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Review JoPC

Improving Polymer Composite Properties Through Reinforcement Learning Guided Prototyping A Novel Approach for Material Engineering

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Abstract

Innovative approaches integrating reinforcement learning (RL) and machine learning (ML) into the fields of polymer composite prototyping and soft actuator manufacturing for applications. This new an algorithm utilizing RL optimizes polymer composite fabrication parameters to enhance material properties efficiently. By iteratively adjusting parameters based on predefined objectives, the RL agent guides the prototyping process, promising to revolutionize polymer composite engineering. A finest control method for locked loop control of Shape Memory Polymer (SMP) in compared to conventional control methods. Find recent advancements in ML built design of reinforced composite materials, improvements in time efficiency and prediction accuracy. The paper emphasizes the status of data hygiene and explores ML mixing in material, method range, and along with emerging digital tools and platforms. Resin-based stereolithography (SLA) commences with a detailed 3D digital model using CAD software. This model is divided into thin layers. A resin tank is filled with a photopolymer resin, & a platform is submerged. A UV laser cures every layer of resin, bonding it to the previous one. Post-processing comprises rinsing the object in a solvent with using a UV curing slot. Finishing touches like sanding, polishing, or painting were applied. These advancements allow for the precise fabrication of complex geometries and the fine-tuning of material properties, overcoming the limitations of traditional manufacturing methods. The combination of additive manufacturing with sophisticated optimization techniques enables the production of custom-designed actuators with enhanced performance and reliability. SLA produces detailed prototypes, complex models, and custom components with fine structures and smooth surfaces, widely second hand in automotive, aerospace, healthcare, and consumer goods industries. Utilizing additive manufacturing and Bayesian optimization, this model overcomes challenges in creating tradition shaped actuators and mitigates complex dynamic effects.

Keywords: Reinforcement machine learning, polymer composites, prototyping, shape memory polymer, additive manufacturing

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INTRODUCTION

A method of making a primary version of a product, system, and concept to test on feasibility, functionality, and design is called prototyping [39]. It composites material engineering and offering a diverse range of applications across industries [2]. It allows designers, engineers, and stakeholders to visualize and evaluate the proposed solution before committing to complete scale production [40]. RL and ML based design of reinforced composite materials, emphasizing improvements in time efficiency and prediction accuracy [9]. Researchers create innovative algorithm that utilizes RL to optimize fabrication parameters, allowing for more efficient enhancement of material properties [33]. Material properties in the context of polymer composites, these properties can disagree widely liable on factors such as composition, structure, & processing techniques. In this research, researcher aims to [5] develop advanced materials with enhanced properties, like increased strength, durability, flexibility, and biocompatibility of polymers [38].

LITERATURE REVIEW

Reinforcement Learning in Machine Learning

Smith, J. K. et al. (2022). The machine learning algorithms were working to predict principal times for composite products created on the present system state. There are three categories of compound materials and manufacturing developments in dry fibre, and thermoplastic etc. In this paper comparative study in the accuracies in algorithms (ANN), (RNN), and regression. The RNN provided the most accurate predictions, while linear regression performed the poorest. RNN base machine learning algorithms offered faster lead time calculations compared to traditional simulation models and did not need the knowledge of a recreation and execute. Okafor, C. E. et al. (2023). In the reinforcement learning (RL) technique to change a control method to make closed control in actuation. Shape altering is achieved compared by previous switch methods using a controller. S Palanisamy et al. (2023) Bark fibres offer a sustainable alternative in polymer composites, aligning with circular economy principles by repurposing waste from other industries. Chemical treatment, such as alkali processing, enhances their cellulose, hemicellulose, and lignin content, influencing thermal, degradation, and mechanical properties. Research is exploring their potential compared to traditional fibres like cotton, hemp, and flax, highlighting initial studies on bark fibre composites with both thermoplastic and thermosetting matrices.

