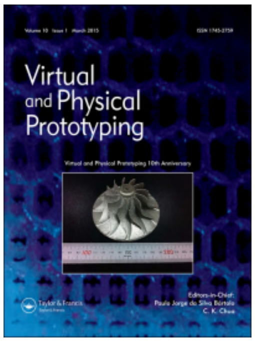

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Mobile robotics and 3D printing: addressing challenges in path planning and scalability

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ABSTRACT

Mobile Additive Manufacturing (MAM) systems are transforming large-scale fabrication across various industries, particularly in building and construction. This review explores recent advancements and ongoing challenges in deploying mobile robots within dynamic additive manufacturing (AM) environments. A primary focus is placed on mobile robots' path planning and real-time navigation methods, identified as critical knowledge gaps that impact the accuracy of printing trajectories. AI-driven techniques, such as deep learning and reinforcement learning, are presented as promising solutions to these challenges, offering improvements in trajectory optimisation, obstacle avoidance, and multi-robot cooperation. However, significant obstacles remain, particularly in scaling up MAM operations while maintaining both precision and efficiency. This review provides analysis of the current state of mobile robotic AM, outlines potential pathways for future research, and underscores the alignment of these technologies with Industry 4.0 objectives, emphasising the ongoing need for innovation to unlock the full potential of mobile robotics in large-scale manufacturing.

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KEYWORDS
Mobile robots; additive manufacturing; path planning; artificial intelligence; industry 4.0

1. Introduction

In recent years, there has been a growing interest in AM, a process that involves using various fabrication methods to shape raw materials into products of different forms [1,2]. AM, also known as 3D printing, refers to the creation of physical objects by adding layers of material on top of each other based on a digital design, free of tooling [3–7]. The first generation of AM processes, introduced in the late 1980s and known as rapid prototyping, was primarily used for creating conceptual models. The second generation, known as rapid tooling, expanded the application to include injection and blow moulding, electrical component machining, and thermoforming [8–10].

AM is a widely recognised technology used for prototyping and producing supportive components during the design phase, as well as a supplementary method in geographical projects and for assessing manufacturing processes [11]. This technology finds extensive use in several industries, including defence, construction, aerospace, medical, and tissue engineering, and for developing smart and graded structures [12–18].

Industry 4.0 has highlighted the critical role of robotic AM in enhancing productivity and optimising resource utilisation. As illustrated in Figure 1, there has been a marked increase in publications over the years, reflecting the growing research interest and advancements in these fields. This trend highlights the expansion of AM research and the increasing significance of robotics within this domain. Substantial improvements in engineering techniques propel the growth, a pressing need for resource optimisation, and innovations in fabrication methods. These factors collectively address AM technologies' escalating industrial demands and sustainability requirements.

1.1. Literature gap

Despite the growing interest in robotic AM systems, there is a research gap in AM using mobile robots, specifically in the navigation domains, particularly in path planning, localisation, and collision avoidance. While existing reviews cover various aspects of robotic AM, including stationary and mobile systems [19,20], they lack an in-depth focus on the algorithmic challenges of mobile

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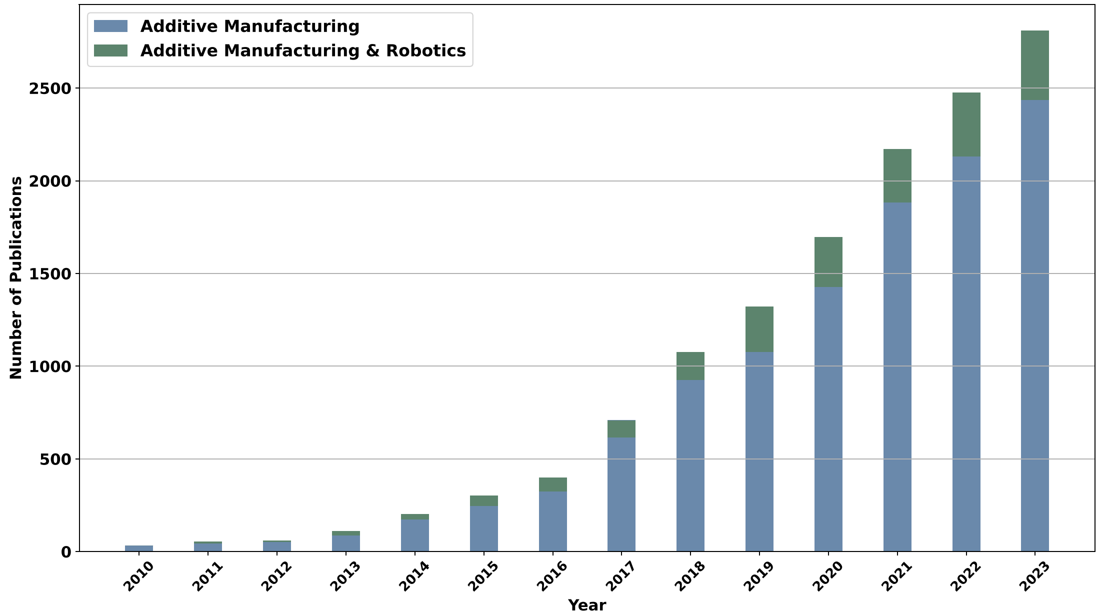

Figure 1. The annual number of scholarly articles in English on AM, with the green segment highlighting those related to Robotics (Scopus).

robot navigation in dynamic AM environments. The gap is particularly evident in areas such as:

1.1.1. Dynamic environments

Current research primarily focuses on traditional path-planning techniques, often insufficient for AM processes' complex and unpredictable nature. AM environments' dynamic and unpredictable nature presents significant challenges for current path-planning algorithms, primarily designed for static or predictable scenarios [19]. This limitation in path-planning capabilities hinders the effective navigation of mobile robots in constantly changing AM workspaces.

Furthermore, traditional methods struggle to keep pace with the continuous evolution of AM processes, where material deposition and tool movements constantly reshape the workspace. This inability to adapt in real-time leads to inefficiencies and raises safety concerns as collisions with newly formed structures or moving tools become more likely Lachmayer et al. [21]. The challenge of real-time obstacle avoidance in such dynamic environments remains a critical area for improvement in mobile robotic AM systems.

1.1.2. Handling complexity

The complexity of AM geometries, often involving intricate and rapidly changing shapes, demands a level of obstacle avoidance beyond simple geometric constraints. Existing algorithms may not be equipped to handle complex obstacles, leading to suboptimal paths or even collisions [22]. This challenge is further exacerbated in large-scale AM operations, where multiple mobile robots must navigate and cooperate seamlessly. Traditional path planning often falls short in coordinating the movements of mobile agents, resulting in decreased efficiency and potential conflicts [19,23].

Additionally, the continuous reshaping of the AM environment poses challenges for accurate robot localisation, an aspect that current research has not adequately addressed [24]. Maintaining precise positioning becomes increasingly tricky as the workspace evolves during manufacturing, impacting the overall performance and reliability of mobile robotic AM systems [19,23]. The limitations of current path planning algorithms in AM highlight the need for innovative approaches that can address real-time adaptation, complex obstacle avoidance, and multi-robot coordination. These advancements are crucial to unlocking the full potential of mobile robots in AM, enabling them to operate safely, efficiently, and cooperatively in this dynamic and challenging environment.

To address these challenges, this review paper will explore the following research questions (RQs):

- **RQ1:** *How can the limited exploration of navigation for mobile robots, including path planning, be addressed in the context of dynamic and complex AM environments?*

  The review examines the importance of efficient navigation methods for MAM in complicated environments, like construction sites, for tasks such as material deposition, inspection, and maintenance. The assessed navigation methods focussed on path planning, localisation, and collision avoidance. Accurate navigation significantly improves mobile manipulators' performance by reducing printing trajectory errors, leading to higher-quality fabricated parts.

- **RQ2:** *How have recent advancements in AI techniques contributed to enhancing robotic AM processes?*

  The study investigates the impact of recent advancements in machine learning (ML) techniques on robotic AM processes. Integrating AI-driven tools, particularly ML models, into robotics-based AM significantly enhances robot control, autonomy, deposition paths, manufacturing time, material usage, and repeatability. Techniques such as DL and RL improve process accuracy, defect detection, material optimisation, and autonomous decision-making. These advancements facilitate real-time monitoring, adaptive structures, and innovations like 4D printing, paving the way for future developments such as 5D printing.
- **RQ3:** *What are the current challenges and opportunities for mobile robot AM?*

  The study examines the current challenges and opportunities for MAM. Mobile manipulators address scalability challenges in AM by offering enhanced manoeuvrability within the working area compared to stationary robotic arms and gantry systems. However, challenges remain in fully realising the potential of 3D printing with mobile manipulators. Robust path-planning algorithms that adapt to real-time and dynamic AM procedures and improvements in real-time and autonomous control are needed. Future opportunities include integrating digital twins (DT) with AM at the factory, machine, and process levels. In robotics-based AM processes, DT enhances toolpath planning, multi-robot cooperative 3D Printing, defect correction, and in-situ quality monitoring through real-time monitoring of digital replicas of robot movements.

1.2. Search taxonomy

This paper aims to synthesise information on emerging technological advancements, current challenges, and prospective future directions in the AM domain, benefiting both industrial practitioners and academic researchers. It explores state-of-the-art developments in robotics-based AM systems, focussing on mobile manipulators, and examines the integration of AI, particularly ML and RL. These technologies are crucial for refining navigation strategies, path planning, localisation, and obstacle avoidance–vital elements in achieving high accuracy and minimal material waste in AM processes. The survey draws from a comprehensive review of literature sourced from leading research databases, including Google Scholar, Scopus, ScienceDirect, and IEEE Xplore. The screened literature encompasses peer-reviewed academic conference papers, journal articles, and books within the intersecting research domains of robotics, automation, computer science, additive manufacturing, and manufacturing engineering.

Table 1 summarises important parameters from recent reviews in robotic AM. These reviews highlight the requirement for better integration between mobile robot navigation–specifically path planning, localisation, and collision avoidance–and the precision of printing trajectories. This review addresses these gaps by examining the interactions between robotic systems, AI, and AM processes. The first section of this paper highlights the role of advanced robotic systems in enhancing AM capabilities. It focuses on how AI-driven methods, such as ML and RL, are increasingly utilised to optimise robotic control, trajectory planning, and deposition accuracy. These AI methods facilitate autonomous decision-making, contributing to real-time adaptations in dynamic AM environments. The following section discusses the pre-processing phase of mobile 3D printing, focussing on the importance of reliable data acquisition through advanced sensor systems. It explores the role of cameras and sensors such as LiDAR and inertial measurement units (IMUs) in providing accurate localisation and environmental data for mobile manipulators. This section also covers integrating sensor fusion systems and SLAM (Simultaneous Localization and Mapping) algorithms to ensure precise navigation and real-time obstacle avoidance. Then, the review explores different navigation strategies, thoroughly analyzing path planning, localisation, and collision avoidance techniques. It also discusses the potential of cooperative multi-mobile robot systems, especially in large-scale AM operations. The review also examines the challenges of deploying mobile 3D printing systems in real-world environments, such as building and construction sites. This section critically assesses the limitations of uneven terrains, dynamic obstacles, and environmental factors (e.g. wind, rain) on both navigation and material deposition. Special attention is given to the interplay between navigation accuracy and printing trajectory control. Finally, the review emphasises future research's need to enhance path planning methods, real-time adaptability, and cooperative mobile robot systems to improve 3D printing further.

2. Additive manufacturing (AM)

Manufacturing encompasses diverse fabrication methods that transform raw materials into products of

Table 1. Key features discussed in recent review papers on robots in AM.

Characteristics	Dörfler et al. [19]	Jiang et al. [20]	Jiang and Ma [24]	Bhatt et al. [4]	Urhal et al. [1]	Evjemo et al. [25]	Dörfler et al. [26]
Stationary robots		✓	✓	✓	✓	✓	
Gantry systems				✓	✓	✓	
Mobile ground robots	✓	✓		✓	✓	✓	✓
Mobile aerial robots							✓
Robots DOF	✓	✓	✓	✓	✓	✓	✓
Path planning algorithms			✓				$*^1$
Collision avoidance	✓		✓				$*^2$
Toolpath generation				✓	✓	✓	
Control strategies	✓	✓		✓		✓	✓
Localization and positioning	✓			✓			✓
AM technologies	✓	✓	✓	✓	✓	✓	✓
AM enhancement: Quality, Accuracy, Efficiency	✓	✓	✓	✓	✓	✓	✓

Notes: $*^1$, $*^2$ have reviewed the mentioned characteristics but not from an algorithmic point of view.

various forms [1,2]. AM, commonly known as 3D printing, is a revolutionary process that creates physical objects by depositing layers of material based on digital designs without the need for traditional tooling [3–7]. Distinct generations have marked the evolution of AM. The first generation, introduced in the late 1980s, focussed on rapid prototyping for conceptual models. The second generation, known as rapid tooling, expanded AM applications to include injection and blow moulding, electrical component machining, and thermoforming [8–10].

AM has become a cornerstone technology in prototyping, production of supportive components during design phases, and as a complementary method in geographical projects and manufacturing process assessment [11]. Its versatility has led to widespread adoption across numerous industries, including defence, construction, aerospace, medical, tissue engineering, and the development of smart and graded structures [12–18]. Bhatt et al. [4] provided a comprehensive review of robotic applications in AM for complex manipulation tasks, highlighting strategies to overcome traditional constraints in the AM process.

One of AM's critical advantages over traditional manufacturing methods is its slicing approach, which converts 3D models into thin planar layers, creating complex geometries. This capability has facilitated the development of multifunctional products such as batteries, kinematic joints, electrical components, solar cells, and multi-material, high-strength components. However, AM is not without challenges. These include the staircase effect, time-intensive fabrication processes, anisotropic material properties, surface finish issues, and the need to consistently use prefabricated structures during manufacturing [22].

The AM process involves several critical steps, as outlined in Table 2, each contributing to the overall efficiency and quality of the final product.

The American Society for Testing and Materials (ASTM) has recognised seven methods for AM, including directed energy deposition, material jetting, powder bed fusion, material extrusion, vat photopolymerization, sheet lamination, and binder jetting [3]. The AM process may use various mechanical systems to control the nozzle and print bed, such as mobile platforms equipped with a robotic arm, gantry robots, or stationary robotic arms [27]. In AM, gantry systems and robotic arms have traditionally been the go-to options, each offering unique advantages in precision and flexibility. A gantry system moves the robot's end-effector, such as a printing nozzle, along cartesian coordinates within a defined rectangular workspace. These systems are capable of accurate large-scale 3D printing but face challenges related to speed and scalability. Cooperative printing, where multiple printheads operate simultaneously, significantly increases fabrication speed by

Table 2. AM steps and related definitions [3].

AM Process	Definitions
Digitizing Designs	Developing digital 3D models using computer-aided design (CAD) software.
File Formats in AM	Standard tessellation language (STL) and additive manufacturing files (AMF) are widely used file formats in AM. They contain geometrical elements related to the CAD model.
Slicing Strategies	STL models must be sliced and stacked layer by layer to form the final model in the AM process.
Algorithmic Paths	Tool Path algorithms generate G-codes based on infill patterns and mechanical and thermal properties.
Optimizing Hardware Setup	Inspection of the AM machine's hardware setup before 3D printing to adjust power, material type, temperature, and thickness.
Streamlining Production	Removing redundant parts after 3D printing can be simple or complex based on the product.
Refinement Phases	AM post-processing time vary depending on the material and printing methods, ranging from short to long-term processes.

dividing the workspace among the nozzles. However, developing collision-free paths for these printheads remains complex, especially in multi-arm setups.

Additionally, installing gantry systems can be time-consuming and costly. The emergence of mobile robots is disrupting the landscape with their portability, expanded workspace, and ability to access challenging environments. This allows mobile robots to be easily deployed to new sites with minimal installation required. Mobile robots boast significantly larger workspaces than fixed robots, making them ideal for printing large-scale parts. Additionally, their mobility allows them to reach areas that are difficult or inaccessible to humans, such as disaster zones, underwater environments, or even space. As demonstrated by multiple studies (see Table 1).

2.1. AM processes

The following studies [28–30] provide an overview of significant large-format AM methods for polymers. They discuss the advantages, disadvantages, and the role of robotics in enhancing each process. These methods are crucial for producing large, complex, functional parts across various industries.

Material extrusion, a scalable method suitable for producing large parts, is significantly enhanced by robotics. The use of low-cost pellet-based feeding and the high-speed extrusion of up to 50 kg/h make it efficient for large-scale manufacturing. However, this method has some drawbacks, including the need for post-processing to achieve satisfactory surface quality, high energy demands, and the possibility of warping due to thermal gradients. Inter-layer adhesion challenges can also impact the overall quality of the final product. The role of robotics in material extrusion is crucial, as it enhances scalability and precision, demonstrating its adaptability. Mobile manipulators, multi-extruder setups, robotic arms, and gantry systems can adjust extrusion paths and speeds in real time, improving efficiency and part quality.

Vat photopolymerization, is known for its high precision and ability to produce smooth surface finishes, making it particularly suitable for creating complex geometries. It also has the advantage of producing seamless large parts, which improves the final product's mechanical performance. Despite these advantages, VAT photopolymerization has limitations, including slow print speeds, limited scalability, and high equipment costs. Additionally, the mechanical properties of parts produced by this method are often less suitable for structural applications. Robotics plays a crucial role in enhancing this process by automating part handling and curing, significantly improving precision, and reducing the need for manual intervention, thus streamlining the production process.

Powder Bed Fusion is known for its ability to produce dense parts with high mechanical strength. It is well-suited for creating high-resolution complex geometries and does not require support structures. However, powder bed fusion has drawbacks, including high energy costs, slow print speeds, and limited build volumes. Scaling up this method can lead to powder wastage and challenges maintaining uniform laser energy distribution. Robotics are essential in powder bed fusion as they enhance material handling and automate post-processing tasks, ensuring greater consistency and precision, particularly when building more prominent or complex parts.

Material Jetting is known for its excellent accuracy and precision, making it a great option for applications that require intricate and multi-material designs. It can print in multiple colours and materials, increasing its flexibility. However, there are some significant drawbacks to this method. The equipment is expensive, the print speed is slow, and the build volume is limited, making the production process costly. Robotics enhance material jetting by enabling complex tool paths and multi-material handling. Thereby reducing the need for manual intervention and increasing design flexibility, ultimately improving process efficiency.

