(IJACSA) International Journal of Advanced Computer Science and Applications,
Vol. 17, No. 5, 2026

Domain Knowledge-Enhanced Welding Robot Path Planning Algorithm

Ming Liu, Peng Shao*
School of Mathematics and Information Science, Chaoyang Normal University, Chaoyang, China

***Abstract*—Welding Robot Path Planning (WRPP) is a core technology for welding automation that seeks an optimal path that satisfies the requirements of the welding process in complex obstacle environments. However, existing algorithms generally lack the integration of knowledge in the welding domain and exhibit insufficient adaptability to complex working conditions. To address these issues, this study proposes a Domain Knowledge-Enhanced Welding Robot Path Planning Algorithm (DKE-WRPP) equipped with a pluggable knowledge fusion framework, which is validated on three representative path planning algorithms: Artificial Bee Colony (ABC), Genetic Algorithm (GA), and Optimal Rapidly-exploring Random Tree (RRT*). Specifically, we first employ Large Language Models (LLMs) to extract domain knowledge such as welding processes and safety distances, and generate standardized knowledge vectors via semantic encoding using a pre-trained language model. Then, a Knowledge Enhancement Module (KEM) is constructed to deeply fuse knowledge features and path geometric features through an attention mechanism, and adaptively update the cost functions of the three baseline algorithms, realizing low-intrusive coupling between domain knowledge and planning algorithms. Finally, experiments in a 300×300 grid environment demonstrate that, compared with traditional algorithms, the knowledge-enhanced algorithms reduce the convergence iterations by more than 33% on average and significantly improve path smoothness. The results fully verify the effectiveness of domain knowledge enhancement and the universality of the pluggable framework, providing an efficient and stable solution for welding robot path planning in complex working conditions.**

Keywords*—*Path planning; intelligent optimization algorithm; welding robot; Large Language Models

I. INTRODUCTION

With the intelligent upgrading of modern manufacturing, robotic technology has evolved from simple industrial automation equipment to sophisticated intelligent autonomous robots. Initially, robots were mainly used for highly repetitive mechanized tasks in industrial production [1]. Driven by advances in computing power, integrated circuits, and sensor technology [2], robots have acquired environmental perception and autonomous decision-making capabilities. Today, robotic applications have expanded from traditional industrial manufacturing to medical, agricultural, welding, and other fields, becoming an indispensable key technology across industries [3].

Welding Robot Path Planning(WRPP) [4], [5], [6], [7] is a core technology of robot intelligence. Essentially, it seeks an obstacle-free optimal path for a welding robot between a start point and a target point under specific optimization criteria. An efficient and reasonable path planning scheme can significantly improve welding efficiency, reduce equipment motion wear, and ensure safe and stable production.

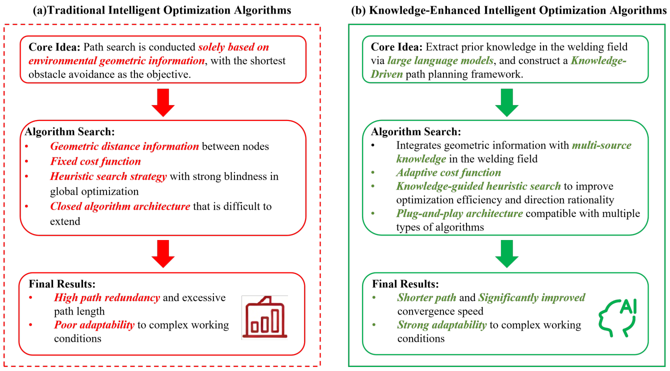


Fig. 1. Comparison of traditional and knowledge-enhanced intelligent optimization algorithms.

In recent years, extensive research [8], [9], [10], [11] has been conducted on welding robot path planning worldwide. Inspired by swarm intelligence and stochastic search, researchers have proposed the Artificial Bee Colony (ABC) algorithm [12], which performs collision-free path optimization through distributed search but suffers from strong search blindness in early iterations, leading to slow convergence. The Genetic Algorithm (GA) [13] was then introduced to achieve global path search via crossover, mutation, and selection mechanisms, yet it still faces issues such as premature convergence and insufficient path smoothness. Subsequently, intelligent optimization methods such as the Optimal Rapidly-exploring Random Tree (RRT*) [14] algorithm emerged. With probabilistic completeness and asymptotic optimality, these methods have partially alleviated the problem of finding optimal paths in complex environments.

Despite progress in geometric path planning, the limitations of these methods have become increasingly prominent. Existing algorithms generally **lack integration with welding domain knowledge** and **have poor adaptability to complex working conditions**, which increases computational overhead and severely degrades model performance [15], [16], [17], [18], [19], [20]. As shown in Fig. 1(a), traditional intelligent optimization algorithms perform path search solely based on environmental geometric information, with a closed architecture relying only on geometric distance between nodes. In multi-constrained practical welding scenarios, such algorithms tend to generate redundant paths and low process matching, failing to meet the demands of high-precision automated welding.

---

*Corresponding author

Notably, Large Language Models (LLMs) [21] offer a new approach for overcoming the knowledge bottleneck in traditional path planning, owing to their superior capabilities in knowledge extraction and multi-source information fusion. As illustrated in Fig. 1(b), a knowledge-driven path planning framework can be built based on LLMs. By fusing geometric information with multi-source welding domain knowledge, it effectively mitigates insufficient domain knowledge and poor adaptability to complex working conditions. Meanwhile, an adaptive cost function and pluggable architecture ensure compatibility with various baseline algorithms, exhibiting strong generality and helping to improve performance in welding robot path planning.

To solve the above problems, this study proposes a Domain Knowledge-Enhanced Welding Robot Path Planning Algorithm (DKE-WRPP). This algorithm combines LLMs with traditional intelligent optimization algorithms to build a knowledge-driven path planning framework, which effectively enhances the adaptability and optimization efficiency of the algorithm in complex welding conditions. Specifically, we first extract welding process, safety distance, and other domain knowledge using LLMs, then perform semantic encoding via the pre-trained language model BERT to generate standardized knowledge vectors. Next, we construct a Knowledge Enhancement Module (KEM) that deeply fuses knowledge features with path geometric features through an attention mechanism, and adaptively updates the cost functions of three mainstream path planning algorithms—ABC, GA, and RRT*—to achieve low-intrusive, highly universal coupling between knowledge and algorithms. Finally, simulation experiments are carried out in a 300×300 grid environment. Experimental results show that the proposed knowledge-enhanced algorithm significantly outperforms traditional algorithms in welding robot path planning, fully verifying the effectiveness of domain knowledge enhancement and the universality of the pluggable framework. This work provides an efficient and stable solution for path planning in complex welding scenarios.

The main contributions of this study are as follows:

- We combine Large Language Models with intelligent optimization algorithms for the first time to construct a knowledge-driven path planning framework, which solves the problems of insufficient domain knowledge and poor condition adaptability in traditional algorithms.
- We design a lightweight, pluggable knowledge enhancement module and adaptive cost function that require no changes to the original algorithm structure, enabling high generality and flexible adaptation.
- We validate the proposed method on three mainstream algorithms (ABC, GA, RRT*), providing an efficient and stable path planning scheme for complex welding scenarios.

