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Artificial Intelligence Technology for Path Planning of Automated Earthwork Machinery

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Keywords: artificial intelligence | automated earthwork machinery | path planning | systematic review

ABSTRACT

The challenging characteristics of earthwork environments—complex, unstructured, and constantly evolving—pose significant challenges for the path planning of automated earthwork machinery. Recent advancements in artificial intelligence (AI) technology have opened new avenues to address these challenges, which are crucial for improving the intelligence level of automated earthwork machinery. However, there is a notable lack of comprehensive analyses on AI-based path planning in earthwork operations. Consequently, we provide a systematic review of four AI technologies currently employed in path planning for earthwork machinery, including (1) evolutionary computation, (2) swarm intelligence, (3) machine learning, and (4) other AI-based technologies. We analyzed the application and performance evaluation results of these technologies across various construction machinery. Through this systematic analysis, we identified several key challenges: (1) multiconstraint earthwork environments, (2) generalization across 3D unstructured sites, (3) adaptability to dynamically uncertain environments, and (4) shortage of on-site validation. We then outline potential future directions: (1) integration of generative AI with reinforcement learning, (2) use of large model technology, (3) adoption of embodied intelligence technology, and (4) conduction of more on-site experiments.

1 | Introduction

Earthwork machinery is a crucial piece of large-scale engineering equipment used in construction, water conservancy, and road engineering. It is extensively employed in tasks, such as earth excavation and land levelling. The development of mechanical automation technology and the new generation of artificial intelligence (AI) technology (Ahmed, Jeon, and Piccialli 2022), have led to the emergence of autonomous earthwork machinery. This advanced machinery integrates key technologies such as environmental perception, planning and decision-making, and automatic control, attracting significant attention from the academic community (Yu et al. 2021; You, Zhou, and Ding 2023). The application of autonomous earthwork machinery not only replaces manual repetitive tasks but also enables operations in challenging climates and extreme environments (Zhou et al. 2023; Eraliev et al. 2022). By improving efficiency, reducing costs, and ensuring personnel safety, it boasts wide-ranging application prospects.

Path planning technology plays a vital role in achieving autonomous construction of earthwork machinery. When the sensing module of autonomous earthwork machinery collects environmental data, the path planning module generates a feasible action path or work trajectory, which is executed by the control system. The fundamental types of path planning for earthwork machinery include complete coverage, point-to-point (PTP), single machine, multimachine operation, two-dimensional (2D), and three-dimensional (3D) path planning. Advanced path planning technology can efficiently devise collision-free routes for different operating scenarios of earthwork machinery or working attachments. Research on path planning technologies is highly important for enhancing the autonomy and intelligence of autonomous engineering machinery.

The path planning of agents has been a widely researched topic (Hu et al. 2022), and with related application technologies are becoming more and more mature. However, path planning for earthwork machinery presents several challenges, including irregular terrain, unknown soil conditions, complex construction process constraints, and other unfavorable factors. Traditional path planning approaches, such as the Dijkstra algorithm and the A* search algorithm, may not be adaptable when dealing with large-scale, high-dimensional, and dynamically changing engineering environments (Xu et al. 2019). Recently, AI technologies such as genetic algorithms (GAs), evolutionary searches, ant colony algorithms, particle swarm algorithms, reinforcement learning (RL), and neural networks have emerged as frontier research in earthwork machinery path planning (Zhang et al. 2022; Sardarmehni and Song 2023).

Considering the widespread application of AI technology in earthwork construction path planning, a comprehensive and systematic review of path planning algorithms based on AI technology is necessary. This review categorizes related AI-based path planning methods into four categories: evolutionary computing, swarm intelligence algorithms, machine learning, and other technologies. It also explores the application of these technologies to different types of earthwork machinery. This review identifies several bottleneck issues in the development of AI technology in earthwork machinery path planning, including poor optimization results under complex constraints, limited generalization ability for 3D unstructured earthwork scenarios, inadequate adaptability to dynamic uncertain construction environments, and a lack of real-world experimentation. On this basis, this review looks forward to future development directions and aims to promote the application of AI technology in the field of earthwork engineering.

The remainder of the review is structured as follows. Section 2 covers the literature search process, bibliometric analysis, and the three main categories of path planning tasks. Section 3 analyzes the four categories of AI technologies in earthwork path planning. Section 4 discusses the application of AI technology to different types of earthwork machinery. Section 5 introduces the evaluation method for the path planning method results, and Section 6 summarizes the challenges and prospects of its application.

2 | Problem Analysis

2.1 | Review Approach

Before conducting the survey, hotspots for the application of AI technology in the field of earthwork machinery and robotics were searched and sorted. Within the context of path planning, we focus on the construction motion, path, and trajectory of the working attachments. Notably, the terms "path planning," "motion planning," and "trajectory planning," have often been used interchangeably and inconsistently in the automated construction literature.

To carry out a comprehensive review of the extant literature, an initial investigation was performed on articles published within the following online databases: the Web of Science, Google Scholar, IEEE Xplore, and Scopus. The terms listed in Table 1 were utilized for the searches.

The entire process of the systematic literature review consisted of reading abstract, conclusion, and performing backward and forward snowballing searches within the reference lists of identified articles to minimize the possibility of missing relevant work. Overall, 81 subject related literature sources were identified for further analysis (Figure 1).

Figure 2 depicts the distribution of the 81 bibliographic records from 1998 to 2024, manifesting a clear upward trend in the number of publications on this topic over the last two decades. Notably, since 2019, there has been a rapid surge in the number of related studies, which can be attributed to the widespread adoption and deep integration of AI technologies in this field. The application of AI technology in earthwork machinery path planning has now become a crucial research task. Consequently, it is anticipated that an increasing number of academic works will be published in this field in the future.

The number of automatic path planning studies for construction machinery varies among countries/regions. As depicted in Figure 3, China and Japan emerge as the two primary nations actively implementing the most correlative applications. Korea,

TABLE 1 | Table with search keywords grouped by category.

Category	Keywords
Earthwork machinery	Automated/autonomous earthwork machinery/vehicles
Problem	Path/route/trajectory OR planning/selection/optimization
Technique	Artificial intelligence/swarm intelligence/reinforcement learning/evolutionary computation/Q-learning/neural network/genetic programming/genetic algorithm/particle swarm optimization/ant colony optimization

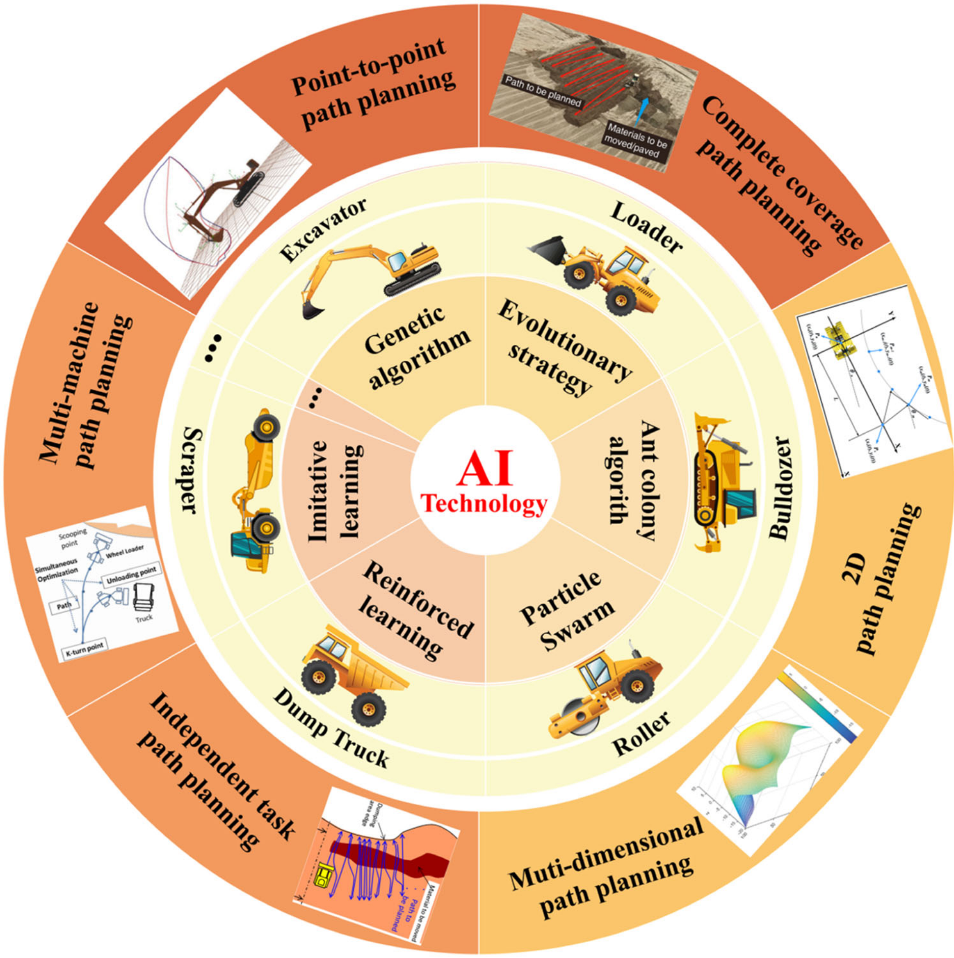


FIGURE 1 | Outline of the framework. [Color figure can be viewed at wileyonlinelibrary.com]

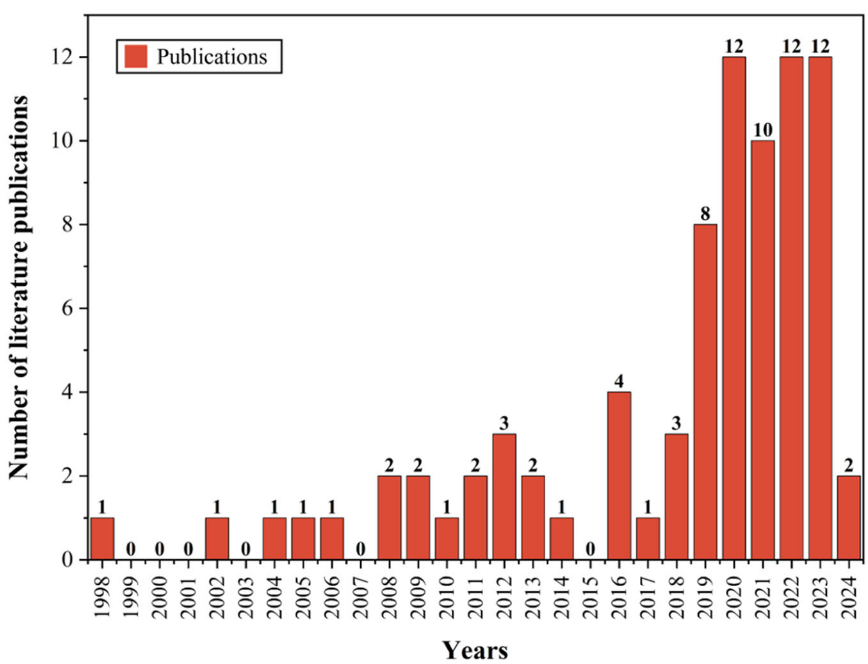


FIGURE 2 | Number of publications on artificial intelligence-based path planning for automated earthwork machinery. [Color figure can be viewed at wileyonlinelibrary.com] the USA, Sweden, Australia, and Canada have also made significant contributions in terms of relevant research.

Keywords represent the main purpose of the article. In this review, the co-occurrence network method is used to visualize the keywords. By visualizing keywords based on co-occurrence networks, we can identify hot spots in the field and summarize the future direction of research development. Figure 4 visually displays a synergistic and evolutionary analysis of the keywords, revealing the research trend of AI for path planning of automated earthwork machinery. The font size represents the importance value of the keyword, while the line represents the relevance of the keyword. Current research in the field of path planning focuses on RL, deep learning and swarm intelligence. Additionally, the core research hotpots are path planning in dynamic environments, multimachine collaborative path planning, and reliable simulation methods.

2.2 | Different Types of Path Planning

As mentioned before, this paper uses "path planning" to represent "path planning," "motion planning," and "trajectory planning," as these concepts have often been indistinguishable in previous studies. In this research, we classify path planning from three dimensions to provide a better explanation and analyze this topic, namely, motion-based path planning, task-based path planning, and dimension-based path planning.

FIGURE 3 | Publications issued by different countries. [Color figure can be viewed at wileyonlinelibrary.com]

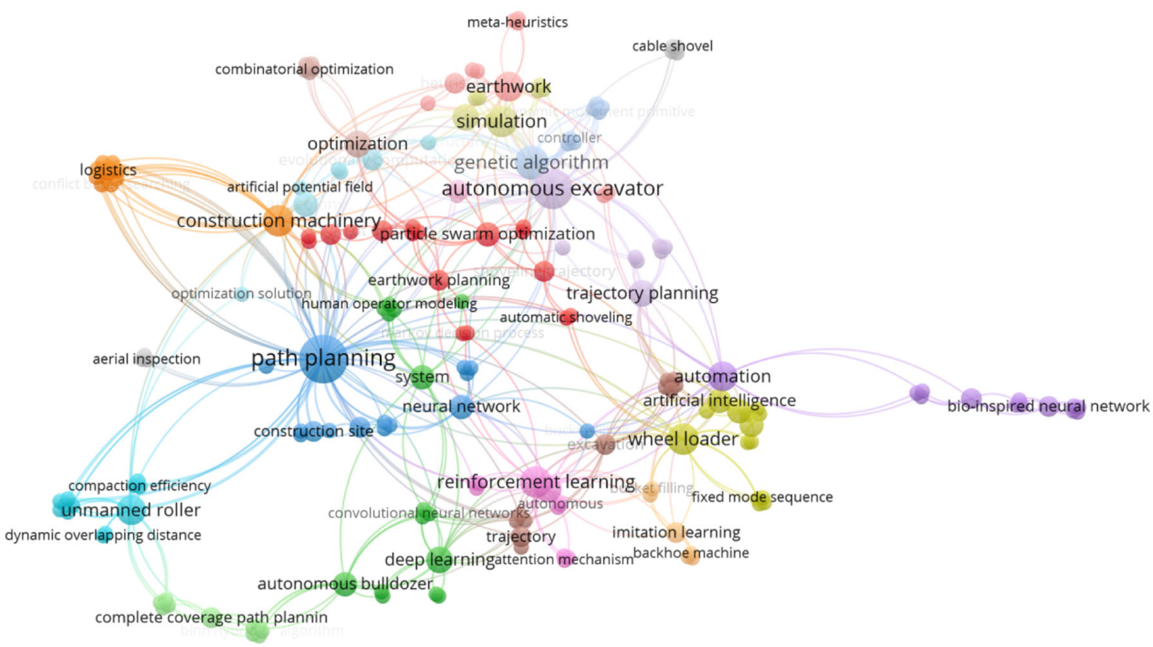


FIGURE 4 | Keywords co-occurrence network. [Color figure can be viewed at wileyonlinelibrary.com]

2.2.1 | Motion-Based Path Planning

From the perspective of construction movement, the path planning of automatic earthwork machinery can be categorized into complete coverage path planning (CCPP) and PTP path planning, which aligns with the traditional classification of path planning. The primary objective of PTP is to identify a collision-free path from the starting point to the endpoint. The CCPP problem involves determining a path that traverses all points of an area while avoiding obstacles (Gao et al. 2022). PTP and CCPP are equally applicable methodologies for addressing different types of path planning problems without any inherent prioritization.