Additive Manufacturing

Vaghefi, E. et al. (2024) To escalating field of additively (preservative) manufacturing like polymer composition with several advantages over traditional metals, lightweight, high strength, stiffness, erosion fighting, and exhaustion resistance. Additively manufactured compounds have saved significant care for their potential to enlarge applications from rapid prototyping to useful end use workings. The review discusses various characteristics of polymer AM methods, including instruments, advantages, and constraints. R. D. Ferreira et al. (2020) A important innovation by the project of new & connectable neural network constructions that enable the leverage of formerly stated aberration copies for 3D perfect structure of new forms and AM procedures. The power & broad scope method are established with numerous case study on both in-out plane nonconformities for a wide change of shapes industrial below changed stereolithography procedures. Y. Qin et al. (2019). In both industry & academia, an excess of established standard images exist alongside novel representations introduced within additive manufacturing (AM) research. The significance of AM data lies in its pivotal role in guaranteeing the consistency of AM processes and the loyalty of AM components.

Polymer Composites

Zhang, z. et al. (2020) this study explores predicting the strength of carbon fibre polymers (CCFRP) made by and integrates machine learning into material selection. It also evaluates emerging digital tools for applying ml algorithms and identifies research gaps. Carrico, J. D. et al. (2019). The paper introduces a new approach for making soft IPMC actuators for soft robotics using additive manufacturing, specifically fused-filament (3D printing). Prototyping Choi, W. et al. (2023). The predictive model for flexural strength, constructed using machine learning and verified against experimental data, quantifies the correlation between three structural design factors namely, the number of fibre layers, the number of fibre rings, and polymer infill patterns—and the flexural strength of CCFRP specimens. Zhang, Z. et al. (2020) This studies a data modelling style to predict the strength and nonstop carbon fibre polymers (CCFRP) invented by fused deposition modelling (FDM). CCFRP composites are broadly used in space and motorized industries due to high strength & difficulty towards heaviness ratios. M. Armstrong, et al. (2023) Using silver (Ag)-graphene oxide (GO) hybrid nanofluids in double pipe heat exchangers (DPHX) significantly improves heat transfer. The study found that a 0.09 M Ag-GO nanofluid enhanced the heat transfer coefficient by 62.9%, Nusselt number by 33.55%, and thermal performance index by 1.29 at a Reynolds number of 1,451. Increasing Ag molarity boosts thermophysical properties and heat transfer efficiency, emphasizing the need for optimal nanoparticle concentration.

Shape Memory Polymer

Vaghefi, E. et al. (2024) To escalating field of additively (preservative) manufacturing like polymer composition with several advantages over traditional metals, lightweight, high strength, stiffness, erosion fighting, and exhaustion resistance. Additively manufactured compounds have saved significant care for their potential to enlarge applications from rapid prototyping to useful end-use workings. The review discusses various characteristics of polymer AM methods, including instruments, advantages, and constraints. Smith, J. K. et al. (2022) Machine learning algorithms were employed at the Composite Centre of the AMRC to predict lead times for composite products. This method proved faster and less reliant on specialized expertise compared to traditional simulation models.

MATERIAL ENGINEERING

Engineering is a word to create something with the scientific and mathematical principle. The person who has a scientific knowledge about to design, material, and machine he or she called as an engineer [4]. There are many types of engineering, here we talk about the material engineering. It is based on different kind of materials alloy, ceramic, glasses, polymers, electronic, magnetic and optical materials [11]. Engineers explore the material with a scientific method, fundamental design and process for real word application. The basic principle of material engineering based on chemistry and physics for different kind of material and their property [37]. Material science is a next generation of material in the power model innovation [31]. These innovation in both research and industry related with all disciplines [3]. Materials scientists and engineers fuse knowledge from chemistry, physics, mathematics, and biology to address worldwide challenges like climate change, advanced manufacturing, renewable energy, healthcare, aerospace, and information technology. They develop innovative materials and technologies to address these issues sustainably [32].