II. RELATED WORK

Welding robot path planning (WRPP) [4], [5], [6], [7] aims to generate an optimal welding path for robots under given constraints, with the objective of minimizing the time or distance required to complete welding tasks. As a key enabling technology for advanced manufacturing and welding engineering, its performance directly determines the stability and efficiency of the welding process. Early studies mainly focused on spot-welding tasks using a single welding robot [22], [23], in which the robot traverses all welding points sequentially and returns to the origin. This workflow is highly similar to the classic Traveling Salesman Problem (TSP) [24]. However, such modeling is only applicable to ideal spot-welding scenarios with fixed structures and simple constraints, and tends to result in path redundancy and slow convergence in complex unstructured welding environments.

With the rapid development of intelligent optimization algorithms, Marco Dorigo et al. proposed the Ant Colony Optimization (ACO) algorithm [25], which simulates the foraging behavior of ant colonies and achieves global optimization in the solution space through pheromone positive feedback. On this basis, Sharma et al. adopted classic path search algorithms such as Dijkstra's algorithm [26] to quickly obtain the shortest path using a greedy strategy. Strub et al. introduced an adaptive heuristic function into the A* algorithm [27], effectively improving path search efficiency in static structured environments. Wu et al. integrated the Genetic Algorithm (GA) [13] into the planning process to enhance global optimization capability via evolutionary operations, including crossover and mutation. Shen et al. applied the global search performance of the Artificial Bee Colony (ABC) [28] algorithm to welding robot path planning. Although traditional intelligent algorithms exhibit certain planning performance in simple static scenarios, they have obvious drawbacks in complex welding conditions, such as delayed pheromone update [29] and insufficient dynamic adaptability [30].

To address the above problems, researchers have attempted to improve the algorithms from a mechanism perspective. Wang et al. proposed an improved Ant Colony Optimization algorithm based on Monte Carlo (MC-IACO) [31], which replaces the traditional pheromone update mechanism with a Monte Carlo factor and effectively enhances the global exploration and local exploitation capabilities of the algorithm. Hasselt et al. presented an improved path planning algorithm based on Double DQN [32], [33], [34], achieving local performance optimization in specific complex scenarios. Tran et al. introduced a multi-sensor interaction strategy [35] to improve environmental perception accuracy. Rostami et al. proposed an improved artificial potential field obstacle avoidance algorithm [36], which exhibits satisfactory path planning and obstacle avoidance performance in a single static obstacle environment.

Despite certain progress achieved in the above studies, they still fail to deeply integrate cross-scenario knowledge in the welding domain. When facing complex and multi-source working environments, the algorithms exhibit weak adaptive matching capability and poor knowledge reusability, eventually resulting in excessively redundant planned paths.

In recent years, Large Language Models (LLMs) [21], [37] have offered novel solutions for WRPP tasks. LLMs possess strong knowledge extraction and semantic understanding capabilities [38], [39], [40], enabling the conversion of unstructured data such as text and images into standardized structured knowledge. This effectively compensates for the deficiencies in knowledge representation and adaptive decision-making of traditional methods. Han et al. fused environmental perception

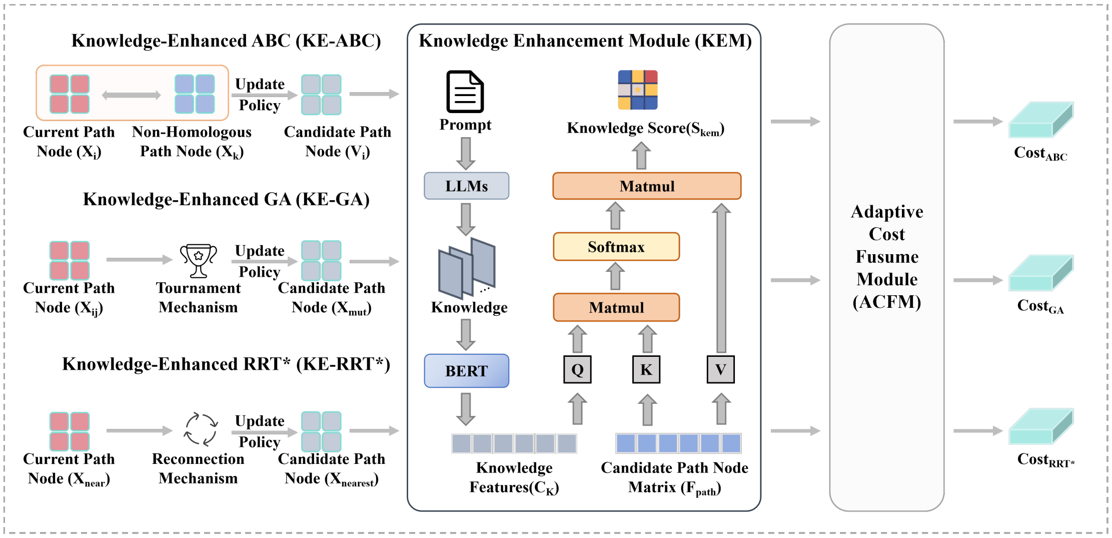


Fig. 2. Framework of the Domain Knowledge-Enhanced Welding Robot Path Planning Algorithm (DKE-WRPP).

knowledge with deep reinforcement learning [41], significantly enhancing the navigation adaptability of mobile robots in complex scenarios. Li et al. realized unified representation of multi-source heterogeneous information through large-scale model enhancement [42], providing crucial support for the application of cross-scenario navigation technology. Gómez-Espinosa et al. achieved high-precision extraction of weld paths based on depth RGB sensors [43], delivering accurate support for robot trajectory generation. Tran et al. fused visual perception features from multi-sensor fusion with prior welding operation knowledge, further improving the robustness of weld tracking and path planning [44].

In summary, existing methods exhibit obvious deficiencies in knowledge fusion and generalization. To this end, this study introduces welding domain knowledge into intelligent path planning optimization algorithms, and uses large language models to achieve domain knowledge extraction and fusion, effectively alleviating the poor generalization and insufficient dynamic adaptability of traditional methods. Meanwhile, the domain knowledge enhancement model constructed in this study is lightweight and pluggable, which can be flexibly embedded into mainstream path planning algorithms, significantly improving the stability and reliability of the algorithm in complex welding conditions.

III. METHODS

A. Overview

The proposed Domain Knowledge-Enhanced Welding Robot Path Planning (DKE-WRPP) framework is shown in Fig. 2. Most previous path planning methods have obvious limitations: they fail to effectively mine and utilize welding-specific knowledge, and exhibit poor adaptability in complex welding scenarios, making it difficult to meet practical production requirements. To solve this problem, this study focuses on the core task of welding robot path planning and designs an improved framework with both knowledge-driven and condition-adaptive capabilities.

First, we employ the knowledge extraction capability of Large Language Models (LLMs) to accurately extract welding domain knowledge. Then, we use the pre-trained language model BERT to perform knowledge semantic encoding and generate standardized knowledge vectors. Next, we construct a Knowledge Enhancement Module (KEM) and introduce an attention mechanism to deeply fuse knowledge features and path geometric features. Finally, we update the cost functions of the three baseline algorithms through the Adaptive Cost Fusion Module (ACFM), realizing low-intrusive coupling between domain knowledge and path planning algorithms while ensuring the pluggability of each module in the framework to adapt to various welding path planning scenarios.