2.2.1.1 | CCPP Problem. The CCPP requires the agent to complete work by navigating any corner of the map, whereas the PTP focuses solely on the starting and ending points, as shown in Figure 5. Meanwhile, CCPP may also involve issues such as collaborative planning of multiple agents and decomposition of operating areas, which will bring advantages and challenges to CCPP (Galceran and Carreras 2013). Most existing research on CCPP pertains to unmanned aerial vehicles (UAVs), automated guided vehicles, cleaning robots, and agricultural vehicles, with limited studies involving earth-moving engineering machinery (Li et al. 2022). When considering CCPP, most excavators, bulldozers, graders, and rollers encounter task scenarios that necessitate complete coverage of the entire construction site. For instance, considering earthwork characteristics and environmental constraints, Kim, Lee, and Seo (2020) established a CCPP model for automated excavators. The cost function of the CCPP algorithm considers the reachability of the dump truck and the external conditions of the working environment, thereby maximizing collaboration with the dump truck to provide practical solutions.

2.2.1.2 | PTP Problem. PTP is the most common model used in path planning. In this model, we incorporate the trajectory of construction units on earthwork machinery, such as the bucket of an excavator and a wheel loader. These working attachments are tasked with moving from one point to another. Although trajectory planning for earthwork machinery may not always require obstacle avoidance, unlike traditional PTP tasks, it still has its own planning and optimization objectives, such as finding the shortest path (Takei et al. 2013).

2.2.2 | Task-Based Path Planning

When assigning tasks to earthwork machinery, path planning issues can be divided into two categories: planning for a single machine with an independent task and planning for scenarios involving multimachine cooperation, as shown in Figure 6.

2.2.2.1 | Independent Work Path Planning. Planning an independent work path is generally based on the task of a single machine, without considering interactions with other machines. For example, in Figure 6a, Hirayama et al. (2019) analyzed a task in a dumping site and planned a path for a bulldozer based on the movement process. Currently, most research focuses on this type of planning, whether it is planning paths for excavators in mining fields (Sarata, Weeramhaeng, and Tsubouchi 2005), a single bulldozer for land levelling (Li et al. 2022), or a roller for compaction work (Zhang et al. 2019). Although path planning research in the field of unmanned vehicles has long studied fleet operations through dynamic awareness, the relevant algorithms in the industry still rely on rule-driven methods. This is also why independent work path planning for automated earthwork machinery remains the mainstream approach. Due to the relatively fixed, simple, and regular nature of construction rules for a single machine, it is

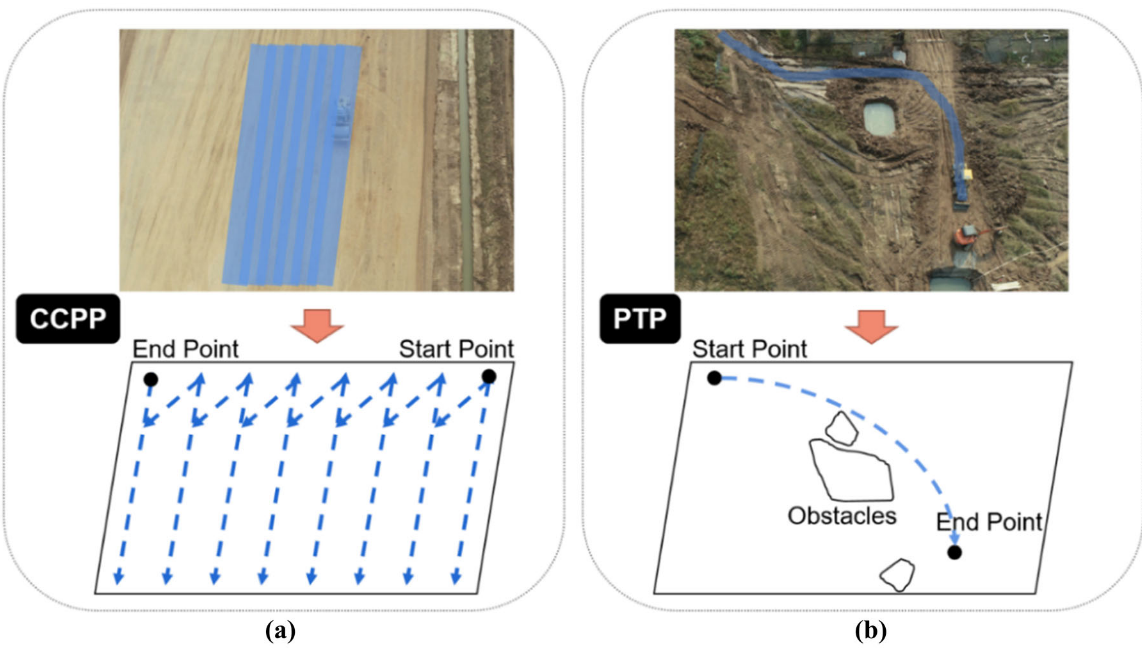
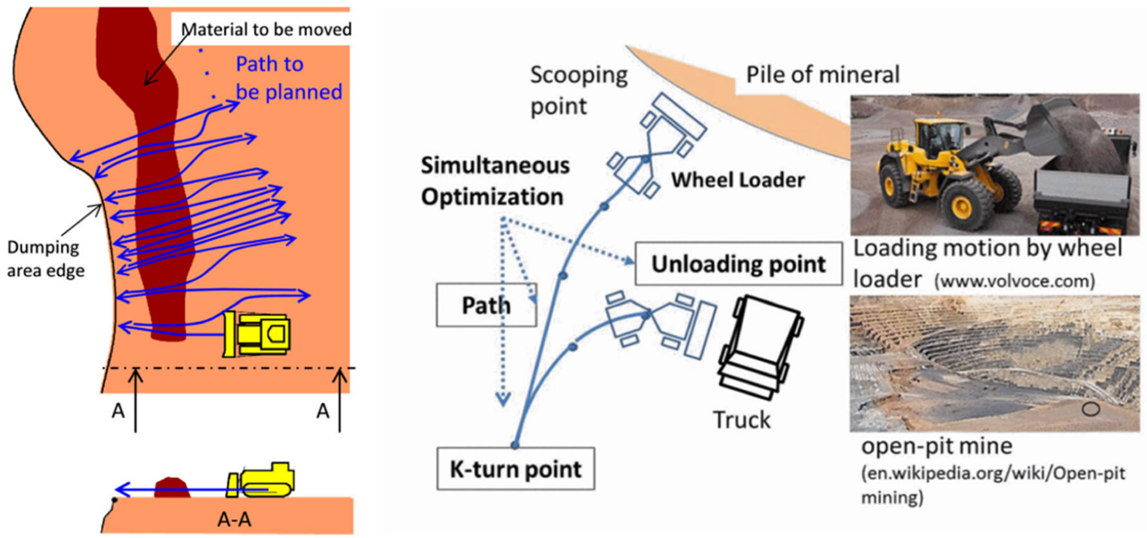


FIGURE 5 | General types of motion-based path planning in earthwork tasks: (a) complete coverage path planning (CCPP) and (b) point-to-point (PTP) path planning. [Color figure can be viewed at wileyonlinelibrary.com]

easier to summarize walking rules and regulations for implementation.

2.2.2.2 | Collaboration Satisfaction Path Planning. Compared with independent work planning, the computational complexity of collaboration satisfaction path planning increases due to the involvement of multiple vehicles and machines. Figure 6b illustrates a collaboration work path completed by a wheel loader and a truck (Takei et al. 2015), which is an example of collaboration satisfaction path planning. A task-oriented model is developed based on the interaction between multiple machines, including the construction rules of multiple operation types. However, only a few approaches have been developed. Stentz et al. (1999) developed a fully automated system that optimizes digging locations, dumping spots in trucks, and obstacle-free paths during the loading process. Implemented effectively, this system matched the speed of human operators in loading trucks. Kim, Lee, and Seo (2020) devised an algorithm accounting for the dump truck's accessibility and the ambient conditions of the working environment, thereby facilitating enhanced collaboration with the dump truck. Table 2 presents examples of task-based path planning in the context of



(a) (b)

FIGURE 6 | General types of task-based path planning in earthwork construction: (a) independent work path planning (Hirayama et al. 2019) and (b) collaborative satisfaction path planning (Takei et al. 2015). [Color figure can be viewed at wileyonlinelibrary.com]

TABLE 2 | Examples of task-based path planning.

Task	Method	Description	Reference
Independent work path	Dynamic programming	In this paper, a wheel loader was used as the object of study to optimize the movement of the loader from the perspective of fuel use efficiency.	Frank, Kleinert, and Filla (2018)
	Nonlinear programming problem and A* algorithm	A novel efficient path planning algorithm for articulated steering vehicles operating in semistructured environments.	Choi and Huhtala (2016)
	D*	A path planning method is presented for unmanned rollers with relatively good accuracy and reliability to autonomously complete the balanced rolling operation of rockfill material.	Zhang et al. (2019)
Collaboration satisfaction path	Complete coverage path planning algorithm	In the paper, a complete coverage path planning method is proposed that considers the characteristics of excavators and the accessibility of dump trucks.	Kim, Lee, and Seo (2020)
	Binary integer programming	The paper proposes a model for mining and other scenarios considering environmental impacts for the optimal configuration of wheel loaders and truck shovels.	Bakhtavar and Mahmoudi (2020)
	Dynamic models and heuristics	This study proposes a path planning method for collaborative multimachine operations, which can be used to determine the optimal digging position of an excavator and the optimal dumping position of a dump truck, as well as the shortest traveling paths.	Stentz et al. (1999)

automatic earthwork. Typically, when solving multiagent collaborative path planning, heuristic search algorithms are not scalable enough, while machine learning-based methods can realize decentralized systems and show promising scalability in high congestion scenarios (Veerapaneni et al. 2024). In addition, related techniques in the field of autonomous driving are also of value, for example, multiobjective optimization function is introduced into ant colony algorithm so as to optimize the spatial collaboration cost and the trajectory cost (Su et al. 2024).

2.2.3 | Dimension-Based Path Planning

According to the dimensions of the working environment, there are two types of path planning: 2D path planning and multidimensional path planning. In the past, researches mainly solve the path planning problem of mobile robot in 2D environment. In recent years, there has been a deeper focus on researching mobile robots operating in 3D space, such as UAVs, autonomous underwater vehicles, and lunar exploration robots. Figure 7a is a typical 2D path, and Figure 7b presents a 3D path based on terrain conditions (Saeedi et al. 2005). Additionally, when path planning includes considerations of the agent's speed and/or acceleration, it is referred to as multidimensional path planning. Path planning in space is a fundamental issue in automated machinery research, and it serves as an important indicator reflecting the level of robot intelligence.

2.2.3.1 | Two-Dimensional Path Model. In the field of earthwork construction, research on 2D path planning has resulted in numerous practical applications. Nezhadali, Frank, and Eriksson (2016) investigated wheel loaders movement patterns during recurring loading cycles, devising improvements to the efficiency of the V-shaped loading route. Separately, Budny and Gutkowski (2012) tackled the challenge of calculating the shortest feasible paths within the operational boundaries of an excavator bucket, exemplifying this through real-world scenarios of earth removal in deep excavations.

2.2.3.2 | Mutidimensional Path Model. Nonetheless, currently, available 2D path planning techniques are struggling to adequately address the requirements for navigation and obstacle avoidance in intricate 3D earthwork terrains (Wenna et al. 2022). There is also a need for planning path in automated construction machinery for earthwork, which falls within the domain of multidimensional path planning. Choi and Huhtala (2016) regarded the wheel loader from a kinematics and geometry perspectives, treating it as a 3D structure from the geometry perspective, so that collision-free paths can be calculated. Similar approaches have been taken in trajectory planning offer the working devices of loaders and excavators. Although several 3D path planning methods have been developed, they are still insufficient for completing the path planning tasks of earthwork machinery. Most scholars continue to utilize traditional algorithms based on geometric model searching, and mathematical optimization to address this issue.

3 | Intelligent Planning Methods

Since the integration of AI in construction, research has increasingly focused on areas, such as GAs, swarming intelligence, fuzzy logic (FL), fuzzy set theory, data mining, multiobjective optimization, and machine learning, which are widely used AI methods (Darko et al. 2020; Debrah, Chan, and Darko 2022). When considering path planning research in automated earthwork machinery, the main methods can be classified into four categories: (1) evolutionary computation methods, (2) swarming intelligence methods, (3) machine learning methods, and (4) other AI methods.

In the research distribution illustrated in Figure 8, machine learning-based path planning research holds a significantly dominant position, representing 37.8% of the total. This includes various methods, including RL and recurrent neural networks, confirming the widespread application and relatively mature technical level of advanced machine learning techniques in the field of earthwork machinery path planning. Conversely, swarm intelligence-based path planning research is

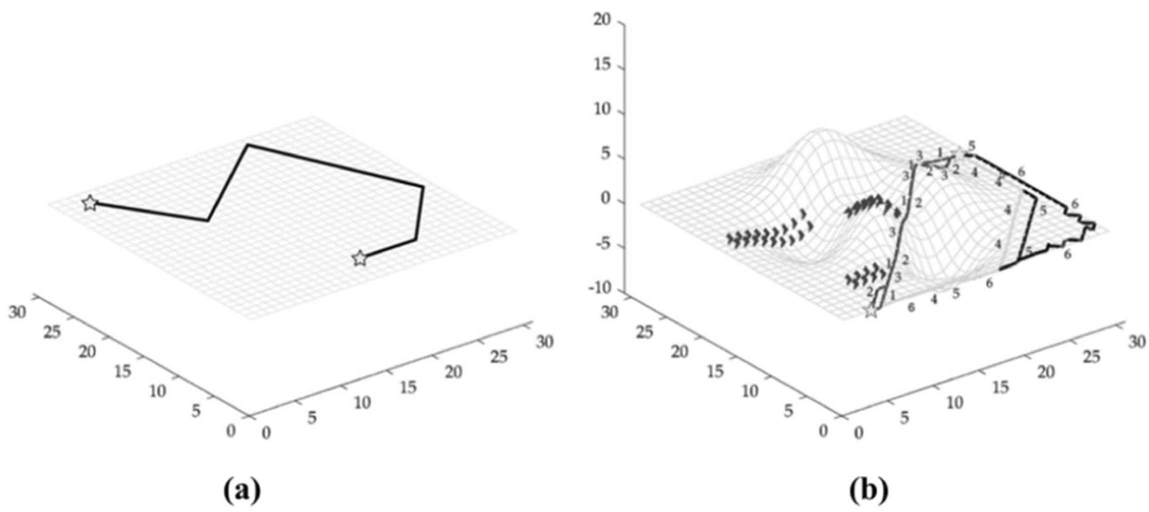


FIGURE 7 | Two-dimensional and three-dimensional path planning in earthwork construction: (a) 2D path planning and (b) multidimensional path planning.