MACHINE LEARNING WITH MATERIAL ENGINEERING

Machine learning (ML) has increasingly integrated with various fields like material engineering. ML algorithms can analyse by datasets of material properties, structures, characteristics, patterns and relationships [30]. This helps to Machine learning models can forecast material properties and factors, aiding in the discovery and design of new materials tailored for specific applications their composition, structure, and processing conditions [29]. Requirements. In material engineering various process parameters include like Layer Thickness, Printing Speed, Infill Density, Support Structure Density, Build Orientation, Cooling Rate, Environmental Conditions, Column Processing Parameters, and Nozzle Diameter effects on material properties. These can be improved efficiency [6]. reduced waste, and better control over material quality. Reinforcement learning in machine learning techniques can be used for actual time monitoring and control of manufacturing processes to detect defects and ensure product quality [28]. Researchers can use reinforcement learning to explore relationships between material composition, structure, and properties, accelerating the materials development process to reducing downtime and preventing costly equipment failures [36]. Reinforcement learning can make a bridge between the gap of nuclear level interactions and macroscopic behaviour material engineering [34].

MATERIAL TRADE WITH THEIR PROPERTIES

Material properties are pivotal in defining how well a material functions for a given purpose [26]. Some key material assets are strength means maximum stress a material, stiffness resistance of a material, toughness like a material to absorb energy, and elasticity which have ability to return to its original shape after deformation [7]. Some properties like thermal how a material responds to changes in temperature, conduct heat means expand or contract with changes in temperature. Electrical conductivity, chemical resistance to corrosion, oxidation, and degradation [8]. Optical properties transparency and refractive index is passes through a material [35]. These material properties are essential for ensuring that polymer composition techniques such as reinforcement learning (RL) and machine learning (ML) can be working to controller the prototyping process and optimize fabrication parameters, leading to enhancements in material properties and overall performance [27].

POLYMERS

Polymers are large molecules consisting of repeating basic units called monomers [24]. Their properties vary based on composition, structure, & processing methods. Polymers are globally use in everyday life in various industries, including plastics, textiles, electronics, automotive, aerospace, and healthcare. Plastics, rubbers, fibres, biopolymers are synthetic polymers [1]. These can be moulded into various shapes and forms. Polyethylene, polypropylene, polystyrene, and polyvinyl chloride (PVC).

The properties of polymers can be routine made through chemical modifications, additives, and processing techniques to meet specific requirements for different applications. Additionally, ongoing research in polymer science aims to develop advanced materials with enhanced properties, such as increased strength, durability, flexibility, and biocompatibility [25]. Polymer composites merge two or more materials with distinct properties to enhance final product performance [5]. Their usage spans industries, leveraging attributes like strength, stiffness, lightness, corrosion resistance, and flexibility [37].