Binder Jetting operates at room temperature, eliminating the thermal distortions common in other AM methods. This method can produce larger build volumes, making it particularly suitable for applications such as sand-casting moulds. However, binder jetting has limitations regarding the materials it can use, particularly with polymers. Additionally, the parts produced often require post-processing to improve their mechanical strength, and the method generally offers lower resolution than other technologies. Robotics enhances binder jetting by improving the precision of material placement and aiding in post-processing tasks. This is especially valuable in high-volume or high-precision applications, where consistency and efficiency are critical.

As shown in Figure 2, robotics enhances various AM methods, with notable contributions in areas like material handling and automated post-processing. Each method benefits from different levels of automation depending on the specific technology, with material extrusion exhibiting the most extensive use of robotic interventions across all categories.

Table 3 highlights various AM technologies that have adopted or have the potential to adopt automation.

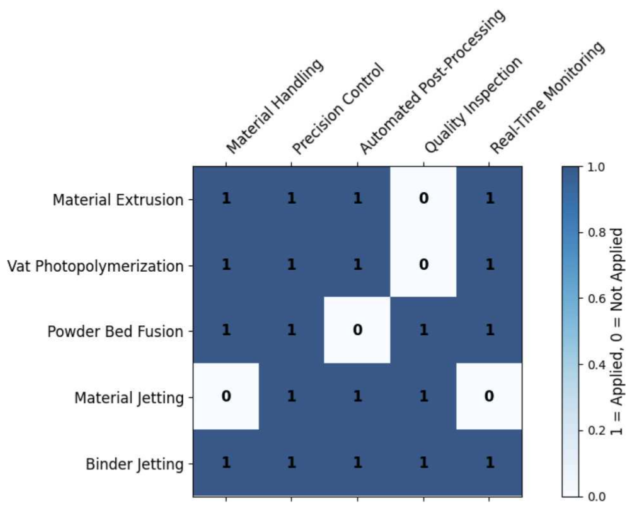

Figure 2. Integration of robotic technologies across five key Additive Manufacturing methods.

Most AM technologies are typically integrated with gantry systems. Still, only a few technologies, such as directed energy deposition, material extrusion, vat photopolymerization, and sheet lamination, have been integrated into robotic arms. It is also worth noting that mobile robots have only been integrated with material extrusion technology [31].

3. Robots and AI in AM

AM increasingly benefits from integrating mobile manipulator robots, which offer several advantages over traditional techniques such as gantry and cable-driven systems. One of the key benefits of mobile manipulators is their flexibility. Unlike gantry systems, which are confined to a fixed build volume, mobile robots can move freely around complex geometries and non-planar surfaces, creating intricate shapes that traditional systems struggle with. For instance, mobile robots with multiple degrees of freedom (6+ DoF) can perform real-time complex deposition tasks, allowing them to print in hard-to-reach areas, such as curved or multi-faceted surfaces. This flexibility makes mobile robots particularly suitable for applications in industries like aerospace and construction, where non-planar surfaces are common [46].

Mobile robots also address the traditional AM technique's economic and scalability limitations. While reliable for small-scale production, Gantry systems become cost-prohibitive when scaling up due to their fixed infrastructure and limited build volume. Expanding this capacity requires substantial capital investment. In contrast, mobile robots can scale without needing large infrastructure, moving across expansive build areas and reducing capital expenditure. Studies have shown that collaborative mobile robots in AM can increase production efficiency by over 70% compared to traditional gantry systems [47].

Cable-driven systems offer a more cost-effective alternative to gantry systems but come with limitations, particularly in precision. For instance, cable-suspended robots provide a more extensive range of motion and greater portability. Still, accuracy issues like cable sagging and oscillation can lead to up to 1 cm deviations in large-scale prints [48]. This level of precision is often insufficient for industries like automotive and aerospace, where accuracy is paramount, despite the economic advantages of cable-driven robots [48].

Hence, Mobile robots are being researched as an alternative that offers significant cost-saving potential. Companies can reduce operational and capital expenses by eliminating the need for expensive, fixed gantry systems. An automotive industry study found that mobile robot manipulators increased production volumes by approximately 30% while reducing operational costs due to their ease of reconfiguration and relocation [49]. This aligns with projections showing that the AM market is expected to reach USD 26.68 billion by 2027, driven by increased demand for custom parts, sustainable manufacturing practices, and innovations in construction and industrial manufacturing [50].

Table 3. Studies linked to AM.

AM Methods	Study	Task Definition
Vat Polymerization	[32–34]	Use light-activated polymerisation to selectively cure a vat of photopolymer resin, layer by layer, to form a solid object.
Material Extrusion	[35,36]	The process of depositing molten or semi-molten material layer-by-layer through a nozzle to create three-dimensional objects.
Powder Bed Fusion	[37,38]	The process in which thermal energy selectively fuses regions of a powder bed.
Material Jetting	[32,39]	Depositing droplets of photopolymer resin layer-by-layer through a nozzle and curing them with ultraviolet (UV) light to create three-dimensional objects.
Binder Jetting	[40,41]	Selectively depositing a binding agent onto a powder bed layer-by-layer through a printhead, bonding the powder particles together.
Directed Energy Deposition	[42,43]	An AM process in which focussed thermal energy (e.g. laser, electron beam, or plasma arc) is used to fuse materials by melting as they are being deposited.
Sheet Lamination	[44,45]	The process in which sheets of material are bonded to form an object.

3.1. Machine learning

ML algorithms can broadly be classified as statistical, deep learning (DL) and reinforcement learning (RL). They enhance the accuracy of specific parameters in real-time applications, such as the AM process, thereby contributing to the creation of sustainable products, as shown in the following studies [51,52]. ML algorithms analyze extensive datasets from sensors and imaging systems and forecast the optimal parameters to attain the most practical combination of material properties while reducing defects in the manufacturing process. One application of ML in defect detection involves identifying patterns that may indicate potential issues, allowing operators to take corrective actions. ML algorithms can be used to develop a prediction model for material properties in the 3D printing process using process parameters and material compositions. The confusion and matching matrix results from supervised and unsupervised learning can guide operators in designing structures with materials for more advanced AM applications. Mypati et al. [53] reviewed AI applications in manufacturing, including an examination of integrating ML with robotics for real-time monitoring and quality control in AM. For example, convolutional neural networks (CNNs) can detect defects and ensure higher-quality fabricated parts by analyzing image data from AM processes. This allows robots to optimise their movements based on the analysed data, leading to improved efficiency and reliability of AM operations.

ML and RL techniques can be utilised for autonomous robot path planning in AM processes to reduce production time, optimise material usage, and minimise human intervention. Mypati et al. [53] highlighted studies on collision avoidance strategies, incorporating algorithms such as fuzzy logic and neural networks. These algorithms process data from multiple sensors to facilitate collision-free robot navigation, particularly in complex manufacturing environments like 3D printing. Recent research has explored the integration of AI into 4D printing, which extends 3D printing by incorporating time as a fourth dimension. Milazzo et al. [54] investigated using 4D printing technology to create parts that can change their attributes over time, such as shape or functionality, in response to external stimuli. They applied AI techniques, specifically classification and regression models, as the fifth dimension to analyze and predict how material properties and design parameters would interact over time in the AM process. This approach facilitated the development of intelligent components, including adaptive structures, self-healing materials, and responsive surfaces.

3.1.1. Statistical learning

ML algorithms are widely used to enhance AM applications, such as predicting bead geometry in a robot-controlled gas metal arc welding (GMAW) system, which is an integral part of the Wire and Arc Additive Manufacturing (WAAM) process. The study by Chandra et al. [55] focuses on various ML algorithms, including linear regression, decision trees (DTs), random forests, XGBoost, and artificial neural networks (ANN). The ML algorithms offer precise control over the AM process. The robotic arm can achieve higher precision in material deposition by using ML predictions for the desired bead geometry.

A similar study By Ding et al. [56] is centred on creating an intelligent weld bead modelling system that employed a Support Vector Machine (SVM) algorithm for robotics-based WAAM. The authors found that SVM can accurately predict welding parameters compared to ANN. SVMs can avoid getting stuck in local minima and converge on a global minimum. Additionally, SVMs displayed a lower risk of overfitting and faster training time. However, using SVMs for training models in industrial applications adds complexity and requires extensive interdisciplinary knowledge to ensure high accuracy and quality. Using SVM model predictions in the WAAM process enhances the capabilities of the robotic arm, particularly in optimising path planning strategies for accurately tracking the cross-sections of the 3D model.The predictive results in Ding et al. study improved the robotic arm's ability to make autonomous decisions, particularly when selecting welding parameters [56].

Random Forest (RF) and Multilayer Perceptron (MLP) were used by Yaseer et al. [57] to forecast optimal parameters for achieving enhanced layer roughness in the robotic WAAM process. The RF and MLP algorithms modelled the non-linear relationships between parameters such as welding torch travelling speed, wire feed speed, weaving amplitude, wavelength, current, and voltage. Various patterns, such as raster, weaving paths, and zigzag, are used to plan the trajectory of a robotic arm end-effector. The study showed that RF predictive outcomes are superior to the MLP algorithm, enhancing robotic arm performance during the AM process. This study found that the RF algorithm requires less parameter tuning, is less affected by noise, performs effectively with smaller datasets, and is computationally efficient compared to the MLP algorithm.

Another study by Chen et al. [58] explored various ML algorithms for detecting rapid surface defects in robotics-based laser additive manufacturing (LAM). Predictive results from the ML algorithms, such as SVM, K-

Nearest Neighbors (K-NN), Gaussian Process, DT, Naive Bayes, ANN, RF, and AdaBoost, have been used to enhance the detection and classification of defects during the AM process. The robotic arm used data from the laser profiler to monitor surface conditions and ensure accurate localisation and positioning of the manufacturing tool concerning the workpiece. The ML structure leveraged unsupervised methods for region clustering and identification of potential defects, followed by supervised classification and categorisation. The k-NN algorithm's training results demonstrated an accuracy of 93.15%, outperforming other algorithms in handling noise and accurately detecting defects in real time in LAM. However, the K-NN algorithm's performance decreases when trained on large datasets due to its reliance on distance-based calculations, leading to high memory consumption.

Along with other traditional ML approaches, the Gaussian Process Regression (GPR) algorithm has also been utilised for non-linear regression, offering uncertainty estimates and predictions. The study by Chen et al. [59] developed a GPR algorithm for predicting optimised parameters that influence top surface roughness during the robotic WAAM process for manufacturing metal parts. This study aimed to eliminate the need for time-consuming post-process machining. The GPR algorithm was trained using multiple input parameters, which include weaving amplitude, wavelength, wire feed speed, and travel speed. The surface roughness of the fabricated part is measured using a 3D laser scanning system. Different patterns such as spiral, raster, contour offset, grid, zigzag, and weaving paths have been studied to improve the trajectory planning in the WAAM process. The authors observed that weaving paths caused desired surface roughness compared to other patterns. The results indicate that implementing a GPR-based predictive model can improve the entire AM process, enhancing the robotic arm's dynamic control [59].

3.1.2. Deep learning

Fueled by big data, powerful hardware, and algorithmic breakthroughs, DL, underpinned by neural networks, has revolutionised ML. Neural networks' capacity to automatically learn hierarchical representations of data has eliminated the need for manual feature engineering. Furthermore, they enable end-to-end training of models, optimising the entire system for superior performance. This, coupled with their inherent scalability, allows them to handle massive datasets and achieve state-of-the-art results across diverse tasks. However, this progress often comes at the cost of interpretability compared to traditional statistical approaches, as the complex decision-making processes within deep neural networks remain somewhat opaque.

The study by Kaji et al. [60] describes the incorporation of a DL algorithm to improve robotics-based AM technology, particularly in the Laser Directed Energy Deposition via Powder Feeding (LDED-PF) process, with a focus on surface anomaly detection. The robotic end-effector is equipped with a laser line scanner to generate 3D point cloud data. These point clouds are then analysed and segmented using the RandLA-Net algorithm, which identifies surface regions as normal, convex, or concave. The training results demonstrated high accuracy, achieving 91.3% and 83.3% in intersection over union metrics. The hand-eye calibration process is essential in this study for accurately establishing the relationship between the coordinate system of the robotic arm (hand) and the laser line scanner sensor (eye). The precise calibration is crucial to ensure collision-free movement of the deposition head along defined paths in the LDED-PF process. Kaji et al. [61] included a pre-developed DL model to enhance the detection of anomalies on surfaces scanned by a laser line scanner during the LDED process. The robotic arm's end effector is equipped with a nozzle that, together with an adaptive trajectory planning algorithm, improves material deposition accuracy on flat, convex, and concave surfaces. Integrating DL for defect detection and adaptive control strategies for trajectory adjustment significantly enhances the robot's performance, thereby improving the quality of the fabricated parts.

In a study by Rao et al. [62], ML techniques, specifically the MLP, are employed to enhance robotic-based gas metal arc additive manufacturing processes. The findings indicate that the MLP algorithm, as a data-driven model, provides better results than physics-based models like finite element simulations, particularly for criteria such as the height, width, and depth of the weld bead. The accurate predictive outcomes of the MLP algorithm are likely to enhance control over the robotic manipulator arm, thereby improving the AM process. A skeleton-based path planning approach is used to create a simplified geometric representation of the intended trajectories, ensuring precise control over material deposition. Additionally, precise control over the weld bead geometry can minimise collision risks between the robotic arm and the workpiece.

Building on the success of DL algorithms, the study by Ren et al. [63] employed Recurrent Neural Networks (RNNs) to model temporal relationships and Deep Neural Networks (DNNs) to enhance robotic based laser-aided AM, by optimising the prediction of thermal fields using data from finite element analysis.

The DL model used in this study achieved a 95% prediction accuracy, demonstrating its ability to establish a strong correlation between scanning patterns and temperature fields, which in turn helps to minimise residual stress and distortion. This approach outperformed traditional methods based solely on finite element simulations. The accurate predictions made by the RNN-DNN model significantly improved laser scanning processes, reducing computational times from hours to minutes.

Since the breakthrough of ImageNet, made possible by the seminal CNN architecture [64], CNNs have been frequently employed in AM process monitoring for their reliable pattern recognition capabilities in image processing. Building on these capabilities, Davtalab et al. [65] developed a deep CNN algorithm designed to identify layer defects during 3D printing using a gantry robot based on input images. The study's findings showed a high F1 score in training, indicating the effectiveness of the deep CNN algorithm for defect detection. This advancement enhances the entire AM process, including the performance of robotic arm manipulators during material deposition, and improves the quality of fabricated parts.

However, using CNN algorithms in industrial settings faces challenges, such as the significant computational resources required for training, which can lead to weak performance in environments with limited infrastructure. Additionally, the lack of labelled training data can significantly diminish the performance of predictive outputs, emphasising the time-consuming nature of data collection and annotation.

3.1.3. Reinforcement learning

RL is a branch of ML where an agent learns to make decisions by interacting with an environment to maximize cumulative reward. The fundamental elements of RL include the *agent*, which is the decision-maker, and the *environment*, which responds to the agent's actions. The environment is described by a set of *states* (S), and at each state, the agent can take an *action* ($a \in A$). After taking action, the agent receives a *reward* ($r \in R$) from the environment. The goal of the agent is to maximize the cumulative reward over time. A *policy* ($\pi(a|s)$) defines the probability of taking action a when in state s, guiding the agent's behaviour. The *value function* ($V(s)$) estimates the expected cumulative reward starting from state s, helping the agent assess the long-term benefit of different states. By continuously interacting with the environment, the agent refines its policy to make more optimal decisions that lead to higher cumulative rewards.

The significance of using RL for automating AM can be seen in the paper by Parisi et al. [66], where RL is used to effectively control the complex dynamics of underactuated systems like tower cranes (TCs) during 3D printing. An intelligent deep reinforcement learning (DRL) agent dynamically activates the crane's DOF to minimise extruder swing and maximize printing speed. The system is modelled with the jib rotating around the tower axis and the trolley moving along the jib while the extruder follows a semi-circular trajectory. The environment, action space, and reward function are defined to allow the agent to control the trolley's polar coordinates and thrust force on the extruder. Using the twin-delayed deep deterministic policy gradient (TD3) algorithm, the agent is trained through simulations, optimising its performance in controlling the swing and maintaining high speeds. After approximately 5000 simulation episodes, the agent achieves stable performance, effectively managing the extruder's swing during the 3D printing process. This DRL framework effectively transforms a tower crane into a 3D printing system, demonstrating the potential of AI-based control systems in complex manufacturing processes. Similarly, Felbrich et al. used DRL for automating AM, as discussed in [67]; the paper discusses the application of DRL to enhance the autonomy of robotic AM in the architectural construction sector. The study combines computational design and robotic fabrication (CDRF) with DRL to enable robots to plan and execute construction tasks autonomously. The DRL framework employs two algorithms, TD3 and Soft Actor-Critic (SAC) [68], to train robotic agents in two case studies: robotic block stacking and sensor-adaptive 3D printing. In the first case study, DRL agents learn to stack blocks autonomously, demonstrating the feasibility of DRL in computational design environments. In the second case study, the agents adaptively 3D print structures by dynamically adjusting to deformations and geometric state changes using sensory feedback. The integration of DRL with real-time physics simulation, geometric state reconstruction, and parametric modelling enables the development of robust autonomous systems capable of performing complex construction tasks with minimal human intervention. The results indicate significant potential for improving efficiency and autonomy in robotic construction through advanced DRL techniques.

The study by Petrik et al. [69] presents a novel framework, RLPlanner, which integrates RL and optimisation techniques to address the challenges of path planning in WAAM. Traditional path-planning methods suffer from poor adaptability, excessive human intervention, and limited transferability across different geometries. RLPlanner overcomes these drawbacks by enabling fully automatic deposition path planning and optimising the welding speed and wire feed rate to enhance the weld bead size and geometry adaptability. The RL-based framework uses Proximal Policy Optimization (PPO) [70] to determine optimal deposition paths and sequential least squares programming for setting process parameters. The study demonstrates RLPlanner's efficacy through computational and experimental evaluations on thin-walled structures such as walls, U-shaped frustums, and complex multi-part geometries like the GUI sign. The results show significant improvements in path planning accuracy, reduced human intervention and enhanced final part quality. However, the authors acknowledge limitations in parameterisation and multi-bead strategy implementation, suggesting future work to develop more general parameterisation techniques and expand RLPlanner's capabilities to accommodate more complex geometries and optimise for uniform temperature distribution during welding. Similarly, the paper [71] presents a significant advancement in applying RL to AM, specifically focussing on WAAM. This approach is crucial for handling complex non-linear systems inherent in industrial processes. RL can manage these complexities more effectively than traditional PID controllers through a model-free approach that learns optimal control strategies by interacting with the environment. The paper emphasises using experimental data to build a Reduced Order Model (ROM) of the WAAM process, enabling accurate simulations for the RL agent to learn and optimise manufacturing processes. RL's adaptive learning based on real-time data is essential for optimising multiple process parameters and improving manufactured components' quality and consistency by minimising the error between desired and actual layer geometries. Developing a WAAM simulator integrating a data-driven ROM with a robotic simulation environment allows extensive testing and optimisation of RL policies, reducing the need for costly physical experiments and ensuring a smoother transition from simulation to real-world application. Additionally, introducing a novel process-based reward function tailored for AM enhances learning efficiency by incorporating aspects such as power consumption and defect rates, ensuring the RL agent maintains process efficiency and quality. While focussed on WAAM, this RL framework is adaptable to other manufacturing processes, highlighting its potential for broader industrial applications and significant cost and time efficiencies by reducing experimental trials and shortening development cycles.

