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Review Article

Optimization of 4D/3D printing via machine learning: A systematic review

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A R T I C L E I N F O

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A B S T R A C T

This systematic review explores the integration of 4D/3D printing technologies with machine learning, shaping a new era of manufacturing innovation. The analysis covers a wide range of research papers, articles, and patents, presenting a multidimensional perspective on the advancements in additive manufacturing. The review underscores machine learning's pivotal role in optimizing 4D/3D printing, addressing aspects like design customization, material selection, process control, and quality assurance. The examination reveals novel techniques enabling the fabrication of intelligent, self-adaptive structures capable of transformation over time. Additionally, the review investigates the use of predictive algorithms to enhance efficiency, reliability, and sustainability in 4D/3D printing processes. Applications span aerospace, healthcare, architecture, and consumer goods, showcasing the potential to create intricate, personalized, and once-unattainable functional products. The synergy between machine learning and 4D/3D printing is poised to unlock new manufacturing horizons, enabling rapid responses to market demands and sustainability challenges. In summary, this review provides a comprehensive overview of the current state of 4D/3D printing optimization through machine learning, highlighting the transformative potential of this interdisciplinary fusion and offering a roadmap for future research and development. It aims to inspire innovators, researchers, and industries to harness this powerful combination for accelerated evolution in manufacturing processes into the 21st century and beyond.

1. Introduction

3D printing, also known as one of additive manufacturing techniques, has undergone a huge advancement since its inception in 1980 [1]. 3D printing has been vastly utilized by the people in every sector whether from the consumers or manufacturers perspective in recent years [2]. It has advanced 3D printing technology to a point where users can now use it to generate their own designs and turn them into products [3]. 3D printing technologies relies on a layer-by-layer deposition of 3D object based on the computer-aided design (CAD) model, or 3D model [4]. With this technology, the 3D model with complex geometry and structures can be manufactured easily which contribute to a vast application in the industry such as soft robotics [5], biomedical appliances [6,7], and construction.

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During the period of 3D printing development, there are some challenges that appear in the real-world applications. In electronics application, the production of 3D printed electronics is not feasible through a conventional manufacturing process. The reason behind this is due to the challenges of fabricating a fully functional electronic components in a single build sequence that can withstand harsh environmental conditions [8]. For instance, to fabricate a flexible 3D electronic device requires a complex 3D printer, such as a hybrid of stereolithography and direct write technology [9], to make it functional and can be applied in the real application. For medical aspects, the source of raw materials for construction of similar and suitable products for human organ and tissues replacement using 3D printing technology are still limited, this has made the development of 3D production of biomedical products to slows down [10]. These applications and challenges have led to extended development of 3D printing, which also can expand to more intrinsic and extrinsic functionality on the 3D model [11,12].

Development in 3D printing has now been extended to support multi-materials, re-establishing it to be able to produce mixtures of different properties in a bid to develop other complex structures intermeshed with the many types of material [13–15]. It is important for applications where the component may need to have one material in some specific regions while another in other regions in terms of mechanical or thermal characteristics. Extrinsically, developments have included increased resolution and accurate control for printers to create fine and complex models [16,17]. Also, there are recent advances in manufacturing that incorporate 3D printing with other methods such as direct write method and stereolithography techniques [15,18]. These hybrid processes are crucial in manufacturing functional electronics and parts, suitable for deployment in challenging conditions. Furthermore, integrating responsive 'smart' materials capable to adapt to various stimuli in the surroundings has led to the advancement of the 4D printing technology where products made through the process are capable to transform shape or function over time hence widening the opportunity of using additive manufacturing [19–21]. From this idea, 4D printing has emerged as a more advanced application of 3D printing with the additional functionality.

The idea of 4D printing initiated by Tibbits at the 2013 technology, entertainment, design (TED) conference where he demonstrates how a static 3D printed object can change its shape overtime [22]. Since then, the researchers are eager to develop the 4D printing technology as it is a new discovery. 4D printing has created some opportunity in expanding the functionality of 3D printing by including the element of smart material. With the addition of smart material into 3D printing, the 4D printed object will be able to have the ability to response to external stimuli, such as heat, light and humidity [23,24]. Fig. 1 below shows the publication that has been published regarding the subject of 4D printing by Scopus.

The development of 3D printing using machine learning has been applied to some application in recent years to optimize the 3D printing performance and processes. For example, Castro et al. has developed a machine learning model that successfully predicted key aspects of 3D printing formulation and in-vitro dissolution properties in drug. It is found that the machine learning can provide high level of prediction accuracy especially in predicting the hot melt extrusion processing temperature, filament aspect, printing temperature and printability [4]. Menon et al. also has applied hierarchical machine learning (HML) for the optimization of silicone elastomer 3D printing, in which they able to increase the printing speed by twofold using the HML algorithm [25]. Recently, Zolfagharian and colleagues created a ML model to predict the bending angle of a 4D-printed soft pneumatic actuator (SPA) and investigate the effect of the input parameters on its bending [20]. However, the development of 4D printing is still behind since the idea of 4D printing is still under development while 3D printing has been widely commercialized throughout the world. The evident of this claim can be proven as shown in Fig. 2 below which shows the number of articles published regarding the application of machine learning for the development of 3D printing compared to 4D printing by Scopus.

Optimization in 3D/4D printing is crucial to achieve the best possible results in terms of speed, quality, and cost-effectiveness of the 3D/4D output. The literature on this subject has expanded significantly covering the application of diverse machine learning algorithms in specific stages of 3D/4D printing process such as printing material selection, design for additive manufacturing, support structure optimization, process parameter optimization, predictive modeling and defect detection/minimization, topology optimization and layer height optimization as captured in Fig. 3.

To the best of our knowledge, there is no review exercise that focuses on the critical evaluation in optimizing 4D printing parameters with machine learning. To raise awareness within the scientific community about the significance of optimizing 4D printing parameters through machine learning, the present review has compiled scattered yet recent literature discussing the potential for maximizing these parameters using machine learning. Section 2 provides an overview of 4D printing, focusing on design and properties, while Section 3 critically examines the selection of smart materials for 4D printing, including shape memory polymers, alloy memory polymers, and hydrogels. Section 4 presents an overview of machine learning (ML). Sections 5 critically and comprehensively survey various methods for optimizing 3D/4D printing parameters. The concluding section highlights future perspectives. This review systematically explores the landscape of 4D printing, smart material selection, and the optimization of 4D printing via ML, providing a comprehensive understanding of the current state of the field. By critically assessing and surveying optimization approaches for 3D/4D printing parameters, the review offers valuable insights into advancements and challenges. The highlighted future perspectives contribute to guiding further research and development in the dynamic

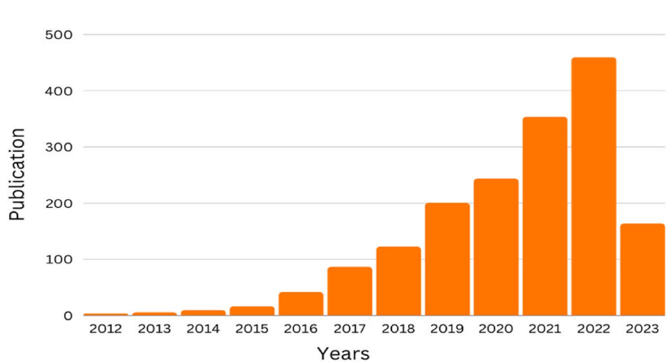

Fig. 1. Number of publications for 4D printing.

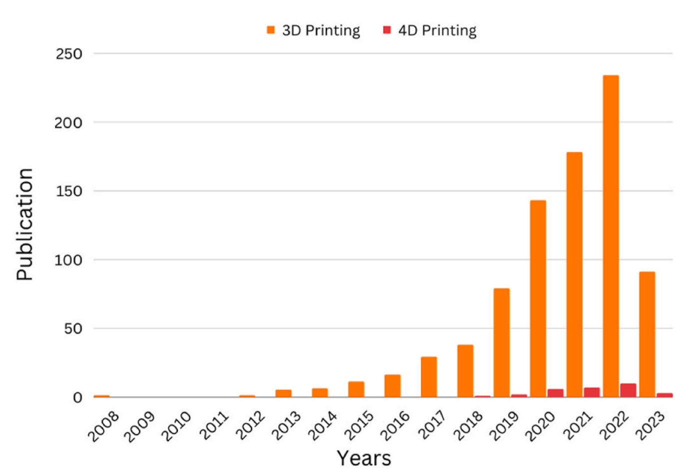

Fig. 2. Comparison of publication regarding machine learning for 3D and 4D printing.

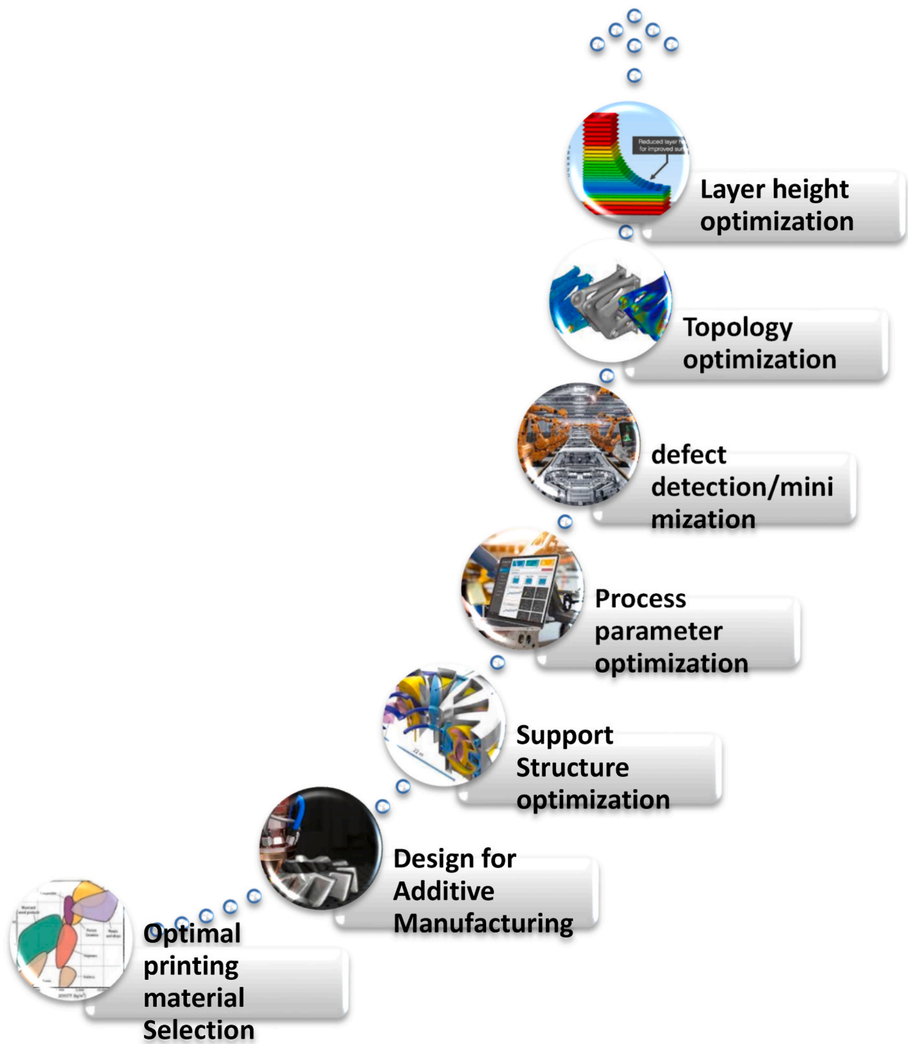

Fig. 3. Machine learning enhanced Optimization aspects in 3D/4D printing.

field of 4D printing and machine learning, underscoring the significance of this review for researchers, practitioners, and industries involved in this interdisciplinary domain.