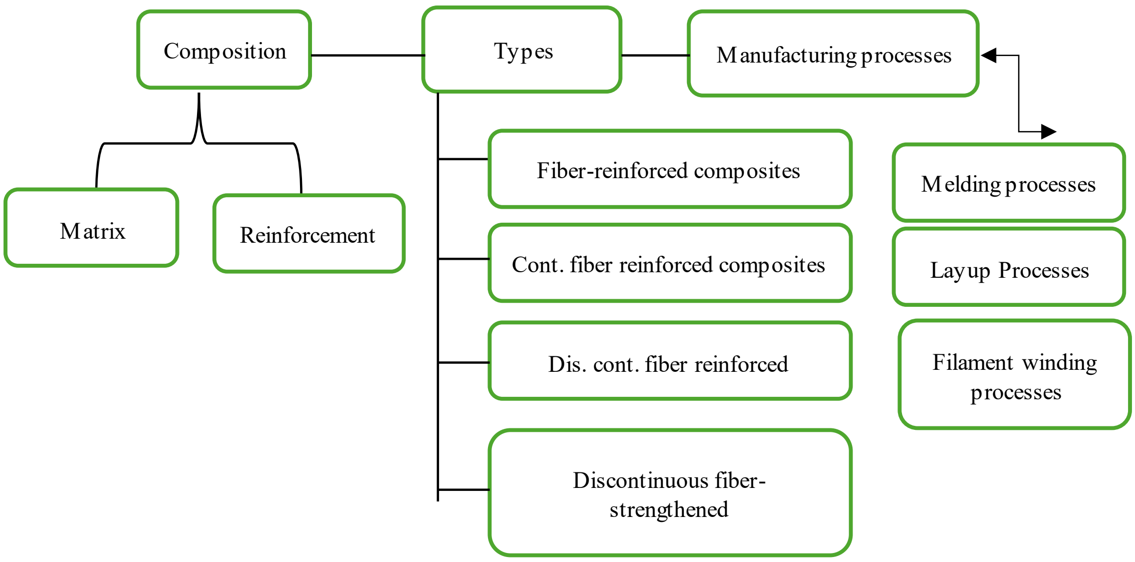

Figure 1. Polymer composites, types and manufacturing processes. created by author.

This is chart 1 the primary the material matrix, typically a polymer resin like polyester, viny ester, or thermoplastic resin such as polyethylene, binds the reinforcement together in a composite [23]. Reinforcement imparts strength and stiffness to the composite construction [35]. Reinforcements in the form of fibres (carbon, glass, aramid) or particles (nanoparticles, microspheres). The fibres can be continuous or discontinuous the material, providing high strength and stiffness. Manufacturing Processes like moulding shaped using various techniques like compression moulding, injection moulding, and resin transfer moulding [3]. Layup of reinforcement and matrix are stacked and cured together, often used in hand layup or Filament winding, alongside automated methods like ATL and AFP, is employed in fabricating polymer composites, forming structures like pipes and pressure vessels by wrapping fibres around a mandrel and saturating them with resin.

SHAPE MEMORY POLYMERS

Shape polymers represent a category of intelligent resources capable of changing their shape in a predetermined manner. This unique property, known shape memory result, enables them to recall and revert to a specific shape [4]. The memory result in polymers is incorporation of molecular structures, unstructured phases. When the material is in its programmed shape one state in a higher temperature, allowing the material to be easily deformed [2]. Their unique properties have a wide range of potential application like Biomedical Devices are used in various biomedical applications, such as stents, sutures, and drug delivery systems [22]. Aerospace, automotive, robotics, textiles etc use actuation and morphing structures, such as adaptive wing structures, active aerodynamic surfaces, to improve performance and efficiency. Smart textiles shape changing garments, and self-healing fabrics, offering enhanced comfort and functionality [9]. Ongoing research aims to further explore and optimize the properties of shape memory to develop innovative applications in areas such as healthcare, aerospace, and robotics [40].

ADDITIVE ENGINEERING

Additive Manufacturing, also known as 3D printing, revolutionizes manufacturing by constructing objects layer by layer digital 3D models [19]. This contrasts by traditional means that involve withdrawing material from a solid block. Improver engineering offers advantages in design flexibility, speed, and cost-effectiveness [39]. The process starts with creating a numerical 3D model, which is then sliced into layers for the additive manufacturing machine to follow [20]. Various technologies like (FDM), Stereolithography (SLA), and Selective Laser Sintering employ different processes & materials. Additive manufacturing finds applications across industries, facilitating rapid prototyping and production of intricate parts with complex geometries [21].

ADDITIVE MANUFACTURING OPTIMIZATION WITH NAIVE BAYESIAN ALGORITHM

In Model 1 Additive Manufacturing Optimization with Naive Bayesian Algorithm can work in quality control assurance in additive manufacturing in satisfactory or defective product based on features like dimensional accuracy, surface finish, and material properties [10]. Navie bayes can be enhance process parameters and ensure consistent product quality. This algorithm can play a significant role in quality control process within additive manufacturing [18].