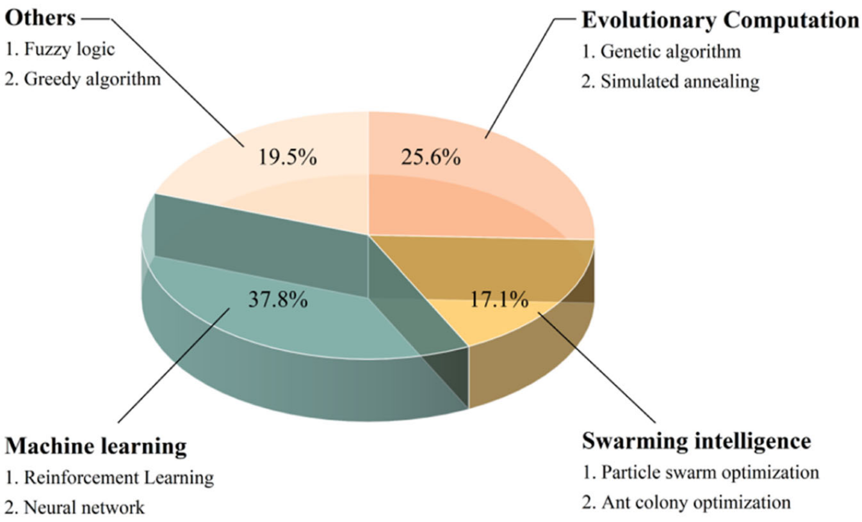


FIGURE 8 | Overview of different artificial intelligence-based path planning researches. [Color figure can be viewed at wileyonlinelibrary.com]

relatively limited, accounting for only 17.1% of the total, primarily focusing on technologies, such as the particle swarm algorithm and ant colony algorithm. This ratio indicates a substantial opportunity for further research and development in this area. Moreover, research based on evolutionary strategies and other AI technologies accounted for 25.6% and 19.5%, respectively. Table 3 presents a series of representative papers in each research subfield selected using rigorous criteria. These studies not only demonstrate the theoretical feasibility of AI technology in the path planning of automatic earthwork machinery but also highlight its extensive application potential and practical value. Subsequently, the specific details of four research topics that are currently receiving significant attention will be elaborated upon.

3.1 | Evolutionary Computation

The field of evolutionary computing includes four types of algorithms: GA, evolutionary strategies, evolutionary programming, and genetic programming (Holland 1992; Fogel 1998). The evolutionary algorithm is widely recognized as the most flexible, efficient, and robust algorithm among all known search algorithms (Beslay, Bull, and Martin 1993). Among these algorithms, the GA is widely utilized in optimization problems and is commonly the preferred choice for path planning (Öztürk, Akdağ, and Ayabakan 2022), particularly for earthwork path planning (Soltani et al. 2002). GAs have been successfully applied to optimize the shoveling operation path of wheel loaders. The PTP path planning method based on GAs has the ability to identify quasioptimal paths for microwheel loader robots (Takei et al. 2013), it produces shorter paths than the traditional V-shaped method (Sarata, Koyachi, and Tsubouchi 2009, 2010). In addressing the problem of operating trajectory for excavator manipulators with multiple joints, traditional methods such as discrete path planning, path planning based on the artificial potential field method, and path planning based on spline interpolation present challenges due to excessive computational requirements and long computation times. Moreover, these methods suffer from significant memory footprint limitations (Jason, Alan, and Nick 2003). On the other hand, GA, as a technology that covers a large search space, effectively handles excavators' tasks in complex front-end working environments while consuming relatively fewer computing resources. Therefore, it can quickly and effectively generate optimal excavator manipulator arm motion trajectories (Jang and Cho 2019). Additionally, it can provide solutions for multi-objective excavation path planning problems in excavation operations (Bi et al. 2020). Nonetheless, when employing GAs for earthwork path planning, randomly initializing the path strategy can result in a slow convergence process (Li et al. 2010). Furthermore, convergence failures may occur during the optimization process, limiting the GA's ability to efficiently and accurately search for optimal paths. To address these limitations, several researchers have enhanced the effectiveness of path planning by improving the GA (Lamini, Benhlima, and Elbekri 2018; Nazarahari, Khanmirza, and Doostie 2019). Gwak, Yi, and Lee (2016) proposed the shortest straight-line initialization method, which initiates the search closer to the near-optimal solution to reduce the calculation time. Additionally, they introduced a new genotype, crossover operator, mutation operator, and shortest straight-line method for initializing the parental chromosomes. Furthermore, they combined geographic information system information to enable path planning of the scraper in a 3D earthwork scene, as depicted in Figure 9. Nevertheless, the GA still faces challenges such as the inability to converge to the optimal solution and low convergence efficiency. Guangwei, Senlin, and Runcai (2019) addressed these challenges by enhancing the GA and incorporating bioinspired neural networks into the genetic coding process to achieve heuristic path correction, resulting in a quick and effective solution to this problem. Additionally, evolutionary strategies, such as the path planning method based on evolutionary hybrid neighborhood search (Utamima, Reiners, and Ansaripoor 2019), offer an effective alternative with superior generalization capabilities across multiple scenarios compared with other evolutionary methods.

3.2 | Swarm Intelligence

Inspired by the behavior of insect swarms, the swarm intelligence algorithm has been widely used in various optimization and robot path planning problems since its proposal. Because of

TABLE 3 | Examples of artificial intelligence algorithms in construction path planning.

Research field	Algorithm	Description	Performance	Reference
Evolutionary computation	Genetic algorithm (GA)	This paper applied the optimization method by GA to the trajectory planning for the wheel loader on scooping and loading operation.	Under the same conditions, this method generates shorter paths and fewer repeated paths.	Takei et al. (2013)
	Evolutionary hybrid neighborhood search	Complete coverage path planning in different scenarios via evolutionary hybrid neighborhood search.	The nonoperating distance is improved by 10.68% and has a better convergence rate.	Utamima, Reiners, and Ansaripoor (2019)
Swarm intelligence	Particle swarm optimization (PSO)	A multiobjective mining trajectory planning method based on PSO that takes into account constraints, such as speed and acceleration.	Comprehensive time-energy-impact trajectories can be obtained, with better search efficiency and easier to find the global optimum.	Feng et al. (2023)
	Ant colony algorithm	On the basis of the 3D terrain model of farmland, an improved ant colony algorithm is used, according to the earthwork transportation task.	Compared with the original ant colony optimization, the evaluation index of the path planning effect of this method was improved by more than 33.3%, which better guided the grader to realize the local leveling.	Jing, Jin, and Liu (2020)
Machine learning	Deep reinforcement learning (RL)	A distributed deep RL algorithm with Proximal Policy Optimization and Long Short-Term Memory is applied to optimize the leveling route of the bulldozer.	The proposed method was able to generate a leveling route that satisfy a high fill rate even without using initial positions for learning, and the generalization performance of the learning agent is demonstrated.	Osaka et al. (2021)
	Supervised learning	This paper combined the benefits of inverse RL and data-driven imitation learning with the efficiency of an optimization-based approach for scooping and dumping trajectories generating.	The approach could generate feasible, collision-free trajectories for the excavator arm.	Zhang et al. (2021)
Others	Fuzzy logic	This study employed a fuzzy logic-driven dynamic window approach for path planning of automated dump trucks.	This method enables automated trucks to navigate accurately towards their destinations across diverse scenarios.	Lei et al. (2021)
	Improved iterative greedy algorithm	This study proposes a multimachine dynamic path planning for automated wheel tractor in various uncertain scenarios based on an improved iterative greedy algorithm.	The optimization algorithm shows excellent performance in uncertain scenarios, exhibiting excellent robustness and environmental adaptability, in addition to saving up to 35% of the job time by optimizing the job path compared with traditional methods	Liang et al. (2021)

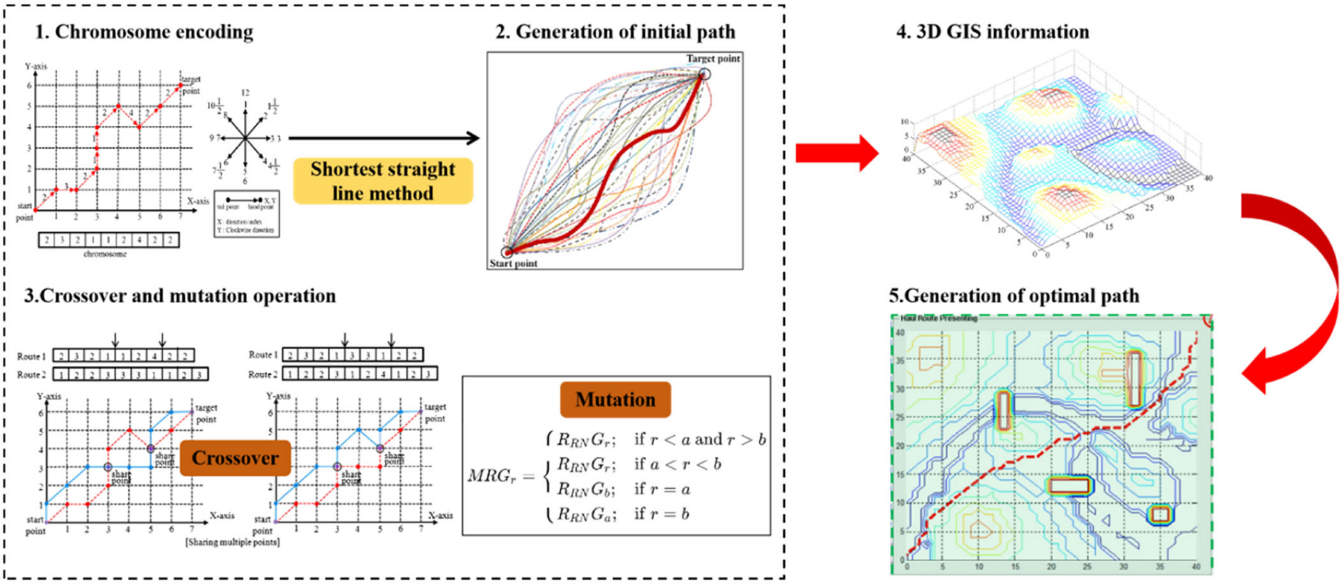


FIGURE 9 | Genetic algorithm in path planning (Gwak, Yi, and Lee 2016). 3D, three-dimensional; GIS, geographic information system. [Color figure can be viewed at wileyonlinelibrary.com]

their simple algorithm, few parameters, fast convergence and other characteristics, perform well in solving optimization problems (Okulewicz and Mańdziuk 2017; Lagos et al. 2018). These algorithms, such as the ant colony algorithm, particle swarm algorithm (Jain et al. 2022), and artificial bee colony algorithm (Karaboga and Basturk 2007), have been extensively applied in the field of conventional path planning (Shao et al. 2020; Chen, et al. 2022; Han et al. 2022) and earthwork machinery path planning (Nassar and Hosny 2012; Higuchi and Uchimura 2022) has been widely used. Jing, Jin, and Liu (2020) developed a 3D path planning method for farmland leveling using an improved ant colony algorithm. The algorithm sets pheromone update rules according to the earthwork transportation task, and then obtains the optimal path for smooth 3D land leveling. Then, the kinematic model of the machine is considered to perform smooth optimization of the path with constraints. The process is shown in Figure 10. Compared with other optimization strategies, swarm intelligence algorithms demonstrate superior adaptability and effectiveness in dealing with multiobjective problems and multimachine path planning (Feng et al. 2023). In the context of earthwork operations, which often involve considering multiple optimization indicators, the high complexity and slow convergence speed of high-dimensional multiobjective optimization present challenges. To address this issue, Jing, Luo, and Liu (2022) implemented a decomposed multiobjective evolutionary algorithm through ant colony optimization (ACO). This approach utilized using the ant pheromone matrix and adjacent solutions to construct optimal solutions. By continuously updating the solution to reactive search conditions, the quality of earthwork grading operations was significantly improved.

While path planning methods based on swarm intelligence offer parallel computation and robustness, they have certain disadvantages, including slow convergence, susceptibility to local optimal paths, and premature convergence (Zhang et al. 2020). To address these issues, researchers have made various improvements. Some have adjusted the optimal information release rules of the ant colony algorithm to reduce searches in irrelevant areas (Li et al. 2021), or modified the upper and lower bounds of the search interval for earthwork machinery path planning (Song 2023). These modifications effectively improve the algorithm's convergence speed. Additionally, Shi et al. (2020) enhanced the global search capability of the group intelligence algorithm by using chaotic optimization to improve the dragonfly algorithm. Wang, Zhao et al. (2021) improved the heuristic information and incorporated the Max–Min Ant System algorithm to restrict the pheromone concentration, thereby preventing it from becoming trapped in local optimal paths. Luo and Shen (2023) improved the ant pheromone release rules by integrating ACO and artificial potential fields, ensuring that pheromone updates effectively enhance the effect of later iterations. Particle swarm optimization (PSO) has also been used in earthwork path planning tasks because it has a relatively fast convergence speed and can generate the optimal transportation route in a shorter time in a complex environment (Nassar and Hosny 2012). To obtain a better solution faster, adjusting the parameters of the PSO algorithm or combining it with other optimization algorithms (Wu et al. 2022) are potential optimization directions. These approaches partially address the problem of algorithms falling into local optimal paths and enhance the independent engineering machinery's path planning ability, making them highly valuable in practical applications.