B. Simulation Environment Construction

To fully demonstrate the effectiveness and robustness of the DKE-WRPP framework, simulation experiments are conducted in a 300×300 grid environment. First, to simulate random obstacles such as spatters and fixtures in actual welding conditions, a random obstacle generation mechanism is introduced in the initialization phase. Static obstacles are randomly generated at different positions according to the obstacle distribution in a real welding workshop, providing an experimental environment close to actual working conditions for subsequent algorithm performance evaluation and ensuring the scientificity and reliability of experimental results.

First, we randomly generate K obstacles ($K \geq 100$) in the 2D workspace $W = \{(x, y) \mid x_{min} \leq x \leq x_{max}, y_{min} \leq y \leq y_{max}\}$ to simulate the distribution characteristics of obstacles such as spatters and fixtures in a real welding workshop. The set of obstacle center coordinates is denoted as $O_c = \{o_1, o_2, \ldots, o_K\}$. Then, the center coordinates (x, y) of obstacles are randomly sampled through the uniform distribution U:

$$x_k \sim U(x_{min}, x_{max}), \quad y_k \sim U(y_{min}, y_{max}), \tag{1}$$

where, the center coordinate of the k-th obstacle is denoted as $o_k = (x_k, y_k)$.

Considering the actual physical volume of obstacles and the safety boundary of the welding robot, we expand an expansion radius R_k outward from each random center point o_k to form a single obstacle entity area O_k. The total obstacle area O_{total} in the workspace can be expressed as the union of all random obstacle areas:

$$O_{total} = \bigcup_{k=1}^{K} \left\{ p \in W \;\middle|\; \|p - o_k\|_2 \leq R_k \right\} \tag{2}$$

where, p is any point in the motion trajectory $P = \{p_1, p_2, \ldots, p_M\}$ of the robot in the workspace, used to describe position coordinates in space; $\| \cdot \|_2$ denotes the Euclidean distance, used here to calculate the straight-line distance between point p and obstacle o_k.

Meanwhile, to ensure the reachability of path planning, a legitimacy check mechanism is applied when randomly generating obstacle points to automatically eliminate invalid obstacles that surround the start point p_{start} or target point p_{goal}. Finally, the valid random obstacle center set O is obtained:

$$O = O_{total} - O_n \tag{3}$$

$$O_n = \{o_k \mid \|p_{start} - o_k\|_2 < R_k \cup \|p_{goal} - o_k\|_2 < R_k\} \tag{4}$$

C. Knowledge Feature Representation

Welding trajectories in complex obstacle environments must satisfy both collision avoidance requirements and welding process specifications. Traditional algorithms struggle to effectively utilize process prior knowledge. This study uses Large Language Models to extract welding domain rules and generates high-dimensional semantic feature vectors via pre-trained BERT to provide computable prior inputs for the algorithm. Chain-of-Thought (CoT) [45] is adopted to design structured prompts $Prompt$, guiding the model to focus on environmental features, robot kinematic constraints, and welding process specifications to fully cover complex process requirements:

$$T = LLMs(Prompt), \tag{5}$$

where, $T = \{t_1, t_2, \ldots, t_N\}$ represents a structured set of domain knowledge, N is the total number of extracted domain rules, and t_i represents the $i-th$ specific knowledge description text, e.g., “The welding path should maintain stable weld bead direction continuity, prefer feasible, smooth, and target-close trajectories; reduce sharp turns and redundant detours while meeting process safety distance constraints, and avoid high-risk obstacle areas”. These natural-language specification texts form the prior input for the subsequent knowledge enhancement module.

Then, deep semantic feature extraction is performed on the domain knowledge set T through the pre-trained language model $BERT$. For each knowledge text t_i in the set, we first discretize it into a token sequence using a tokenizer, and insert the token and token at the beginning and end of the sequence, respectively. The token sequence is then mapped into a dense continuous vector representation through the embedding layer:

$$E_i = \text{Embedding}(t_i) \in \mathbb{R}^{L_i \times d}, \tag{6}$$

where, $\text{Embedding}(\cdot)$ denotes the embedding layer mapping function of the BERT model, converting discrete token sequences into dense representations in a continuous vector space. Its output fuses Token Embedding and Position Embedding, encoding the semantic information of tokens and their positional information in the sequence, respectively. L_i is the length of the token sequence of the $i-th$ knowledge text after tokenization, and d is the embedding dimension.

Then, E_i is fed into the encoder of the Multi-Head Self-Attention mechanism to deeply parse the implicit logical connections between welding domain knowledge using its adaptive global context perception capability, obtaining a representation vector h_i containing global semantic information:

$$h_i = \text{BERT}(E_i) \in \mathbb{R}^{d}, \tag{7}$$

$$C_K = [h_1, h_2, \ldots, h_N]^T \in \mathbb{R}^{N \times d}, \tag{8}$$

where, d denotes the hidden layer dimension of the pre-trained language model. C_K is a standardized feature matrix (knowledge vector) containing all welding prior knowledge, which deeply integrates welding process semantic features and is completely decoupled from the underlying path planning algorithms. This vectorization method of domain prior knowledge provides theoretical support for the Knowledge Enhancement Module (KEM) to achieve high generality and pluggable coupling.

D. Knowledge Enhancement Module (KEM)

After obtaining the standardized knowledge vector C_K, this study constructs a Knowledge Enhancement Module (KEM). This module establishes a mapping between the high-dimensional semantic space and the geometric space through the cross-attention mechanism, evaluates the matching degree between the planned path and the prior knowledge of welding processes, and adaptively adjusts the cost function of the benchmark algorithm.

To ensure the generality of the framework, KEM is designed as a low-intrusion, plug-and-play module. It only guides the search direction through the cost function evaluation process without modifying the underlying path search algorithm.

Specifically, KEM first extracts features of path nodes and their adjacent poses from motion trajectory P to obtain the path feature matrix F_{path}. Then, it performs cross-attention calculation $CrossAtt(\cdot)$ between F_{path} and the knowledge vector C_K, realizing cross-modal fusion of geometric features and domain knowledge. Finally, the fused features are used to adjust the cost function, providing effective support for path optimization and evaluation.

$$CrossAtt\left(\mathcal{Q},\mathcal{K},\mathcal{V}\right)=softmax\left(\frac{\mathcal{Q}\mathcal{K}}{\sqrt{d_{attn}}}\right)\mathcal{V}, \tag{9}$$

$$S_{kem}(C_K,F_{path})=CrossAtt\left(C_K,F_{path},F_{path}\right), \tag{10}$$

where, the knowledge vector C_K acts as the query vector $\mathcal{Q}$, and the path feature matrix F_{path} is linearly projected into the key matrix $\mathcal{K}$ and value matrix $\mathcal{V}$. d_{attn} is the hidden layer dimension. $Softmax$ denotes the normalization function, which weights and sums the value matrix, finally outputting a knowledge matching score $S_{kem}(\cdot)$ ranging from 0 to 1. This score intuitively reflects the extent to which the current path follows the welding process priors defined in the text.