2. 4D printing

4D printing can be defined as a targeted evolution of 3D printed structure, in terms of shape, property and functionality, which it has the capability of self-assembly, multifunctionality and self-repair [26]. The capabilities of 4D printing are determined by utilizing the right combination of smart materials in three-dimensional spaces [27]. Fig. 4 shows the characteristic differences between 4D printing and 3D printing. The fundamental of 4D printing can be classified into five aspects which are 3D printing facility, stimulus, smart material, interaction mechanism and mathematical modelling [28]. These aspects are important to make sure the object is produced with suitable equipment and material according to its functionality [26].

The technology for 4D printing can also be regarded as 3D printing since the process of producing 4D printable object is the same as producing the usual 3D printable object [12]. The functionality of stimulus reaction can still be applied after being printed since it does not affect the features of 4D printing itself [29]. The printing technologies that are commonly used for 4D printing application are fused deposition modelling (FDM) [30] also known as fused filament fabrication (FFF), The Fused Deposition Modeling (FDM) or Fused Filament Fabrication (FFF) is inexpensive and works with various types of materials; thus, it is suitable for both medical devices and soft robotics applications because of the morphable structure [31]. Digital Light Processing (DLP) is ideal for resolutions that are useful in designing responsive textiles and even airplane parts [32]. Selective Laser Melping (SLM) creates parts with high and accurate accuracy of metals that can respond to thermal or mechanical conditions, helpful in aerospace and automotive industries [33]. Directed Energy Deposition (DED) is used in the formation of self-repairing parts from a variety of materials that can be useful in aerospace and defense industries [34]. Direct Ink Writing (DIW) involves extruding viscous inks to create soft materials like hydrogels that have applications in soft robotics and personalized biomedical solutions [35].

2.1. Influence of external stimuli on 4D printing

The idea of 4D printing is not only relying on the ability to “self-assembly” in order to fulfill the task that has been assigned. The concept of 4D printing itself relates to the technique using 3D printing technologies on stimulus-responsive active materials which causes physical or chemical changes in the material composition with time [36]. The stimulus can be in the form of physical or chemical form, such as humidity, pH, light intensity and temperature [37]. 4D printing has brought the ability to fulfill desired transformation function. By having 3D objects to gain a behavioral capability, 4D printing has the capability

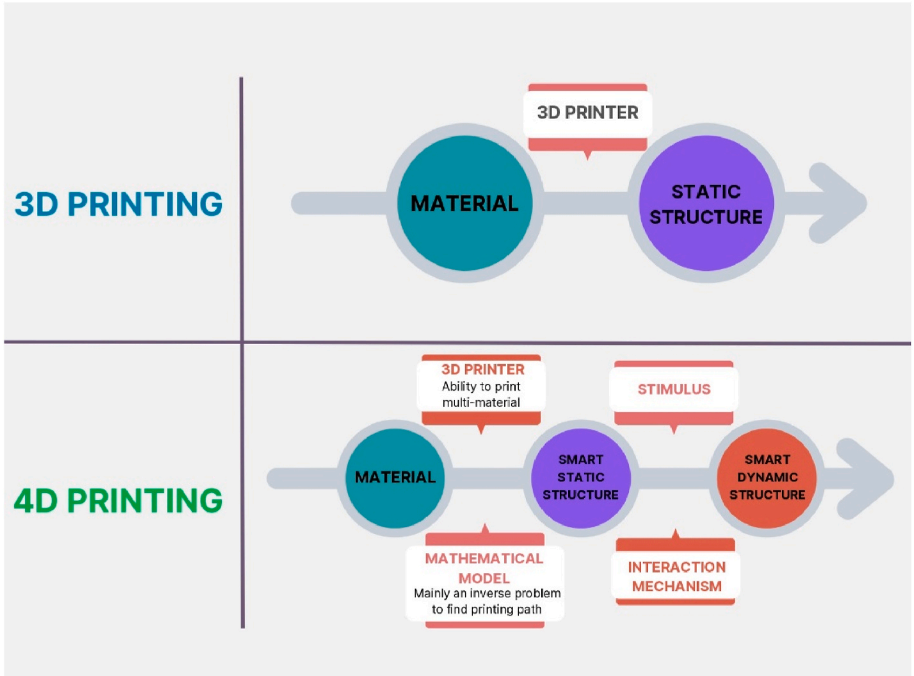

Fig. 4. The difference in 3D printing and 4D printing [26].

to improve biomimicry [38] and soft robotics [5] application. The literature explores how different stimuli applied to 3D objects might modify their function and behavior. Based on the number of publications (Fig. 2), the following variables related to the environment have received the greatest attention in the scientific literature: temperature, light, water, magnetic, pH, electric, and humidity.

Humidity as an external stimulus in 4D printing induces various material behaviors, including expansion, contraction, and actuation, allowing for shape changes in response to moisture levels. It enables materials to bend, fold, or morph surfaces, enhancing their adaptability in different environments. Humidity can also trigger self-healing properties, where materials repair themselves under moist conditions, and control porosity, affecting structural integrity and permeability [24,39]. Additionally, some materials change color when exposed to humidity, providing visual indicators. These behaviors facilitate innovative applications in soft robotics, smart textiles, adaptive sensors, and other fields requiring responsive and multifunctional materials. Each of these triggers for 4D printing technology is summarized below in Table 1 along with its respective benefits, drawbacks, and potential uses.

3. Smart materials

The main factors in selecting the material for 4D printing are smartness and printability [41,42]. Consequently, the nature of smart material (SM)s depends upon the association of the technical function (sensor, transducer, or actuator), the stimulus, and the substance or material itself (particularly metal, alloy, polymer and ceramic). It is essential to select a material which has the ability to respond when it is interacting with a stimulus. Therefore, smart material is the best option for 4D printing application since it is a stimulus-responsive materials [43]. In definition, SM is a material that changes its own behavior in its own manner for a response to a certain stimulus. Smart material also known as unconventional actuator as the structure of the material can consists of sensing, actuation, and mechanical ability [44]. It is also referred to as active material since its behavior is always changing due to the external stimulus.

There are some types of smart materials that can be used in 4D printing for more advanced applications in today's industry. Some of them are smart memory alloy (SMA), smart memory polymer (SMP) and hydrogels. These materials are common for 4D printing applications since the change of the material behavior is significant when observation is made on different condition. Each of them has different purpose and functionality for different circumstances [12]. Fig. 5 is an adaptation of the taxonomy that was proposed by Demoly et al., 2021, and it displays the functional classification of the SMs. It also gives a peek at prospective design concepts that need to be appreciated. These are supported by a more general category of transformation principles, such as expand-collapse, fuse-divide, and expose-cover, in addition to supporting transformation enablers such as furcation, function sharing, and shelling.

The advancement of 3D printing technology has resulted in the development of 4D printing, which signifies a notable breakthrough in the domain of additive manufacturing. 4D printing expands upon 3D printing by incorporating an extra dimension, which can be either spatial or temporal. This enables printed objects to change and develop in terms of their shape, properties, and functionality in response to external triggers or influences (Chu et al., 2020; Halligan et al., 2023; Peerzada et al., 2020). This evolution takes place either simultaneously with the 3D printing process or after the production of the 3D object, resulting in the development of dynamic and adaptable structures (Azhar and Pei 2022; Yang Liu et al., 2019). The concept of 4D printing is based on the integration of precise structures and intelligent features to facilitate applications in sophisticated sectors like medicine and aerospace [45]. It is seen as a promising new technique and the next stage in additive manufacturing, with the ability to create intricate structures that can change over time (Bagheri and Jin 2019; Munteanu et al., 2021; Peerzada et al., 2020).

The transition from 3D to 4D printing has been linked to the advancement of new materials and composites specifically designed for energy-efficient 4D printing, emphasizing the convergence of materials science and 4D printing technology [46]. Moreover, the advancement of 3D printing technology has generated significant attention because of its affordable nature and ability to create intricate structures. This has paved the way for the development of 4D printing [47]. Furthermore, the progress of 3D printing is associated with the breakthroughs in photopolymerization-based 3D printing and the creation of innovative

Table 1
Summary of stimulus factors used in 4D printing technology [40].

Stimulus	Advantages	Limitations	Applications
Temperature	• Control the adjustment in a fabricated object - Perform mechanical manipulations. • Ease of operation	• Damaged cells • Slow response • Complicated	• Biomedical • Drug delivery • Tissue engineering
Light	• Rapid switching • Precise focusing • Biocompatibility • Sustainability • Control of mechanical property	• Potential toxicity • Diminished shape transformation • Heat generation • Complexity	• Drug delivery • Optical devices
Water	• Controllable • Convenient • Reduced temperature	• Slow reaction times	• Drug delivery
Magnetic	• Quick response • Safety • Rapid response • Remote guide	• Highly reactive • Aggregation affinity • Complication with nanoparticles in living systems • High density	• Drug delivery • Fastening purposes
pH	• Achieve various structure behaviors. • Improved response • Biodegradation • Biocompatibility	• Limited applicability	• Drug delivery • Soft robots • Medical • Food packaging • Spinal cord regeneration • Tissue engineering
Electric	• Speed • Remote control	• Localized heat - Membrane disruption - Cell death	• Drug delivery • Artificial muscle • Tissue regeneration
Humidity	• Perform various behaviors. • Low cost • Environmentally friendly	• Slow response • Need for precise control	• Artificial muscles • Sensors • Biomedical

3D printable photopolymers. These developments have significant implications for the progression towards 4D printing. The study of shortcomings in 3D printing processes has also examined the development of 3D printing technology, highlighting the significance of comprehending the temporal evolution of internal material tension, dimension, and shape as potential sources of inaccuracies in 3D printing.

Within the fields of health and materials science, the advancement of 3D printing has facilitated the creation of 3D-printed structures that could modify their properties and functions over time. This aligns with the ideas of 4D printing [48]. In addition, the advancement of 3D printing has played a crucial role in developing 3D-printed monolith composites that have improved photocatalytic capabilities. This shows the possibility for further progress in catalysis and materials science through the progression towards 4D printing. Smart materials have revolutionized the way products are manufactured, opening new possibilities for the development of advanced medical devices and implants (Kabirian, Mela, and Heying 2022; Ibanga et al., 2023). The integration of smart materials with 4D printing has also led to the creation of shape-memory polymer systems that exhibit self-healing properties, offering exciting potential for various applications in medicine and materials science [49].

Moreover, smart materials have been instrumental in enhancing sustainability and energy efficiency in architectural applications. They have been suggested as key features for the competitiveness of twenty-first-century sustainable architecture, allowing controlled transmission of light and heat into buildings, thereby improving daylighting and energy consumption (Omar, Mohamed, and Al-Nasr Ahmed 2022; L. Zhang et al., 2021).