3.3 | Machine Learning

Machine learning generally consists of three parts: supervised learning, unsupervised learning, and RL. Path planning methods based on machine learning techniques have attracted significant attention in resolving motion planning issues due to their ability to handle complex problems and generalize well (Zhou, Huang, and Fränti 2022). Additionally, they exhibit good adaptability when dealing with path planning problems in unstructured earthwork scenarios. For instance, Lee et al. (2008) achieved optimal trajectory for earthwork operations by

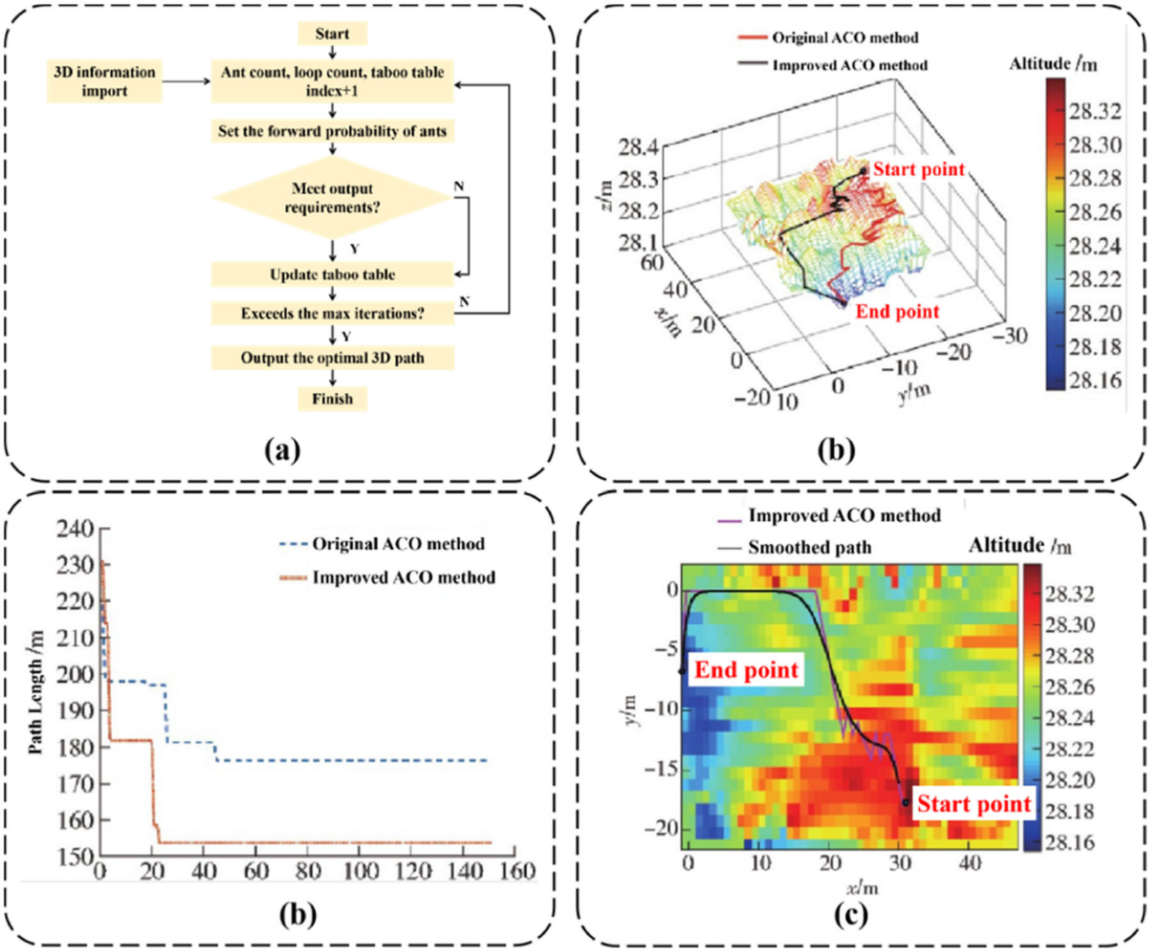


FIGURE 10 | Ant colony optimization (ACO) in path planning (Jing, Jin, and Liu 2020). (a) ACO-based path planning, (b) 3D path generation, (c) optimal path length, and (d) path smoothing optimization. 3D, three-dimensional. [Color figure can be viewed at wileyonlinelibrary.com]

utilizing a neural network-based soil model and path decisions derived from constraints. Traditional path planning methods face limitations in terms of calculation efficiency and adaptability when confronted with challenges such as multiple obstacles (pedestrians, puddles, stones, and warning signs) in a 3D unstructured earthwork construction site. Hence, Xu et al. (2019) proposed a path planning approach based on support vector machine (SVM) and the longest reachable path with route correction (Longest Achievable Path with Course Correction [LAP-CC]) for articulated road rollers, providing barrier-free support through SVM-based spatial extraction. This method offers advantages, such as simplicity, feasibility, low computational cost, and good repeatability. It is worth mentioning that the aforementioned algorithm is only applicable to static environments. For path planning problems in dynamic environments, machine learning algorithms have better adaptability to dynamic path planning tasks due to their more flexible operation capability. Yang and Meng (2001) proposed a biologically inspired neural network (BINN), which has the advantages of high real-time performance and adaptability to dynamically changing environments. However, practical applications of the BINN may still have certain shortcomings. To overcome this, Sun et al. (2022) developed a dynamic path planning model called CA–BINN. The model combines cellular automata (CA) to effectively reconstruct the complex dynamic earthwork environment, and uses the cellular state in CA as the external input of the BINN algorithm. At the same time, the BINN algorithm is improved by combining the neural activity value calculation shunt equation under the CA framework. By implementing this method, the paving smoothness of multi-stack overall paving operations can be improved by 28%, while the ineffective path ratio decreases by 47%.

RL, through its iterative optimization of path strategies by interacting with the environment and maximizing rewards, demonstrates efficient adaptation to complex dynamic unstructured scenarios. By deeply integrating neural network technology, deep RL enhances the understanding of environmental state characteristics and the ability to search for optimal paths. Consequently, RL-based path planning algorithms have found wide-ranging applications. As shown in Figure 11, Kawabe, Takei, and Imanishi (2021) applied a deep RL-based path planning method to wheel loader earthwork operations. Mileage can be evaluated based on the number of features in the state space and the selected shoveling points. This method allows for interactive planning of appropriate routes in response to changing state spaces. To address the challenge of drastic scene changes caused by continuous earthwork operations, Choi and Han (2023) proposed the use of an attention mechanism in an RL model. This mechanism enables the model to effectively focus on scene change information and make informed plans. However, methods based on RL are susceptible to falling into suboptimal paths,

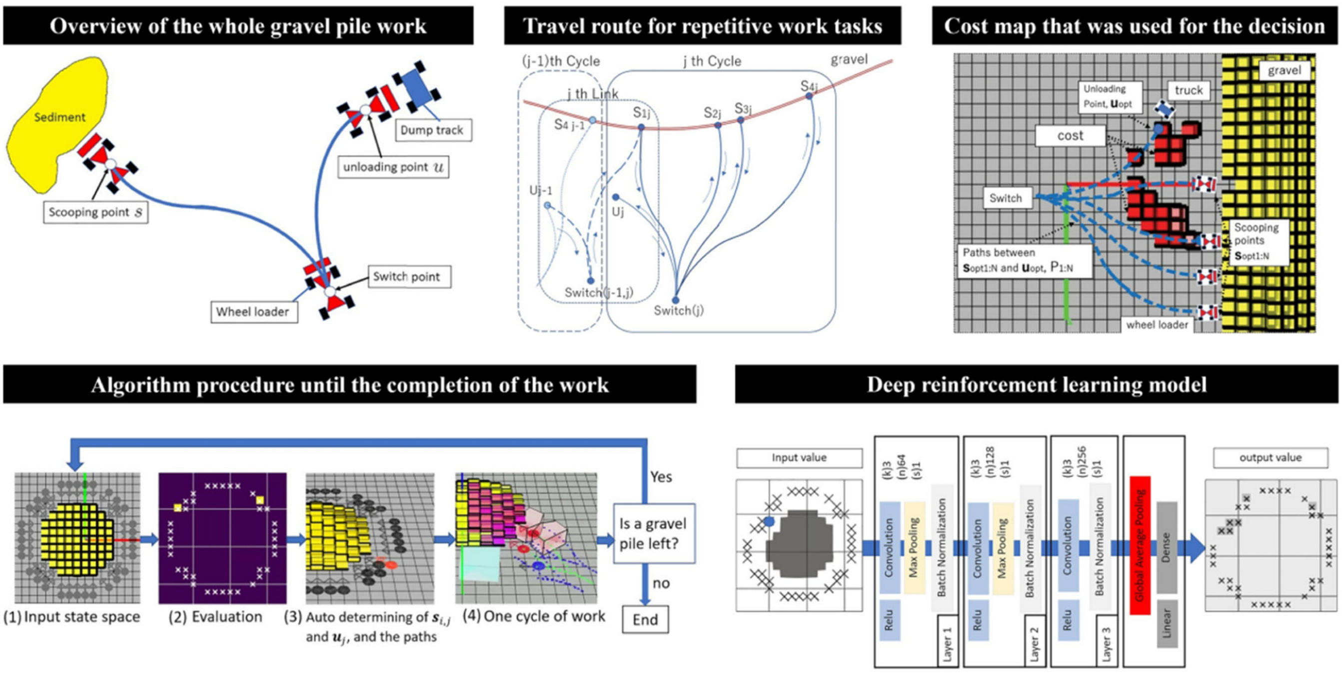


FIGURE 11 | Deep reinforcement learning in path planning (Kawabe, Takei, and Imanishi 2021). [Color figure can be viewed at wileyonlinelibrary.com]

and path planning itself can be time-consuming. In this regard, Jian et al. (2023) proposed a path planning method based on double-delayed deep deterministic policy gradient (TD3) using residual networks to accelerate the convergence process, which has the advantages of short planning time and fast convergence speed. Some other applications of RL are also of great reference significance. For example, for dynamic path planning problems, Chen used the deep RL algorithm Soft Actor–Critic and designed a comprehensive reward function for dynamic obstacle avoidance and target approach, which improved the success rate of dynamic obstacle avoidance. Chu designed a dynamic composite reward function to overcome adverse disturbances (Chen et al. 2022; Chu et al. 2023). In addition, if the dynamic parameters of the machine can be more accurately identified (Wu, Wang, and You 2010), it will be helpful to achieve accurate path planning. When solving the multiagent path finding problem, in addition to using RL methods, supervised learning methods can also be used to reduce training time and computational costs (Abreu 2022).

3.4 | Others

In addition to the aforementioned AI technologies, several other methods of AI have been implemented in the domain of path planning for earthwork engineering machinery. These methods have shown promising performance in addressing specific issues. These methods include FL techniques, greedy algorithms, and domain search strategies. Fuzzy logic (Zadeh 1965), introduced in 1965, uses FL theory to process imprecise and ambiguous information. This enables efficient optimization of driving routes for earthwork machinery in unknown and uncertain environments (Mac et al. 2016). Soltani and Fernando (2004) investigated a path planning method based on FL for various construction machinery. This method demonstrated superior capabilities in optimizing routes under uncertain conditions. Wang, Liu et al. (2011) employed an adaptive neural fuzzy system that combines FL with neural networks. This integration enhanced the operational quality of earthwork machinery in unpredictable environments. Fuzzy logic algorithms have some disadvantages, such as the optimal path depends on fuzzy reasoning rules. The accuracy of the results can be improved by combining them with other algorithms. Lei et al. (2021) used FL to adjust the weight of the dynamic window approach (DWA) to improve the accuracy of the path. AlKhlidi, Abdulsadda, and Al Bakri (2021) proposed a fuzzy PSO algorithm that combines PSO with FL, which can improve the problem of the PSO algorithm falling into the local optimal solution.

Furthermore, greedy algorithm-based path planning selects the current best solution at each decision step without considering the long-term global optimum. This approach effectively guides equipment along paths of minimal cost or maximum efficiency. Oksanen and Visala (2009) developed two full-coverage path planning methods based on greedy algorithms specifically for agricultural earthwork machinery. These methods strike a balance between complexity and efficiency, avoiding unnecessary traversal and redundant calculations. They provide approximate optimal solutions within reasonable time frames. For the dynamic path planning problem involving multi-machine parallel operations in uncertain scenarios, Liang et al. (2021) adopt a neighborhood search method to refine the iterative greedy strategy. This algorithm can adaptively and quickly adjust the planned route in the face of uncertainty. In addition to the above, the Bayesian algorithm is also a potential method. Choudhury, Srinivasa, and Scherer (2018) proposed a motion planning method combined with a Bayesian active learning paradigm, which can be used to quickly find collision-free paths.

4 | Applications of AI on Earthwork Machinery

Considering the significant disparities in mechanical structures and operational tasks among various earthmoving engineering machinery, each type of earthwork machinery has different concerns and challenges when planning paths, such as different construction objectives, specific constraints, different safety distances, and so forth. This chapter aims to specifically analyze how AI technology is applied to resolve different mechanical path planning issues while also examining the advantages and disadvantages of various AI technologies in practice. Figure 12 provides a clear depiction of the distribution of studies conducted in the field: research relating to excavators accounts for a substantial proportion, amounting to 31.2%. This is followed by loaders (20.8%), dump trucks (19.5%), and bulldozers (11.7%), with the least amount of research focused on road rollers, accounting for 10.4%.

4.1 | Excavators

Excavators are heavy-duty engineering machinery equipment that includes key structures, such as fuselages, booms (large arms), and bucket arms (small arms). Their mobility is relatively limited, and frequent adjustments to the direction of the fuselage can negatively impact operational efficiency. As a solution, Yao, Feng et al. (2023) developed a novel spacing adjustment model and corner area turning method for excavator path planning. The objective was to dynamically adjust the parallel path spacing, enhance corner coverage, and reduce the number of machinery turns. Additionally, when designing the excavation path, factors such as the fallback phenomenon of the outermost soil mass and the 3D working space limitations of the excavator must be considered. Thus, it becomes crucial to establish a reasonable reserved area (Figure 13a) and incorporate a certain degree of path overlap (Figure 13b) to ensure complete excavation of the material (Seo et al. 2011).