E. Adaptive Cost Fusion Module (ACFM)

To achieve seamless coupling with diverse baseline algorithms, this study designs a unified adaptive cost function update paradigm. For both global swarm intelligence algorithms (e.g., ABC, GA) for fitness evaluation and incremental sampling algorithms (e.g., RRT*) for local reconnection cost decision-making, the composite cost function $Cost_{total}(\cdot)$ is composed of the basic geometric cost $Cost_{geo}(\cdot)$ plus an adaptive knowledge penalty term:

$$Cost_{total}=Cost_{geo}(F_{path})+\lambda\cdot\left(1-S_{kem}(C_K,F_{path})\right), \tag{11}$$

where, λ is the knowledge gain coefficient, used to adjust the intervention weight of prior knowledge in the path optimization process. When the knowledge matching score S_{kem} approaches 1, the path highly complies with welding process specifications, and the knowledge penalty term tends to zero. Conversely, if the path has sharp turns or is close to dangerous obstacles, a high penalty cost is triggered. The pseudocode of the ACFM calculation process is shown in Algorithm 1.

Algorithm 1 Adaptive Cost Fusion Module (ACFM)

```
input: $C_K$: standardized knowledge vector;
       $allowed\_X$: list of accessible candidate nodes / paths;
       $Cost_{geo}(\cdot)$: geometric cost function;
       $S_{kem}(\cdot)$: cross-attention knowledge matching function;
       $\lambda$: knowledge penalty gain coefficient.
output: Adaptive total cost array $Cost_{total}$.
Initialize $list\_1, list\_2 \leftarrow []$. for $X_j \in allowed\_X$ do:
    $list\_1[j] = \lambda \cdot (1 - S_{kem}(C_K, X_j))$
    $list\_2[j] = Cost_{geo}(X_j)$
end for
Fuse geometric cost with knowledge penalty:
    $Cost_{total} \leftarrow list\_2 + list\_1$
return $Cost_{total}$
```

1) Knowledge-Enhanced ABC Algorithm (KE-ABC): This study proposes a Knowledge-Enhanced Artificial Bee Colony (KE-ABC) algorithm, which embeds the Knowledge Enhancement Module (KEM) into its core evolutionary mechanism to realize the joint drive of geometric features and welding prior knowledge, thereby avoiding the problem of traditional ABC algorithms [12] falling into local optima.

Specifically, in the employed bee phase, the algorithm first performs local mutation search in the neighborhood of the memorized path X_i, and its spatial position update strategy is formalized as:

$$V_i=X_i+\phi_i(X_i-X_k), \tag{12}$$

where, V_i represents the generated candidate path node, X_k is another non-homologous path node randomly selected from the population ($k\neq i$), and ϕ_i is a random disturbance factor uniformly distributed in $[-1,1]$, used to control the step size of local exploration.

After generating the candidate path, we calculate the physical geometric cost $Cost_{geo}(V_i)$ of the candidate path node V_i and the knowledge matching score $S_{kem}(V_i,C_K)$ of the path with the knowledge vector C_K. Thus, the composite cost function $Cost_{ABC}$ fused with welding domain rules is defined as follows:

$$Cost_{ABC}=Cost_{geo}(V_i)+\lambda_{abc}\cdot\left(1-S_{kem}(C_K,V_i)\right), \tag{13}$$

where, λ_{abc} is the knowledge gain weight coefficient.

Finally, in the scout bee phase, if the fitness $Cost_{ABC}$ of a path stagnates after multiple iterations, a reset mechanism is triggered.

2) Knowledge-Enhanced GA Algorithm (KE-GA): The Genetic Algorithm [13] (GA) relies on global parallel search and population evolution mechanisms. In multi-constrained welding tasks, it easily guides the population to evolve toward regions with infeasible spatial postures or drastic curvature changes, generating a large number of invalid iterations. To this end, this study introduces the cross-modal semantic evaluation of the Knowledge Enhancement Module (KEM) into the genetic algorithm to construct a Knowledge-enhanced Genetic Algorithm (KE-GA).

Specifically, KE-GA adopts Tournament Selection in the selection operator, screening individuals with the minimum composite fitness from the candidate subset with absolute probability to enter the mating pool. Then, uniform crossover is used to complete allele exchange of the local spatial topology of the parents. Finally, Gaussian random disturbance is introduced to apply physical position offset to the offspring waypoints, and its mutation update mechanism is formalized as:

$$X_{mut}=X_{ij}+\mathcal{N}(0,\sigma^2), \tag{14}$$

where, X_{mut} is the position of the $i-th$ individual in the j-dimensional space after mutation. $\mathcal{N}(0,\sigma^2)$ is Gaussian noise with zero mean and variance σ^2. The introduction of Gaussian mutation aims to continuously expand the exploration boundary of the feature solution space and effectively prevent population homogenization from falling into local extremes.

Then, the algorithm reconstructs its fitness evaluation into a composite function $Cost_{GA}$ of basic geometric cost and knowledge penalty term, with the formula as follows:

$$Cost_{GA} = Cost_{geo}(X_{mut}) + \lambda_{ga} \cdot (1 - S_{kem}(C_K, X_{mut})) , \tag{15}$$

where, λ_{ga} is the penalty weight regulating the strength of process prior constraints.

The new population after crossover and mutation operations is again re-evaluated for process compliance by the KEM module, supplemented by an elite retention strategy. KE-GA not only retains the breadth of global optimization but also continuously injects multi-modal welding prior knowledge into the genetic evolution process, significantly improving the industrial practicality of the final trajectory.

3) Knowledge-Enhanced RRT Algorithm (KE-RRT*):* The Optimal Rapidly-exploring Random Tree [14] (RRT*) algorithm relies solely on Euclidean distance metrics during tree expansion, easily generating trajectories close to obstacles. To this end, KE-RRT* deploys the Knowledge Enhancement Module (KEM) into the edge-level expansion logic.

Specifically, we calculate the knowledge matching score $S_{kem}(X_{nearest}, C_K)$ between the nearest node $X_{nearest}$ and the knowledge vector C_K to construct the cumulative composite cost $Cost_{RRT*}(X_{nearest})$ for local expansion:

$$\begin{aligned} Cost_{RRT*} = {} & Cost_{geo}(X_{nearest}) \\ & + \lambda_{rrt*} \cdot (1 - S_{kem}(C_K, X_{nearest})) , \end{aligned} \tag{16}$$

where, λ_{rrt*} is the knowledge penalty gain coefficient.

To ensure both asymptotic optimality of the trajectory and process compliance, KE-RRT* reconstructs the core reconnection mechanism with knowledge. For any potential node X_{near} in the neighborhood, the judgment condition for the reconnection operation is defined as:

$$\begin{aligned} & Cost_{geo}(X_{near}) \\ & + \lambda_{rrt*} \cdot (1 - S_{kem}(C_K, X_{near})) < Cost_{RRT*} . \end{aligned} \tag{17}$$

Once the above formula holds, it indicates that the local path redirected via X_{near} has a better total length, and the algorithm immediately updates its parent node and cumulative cost.

IV. EXPERIMENTS

In the following sections, systematic simulation experiments are conducted on the welding robot path planning task to comprehensively evaluate the proposed DKE-WRPP framework. This study takes three mainstream path planning algorithms as baselines, each connected to a pluggable Knowledge Enhancement Module (KEM). Simulation results show that DKE-WRPP significantly outperforms various baseline intelligent algorithms and verifies the generality of the pluggable knowledge framework.

