of quality or performance product material and geometric properties. This could be represented graphically to assist operators in controlling the process parameters of manufacturing equipment and machines.

Thereafter, the methodologies for defining the PW by means of physical and numerical experiments were subjected to analysis. The application of the DOE methodology was analysed in different manufacturing processes with a view to planning the parameter combination with experiment reduction measures. ML techniques were employed using predominantly image data for classification and tabular data for predictions using regression models.

The following points, based on Table 3, provide a summary of the techniques used to identify PW. In order to achieve this, the number of articles is cited in accordance with the manufacturing process type, solely based on primary forming, dividing, forming, and joining processes and the techniques that were predominantly employed, namely, ML, DOE, and ML with DOE use.

- It has been determined that approximately 20% of the total articles (8 of 43 articles) employed a combination of DOE and ML to identify the corresponding PW in manufacturing processes. This has led to further developments in AM processes, particularly in L-PBF processes and DED processes. The application of DOE techniques is more prevalent than ML, with nearly half of the articles employing DOE techniques (20 of 43 articles without combing ML).
- The majority of articles focus on defining the PW in the context of AM processes. This is due to the recent developments in the field of AM, where new materials and parts are being fabricated using materials that are challenging to machine. Additionally, there is a growing interest in green manufacturing, which further contributes to the prominence of this topic in the literature [249].
- The principal techniques employed to identify the PW using ML are regression techniques, which yielded 14 out of 19 results, and classification techniques, which yielded 5 results. The principal regression techniques employed were decision tree-based models such as RF and XGBoost, SVR, and GP, which was used to include uncertainties inherent to manufacturing processes. Less frequently used were ANN. In contrast, the classification techniques were

predominantly employed, with RF, SVM, ANN and deep neural networks being the most utilised. These were primarily applied to image data.
- The most frequently employed DOE techniques are classical DOE (25 out of 30), which encompasses full factorial design, Taguchi, central composite design, and Box-Behnken methods. The modern DOE technique examined the most in this paper is Latin hypercube sampling. Moreover, ANOVA was employed on eight occasions, while Signal-to-Noise associated with Taguchi experiments was employed on three occasions. This is comparable to the number of instances in which DOE with ML techniques was employed.

Table 3. Number of articles according the manufacturing process using different techniques for PW identification.

	Machine Learning (ML)	Design of Experiments (DOE)	ML + DOE
Primary Forming	7	9	8
Dividing	2	4	0
Forming	0	2	0
Joining	0	5	0
Coating	0	4	1
Modifying material property	1	0	0

7. Conclusion

In conclusion, both the Design of Experiments (DOE) and machine learning (ML) techniques have been demonstrated to be invaluable tools for the definition of manufacturing process windows. A key benefit of DOE is that it provides a structured approach to systematically vary input factors and observe their impact on output responses. This allows for the identification of optimal process settings, which is a crucial aspect in many manufacturing processes. In contrast, machine learning provides access to sophisticated algorithms that can discern intricate relationships, thereby facilitating the identification of optimal classifiers.

The combination of these methodologies allows for a more comprehensive and accurate understanding of the manufacturing process scope [208] The application of DOE enables the efficient exploration of the design space, facilitating the identification of critical factors. Furthermore, machine learning can be employed to develop predictive models that capture the intricate interactions between these factors [250]. This synergistic approach enables us to:

- Enhance process robustness: By precisely defining the process window, we can minimize the risk of producing non-conforming products, reduce the number of requested experiments and improve overall quality.
- Optimize manufacturing process efficiency: Through targeted experimentation and data-driven modeling, we can identify the optimal operating conditions.
- Accelerate product development: By rapidly characterizing the process window, we can increase agility in responding to market demands.

- Improve the manufacturing sustainability by reducing the number of experiments by adding expert knowledge to explore and exploitation of experimental data.

A further area meriting investigation within the field of PW identification is that of their transferability. In the event of a known PW, the utilisation of a novel material or machine would necessitate the testing of all parameter combinations for the purpose of PW calibration. As [251] has indicated, this approach may prove to be inefficient and time-consuming.