When strategizing the ideal path for excavation operations, an unfavorable initial excavation angle will result in increased resistance. Moreover, booms with 4–7 joints must also meet various criteria to ensure efficient and safe operation. To address this complex optimization problem involving multiple constraints, Yao, Feng et al. (2023) employed the particle swarm algorithm to generate a trajectory for mining cycle operations, which served as a training sample for the physics-informed neural network (PINN) model. This trained PINN model was then integrated into the planning module, ultimately achieving an efficient and uninterrupted mining trajectory, as depicted in Figure 14. However, there still exists a discernible disparity when compared with experienced operators. Consequently, Feng et al. (2024) combined Gaussian mixture regression to extract the expert trajectory of a driver. Subsequently, they utilized dynamic movement primer enhanced by a GA to learn and generate the optimal trajectory. To address any potential

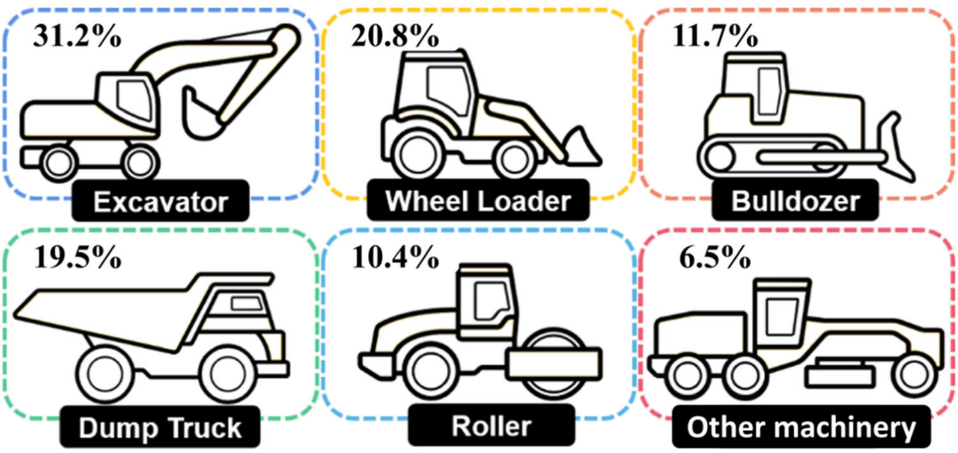


FIGURE 12 | Distribution of research contexts of earthwork machine. [Color figure can be viewed at wileyonlinelibrary.com]

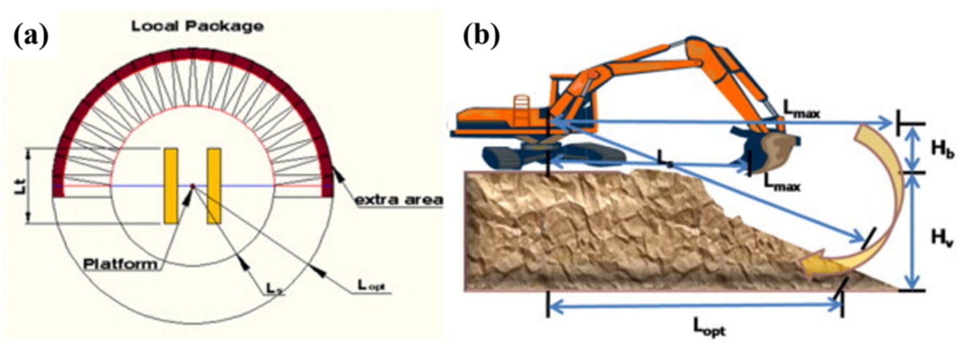


FIGURE 13 | Constraint analysis for excavator path planning (Seo et al. 2011): (a) reserved area and (b) operating space. [Color figure can be viewed at wileyonlinelibrary.com]

limitations stemming from expert data sets, Guo et al. (2022) trained a deep neural network through supervised learning and continuously added expert trajectories to the imitation learning data set, eventually resulting in smoother mining operations under multiple constraints. When an excavator is operating, it is necessary to avoid obstacles such as gravel in time, and local path planning is the key. Zhou et al. (2024) proposed a local path planning algorithm based on Optimized Q-Learning and used root mean square propagation in the learning rate adjustment. Vashisth et al. (2024) realized adaptive local path planning in dynamic scenes through dynamic graphs and deep RL.

4.2 | Wheel Loaders

Wheel loaders are a type of articulated engineering machinery. Their main structure consists of two connected parts by a precision pivot joint. The front part is equipped with a connecting rod and a bucket system, which is primarily used for efficient removal, loading, transferring and transporting of materials in earthmoving scenarios, such as mines and construction sites (Dadhich et al. 2016). A so-called "V-shaped" path planning method is commonly used (Sarata, Koyachi, and Sugawara 2008). This method simulates the real path of a manned loader during scooping and unloading. However, this method fails to adequately account for the hinged shape of the wheel loader, resulting in longer path planning results. Inspired by the real movement posture of the loader, Takei et al. (2013) considered the direction of the loader's basic movement. This is illustrated in Figure 15a, where multiple basic movements are combined into a single gene starting from the initial point. The GA is then used to search for the optimal scooping and unloading path. Another challenging problem related to wheel loaders is how to plan the bucket trajectory during loading operations to improve the full load rate. Unlike excavators, the bucket of a wheel loader is less flexible and encounters complex resistance conditions, particularly when dealing with high-density materials, as shown in Figure 15b. To address this issue, Dadhich et al. (2016) studied a trajectory planning method for loader shoveling operation based on deep RL. This method combines a linear regression model based on lifting and dumping actions to simulate the driving behavior of a skilled operator. To enhance the performance in unknown and complex operating environments, the actor–critic RL algorithm is applied to coarse gravel environments for trajectory planning. Remarkably, efficient trajectory planning can be achieved with only a small amount of expert data guidance (Dadhich et al. 2020). In

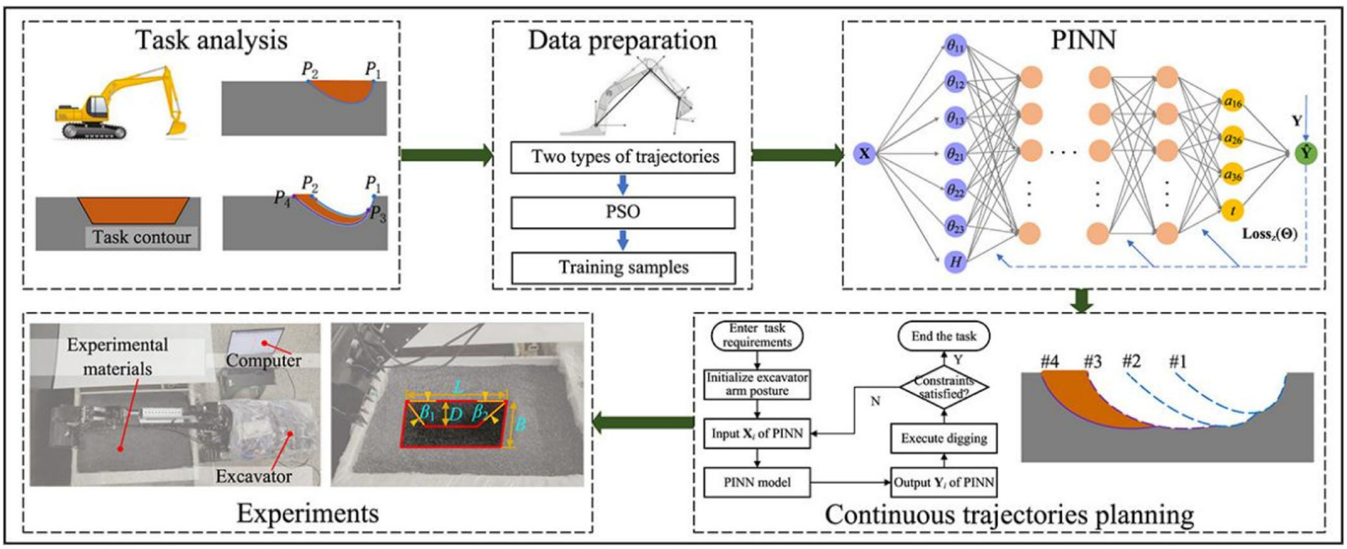


FIGURE 14 | The application of AI technology to excavator, including path planning (Yao, Zhao, et al. 2023). AI, artificial intelligence; PINN, physics-informed neural network; PSO, particle swarm optimization. [Color figure can be viewed at wileyonlinelibrary.com]

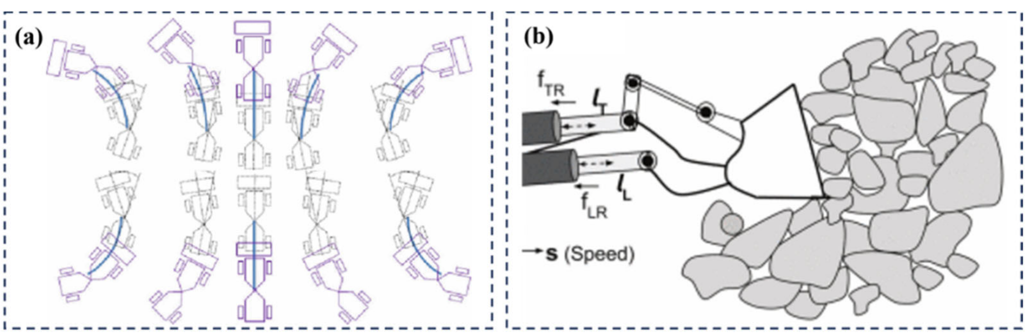


FIGURE 15 | Typical challenges for path planning of wheel loaders: (a) articulated steering analysis (Takei et al. 2013) and (b) unknown material resistance (Dadhich et al. 2016). [Color figure can be viewed at wileyonlinelibrary.com] regard to bucket trajectory planning under different working conditions, Yu, Huai, et al. (2020) proposed the use of the particle swarm algorithm to optimize trajectory parameters. By doing so, the theoretical optimal working trajectory of the wheel loader can be generated. This method also holds potential for application to different types of materials.

4.3 | Dump Trucks

Dump trucks play a vital role in earthwork construction as indispensable transportation tools. The introduction of autonomous dump trucks with self-driving capabilities has significantly reduced labor costs and increased transportation efficiency. In the autonomous driving process, path planning is a crucial step. Traditional methods such as rapidly exploring random tree and D* have been used for path planning of these vehicles in construction sites or mining environments, focusing on finding the shortest route but overlooking the directional aspect upon arrival at the destination point. Given their status as large-scale engineering machinery, practical applications require not only safe and efficient navigation to the target position but also precise orientation toward the appropriate working direction for smooth loading or unloading operations. Although some researchers have addressed the direction issue during path planning (Cirillo 2017), it has often resulted in excessively lengthy searches for optimal paths and low search efficiency. To overcome this challenge, Lei et al. (2021) implemented an adaptive DWA based on FL, which continuously adjusts the direction weight (Dirik et al. 2017) to adaptively steer, ensuring both high precision and rapid progression (Figure 16a).

The continuous heavy operation of large dump trucks can lead to road degradation, which Liu and Chai (2019) considered when resolving the complex-constrained path optimization problem using a GA with elite selection. When faced with obstacles, a dump truck must intelligently identify its turning position to generate a seamless path. Akegawa et al. (2022a) employed a data-driven method to generate smooth turning and reversing trajectories that cater to such requirements (Figure 16b). For large six-wheel dump trucks with substantial turning radii, an adaptive turning path planning method (Akegawa et al. 2022a) allows for the swift generation of a smooth path in response to changes in the target position. Additionally, self-driving dump trucks can benefit from advanced AI technologies used in autonomous driving, particularly those related to logistics and transportation (Teng et al. 2023; Zhao et al. 2024), such as imitation learning (Yan et al. 2023), multiagent reinforcement learning (Yu, Wang, et al. 2020), and bionic neural network. among others. However, the limitations of constraints, such as turning radius and safety distance parameters, need to be considered while resorting to related technologies. Mining trucks operating in complex environments should have flexible obstacle avoidance and collaboration capabilities, and related algorithms from fields such as computer games have potential application value. For example, Chen (2023) proposed an improved ant colony algorithm based on artificial potential fields, which can achieve real-time and reliable local path planning for soccer robots.

4.4 | Bulldozers

Bulldozers are commonly used in earthwork operations, such as site levelling and edge dumping. They utilize their blades to perform shoveling, transportation, and dumping tasks by pushing materials. According to experienced drivers' insights, bulldozers should aim to push soil in a straight line during these operations to minimize material spillage from the sides. Hirayama et al. (2019) developed a path planning algorithm specifically for bulldozers, as shown in Figure 17a. However, this algorithm only considered performance under a single soil pile scenario. In material spreading operations, the “three-knife method,” which involves making three passes over the material pile, is often employed. Taking this principle into account, Sun et al. (2022) applied the CA–BINN algorithm for path planning and successfully achieved efficient earthwork spreading. Unlike

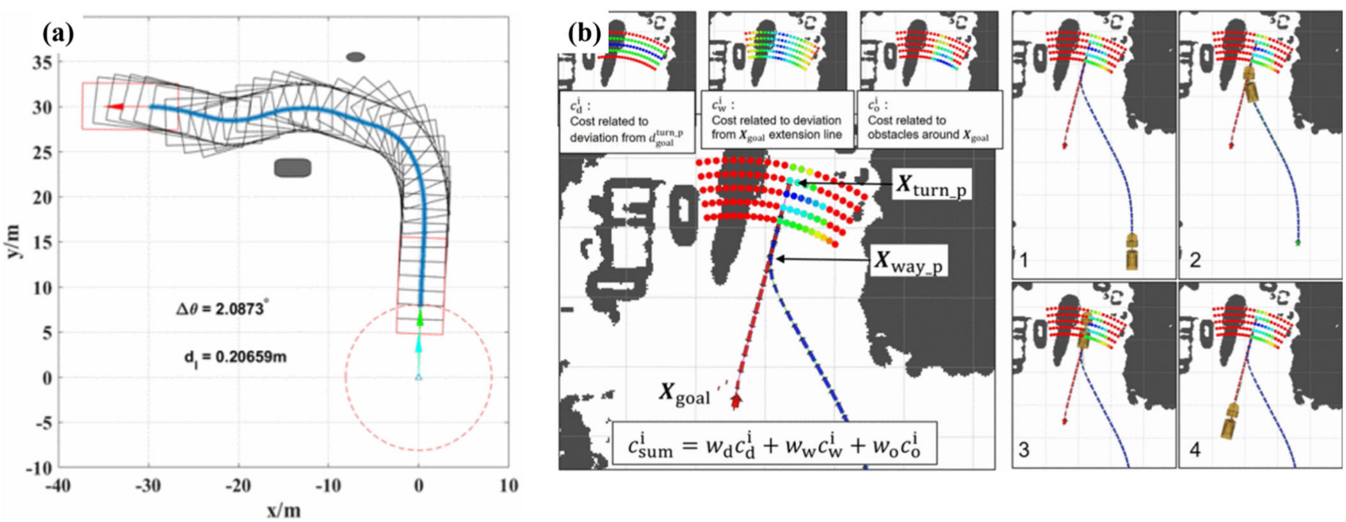


FIGURE 16 | Major challenges in path planning for dump trucks: (a) adaptive dynamic window approach-based directional adjustment (Lei et al. 2021) and (b) determination of optimal turning positions for reversing trucks (Akegawa et al. 2022b). [Color figure can be viewed at wileyonlinelibrary.com]