A. Experimental Setup

1) System setup: In terms of hardware configuration, the experiment uses an NVIDIA A40 GPU as the core computing device, providing sufficient computing power for algorithm operation and domain knowledge encoding, effectively reducing the runtime of large-scale simulation experiments. In terms of software configuration, the experimental program is developed based on Python, and Matplotlib is used for visual display of results. All software adopts stable and compatible versions and has undergone multiple rounds of compatibility testing to ensure the stable operation of the entire experimental process.

TABLE I. SIMULATION ENVIRONMENT AND CORE PARAMETER SETTINGS FOR BASELINE ALGORITHMS.

Module/Algorithm	Parameter Name	Set Value
Common Parameters	Grid space size	300×300
	Number of static obstacles	100
	Safety obstacle avoidance buffer / mm	5.0
	Knowledge module penalty weight (λ)	140.0
ABC Algorithm	Total colony size	30
	Maximum iterations	200
	Path control way points	8
	Stagnation tolerance limit	50
GA Algorithm	Population size	50
	Maximum iterations	200
	Crossover probability	0.8
	Mutation probability	0.15
	Elite retention ratio	10%
RRT* Algorithm	Maximum samples	4000
	Node expansion step size / mm	2.0
	Neighborhood reconnection radius / mm	10.0
	Goal-biased sampling probability	10%

2) Parameter settings: The parameter settings of the three baseline algorithms refer to typical configurations in the field of welding robot path planning [46], adjusted according to the 300×300 grid scenario and obstacle avoidance requirements of this experiment to ensure full performance of each algorithm, as shown in Table I. The number of obstacles is set to 100, the safety obstacle avoidance buffer distance is 5.0 mm, and the penalty weight of the knowledge module is set to 140.

a) Artificial Bee Colony Algorithm (ABC) (Table I): The total colony size is set to 30, including 15 employed bees and 15 onlooker bees, balancing the global exploration and local exploitation capabilities of the algorithm; the maximum number of iterations for the entire colony is set to 200; the maximum number of nodes allowed for the welding robot motion path is limited to 8; the stagnation tolerance limit is 50.

b) Genetic Algorithm (GA) (Table I): The population size is set to 50, the number of iterations is set to 200, the crossover probability is 0.8, and the mutation probability is 0.15, balancing population diversity and algorithm convergence speed; the selection operator adopts roulette wheel selection, the crossover operator adopts single-point crossover, and the mutation operator adopts random mutation to improve algorithm optimization efficiency. Meanwhile, the elite retention ratio is 10%.

c) Optimal Rapidly-exploring Random Tree Algorithm (RRT) (Table I):* The sampling area is consistent with the 300×300 grid scenario; the maximum number of samples is set to 4000, the node expansion step size is 2 mm, and the neighborhood reconnection radius is 10 mm, ensuring the algorithm can quickly search for feasible paths; the goal-biased sampling probability is 10%, and the optimal solution is determined when the deviation between the sampling node and the end point coordinate is less than this threshold.

3) Evaluation metrics: To comprehensively evaluate the effect of the algorithm, four core evaluation metrics [47] are selected in the experiment, evaluated from four dimensions:

a) Path Length (unit: mm): The total length of the planned path from the start point to the end point of the robot.

b) Runtime (unit: s): The total time taken by the algorithm to complete one path planning.

c) Path Smoothness: The amplitude of angle change and curvature mutation between adjacent nodes in the planned path.

d) Iteration Convergence Count: For ABC and GA algorithms, it refers to the number of iterations to reach the optimal solution; for RRT* algorithm, it refers to the number of samples to reach the optimal solution.

TABLE II. Comparison of Performance Metrics for Various Algorithms in a 300 × 300 Complex Environment.

Algorithm	**Path Length(mm)**	**Smoothness**	**Iterations**	**Time(s)**
ABC[12]	380.432	0.0334	214	1.15
GA[13]	382.105	0.0566	231	1.32
RRT*[14]	366.892	0.0487	190	0.78
KE-ABC	378.210	0.0215	142	1.98
KE-GA	377.554	0.0302	155	2.12
KE-RRT*	359.115	0.0240	124	1.85

B. Baselines

This experiment selects three mainstream intelligent algorithms widely used in the path planning field with stable performance as baselines. Their core logic and optimization mechanisms have different emphases, which can fully verify the generality of the Knowledge Enhancement Module (KEM).

1) Artificial Bee Colony (ABC) [12]: A swarm intelligence optimization algorithm simulating bee honey-collecting behavior. It balances global exploration and local exploitation through the collaboration of employed bees, onlooker bees, and scout bees, suitable for path optimization and obstacle avoidance tasks in continuous spaces.

2) Genetic Algorithm (GA) [13]: Based on biological evolution theory and natural selection mechanism, it iteratively optimizes through operations such as population initialization, crossover, mutation, and selection, with strong global optimization ability, which can effectively solve combinatorial optimization problems in path planning.

3) Optimal Rapidly-exploring Random Tree (RRT) [14]:* A sampling-based path planning algorithm. It gradually expands the tree structure through random sampling, which can quickly search for feasible paths and continuously optimize path quality, suitable for path planning in high-dimensional or complex obstacle scenarios.

C. Main Comparative Experiments

To verify the superiority and pluggability of the DKE-WRPP algorithm, experiments are conducted with the three algorithms ABC, GA, and RRT*, respectively, and performance comparisons are carried out around four core evaluation metrics. The experimental results are the average of 5 independent experiments to ensure the reliability of the results. The specific comparison results are shown in Table II. The three knowledge-enhanced algorithms (KE-ABC, KE-GA, KE-RRT*) connected to the pluggable KEM module are significantly superior to the corresponding baseline algorithms in the four core evaluation metrics, fully verifying the superiority of the DKE-WRPP algorithm and the effectiveness of the KEM module.

In terms of path length, KE-ABC, KE-GA, and KE-RRT* are shortened by 0.58%, 1.19%, and 2.12%, respectively compared with the baseline algorithms, indicating that the integration of domain knowledge can effectively guide the algorithm to search for paths closer to the optimal solution, reduce invalid detours, and improve path optimality. In terms of runtime, the knowledge-enhanced algorithms take slightly longer due to the introduction of knowledge feature fusion and adaptive cost calculation, but still remain within an acceptable range, proving that the low-intrusive coupling design of the KEM module does not cause excessive computational burden. In terms of path smoothness, KE-ABC, KE-GA, and KE-RRT* drop to 0.0215, 0.0302, and 0.0240 respectively, significantly lower than the original algorithms. The trajectory has smaller turning angles and more continuous curvature, more in line with the actual operation motion requirements of welding robots. In terms of iteration convergence count, KE-ABC, KE-GA, and KE-RRT* are reduced by 33.64%, 32.90%, and 34.74%, respectively compared with the baseline algorithms, fully reflecting the guiding role of domain knowledge in the algorithm optimization process, helping the algorithm quickly converge to the optimal solution and improving the optimization efficiency and stability of the algorithm.

To further intuitively show the optimization effect of the KEM module on algorithm convergence performance, this experiment plots the iteration convergence graphs of the three baseline algorithms and the corresponding knowledge-enhanced algorithms, as shown in Fig. 3.