In the field of structural health monitoring, the development of embedded sensors and smart structures has been a significant area of research, emphasizing the importance of smart materials in advancing engineering technologies [50]. Additionally, smart materials have been applied in strain sensing and crack detection in masonry structures, demonstrating their versatility in diverse engineering applications [51].

The advancements in smart materials have also led to the development of smart windows with spectrally selective properties, enabling high near-infrared light shielding and controllable visible light transmittance, showcasing the potential for smart materials in energy-efficient building technologies [52].

3.1. Smart memory alloy (SMA)

SMA is a metal alloy that changes its phases or states when exposed to external stimulus such as temperature and load. SMA can retain its original shape after being deform in various way, which is cause by the super elastic behavior of the metal alloy. The transformation is taken place in austenite-martensite transformation (forward phase) and martensite-austenite transformation (reverse phase) [53]. The phase change will cause the fracture toughness of SMA to increases greatly which temperature is the main factor the phase change [54].

The application of SMA is widely applied in medical and engineering sectors. In civil engineering sector, iron-based SMA, such as Fe–Mn–Si alloy, is used to repair and reinforce the building structure [37]. Another application for the medical field is Nitinol which can be applied for biomedical implant. For instance, in simple application, Nitinol paperclip has SMA properties to make sure the paper will form to its original shape after being deformed by compiling a large amount of paper [44]. In medical application, NiTi self-expendable neurosurgical stent is used for clearing the blockage in the artery using SMA properties [55].

3.2. Shape memory polymer (SMP)

The process of SMP involves shape deforming, shape fixing and evacuation of external stress. The polymer is required to be deformed first under external stress along with heating process before shape memory process taken place. The current shape will retain its shape for a long time if there is no external stimulus. When the SMP is stimulated by a certain stimulus, such as light, heat or humidity, the SMP will retain its original shape. When an SMP is subjected to a specific temperature stimulus (Fig. 6), it undergoes a reversible phase transition, enabling it to recover its original shape from a temporary deformed state. This process is governed by the thermomechanical properties of the SMP and is crucial for its diverse applications in various fields, including biomedical implants and aerospace engineering. The shape memory cycle of SMPs begins with the programming stage, where the polymer is deformed into a temporary shape at an elevated temperature, known as the programming temperature. During this stage, the polymer chains are oriented and fixed into the temporary shape through physical or chemical cross-linking, allowing the SMP to retain this shape when cooled to a lower temperature. This temporal process is maintained until the SMP is exposed to the triggering stimulus, typically heat, which initiates the recovery process. Upon exposure to the triggering stimulus, the recovery stage is activated, leading to the restoration of the original shape of the SMP. The SMP undergoes a phase transition, reverting from the temporary deformed state to its original shape as it returns to the programming temperature. This phase transition is accompanied by the release of stored elastic energy, enabling the SMP to recover its initial form with high precision and repeatability. The recovery process is a key characteristic of SMPs, allowing them to exhibit shape memory behaviour and recover their original shape upon exposure to an appropriate

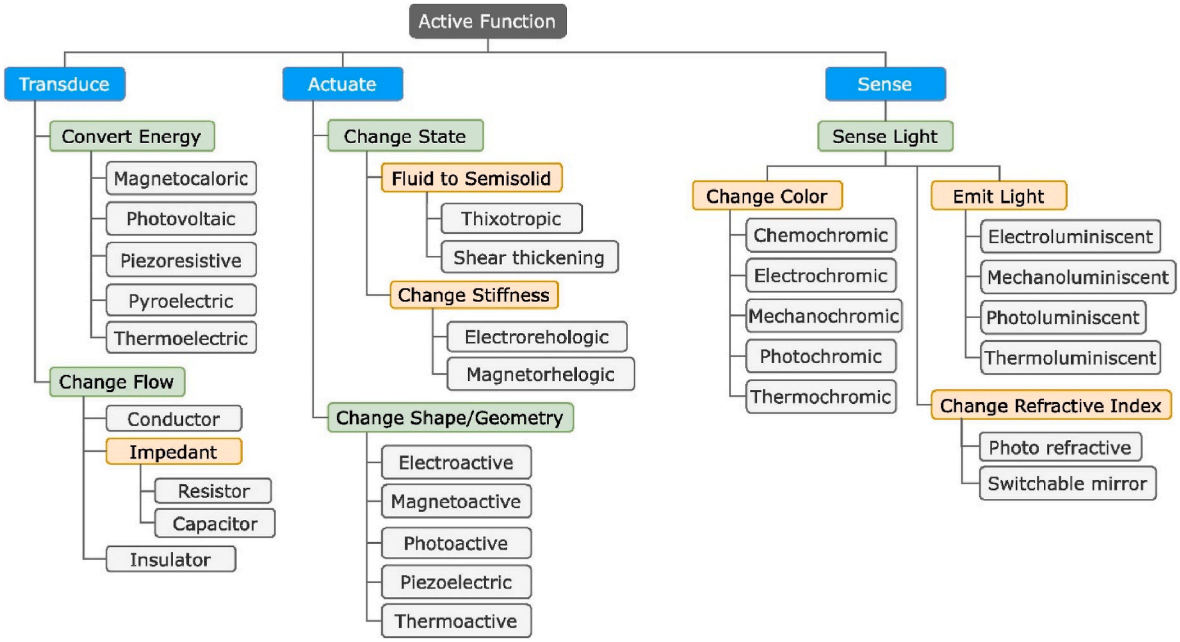

Fig. 5. The functional classification of the smart materials by using functional language for design and engineering [38].

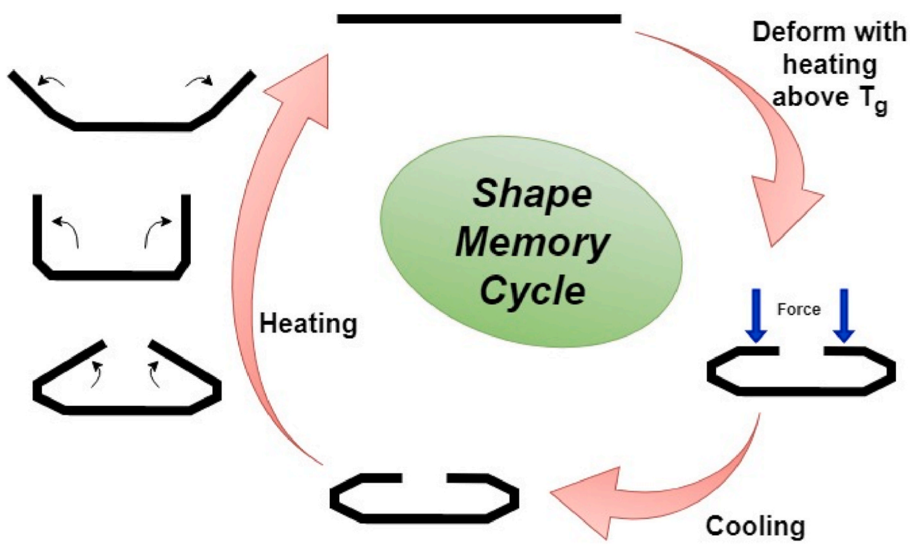

Fig. 6. Process of SMP cycle [56].

stimulus.

SMP is lighter, more flexible and has higher biocompatibility than SMA which make it more often to be used by the industries. SMP can also recover a higher degree of strain and consume greatly lower energy during the shape memory process [57]. The application of SMP is mostly in aerospace and medical industries to produce a complex shape on certain part of the system. For instance, synthetic polymers, such as polycaprolactone (PCL) and polylactic acid (PLA)-based SMP, are used in biomedical application where it represents the biodegradable substances in comparison to natural extracellular matrix (ECM) proteins. The SMP have shown much lesser immunological reaction compared to ECM which is beneficial for biomedical industry in the future [58,59].

Industrial sectors experience enormous transformation with the help of Shape Memory Polymers (SMPs) in 3D and 4D printing processes. SMPs further make it possible to develop structures with responsive properties for performance enhancement in aerospace [60](Wang et al. , 2018). In biomedical applications, SMPs help develop dynamic implants and devices primarily benefiting the health care of the patients [61]. Manuscripts in robotics use 4D printed SMPs in soft robots that are sensitive with surroundings [62]. For instance, smart materials in automobiles include SMPs for smart tires and adaptive automotive interior [63] whereas textiles and apparels use SMPs in smart fabrics to enhance functionality and comfort [64]. These technologies have tremendously boosted industrial production through the formulation of material that can self-adaptive and self-healing hence minimizing on the costs that can be incurred in frequent repairs while at the same time prolonging the life of products. In aerospace and automotive industries, the desired components increase the efficiency and lifespan through changes in various conditions [65]. This technology helps to reduce work in progress cycle time through smart materials that are already self-assembling which dramatically reduces assembly time and costs [66]. In the same manner, with the help of 4D printing, it is possible to develop unique products that would fit certain environments, for example, medical implants that adapt to the person's movements to enhance compatibility and comfort

[67]. The cost of implementing the 4D printing technology is dependent on several factors but will require substantial funding in a specialized device and software. Modern commercial 4D printers range between \$50,000 – \$500,000 depending on the capacity of the equipment. 4D printing materials such as shape-memory polymers, hydrogels; are costlier than that of a general 3D printing material. Prices can range from \$50 to \$1000 per kilogram [68]. Basic CAD software price ranges from \$100 - \$1000 per year while advanced CAD software with simulation capabilities ranges from \$1000 - \$10,000+ per year [69]. Still, the net return on investment that is accrued from improved efficiency and a concomitant decrease in operation costs is a good enough reason to apply this innovation in industries.

3.3. Hydrogels

Hydrogels are a hydrophilic polymeric material which has an ability to change its volume significantly in response to external stimuli. It has lower mechanical strength and extremely brittle compared to SMP [70]. To counter its weak body, it can be generally infused with secondary polymeric network to increase its mechanical strength. For instance, interpenetrating network (IPN) hydrogels is one of the results of hydrogels that has been crosslinked between ionic and covalent bond with other polymeric network to overcome the weakness of hydrogels [71].

Recently, hydrogels are used to fabricate artificial muscles that can mimic the performance of real muscles as close as possible. However, there are still lacking in quick response when interacted with external stimuli. The hydrogels only able to undergo huge deformation, converting chemical energy to mechanical energy and generate high strokes which is partially following the mechanism of real muscles [72]. Table 2 provides a summary of the materials mentioned in this review.

3.4. Piezoelectric

Piezoelectric materials have the capacity to produce an electric charge when subjected to mechanical stress, rendering them highly useful for applications such as sensors, actuators, and energy harvesting devices. Piezoelectric materials have become increasingly important since the period following World War II, primarily because of the identification of ceramics that can adjust physical characteristics like piezoelectric constant, dielectric permittivity, and stiffness to meet specific needs [73]. Piezoelectric materials, such as lead zirconate-titanate (PZT) and barium titanate ($BaTiO_3$), are widely utilized in energy harvesting applications due to their exceptional piezoelectric capabilities. This has garnered great interest in the field [74]. Moreover, the effectiveness of piezoelectric materials relies on the piezoelectric constants and elastic properties, emphasizing the significance of material features in attaining desired functions [75]. The progress in materials and manufacturing techniques has facilitated the development of piezoelectric materials using printing methods. This has allowed for their use as flexible sensors, actuators, and generators in the domain of flexible electronics [76]. Furthermore, the incorporation of screen-printed piezoelectric sensors for detecting force impacts in intelligent multifunctional glass applications has showcased the versatility and novelty of piezoelectric materials in various applications [77].