However, the experiment characterisation did not yield any prior knowledge until all the experiments had been carried out following a classical DOE, which could result in additional costs and time-consuming experiments that are not necessarily informative. For this reason, the DOE methodology, as presented in the literature, is of interest with regard to the definition of sample points and the creation of a surrogate model. Similarly, in the context of machine learning implementation, there are inherent limitations. In particular, if a physics-based model exists, it may be infeasible to apply image detection directly, particularly during the early stages of the manufacturing process. It is therefore necessary to adopt a transferable and adaptable approach to modelling in order to address this challenge. Moreover, the advancement and implementation of adaptive DOE or active learning may incorporate physical knowledge through the reduction of experiments in existing machine learning classification techniques, thereby identifying the corresponding process window [181].

In summary, the integration of DOE and machine learning offers a robust and flexible framework for defining manufacturing process windows. By capitalising on the respective strengths of both techniques, manufacturers can achieve substantial enhancements in product quality and manufacturing process efficiency.

Statements & Declarations

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Author contribution All authors contributed to the study conception and design. Formal analysis, investigation, and methodology were performed by Manuel Lopez Cabrera, Wahb Zouhri, Sandra Zimmer-Chevret, and Jean-Yves Dantan. Visualization was performed by Manuel Lopez Cabrera. The first draft of the manuscript was written by Manuel Lopez Cabrera and all authors commented on the previous versions of the manuscript. All authors read and approved the final manuscript.

Data availability Not applicable

Code availability Not applicable

Ethical approval. Not applicable

Appendix

Table 4. State-of-the-art articles following manufacturing process classification given in the DIN 8580 norm. This table specifies the material used, if the metal or alloy used a different mention on the list is noted by (O) to indicate other, polymers (P), ceramics (Ce), composites (Co) and includes semiconductor devices parts (SD), if manufacturing process machine (MPM) is mentioned, and metrology equipment (ME) is mentioned, the use of process parameter concept associated and if they are only mentioned denoted with M: process window (PW), process map (PM), or process-structure-property-performance (PSPP).

Manufacturing Process Group	Manufacturing Process	Ref.	Material									MPM	ME	Concept used		
			Metal and alloys					P	Ce	Co	SD			PM	PSPP	PW
			Fe	Al	Ti	Ni	O									
Primary Forming	Flash Sintering	[252]							✓			✓	✓	✓		
	Moulding	[42], [56], [106], [198], [235], [253], [254]						✓				✓				✓
	DED process	[199]			✓							✓	✓			✓
		[200], [201]				✓						✓				✓
	Direct Laser Deposition	[236]					✓					✓	✓	✓		M
	EBM process	[97], [255]			✓							✓	✓	M		✓
	Fused Filament Fabrication	[256], [257]	✓					✓				✓	✓			✓
	Laser-based DED	[258]			✓	✓								✓		
	LMD process	[58], [99], [237]			✓	✓	✓					✓	✓			✓

Manufacturing Process Group	Manufacturing Process	Ref.	Material									MPM	ME	Concept used		
			Metal and alloys					P	Ce	Co	SD			PM	PSPP	PW
			Fe	Al	Ti	Ni	O									
	L-PBF process	[84], [185], [202]–[208], [238], [239], [259]–[266]	✓	✓	✓	✓	✓					✓	✓	M✓		✓
	Metal Additive Manufacturing	[267]					✓							✓	M	
	PBF-EB process	[76], [81]			✓							✓	✓	M		✓
	SEBM process	[80], [95]		✓	✓							✓	✓			✓
	SLM process	[7], [100], [101], [103], [209], [218], [240], [268], [269]	✓		✓		✓			✓		✓	✓	✓	M	✓
	Semi-solid Wire-feed AM.	[270]		✓								✓	✓			✓
	WAAM process	[87]	✓									✓	✓			✓
Dividing	Drilling	[119]								✓		✓	✓	✓		
	Grinding	[241]		✓								✓	✓			✓
	High-speed milling	[88]				✓						✓				✓
	Laser Cutting	[70]	✓		✓		✓					✓	✓	✓		✓
	Machining	[210], [271]	✓	✓		✓	✓					✓	✓	✓		✓