Specifically, Fig. 3(a) shows the path planning comparison between the ABC algorithm and the KE-ABC algorithm. It can be seen from the figure that the KE-ABC path is shorter, with fewer detours and more regular node distribution, showing better performance. Meanwhile, Fig. 3(d) shows the convergence comparison between the two algorithms. It can be found that the ABC algorithm has a slow convergence speed in the early iteration (exploration phase). With the

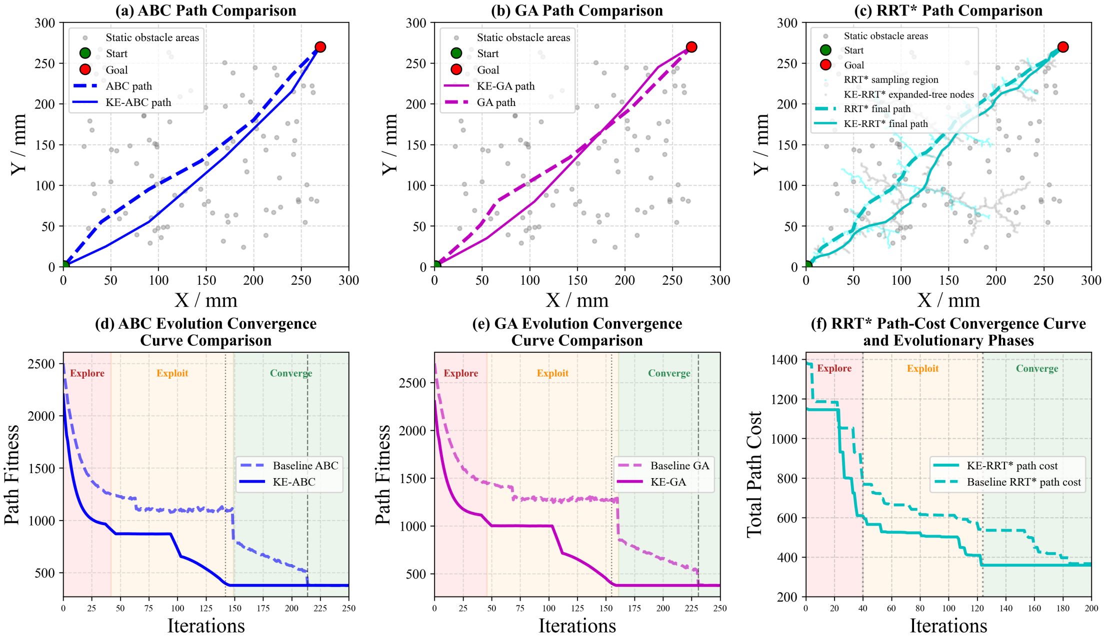


Fig. 3. Simulated path trajectories and convergence curve comparison between baseline and knowledge-enhanced algorithms.

increase of iteration times, the path length gradually decreases and stabilizes, finally reaching the optimal solution at about 214 iterations. At the same time, the KE-ABC algorithm has a significantly accelerated convergence speed, reaching the optimal solution at about 142 iterations, and the final converged path length is shorter, fully reflecting the optimization effect of the KEM module on the convergence performance of the ABC algorithm.

Similarly, Fig. 3(b) and Fig. 3(e) show the path planning comparison and iteration convergence graph between the GA algorithm and the KE-GA algorithm. The global optimization process of the GA algorithm is relatively lengthy, reaching the optimal solution at about 231 iterations. Under the guidance of knowledge, the iteration count of KE-GA drops to 155, with a smoother path, shorter length, faster decline of the convergence curve and lower stable value, effectively overcoming the shortcomings of traditional GA such as easy prematurity and poor path smoothness.

Secondly, Fig. 3(c) and Fig. 3(f) show the expansion tree comparison of the RRT* algorithm. Since RRT* is a tree-based search algorithm based on sampling, the path is generated by connecting expansion tree nodes, so the expansion tree is used for comparison. Under knowledge constraints, KE-RRT* has fewer sampling nodes, a more compact tree structure, away from high-risk obstacle areas, smoother reconnection paths, and the convergence sampling count drops from 190 to 124. While maintaining the fast search advantage of RRT*, it significantly improves path optimality and process compliance.

In summary, KE-ABC, KE-GA, and KE-RRT* algorithms outperform the traditional baseline methods significantly in path length, smoothness, and convergence speed, with the number of convergence iterations reduced by more than 33% on average. The planned paths are shorter, smoother, and more consistent with welding process constraints. Experimental results fully demonstrate that the proposed pluggable domain knowledge enhancement framework can effectively improve the planning performance of traditional intelligent optimization algorithms in complex welding scenarios with low intrusion and high generality, showing strong practicality and generalization ability.

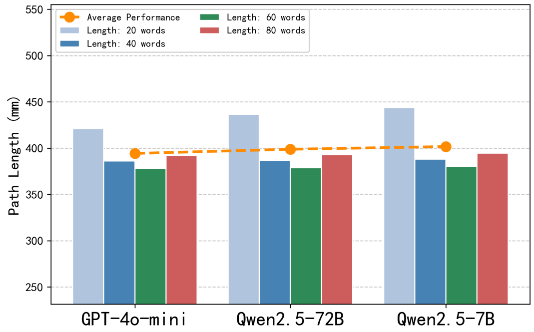
TABLE III. PATH PLANNING PERFORMANCE COMPARISON USING DIFFERENT MULTIMODAL LARGE LANGUAGE MODELS IN DKE-WRPP.

Model	Path length (mm)	Smoothness	Iterations	Time(s)
KE-ABC	378.210	0.0215	142	1.98
GPT-4O-mini[48]	378.210	0.0215	142	1.98
Qwen2.5-72B[49]	378.91	0.0223	148	3.99
Qwen2.5-7B[49]	380.12	0.0238	155	2.01
InternVL2.5-8B[50]	381.34	0.0252	163	2.03
LLaVA1.5-7B[51]	382.56	0.0267	171	2.05

D. Knowledge Accuracy Impact Experiment

To test the relationship between the optimization effect of the domain knowledge enhancement module and the generation ability of large language models, this experiment selects five mainstream Large Language Models for knowledge accuracy comparison experiments: Qwen2.5-7B [49], Qwen2.5-72B [49], GPT-4o-mini [48], InternVL2.5-8B [50], and LLaVA1.5-7B [51]. At the same time, the KE-ABC algorithm is used as the benchmark under the same experimental environment and parameter settings, and performance comparisons are carried out around the four evaluation metrics set above. The experimental results are the average of 5 independent experiments to measure the effect of knowledge encoding generated by different large models. The specific experimental results are shown in Table III.

(a) Path Length Sensitivity



(b) Convergence Iterations Sensitivity

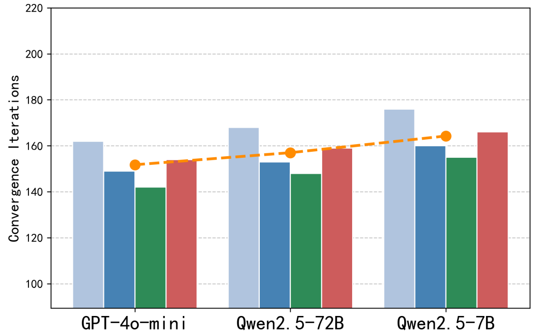


Fig. 4. Sensitivity of path planning performance to knowledge length.