Researchers in the field of structural engineering have investigated the use of piezoelectric materials to regulate the shape of hybrid functionally graded plates. This technique involves manipulating the stiffness and thickness ratios of the plates to reduce stress concentration [78]. Moreover, the examination of intelligent functionally graded beams integrated with piezoelectric materials through finite element techniques has demonstrated the simultaneous impacts of piezoelectric materials as both actuators and sensors, emphasizing their importance in the field of structural engineering applications [79]. The utilisation of piezoelectric materials for energy generation has been extended through the advancement of biocompatible nanogenerators. These nanogenerators exploit the capacity of piezoelectric materials to convert mechanical energy into electrical energy [80]. Moreover, the potential for utilizing piezoelectric actuators as intelligent materials to mitigate vibrations in wind turbine blades has been suggested, showcasing the wide-ranging uses of piezoelectric materials in the realm of sustainable energy [81].

The field of composite materials has introduced the concept of longitudinally piezoelectric fiber-reinforced composite (PFRC) materials. This has led to research on their mechanical and piezoelectric properties, which has expanded the range of applications for piezoelectric materials in composite structures [82]. Furthermore, researchers have investigated the customization of piezoelectric coefficients to boost the control capability of piezoelectric distributed actuators. This has resulted in the creation of new piezoelectric composite materials that possess improved capabilities [83]. The versatility of piezoelectric smart materials has been showcased by utilizing cellulose-based electro-active paper sensors, which have demonstrated their potential in artificial muscle applications and piezo-type sensing technology [84]. Moreover, the use of piezoelectric materials and shape memory alloys has been thoroughly examined in relation to intelligent materials and structures, highlighting its importance in aeronautical engineering and the use of composite materials [85]. The widespread use of piezoelectric actuation devices and smart structures has been emphasized, demonstrating the wide range of applications and accomplishments in the realm of piezoelectric smart materials [86]. Furthermore, researchers have examined how anisotropic piezoelectric actuators affect the aerodynamic forces on wings, resulting in progress in the creation of innovative piezoelectric materials for use in aerospace applications [87].

Table 2
An overview of the 4D printing materials [40].

Material	Advantages	Applications
Shape- memory polymer	• Low cost and density • Lightweight • High recovery strain • Biodegradability • Sustainability • Biocompatibility • High-quality product	• Biomedical • Aerospace • Automobile • Textiles • Industrial
Shape- memory alloy	• Excellent conductor of heat and electricity • High strength and recovery stress • Compatibility	• Aerospace • Neurosurgical • Biomedical • Automobile
Hydrogel	• Biocompatibility • Transparency • Stretchability • Ionic conductivity • Simplicity of modification • Absorb large amounts of fluid	• Healthcare • Agriculture • Tissue engineering

3.5. Magnetostrictive

The field of magnetostrictive smart materials has made notable progress and accomplishments in many areas such as energy harvesting, vibration control, biomedical applications, and composite materials. The combination of magnetostrictive materials with cutting-edge technologies has resulted in the creation of new devices and systems that have improved functionality and performance.

Magnetostrictive materials have been thoroughly investigated for their potential in energy harvesting applications, particularly in the field of modelling and characterising magnetostrictive vibration energy harvesters. The developments mentioned encompass material-level modelling, lumped parameter models, and finite element models. These advancements have played a significant role in the creation of highly efficient magnetostrictive energy harvesting devices [88]. Moreover, researchers have examined the capabilities of magnetostrictive materials in both passive damping and active vibration suppression. These investigations have highlighted the importance of these materials in the fields of vibration control and structural engineering applications (Munjal, Trivedi, and Sarma 2008; Bandopadhya, Bhattacharya, and Dutta 2007).

The biocompatibility and multifaceted properties of magnetostrictive materials, like Galfenol, have been studied in the field of biomedical applications. These materials have shown potential for remote microactuation in cells, which could lead to the development of biomedical devices and microactuators. This research offers promising opportunities in the field [89]. The study conducted by Zhao and Sui (2021) has examined the potential of magnetostrictive materials in temperature compensation design for large magnetostrictive actuators. The research emphasises the importance of these materials in precision control systems and multiphysics applications. The broad spectrum of accomplishments associated with magnetostrictive smart materials also include composite materials and structural engineering. Research has been conducted on the advancement and utilisation of magnetostrictive short fibre composites, demonstrating their potential for use in sensors and energy-harvesting devices [90]. In addition, the utilisation of smart magnetostrictive composites for flexible manipulators has shown the capability of magnetostrictive materials to achieve active damping and control in structural systems. This has been proved through the modelling of hybrid damping schemes [91].

The versatility of magnetostrictive materials in ultrasonic sound generators, position sensors, and micromotional control has been emphasized, highlighting their wide range of applications in many technical and industrial fields [92]. In addition, the creation of a feedback control system to manage the vibration of magnetostrictive plates under follower force has shown the capability of magnetostrictive materials as intelligent elements in vibration management systems [93].

3.6. Shape-memory ceramics (SMCs)

Shape-memory ceramics smart materials have made notable advancements and found practical uses, especially in the fields of medicinal implants and aerospace engineering. The incorporation of shape-memory ceramics with cutting-edge technologies has resulted in the creation of new devices and systems that have improved functionality and performance. SMCs have demonstrated potential in the field of biomedical implants for creating biocompatible and biodegradable materials that might be used in many biomedical applications. The utilisation of shape-memory thermoplastics in the development of a smart degradable suture exemplifies the capabilities of these materials in the field of biomedical applications [94]. Moreover, the advancement of shape-memory ceramics that possess exceptional energy output, energy damping, and high-temperature resistance has established them as a novel category of actuators or intelligent materials with distinct characteristics. Consequently, they are well-suited for biomedical applications like load-bearing scaffolds and packaging materials for biomedical microelectrodes.

SMCs have been explored for their potential in the field of aerospace engineering due to their promise in innovative materials and structural applications. The study of SMPs and their composites in aerospace applications emphasises the versatility of SMPs and composites, demonstrating their potential for utilisation in aerospace engineering [95]. Moreover, the advancement of SMCs that demonstrate consistent super elastic deformation has noteworthy consequences for potential energy dissipation and micro-actuation uses, establishing them as viable materials for aerospace engineering [96]. In addition, the creation of shape-memory ceramics that can repeatedly undergo super elastic deformation has potential implications for energy damping and micro-actuation applications, making them very attractive materials for use in structural engineering. Researchers also have investigated the application of SMCs and its composites, in the field of dentistry, demonstrating their potential for use in dental procedures [97].

3.7. Colloidal

Colloidal smart materials refer to a wide variety of materials, such as colloidal suspensions, nanoparticles, and liquid crystal colloids. These materials possess distinct qualities that result from their small size and the way their particles interact with each other. Colloidal self-assembly approaches have been instrumental in the development of smart nanostructured materials, offering a versatile platform for the design and fabrication of advanced materials with tailored functionalities [98]. The use of colloidal self-assembly has shown promise in the creation of smart materials with multifunctional properties, paving the way for the next generation of advanced materials with diverse applications in nanotechnology and nanostructures. Colloidal suspensions can undergo reversible phase changes when exposed to external stimuli. This property makes them well-suited for use in tuneable photonic devices and adaptive materials. The development of super-resolution optical microscopy has enabled the detailed characterization of smart colloidal microgels, offering insights into their network morphology and potential applications in a wide variety of fields, including medicine and materials science [99]. These achievements have positioned colloidal materials as promising candidates for diverse applications, including drug delivery systems, tissue engineering, and biomedical diagnostics.

The design and development of photo- and pH-responsive hybrid colloidal particles have demonstrated the potential of colloidal smart materials in achieving stimuli-responsive behavior, making them suitable for a wide range of smart applications [100]. The pronounced photochromic effect and high fatigue resistance of these colloids have opened new avenues for the development of smart materials with applications in sensors, actuators, and responsive devices. Thermoresponsive nanoparticles with cyclic-polymer-grafted shells have received significant attention in recent years, showcasing the potential of colloidal smart materials in achieving responsive behavior to temperature changes [101]. These achievements have positioned thermoresponsive colloidal materials as promising candidates for applications in drug delivery, controlled release systems, and responsive coatings. The development of smart-responsive colloidal capsules has emerged as an innovative tool for designing multifunctional lubricant additives, offering enhanced lubrication performance and tailored functionalities for diverse industrial applications [102]. This work has opened a new avenue for customizing multifunctional additive packages by utilizing smart colloidal capsules in lubrication science.

4. Optimization of 3D/4D printing via machine learning

The optimization of 3D/4D printing through machine learning merges advanced manufacturing technologies with artificial intelligence. This section reviewed how machine learning enhances printing processes, covering aspects such as design customization, material selection, process control, quality assurance, and topology optimization. It highlights the role of AI in achieving efficiency, precision, and innovation in additive manufacturing, paving the way for future advancements.

4.1. Optimal printing material selection

Selecting the appropriate material is of utmost importance for both the 3D/4D printing process and the specific application of the printed products. This is crucial due to the distinct material types and properties that can significantly influence the final quality and performance of the product. The categorization of 3D/4D printing technologies is based on different printing methods primarily determined by the materials employed. This material choice directly impacts the mechanical and thermal characteristics, as well as the responsive features of the end products. Therefore, 3D/4D printing demands the utilisation of intelligent or adaptive materials that can modify their attributes in response to external stimuli. Making the correct material selection is a pivotal phase in the printing process, leading to creations with enhanced functionality, favorable mechanical properties, and tailor-made 3D geometries [103].

Fig. 7 illustrates the hierarchical approach to material selection within 3D/4D printing, incorporating machine learning elements. Material-related knowledge is also considered a cornerstone of the 4D printing paradigm [19]. While material selection invariably seeks to embody desired mechanical attributes and plays an essential role in defining structure and form, it has expanded to encompass technical functionalities and machine learning tools tailored to specific objectives. Optimal material selection involves numerous variables, making it challenging to track the necessary properties for a part's material and determine the ideal fit. This is where machine learning steps in. Zolfagharian and co-workers [104] recently highlighted that machine learning and deep learning methodologies offer promising solutions to address these intricate challenges. Ramezani and Mohd Ripin [15] emphasized the growing significance of machine learning and AI-driven material selection in advancing fabrication processes, including 4D printing. Machine learning can enhance printing efficiency through generative design and testing during pre-fabrication and material selection stages [103]. These technologies predict the behavior of 4D-printed materials and structures, guiding the selection of materials, geometries, and fabrication parameters to achieve the intended functionalities.

Material selection transcends mere choice; it embodies a strategic optimization process that holds the crux to unlocking unparalleled efficiency, sustainability, and cost-effectiveness for 3D/4D products. Each decision within material selection is a pivotal stride toward the holistic optimization of the entire 3D/4D product lifecycle. Machine learning, a transformative powerhouse in optimization and material selection, has redefined how designers approach intricate optimization challenges [105]. Sun et al. [106], introduced an innovative approach that melds machine learning (ML) and evolutionary algorithms (EAs) to tackle the inverse problem of optimizing 4D-printed active composite structures. Hamel and co-workers [107], converged the finite element method with evolutionary algorithms to fine-tune the distribution of shape transformation in 3D/4D printed components. This optimization methodology was scrutinized through various illustrative cases in active composite design, demonstrating concurrence between the target form and the best ML-derived solution.