A diverse set of optimal part designs was explored by Venugopal et al. [72] using a novel RL-based topology optimisation (TO) and generative design approach. This method employs the Upper Confidence Bound (UCB) strategy to effectively explore and exploit different design spaces, ensuring that the resultant topologies optimise structural compliance and thermal conduction while adhering to Design for Additive Manufacturing (DfAM) constraints [72]. By incorporating support minimisation and thin feature minimisation filters, the proposed RL method enhances manufacturability without relying on extensive training data, which is often required by traditional DL methods. This approach significantly improves the scalability and practical application of TO in real-world scenarios, addressing the challenge of creating functionally superior, additive-manufacturing-friendly designs that conventional methods often overlook. Optimizing toolpath strategies using RL addresses the challenges of high-dimensional design spaces, reducing the need for trial-and-error methods.

RL has been used to dynamically learn and adapt toolpath designs through interactions with the AM environment, allowing for the efficient development of optimal paths for complex geometries. This is demonstrated in a study by Mozaffar et al. [73], which evaluates three RL formulations–policy optimisation, value function optimisation (Q-learning), and model-based RL–and finds that model-free approaches like Deep Q-Networks (DQN) [74], PPO [75], and SAC are particularly effective for high-dimensional tasks. The research highlights that RL algorithms perform better with dense reward systems, where feedback is frequent, such as rewarding correct material deposition, with PPO achieving the highest scores in both dense and sparse reward scenarios. A virtual AM environment was created to train RL agents, allowing them to iteratively learn and improve toolpath designs, enhance the final part quality, and reduce defects. This approach revolutionises automated AM by enabling sophisticated and efficient toolpath design, particularly when using dense reward systems, ultimately enhancing part quality and reducing manufacturing defects [73].

Automated AM needs optimised process parameters to maintain repeatability, control microstructure, and minimise defects. Traditional methods, like the design of experiments and statistical process mapping, often fall short due to high data requirements and a lack of real-time adaptability. The study by Dharmadhikari et al. [76] proposes an off-policy RL framework based on Q-learning to dynamically optimise process parameters such as laser power and scan velocity in metal AM. This framework uses an experimentally validated Eagar-Tsai formulation to emulate the laser-directed energy deposition environment, where the laser operates as an agent navigating through the parameter space to maximize rewards based on achieving a desired melt pool depth. By continuously interacting with the environment and updating a Q-table, the RL agent can identify optimal parameter combinations without prior information, reducing the need for extensive trial-and-error experiments [76]. This approach has shown congruence with experimental observations, providing an efficient and adaptable model-free method and offering a powerful tool for on-the-fly optimisation in AM systems.

3.2. Toolpath generation

Toolpath generation is critical to many AM processes, including directed energy deposition (DED), WAAM, and more. The toolpath directly influences the final product's quality, mechanical properties, build rate, and precision. Efficient toolpath strategies ensure optimal material deposition, reduce the risk of defects such as porosity and cracks, and improve the overall structural integrity of the manufactured parts. Automated toolpath generation is particularly significant because it enhances the reproducibility and scalability of AM processes, making them more suitable for industrial applications.

Manual tool path identification for carved layers using high-DOF robotic arms is challenging, as Wu et al. [77] and Huang et al. [78] demonstrated. Various techniques, such as dividing large models into smaller sections or 3D printing without supports, have been developed to simplify this process, though they often require manual assembly [79]. Developing rotational trajectory motions could eliminate the need for manual assembly, yet existing methods are still based on planar layer development. Time-intensive tool-path algorithms work on multiple axes, including the visibility map algorithm [80], path planning in a cluttered environment with tools and work-pieces while maintaining collision-free paths [81], and algorithms for developing tool paths without gouging effects, improving machine dynamics [82,83]. To effectively use the required hardware setups, generating collision-free tool path algorithms for AM must be improved [84]. One approach is to add curved surface layers on top of each other to fabricate a solid model, meeting conditions like avoiding overlap, accurate approximation, and reachable surface patches. This process involves analyzing the environment, creating polygonal surface meshes, and determining tool paths based on Fermat-spiral curves.

The study by Biegler et al. [85] focussed on automated toolpath generation for DED, exploring 'zig-zag' and 'contour-parallel' strategies. Their research demonstrated that while zig-zag patterns were effective, they faced challenges in curved and narrow areas, whereas contour-parallel patterns struggled with sharp angles. The study highlights the geometry-dependent nature of toolpath strategies and their influence on material properties like microstructure and porosity. Similarly, Xiao and Joshi [86] addressed the complexities of generating toolpaths for heterogeneous objects (HOs) in DED, which involve multiple material compositions within a single layer. Their approach accounted for material changes and machine limitations, demonstrating through simulations that their method was efficient and flexible for various HOs. They emphasised the importance of material location accuracy and suggested further research on the impact of pixel size on toolpath generation.

In WAAM, an algorithm was developed by Ding et al. [87] to decompose 2D geometries into convex polygons, enabling the generation of continuous toolpaths using zigzag and contour patterns. This approach aimed to enhance surface accuracy and reduce starting-stopping points. Their results indicated superior surface quality compared to existing methods, demonstrating the efficacy of their strategy in meeting WAAM design requirements. Further advancing the field, Ding et al. [88] focussed on creating an automated system for robotic arc-welding-based AM, which integrated modules for bead modelling, slicing, and deposition path planning. They successfully fabricated a thin-walled aluminium structure using only a CAD model, showcasing the system's potential for fully automated production. This study marked significant progress towards practical, highly automated AM systems, emphasising the integration of various modules for seamless operation.subsectionTooling System Integrating advanced tooling systems is crucial in the AM process as it determines fabricated parts' efficiency, precision, and quality. AI-driven path-planning algorithms have led to notable advancements in tool paths for parts with complex geometries. These algorithms consider material and thermal properties and mechanical constraints to generate collision-free tool paths. AI can improve tooling systems by providing real-time monitoring and predictive maintenance. ML models analyze sensor data to predict tool wear and failure, allowing for proactive maintenance and minimising downtime. Generative design algorithms significantly advance the integration of AI applications and tooling systems. These algorithms can automatically generate and evaluate multiple tooling designs based on predefined criteria. The AM using collaborative robots (cobots) notably impacts tooling systems. Cobots equipped with advanced AI-based localisation and navigation hardware can work alongside human operators to efficiently carry out complex tooling tasks. These cobots can adjust their operations based on real-time feedback from the manufacturing environment through a process known as adaptive learning [89].

AI techniques can monitor and control the process of robotic-based WAAM tooling systems. This includes process parameter control, defect detection, and RL methods to address model non-linearity and uncertainties. Data from sensors, including weld pool images, voltage, and current, is analysed using DL models to detect defects in real time and adjust process parameters. The WAAM workstation comprises a weld monitoring system (WMS), a motion platform, and welding equipment to gather and analyze data from the welding process. WMS sensors collect welding process parameters, and AI techniques are used for closed-loop control and online quality inspection. Recent developments in RL have enhanced the creation of adaptive control strategies within WAAM tooling systems, enabling the dynamic optimisation of process parameters. As a result, challenges related to the stochastic nature of the welding process can be minimised, leading to improved quality of the fabricated parts. The integration of AI-driven tools and WAAM tooling systems has advanced, but there are still barriers. For example, ML and DL algorithms require significant computational power, extensive data collection, and resource-intensive processing capabilities [90].

4. Mobile robots in AM

Numerous studies have explored the application of AM for both on and off-site fabrication of large structures with various robotic technologies, such as robotic arms, gantry systems, and mobile robots. These research objectives are to minimise the constraints associated with continuous and stationary 3D printing of free-form structures and assembling different parts. However, the development of large-scale trajectories with flexible geometries is primarily limited to stationary robotic arms, gantry-crane robots, and ground mobile robots. Multiple mobile robots can work together to achieve more scalable and flexible solutions during the 3D printing process.

Several researchers have explored the possibility of 3D printing while in motion. Keating et al. [91] designed a robotic system that includes a mobile platform with tracking capabilities and a dual robotic arm system composed of electric and hydraulic arms named the Digital Construction Platform (DCP). The main goal of this system is to print large structures upon arrival at the specified location. In a study by Zhang et al. [92], the limitations of classical AM methods, including the use of stationary robotic arms and gantry robots, were identified as significant hurdles to scalability. To overcome these challenges, the team deployed a group of mobile robots, which worked together to 3D print a large single-piece concrete structure. AM with mobile robots could be a promising approach to tackle scalability issues. However, it is worth noting that this method's proper assembly of interfaces remains challenging. It is critical to have accurate motion, coordination, and localisation planning to facilitate the implementation of concrete 3D printing using a team of mobile robots. The study was centred on developing a 3D printing concrete system using a holonomic mobile platform designed to enable fast tracking with a 6 DOF robotic arm mounted on it. Moreover, the platform has a stereo camera, a pump, and localisation and odometry sensors. The present research methodology limited the AM process to instances where the printing device is stationary. This approach effectively limits the size of a structure that can be produced in a single operation by a single robot. The present study's findings and knowledge gaps have led to the development of a subsequent research work by Zhang et al. [93] that aims to enhance the functionality of mobile robots by enabling them to perform concrete printing while in motion.

Sustarevas et al. [94] proposed a 3D printing system named MAP that employs a 4-legged omnidirectional mobile platform equipped with a high DOF robot arm. Due to its innovative structure, this robotic system can accelerate the AM process and enhance the flexibility of mobile robots working in congested spaces. Sustarevas et al. [95] researched the control strategies employed for autonomous AM using a group of mobile robots in the building and construction industry. The study aims to address the scalability constraints associated with constructing large structures that are bigger than the size of a single robot. The research focuses on performing AM in dynamic environments. A mobile robotic platform named YouWasp was developed with an extruder to evaluate the functionality of the proposed methodology as an autonomous extrusion design.

Several studies have been conducted to improve the efficacy of multi-robot operations and task allocation. These studies have focussed on developing strategies and techniques for enhancing the coordination and cooperation of multiple robots to achieve optimal performance. Yan et al. [96] analysed efficient coordination methods in facilitating multi-robot operations. The authors identified communication mechanisms, planning strategies, and decision-making structures as crucial elements that enable effective coordination among multiple robots. Sustarevas et al. [97] have continuously researched using mobile manipulators to enhance automation systems in the construction industry. The printing framework comprises two main subframes: Printing while stationary and moving. The first approach involves precisely depositing material on a defined surface while the mobile robot is stationary. However, this method requires frequent relocation of the robot, which can be time-consuming and not ideal for continuous printing. The second approach, printing while moving, can overcome the relocation issue of the stationary model and allow printing to be performed faster. However, this method may result in a less accurate fabricated structure, and a complex implementation process is required to prepare the system.

MAM systems benefit from the interaction of robots with one another or with humans during the manufacturing process. In Collaborative MAM systems, humans work directly with mobile robots in a shared manufacturing environment. These robots, equipped with safety sensors, assist operators by handling repetitive tasks, such as material deposition, while operators focus on decision-based actions like real-time adjustments and quality control. In contrast, Cooperative MAM systems involve multiple mobile robots working together autonomously, without human intervention. These robots coordinate their movements in parallel to 3D print different sections of a large structure or execute steps of the AM process sequentially. By communicating with each other, the mobile robots adapt their movements and actions to achieve more scalable outcomes.

The increasing demand for large-scale AM solutions has led to the development of novel manufacturing approaches. One such approach is swarm manufacturing, introduced by Poudel et al. [98], which presents a distributed manufacturing paradigm where numerous mobile robots work cooperatively to 3D print products more efficiently and quickly. The primary strategy used in this study is dividing large parts into smaller chunks, which are printed simultaneously by multiple mobile robots. The system employs either the divide-and-conquer or same-side chunking strategy, where material is deposited on sloped surfaces to bond the chunks properly. The system architecture consists of hardware and software components. The software manages chunking, scheduling, slicing, and simulation to ensure collision-free 3D printing without duplicating efforts. The hardware includes SCARA (Selective Compliance Assembly Robot Arm) arms, a mobile platform for transporting printers, modular floor tiles that assist navigation, and a wireless network for precise coordination. The mobile platform, equipped with mecanum wheels for omnidirectional movement, uses infrared sensors and barcodes embedded in floor tiles for precise localisation.

Additionally, a camera scans the barcodes to facilitate navigation, while a robust wireless network enables communication between the SCARA printers and mobile platforms. The system uses WAIT and NOTIFY commands for synchronisation during printing. Modular floor tiles also provide continuous power when the SCARA printer is mounted. Physical validation included fabricating a large-scale honeycomb artwork using 16-floor tiles, 2 SCARA printers, and one mobile platform, as well as printing the AMBOTS logo. Future research directions include utilising robot arms with more DOF, larger robots for taller objects, automated filament replacement, and AI-driven software to enable autonomous decision-making for mobile 3D printers.

Dörfler et al. [19] reviewed the challenges of 3D printing with mobile manipulators in construction sites, which are complex environments with varying terrain and obstacles. Mobile manipulators should use advanced mobility systems, localisation techniques, and real-time mapping to navigate complex terrain during AM processes. The mobile platform is designed with different types of wheels, such as differential drive or omnidirectional, to navigate uneven terrain and transport heavy payloads for material deposition. The manipulator with multiple DOF enables precise material deposition while working in a cluttered construction environment. The manoeuvrability and operational range of the mobile robot can be further enhanced by incorporating climbing capabilities for vertical or inclined operations. MAM for building and construction is often a time-consuming process. As a result, multi-robot setups are considered a promising solution to minimise time wastage. Mobile robots coordinate their movements and share environmental data through decentralised task allocation systems. This method ensures that if an obstacle appears in one robot's path, others in the system can take over tasks or adjust their positions. Absolute and relative localisation are two common categories within the robotics domain. They are combined to ensure collision-free navigation. Absolute localisation uses external tracking systems, such as total stations or optical markers, to accurately position mobile manipulators within a construction site. On the other hand, relative localisation depends on sensor fusion from onboard systems (e.g. wheel odometry, Inertial Measurement Units (IMUs)) for autonomous navigation. Real-time path planning allows a mobile manipulator to recalculate its path autonomously when it detects an obstacle. This functionality is crucial in multi-robot systems, where if one robot's path is blocked, others can continue their tasks, ensuring continuous 3D printing. Building on previous work, Dörfler et al. [26] recently published new findings on improving mobile 3D printing within building and construction sites. For example, multi-sensor fusion, combining exteroceptive and proprioceptive sensors, can enhance adaptation to uneven ground, inclines, and obstacle avoidance when navigating complex terrains. Leveraging model predictive control (MPC) for mobile manipulators' whole-body motion control enhances mobile platform synchronisation and the manipulator's end-effector, printing nozzle, for collision-free material deposition while in motion. Precisely controlling and perceiving environmental disturbances such as rain, wind, and sunlight and monitoring printed structures contribute to ensuring precise MAM, especially in concrete 3D printing. As mentioned previously, the ability of mobile manipulators to print while in motion also depends on precise path planning methods, such as the RRT* algorithm, to find the optimal path and ensure smooth 3D printing despite the complexity of the terrain. The study further emphasises the need to explore the connection between mobile manipulator navigation strategies and printing trajectories. The future of mobile 3D printing can be enhanced through cooperation between aerial and ground-based mobile robots to achieve greater scalability and reach the full potential of mobile setups.

4.1. Data acquisition and sensors

Accurate and reliable data acquisition is the foundation of mobile AM systems. In these systems, robotics, sensors, and AI work together to ensure high precision and adaptability, especially in complex environments like construction sites. Sensors play a pivotal role in gathering real-time data on various critical parameters, including temperature, material flow, robot positioning, and environmental conditions.

4.1.1. Localization and mapping

Localization accuracy is paramount for mobile robots navigating construction or industrial environments, where positioning errors can impact print precision. Traditional localisation methods such as GPS offer limited accuracy, often within ±5 cm, which is insufficient for AM needs [21,99]. To address this, mobile robots rely on sensor fusion techniques, integrating data from exteroceptive sensors (e.g. LiDAR and depth cameras) with proprioceptive sensors (e.g.Inertial Measurement Units (IMUs) and visual odometry). These sensor fusion methods combine data from multiple sources to better understand the robot's surroundings.

For instance, mobile robots use Simultaneous Localization and Mapping (SLAM) algorithms, including advanced systems such as ORB-SLAM3, Dyna-SLAM, OKVIS2, and MAVIS, to autonomously generate real-time maps and track their positions. These SLAM algorithms are vital for navigating uneven terrain and avoiding obstacles, enabling mobile robots to continuously perform tasks like material deposition and inspection while maintaining precise localisation [100–103].

4.1.2. Exteroceptive and proprioceptive sensors

The exteroceptive sensors like LiDAR (Light Detection and Ranging) and depth cameras allow mobile robots to perceive their external environment, detecting obstacles and measuring distances with high accuracy. These sensors are essential for creating 3D maps of the surroundings and identifying obstacles such as debris, machinery, or human workers. This capability enables autonomous navigation in cluttered and dynamic environments like construction sites.

Proprioceptive sensors, including IMUs and wheel odometry, provide the robot with information about its movements. IMUs, which measure acceleration and rotation, help track the robot's orientation and velocity, while wheel odometry gives data on the robot's displacement by measuring the rotation of its wheels. These sensors allow the robot to adapt its movements as the terrain changes.

4.1.3. Visual SLAM and multi-Sensor fusion

Visual SLAM systems further enhance mobile robots' ability to map environments and navigate them effectively. These systems rely on cameras to capture images of the environment and, when combined with IMU data, generate detailed 3D maps. Mobile robots using visual SLAM can identify and avoid obstacles in real time while maintaining accurate material deposition paths.