Manufacturing Process Group	Manufacturing Process	Ref.	Material									MPM	ME	Concept used		
			Metal and alloys					P	Ce	Co	SD			PM	PSPP	PW
			Fe	Al	Ti	Ni	O									
	Micro-Electrical Discharge Machining (EDM)	[242]								✓		✓	✓			✓
	Power Skiving	[272]					✓							✓		M
	Turning	[176]	✓	✓								✓	✓			✓
Forming	Automated Fibre Placement	[129]								✓						✓
	Extrusion	[4], [273]				✓				✓		✓		✓		✓
	Inclined compression beading	[274]	✓													✓
	Laser dieless drawing.	[96]					✓									✓
	Metal Forming	[109], [117]		✓						✓		✓	✓			✓
	Rolling	[275], [276]	✓				✓						✓	✓		✓
	Sheeting Forming	[69], [243]	✓	✓										✓		✓
	Thixoforming	[277]		✓			✓					✓	✓			✓
Joining	FSW process	[55], [74], [278], [279]		✓	✓		✓					✓	✓	✓		✓
	Hot Gas Welding	[245]								✓		✓	✓			✓
	Laser beam welding	[228], [280]		✓			✓					✓				✓
	Laser Hot-Wire	[281]	✓									✓				✓

Manufacturing Process Group	Manufacturing Process	Ref.	Material									MPM	ME	Concept used		
			Metal and alloys					P	Ce	Co	SD			PM	PSPP	PW
			Fe	Al	Ti	Ni	O									
	Mini-wave Soldering	[244]					✓					✓	✓			✓
	Resistance Welding	[92]								✓		✓	✓			✓
	Ultrasonic Consolidation	[162]		✓									✓			✓
	Vaporizing Foil Actuator Welding	[67]			✓								✓			✓
Coating	Aerosol Jet 3D printing	[211]						✓				✓				✓
	Cladding	[246], [247]				✓	✓					✓	✓	✓		✓
	Inkjet printing	[282]						✓				✓	✓			✓
	Plasma-sprayed yttria-stabilized zirconia (YSZ)	[115], [227]					✓					✓	✓	✓		✓
	Sputtering	[283]					✓						✓			✓
Modifying material property	Austempering	[104]	✓										✓			✓
	Laser heat treatment	[120]	✓									✓	✓	✓		
	Laser Peening	[284]			✓							✓	✓			✓
	Thermomechanical Treatment	[131]	✓													✓

Manufacturing Process Group	Manufacturing Process	Ref.	Material									MPM	ME	Concept used		
			Metal and alloys					P	Ce	Co	SD			PM	PSPP	PW
			Fe	Al	Ti	Ni	O									
Semiconductor device fabrication	Etching	[73]									✓	✓	✓			✓
	Excimer laser crystallization	[285]									✓		✓			✓
	Laminate Consolidation	[134]									✓		✓			✓
	Lithography	[286]–[290]									✓					✓
	Self-aligned Silicide	[248]									✓					✓

Table 5. PW regrouped by their methodology proposed in the case of the same manufacturing processes. The next abbreviations are used according to its aim of using PW concept: generation or construction (C), definition (D), optimisation (O), the key parameters that are mentioned, process parameters (PM), material properties (MP), the criteria to identify it: geometrical (G), mechanical (M), the dimension or number of parameters considered: 2D (2), 3D (3) and if an aspect is not mentioned (-), the width of PW: narrow (N), wide (W), the type of data sources: analytical models (A), literature (L), simulations (S), physical experiments (P), and if extra verification experiments were carried out (VE), the methodology employed: physical experiments (P), analytical models and simulations (AS), machine learning (ML), and design of experiments (DOE).

Manufacturing Process Group	Manufacturing Process	Ref.	Process / Processing Window												Data						Methodology			
			Use			Parameter		Criteria		Dimension			Width		Source					VE	P	AS	ML	DOE
			C	D	O	PP	MP	G	M	2	3	-	N	W	-	A	L	S	P					
Primary Shaping	Flash Sintering	[252]	✓			✓			✓	✓					✓				✓		✓			
	Injection Moulding	[56]	✓			✓		✓	✓		✓				✓		✓		✓	✓			✓	
	Moulding	[42], [253], [254]	✓	✓	✓	✓		✓	✓	✓		✓			✓	✓		✓	✓	✓		✓		
		[198]	✓			✓			✓			✓	✓						✓	✓			✓	✓
		[106], [235]	✓		✓	✓	✓	✓	✓	✓		✓	✓		✓	✓			✓	✓		✓		✓
	DED process	[199], [201]	✓		✓	✓			✓		✓				✓	✓		✓	✓	✓			✓	
		[200]	✓		✓	✓			✓	✓					✓			✓		✓			✓	✓
	Direct Laser Deposition	[236]	✓		✓	✓		✓			✓				✓				✓					✓
	Fused Filament Fabrication	[256], [257]	✓			✓			✓		✓	✓	✓		✓			✓	✓	✓	✓			
	Laser-based DED	[258]	✓			✓			✓			✓			✓				✓		✓			