Machine learning algorithms possess the capacity to scrutinize extensive datasets culled from diverse sources, encompassing material attributes, performance records, and historical data. This data-driven approach underpins well-informed decisions by uncovering correlations, patterns, and latent connections. Su and co-authors [108]

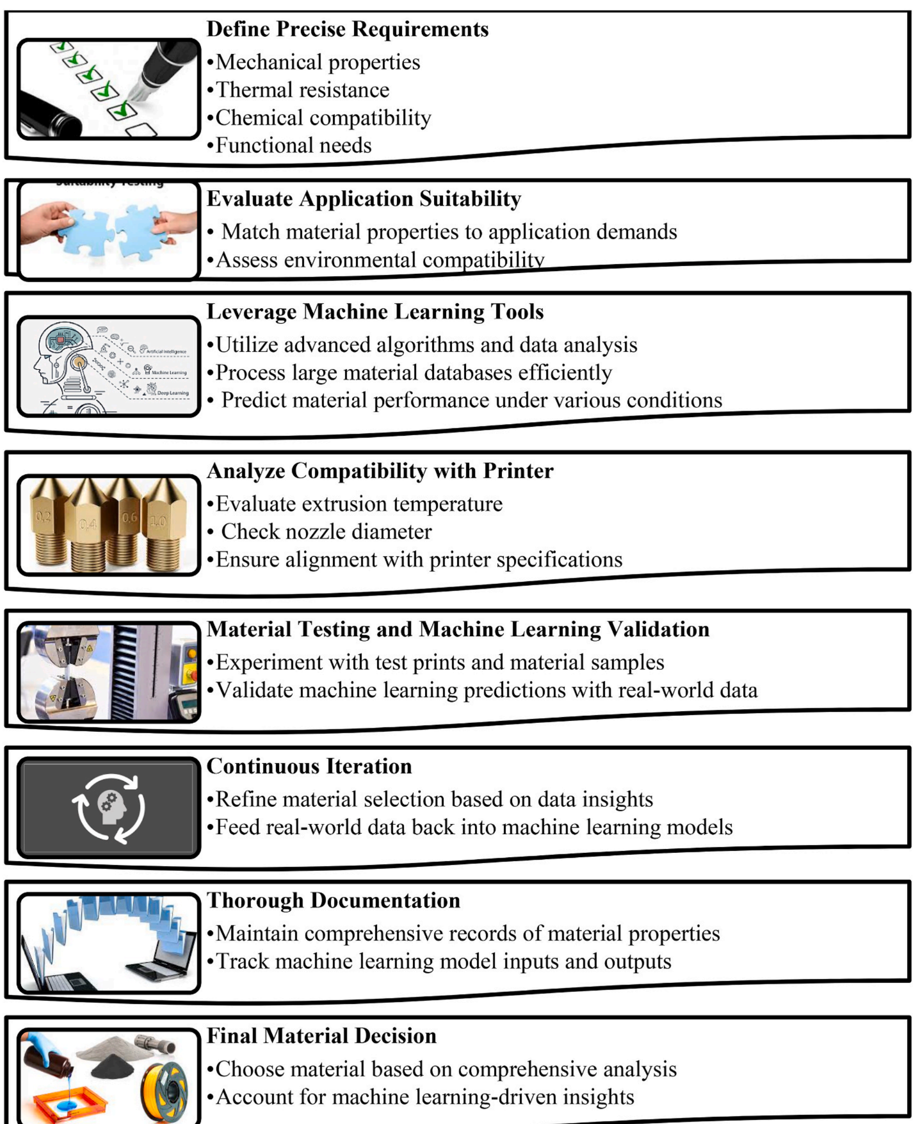

Fig. 7. Material Selection Process in 3D/4D Printing with Machine Learning components.

unfolded a comprehensive data-driven workflow empowered by an ensemble of ML algorithms for 4D printing. Their study exemplified the application of ensemble ML algorithms in optimizing and forecasting the morphing mechanisms of 4D-printed active structures. Zhao and colleagues [109] advanced an optimization methodology for grayscale DLP-printed rectangular blocks through machine learning and evolutionary algorithms. Their approach encompassed automated finite element model-based assessment, predicting material deformation shapes with arbitrary grayscale distributions while accounting for nonlinear mechanical behaviors. Clearly, optimization and material selection invariably entangle intricate trade-offs among multiple criteria. Machine learning models have excelled in navigating this intricacy, adroitly handling myriad variables simultaneously to arrive at solutions that impeccably balance competing objectives. Recently, Ji et al. [110] harnessed reinforcement machine learning to craft an optimal control method for closed-loop control of thermal Shape Memory Polymer actuation in 4D printing.

Machine learning's forte lies in prognosticating outcomes based on historical data. In the realm of material selection, this equates to forecasting how diverse materials will perform under specific conditions, facilitating the choice of the most fitting material for a given application. Zolfagharian et al. [20] devised a machine learning model to predict the bending angle of a 4D-printed soft pneumatic actuator. The results demonstrated the model's precise predictions aligned with finite element and experimental data, underscoring its viability for 4D printing modeling of dynamic structures and soft robots. Machine learning techniques shine notably in optimizing high-dimensional spaces; precisely where conventional methods might falter due to the profusion of variables [111,112]. This prowess holds immense value in material selection for 3D/4D printed components, where the simultaneous consideration of diverse properties is paramount.

4.2. Design for additive manufacturing

Incorporating the additive manufacturing process into the design of 3D/4D models involves incorporating features and geometries that can be printed layer by layer efficiently, avoiding intricate supports and overhangs. Within this context, machine learning emerges as a pioneering force within the domains of 3D and 4D printing optimization and design. This was exemplified by Paz and co-workers [113], who devised an optimization technique that melds Latin Hypercube design of experiments, Kriging metamodel, and custom genetic algorithms. This approach optimized the design of 4D printed components with diverse shapes, boundary conditions, and requirements. The adeptness of most machine learning models to decipher intricate patterns, process intricate data, and iteratively refine solutions has catalyzed advancements in these cutting-edge 3D and 4D printing processes [21,114]. Machine learning can analyze a diverse array of extensive datasets to uncover hidden optimal structures for 3D printing. In another study, Lim et al. [115] effectively harnessed machine learning tools to discover an optimal structure that met the mechanical and structural stability requisites for cranial reconstruction using 3D printing technology.

Attaining superior printing quality via 3D printing settings necessitates a grasp of printing parameters gained through experience and knowledge. Within additive manufacturing, refining process parameters stands as a pivotal facet, as manual changes to software parameters lack a definitive forecast of 3D print quality [116]. Fortunately, machine learning possesses the capability to dissect real-time process data for parameter optimization, augmenting both print quality and efficiency. Tamir and co-authors [117] proposed both open-loop and closed-loop machine learning models, amalgamating them to monitor the influence of processing parameters on printed part quality. This encompassed an open-loop classification model using experimental 3D printing data and a closed-loop control algorithm that synergized open-loop machine learning models with a fuzzy inference system to generate optimized processing parameters for improved printed part properties (Fig. 8). These machine learning-driven simulations serve as the blueprint for triumphs in 3D and 4D printing. Additionally, Zhang et al. [118] introduced a method that integrates classic machine learning methodologies, including space-filling-based experimental design, clustering, classification, regression, and multiobjective optimization. Their approach is tailored to aerosol Jet 3D printing based on droplet morphology.

A study carried out by Conev et al. [119] delved into the utilisation of machine learning to differentiate between 3D printing configurations likely to yield subpar prints and those with more potential. The models were built upon Random Forests, trained and evaluated on a dataset derived from the fabrication of porous polymer scaffolds through extrusion-based 3D printing. Their investigation also sheds light on an effective strategy for collecting data to train machine learning models for predicting printing quality in extrusion-based 3D printing of biomaterials. Yu and Jiang [120] underscored the integration of machine learning into 3D printing processes across various fronts, including process optimization, dimensional accuracy analysis, defect detection, and material property prediction.

Implementing additive manufacturing (AM) technologies systematically with a focus on process-parameter optimization requires an integrated approach to various influencing factors. The literature reveals that optimizing process parameters is essential for achieving high-quality and reliable production outcomes in AM [121,122]. Material properties are foundational in the optimization process. Different materials like polymers, metal, ceramics as well as composites like for example, have properties which enable them to exert a major influence on the AM process [123]. The characteristics which are integral to powder properties used the powder-based method include the size of particles and location influence the flowability for the powder; the density and quality of layers when it is deposited [124]. Amorphous bulk thickness can be viewed as one of the process-related factors because it determines the resolution and accuracy of the printed part topography [125,126]. As a result, while the thinner layers can improve the image quality and density of the print, the consequence of this is increased printing time [127]. Build orientation is another significant factor, affecting mechanical properties and surface finish. Optimal orientation can minimize the need for support structures and enhance part strength [128].

Printing speed is a critical factor that influences both production

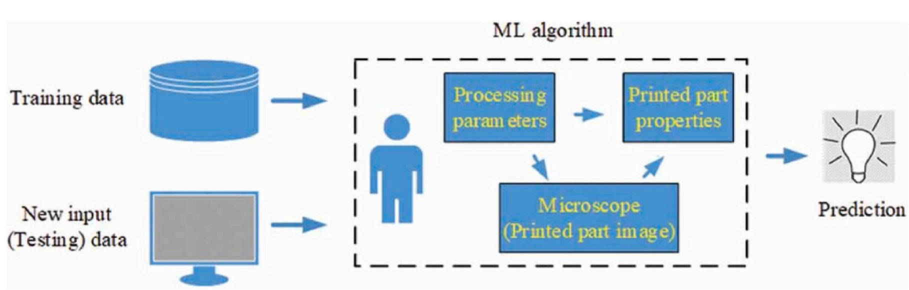

Fig. 8. Open-loops based (offline) optimal parameter settings [117].

time and part quality. Higher speeds can reduce production time but may compromise the bonding between layers, affecting the structural integrity of the part [129,130]. The extrusion or deposition rate, particularly in material extrusion processes, impacts the dimensional accuracy and internal structure of the part [120,131]. Thermal parameters, including build chamber temperature, extruder or nozzle temperature, and cooling rate, play pivotal roles in the AM process. Maintaining an optimal build chamber temperature helps prevent warping and residual stresses, especially in thermoplastics and metals [132]. Proper control of the extruder or nozzle temperature ensures the material is adequately melted and deposited, while the cooling rate can influence the crystallinity and internal stresses of the final part [133].