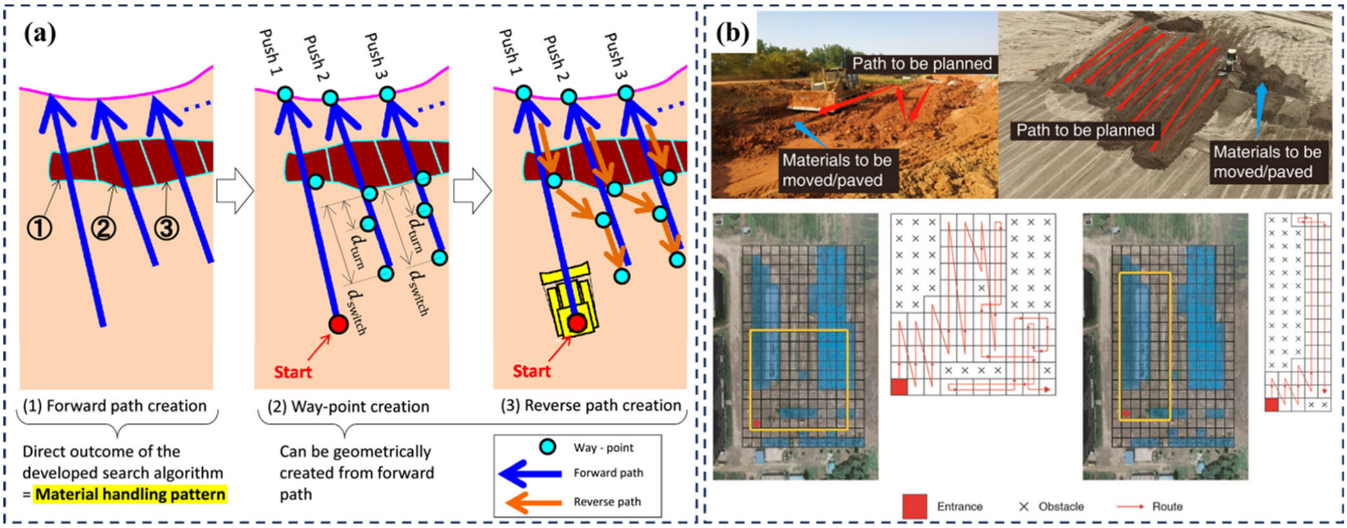


FIGURE 17 | General two kinds of path planning for a bulldozer: (a) interaction with a soil pile (Hirayama et al. 2019) and (b) coverage path planning (Li and Zhou, Huang, and Fränti 2022). [Color figure can be viewed at wileyonlinelibrary.com]

typical construction machinery, bulldozers that perform full-coverage path planning often choose to reverse at a specific angle instead of turning to avoid obstacles or change direction. Traditional path planning methods can lead a bulldozer into a confined "dead zone" due to limited maneuverability. Li et al.(2022) combined the BINN and A* algorithms. In this approach, the first unvisited point within the path becomes the next target, allowing the bulldozer to escape dead zones and continue subsequent coverage tasks. This enhances the bulldozer's full-coverage path planning, as shown in Figure 17b. Matsubara, Tanabe, and Uchimura (2019) developed a distributed deep reinforcement algorithm Advantage Actor–Critic for sediment block clearing path planning approach. However, their approach did not sufficiently account for the movement strategy. To address this problem, Kuzu, Ohashi, and Uchimura (2020) employed a GA to conduct multidirectional and continuous global random searches. This approach generated a route that more closely resembled that of an expert driver. Despite these advancements, the aforementioned methods are not robust enough to handle dynamic environments. Consequently, Osaka et al. (2021) integrated the long short-term memory (LSTM) network into the proximal policy optimization framework. This integration significantly improved the effectiveness of the algorithm in complex and evolving scenarios. Furthermore, You et al. (2022a, 2022b) proposed an end-to-end reversing trajectory planning technology for automated bulldozers. This technology has demonstrated practical application advantages in highly unstructured and construction settings.

4.5 | Rollers

Road rollers play a crucial role in compaction operations for large-scale infrastructure projects, such as highways, railways, and dams (Jia 2016), where soil compaction is achieved through automated and vibratory processes. The primary challenge for automated road rollers is ensuring uniform coverage of the work area, which requires strategic spatial allocation and advanced path planning strategies. However, external environmental disturbances and inherent body vibrations often impede straight-line traversal, necessitating adaptive and precise path optimization methods to ensure complete coverage, especially around edge areas. In response to this challenge, Wang et al. (2020) addressed this challenge by implementing a real-time hill-climbing search algorithm that determines the optimal strip overlap distance, thereby reducing overrolling compared with fixed overlap distance path planning methods. The unique steering mechanism of road rollers imposes curvature constraints, typically limiting their operation to forward or backward linear motion. Additionally, they must adhere to nonintegral motion constraints throughout their operation cycle. To address these complexities, Xu et al. (2019) proposed a path planning approach grounded in SVM and the LAP-CC for automated roller, which solved a problem that traditional path planning methods did not consider, namely, how to solve the problem that the vehicle's unidirectional motion cannot plan a feasible path, as shown in Figure 18, indicating that this method can also adapt to complex 3D terrain. The improved goal-directed rapidly exploring random tree has also proven effective in identifying feasible paths for unmanned rollers (Xu et al. 2020), accommodating multiple forward and backward movements. Regarding the cooperative operation of multiple unmanned rollers, Shi et al. (2022) introduced a multiunmanned roller path planning method based on GAs, which generates collision-free paths within workspaces characterized by obstacles and irregular boundaries. Furthermore, refinements to the dragonfly algorithm (Shi et al. 2020) and ant colony algorithm have been applied to the full-coverage path planning task of an unmanned roller cluster. These enhancements generate the most efficient operational paths for each individual roller, significantly reducing equipment idle time and minimizing overall redundant, ultimately enabling highly efficient and collaborative compaction operations among multiple machines.

4.6 | Others

AI-based path planning algorithms have also been extended to equipment types, such as graders and scrapers, although research in this area remains relatively limited, due to their less

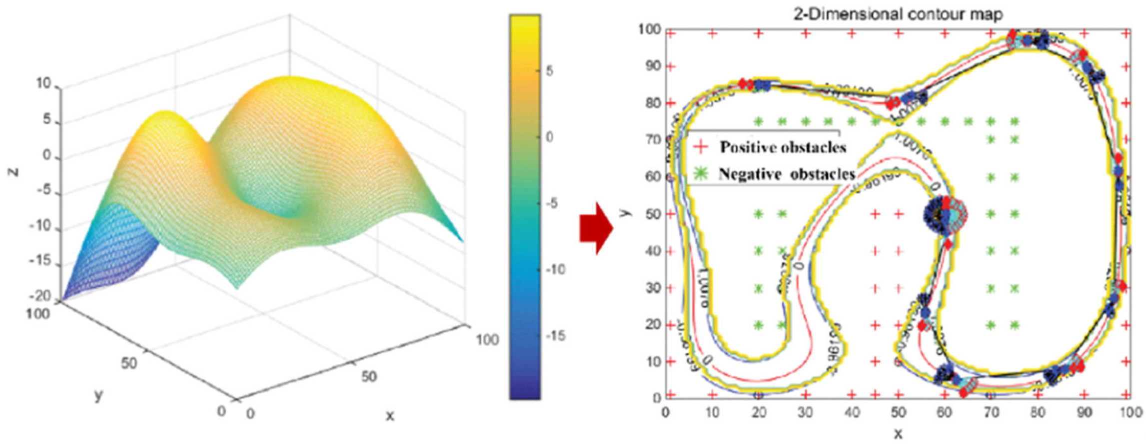


FIGURE 18 | An application of artificial intelligence path planning on roller (Xu et al. 2019). [Color figure can be viewed at wileyonlinelibrary.com]

frequent utilization in earthwork operations. In a notable contribution (Kurniawan et al. 2017), Kurniawan formulated an optimization model for grader routing based on the Bandit algorithm, which was tailored specifically for mining transportation road maintenance tasks. This model has demonstrated a substantial improvement in efficiency, surpassing 40%, in terms of reducing the duration required for road maintenance. Jing, Jin, and Liu (2020) employed the ant colony algorithm to solve the complex 3D path planning problem associated with graders, considering the inherent constraints imposed by the grader's turning radius. Furthermore, AI-informed path planning techniques are similarly being implemented in scrapers to enhance performance in activities such as earthwork leveling (Gwak, Yi, and Lee 2016; Jing, Luo, and Liu 2022), thereby contributing to the professional domain with advanced technological solutions.

Path planning for earthwork machinery presents various challenges due to the complexity of its mechanical structures and functional limitations. Earthwork equipment must adhere to numerous complex constraints while navigating and performing operations. Moreover, nonmechanical constraints such as varying terrain conditions and dynamically evolving environments within earthwork scenarios significantly compound the intricacy of path planning tasks. However, the application of advanced AI techniques, including evolutionary algorithms, swarm intelligence, and machine learning, has to some extent mitigated or resolved these difficulties. These technologies enable the efficient generation of path solutions that exhibit heightened adaptability and superior performance, demonstrating promising potential for broad-scale application in practice (Grigorescu et al. 2020; Liu et al. 2023).

5 | Performance Assessment

5.1 | Planning Objectives/Metrics

Path planning aims to generate the most efficient route plan for earthwork machinery or working attachment, improving efficiency, minimizing consumption, and increasing safety. Given the range of earthwork operations and the complexity of associated tasks, researchers have different focuses and objectives when addressing path planning issues. Therefore, we classify path planning objectives into two primary categories: single-objective path planning and multiobjective path planning.

5.1.1 | Single-Objective Path Planning

Single-objective path planning primarily focuses on maximizing or minimizing a specific performance indicator. The most common single optimization goal is to minimize the path length. In the case of long-distance earthwork transportation tasks, scholars concentrate on reducing fuel consumption by finding the shortest possible transport distance (Figure 19a), Zhang et al. (2022) utilized an adaptive GA for autonomous mining trucks to determine the shortest haulage path, resulting in a 38% reduction in fuel consumption. Burdett and Kozan (2014) combined simulated annealing and evolutionary search algorithms to address complex dynamic and 3D environment path searches. The objective function used was the minimum fuel consumption to identify the shortest or least costly route. In addition to earthwork transportation, the shortest path problem also applies to other earthwork projects. A new tabu search embedded simulated annealing algorithm developed by Lim, Rodrigues, and Zhang (2005) reduced the distance by 21%. Sardarmehni and Song (2023) employed RL to optimize the wheel loader's path with the lowest energy consumption, considering power increases from bucket movement and steering. Choi and Han (2023) introduced an RL model with an attention mechanism that reduced earthwork transportation time by 18.6%. Liang et al. (2021) targeted the total operation time as a comprehensive optimization objective. They applied an improved greedy algorithm for path planning in uncertain scenarios, resulting in a 35% reduction in operating time and significantly enhancing work efficiency. Other optimization goals in earthworks include minimum time consumption (Yang et al. 2021) (Figure 19b) together with total minimum turning distance (Zhang, Yao, and Zhang 2024) (Figure 19c), and maximum coverage area (Osaka et al. 2021). While optimizing a single metric can lead to significant improvements, it may cause performance degradation

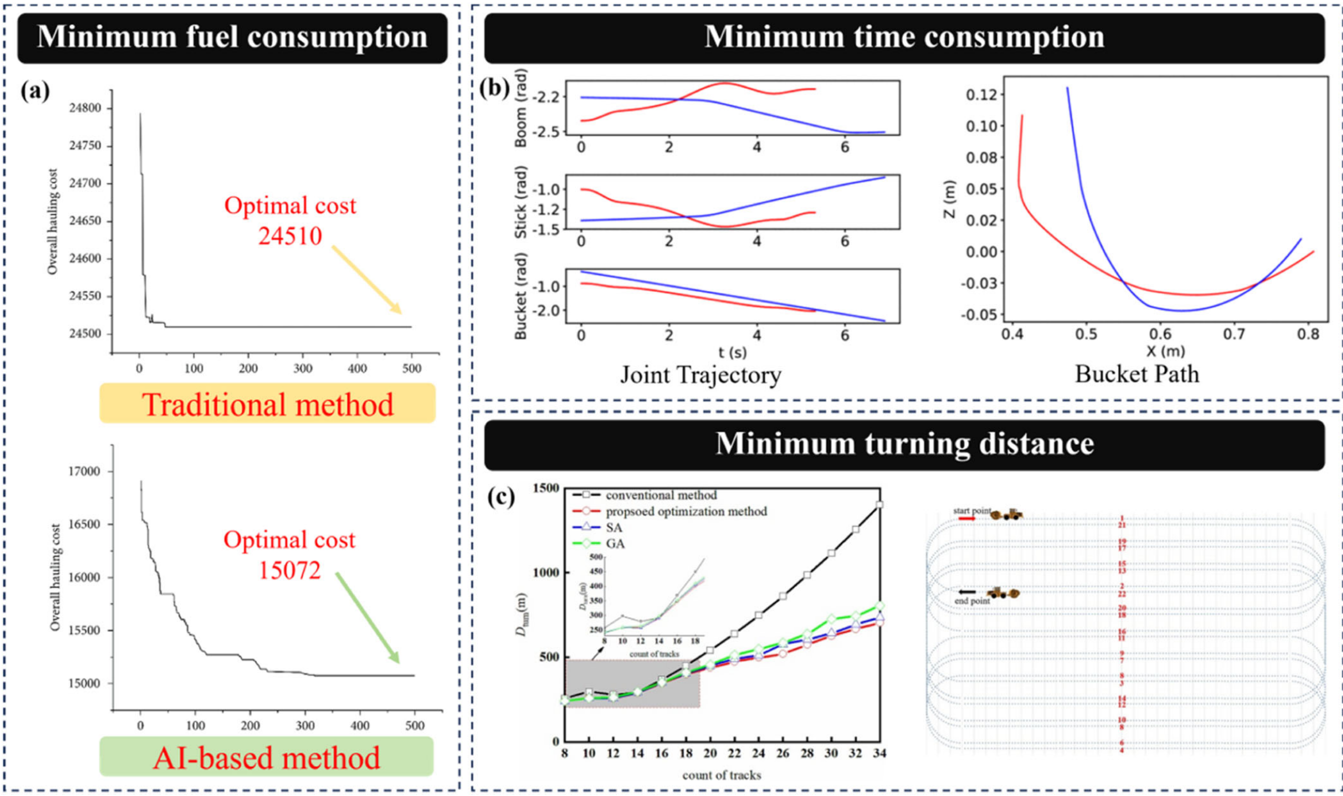


FIGURE 19 | Single-objective optimization results: (a) minimum cost (Zhang et al. 2022), (b) minimum time consumption (Zhang, Yao, and Zhang 2024), and (c) minimum turning distance (Osaka et al. 2021). [Color figure can be viewed at wileyonlinelibrary.com]

in nonkey metrics to achieve optimal results for a single core metric.