Multi-sensor fusion techniques integrate data from both exteroceptive and proprioceptive sensors to improve the robot's ability to adapt to uneven terrain, inclines, and dynamic obstacles. For example, mobile manipulators may combine LiDAR data with IMU and camera inputs to enhance the accuracy of navigation and path planning, even in challenging conditions such as rain or uneven surfaces [26].

4.1.4. Real-Time process monitoring and pre-processing

In addition to localisation and navigation, sensors contribute significantly to real-time process monitoring in AM. Mobile robots equipped with High-Speed Video Cameras (HSVCs) and Millimeter-Wave (MW) Sensors provide precise monitoring of droplet size, velocity, and shape, especially in processes like Droplet-on-Demand Liquid Metal Jetting (DoD-LMJ) [104]. These sensors capture critical data used for process optimisation and anomaly detection, ensuring that the material is deposited accurately.

The data gathered from these sensors is processed using AI models, such as CNNs and non-linear autoregressive neural networks (MLP-NARX), which can predict droplet stability and make real-time adjustments to process parameters like nozzle pressure and material flow. These adjustments ensure consistent print quality and minimise the risk of defects during the printing process [105]. Future advancements in sensor technology will further enhance mobile 3D printing. The research will focus on expanding the Degrees of Freedom (DoF) in robotic arms, developing larger robots for taller structures, and improving sensor-based adaptive decision-making. AI-driven systems will enable greater autonomy in decision-making, allowing mobile robots to navigate better and adjust their processes on the fly [26]. Additionally, the integration of aerial and ground-based mobile robots can improve scalability and operational range in large-scale construction projects.

4.2. Challenges

Robotic and automated AM face multiple challenges, including fabrication time, versatility, efficiency, precision, and scalability. Specifically, limitations related to the time it takes to fabricate parts, the versatility of the robots in handling different materials and parts, and the overall efficiency of the manufacturing process are significant hurdles. Teams of robots have been proposed as a solution to these challenges, emphasising the potential to enhance fabrication speed and versatility by distributing tasks among multiple robots [92].

One of the promising solutions to these challenges is the application of sophisticated path-planning strategies, especially for mobile robots. Path planning can optimise movements, enhance accuracy, and speed up the overall performance in constructing structures, including concrete structures without formwork. This is critical for improving robotic AM's precision, efficiency, and scalability by guiding mobile robots to execute tasks with optimised trajectories, minimising fabrication time and material waste [106,107].

Integrating path planning with real-time information, like 2D laser scanning, has significantly improved process control. This approach allows for adjustments based on layer height deviations during printing, enhancing process stability and accuracy for large-scale components [108]. Furthermore, automated process planning benefits from hybrid multi-resolution layers and path-planning algorithms, especially for material extrusion AM. These algorithms ensure smooth material deposition and prevent collisions during the build process, improving surface quality and build time efficiency [109].

Efficiently planning cleaning paths is another complex challenge, particularly when dealing with residual powder that resembles printed parts in colour and texture. Integrating image segmentation and eye tracking has been proposed to refine robot path planning, thus enhancing efficiency and accuracy in AM processes [110].

Improvements in robotic/automated AM are further discussed in terms of optimising AM parameters for composite materials, robotic path planning for efficient layering, and an integrated process control technique. These advancements emphasise the need for a holistic approach that includes precise robotic path planning and real-time adaptation [111,112]. Focused developments in path planning for mobile robots promoting autonomous path planning capabilities, such as vision systems for high precision and reliability, could significantly advance the field. Implementing such strategies enables circumventing obstacles in complex environments and automating the feature extraction process for optimal manufacturing paths, highlighting path planning as a critical enabler for the next advancements in robotic and automated AM [113,114].

5. Path planning for Mobile robots

Path planning refers to determining a continuous path, either smooth or curved, from a start point to an endpoint in the Configuration space (C-space). Optimal path planning may require supplementary methods, such as defining a cost function based on specific criteria like travel time and distance. Trajectory planning, which falls within the dynamic aspects of robots, involves considering how a robot manipulator follows trajectories or how a mobile manipulator moves [115].

Path planning strategies for cooperative AM using robots can be classified into six categories: online, offline, centralised, decentralised, coupled, and decoupled [116,117]. The online approach suits unpredictable environments with dynamic object motion, while offline algorithms are suited for static environments with slow motion of objects suitable for AM applications. The coupled planning approach treats the robot as a single model and explores the robot's configuration space.

In contrast, the decoupled approach develops a separate, collision-free path for each robot [118]. The centralised methodology is based on developing a path planner for all operating robots. The centralised

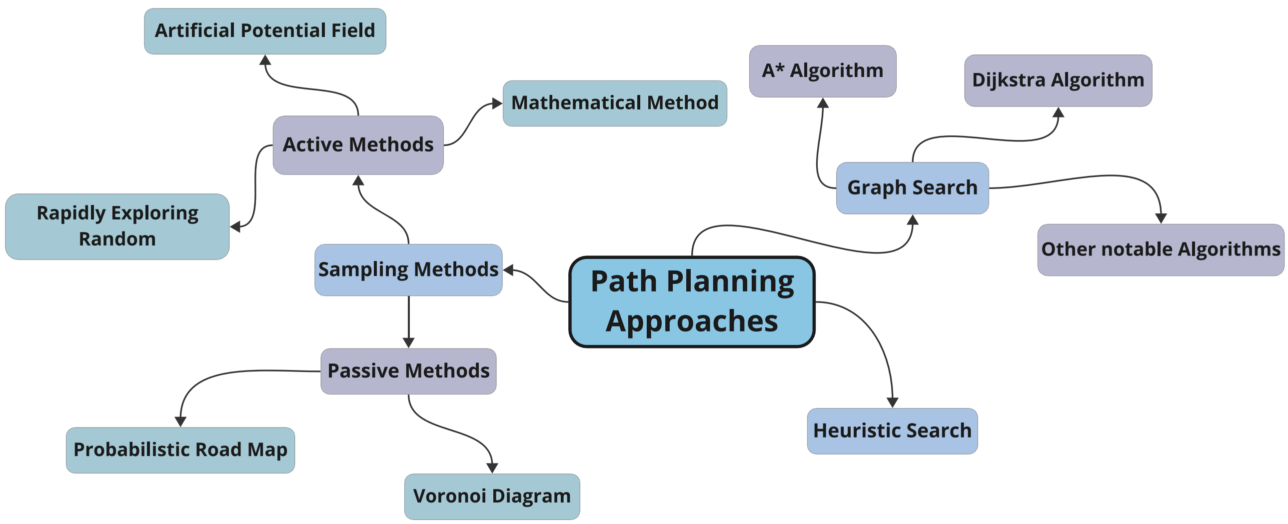

Figure 3. Different path planning methods of using robots in additive manufacturing.

approach enables the system to function as a single entity for developing paths, with a global vision of each robot's positioning and detailed information on all system elements. The centralised approach may have limitations, such as reduced scalability and strength [115]. Distributing data exchange and decision-making among all robots in decentralised planners may result in complexity with less efficient solutions [119]. AM with cooperative, mobile manipulators utilises both centralised and decentralised approaches, differing in production scale. The centralised approach is suitable for operating with few robots within a short time frame and for small-scale productions. At the same time, decentralised methods are used for large-scale trajectory 3D printing [120].

Reducing the computational time is crucial in developing path planning algorithms, as it can contribute to achieving optimal solutions. According to Madridano et al. [115], Multi-Robot Systems (MRS) path-planning algorithms are classified into different categories, as illustrated in Figure 3.

Figure 4 depicts the end-to-end workflow in MAM, from creating the CAD model to finalising the G-code for printing. This process involves tessellation, slicing, and path planning procedures, ensuring an optimal, collision-free print.

5.1. Graph search

Graph-based methods are fundamental tools in various fields for solving complex problems related to pathfinding and optimisation. These methods leverage graph theory to model networks of nodes and edges, allowing for efficient traversal and analysis. In robotics and other domains, graph-based algorithms enable the determination of optimal routes, efficient resource allocation, and the navigation of intricate environments. The algorithms discussed here, including A*, D*, and Dijkstra, represent different approaches to using graph structures to solve specific challenges in pathfinding and route optimisation, each with unique strengths and limitations. Their continuous refinement and adaptation to new contexts underscore their critical role in advancing technology and improving operational efficiencies.

5.1.1. A* algorithm

While the A* algorithm offers a powerful pathfinding solution, it has limitations. These include high memory usage, computational overhead, dependence on a well-designed heuristic, difficulties in dynamic environments, scalability, and balancing optimality with performance. Additionally, path smoothing might be required. To address some of these limitations, Kalidi et al. [121] proposed the T algorithm. This approach combines A* with temporal logic to find optimal paths that satisfy time constraints. Their experiments showed that T* outperforms existing algorithms in 2D and 3D pathfinding tasks within large workspaces, reducing the number of explored nodes and path generation time.

Similarly, Lin et al. [122] introduced an improved A* Algorithm for automated guided vehicles (AGVs). This version of the A* algorithm incorporates weighted Manhattan distance as the heuristic function and a turning penalty mechanism to reduce redundant points and turning points. The results show improved search efficiency and path smoothness[122].

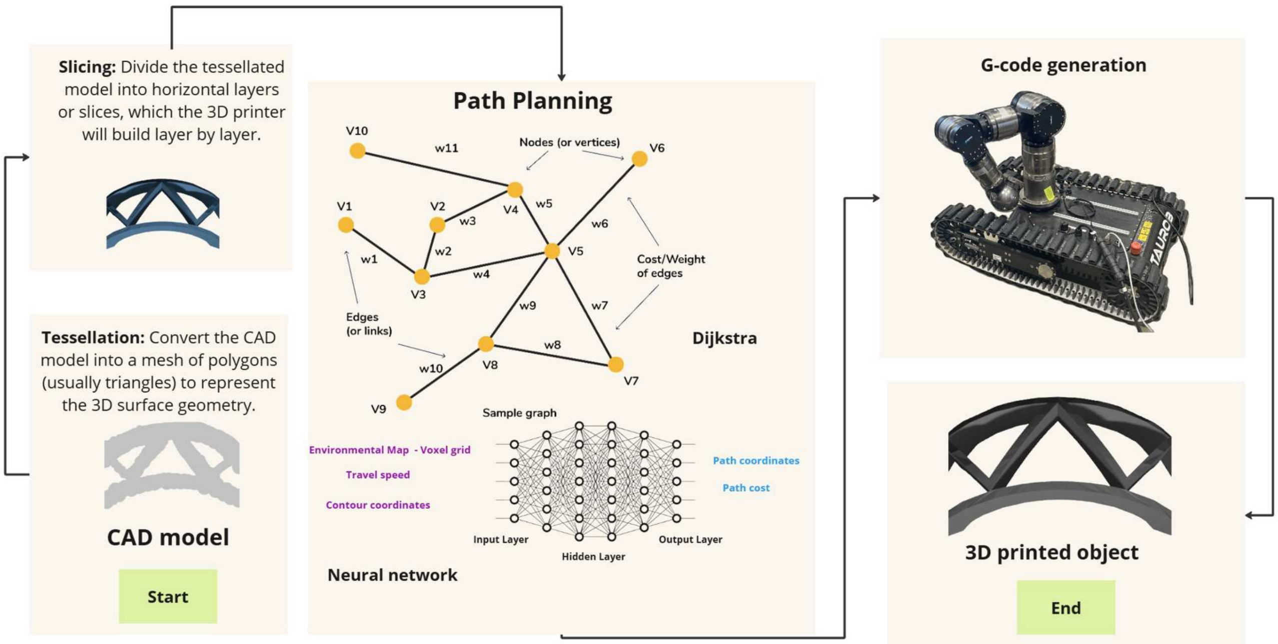

Figure 4. Start by creating or obtaining the CAD model of the object to be printed. Convert this model into a tessellated mesh of triangles, yielding mesh vertices and faces data. Slice the tessellated model into thin layers to produce 2D contour cross-sectional data for each layer. In path planning, use Dijkstra's algorithm to generate optimal paths and extract features, then train a neural network with this data. For prediction, input the tessellated mesh, sliced contours, environmental grid map, start/goal positions, and robot state into the neural network, which predicts an initial feasible path. Refine this path with Dijkstra's algorithm to ensure it is optimal and collision-free, resulting in final path coordinates. Convert these coordinates into G-code for 3D printing. Load the G-code into the printer and execute the layer-by-layer printing process. The final output is the printed object, ready for use or further processing.

In work by Lim et al. [123], optimality was introduced using a weighted colour graph, which captures both geometric and semantic information within the search space. They proposed the class-ordered A (COA*) algorithm, which heuristically constructs an optimal search tree to find the globally optimal path in the weighted colour graph. This algorithm outperforms the traditional A* algorithm in finding uncertain paths.

Addressing the challenges faced by the A* algorithm in real-time path planning and collision-free navigation in large-scale dynamic environments, Zhong et al. [124] simplified the calculation of the distance cost in the risk cost function, extracted key path points, and reduced the number of nodes. They achieved effective path tracking and obstacle avoidance by integrating the adaptive window method. Simulation results indicate that this algorithm meets the real-time requirements of mobile robots in large-scale environments. Li et al. [125] introduce significant improvements to the traditional A* algorithm and integrate it with the Dynamic Window Approach (DWA) for enhanced mobile robot path planning. The improvements to the A* algorithm involve an adaptive adjustment step algorithm, which dynamically changes the step size based on the density of obstacles in the environment. This adaptive step size reduces the number of nodes and improves the efficiency and safety of the search process. Additionally, using cubic Bezier curves smooths the path by minimising sharp turns and large angles, which are common issues in the traditional A* algorithm. This optimisation results in a more efficient path that is easier for the robot to follow and reduces the mechanical strain on the robot's motors.

The integration with the DWA in [125] addresses the shortcomings of the A* algorithm in dynamic environments where obstacles may move. DWA is a local path planning method that evaluates potential trajectories based on the robot's current velocity and acceleration constraints, allowing for real-time obstacle avoidance. By combining the global path planning capabilities of the improved A* algorithm with the local adaptability of DWA, the hybrid algorithm ensures that the robot can navigate complex environments effectively. The results of this hybrid approach are noteworthy. Compared to the traditional A* algorithm, the hybrid method reduces the number of turns by 50% and the path length by 3.62%. It also reduces the average time consumption by 10.27%, decreases the number of path inflection points by 57.14%, and improves accuracy by 33.33%. These improvements demonstrate that the hybrid algorithm is more efficient and more effective in navigating static and dynamic obstacles in complex environments, making it a robust solution for real-time path planning in mobile robots.

Due to the low accuracy of existing terrain-matching methods in areas with small eigenvalues, a study proposed by Li et al. [126] seabed terrain-matching navigation algorithm based on the A* algorithm for use with AGVs. This new method primarily uses terrain information to analyze area-matching performance. The planning algorithm includes a dynamic matching algorithm, cost function, search length and min-length, second-goal point, and dynamic path planning algorithm, all based on the A* algorithm. Terrain-entropy and terrain-variance-entropy are introduced as criteria in the cost function to represent matching performance. Joint criteria, calculated by a back propagation neural network, and fuzzy criteria were also introduced and validated through simulation experiments. Simulations showed this approach could avoid obstacles with less-than-perfect matching and shorten the path length [126].

The traditional A* algorithm also does not account for turning costs and redundant path points, which compromises the safety of AGVs. A turning cost function by Sang et al. [127] addresses this. The cost function was added to avoid detours and frequent turns of the AGVs. Additionally, the number of search points near obstacles was reduced to maintain a safe distance and determine redundancy by checking for obstacles around each path point, thereby optimising the trajectory. Compared to the traditional A* algorithm, this improved approach reduces path length, search time, and the number of nodes, making it more suitable for AGVs in dynamic environments.

Similarly, In response to the A* algorithm excessive node traversal, long search times, unsmooth paths, proximity to obstacles, and applicability only to static maps, a path planning method integrating an adaptive A* algorithm and an improved DWA is proposed by Liao et al. [128]. The adaptive A* algorithm introduces an adaptive weight value to the heuristic function and uses the Douglas-Peucker thinning algorithm to eliminate redundant points [129]. This enhances the path search efficiency and smoothness. The improved DWA algorithm incorporates a trajectory point estimation function into its evaluation function, optimising the path smoothness based on the B-spline curve method. This integrated approach allows for dynamic obstacle avoidance and real-time path optimisation, improving the performance in both simulation and real environments. The simulation results demonstrated that this method can significantly reduce path length, turning angles, and search times while maintaining a safe distance from obstacles. This makes it suitable for use in dynamic environments, enhancing the navigation efficiency of autonomous mobile robots.

5.1.2. Dijkstra algorithm

The Dijkstra algorithm's application across various studies demonstrates its versatility and effectiveness in path planning for AM and other domains. Its primary advantage lies in finding the shortest path in weighted graphs, which is crucial for optimising material deposition paths in 3D printing and ensuring efficient navigation in robotic systems.

A novel path-planning algorithm was developed to address issues of localisation uncertainty in GPS-denied environments. The approach introduced by Wang et al. [130] combines statistical characteristics of localisation error caused by dead-reckoning, generating replanned paths with minimum cumulative error uniformly distributed in the search space. The algorithm significantly reduces cumulative error and enhances safety during collision avoidance, as validated through simulations and real-world scenarios [130].

A methodology for direct pedestrian pathfinding in urban environments using point clouds was proposed by Balado et al. [131]. The Dijkstra algorithm was applied to transform these point clouds into navigable graphs, addressing urban static elements and dynamic obstacles. The study demonstrated the feasibility of generating safe and real routes for pedestrians and wheelchair users in complex urban settings, validating the effectiveness of the generated paths through visual analysis [131]. For automated AGVs under dynamic conditions, an optimal path planning method was developed by Kim et al. [132] using the Dijkstra algorithm to minimise energy consumption and operation time, considering mass and road conditions variations. This method demonstrated significant improvements in AGV efficiency and operational performance in logistic centres, validated through simulation and practical application [132].

An automated planning approach for robotic multi-resolution AM was introduced, using the Dijkstra algorithm to generate smooth material deposition paths, avoiding collisions and ensuring efficient material usage [39]. Bhatt et al. integrated multi-resolution layers, the method improves surface quality without increasing build time, which was validated by building multiple parts and demonstrating the benefits of this approach [39]. In [133], stress-based tool-path planning methodology for fused filament fabrication was presented, using the Dijkstra algorithm to minimise nozzle jump distances and optimise the tool paths based on the maximum principal stress directions. This stress-based path planning significantly enhances the mechanical performance of printed components, validated through stretching tests and analysis using digital image correlation and scanning electron microscopy [133].