Mechanical factors such as print bed adhesion and the design of support structures are also critical. Adequate bed adhesion is crucial mainly to avoid warping and dimensional distortion of the model, the adequate design and removal of support structures to create a geometry that has overhanging features [113,134,135]. Over time, environmental conditions such as humidity and quality of air can affect material as well as quality of prints. When moisture or contaminants are present, they go on to affect hygroscopic materials therefore causing defects to products [97]. However, there are certain issues such as external vibrations and stability to address during the course of the actual printing to ensure good and quality prints [110]. Specific contingencies like heat treatment and surface finishing after the printing process help in enhancing the mechanical properties and surface finish of the printed parts. Techniques such as sintering can help in reducing internal stresses in the material while improving its properties, and techniques such as sanding, polishing or any surface coating, increasing surface finish and accuracy of dimensions [136]. In-situ monitoring and control systems are therefore very important for the continual measurement of the process parameters [137,138]. It also makes it possible to track the process using sensors and feedback loops that provide alerts of deviations with suggestions for making adjustments in real-time, thus maintaining product quality [76,139,140]. Another advancement of adaptive control techniques that control parameters in real-time data further improves the stability of the process and the quality of the part [141]. Simulation models, including finite element analysis (FEA) and Machine learning algorithms, are essential tools for understanding the effects of process parameters on AM outcomes. These simulations can predict thermal, mechanical, and microstructural behavior during the AM process, providing valuable insights for parameter optimization and reducing the need for extensive experimental trials [14,142]. Machine learning algorithms unlock the realm of multi-material designs in 3D and 4D printing, orchestrating intricate material distributions for optimal outcomes. Athinarayanarao et al. [14] accomplished optimal material property distribution within a voxelized structure using a finite element analysis-based evolutionary algorithm. Their approach amalgamated the benefits of optimizing both material distribution and layout via topology optimization, resolving the inverse design challenge of attaining an optimal design for a target shape change by incorporating void voxels. Their findings further highlight the efficacy of machine learning as a powerful tool for designing 4D-printed active composites. Hence, machine learning navigates the intricate terrain of material properties and dynamic shifts in 4D, resulting in multifunctional structures.

4.3. Support structure optimization

Support structures play a pivotal role in complex 3D printing models, but they can also result in longer print times, increased material consumption, and additional post-processing efforts. An effective strategy to mitigate the need for excessive support structures involves orienting the model in a manner that minimizes overhangs and bridges. Overhangs refer to parts of the model extending beyond the previous layer, while bridges are segments spanning gaps [142]. Both necessitate supports to prevent drooping or sagging. Employing machine learning tools generates support structures that optimize material usage while upholding print quality.

The literature widely attests to the potency of machine learning in optimizing support structures throughout 3D and 4D printing procedures. For instance, Li and Peng [16] proposed a 3D model segmentation technique grounded in deep learning to enhance surface quality and diminish support structures in 3D printed models. Their approach entailed designing training datasets based on sub-graphs encompassing printing attributes of the original 3D model, including surface quality, support structures, and normal curvature. These support structures are indispensable in upholding the integrity of intricate designs and overhanging features. Dabbagh and co-workers [143] introduced machine learning-empowered optimization for extrusion-based 3D printing. This has the potential to curtail trial-and-error steps before printing, ultimately expediting the design-to-end-product timeline while curbing material wastage and enhancing cost efficiency. In a comparison, Rojek et al. [144] evaluated the optimization of 3D printing attributes with respect to the maximum tensile force of an exoskeleton sample using both traditional artificial neural networks and a deep learning approach involving convolutional neural networks. Machine learning algorithms proficiently analyze intricate 3D and 4D geometries to pinpoint regions necessitating support structures.

Hierarchical machine learning was applied to 3D printing of silicone elastomer through freeform reversible embedding by Menon and colleagues [25]. This demonstrated the efficacy of hierarchical machine learning as a versatile tool for planning and optimizing additive manufacturing of soft materials via the freeform reversible embedding technique (Fig. 9). Machine learning identifies defects and areas where excessive supports are redundant, thereby minimizing material usage [145]. This optimization conserves resources, leading to cost reductions and a diminished environmental footprint. The utilisation of convolutional neural network-deep learning models results in a more streamlined and automated 3D printing process, with the potential to mitigate the widespread issue of product variability in 3D printing. Machine learning's predictive capabilities extend to determining appropriate support structures based on geometry, ensuring effective stabilization while minimizing contact points requiring removal [146].

Through strategic placement of supports, machine learning can curtail print times, facilitating quicker production without compromising structural integrity. Polamaplly et al. [130] devised an extrusion-based 3D printing process for thermoset biopolymers to fabricate support structures. Their investigation identified a suitable biomaterial for support structures, addressing challenges related to poor dissolvability and the generation of toxic waste from existing materials. Machine learning displays potential in identifying weak points in designs and introducing supports that reinforce those areas. This augments stability during printing and minimizes the risk of failure [147]. Machine learning models predict print success based on support placement, ensuring strategic positioning to prevent print failures and minimize reprinting [141].

4.4. Process parameter optimization

Process parameter optimization in 3D/4D printing using machine learning involves using data-driven techniques to determine the best combination of printing control factors (e.g., printing speed, layer height, temperature etc) that result in optimal print quality, efficiency, and material usage [148]. Fig. 10 shows the steps involved in machine learning based process parameter optimization in 3D/4D printing process.

Data collection encompasses the process of acquiring pertinent data aligned with the goals and objectives of the 3D/4D printing project. A fundamental step in the machine learning pipeline involves gathering data for training the machine learning model [149]. This data should encompass details about utilized printing parameters (e.g., layer height, print speed, temperature), material attributes, sensor readings, and resultant print quality indicators like strength, surface finish, and defects

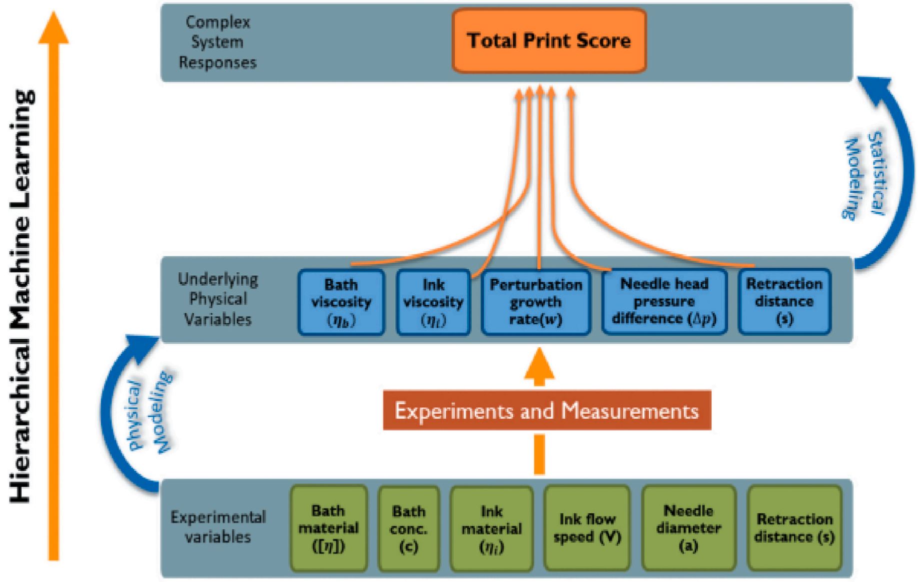

Fig. 9. Illustration depicting the Hierarchical Machine Learning (HML) model of the Fluidized Bed Electrodeposition (FRE) process [25].

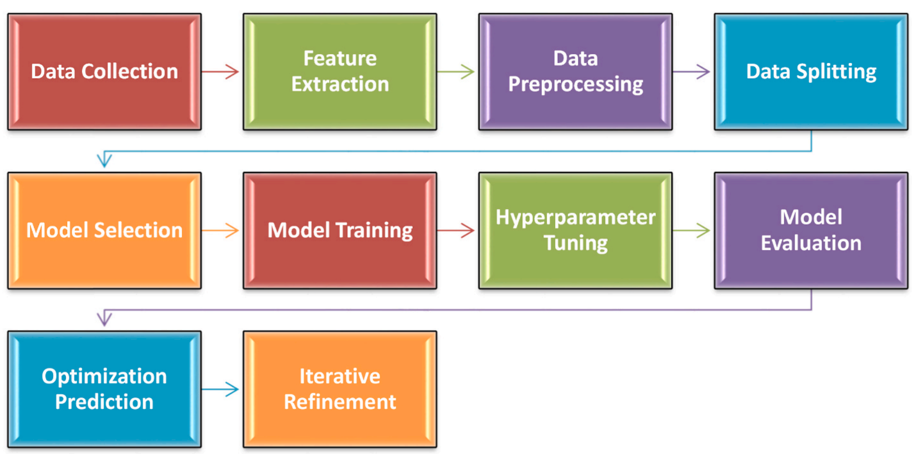

Fig. 10. Steps involved in machine learning based process parameter optimization in 3D/4D printing process.

[150].

Feature extraction from the accumulated data encompasses numerical values of process parameters, categorical variables (e.g., material type), and sensor data. Xie et al. [151] devised an automated feature extraction approach employing convolutional neural network optimization for real-time warping monitoring in 3D printing. Furthermore, computed metrics such as print time, material consumption, and print success/failure can also serve as informative features. Zhang et al. [140] introduced a deep network algorithm for diagnosing faults in three-dimensional printers using attitude data with low measurement precision. Specifically, feature enhancement was developed to improve clustering performance, replacing the traditional comprehensive feedback fine-tuning in deep models. Other researchers such as [152] have formulated innovative feature extraction methods to recover 3D models via curvature-based shape distribution. In essence, feature extraction transforms raw data into numerical attributes, facilitating seamless data preprocessing while preserving the original dataset's information. It yields superior outcomes compared to applying machine learning directly to raw data [153].

Data preprocessing and division entail cleansing the data to address missing values, anomalies, and discrepancies prior to segmenting the dataset into training, validation, and testing sets. Yu (2019) devised a technique to preprocess G-codes in advance on the PC side, surmounting limitations tied to existing 3D printer control systems' original file processing mode. This phase stands as an essential component of 3D/4D printing optimization through machine learning. Preprocessing, data partitioning, and the elimination of irrelevant or redundant information aid in mitigating the risk of overfitting and enhancing the model's aptitude to generalize to new 3D/4D printing data. Data preprocessing can also enhance the model's interpretability [154].

Model selection and training entail identifying the appropriate machine learning algorithm for the optimization task. Recent successful models deployed in 3D/4D printing optimization encompass regression algorithms like linear regression, decision trees, and random forests [124,155] for continuous output variables (e.g., print quality metrics), and classification algorithms like logistic regression and support vector machines for categorical optimization tasks (e.g., print success/failure). These models ascertain the correlation between input process parameters and desired outputs like print quality and success/failure [137].

Hyperparameter tuning and model evaluation phases ensure the model's ability to generalize effectively to new data and prevent overfitting to training data. Hyperparameter optimization entails selecting an optimal set of hyperparameters for a learning algorithm [156]. Nguyen (2019) [157] examined Bayesian optimization for expediting hyperparameter tuning, spotlighting contributions and outlining future research directions. The testing dataset is commonly used to assess the model's performance [5]. Depending on the optimization task, metrics such as Coefficient of Determination (R2), Root Mean Square Error (RMSE), Mean Average Error (MAE), Standard Error of Prediction (SEP), accuracy, precision, recall, etc., can gauge the model's efficacy [158,159].

Prediction and optimization underpin numerous real-world analytics challenges across various domains [160]. Kumar et al. [161] ascertained that machine learning has the potential to unveil untapped insights, furnishing decision support for sustainable additive manufacturing. Kumar and co-workers [162] maintained that once the model is trained and validated, it can predict optimal process parameters for novel 3D/4D printing projects. The model recommends suitable parameter values based on learned patterns from the training data, aligning with intended print quality or efficiency targets [3].