5.1.2 | Multiobjective Path Planning

Multiobjective path planning aims to overcome the limitations of single-objective methods in real-world earthwork projects. Soltani and Fernando (2004) addressed safety concerns in earthwork machinery by employing a FL-based multiobjective path planning method. This method focused on minimizing the path length and proximity to danger zones and maximizing visibility, resulting in the generation of safer and more distance-efficient paths. However, this approach may not be as effective in more complex scenarios. Deep RL has also been utilized to solve multiobjective path planning problems in shovel loading scenarios (Jian et al. 2023). Jing, Luo, and Liu (2022) addressed the complex interplay between the shortest working time, minimum steering angle, and minimum cost in land levelling operations. They used an improved multiobjective ant colony algorithm to find better Pareto front solutions, as illustrated in Figure 20a. The experimental results demonstrated that compared with other algorithms, this method exhibit significant improvements in land levelling (Figure 20b). Feng et al. (2023) optimized for the shortest time, smallest energy consumption, and smallest joint impact by utilizing an improved particle swarm algorithm. Despite the computational demands of multiobjective optimization. Yao, Zhao et al. (2023) combined machine learning technology with PINN and PSO to enhance the flexibility of path generation in solving the multiobjective path optimization problem involving excavation time, energy consumption, and bucket filling rate. In addition to the above objectives, factors such as the roll stability of the machine should also be considered comprehensively, and can be further combined with the iterative learning control method (Wu et al. 2021) to generate a stable emergency obstacle avoidance path strategy, which is of great significance for stable operations in highly uncertain earthmoving environments.

5.2 | Planning Validation

On-site experiments play a crucial role in substantiating the efficacy of path planning results, necessitating exposure to diverse environmental conditions to ensure thorough verification. However, our review indicates that only 42% of the surveyed literature has validated their proposed algorithms through actual field tests. This trend can be attributed to several factors. First, the high cost and complex implementation processes often hinder the execution of on-site validation experiments. Second, the fact of AI technology in earthwork path planning is still in the early stages of development, with further advancement before wider adoption in field experimentation. Considering these aspects, three prevailing verification methods have been identified: simulation-based verification, experimental verification using controlled models, and direct on-site experimental validation. Table 4 provides an overview of the experimental configurations, path planning verification results, and additional relevant information.

The simulation of the earthwork environment generally provides a more realistic working environment by simulating various

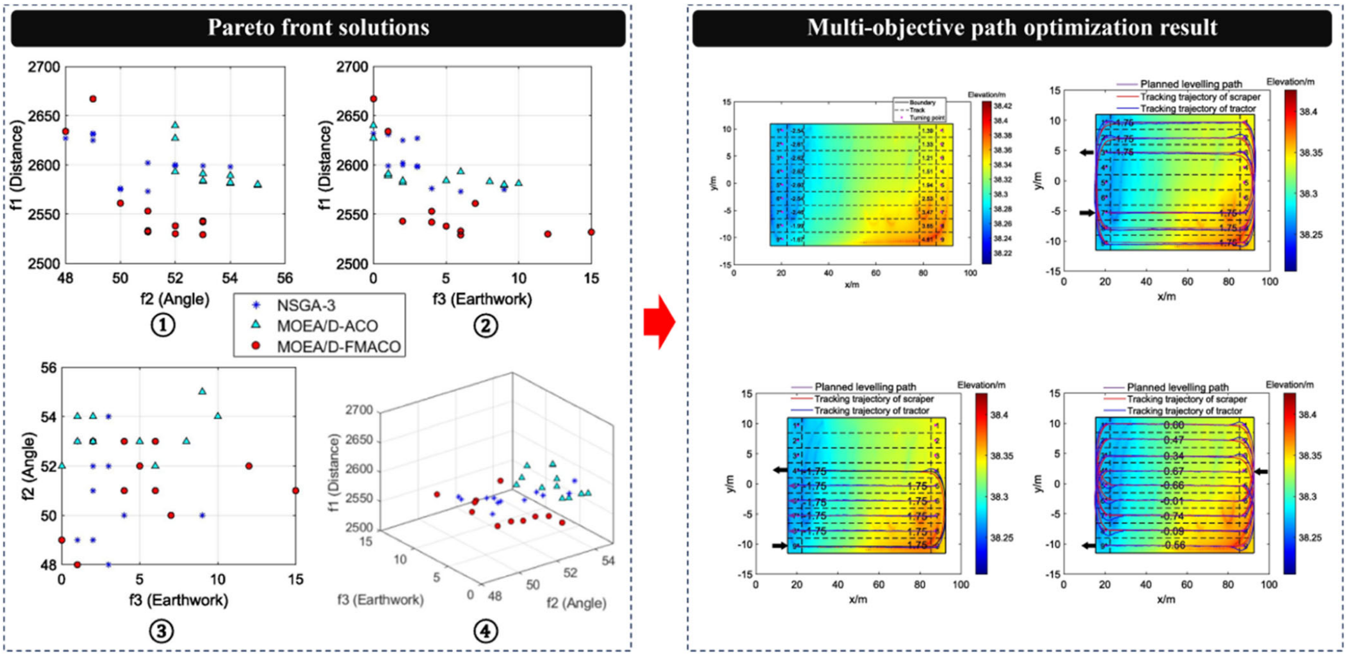


FIGURE 20 | Multiobjective path optimization for autonomous land leveling operation (Jing, Luo, and Liu 2022): (a) Pareto front solutions for the proposed algorithms in the test fields and (b) path planning results of the land leveling operation. ACO, ant colony optimization; D-FMACO, decomposition and further mutation ant colony; MOEA, multiobjective evolutionary algorithm; NSGA, non-dominated sorting genetic algorithm. [Color figure can be viewed at wileyonlinelibrary.com]

TABLE 4 | Analysis of earthwork machinery path planning experiments.

Type	Experimental settings	Algorithm	Validation results	Reference
Simulation	Method: Raster map Area details: In a 30 × 30 grid with obstacles	Improved potential field ant colony algorithm	The best path length of 47.36 was generated around the 20th iteration	Li et al. (2021)
	Method: Sediment motion simulator Area details: In a 50-m^2 simulated environment with sediments	Distributed deep reinforcement learning	Average sediment filling rate of over 95% under the optimal path	Osaka et al. (2021)
Scaled model test	Method: Tests on manipulator arm Area details: In an environment of approximately 4 m^2 with complex rigid materials	A learning-based method	The planner enables higher fill rates and success rates of excavations	Lu and Zhang (2021)
	Method: Tests on wheel loader-type miniature robot Area details: In a 1.4 m × 1.4 m scooping and loading scenario	Improved genetic algorithm	The optimal path is 18.9% shorter than the traditional "V-shaped" path, while the repetition time is shorter.	Takei et al. (2013)
On-site experimental test	Method: Tests on Shantui SD17 bulldozer Area details: In a 75 m × 25 m real earthwork leveling site	BINN hybrid A* algorithm	Reduction in path length, number of turns and repetition rate, while ensuring full-coverage operations	Li et al. (2022)
	Method: Tests on a 5-tonne loader Area details: In a real gravel material loading scenario	Beetle antennae search	Compared with manual operations, the mean fuel consumption per unit shovel weight decreased by 20.35% and the average operating time decreased by 12.08%	Chen et al. (2023)

static obstacles and other elements, as well as complex 3D scenes, or simulating the dynamic changes of the earthwork environment, and even the process of environmental interaction during construction. Due to its repeatability and controllability, Simulation-based validation is an advantageous and cost-effective approach for refining and enhancing algorithms. At the same time, the simulation verification method can meet the needs of technical verification under different scenarios and working conditions. Takei et al. (2015) utilized computational simulations to validate an algorithm for determining optimal paths. Figure 21 demonstrates the process of setting four scooping points randomly and identifying one optimized loading point, along with four corresponding optimized routes. Li et al. (2021) constructed a grid map and used it to simulate earthwork machinery operations in diverse static obstacle environments. After 20 iterations, the simulation successfully converged on the optimal path length, validating the effectiveness of the ant colony algorithm for path planning. Osaka et al. (2021) recognized the need for frequent environmental interactions in RL and developed a sophisticated simulator capable of simulating realistic sediment conditions. This simulator provides a more realistic environment for RL-driven path planning in earthwork tasks. Burdett and Kozan (2014) approached dynamic and 3D situations by employing digraphs to model evolving terrains. Through numerical analysis, they demonstrated that this model identifies both the shortest path and the route with minimum costs. Kawabe, Takei, and Imanishi (2021) conducted simulations involving large-scale environmental changes during gravel pile transportation. These simulations verified the adaptability of their proposed RL method to unforeseen and changing environmental conditions.

When dealing with complex scenarios, the verification of path planning algorithms through simulations can be hindered by significant computational demands and potential limitations in accurately simulating real-world environments. In response to this challenge, the use of model machines provides notable flexibility, aiming to accurately replicate trajectory planning in real conditions via scale models. Lu and Zhang (2021) utilized an arm excavator named "Franka Panda," which is equipped with a 3D-printed bucket, to simulate a standard four-degree-of-freedom excavator, thereby validating a learning-based excavation trajectory planning method. The experimental results demonstrated that this planner achieves higher fill rates and mining success rates. To study the performance of wheel loaders during scooping operations, Takei et al. (2013) constructed a miniature robotic wheel loader, named "Yamazumi4." This one-twentieth-scale replica of a real loader is thoroughly designed to accurately simulate the fundamental motion characteristics of a wheel loader, serving as an effective platform for

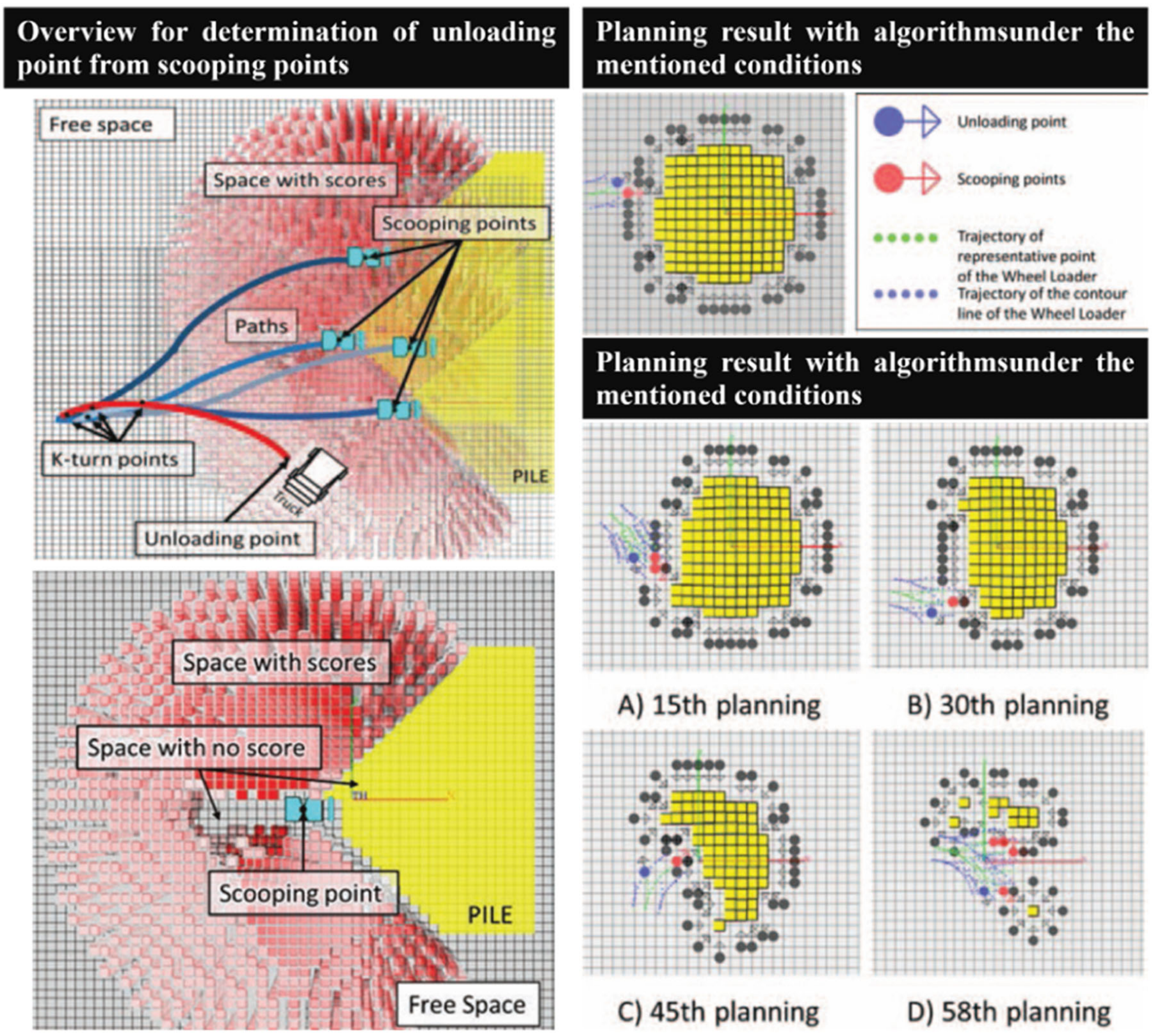


FIGURE 21 | Simulation of the optimal path planning results (Takei et al. 2015). [Color figure can be viewed at wileyonlinelibrary.com]

assessing its path planning effectiveness within scooping operation contexts. To assess the stability of trajectory generation across different terrains and obstacle configurations, Huh et al. (2023) designed and built a scaled-down simulated mining robot. The purpose of this study was to validate a planning system based on LSTM networks that integrates an anticollision algorithm to generate continuous and collision-free excavation trajectories, as illustrated in Figure 22. The experiment successfully verified the reliability of the planning system under complex environmental conditions.