Table 1 Containing features accurate parameters, predictive maintenance and continuous improvement in dimensional accuracy, surface finish, and material properties of manufactured parts. This algorithm can provide a powerful tool for quality control in additive manufacturing by enabling rapid and accurate classification of manufactured parts, process parameters, maintenance, and improvement of product quality [12]. The thickness layer deposited in the printing process can affect the surface finish, dimensional accuracy, and mechanical properties of the final part. The build platform affects the build time, as well as the resolution and quality of the printed part [13]. The temperature of the print environment can impact material flow, adhesion between layers, and overall part quality [38].

Table 1. Naive bayes algorithms use parameters in quality control assurance in additive manufacturing. created by author.

Accurate parameters for additive manufacturing	**Predictive maintenance**	**Continuous improvement**
Layer Thickness	Sensor Integration	Goals and Objectives
Printing Speed	Condition Monitoring	Gather Data and Analyse Performance
Infill Density	Fault Detection	Root Cause Analysis
Support Structure Density	Prescriptive Maintenance	Test and validate
Build Orientation	Integration with Maintenance Management Systems	Monitor and Measure
Cooling Rate	Prescriptive Maintenance	Feedback and Communication
Environmental Conditions	Alerts and Notifications	Training and Skill Development
Post-Processing Parameters	Data Acquisition	
Nozzle Diameter		