4.5. Critical discussion on application of intelligent algorithms and soft computing techniques to optimize quality objectives parameters

The application of application of intelligent algorithms and soft computing techniques such as machine learning (ML) and artificial intelligence (AI), to optimize quality objectives parameters in 4D/3D printing processes has been discussed extensively in the literature [127,140,163]. These algorithms analyze vast datasets generated during AM to predict and control quality outcomes. For instance, ML techniques such as neural networks [164,165], decision trees [108,166,167], and support vector machines have been employed to predict surface roughness and dimensional accuracy based on process parameters [5]. These models having collection of past data may able to find some relationship and co-relation which could not be possible by using conventional way of analysis Soft computes including fuzzy logic, genetic algorithm, evolutionary computing go well with intelligent algorithms used to enhance 4D/3D printing because they are able to handle uncertainty and complexity involved in these processes [168,169].

Among these factors are layer thickness, scan speed and laser power, which can be targeted through these techniques to work on surface quality, a primary area of improvement. Studies show that ML models can predict surface roughness effectively by analyzing these parameters [20,129,125,126]. Additionally, genetic algorithms optimize process parameters to minimize surface roughness, enhancing the aesthetic and functional quality of printed parts [133,138,168,170,171].

Part strength and mechanical properties are crucial in 4D/3D printing processes. Intelligent algorithms predict properties like tensile strength and hardness based on input parameters and material characteristics [109,172,173]. Neural networks have been trained to forecast the tensile strength of parts produced by selective laser sintering (SLS) and fused deposition modeling (FDM) [13,174]. Evolutionary algorithms optimize infill patterns and density, critical determinants of part strength in FDM [175–177].

Dimensional accuracy impacts how well the 4D/3D printing parts fit and perform. Fluctuations in process parameters often mean that the final piece does not adhere to the intended dimensions and therefore does not meet the design requirements [144,158]. Intelligent algorithms have been employed to predict and correct these deviations. Support vector regression models and fuzzy logic systems dynamically adjust process parameters to maintain dimensional accuracy throughout the build process [120,131,177].

Thermal stability, essential for maintaining the integrity of printed parts, is another area improved by intelligent techniques. During the 4D/3D printing processes, uneven heating and cooling can lead to thermal stresses and distortions. Machine learning models predict thermal behavior based on process parameters and material properties, enabling the optimization of temperature profiles to minimize thermal distortions [178,179]. Genetic algorithms have also been used to design optimal heating strategies that enhance thermal stability [180].

Material efficiency, critical for cost-effective and sustainable manufacturing, can also be optimized using intelligent algorithms. By analyzing the relationship between process parameters and material usage, ML models predict the optimal settings to minimize material waste while maintaining part quality. Evolutionary algorithms optimize the design and orientation of parts to maximize material efficiency and minimize support structures [181,182].

4.6. Predictive modeling and defect detection/minimization

A prominent trend in research is the capacity of machine learning to forecast potential defects or failures in 3D/4D printing projects by scrutinizing patterns within data from prior prints. Detecting these anomalies at each layer level of the product holds significant importance [183]. In a parallel vein, Khan et al. [145] devised a convolutional neural network-deep learning model aimed at real-time identification of detrimental defects to avert production losses and decrease human intervention for quality assessments in 3D printing. The outcomes of their investigation present a refined and automated 3D printing process, capable of mitigating the pervasive challenge of product variability in 3D printing. Through recognizing linkages between specific process configurations and defects, machine learning models have the ability to prognosticate instances of potential print failure, subsequently furnishing essential recommendations on adjusting print parameters to circumvent such predicaments [135]. Refer to Fig. 11 for an illustration of the constituents within machine learning-driven predictive modeling and the minimization of defects in the 3D/4D printing process.

Machine learning algorithms possess the potential to be trained in a manner that enables them to identify and categorize defects within 3D/4D printed objects. This process involves compiling datasets of images or sensor data from both flawless and defective 3D/4D printed items. Kaya (2023) [184] introduced a novel hybrid optical sensor that employs deep learning to detect micro-sized defects on large 3D printed circuit boards. This study also employed a deep learning classifier, utilizing convolutional neural network algorithms, to categorize defects within the printed circuit boards. Researchers have harnessed computer vision and artificial intelligence for real-time remote defect detection in 3D printing [165]. Typically, the defects are found on a considerable scale, often visible in prominent areas of the object through a capturing camera. In such cases, deep convolutional neural networks can be trained using images showcasing evident stringing issues, then deployed in real-time to identify and predict instances of stringing through video camera feeds. Furthermore, models can become proficient at accurately detecting and classifying defects like surface irregularities, voids, cracks, and layer misalignments using techniques such as convolutional neural networks [185], deep learning-assisted real-time defect detection [186], and closed-loop adjustments for image data [187].

Predictive Maintenance constitutes a condition-based strategy that performs maintenance actions when needed, avoiding unnecessary preventive measures or potential failures [188]. Machine learning models can predict 3D/4D printer failures and defects by leveraging historical data and real-time sensor readings. These models can anticipate potential issues and trigger maintenance actions prior to the occurrence of defects by analyzing sensor data such as temperature, pressure, and material flow rates. Arora and Prithviraj (2022) [131] emphasized the importance of assessing printability and optimizing process parameters in achieving defect-free prints. Machine learning algorithms can uncover complex relationships between various process parameters like print speed, layer height, and [133,189] and the likelihood of defects. Genetic algorithms [170] and reinforcement learning [190] are often utilized for discovering optimal parameter settings that minimize defects.

Anomaly detection, employed in root cause analysis, assists in identifying root causes of issues through assessing deviations from expected behavior. In the context of 3D/4D printer defects, machine learning can play a pivotal role in identifying underlying causes. Petsiuk

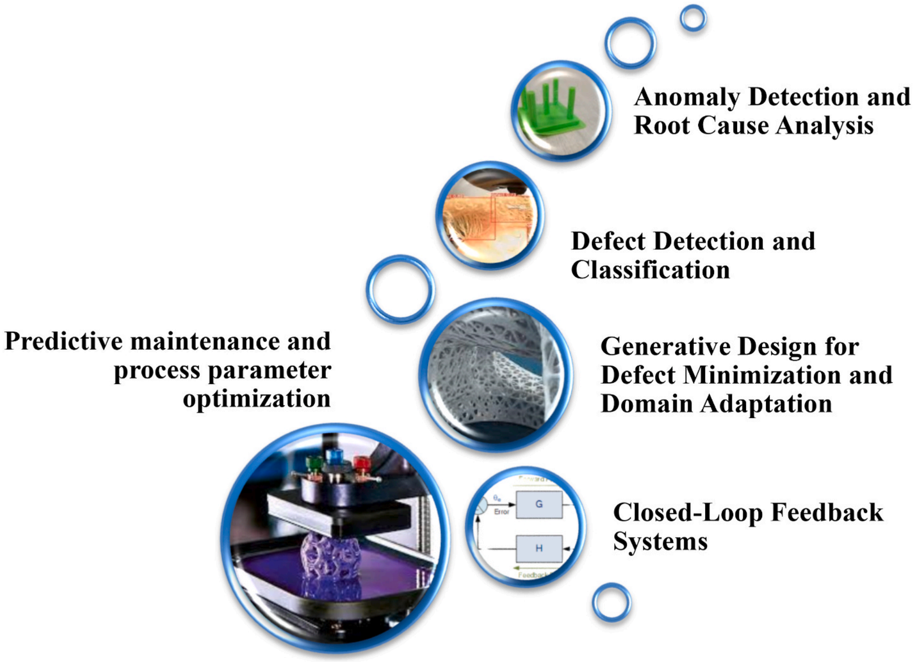

Fig. 11. Machine learning based predictive modeling and defect detection/minimization in 3D/4D printing process.

and Pearce (2022) [127] introduced an open-source method for detecting 3D printing anomalies, utilizing image comparison between 3D printed layers captured by a stationary camera and G-code-based reference images. Recognition of visual deviations was achieved by analyzing histograms of oriented gradients of local image areas. This observation is further supported by Goh and co-workers [123], who incorporated computer vision and object detection models in an on-site monitoring system for real-time defect detection and correction during extrusion-based 3D printing. This approach successfully demonstrated autonomous correction during printing. These findings provide a rich dataset for machine learning-based anomaly detection research [191–193].

Machine learning facilitates closed-loop feedback systems, where real-time defect information adjusts and optimizes 3D/4D printing parameters dynamically [194]. Various techniques, including neural networks [195], reinforcement learning [121], deep convolutional neural networks and conditional adversarial networks [138] have been integrated with closed-loop control frameworks to stabilize and optimize 3D/4D printing processes. This approach generates precise feedback for smart printers, enabling them to identify and address build issues autonomously. The closed-loop machine learning algorithm enhances additive manufacturing quality, resulting in improved parts with fewer quality issues, less time wastage, and material conservation [122,196]. Research consistently indicates that this system can correct defects in subsequent layers seamlessly as they are detected during the printing process.

Generative design for defect minimization leverages machine learning algorithms to generate numerous optimized 3D printing solutions based on user-specified parameters and constraints [197,198]. Generative design enables designers to explore a range of solutions while considering manufacturing limitations, materials, and mechanical responses. Li et al. [199] showcased the effectiveness of convolutional generative adversarial encoders in creating and optimizing fault detection models from normal 3D printer signals. Saberironaghi and co-workers [200] highlighted mainstream methods of industrial defect detection in 3D printing, including deep learning-based 3D defect reconstruction and parameter optimization. Jin et al. [164] demonstrated anomaly monitoring in 3D bioprinting using deep neural networks. Their study reported high accuracy in detecting anomalies using convolutional neural network methods. Generative design, powered by machine learning, offers optimal solutions to reduce the occurrence of defects in the 3D printing process.

4.7. Topology optimization

Topology optimization involves determining the optimal distribution of materials within a specified design area, which is a common practice in 3D/4D printing. By integrating machine learning techniques, topology optimization presents an innovative approach to enhancing the capabilities of 3D and 4D printing processes. Kim and co-authors [201] showcased a novel framework that employs the representative volume element method and a machine learning model to establish continuous anisotropic effective material properties. This approach is utilized for simultaneous design of overall topology configuration and local fiber material layout in functionally graded composite structures. Their method demonstrated success in minimizing structural compliance through 2D and 3D numerical examples. Machine learning revolutionizes the topology optimization of 3D/4D printing by revolutionizing how designers explore the design space. A range of machine learning algorithms, including neural networks [202] and generative adversarial networks [203] are employed to learn from existing designs and generate novel configurations that adhere to constraints while optimizing performance. This amalgamation of machine learning and topology optimization sparks creative insights, resulting in optimized designs that traditional methods might overlook.