The Dijkstra algorithm's application across these studies highlights its versatility and effectiveness in different path-planning scenarios [39,130–133]. Its primary advantage is in finding the shortest path in weighted graphs, which is crucial for optimising material deposition paths in 3D printing and ensuring efficient navigation in robotic systems. However, one notable limitation of the Dijkstra algorithm is its dependence on complete graph information, which can be challenging in highly dynamic or uncertain environments. While it excels in static or relatively stable conditions, its performance can degrade when dealing with real-time changes and dynamic obstacles. Adaptive techniques and real-time updates are essential to enhance their applicability in such scenarios, as demonstrated by integrating heuristic methods and dynamic adjustments.

Path planning for mobile robots in the study by Bai et al. [134] is achieved through a method designed to minimise travel time between two locations in a time-invariant drift field with obstacles. The approach involves a grid-based modelling technique that divides the environment into small square cells, marking those occupied by obstacles as unfeasible. The algorithm calculates the optimal path by considering the influence of environmental currents and obstacles, using Dijkstra's algorithm on a weighted digraph to determine the shortest travel time between any two locations. This provides a travel cost matrix that is used for task assignments. The overall method is evaluated through simulations demonstrating its effectiveness in producing near-optimal solutions compared to traditional genetic and greedy algorithms. The proposed distributed task assignment algorithm further enhances efficiency by enabling local communication among vehicles to assign tasks, guaranteeing that all visiting demands are met within a travel time that is at most twice the optimal when the travel cost matrix is symmetric. This approach proves scalable and efficient in varied operational scenarios, ensuring robust performance in complex environments.

In the study [135], Luo et al. enhanced the traditional Dijkstra algorithm to address path planning on complex surfaces, such as wild terrains, planetary grounds, and game scenes. By employing Delaunay triangulation, the surface environment is modelled and transformed into a 2D plane while maintaining triangle side lengths, allowing the algorithm to identify the shortest paths more accurately. This extended algorithm significantly improves path accuracy and smoothness over traditional methods, particularly in single-robot single-target and multi-robot multi-target tasks. Incorporating this extended Dijkstra algorithm for mobile robots enables more precise and efficient navigation across varied terrains. The robots can use real-time surface modelling and path recalculations to navigate dynamic environments, coordinate multi-robot missions effectively, and ensure safer and more reliable operations. This approach enhances the robots' capability to handle complex navigation challenges, ultimately improving mission efficiency and operational performance.

5.1.3. Other notable algorithms

Inspired by the A* algorithm, the Lambda Algorithm* uses a closed list to store sequential path nodes and an open list for extending nodes [136]. A smoothing process reduces path length and improves efficiency. Lambda* has been shown to decrease time consumption significantly with a slight increase in path length compared to A*. The key benefit is its ability to streamline the pathfinding process while maintaining manageable path lengths. Nevertheless, the slight increase in path length could be a drawback in applications where the shortest possible path is critical.

The Multi-Objective Path-Based D Lite (MOPBD) is designed for multi-objective optimisation problems, balancing multiple objectives such as travel risk and arrival time [137]. MOPBD* uses a path-based expansion strategy to prune dominated solutions, improving search efficiency while approximating the Pareto-optimal front. It runs significantly faster than traditional methods for multi-objective path planning [137]. Its strength lies in handling complex, multi-criteria decision-making processes effectively. However, managing multiple objectives and ensuring an efficient search process might challenge real-time implementations in highly dynamic environments.

5.2. Heuristic search

Genetic algorithms (GAs) are inspired by natural selection and evolution, making them effective for global search and optimisation. They encode potential solutions as chromosomes, which evolve over generations to find the optimal path. This method is particularly useful in static environments with fixed obstacles, as it can explore a vast search space and converge on an optimal solution with relatively low computational power compared to other methods.

In path planning for mobile robots, [138] uses a fixed-length chromosome representation where each gene corresponds to a waypoint or node in the workspace. The fitness function evaluates the path based on criteria such as distance travelled, smoothness, and clearance from obstacles. Operators like crossover and mutation introduce variability, enabling the algorithm to explore different paths and improve over generations. This approach has been shown to produce optimal paths efficiently in simulations, demonstrating its potential for real-world applications in environments. Similarly, the study by Tu and Yang et al. [139] demonstrated that GAs, with their variable-length chromosomes, can effectively navigate both static and dynamic environments by evolving collision-free paths. This approach is robust, requiring no prior knowledge of the environment and capable of optimising paths through natural selection principles. Applying these algorithms in AM could further enhance production efficiency by optimising tool paths, reducing waste, and improving the quality of printed parts.

The study by Sathiya et al. [140] explores using heuristic search algorithms for trajectory planning. It focuses on two techniques: a new variant of heterogeneous multi-objective differential evolution (HMODE) and the elitist non-dominated sorting genetic algorithm (NSGA-II). These algorithms are used to determine optimal trajectories for a wheeled mobile robot with a differential drive, considering various objectives and constraints to avoid obstacles and minimise travel time and actuator effort. They aim to find a set of optimal solutions, known as Pareto fronts, where no single solution is superior in all objectives [141]. In [140], the trajectory of the mobile robot is represented using cubic Non-Uniform Rational B-Splines (NURBS), optimising the control points as decision variables for smooth and flexible path design. NSGA-II retains good solutions across generations using elitism, Pareto dominance sorting, and crowding distance, while HMODE combines different Differential Evolution strategies to balance exploration and exploitation, evaluated using metrics like RNI, SSM, Algorithm Effort, and Optimizer Overhead to ensure quality and efficiency.

Another common mobile robot path planning approach uses a grid-based system where feasible and infeasible paths are identified. This was done by Fetanat et al. [142], where the grid includes numbered locations and obstacles, with the goal of finding optimal locations for the robot to change direction while minimising the objective function from the starting point to the target point. The authors used GA for selection, crossover, and mutation to evolve solutions, emphasising natural evolution principles for optimal pathfinding by exploring the solution space and ensuring diversity and convergence. Pattern Search (PS) iteratively updates points by creating mesh and polling objective function values, while Particle Swarm Optimization (PSO) models social behaviour to balance exploration and exploitation by updating particle positions based on personal and global bests. The effectiveness of these algorithms is also assessed through objective function values, convergence time, and performance in both static and dynamic environments. In [142], the authors compare GA, PS, and PSO, highlighting PSO's accuracy and minimisation capabilities, while PS demonstrates faster convergence times.

Building on the success of GAs, Qu et al. [143] introduced an improved GA for mobile robot path planning that uses a combination of genetic operators and a co-evolutionary mechanism to find optimal paths. The authors use a grid-based system with static obstacles and integer-number encoding for paths representing the robot's environment. The fitness function evaluates paths based on length, safety, and smoothness, considering the sum of path lengths, the shortest distance to obstacles, angles between path segments for feasible paths, and the proportion of path segments crossing obstacles for infeasible paths. Genetic operators include a roulette wheel and elitist selection to ensure high fitness [144], a two-point crossover for gene recombination, mutation to introduce diversity, and a modification operator to refine paths by removing unnecessary nodes and avoiding obstacles. The Co-evolutionary Improved Genetic Algorithm (CIGA) employs a co-evolution mechanism for multiple robots, uses a cross-function to prevent path collisions, and facilitates periodic information exchange between subpopulations to propagate optimal solutions, showing superior performance in various environments and faster convergence compared to conventional GA and Ant Colony Optimization (ACO).

Additionally, hybrid approaches combining PSO and Grey Wolf Optimization (GWO) algorithms have been proposed [145]. Where the environment is modelled as a 2D map with static, rectangular obstacles and a circular robot with a safety circle for collision detection. The fitness function evaluates paths based on length and smoothness, aiming for the shortest path and minimal angle differences between successive waypoints. The hybrid PSO-GWO approach leverages PSO's fine-tuning and GWO's exploration capabilities, enhanced by evolutionary programming with mutation operators to refine path vertices and ensure obstacle avoidance. The algorithm operates through initial path generation stages, local feasibility search, and dynamic collision avoidance. Simulations demonstrate that this method outperforms conventional techniques like direct artificial bee colony (DABC) [146], hybrid cuckoo search-Bat algorithm (CS-BA) [147], hybrid genetic algorithm with particle swarm optimisation (GA-PSO) [148], multiobjective whale optimisation algorithm (MWOA) [149] and PSO [150] algorithms regarding path feasibility, length, and computational efficiency. The study by Gul et al. validates the approach in various environments, showing its effectiveness in producing optimal paths [145].

5.3. Sampling method

The sampling-based approach is a very popular method for path planning. This method randomly maps the environment to find the optimal path between two points. This requires a mathematical representation of the workspace, where the sampling usually consists of nodes or cells. The algorithm checks if a new point is in free space in each step. If it is, it connects this point to other nearby samples, building a graphical representation of the free space. The sampling-based approach can be broadly categorised into two methods, Active and Passive, which can be seen in Table 4.

Passive methods, such as Probabilistic Road Maps (PRM) and Voronoi Diagrams, involve creating a comprehensive map of the environment first and then finding the optimal path through this pre-constructed network. These methods are advantageous because they are efficient for multi-query problems, can handle high-dimensional spaces, and are suitable for large, open areas. However, they require preprocessing, can be inefficient for single-query problems, and may not be effective in narrow passages. Voronoi Diagrams, in particular, provide clear space partitioning and can handle complex environments, though they are computationally intensive and may not handle dynamic changes well.

Active methods, including Rapidly Exploring Random Trees (RRT) and Artificial Potential Fields, focus on optimising the path in real-time or iteratively. These methods efficiently explore large spaces and can handle complex environments with less preprocessing. RRTs are particularly noted for their ability to produce paths quickly, though these paths may be suboptimal and require smoothing. Artificial Potential Fields are simple and intuitive to implement, with fast computation and smooth path generation, but they can get stuck in local minima and may struggle with complex environments. Additionally, mathematical methods offer exact solutions and can be highly optimised for specific tasks, making them effective in structured environments. However, they are computationally expensive, may not be adaptable to dynamic changes, and require detailed environmental knowledge. A key characteristic of these methods is that they are not complete, meaning they might not find a path even if one exists. The 'Narrow Passageway' problem exemplifies this [164], where a narrow corridor connects two areas, and insufficient sampling can fail to find nodes in the corridor, leading to no solution. Techniques exist to mitigate this issue, such as increased sampling density, but they often compromise the primary advantage of sampling methods–computational efficiency in high-dimensional environments. Additionally, sampling methods can produce jagged paths, requiring path smoothing to achieve smoother, more natural movement.

5.3.1. Passive methods

Voronoi diagram: Voronoi diagrams are a common approach in tool path planning first introduced by

Table 4. Comparison of sampling methods for path planning in robotic additive manufacturing.

Passive Methods			
Method	References	Advantages	Disadvantages
Voronoi Diagram	[148,151,152]	▷ Provides clear partitioning of space ▷ Can handle complex environments ▷ Efficiently generates non-overlapping regions	▷ Computationally intensive ▷ May not handle dynamic changes well ▷ Can be complex to implement
Probabilistic Road Map (PRM)	[153–155]	▷ Efficient for multi-query problems ▷ Can handle high-dimensional spaces ▷ Suitable for large, open areas	▷ Requires preprocessing ▷ Can be inefficient for single-query problems ▷ May not be effective in narrow passages
Active Methods			
Method	References	Advantages	Disadvantages
Rapidly Exploring Random Tree (RRT)	[156–158]	▷ Efficiently explores large spaces ▷ Can handle complex environments ▷ Requires less preprocessing	▷ Can produce suboptimal paths ▷ Paths may be jerky and need smoothing ▷ May struggle with narrow passages
Artificial Potential Field	[159,160]	▷ Simple and intuitive to implement e ▷ Fast computation ▷ Smooth path generation	▷ Can get stuck in local minima ▷ May have difficulty with complex environments ▷ Not suitable for all obstacle types
Mathematical Methods	[161–163]	▷ Provides exact solutions ▷ Can be highly optimised for specific tasks ▷ Effective in structured environments	▷ Computationally expensive ▷ May not be adaptable to dynamic changes ▷ Requires detailed environmental knowledge

Bhattacharya et al. [151]. It creates a topological connection that divides space into regions based on the location of the obstacles. The diagram ensures equal distances between edges and the nearest objects. A starting point is chosen to construct the diagram where its minimum distance to the surrounding obstacles is the same. The remaining regions are then calculated based on the environment's obstacles, fragmenting the workspace until all areas are accounted for.

Voronoi diagrams are crucial in path-planning algorithms for mobile robots, especially in complex and dynamic environments. The paper by Ayawli et al. [152] presents a novel method combining the Voronoi Diagram (VD) and Computational Geometry Technique (CGT), termed VD-CGT. This method starts by categorising moving obstacles to ascertain their collision threat levels and possible replanning decisions. Initially, the path is computed using VD and other algorithms like A-star and cubic spline. CGT is then used to compute a small region around detected obstacles, within which the roadmap is recalculated using VD. This method improves path replanning performance by reducing unnecessary computations, thereby optimising both time and path cost [152].

Similarly, Huang et al. [148] proposed a navigation strategy with path priority (NSPP) for multi-robot systems, using a Generalized Voronoi Diagram (GVD) to divide the map based on each robot's path priority. The NSPP allows for efficient, collision-free path planning by prioritising the paths of more critical robots and adjusting the paths of others accordingly. The performance of NSPP, when compared to methods like the Shortest Distance Algorithm (SDA) and Reciprocal Orientation Algorithm (ROA), shows better average trajectory lengths and efficient navigation [148]. In a separate study, Chi et al. [165] the use of Voronoi diagrams was expanded to address the 'trap space problem' in complex environments like mazes. A GVD was employed to guide the sampling process of RRTs, ensuring connectivity in free space. By extracting features from the GVD and using a feature matrix to reduce redundancy in the roadmap, this method improves real-time motion planning efficiency by providing a heuristic path that optimises the sampling process of RRTs [165].

A new method called the Morphological Dilation Voronoi Diagram Roadmap (MVDRM) algorithm was introduced to tackle unsafe path computation and high computational complexity. This approach introduced by Ayawli et al. inflates obstacles before path computation to ensure safety. It strategically distributes sample nodes to reduce time and space complexity, resulting in faster path computation. Compared to traditional VD and PRM methods, MVDRM is superior in terms of safety, computation time, and success rate [166].

The study by Turanli and Temeltas et al. [167] introduces a novel approach for coordinating mobile agents using Guaranteed Power Voronoi Diagrams (GPVD), which account for imprecision in localisation and allow regions assigned to each agent to be adjusted based on predefined weights, similar to Power Voronoi Diagrams. The key innovation is an adaptive coordination algorithm based on GPVDs, incorporating adaptive coverage control. This method ensures that regions adapt dynamically to positioning uncertainties, making it useful in environments where precise localisation is challenging. The Lyapunov-type stability proof of the algorithm ensures system stability, and simulations demonstrate the algorithm's efficiency in adjusting region areas according to localisation uncertainties and weight parameters. This results in effective coordinated motion, making the proposed method promising for applications requiring adaptive coverage control in the presence of localisation uncertainties. This approach could be particularly beneficial in AM processes by improving the coordination and coverage of multiple robotic agents responsible for material deposition and quality inspection tasks, ensuring efficient and precise operations despite positional uncertainties [167].

Overall, Voronoi diagrams offer significant advantages in path planning, such as efficient roadmap construction, obstacle avoidance, and optimal pathfinding. These algorithms are instrumental in dynamic and complex environments where safety and computational efficiency are critical.

Probabilistic Road Map (PRM): PRM is a passive sampling-based algorithm that efficiently explores large workspaces with lower computational costs than other methods. It randomly selects locations in the C-space, checking if they are in free space or occupied by obstacles. If in free space, the node is connected to its nearest neighbours, creating a continuous, obstacle-free path between them. This process repeats, constructing a network within the C-space, which can then be analysed by other network-based methods to find an optimal path between start and end points. The ability of PRM algorithms to efficiently explore 3D spaces with low computational costs makes them particularly valuable in path planning for AM processes. In these complex environments, PRM can be used to generate collision-free paths for the print head or robotic arm, optimising the printing process. Additionally, the reusability of the generated network is beneficial in multi-tool or multi-material printing scenarios, where multiple paths need to be planned simultaneously. Moreover, PRM's ability to handle high-dimensional C-space makes it suitable for planning complex toolpaths involving multiple DOF, such as in 5-axis machining or intricate 3D printing patterns. This flexibility and efficiency contribute to PRM's growing popularity in path planning research for multi-UAV systems and other robotic applications.

Recent advancements in PRM methods have significantly improved path planning for mobile robots, making these methods highly applicable in complex and dynamic environments, including AM processes. Santiago et al. [153] explored the integration of genetic algorithms with PRM to enhance navigation. Their study demonstrated that while genetic algorithms provide smoother paths, PRM generates collision-free paths in real-time applications more efficiently, highlighting the importance of selecting appropriate algorithms for specific scenarios [153].

A Hybrid Potential-based Probabilistic Roadmap (HPPRM) was developed, merging PRM with the Artificial Potential Field (APF) method. This hybrid approach was introduced by Ravankar et al. [168], improving sampling distribution to address the narrow passage problem, resulting in improved goal planning, higher success rates, and reduced computation costs. It is particularly effective in environments with static and dynamic obstacles, making it well-suited for real-time applications [168].

To enhance connectivity in narrow passages, Liu et al. [154] proposed an improved PRM algorithm that incorporates a branching random walk technique, was proposed. This method reduces collision detection time and increases efficiency, enabling reliable path planning in challenging environments with difficult narrow passages [154]. PRM was further optimised for complex environments with multiple narrow channels by combining it with APF. This approach increases sampling density in narrow spaces, improving the success rate of collision-free path planning. A bidirectional A* algorithm optimises the query process, ensuring efficient pathfinding and reduced computational time [169]. An improved PRM method for manipulators was presented by Chen et al. [155] that incorporates a virtual force field to enhance sampling strategies. This method increases sampling density in narrow passages while reducing redundancy in open spaces, ensuring high connectivity in the roadmap. The effectiveness of this approach in cluttered environments demonstrates its applicability to high-dimensional manipulators [155].