In addition, real-site validations provide insights into the actual performance of path planning results. Son et al. (2020) employed a multilayer perceptron neural network model to authenticate their method across multiple practical scenarios by learning from the real operational trajectory data of expert miners, thereby demonstrating certain levels of generalizability. In another study, Shi et al. (2022) investigated the compaction path planning problem for unmanned rollers under various construction materials, such as rockfill, filter materials, and core wall materials, as depicted in Figure 23. Their research findings indicate that the proposed stripe GA can be effectively utilized in earth compaction tasks when encountering multiple obstacles and diverse material compositions.

6 | Analysis and Discussions

6.1 | Main Challenges

6.1.1 | Complexity of Multiconstrained Path Planning in Earthwork Operations

Complexity of multiconstrained path planning in earthwork operations: In the process of devising operational paths for earthwork machinery, careful consideration must be given to various internal and external constraints, such as the minimum turning radius of construction equipment and mandatory safety distances. Simultaneously, to ensure efficient, safe, and cost-effective execution of earthwork projects, multiple optimization objectives must be balanced, increasing the complexity of solving path planning challenges. Although swarm intelligence and other methods have shown stronger adaptability in dealing with path planning challenges in earthwork environments, such as full-coverage path planning under steering angle constraints and excavation trajectory planning under initial excavation angle and joint angle constraints (Yao, Feng, et al. 2023), However, when addressing the multiconstrained path planning problem in earthwork machinery. These drawbacks include failure to converge on solutions, becoming stuck in local optimums, slow convergence rates, and insufficient solution accuracy.

6.1.2 | Generalization in Unstructured 3D Environments

The path planning of earthwork machinery in 3D terrain is a crucial consideration. On the basis of engineering experience, 3D earthwork areas typically have unstructured characteristics, which presents a significant challenge to the generalization ability of path planning models. Some studies have begun to introduce machine learning algorithms, such as strategies for optimizing neural networks (Hodel 2018) or deep RL methods (Osaka et al. 2021), to enhance the generalization of path planning algorithms to diverse earthwork scenarios. However, most current research focuses only on 2D planar path planning technology and lacks investigations into 3D unstructured earthwork areas. As a result, path planning algorithms have limited generalizability for complex 3D terrains. Some existing

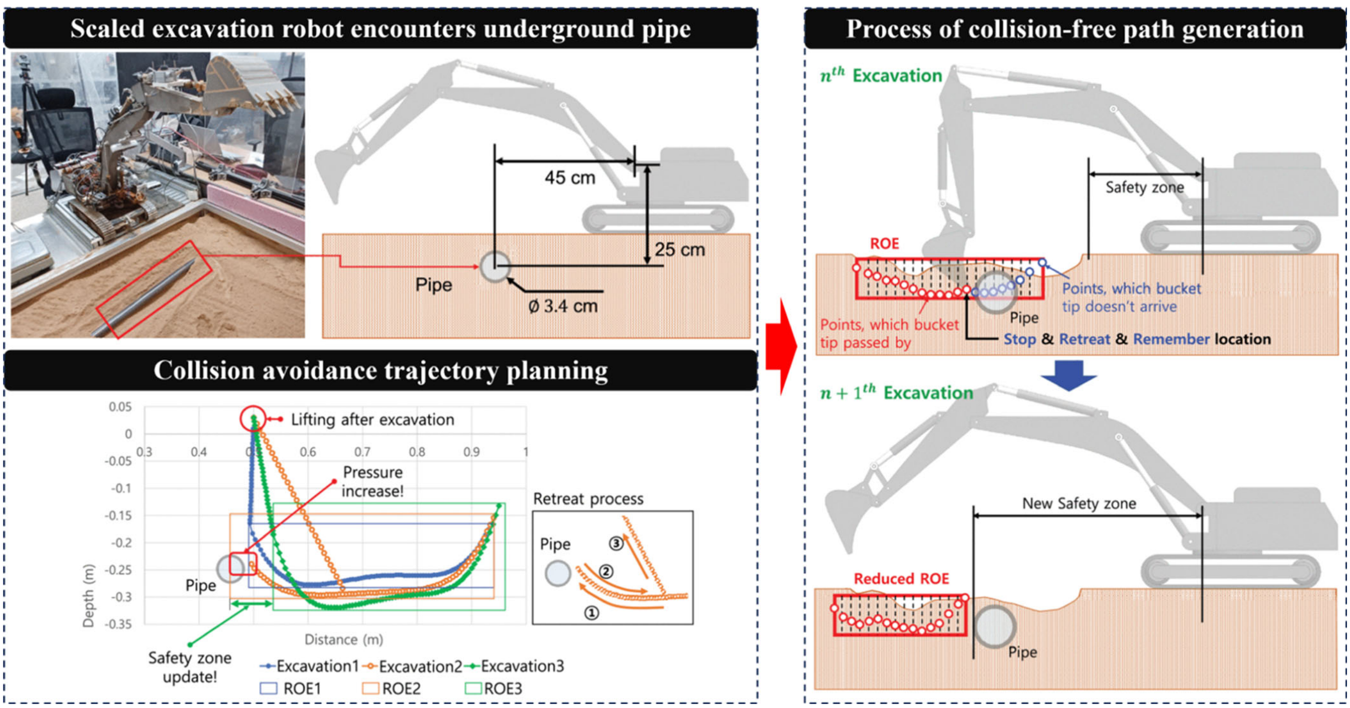


FIGURE 22 | Experiments on trajectory planning for a scaled excavation robot (Huh et al. 2023). [Color figure can be viewed at wileyonlinelibrary.com]

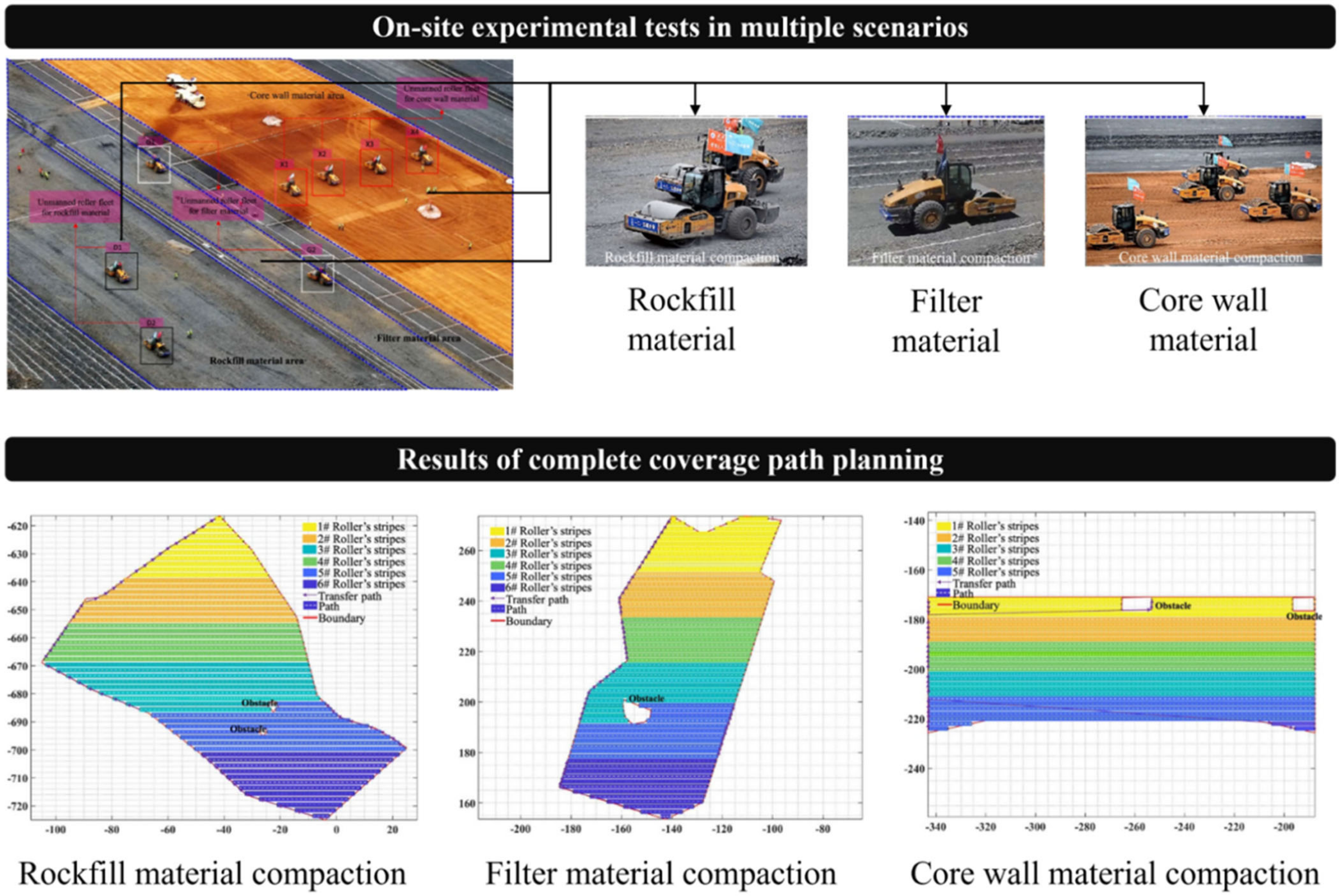


FIGURE 23 | On-site experimental tests with real-sized machines in multiple scenarios (Shi et al. 2022). [Color figure can be viewed at wileyonlinelibrary.com]

research has introduced machine learning algorithms to enhance the generalizability of path planning algorithms for diverse earthwork scenarios. However, these studies have not considered the adverse effects of scene changes, seasonal changes, and severe weather. Therefore, it is crucial to design a comprehensive model for the field of earthworks that can demonstrate good generalizability across multiple scenarios and time periods.

6.1.3 | Adaptability to Dynamic Uncertain Environments

The dynamic path planning of earthwork machinery is a critical concern due to the constant and unpredictable changes in the work environment caused by human activities and interactions with other construction machinery. Failure to adequately factor in these uncertainties during the planning process can increase operational risks. However, devising optimal paths in such dynamic environments is a challenging research problem. Scholars have introduced methods based on enhanced bioinspired networks or FL to address this issue (Lei et al. 2021), or based on collecting obstacle information, obstacle characteristics and physical kinematics, combined with local search particle swarm algorithm to solve the problem of reliable path planning in a dynamic environment (Hu et al. 2022). Despite these advancements, generating consistently optimal paths at an acceptable speed remains a challenge under uncertain conditions. Therefore, there is a pressing need for earthwork machinery to improve its capacity to interact with and adapt to the environment during path adjustment, which would ultimately enhance efficiency and safety in dynamic scenarios.

6.1.4 | Lack of On-Site Experiments in Real Earthwork Scenarios

Currently, there is insufficient research and application of path planning algorithms based on AI technology in real earthwork operation scenarios. According to previous studies and the summary in Table 4, although real-machine experiments are necessary, less than half of the studies use field experiments to verify the performance of the algorithm. This is because it is difficult to simulate real earthwork operation scenarios, such as complex and uncertain soil conditions, and nonideal travel speeds and operation speeds. However, the real earthwork operation environment cannot be fully simulated through simulation experiments and model machine experiments, resulting in inaccurate path planning results. Furthermore, studies have indicated that uncertainty factors in actual operations (Wu et al. 2018) can affect the final path planning results (Gwak, Yi, and Lee 2016), suggesting that simulation results may not be ideal or even valid for real-site verification.

6.2 | Recommendation for Future Work

6.2.1 | Combination of Generative AI With RL

Compared with other AI technologies, generative AI technologies, such as generative adversarial networks and diffusion models, have the ability to learn from data and generate new and diverse outputs. They excel at handling complex and uncertain problems. Conditional generative adversarial network and diffusion model technologies have been utilized in the path planning of autonomous robots, enabling the generation of optimal collision-free paths in complex environments (Ma et al. 2022; Carvalho et al. 2023) and generating reliable paths under internal and external constraints (Yu et al. 2021; Lembono et al. 2021). By integrating the interactive learning advantages of RL with self-game ideas inspired by generative adversarial networks (Wu et al. 2019; Franceschelli and Musolesi 2024), or by using diffusion models to model complex distribution trajectories or improve strategy expressiveness (He et al. 2024), the path planning problem of earthwork machinery can be further improved to solve complex environmental constraints.

6.2.2 | Application of Large Model to 3D Path Planning

To effectively address the complexities of path planning in unstructured 3D environments, it is crucial for the path planning algorithm to have substantial generalization capacity. This capacity ensures the robustness and adaptability of the path planning process across diverse scenarios and terrains. In recent years, large model technology (Hu et al. 2023) has made it possible to solve this problem. This is because large-scale models display exceptional generalizability, maintaining a high level of adaptiveness even in unfamiliar situations. Therefore, leveraging large-scale model technology enables the generation of highly accurate and resilient path solutions in unknown, unstructured 3D settings.

6.2.3 | Adaptive Path Planning via Embodied Intelligence

In dynamic contexts, earthwork machinery must possess real-time environmental interaction capabilities. These capabilities allow machinery to quickly adjust its trajectory and avoid obstacles while maintaining an optimal course. Embodied intelligence technology utilizes sensors and actuators to interface with the environment. This enables a robot to make appropriate decisions and execute actions in response to changing environmental conditions, enhancing its adaptability to complex and evolving environments (Zurbrugg et al. 2022). Integrating this technology into earthwork machinery can strengthen its adaptability to dynamically changing surroundings, optimizing its travel route for efficient and safe navigation.

6.2.4 | Conduction of Real On-Site Validation and Application

At present, most research relies heavily on simulations to validate AI-based path planning technologies. However, due to the challenge of accurately replicating real-world physical conditions through simulations, conducting validations in real-world scenarios is vital. Therefore, a comparative analysis of key performance indicators such as path length and time consumption should be conducted under various construction conditions, including site typologies, terrain slopes and flatness, and mechanical characteristic parameters. This analysis will thoroughly explore the specific mechanisms by which these construction conditions impact the effectiveness of path planning results. Additionally, the effectiveness of path planning under nonideal or suboptimal construction conditions must also be considered. From a practical standpoint in earthwork engineering, the use of appropriately designed AI path planning techniques, or targeted enhancements to existing methodologies, significantly contributes to promoting the deeper application and integration of this technology within the field of earthwork construction.

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Data Availability Statement

The data that support the findings of this study are available on request from the corresponding author. The data are not publicly available due to privacy or ethical restrictions.

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