Machine learning algorithms hold the potential to bolster and enhance the design phase of 3D and 4D printing processes through topology optimization. These algorithms have the capacity to create inventive and efficient geometric designs by systematically removing material from a designated design space while preserving structural integrity, other technical details are captured in Table 3. This methodology can lead to more lightweight and robust structures [134]. Kallioras and Lagaros (2021) [204] introduced a pioneering generative design framework that integrates machine learning into generative design, facilitating compatibility with 3D printers. The framework's proficiency in addressing diverse problems was validated through testing on benchmark topology optimization challenges frequently used in the field. Oh et al. [205] proposed an artificial intelligence-based deep

Table 3
Technical details of machine learning applications in 3D/4D printing optimization

Aspect of Printing Process	Machine Learning Model	Data Requirements	Optimization Goals
Design Customization	Generative Adversarial Networks (GANs)	3D model data, design parameters	Create unique and complex designs, improve customization options
Material Selection	Random Forest, Support Vector Machines	Material properties, historical performance data	Predict optimal material combinations, enhance material properties
Process Control	Reinforcement Learning	Real-time process data, environmental conditions	Adjust parameters dynamically to maintain quality, reduce errors
Quality Assurance	Convolutional Neural Networks (CNNs)	High-resolution images, defect data	Detect defects in real-time, improve print quality
Topology Optimization	Genetic Algorithms, Evolutionary Models	Structural data, load conditions	Optimize structural designs for weight, strength, and material efficiency
Print Speed Optimization	Bayesian Optimization	Print speed data, layer information	Find optimal print speeds, balance between speed and quality
Energy Consumption	Neural Networks	Energy usage data, process parameters	Minimize energy consumption while maintaining print quality
Dimensional Accuracy	Regression Models	Measurement data, printer settings	Ensure dimensional accuracy of printed parts, reduce deviations

generative design framework capable of generating numerous design options that are both aesthetically pleasing and optimized for engineering performance. Their approach combines topology optimization and generative models like generative adversarial networks iteratively, fostering exploration of new design options and generating an array of designs from limited previous design data.

Previous studies employ a spectrum of machine learning methods for topology optimization in 3D and 4D printing, ranging from boundary equilibrium generative adversarial networks [163] to Bayesian regularization networks [206] and deep convolutional neural networks [207]. These machine learning-driven topology optimization methodologies enable users to incorporate a machine learning approach into their designs, enhancing efficiency in 3D and 4D printing processes through non-iterative strategies. The proposed methods significantly decrease computational time while enhancing structural performance and design quality of printed components. These studies present a fresh perspective on topology optimization in 3D printing and underscore the potential of machine learning in advancing the efficiency and accuracy of this process.

In 3D/4D printing, the requirement for detailed simulations during each iteration can be time-consuming, necessitating the integration of machine learning-driven surrogate models. Costa and colleagues [208] explored computationally efficient topology optimization employing surrogate models to represent material and geometrical properties in continuous topology optimization approaches. These models approximate complex simulation outcomes, allowing optimization algorithms to explore design variations more rapidly [209]. Utilizing artificial intelligence-equipped printing technologies trained on analogous design challenges expedites topology optimization tailored for 3D/4D printing scenarios. This knowledge transfer across various printing domains, as per Pugliese and Regondi (2022) [210], accelerates optimization processes and leverages accumulated expertise. The synergy between topology optimization and machine learning in 3D/4D printing also addresses uncertainty. Bayesian optimization, guided by machine learning, introduces uncertainty estimates into the optimization process. Kim et al. [211] introduced a convolutional neural network-guided Bayesian optimization framework, strategically maximizing the surface-to-volume ratio of 3D printed lattice supercapacitors. This framework applied Bayesian optimization to printing parameters to exploit regions favoring uniform and narrow lines. This capability is especially valuable in dealing with fluctuating material properties and inherent manufacturing uncertainties characteristic of 3D printing.

4.8. Layer height and resolution optimization

Optimal layer height and resolution selection significantly affects both the speed and quality of the printing process. While finer layers yield smoother surfaces, they can slow down printing [212]. Thus, striking the right balance is a crucial optimization challenge, which can be efficiently addressed using machine learning algorithms. Wang et al. [213] devised an adaptive layering algorithm to harmonize the optimization of printing quality and efficiency for varying printing requirements. Their research effectively formulated a multi-objective optimization model considering printing quality, printing time, and layer height, based on surface feature variations, profile slopes, and model curvature.

Machine learning assumes a pivotal role in fine-tuning layer height and resolution parameters in 3D and 4D printing, leading to elevated print quality, reduced production time, and enhanced overall performance [139]. Regarding print quality anticipation, machine learning models can acquire insights from a dataset encompassing print outcomes with diverse layer heights and resolutions. This was illustrated by Si et al. [214], who examined the influence of fan speed on printing quality, introducing a plugin that forecasts and supervises fan speeds during printing. Their plugin aims to thwart cyberattacks that specifically target fan speed. In a related investigation, Vaid et al. [125] established the optimal printing temperature for a cylindrical shaft, minimizing dimensional variance in fused deposition modelling 3D printing technology. Artificial intelligence prediction models were employed to explore the impact of extrusion and build-plate temperatures on fluctuations in printed sample dimensions.

By employing machine learning algorithms like genetic algorithms or Bayesian optimization [128], iterative exploration of parameter space is feasible to pinpoint the layer height and resolution combination that mitigates defects and maximizes 3D printing efficiency. Accumulating insights from diverse studies underscores the potential of machine learning models to predict print quality based on varying parameter combinations. This aids in selecting optimal layer height and resolution settings, ensuring the desired quality standards are met and streamlining the quest for optimal configurations. For instance, Ulkir and colleagues [168] employed a cascade-forward neural network (CFNN) combined with a genetic algorithm to determine the optimal combination of input parameters for predicting and minimizing the surface roughness of samples produced through Fused Deposition Modelling on a 3D printer. Utilizing a Box–Behnken Design with four independent printing parameters at three levels, they fabricated 25 parts with a 3D printer and conducted roughness tests on the produced parts. The hybrid algorithm demonstrated superior performance, yielding the best results for predicting and optimizing surface roughness in 3D-printed parts. The trained CFNN, equipped with optimized parameters, exhibited enhanced accuracy in surface roughness prediction compared to previous random test results.

5. Challenges of using Machine Learning and Artificial Intelligence technologies in additive manufacturing

While adopting and using ML and AI tools for AM has several benefits related to process enhancement and greater efficiency, it also has some drawbacks. One major weakness is the quality and quantity of data that is needed to get the best results [145,215,216]. Many parameters in AM process rely on the prediction of ML models and the more data are available the better the models are. Yet, acquiring sufficient high-quality data can be quite a daunting task, mainly because of the diverse AM procedures and types of material employed [217,218]. Yet another disadvantage is related to the interpretability of the obtained ML models [17,219,220]. Decision making in these technologies is often black-boxed, which may be an issue in the case of using these technologies in applications when it is imperative to understand the reasoning behind an idea or a choice [17,221].

In addition, there is an issue with the generalization capability of the models used today's deep learning. Parameters obtained in specific dataset may not be suitable for other materials, machines or operating conditions. This problem occurs since AM processes have a level of randomness in them and this can cause differences in model performance from one scenario to another [199,222,223]. Another issue surrounding the application of Machine Learning and Artificial Intelligence tools into existing AM Systems is the interconnectivity of the two. Incompatibilities, the requirement of a large number of computations in real time, as well as the challenges of introducing socioeconomic indicators and integrating monitoring systems can become the key elements inhibiting the real application of these technologies [25,123,138,195]. Also, as shown in Table 4, the first-time installation cost of implementing AI driven systems may be expensive especially for the SMEs thus limiting the extent to which it is adopted [12,224,225]. The applied models are known to be very effective, but the question is how strong and reliable they are. AM processes can be sensitive to small changes in parameters or environmental conditions, and ML models need to be robust enough to handle such variations without compromising performance, however, ensuring robustness requires extensive validation and testing, which can be resource-intensive.

Table 4
Summary of challenges and limitations in the integration of Machine Learning and Artificial Intelligence

Challenge/ Limitation	Description	Impact
Data Quality and Quantity	Insufficient or low-quality data for training ML models can lead to inaccurate predictions and suboptimal performance.	Hinders model accuracy and reliability.
Computational Resources	High computational power is required to process complex algorithms and large datasets.	Increases cost and limits accessibility for smaller enterprises.
Model Interpretability	Difficulty in understanding and interpreting ML models, especially deep learning models.	It undermines confidence with the current users and potential users of the products and services
Integration with Existing Systems	Challenges in integrating ML and AI technologies with existing manufacturing systems and workflows.	Causes disruptions and requires significant changes to current processes.
Real-time Processing	Difficulty in achieving real-time data processing and decision-making due to computational and latency issues.	Limits the ability to make timely adjustments during the printing process.
Cost	High costs associated with implementing and maintaining ML and AI technologies.	Restricts its usage, particularly for SMEs.
Skill Gaps	Lack of skilled professionals with expertise in both additive manufacturing and ML/AI technologies.	Slows down implementation and innovation.
Robustness and Reliability	Ensuring the robustness and reliability of ML models in diverse and changing manufacturing environments.	Leads to potential failures and inconsistencies in production.

6. Future outlook

The insights derived from this systematic review illuminate a compelling future outlook, signalling the transformative potential that lies in the optimization of 4D/3D printing through machine learning—a synergy that has the capacity to revolutionize the contemporary landscape of manufacturing. The amalgamation of these cutting-edge technologies not only opens new horizons but also sets the stage for a paradigm shift in how we conceptualize and realize the production of intricate structures and functional materials.

The comprehensive analysis conducted in this review accentuates the profound implications of machine learning in fine-tuning various facets of the 4D/3D printing process. From influencing design and material selection to refining process control and ensuring quality assurance, machine learning emerges as a linchpin in elevating the efficiency and efficacy of additive manufacturing. This newfound understanding serves as a solid foundation for envisioning a future where the synthesis of machine learning and 4D/3D printing becomes integral to the manufacturing fabric.

Looking ahead, the potential for customization, efficiency, and sustainability in the production of complex structures becomes increasingly evident. The synthesis of machine learning and 4D/3D printing not only streamlines existing manufacturing processes but also paves the way for the creation of adaptive, intelligent, and personalized products. The implications extend across various industries, including healthcare, aerospace, architecture, and consumer goods, indicating a future where tailored solutions become the norm rather than the exception.

In healthcare, for instance, bespoke medical implants and prosthetics could be rapidly manufactured to meet specific patient needs. In aerospace, the ability to swiftly produce intricate components tailored to precise specifications promises advancements in efficiency and performance. Architectural designs can evolve into dynamic, responsive structures, and consumer goods may undergo a revolution with personalized and intelligent products.

This future outlook hints at a manufacturing landscape where agility, innovation, and customization converge to redefine possibilities. The collaborative dance between machine learning and 4D/3D printing, as explored in this review, serves not only as a reflection of the present state of these technologies but also as a harbinger of the transformative potential awaiting exploration in the manufacturing landscape of the future.

7. Conclusions

In conclusion, this systematic review has shed light on the transformative potential of optimizing 4D/3D printing using machine learning which could revolutionize the landscape of modern manufacturing. The synthesis of these two cutting-edge technologies has unveiled unprecedented possibilities for customization, efficiency, and sustainability in the production of complex structures and functional materials. Through a comprehensive analysis of existing literature and research, this review has underscored the critical role of machine learning in optimizing various aspects of the 4D/3D printing process, ranging from design and material selection to process control and quality assurance. Moreover, the exploration of diverse applications across industries has emphasized the wide-ranging impact of this integration, hinting at a future where personalized, adaptive, and intelligent products become the norm rather than the exception. The potential to cater to specific needs in fields like healthcare, aerospace, architecture, and consumer goods hints at a world where bespoke solutions can be rapidly manufactured, pushing the boundaries of innovation and customization.

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Declaration of competing interest

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

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