Finally, PRM was combined with spline techniques to generate smooth trajectories for wheeled mobile robots. This integration ensures that the generated paths are dynamically and geometrically feasible, satisfying direction constraints and making the method suitable for real-time trajectory planning [170]. This approach can be adapted to benefit AM processes by applying similar principles. In 3D printing, for example, smooth trajectories can optimise print head movement, reducing printing time and improving surface quality. For complex multi-axis 3D printing, the combination can ensure smooth transitions between axes and prevent collisions. Directed Energy Deposition (DED) can optimise material deposition paths, enhancing product quality. Additionally, this approach can be applied to post-processing operations like CNC machining, and it enables real-time path adjustments for adaptive manufacturing, ensuring safe and efficient operation while meeting geometric and dynamic constraints.

5.3.2. Active methods

Rapidly exploring Random Tree (RRT): The RRT method strategically samples the environment with the initial and goal locations in mind, making it adept at handling problems with multiple DOF. This feature benefits mobile robots and robotic arms, allowing for efficient navigation and task execution in complex spaces. In the context of AM processes, RRT can be used to optimise the coordination and movement of mobile robots responsible for tasks such as material deposition, inspection, and maintenance. The RRT constructs a tree-like graph in a C-space divided into free and obstacle spaces. Both the start and destination nodes are placed in the free space. Then, a random node within the free space is introduced and connected to the start node. The algorithm checks if the end node is reachable from this new node. If not, another random node is connected to the end node, and the algorithm checks if this node can reach the branch from the start node. This process continues, with the branches from the start and end nodes growing outward in each iteration. This approach efficiently explores the free space as the tree grows and simultaneously explores the C-space from both ends. In each iteration, the system attempts to extend one of the branches by generating a random sample. If successful, the next step tries to connect the two branches. If a connection is made, a path is established between the start and end nodes; otherwise, the process repeats with the other branch.

Hence, to enhance path planning efficiency, the basic RRT structure was extended to a graph-based approach called Rapidly-exploring Random Graphs (RRG) introduced by Kala et al. [156]. This method allows for simultaneous exploration from multiple points, resulting in a well-connected graph that outperforms traditional RRT and PRM, particularly in multi-robot scenarios, due to its extensive exploration capabilities and improved computational efficiency. RRG is highly suitable for environments requiring complex navigation and coordination, such as AM setups with multiple robots [156]. Similarly, the RRT algorithm was modified by Zhang et al., incorporating a target bias search strategy and a new metric function considering both distance and angle [157]. Neural networks were also employed for curve post-processing to achieve smoother paths. These modifications improved real-time performance and the generation of shorter, smoother paths, making this approach effective for complex path-planning tasks. In AM, such improvements can lead to more efficient and precise navigation for mobile robots, reducing errors during critical operations [157].

A predictive path planning algorithm for dynamic environments was developed based on RRT [158]. By pre-searching the global approximate optimal path and incorporating movement predictions for both the robot and dynamic obstacles, the predictive RRT (P-RRT) algorithm enhances search speed, reduces path cost, and lowers collision probability was proposed by Zhang et al. This makes P-RRT effective in dynamic settings where traditional RRT methods struggle, such as AM environments where robots must adapt to changes caused by other robots or machinery [158].

An autonomous exploration system was proposed for unknown indoor environments that combine RRT with frontier 2D-SLAM techniques by Wu and Lin et al. [171]. This system uses RRT to identify frontier points and guides the robot to unexplored areas, optimising map construction. Integrating frontier-based exploration strategies addresses RRT's limitations in obstacle-rich environments, ensuring efficient and autonomous map generation, particularly useful in large-scale AM environments [171]. Recently, Sustarevas et al. [172] researched to achieve fully autonomous 3D printing to improve the sustainability of the manufacturing process. They developed the Task Consistent Path Planning (TCPP) algorithm, which employs an RRT* algorithm to search for paths. This was validated by the inverse reachability map, which completes the whole-body Model Predictive Controller. The TCPP algorithm enables the mobile robot to continuously deposit material on long trajectories, significantly different from previously applied path planning methods.

An extended RRT-based dynamic path planning and replanning method was presented by Connell et al. [173]for mobile robots. This approach allows for real-time path modification in response to moving obstacles, leveraging the Rewire function of RRT* for efficient replanning. The shared node information in multi-robot scenarios further enhances path planning efficiency. For AM, this method enables robots to dynamically adapt their paths in response to unexpected changes, such as new tasks or obstacles [173]. Further building on RRT, the study by Zhenghao Zhang et al. [158] introduces a novel P-RRT algorithm that enhances the standard RRT by incorporating predictions about the movements of both the robot and dynamic obstacles to improve path planning in dynamic environments. Initially, the P-RRT algorithm performs a global pre-search using RRT* to find an approximate optimal path in the static part of the environment, which serves as a baseline for subsequent re-planning. By using the velocities of the robot and dynamic obstacles, the algorithm predicts future positions and adjusts the path accordingly. When potential collisions are detected, the path is split and reconnected using a bidirectional search while considering static and dynamic obstacles. The algorithm calculates the collision probability for each node based on distance and direction, discarding nodes with high collision probabilities to ensure safer path planning. Simulations and real-world experiments demonstrated that the P-RRT algorithm produced more stable and efficient paths, reducing collision probabilities and path lengths, thereby confirming its practical applicability for mobile robots in dynamic environments. Similarly, the RRT algorithm was improved by Wang et al. introducing target bias sampling, adaptive step size, and cubic B-spline curve smoothing [174]. These enhancements by Wang et al. reduce search time, path length, and node redundancy, making the algorithm highly effective for path planning in narrow and complex environments. These improvements, demonstrated in both simulations and physical tests with an insect-like mobile robot, result in significant gains in efficiency and path quality, which are valuable for precise and uninterrupted operations in AM settings with tight spaces and complex layouts [174].

In the context of AM, these advancements in RRT methods can significantly enhance the coordination and movement of mobile robots involved in tasks such as material deposition, inspection, and maintenance. Robots can navigate complex manufacturing environments more efficiently by leveraging improved sampling strategies and real-time replanning capabilities, ensuring precise and collision-free operations.

Artificial Potential Field (APF): The APF is a significant area of interest within mobile robot navigation for applications such as real-time obstacle avoidance, as presented by khatib et al. [175] in 1986. The study by Patle et al. [159] showed the logic behind APF algorithms involves treating the robot as a node attracted by goals and repelled by obstacles, creating attractive and repulsive forces in a potential field. The APF algorithm facilitates smooth and continuous navigation, particularly in static environments, where predictions are more reliable than in dynamic environments, where objects are in motion. Integrating dynamic potential functions and velocity planning criteria can enhance the functionality of APF algorithms in dynamic environments. This integration allows robots to adapt their paths more efficiently to respond to sudden environmental changes, which is crucial for real-time applications. The APF algorithm may cause robots to get stuck in local minimums when navigating a complex series of obstacles, potentially stopping the robot from reaching its goal. Robots can avoid becoming trapped in local minimums by utilising harmonic functions and integrating potential functions during the initialisation of APF algorithms. When considering potential solutions for improving the performance of mobile robots while navigating using APF algorithms, it is essential to note that they may still encounter challenges, particularly when the goals are located close to obstacles. Recent research indicates that combining APF algorithms with genetic and swarm optimisation algorithms can reduce oscillations and improve robot navigation.

However, APF is not without its issues, as noted by Qin et al. [160]. Specifically, APF algorithms can lead to inaccurate path planning because they do not account for the mechanical properties of robots, such as inertia and maximum turning angles. Further adjustments may be considered to enhance robots' local and global controllability in dynamic and static environments for obstacle avoidance. One potential approach involves using a bacterial potential field, which integrates APF and bacterial evolutionary algorithms. Results indicate an improvement in the functionality of the APF algorithm by integrating RL to adjust the potential field parameters dynamically.

Furthermore, APF can be combined with the chaotic bat algorithm to accelerate convergence and prevent being stuck in local optima while navigating complex environments. The vectorial APF method is another variation of the APF method that could improve dynamic obstacle avoidance in three-dimensional spaces by calculating the combined forces' direction. The APF algorithms are known for their simplicity of implementation, as they do not necessitate extensive computational resources or detailed map information, rendering them suitable for real-time applications. The obstacle avoidance in the APF algorithm can be enhanced by incorporating virtual obstacles, which can help decrease the risk of colliding with real obstacles [176].

The integration of evolutionary algorithms with traditional path-planning methods has shown promising results in enhancing robot navigation capabilities. A notable advancement in this area is the membrane evolutionary artificial potential field (memEAPF) model, which combines the APF with GA [177,178]. This hybrid approach addresses some of the limitations of traditional APF methods while leveraging the strengths of evolutionary computation. The memEAPF model offers several key advantages for robot navigation in dynamic environments. Incorporating evolutionary algorithms significantly reduces the likelihood of getting trapped in local optima, a common issue with standard APF implementations [179].

Additionally, the model utilises parallel processing techniques, which can greatly improve computational efficiency, allowing for faster path planning and obstacle avoidance. Orozco-Rosas et al. introduced this innovative hybrid approach, demonstrating its potential to enhance robot navigation capabilities [180]. Their work showcases how the memEAPF model can effectively combine the reactive nature of APF with the global optimisation capabilities of genetic algorithms. However, it's important to note that the memEAPF model's advanced features come with increased complexity. The integration of evolutionary algorithms and parallel processing requires substantial computational resources. This dependency on advanced hardware may limit the model's applicability in constrained computational resources, potentially impacting the navigation process under such conditions.

Integrating RL with traditional path-planning methods has led to innovative approaches in mobile robot navigation. One such advancement is the black-hole potential field (BHPF) model, which combines the APF algorithm with RL techniques. This hybrid approach aims to enhance robot navigation in dynamic environments by introducing predefined attractive forces called 'black holes' within the potential field. Yao et al. [181] introduced this innovative BHPF approach, demonstrating its potential to enhance mobile robot navigation capabilities in dynamic environments. Their work highlights the synergistic benefits of combining APF with RL, offering a promising direction for future research in robot path planning and obstacle avoidance. The BHPF model leverages RL-trained agents to navigate complex environments, avoiding local minima – a common issue in traditional APF methods – and steadily progressing towards the goal. Its trial-and-error learning approach allows the agent to continuously refine its navigation strategies, adapting to environmental complexities over time. However, the effectiveness of the BHPF model heavily depends on careful calibration of the black hole domains. Striking the right balance is crucial: overly large domains may lead to overlapping gravitational fields, potentially confusing the robot, while excessively small domains might not provide sufficient guidance.

5.4. Mathematical method

Mathematical methods for trajectory planning are defined by their use of kinematic and dynamic constraints to model the system and its environment. These constraints, expressed as equations or inequalities within a cost function, are minimised to determine an optimal trajectory. This focus on dynamic constraints and cost optimisation is why these methods are specifically referred to as trajectory planning algorithms. However, the mathematical models underpinning these methods can be complex, leading to high computational costs. Strategies such as discrete decision processes or the division and combination of algorithms can mitigate this, tackling the overall path-planning problem in a more manageable way.

Optimal Control (OC), a mathematical model for trajectory planning, extends linear methods by employing an infinite number of variables to determine the optimal state and path from a set of differential equations. Solutions are often derived using the Hamiltonian and the maximum principle, ultimately generating a globally optimal path [182]. While not confined to a single algorithm, OC offers a framework for various procedures to achieve autonomous navigation in MRS.

Model Predictive Control (MPC), a prominent OC technique, predicts future system behaviour to identify optimal control actions. Spurny et al. [161] formulated an MPC algorithm for planning leader trajectories and controlling follower robots, successfully generating collision-free paths amidst static and dynamic obstacles while maintaining formation. The study by Luis et al. [162] introduces a Distributed Model Predictive Control (DMPC) algorithm for real-time trajectory generation in MRS, using on-demand collision avoidance to compute non-colliding trajectories efficiently. The algorithm incorporates an event-triggered replanning strategy to manage disturbances, significantly reducing travel time and improving success rates in dense multi-agent environments compared to the Buffered Voronoi Cells (BVC) approach. Simulation results demonstrated over 90% success with up to 30 quadrotor agents in an 18 m^3 arena, and experimental validation was conducted with a swarm of 20 drones, showcasing the algorithm's practical applicability and efficiency in dynamic and dense settings. Another study [163] by Hang et al. introduces another alternative to traditional MPC. It integrated a path-planning algorithm for unmanned ground vehicles (UGVs) that addresses both collision avoidance and lateral stability in high-speed conditions. The algorithm combines the visibility graph method for global path planning to navigate static obstacles and nonlinear model predictive control (NMPC) for local path optimisation, considering lateral stability and constraints such as minimum turning radius and safe distance. Additionally, multivariate Gaussian distribution (MGD) and polynomial fitting are used to predict the trajectories of moving obstacles, enabling the UGV to adjust its path in real time to avoid collisions. The comprehensive algorithm was tested through four simulation scenarios that validated its effectiveness in avoiding static and dynamic obstacles while ensuring the vehicle's lateral stability. Results demonstrated that the proposed method outperforms traditional algorithms like GAs regarding path quality and control, proving its capability in high-speed and complex environments.

The study by Wang et al. [183] introduces a robust MPC strategy for precise trajectory tracking of four-Mecanum-wheeled omnidirectional mobile robots (FM-OMRs). By developing a kinematics model with constraints, formulating a trajectory tracking error model, and employing a delayed neural network for efficient real-time quadratic programming (QP) solving, the research ensures the robot's adherence to predetermined paths despite disturbances and constraints. This approach is validated through simulations demonstrating effective trajectory tracking and robustness. Combining this robust MPC strategy with path planning in AM can significantly enhance the precision and reliability of robotic arms or mobile platforms that move printing heads or materials. For example, FM-OMRs equipped with this control strategy can navigate and position accurately within a 3D printing workspace, following complex paths generated by path planning algorithms to construct large structures layer by layer. In a similar study, Azizi et al. [184] a novel approach to path planning and control using NMPC. This research also focussed on FM-OMRs, emphasising their manoeuvrability in dynamic settings. The authors employ Kane's method to derive the robot's differential equations of motion and convert them to a discrete state-space form suitable for NMPC. The core innovation lies in integrating the Velocity Obstacles (VO) approach within the NMPC framework, allowing the robot to dynamically avoid both stationary and moving obstacles while adhering to physical constraints. The study determines optimal parameters for the control system by conducting stability and performance analyses, ensuring the robot's stabilisation and collision-free navigation even in complex environments. Extensive simulations validate the proposed NMPC-based controller's effectiveness, demonstrating its capability to maintain the robot's desired configuration and safely navigate through densely populated areas. This integration of VO with

NMPC showcases significant advancements in ensuring robust path planning and control in real-time, dynamic scenarios. In another study, Zuo et al. [185] proposes a Progressive Model Predictive Control Scheme (PMPCS) integrating local planning and path tracking for intelligent vehicles. This scheme employs an improved Particle Swarm Optimization (IPSO) based MPC to efficiently address path planning and trajectory tracking problems. The PMPCS reduces computational burden through seamless connection and mutual promotion between planning and tracking optimisations. The planning module incorporates an APF to ensure collision-free paths by treating dynamic safety constraints as repulsive forces and considering traffic lights through a pseudo-velocity planning method. The control module applies IPSO to solve nonlinear MPC issues, optimising the path while considering obstacles and traffic conditions. Simulation results verify the effectiveness of PMPCS, demonstrating reduced collision probabilities, improved path stability, and enhanced computational efficiency compared to traditional hierarchical algorithms.

For more information on MPC, The paper by Nascimento et al. [186] provides a comprehensive review of MPC applications in the trajectory tracking of nonholonomic mobile robots. The authors highlight the significant advantages of MPC in handling the complex dynamics and uncertainties associated with nonholonomic systems compared to classical control methods. Moreover, the paper categorises the types of mobile robots and their locomotion mechanisms, addressing indoor and outdoor scenarios, and underscores the critical issues of control stability, sensor noise, and computational constraints.

Another notable technique is Covariant Hamiltonian Optimization for Motion Planning (CHOMP), which enhances path quality by optimising a functional objective focussed on smoothing and obstacle avoidance. Rooted in advanced geometric principles, CHOMP has proven to be a powerful tool for path planning [187]. You et al. [188] presented an advanced path-planning method for wheeled mobile robots (WMRs) that combines an energy-based cost map with an improved dual CHOMP method. This approach addresses the challenges of navigating complex and uncertain terrains by creating an energy-efficient path while ensuring probabilistic completeness through a robust active set algorithm and a randomised variant based on simulated annealing and Hamiltonian Monte Carlo methods. The simulation results demonstrate that the proposed method generates time-efficient, energy-efficient, and smooth paths, making it suitable for high-dimensional path planning tasks with non-convex cost functions. An alternative approach combines sampling-based techniques and model-based optimisation via quadratic programming for efficient and feasible online trajectory planning in known environments. The paper by Leobardo et al. [189] proposed a method that generates an obstacle-free path using a sampling-based planner and then formulates a convex optimisation problem over this path to account for the robot's dynamic constraints. This approach avoids the need for iterative solutions, ensuring feasibility and improving computation time and success rate compared to state-of-the-art methods. The method's effectiveness is demonstrated through simulations and real-world experiments with a quadcopter navigating in highly cluttered environments, showcasing significant improvements in performance metrics.

In AM, particularly in complex and dynamic environments, the precision and efficiency of path planning are crucial. Integrating this hybrid method for online trajectory planning can significantly enhance the performance of robotic systems used in AM. The sampling-based path planning can ensure collision-free paths in the cluttered workspace of a manufacturing setup, while the model-based optimisation ensures that the dynamic constraints of the robotic arms or mobile platforms are respected. This approach can lead to more efficient toolpath generation, minimising the risk of collisions, reducing energy consumption, and improving the overall speed and quality of the manufacturing process. The ability to quickly re-plan trajectories in response to changes in the environment or manufacturing requirements can further enhance the adaptability and reliability of AM systems.

5.5. Collision avoidance

Key contributions and approaches for collision and obstacle avoidance in path planning for mobile robots encompass a range of innovative methods designed to enhance navigation safety and efficiency. These include the Beam Curve Method (BCM), which integrates the beam and curve velocity methods to optimise paths in dynamic environments. The Linear-Quadratic Gaussian (LQG)-Obstacles method combines Kalman filtering and Linear Quadratic Regulator (LQR) feedback control to navigate through uncertain environments smoothly. The continuous-control-obstacles (CCO) approach ensures collision avoidance by using a high-order sliding mode differentiator. Fuzzy logic controllers (FLC) effectively handle complex dynamic environments using sensor data. Visibility graph methods combined with Nonlinear Model Predictive Control (NMPC) optimise paths while considering dynamic obstacles and constraints. Additionally, methods like Maximum-

Speed Aware Velocity Obstacle (MVO) and Roaming Trails integrate real-world constraints and combine offline planning with real-time adaptations.