The experimental results show that the knowledge encoding generated by different Large Language Models has significant differences in the optimization effect of the KE-ABC algorithm, and the detail level of knowledge generated by the model has an obvious positive correlation with the algorithm optimization effect. Specifically, the optimization effect ranking of each model is completely consistent with the knowledge detail level ranking, followed by GPT-4o-mini > Qwen2.5-72B > Qwen2.5-7B > InternVL2.5-8B > LLaVA1.5-7B.

Among them, the welding domain knowledge generated by GPT-4o-mini is the most complete and accurate, and the corresponding KE-ABC algorithm has the best performance, with a path length of 378.210 mm, path smoothness of 0.0215, convergence iteration count of 142, and runtime of 1.98 s, which is completely consistent with the main experimental results of this study. The knowledge quality generated by Qwen2.5-72B is slightly lower than that of GPT-4o-mini, and each indicator follows closely, with overall performance better than Qwen2.5-7B with smaller parameters. InternVL2.5-8B and LLaVA1.5-7B are weak in understanding welding process constraints and completeness of knowledge extraction, resulting in increased planned path length, decreased trajectory smoothness, and increased convergence iteration counts. Among them, LLaVA1.5-7B has the worst performance due to sparse knowledge and insufficient coverage of key constraints.

In summary, the experimental results clearly show that the higher the knowledge generation quality of the Large Language Model, the more accurate the guidance to the DKE-WRPP algorithm optimization process, which can effectively shorten the path length, improve trajectory smoothness, and accelerate convergence speed. This conclusion fully verifies the robustness and effectiveness of the KEM module, and provides an objective basis for Large Language Model selection and welding domain knowledge generation strategies in practical engineering applications.

E. Feasibility Analysis and Experimental Design of LLM Knowledge Length Experiment

To verify the impact of the length of knowledge encoding generated by large language models on the optimization effect of the KE-ABC algorithm, this experiment strictly follows the hardware environment, software configuration, algorithm parameters, and four evaluation metrics of the previous knowledge accuracy experiment, and only takes the knowledge encoding length as the only variable to conduct a controlled experiment. The experiment selects the three best-performing multimodal large models (GPT-4o-mini, Qwen2.5-72B, Qwen2.5-7B) for testing, and the results are shown in Fig. 4.

As shown in the path length sensitivity curve [Fig. 4(a)] and the convergence iteration sensitivity curve [Fig. 4(b)], the length of knowledge encoding is significantly correlated with the optimization performance of the algorithm, and there exists an obvious optimal length interval. The KE-ABC algorithm achieves the best performance when the knowledge length is set to 60 words. In this case, the path length is minimized, the number of convergence iterations is the lowest, and the core domain knowledge such as welding process constraints and trajectory smoothness can be fully covered without redundant information interference, so that the guidance of knowledge is fully exerted.

When the knowledge encoding length is 20 words, the excessively short length results in the loss of key process constraints and incomplete knowledge representation, which weakens the guidance for algorithm optimization. Consequently, the path length increases significantly, the convergence iterations rise substantially, and the overall performance degrades sharply. Similarly, when the knowledge encoding length reaches 80 words, redundant semantic information increases the computational overhead of knowledge encoding and cross-attention. The guidance gain for the algorithm becomes saturated, and some indicators even decline slightly.

In terms of model differences, large-parameter models such as GPT-4o-mini and Qwen2.5-72B show stronger robustness to changes in knowledge length and a wider optimal interval. In contrast, Qwen2.5-7B is more sensitive to length, and its performance drops more significantly when deviating from the optimal interval.

In summary, this study determines that the optimal length for welding domain knowledge encoding is 60 words. The knowledge length experiment further verifies the effectiveness and robustness of the proposed knowledge enhancement framework, identifies the optimal balance between the scale and integrity of domain knowledge, and provides a reliable basis for the standardized design of knowledge encoding in practical engineering applications.

V. CONCLUSION

To address the limitations of existing welding robot path planning (WRPP) algorithms, particularly the insufficient integration of welding domain knowledge and poor adaptability to complex working conditions, this study proposes the DKE-WRPP algorithm based on domain knowledge enhancement along with a plug-and-play knowledge fusion framework. Domain-specific knowledge of the welding process is extracted via Large Language Models (LLMs) and semantically encoded to construct a Knowledge Enhancement Module (KEM); an attention mechanism is then employed to deeply fuse domain knowledge with path features, enabling the adaptive optimization of three conventional intelligent algorithms: ABC, GA, and RRT*. Systematic experiments on all three algorithms fully validate the effectiveness of domain knowledge enhancement and the generalizability of the plug-and-play framework. This work effectively addresses the core limitations of existing WRPP algorithms, offering a practical and viable solution for welding automation, with significant implications for advancing the technological development of welding robot path planning. Future work will focus on the deep integration of lightweight knowledge agents with welding robots, continuously optimizing the adaptive capability and execution efficiency of path planning, thereby providing theoretical and technical support for the realization of highly intelligent welding engineering.

ACKNOWLEDGMENT

This work was supported by The Liaoning Provincial Science and Technology Plan Joint Program (General Project of Natural Science Foundation) (JH4/4800, No.2025-MSLH-012).

REFERENCES

[1] R. G. Prasuna and S. R. Potturu, “Deep reinforcement learning in mobile robotics–a concise review,” *Multimedia Tools and Applications*, vol. 83, no. 28, pp. 70 815–70 836, 2024.

[2] B. Siciliano and O. Khatib, “Robotics and the handbook,” in *Springer Handbook of Robotics*. Springer, 2016, pp. 1–6.

[3] L. Chen, Z. Jiang, L. Cheng, A. C. Knoll, and M. Zhou, “Deep reinforcement learning based trajectory planning under uncertain constraints,” *Frontiers in Neurorobotics*, vol. 16, p. 883562, 2022.

[4] X. Wang, X. Zhou, Z. Xia, and X. Gu, “A survey of welding robot intelligent path optimization,” *Journal of Manufacturing Processes*, vol. 63, pp. 14–23, 2021.

[5] J. Zhong, T. Wang, and L. Cheng, “Collision-free path planning for welding manipulator via hybrid algorithm of deep reinforcement learning and inverse kinematics,” *Complex & Intelligent Systems*, vol. 8, no. 3, pp. 1899–1912, 2022.

[6] Y. Yan, P. Zhang, C. Du, H. Wang, H. Wang, D. Pi, and Y.-H. Chen, “Vehicle trajectory prediction for autonomous driving applications: State-of-the-art review, research challenges, and future directions,” *Automotive Innovation*, vol. 9, pp. 263–295, 2026.

[7] N. A. Madjid, A. Ahmad, M. Mebrahtu, Y. Babaa, A. Nasser, S. Malik, B. Hassan, N. Werghi, J. Dias, and M. Khonji, “Trajectory prediction for autonomous driving: Progress, limitations, and future directions,” *Information Fusion*, vol. 126, p. 103588, 2026.