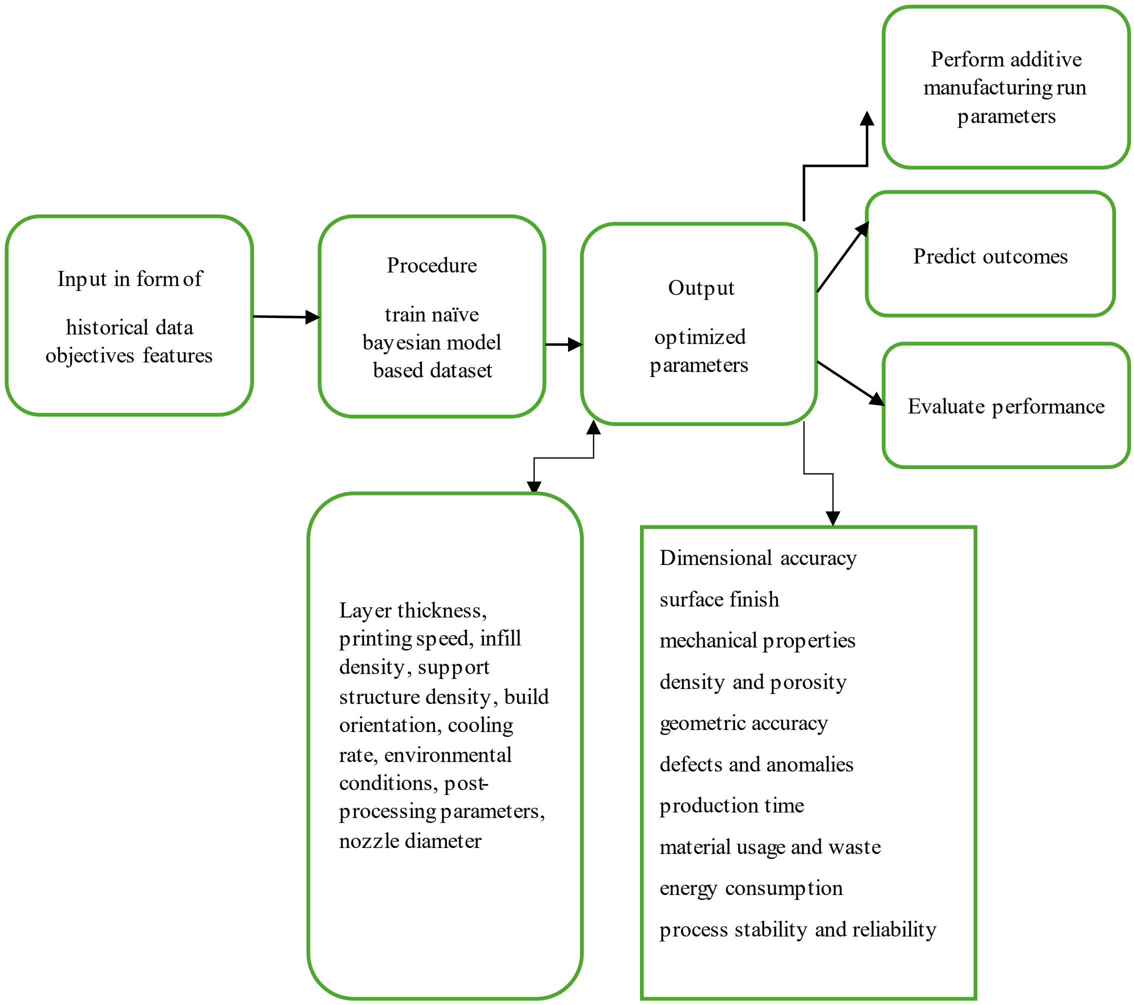

Figure 2. Additive manufacturing optimization with naive bayesian algorithm created by author.

THE SEVEN TYPES OF ADDITIVE MANUFACTURING

i. Stereolithography a container of liquid photopolymer resin cured by ultraviolet light to body parts layer by sheet. An ultraviolet laser with process traces the cross-section of the part on the surface of the liquid resin, solidifying it and shaping it as desired.

ii. Selective Laser Sintering high mechanical laser selectively powdered solid, classically plastic or metal, layer in layer.

iii. Fused statement displaying thermoplastic filament physical with a animated nozzle. The layers fuse together as they cool, forming the final part.

iv. Selective Laser Melting is used metal powders. A high-powered laser melts and fuses metal powder elements together to build up a part layer by layer. We use in aerospace, automotive, and medical industries for producing metal components with complex geometries.

v. Electron Beam Melting is another metal uses an electron beam, as opposed to a laser, to melt and fuse metal powder. Vacuum conditions, material properties, this method is particularly suitable for aerospace & medical applications.

vi. Binder Jetting is an additive manufacturing technique where a liquid binding agent is selectively deposited onto a bed of powder material, such as metal, plastic, or sand, layer by layer. The green part undergoes post-processing called curing or sintering. Direct Energy Deposition known as laser engineer shaping metal deposition (DMD), uses a focused energy source, fuse material as it is deposited onto a substrate. It's commonly used for repairing or adding material to existing parts, shape components.

THE CHARACTERISTICS OF POLYMER COMPOSITES ARE DEPENDENT ON THESE FACTORS

The characteristics of polymer composites are influenced by several key factors. These factors related to the polymer matrix, the reinforcing phase, and the interactions between components.

Thermoplastic can be remelted and reshaped, but thermosetting polymers cure into a rigid structure that cannot be remelted. Glass transition temperature, melting point, and molecular weight, significantly impact the composite's characteristics. Reinforcements can be fibers (glass, carbon, aramid), particles, or nanoparticles (silica, carbon nanotubes, graphene), Shape and Size (micro or nano), the length-to-diameter ratio (aspect ratio) affects the load transfer and mechanical properties.

The properties like stiffness, strength, and density. Higher reinforcement content typically enhances mechanical properties up to a certain limit. The strength of the bond between the polymer matrix and the reinforcement affects the stress transfer and overall performance of the composite. Modifications of reinforcement surfaces can improve interfacial bonding and compatibility with the matrix.

Processing Techniques

Manufacturing method melding, extrusion, lay-up, and resin transfer melding can affect the microstructure. Temperature, pressure, curing time, and cooling rate during processing influence the final properties of the composite. Environmental factors temperature, moisture and chemicals are affecting the composite's durability and mechanical properties.

UV Radiation additives and modifiers plasticizers, stabilizers, and fillers are additives can enhance processability, stability, and performance characteristics. Flame retardants can improve the fire resistance of the composite material. These factors is crucial for designing polymer composites with specific applications.