The BCM introduces Fernandez et al. and enhances local obstacle avoidance for mobile robots in cluttered and partially known environments [190]. This method integrates the Beam Method (BM) and the Curvature Velocity Method (CVM). The BM calculates the optimal one-step heading to identify a collision-free direction, while the CVM uses this heading to determine the optimal linear and angular velocities. This integration allows the BCM to provide better path optimisation in dynamic and populated environments, significantly improving over the CVM and the Lane-Curvature Method (LCM). This method is particularly effective in guiding robots through populated areas by providing robust, collision-free paths [190].

Addressing the challenge of collision avoidance for robots with limited sensing and information about obstacles, Phan et al. proposed a runtime approach based on the Simplex architecture that ensures collision-free navigation by using constraints on sensor readings to maintain three safety properties: static safety, passive safety, and passive-friendly safety [191]. The geometric-based switching condition ensures real-time adherence to these safety constraints, providing runtime assurance for collision-free navigation despite limited sensing capabilities. This method suits environments where detailed environmental data is unavailable [191]. Another robust collision-avoidance method for mobile robots dealing with uncertain dynamics and moving obstacles is proposed based on CCO by Ricardo et al. [192]. This method used an overdamped low-pass filter and a high-order sliding mode differentiator to generate smooth position commands and estimate obstacles' maximum accelerations. This ensures collision avoidance while respecting velocity constraints and effectively guides robots to their desired positions without collisions in dynamic environments [192].

A motion saliency-based collision avoidance method for dynamic environments identifies and prioritises dynamic objects posing the most danger. Guo et al. [193] used a B-spline curve to predict their movement, and combining this with NMPC for avoidance, this approach reduces computational complexity and generates smoother, more efficient obstacle-free paths. Experimental validation shows clear advantages over conventional methods regarding computational cost and trajectory optimisation [193]. A similar approach was proposed by Guo et al. [194], which introduced a dynamic obstacle avoidance method using dynamic risk region constructs a dynamic risk region using extended Kalman filter state estimation, integrating it with NMPC. This method allows robots to manoeuvre in advance, producing smoother and more efficient avoidance trajectories. Experimental validation shows its effectiveness in various scenarios, highlighting significant advantages in computational efficiency and trajectory control compared to traditional methods. This dynamic risk region approach enhances the robot's ability to handle dynamic obstacles and adjust its path proactively [194]. Enhancing the collision avoidance capabilities of mobile robots in dynamic indoor environments, an FLC is designed by Oleiwi et al. to handle complex environments with multiple known and unknown dynamic obstacles using onboard sensor information. This approach successfully navigates mobile robots in structured 2D environments, overcoming the limitations of prior controllers and showing potential for real-world indoor applications. Its adaptability and effectiveness make it suitable for dynamic indoor environments [195].

Optimal trajectory generation for robots is achieved using an ACO algorithm introduced by Beschi et al. [196]. This method addresses motion planning problems by exploiting kinematic redundancy to optimise execution trajectories while respecting robot kinematics and dynamics constraints. Validated in real-world scenarios such as machining and AM, this approach demonstrates faster convergence and better repeatability than other solvers, making it effective for optimising robotic tasks in complex industrial environments [196]. Another study by Ntakolia et al. [197] presents a novel two-level hierarchical architecture for path planning that combines global and local strategies. This approach addresses the need for autonomous navigation in dynamic environments, particularly for assistive systems for individuals with disabilities. The global path planning also employs a Chaotic Ant Colony Optimization with a Fuzzy Logic (CACOF) algorithm to construct the initial path, integrating chaotic maps for probabilistic updates and fuzzy logic for evaluating multi-objective criteria such as distance, number of obstacles and smoothness of turns. For local path planning, lightweight deep convolutional neural networks, specifically YOLOv5, alllow for real-time obstacle detection. The local navigation is further refined using a Fuzzy Bug-like algorithm, which dynamically adjusts the route to avoid static obstacles. Ntakolia et al. used extensive simulations based on real-world topologies to demonstrate the system's computational efficiency and effectiveness, making it suitable for real-time applications. This integrated approach can significantly enhance the operational safety and efficiency of robots in AM and construction sites, ensuring seamless human-robot collaboration. The framework's ability to dynamically adapt to changing environments and avoid collisions in real-time highlights its potential for practical deployment in these challenging and variable workspaces.

The MVO algorithm, introduced by Xu et al. [198], is designed to avoid high-speed obstacles by extending the velocity obstacle region to predict collisions beyond the immediate time horizon, incorporating constraints like limited sensing field of view and kinematic limitations. Simulations and experiments demonstrate its efficacy in dynamic scenarios, ensuring feasible solutions for both current and future control steps to enhance navigation safety and efficiency. The Roaming Trails approach, proposed by Sgorbissa et al. [199], integrates a priori knowledge with local perceptions, combining offline path planning with real-time obstacle avoidance. It defines areas for path deviation to prevent deadlocks, balancing global planning with real-time reactive behaviours. Tested extensively in real-world experiments, it enhances the robustness and reliability of mobile robot navigation. The LQG-Obstacles method, developed by van den Berg et al. [200], combines LQG feedback control with collision avoidance by integrating Kalman filtering for state estimation and a LQR for feedback control. It defines control objectives to avoid collisions with high probability, allowing for smooth and safe navigation in complex, uncertain environments, particularly effective for robots like quadrotor helicopters.

For more information on obstacle avoidance, wang et al. [201] comprehensive review of local obstacle avoidance explores methods for wheeled mobile robots in unknown environments and covers various methods, including APF-based, meta-heuristic-based, neural network-based, fuzzy logic-based, and quadratic optimisation-based approaches. Highlighting the advantages and disadvantages of each method, the review emphasises the potential of fusing multiple methods for improved adaptability [201].

5.5.1. Applications in additive manufacturing

These advanced collision and obstacle avoidance methods can significantly improve AM processes involving mobile robots by enabling precise and efficient navigation through complex factory layouts. Techniques like the BCM (Fernandez et al., [190]) and B-spline combined with NMPC (Guo et al., [193]) help robots avoid collisions with machinery and human workers, reducing downtime and increasing overall productivity. Runtime approaches based on Simplex architecture ensure that robots can navigate safely even with limited environmental information, making them adaptable to dynamic manufacturing environments (Phan et al., [191]). Additionally, robust methods like those based on Continuous-Control-Obstacles (CCO) and dynamic risk regions ensure that robots can handle varying obstacle velocities and dynamic changes, which are common in manufacturing settings (Ricardo et al., [192]). By integrating these advanced navigation techniques, mobile robots in AM can operate more reliably and efficiently, enhancing the scalability and flexibility of manufacturing operations. By integrating these advanced navigation techniques, mobile robots in AM can operate more reliably and efficiently, enhancing the scalability and flexibility of manufacturing operations (see Table 5).

The MVO algorithm, developed by Xu et al. [198], benefits environments with high-speed dynamic obstacles, such as other moving robots or machinery, by extending the velocity obstacle region and considering real-world constraints. This ensures mobile robots can navigate safely and efficiently, even when faced with fast-moving objects, enhancing operational safety and maintaining continuous and effective AM processes. The Roaming Trails approach by Sgorbissa and Zaccaria [199] combines offline path planning with real-time obstacle avoidance, allowing mobile robots to deviate from their set paths to navigate around obstacles. This flexibility prevents deadlocks and ensures continuous task execution, making mobile robots more reliable and robust in dynamic construction site workflows. The LQG-Obstacles method, proposed by van den Berg et al. [200], integrates advanced control techniques with collision avoidance, enabling precise navigation through environments with significant motion and sensing uncertainties. This capability ensures smooth and safe navigation, maintaining high levels of accuracy and efficiency in AM processes, even in complex and uncertain settings. Collectively, these algorithms provide a comprehensive suite of path planning and collision avoidance strategies, enhancing the functionality and safety of mobile robots in AM, leading to more efficient and reliable processes, minimising downtime, and maximising productivity in dynamic and collaborative environments.

5.5.2. Toolpath generation

Toolpath generation is critical to many AM processes, including directed energy deposition (DED), WAAM, and more. The toolpath directly influences the final product's quality, mechanical properties, build rate, and precision. Efficient toolpath strategies ensure optimal material deposition, reduce the risk of defects such as porosity and cracks, and improve the overall structural integrity of the manufactured parts. Automated toolpath generation is particularly significant because it enhances

Table 5. Key contributions, approaches, and limitations of various studies in mobile robot collision avoidance.

Study	Key Contribution	Approach	Limitation
Fernández et al. [190]	Introduced BCM enhancing CVM by integrating BM for better local obstacle avoidance.	BCM uses BM to calculate the best heading direction, which CVM uses to determine optimal velocities for navigation.	BCM requires precise obstacle geometry, limiting its applicability in highly dynamic and cluttered environments.
Phan et al. [191]	Runtime approach using Simplex architecture to ensure collision avoidance for robots with limited sensing and information.	Simplex architecture uses constraints on sensor readings to guarantee safety, with a geometric-based switching condition.	Assumes conservative worst-case scenarios, potentially leading to overly cautious navigation.
Van Den Berg et al. [200]	LQG-Obstacles method combining LQG feedback control with collision avoidance under motion and sensing uncertainty.	Integrates Kalman filter for state estimation and LQR feedback controller in a closed-loop dynamics model.	Limited to robots with simple geometries and controllable linearised dynamics.
Ricardo & Santos [192]	Robust collision-avoidance method for mobile robots with uncertain dynamics and varying obstacle velocities.	Uses CCO approach, overdamped low-pass filter for smooth commands, and high-order sliding mode differentiator for acceleration estimates.	High computational demand for real-time implementation in complex environments.
Oleiwi et al. [195]	Fuzzy logic controller for collision avoidance in dynamic indoor environments, improving existing controllers.	Improves fuzzy logic controllers to handle known and unknown dynamic obstacles using onboard sensors.	Limited by the complexity and tuning of fuzzy rule sets.
Ravankar et al. [202]	Algorithm for autonomous and safe navigation in vineyards, avoiding dynamic obstacles smoothly.	Uses Lidar sensor data for obstacle detection and trajectory smoothing without GPS.	Dependent on accurate Lidar data, which can be affected by environmental conditions.
Beschi et al. [196]	Optimal trajectory generation using Ant Colony Optimization for industrial robots in machining and additive manufacturing.	Formulates kinodynamic optimisation problem, utilising kinematic redundancy to optimise trajectories while respecting constraints.	High computational cost and complexity in dynamic environments.
Guo et al. [193]	Motion saliency-based collision avoidance for dynamic environments, identifying and predicting dangerous objects' movements.	Calculates saliency of dynamic objects, uses B-spline curves and NMPC to predict and avoid collisions.	Computationally intensive and requires precise motion prediction of dynamic obstacles.
Xu et al. [198]	MVO method for avoiding high-speed obstacles in dynamic environments.	Expands velocity obstacle region, considering obstacles moving faster than the robot's maximum speed, ensuring feasible solutions.	Limited by the robot's maximum speed and sensor range.
Sgorbissa & Zaccaria [199]	Roaming Trails approach for mobile robot navigation, combining global planning with local perceptions to avoid deadlocks.	Represents path as a chain of areas, allowing deviation within boundaries for obstacle avoidance.	Potentially inefficient in highly dynamic environments with frequent changes.
Guo et al. guo2022obstacle	Dynamic obstacle avoidance method with a dynamic risk region, considering uncertainty in dynamic environments.	Constructs dynamic risk region using extended Kalman filter state estimation and combines with NMPC.	Limited by the accuracy of the state estimation and the complexity of dynamic environments.

the reproducibility and scalability of AM processes, making them more suitable for industrial applications.

Manual tool path identification for carved layers using high-DOF robotic arms is challenging, as Wu et al. [77] and Huang et al. [78] demonstrated. Various techniques, such as dividing large models into smaller sections or 3D printing without supports, have been developed to simplify this process, though they often require manual assembly [79]. Developing rotational trajectory motions could eliminate the need for manual assembly, yet existing methods are still based on planar layer development. Time-intensive tool-path algorithms work on multiple axes, including the visibility map algorithm [80], path planning in a cluttered environment with tools and work-pieces while maintaining collision-free paths [81], and algorithms for developing tool paths without gouging effects, improving machine dynamics [82,83]. To effectively use the required hardware setups, generating collision-free tool path algorithms for AM must be improved [84]. One approach is to add curved surface layers on top of each other to fabricate a solid model, meeting conditions like avoiding overlap, accurate approximation, and reachable surface patches. This process involves analyzing the environment, creating polygonal surface meshes, and determining tool paths based on Fermat-spiral curves.

The study by Biegler et al. [85] focussed on automated toolpath generation for DED, exploring 'zig-zag' and 'contour-parallel' strategies. Their research demonstrated that while zig-zag patterns were effective, they faced challenges in curved and narrow areas, whereas contour-parallel patterns struggled with sharp angles. The study highlights the geometry-dependent nature of toolpath strategies and their influence on material properties like microstructure and porosity. Similarly, Xiao and Joshi [86] addressed the complexities of generating toolpaths for heterogeneous objects (HOs) in DED, which involve multiple material compositions within a single layer. Their approach accounted for material changes and machine limitations, demonstrating through simulations that their method was efficient and flexible for various HOs. They emphasised the importance of material location accuracy and suggested further research on the impact of pixel size on toolpath generation.

In WAAM, an algorithm was developed by Ding et al. [87] to decompose 2D geometries into convex polygons, enabling the generation of continuous toolpaths using zigzag and contour patterns. This approach aimed to enhance surface accuracy and reduce starting-stopping points. Their results indicated superior surface quality compared to existing methods, demonstrating the efficacy of their strategy in meeting WAAM design requirements. Further advancing the field, Ding et al. [88] focussed on creating an automated system for robotic arc-welding-based AM, which integrated modules for bead modelling, slicing, and deposition path planning. They successfully fabricated a thin-walled aluminium structure using only a CAD model, showcasing the system's potential for fully automated production. This study marked significant progress towards practical, highly automated AM systems, emphasising the integration of various modules for seamless operation.

5.6. Localization and positioning

Mobile robot localisation and positioning are essential aspects of navigation, enabling pose estimation using recorded sensor data within the operating environment. There are various classifications for localising mobile robots based on their initial position. Position tracking is a method used by mobile robots to continuously update their position using sensor data, starting from an initial known position. Another approach is global localisation, where the robot does not know its initial position and must identify its location from scratch. In the Kidnapped Robot Problem, the robot is relocated to a previously unknown environment and relocalises itself based on updated sensor data. Panigrahi et al. [203] conducted a review of different localisation approaches employed in autonomous mobile robots, including probabilistic approaches, autonomous map building and radio frequency identification (RFID).

Markov Localization is a probabilistic method that discretizes the state space to handle initial positions in unknown environments accurately. Other probabilistic approaches, such as the Kalman Filter (KF) and its extended versions, are more suitable when the initial position is known, and the Extended Kalman Filter (EKF) effectively handles nonlinearities. The Unscented Kalman Filter (UKF) performs better than the EKF by minimising linearisation errors. Evolutionary-based localisation methods, such as GAs, PSO, and Differential Evolution, can overcome the limitations of traditional localisation methods. They can reduce computational time and perform better in unknown and noisy environments. Evolutionary approaches may necessitate precise parameter tuning and substantial processing power.

The mobile robot's positioning is determined by its proximity to tags in the operational environment using onboard RFID readers. The RFID method is a cost-effective and easy-to-implement way to precisely identify mobile robot positioning in indoor environments. However, mobile robots may struggle to achieve precise RFID localisation in cluttered environments. Combining RFID with Kalman Filter, Monte Carlo localisation, and Bayesian filters can address the shortage. However, it is essential to note that this approach may involve intensive computational operations, which can increase the complexity of the procedure. An essential method for autonomous navigation of unexplored areas is SLAM. This method allows a mobile robot to create a map of its environment while simultaneously determining its location. The SLAM process starts with the mobile robot's prediction of its new position based on specific criteria, such as its wheel movement. As the mobile robot moves in the environment, the uncertainty will increase. The mobile robot uses recorded sensor data to observe its surrounding environment, which can correctly predict poses and decrease uncertainty. The mobile robot updates its belief about its position and map using Bayes' rule. Finally, mobile robots can identify various environmental details, including walls, corners, and obstacles. The current traditional SLAM methods require further improvements to handle dynamic environments with sudden changes in object locations effectively and reduced computational load. Panigrahi et al. have classified autonomous map building into different categories, such as EKF-SLAM, UKF-SLAM, SLAM-based brain-controlled robot localisation, and Evolutionary-SLAM.

In a study on digital fabrication, Sandy et al. [204] used a mobile robot known as the In-situ Fabricator (IF) at construction sites. The study examined the mobile robot's capability to locate and position itself independently with sub-centimetre accuracy using onboard sensing without relying on additional references or markers. Developing robotic systems independent from external infrastructure is necessary in a cluttered and dynamic environment like construction sites. Track slip is a common issue within construction sites that can disrupt the precise digital fabrication process. The IF uses laser range finders and inertial measurement units to accurately determine its pose and continue the fabrication process without interruption. The intensive computational procedures of optimisation algorithms may impact the accuracy of real-time estimation of mobile robot pose and trajectory planning, necessitating the improvement of these algorithms. Buchlia et al. [205] further advanced the IF's capabilities by studying its ability to create large-scale trajectories in situ, specifically for concrete structures. This study marked a significant milestone in the localisation and positioning of the IF in construction applications, paving the way for exciting possibilities such as using mobile robots in applications like AM. The study focussed on achieving precise measurements of the mesh contour by utilising a stereo camera pair centred at the mesh mould metal tooltip. The tool head design was enhanced by incorporating a customised hydraulic gripper and utilising various resistive welding technology.

A contour tracking control system utilising a 2D laser scanner mounted on the end effector arm of a mobile manipulator has been developed by [21] to accurately follow the contours of large-scale structures. This system is designed to optimise material deposition in AM and assembly processes using a mobile manipulator while also enhancing localisation in challenging conditions within large-scale manufacturing settings [21]. The real-time 2D profile recognition system enables the mobile manipulator to make dynamic path adjustments, ensuring accurate material deposition and stable layer construction. However, environmental factors such as dust and debris can pose challenges, potentially resulting in errors in contour tracking. Additionally, the system relies on powerful computational capabilities for real-time data processing, robust control designs, and continuous laser scanner calibration and monitoring, which may present additional challenges within the AM process.