Manufacturing Process Group	Manufacturing Process	Ref.	Process / Processing Window												Data					Methodology				
			Use			Parameter		Criteria		Dimension			Width		Source					VE	P	AS	ML	DOE
			C	D	O	PP	MP	G	M	2	3	-	N	W	-	A	L	S	P					
	LMD process	[99]	✓	✓		✓			✓			✓	✓						✓		✓			
		[237]	✓			✓			✓		✓				✓				✓	✓				✓
		[58]	✓		✓	✓			✓		✓				✓				✓	✓			✓	✓
	L-PBF process	[259]–[261], [263]	✓		✓	✓		✓	✓	✓		✓		✓	✓				✓		✓			
		[262], [264]–[266]	✓		✓	✓		✓	✓	✓		✓			✓	✓		✓	✓	✓		✓		
		[185], [202], [203]	✓		✓	✓		✓	✓	✓		✓			✓	✓	✓		✓	✓			✓	
		[204], [207]	✓			✓		✓	✓		✓				✓			✓	✓	✓		✓	✓	
		[205], [208]	✓			✓			✓		✓		✓			✓			✓	✓		✓	✓	✓
		[206]	✓			✓		✓	✓			✓			✓				✓	✓			✓	✓
		[84], [238], [239]	✓		✓	✓		✓	✓	✓	✓				✓				✓	✓				✓
	Metal Additive Manufacturing	[267]	✓	✓		✓		✓	✓			✓			✓	✓	✓					✓		
	PBF-EB process	[81]	✓			✓		✓	✓		✓				✓	✓			✓	✓		✓		

Manufacturing Process Group	Manufacturing Process	Ref.	Process / Processing Window													Data					Methodology			
			Use			Parameter		Criteria		Dimension			Width			Source				VE	P	AS	ML	DOE
			C	D	O	PP	MP	G	M	2	3	-	N	W	-	A	L	S	P					
		[76]	✓	✓	✓	✓			✓		✓				✓				✓	✓			✓	✓
	SEBM process	[80], [97]	✓			✓			✓		✓	✓		✓	✓	✓		✓	✓	✓		✓		
		[95], [255]	✓			✓		✓	✓	✓		✓			✓				✓		✓			
	SLM process	[100], [268], [269]	✓			✓	✓	✓	✓	✓		✓	✓		✓				✓		✓			
		[101], [103]	✓			✓		✓	✓		✓	✓			✓	✓	✓	✓		✓		✓		
		[209]	✓			✓			✓		✓				✓	✓				✓		✓	✓	✓
		[7]	✓			✓			✓			✓			✓				✓				✓	✓
		[218]	✓	✓		✓		✓				✓			✓	✓		✓				✓		✓
		[240]	✓		✓	✓			✓			✓			✓				✓	✓				✓
	Semi-solid Wire-feed AM	[270]	✓			✓			✓		✓		✓						✓		✓			
	WAAM process	[87]	✓			✓		✓	✓		✓				✓			✓		✓				✓
Dividing	Drilling	[119]	✓		✓	✓		✓	✓						✓				✓	✓				✓
	Grinding	[241]	✓			✓			✓			✓			✓	✓			✓	✓		✓		✓
	High-speed milling	[88]			✓	✓		✓	✓		✓				✓				✓	✓				✓
	Laser Cutting	[70]	✓	✓		✓			✓												✓			
	Machining	[210]	✓			✓		✓	✓	✓					✓		✓		✓	✓			✓	
		[271]	✓			✓			✓			✓			✓	✓	✓			✓		✓		
	Micro-EDM	[242]	✓			✓			✓			✓			✓				✓	✓				✓