THE SEVERAL ELEMENTS THOSE INFLUENCE THE CHARACTERISTICS OF A POLYMER

A polymer is influenced by several elements, which can be broadly categorized into the chemical composition, molecular structure, and physical properties of the polymer. Chemical Composition Monomer are nature of the building blocks used to synthesize the polymer significantly affects and its properties. Copolymerization is different monomers in a copolymer can create materials with handmade properties, such as improved flexibility, strength, or chemical resistance.

Molecular Weight of a polymer, typically expressed as number-average (Mn) or weight-average (Mw) molecular weight, influences its mechanical properties, thermal properties, and processability. Higher molecular weight generally leads to higher strength and toughness but can make processing more difficult. A polymer sample affects its viscosity, melt behaviour, and mechanical properties.

The polymer chains linear, branched, or crosslinked properties like density, melt viscosity, and mechanical strength. Crosslinked polymers are typically more rigid and heat-resistant. The degree of crystallinity, or the extent to which polymer chains are ordered in a regular, repeating pattern, affects the mechanical strength, stiffness, thermal resistance, and barrier properties. Polymers can be amorphous, semi-crystalline, or crystalline. Tacticity of polymer chains, such as isotactic, syndiotactic, or atactic configurations, influences crystallinity and physical properties. Thermal, glass transition temperature, melting temperature, thermal stability, tensile strength, elastic modulus, and toughness, transparency, opacity, and colour, plasticizers, stabilizers, and fillers allows for the design and selection of polymers with specific properties to particular applications, from packaging materials to high-performance engineering plastics.

AN EXAMPLE OF STEREOLITHOGRAPHY (SLA) RESIN-BASED ADDITIVE MANUFACTURING PROCESS

Process Chat 1 Resin-Based Additive Manufacturing Process in Stereolithography The process starts by creating a detailed 3D digital model using CAD software. This digital model acts as the blueprint for the subsequent stages, particularly the Binder Jetting process [17]. CAD software allows designers to precisely define the dimensions, shapes, and intricate details of the object they want to produce [37]. This digital blueprint serves as the foundation for guiding the additive manufacturing process, ensuring that the final product matches the intended design accurately [18]. defines a geometry of the object to be printed. slicing into thin horizontal layers to a cross-section of the object and resin tank is filled with a liquid photopolymer resin have specific properties handmade to the desired application, such as strength, flexibility, or transparency. A platform is submerged the resin tank with a tinny layer resin spread evenly across a platform's surface [13]. A UV laser or projector light hits the resin, it solidifies or cures, forming the current layer of the object. Each new layer of resin is exposed to light and cured, bonding to the previous layer. Post-processing steps rinsing in a solvent or a UV curing chamber to remove excess resin. The printed object comes in Finishing processes such as rubbing, shining, painting is applied to attain the desired outward finish & appearance [11]. An application of SLA resin-based additive manufacturing is in the production of highly detailed prototypes, intricate models, or custom components with fine features and smooth surface finishes. SLA is also rummage-sale in trades, including automotive, space, healthcare, and consumer goods, of rapid prototyping, product development, and manufacturing of end use parts [36].

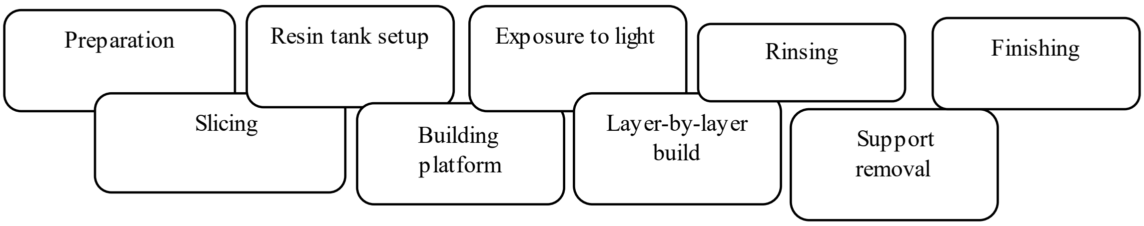

Figure 3. Resin-based additive manufacturing process in stereolithography. created by author.