In a separate study, Lachmayer et al. [99] developed a two-stage localisation strategy for a mobile manipulator equipped with autonomous sensing and localisation hardware setup for a multi-step AM process of a column formwork for a construction site. The mobile manipulator can deposit material with high-end effector positioning precision while moving between different fabrication positions, demonstrating its ability to fabricate column segments from various locations. The two-stage localisation strategy involves initial global localisation followed by refined localisation using 2D SLAM and a high-resolution 2D laser profile scanner. External localisation systems are unnecessary in the utilised localisation setup. The 2D laser profile scanner facilitates the creation of detailed 3D point clouds, essential for collision prevention with the robot's end effector and previously printed layers. The mobile manipulator onboard system is designed to operate in various environmental conditions, such as changing lighting and dust levels at the site. The use of onboard sensors may pose certain challenges. For instance, the initial localisation accuracy with 2D SLAM was approximately ±5 cm, which was insufficient for fabricating the column formwork. This was enhanced to ±3.5 mm by employing a 2D laser profile scanner to align the captured point clouds. Various limitations act as barriers to precise AM processes of the column formwork. These limitations include material deformations during the curing process, restrictions in the laser scanner range, and the intensive computational procedure of the iterative closest points algorithm for point cloud registration.

A cost-effective two-wheel differential drive mobile robot for AM of large-scale trajectories has been introduced by Xu et al. [206] to address the limitations of conventional gantry-based 3D printers. This 3D printing system is designed to provide precise fabrication without requiring frequent manual calibration. The navigation of the mobile robot is guided by a top-down projector equipped with learning-based visual servoing, and the robot is equipped with a camera for visual feedback and precise trajectory control during 3D printing of high-quality structures [206]. The localisation setup used in this study offers millimetre-level precision with limited operator intervention, eliminating the need for expensive Vicon systems with complex calibration setups. Additionally, the mobile robot's non-holonomic design prevents slippage issues often encountered with omni-wheel mobile robots, ensuring accurate collaborative AM processes. However, maintaining stability during 3D printing can be challenging for the mobile robot, potentially impacting the accuracy of the printed part. Fluctuations in surrounding lighting conditions can also adversely affect the quality of the projected image, posing additional challenges for the visual servoing system. Despite these issues, holonomic mobile robots, although offering superior manoeuvrability and navigation capabilities, come with their own set of challenges.

6. Challenges and future directions

Further research must assess how advanced ML techniques can enhance AM technologies. ML and AM methods are closely linked and can be used to optimise temperature, print speed, and material flow in real-time fabrication processes. Additionally, ML techniques can aid in developing more precise predictive models to decrease material waste, energy consumption, and production downtime, extend machinery lifespan, detect defects, and develop higher-quality outputs.

Exploring precise navigation for mobile manipulators during 3D printing requires additional research into real-time path planning and dynamic obstacle avoidance. One potential approach could include additional investigation into robust RL methods, like Deep Deterministic Policy Gradient (DDPG) algorithms. The study by Yu et al. [207] discusses mobile robot path planning using the DDPG algorithm, known for being off-policy, model-free, and employing DL and RL techniques. DDPG is well-suited for environments with continuous action spaces. It is particularly effective for learning optimal policies in complex and continuous path-planning tasks. The DDPG algorithm utilises a deterministic policy gradient, which provides stable performance compared to stochastic policy algorithms. This stability is attributed to its capability to reduce variance during action selection. Furthermore, the algorithm is designed with an off-policy attribute, enabling it to reuse historical data stored in a replay buffer. This feature breaks the correlation between consecutive learning updates, enhancing learning efficiency. During the training phase, the risk of overfitting exists, potentially reducing the model's ability to generalise for unseen environments due to its reliance on high-reward experiences in some cases. The algorithm's deterministic policy nature can lead to the possibility of convergence to local optima, which may result in incomplete exploration of the state space. To mitigate this, adding noise, such as the Ornstein-Uhlenbeck, can be beneficial. The SAC and PPO may have faster convergence speeds and better adaptive mechanisms than DDPG, indicating a superior balance of exploration and exploitation. DDPG generally requires fewer computational resources, potentially providing a superior advantage over SAC and PPO, which typically require larger model sizes. This can be challenging for industrial applications with limited infrastructure. The study conducted by Zhao et al. [208] aims to address the limitations of classical DDPG algorithms by integrating a duelling network into the critic network. The integration aims to enhance Q-value estimation accuracy by dividing it into action advantage and state value components. This approach is expected to improve the evaluation of future action rewards across different states. Using cosine and Euclidean distances has been found to improve mobile robot pose estimation and enhance state exploration. The Dueling DDPG demonstrates faster convergence during training than DDPG, leading to higher overall reward values and improved path-planning strategies within complex environments. However, the Dueling DDPG may introduce higher computational complexity, particularly when initialising the cosine distance in the reward function, requiring more precise parameter tuning for different test environments. Zhao et al. [209] conducted a study that indicates the DDPG algorithm can enhance trajectory planning for robotic arms in the textile industry. Based on its Actor-Critic architecture, the DDPG algorithm's performance in continuous action spaces could potentially enable precise control of robotic arm movements. The hierarchical memory structure of DDPG utilises First-In-First-Out and full retention strategies to improve learning during training and reduce the likelihood of forgetting previous actions. The findings suggest combining the DDPG structure with other ML models can improve robotics capabilities for different AM technologies. A study by Gong et al. [210] explores mobile robot path planning using DDPG algorithms in combination with supervised learning methods, such as Long Short Term Memory (LSTM), and mixed noises, such as Ornstein-Uhlenbeck and Gaussian. The results indicate improvement in convergence speed, training efficiency, decision-making, action selection, and reward function within complex environments compared to conventional DDPG algorithms. In the experiment, the mixed noise LSTM-DDPG model decreased training time by 18.8% and attained a success rate of 87%, compared to 76% for the conventional model in reaching the target point. This could potentially save a significant amount of time. The complex and dynamic nature of AM processes necessitates the use of robust RL-based algorithms, particularly for precise material deposition and efficient navigation around obstacles. The optimisation of localisation methods, including SLAM, can enhance real-time mapping and positioning accuracy, ensuring precise movement of the nozzle during material deposition.

Singh et al. [211] conducted a review study on various Vision-Guided Robotics (VGR) systems that can enhance robots' adaptability in complex environments. Future research efforts could focus on improving vision systems to enhance material deposition accuracy during the AM process using mobile manipulators, which may help minimise errors and improve the quality of fabricated parts. Vision-guided systems facilitate adaptive path planning for mobile manipulators to enhance navigation precision, minimising the potential for collisions with deposited materials and other mobile robots in cooperative printing systems. Robust hardware vision equipment supports continuous monitoring and inspection of the manufacturing process, which is critical for defect detection during the AM process, particularly for layer-wise quality control. Advancements in vision systems within AI technologies have the potential to enhance decision-making capabilities, leading to more autonomous operations.

The future of 3D printing utilising mobile manipulators may extend beyond current applications, such as construction sites, precise material handling, and assembly of complex components, into new domains. For instance, utilising mobile manipulators to 3D print complex components like composite panels can improve production scalability in various industries, including aerospace, automotive, rail, and aviation. Future trends in AM processes utilising mobile manipulators focus on improving sustainability by reducing material waste through precise control of deposition and assembly processes.

One of the most research-intensive aspects of robotic AM is DT's development. A DT a digital replica of a physical asset and comprises various aspects such as sensing and control models, statistical models, big data analytics, and AI. The adoption of DT is increasingly prevalent in the manufacturing sector due to applications such as product development, preventive/prescriptive maintenance, performance optimisation, and fault detection. Due to the complexity of the manufacturing process and the large datasets involved (either from sensors or computer simulations), a digital twin requires the use of advanced modelling techniques and ML to create a dynamic and real-time virtual representation, as shown in Figure 5. This has led to efforts in both academics and industry to develop and deploy DT for AM methods [212,213]. The implementation of DTs in AM can be classified into three levels i.e. factory level, machine level and process level [214]. The material extrusion process of desktop-based 3D printers is a popular choice for DTs that can help in optimising processing parameters and providing predictions for part quality using ML algorithms [215,216].

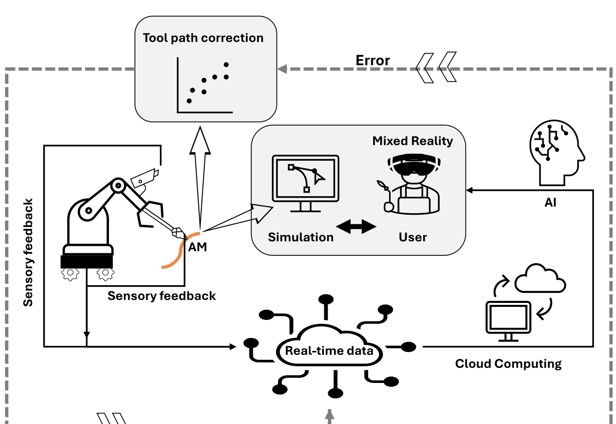

Figure 5. Real-time DT for Robotic AM. This schematic illustrates the real-time integration of a DT in the robotic AM process. The system continuously updates by sending real-time sensory feedback from the robots and sensors in use to the user via cloud computing, managed by AI. Errors in the system are detected and adjusted accordingly, ensuring optimal performance and precision.

Since incorporating robots with AM has numerous advantages, the concept of DT has been extended to include them as well. For example, Cai et al. [217] demonstrated a DT for toolpath planning and simulation of a reconfigurable AM system made of two desktop robotic arms, aided by augmented reality (AR) to communicate the layout information and avoid collisions for a higher material deposition rate. Similarly, Li et al. [218] demonstrated the use of AR and digital twin for a novel multi-robot collaborative manufacturing system with human-in-the-loop control, specifically for robot motion planning using an RL algorithm in the DT to replace the conventional kinematics-based robot movement. Moreover, early detection and correction of defects are vital to avoid build failures, especially for metal AM. Chen et al. [219] developed a multi-sensor fusion-based digital twin for in-situ quality monitoring and defect correction in a robotic laser-directed energy deposition metal AM process, used to predict part quality using ML and optimised robot toolpath generation for defect correction. Xu et al. [220] addressed the challenges of consistency and accuracy in large-format metallic parts produced by directed energy deposition AM processes by integrating a laser line scanning sensor into a robot-based laser-aided additive manufacturing (LAAM) system for on-machine measurement of part geometry. They developed a digital twin of the robotic LAAM system, which shows the digital replica of the robot and its physical movement in real time. The work by Zhu et al. [221] investigates the feasibility of a digital twin for a robotic cell to control metallurgic properties and part distortion in metallic parts. They investigated the control system, slicing software and path planning protocols for two different robots to provide a generic digital twin solution for an AM cell that can be implemented in other robots. These works highlight the strong interrelationship among different Industry 4.0 pillars, such as robots, AM and AR, complemented by ML and DT. As discussed in earlier sections, one key aspect to note is the focus on optimised tool path generation for AM, which can offer many benefits.

7. Conclusion

This review has thoroughly examined MAM systems' current state and future potential. Integrating mobile robots offers several distinct advantages, including enhanced flexibility, scalability, and the capacity to operate effectively in dynamic AM environments. However, significant challenges must be overcome for MAM systems to realise their full potential. Our investigation was structured around three key research questions addressing critical aspects of MAM implementation.

Firstly, we examined mobile manipulators' navigation and path-planning challenges in dynamic and complex AM environments. While significant advances have been made in developing algorithms that enable mobile manipulators to autonomously navigate and execute tasks such as material deposition, inspection, and maintenance, these systems still struggle with real-time adaptability, particularly when encountering unpredictable obstacles and evolving manufacturing conditions. Integrating advanced sensor technologies like LiDAR and visual SLAM has improved localisation accuracy and obstacle detection. However, further optimisation is required to adapt these systems for large-scale AM environments. Our findings highlight the critical role of advanced path planning in achieving higher-quality and more efficient manufacturing outcomes.

Secondly, we explored how recent advancements in AI techniques have enhanced robotic AM processes. Integrating AI-driven tools, particularly ML, DL, and RL models, has significantly improved various aspects of robotics-based AM systems. These advancements have notably enhanced robot control, autonomy, deposition path accuracy, manufacturing speed, material utilisation, and process repeatability. These innovations optimise current AM processes and pave the way for future developments, such as 5D printing.

Lastly, we analysed the current challenges and opportunities for MAM. Mobile 3D printing is set to revolutionise AM processes, particularly in large-scale construction environments. Teams of mobile robots working together on construction sites offer a scalable solution to the limitations of single-mobile robot systems, enabling the fabrication of larger, more complex structures. Swarm manufacturing, where multiple mobile robots coordinate to perform parallel tasks, has emerged as a promising approach to improve efficiency and scalability. Developing robust path-planning algorithms capable of adapting to real-time and dynamic AM environments is critical to the success of these systems. Looking ahead, integrating Digital Twin technology with AM presents an exciting opportunity. Digital Twin can significantly enhance toolpath planning, multi-robot coordination, defect detection and correction, and in-situ quality monitoring by providing real-time digital replicas of robot movements and processes.

In conclusion, while mobile robots and AI have transformed AM, technical challenges remain. Future research should prioritise the advancement of AI-driven methods for data acquisition and the development of more robust path-planning and control systems for mobile robots. Furthermore, the combined use of ground and aerial mobile robots for 3D printing presents a promising opportunity to fully unlock the potential of MAM systems. This approach enables them to address the demands of large-scale and complex manufacturing processes across industries such as construction and aerospace, aligning with the objectives of Industry 4.0.

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Data availability

Data sharing not applicable – no new data generated Data sharing does not apply to this article as no new data were created or analysed in this study.

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Disclaimer

Views and opinions expressed are those of the authors only and do not necessarily reflect those of the European Union, UK Research and Innovation (UKRI). Neither the European Union nor UKRI can be held responsible for them.

Abbreviations

AM	Additive Manufacturing
AMF	Additive Manufacturing File
ASTM	American Society for Testing and Materials
ACO	Ant Colony Optimization
ANN	Artificial Neural Networks
AI	Artificial Intelligence
APF	Artificial Potential Field
AGVs	Automated Guided Vehicles
AR	Augmented Reality
BCM	Beam Curve Method
BM	Beam Method
BHPF	Black-Hole Potential Field
BVC	Buffered Voronoi Cells
CACOF	Chaotic Ant Colony Optimization with a Fuzzy Logic
COA*	Class-Ordered A
CIGA	Co-evolutionary Improved Genetic Algorithm
CMT	Cold Metal Transfer
COBOTS	collaborative robots
CGT	Computational Geometry Technique
CDRF	Computational Design and Robotic Fabrication
C-space	Configuration Space
CCO	Continuous-Control-Obstacles
CNN	Convolutional Neural Network
CHOMP	Covariant Hamiltonian Optimization for Motion Planning
CVM	Curvature Velocity Method
CL-WAAM	Curved Layer Wire and Arc Additive Manufacturing
DL	Deep Learning
DNN	Deep Neural Network
DRL	Deep Reinforcement Learning
DQN	Deep Q-Network
DOF	Degrees Of Freedom
DfAM	Design for Additive Manufacturing
DCP	Digital Construction Platform
DT	Digital Twins
DED	Directed Energy Deposition
DABC	Direct Artificial Bee Colony
GMAW	Gas Metal Arc Welding
GPR	Gaussian Process Regression
GVD	Generalized Voronoi Diagram
GA	Genetic Algorithm
GWO	Grey Wolf Optimization
GPVD	Guaranteed Power Voronoi Diagram
HMODE	Heterogeneous Multi-Objective Differential Evolution
HOs	Heterogeneous Objects
HPPRM	Hybrid Potential-based Probabilistic Road Map
CS-BA	Hybrid Cuckoo Search-Bat Algorithm
GA-PSO	Genetic Algorithm with Particle Swarm Optimization
IPSO	Improved Particle Swarm Optimization
IF	In-situ Fabricator
IMUs	Inertial Measurement Units
KF	Kalman Filter
K-NN	K-Nearest Neighbor
LCM	Lane Curvature Method
LAM	Laser Additive Manufacturing
LDED-PF	Laser Directed Energy Deposition via Powder Feeding
LQR	Linear Quadratic Regulator
LQG	Linear Quadratic Gaussian
LSTM	Long Short Term Memory
FNR	Luxembourg National Research Fund
ML	Machine Learning
MLP	Multi-Layer Perceptron
MVO	Maximum Speed Aware Velocity Obstacle
memEAPF	membrane Evolutionary Artificial Potential Field
MPC	Model Predictive Control
MVDRM	Morphological Dilation Voronoi Diagram Road Map
MRS	Multi-Robot Systems
MOPBD	Multi-Objective Path-Based D Lite
MWOA	Multiobjective Whale Optimization Algorithm
MGD	Multivariate Gaussian Distribution
NSPP	Navigation Strategy with Path Priority
NURBS	Non-Uniform Rational B-Splines
NSGA-II	Non-Dominated Sorting Genetic Algorithm
NMPC	Nonlinear Model Predictive Control
OC	Optimal Control
PSO	Particle Swarm Optimization
P-RRT	Predictive RRT
PRM	Probabilistic Road Map
PMPCS	Progressive Model Predictive Control Scheme
PPO	Proximal Policy Optimization
QP	Quadratic Programming
RFID	Radio Frequency Identification
RRT	Rapidly Exploring Random Tree
RRG	Rapidly-exploring Random Graphs
ROA	Reciprocal Orientation Algorithm
RL	Reinforcement Learning
RL-ILSMH	Reinforcement Learning Iterated Local Search Meta Heuristic
SDA	Shortest Distance Algorithm
SLAM	Simultaneous Localization and Mapping
SAC	Soft Actor-Critic
STL	Standard Tessellation language
SVM	Support Vector Machine
TCPP	Task Consistent Path Planning
TO	Topology Optimization
TCs	Tower Cranes
TD3	Twin-Delayed Deep Deterministic Policy Gradient
UKRI	UK Research and Innovation
UV	UltraViolet
UGVs	Unmanned Ground Vehicles
UKF	Unscented Kalman Filter
UCB	Upper Confidence Bound
VO	Velocity Obstacle
VGR	Vision Guided Robotic
VD	Voronoi Diagram
WAAM	Wire and Arc Additive Manufacturing
WMS	Weld Monitoring System
WMRs	Wheeled Mobile Robots

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