Manufacturing Process Group	Manufacturing Process	Ref.	Process / Processing Window												Data					Methodology				
			Use			Parameter		Criteria		Dimension			Width		Source					VE	P	AS	ML	DOE
			C	D	O	PP	MP	G	M	2	3	-	N	W	-	A	L	S	P					
	Power Skiving	[272]	✓			✓			✓		✓				✓	✓		✓				✓		
	Turning	[176]	✓			✓			✓		✓				✓					✓			✓	
Forming	Automated Fibre Placement	[129]	✓		✓	✓	✓		✓	✓					✓	✓		✓				✓		
	Extrusion	[4]	✓			✓			✓	✓			✓			✓		✓				✓		✓
		[273]	✓		✓	✓			✓				✓			✓				✓		✓		
	Inclined compression beading	[274]	✓			✓			✓			✓			✓			✓	✓	✓		✓		
	Laser dieless drawing.	[96]	✓			✓			✓			✓			✓	✓		✓				✓		
	Metal Forming	[109], [117]	✓	✓	✓	✓			✓	✓	✓		✓		✓	✓	✓	✓				✓		
	Rolling	[275], [276]	✓		✓	✓			✓	✓			✓		✓	✓		✓	✓	✓		✓		
	Sheeting Forming	[243]			✓	✓			✓			✓			✓			✓						✓
		[69]	✓	✓		✓	✓		✓				✓					✓	✓	✓		✓		
	Thixoforming	[277]	✓			✓			✓	✓			✓			✓			✓			✓		
Joining	FSW process	[74]	✓			✓			✓	✓					✓	✓	✓	✓				✓		✓
		[55], [278], [279]	✓	✓		✓			✓	✓		✓			✓	✓	✓	✓		✓		✓		
	Hot Gas Welding	[245]			✓	✓			✓		✓				✓				✓					✓

Manufacturing Process Group	Manufacturing Process	Ref.	Process / Processing Window												Data					Methodology				
			Use			Parameter		Criteria		Dimension			Width		Source					VE	P	AS	ML	DOE
			C	D	O	PP	MP	G	M	2	3	-	N	W	-	A	L	S	P					
	Laser beam welding	[280]	✓			✓			✓					✓					✓	✓	✓			✓
		[228]	✓			✓			✓	✓					✓	✓			✓	✓		✓		✓
	Laser Hot-Wire	[281]	✓			✓			✓		✓				✓		✓	✓		✓		✓		
	Mini-wave soldering	[244]	✓			✓		✓		✓			✓						✓	✓				✓
	Resistance Welding	[92]	✓	✓		✓			✓	✓			✓						✓		✓			
	Ultrasonic Consolidation	[162]	✓			✓			✓		✓				✓				✓		✓			
	Vaporizing Foil Actuator Welding	[67]	✓			✓			✓			✓			✓				✓	✓	✓			
Coating	Aerosol Jet 3D printing	[211]	✓		✓	✓			✓	✓					✓	✓			✓	✓		✓	✓	✓
	Cladding	[246], [247]	✓		✓	✓		✓	✓	✓	✓				✓				✓	✓				✓
	Inkjet printing	[282]	✓			✓			✓			✓			✓				✓		✓			
	Plasma-sprayed YSZ	[115], [227]	✓	✓		✓	✓		✓		✓	✓	✓		✓	✓			✓	✓		✓		✓
	Sputtering	[283]	✓	✓		✓			✓	✓					✓				✓			✓		
Modifying material property	Austempering	[104]	✓	✓		✓			✓	✓			✓						✓		✓			

Manufacturing Process Group	Manufacturing Process	Ref.	Process / Processing Window													Data				Methodology				
			Use			Parameter		Criteria		Dimension			Width			Source				VE	P	AS	ML	DOE
			C	D	O	PP	MP	G	M	2	3	-	N	W	-	A	L	S	P					
Semiconductor device fabrication	Laser Heat Treatment	[120]	✓			✓			✓	✓					✓	✓						✓		
	Laser Peening	[284]	✓			✓			✓			✓			✓				✓		✓			
	Thermomechanical Treatment	[131]	✓			✓			✓	✓					✓			✓		✓			✓	
	Etching	[73]	✓		✓	✓			✓			✓			✓				✓					✓
	Excimer laser crystallization	[285]	✓	✓		✓			✓				✓						✓	✓		✓		
	Laminate Consolidation	[134]	✓			✓			✓	✓					✓			✓		✓		✓		
	Lithography	[286]–[290]	✓	✓	✓	✓		✓	✓	✓		✓	✓		✓		✓		✓	✓	✓			
	Self-aligned Silicide	[248]	✓			✓			✓			✓			✓				✓					✓

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