DIMENSIONAL ACCURACY AND PRECISION BY MACHINE LEARNING

3D printing known additive process where each layer has dimensional inaccuracy. Accuracy relies on various factors including the specific 3D printing process utilized hardware design, resin properties, print settings, and post-processing plan [15]. Resin printers are considered among the greatest accurate & precise 3D production processes available model and manufacturer technology has differences in accuracy and precision in specifically the size, shape, and uniformity of light curing [7]. In the realm of 3D printing, achieving true value entails ensuring that the sizes designed in CAD align precisely with the printed object. Repeatability refers to the consistency of 3D printing, reflecting the machine's ability to produce expected results reliably across multiple prints [16]. Tolerance is a critical factor, especially in components with dynamic mechanical properties, such as a simple plastic enclosure.

EFFECTS OF REINFORCEMENT LEARNING (RL) ALGORITHMS USE IN RESIN-BASED 3D PRINTING PROCESSES

RL can converge on the most efficient settings for print parameters like exposure time, layer height, curing intensity, and resin thickness to achieve optimal print quality and minimize print failures. Adaptive generates support structures is custom-made to the specific geometry of each print [6]. Reinforcement learning to detect common print failures layer delamination, warping, pausing the print, adjusting resin flow, or modifying medicinal intensity to save the print or damage. Damage in means resin flow, minimize resin consumption, minimize downtime, maximizing print efficiency and peak in efficiency [14]. These algorithms can enhance resin-based 3D printing processes by continuously learning from past experiences and autonomously optimizing various aspects of the printing workflow to improve print quality, efficiency, and reliability.

RESIN-BASED 3D PRINTING WITH REINFORCEMENT LEARNING FOR SUSTAINABILITY

The printing process parameters, layer thickness, exposure time, and support structures, to minimize material waste [13]. Reinforcement learning models can help reduce resin consumption and promote sustainable manufacturing performs [35]. Develop intelligent systems for recycling and reusing resin materials in 3D printing processes by reducing waste generation and resource consumption [10]. The environmental impacts of different printing strategies, material choices, and end-of-life situations, reinforcement learning models can inform decision-making to minimize environmental burdens and maximize sustainability outcomes. Supply chain logistics and distribution networks for resin-based 3D printing materials, reducing transportation-related emissions and energy consumption [11]. Advance environmental sustainability in additive manufacturing and contribute to the transition to a more sustainable and circular economy.

FUTURE WORK AND LIMITATION

Reinforcement learning in machine learning algorithms active to printing parameters in SLA and DLP processes. In dynamically adjusting factors like time, layer thickness, resin composition based enhance printing efficiency, accuracy, and quality. Material development, print failure detection and recovery, optimize multi-material printing processes in SLA and DLP researchers can unlock new capabilities and overcome existing challenges in the field [8]. Some limitations in this research papers in the domain of Resin 3D printing processes, such as SLA & DLP utilize photopolymerization to create objects layer by layer. In SLA, a UV laser selectively cures liquid resin, while in DLP, a digital light projector cures entire layers simultaneously. These methods offer high resolution and detail, making them ideal for producing intricate and precise parts is limited experimental conditions, Insufficient data, simplifications to model the resin-based 3D printing process are limitations to assess the robustness and significance of the findings presented.

CONCLUSION

The combination of reinforcement learning (RL) with resin-based 3D printing processes important ability for advancing environmental sustainability in additive manufacturing. Researchers cover many aspects of the printing process, material selection, energy efficiency, waste reduction, and supply chain management, to minimize environmental impact and encourage sustainable observes. Key areas for future research include material selection for sustainability, reducing energy consumption, minimizing material waste recycling and reuse, conducting lifecycle assessments to environmental performance, supply chain logistics, and sustainable policies and regulations. Resin printing offers high precision, achieving consistent results depends on various factors, requiring careful management for reliable outcomes.

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