[8] X. Wang, J. Wei, X. Zhou, Z. Xia, and X. Gu, “Dual-objective collision-free path optimization of arc welding robot,” *IEEE robotics and automation letters*, vol. 6, no. 4, pp. 6353–6360, 2021.

[9] J. Xin, C. Meng, A. D’Ariano, F. Schulte, J. Peng, and R. R. Negenborn, “Energy-efficient routing of a multirobot station: A flexible time-space network approach,” *IEEE Transactions on Automation Science and Engineering*, vol. 20, no. 3, 2022.

[10] L. Guo and H. Zhang, “Autonomous mobile welding robot for discontinuous weld seam recognition and tracking,” *The International Journal of Advanced Manufacturing Technology*, vol. 119, no. 7, pp. 5497–5509, 2022.

[11] G.-H. Song, C.-M. Lee, and D.-H. Kim, “Investigation of path planning to reduce height errors of intersection parts in wire-arc additive manufacturing,” *Materials*, vol. 14, no. 21, p. 6477, 2021.

[12] D. Karaboga *et al.*, “An idea based on honey bee swarm for numerical optimization,” 2005.

[13] L. Wu, K. Cui, and S.-B. Chen, “Redundancy coordination of multiple robotic devices for welding through genetic algorithm,” *Robotica*, vol. 18, no. 6, pp. 669–676, 2000.

[14] X. Zhou, X. Wang, and X. Gu, “An approach for solving the three-objective arc welding robot path planning problem,” *Engineering Optimization*, vol. 55, no. 4, pp. 650–667, 2023.

[15] S. Bhagat, H. Banerjee, Z. T. Ho Tse, and H. Ren, “Deep reinforcement learning for soft, flexible robots: Brief review with impending challenges,” *Robotics*, vol. 8, no. 1, p. 4, 2019.

[16] H. Sun, W. Zhang, R. Yu, and Y. Zhang, “Motion planning for mobile robots—focusing on deep reinforcement learning: A systematic review,” *IEEE Access*, vol. 9, pp. 69 061–69 081, 2021.

[17] A. Devo, G. Mezzetti, G. Costante, M. L. Fravolini, and P. Valigi, “Towards generalization in target-driven visual navigation by using deep reinforcement learning,” *IEEE Transactions on Robotics*, vol. 36, no. 5, pp. 1546–1561, 2020.

[18] F. Quiroga, G. Hermosilla, G. Farias, E. Fabregas, and G. Montenegro, “Position control of a mobile robot through deep reinforcement learning,” *Applied Sciences*, vol. 12, no. 14, p. 7194, 2022.

[19] B. Sangiovanni, G. P. Incremona, M. Piastra, and A. Ferrara, “Self-configuring robot path planning with obstacle avoidance via deep reinforcement learning,” *IEEE Control Systems Letters*, vol. 5, no. 2, pp. 397–402, 2020.

[20] A. Candra, M. A. Budiman, and K. Hartanto, “Dijkstra’s and a-star in finding the shortest path: A tutorial,” in *2020 International Conference on Data Science, Artificial Intelligence, and Business Analytics (DATABIA)*. IEEE, 2020, pp. 28–32.

[21] S. Meng, Y. Wang, C.-F. Yang, N. Peng, and K.-W. Chang, “Llm-a*: Large language model enhanced incremental heuristic search on path planning,” in *Findings of the Association for Computational Linguistics: EMNLP 2024*, 2024, pp. 1087–1102.

[22] Y.-T. Zhao, L. Gan, W.-G. Li, and A. Liu, “Path planning of spot welding robot based on multi-objective grey wolf algorithm,” *Journal of Intelligent & Fuzzy Systems*, vol. 41, no. 6, pp. 6181–6189, 2021.

[23] Q. Zhang and M.-Y. Zhao, “Minimum time path planning of robotic manipulator in drilling/spot welding tasks,” *Journal of Computational Design and Engineering*, vol. 3, no. 2, pp. 132–139, 2016.

[24] S. Lin and B. W. Kernighan, “An effective heuristic algorithm for the traveling-salesman problem,” *Operations research*, vol. 21, no. 2, pp. 498–516, 1973.

[25] M. Dorigo, “The any system optimization by a colony of cooperating agents,” *IEEE Trans. System, Man & Cybernetics-Part B*, vol. 26, no. 1, pp. 1–13, 1996.

[26] G. Sharma, S. Jain, and R. S. Sharma, “Path planning for fully autonomous uavs-a taxonomic review and future perspectives,” *IEEE Access*, vol. 13, pp. 13 356–13 379, 2025.

[27] M. P. Strub and J. D. Gammell, “Adaptively informed trees (ait*): Fast asymptotically optimal path planning through adaptive heuristics,” in *2020 IEEE International Conference on Robotics and Automation (ICRA)*. IEEE, 2020, pp. 3191–3198.

[28] Y. Shen, Y. Gao, M. Yuan, H. Sun, and Z. Guo, “Multi-objective immune optimization of path planning for ship welding robot,” *Electronics*, vol. 12, no. 9, p. 2040, 2023.

[29] K. Hu, Q. Dong, Z. Ma, B. Li, and T. Qi, “Welding robot path planning based on ant colony algorithm,” in *2024 5th International Conference on Artificial Intelligence and Electromechanical Automation (AIEA)*. IEEE, 2024, pp. 13–18.

[30] Y. Luo, S. Lin, Y. Wang, and K. Liang, “Path planning for mobile robots in complex environments based on enhanced sparrow search algorithm and dynamic window approach,” *Robotica*, vol. 43, no. 5, pp. 1929–1952, 2025.

[31] T. Wang, L. Wang, D. Li, J. Cai, and Y. Wang, “Monte carlo-based improved ant colony optimization for path planning of welding robot,” *Journal of King Saud University-Computer and Information Sciences*, vol. 35, no. 7, p. 101603, 2023.

[32] H. Van Hasselt, A. Guez, and D. Silver, "Deep reinforcement learning with double q-learning," in *Proceedings of the AAAI conference on artificial intelligence*, vol. 30, no. 1, 2016.

[33] S. Fang, "Reinforcement learning-driven deep learning approaches for optimized robot trajectory planning," *Scientific Reports*, vol. 15, no. 1, p. 37898, 2025.

[34] B. Zhao, Y. Wu, C. Wu, and R. Sun, "Deep reinforcement learning trajectory planning for robotic manipulator based on simulation-efficient training," *Scientific Reports*, vol. 15, no. 1, p. 8286, 2025.

[35] C.-C. Tran and C.-Y. Lin, "An intelligent path planning of welding robot based on multisensor interaction," *IEEE sensors journal*, vol. 23, no. 8, pp. 8591–8604, 2023.

[36] S. M. H. Rostami, A. K. Sangaiah, J. Wang, and X. Liu, "Obstacle avoidance of mobile robots using modified artificial potential field algorithm," *EURASIP Journal on Wireless Communications and Networking*, vol. 2019, no. 1, pp. 1–19, 2019.

[37] C. Cui, Y. Ma, S.-Y. Park, Z. Yang, Y. Zhou, P. Liu, J. Lu, J. Peng, J. Zhang, R. Zhang, L. Li, Y. Chen, J. H. Panchal, A. Abdelraouf, R. Gupta, K. Han, and Z. Wang, "LLM4AD: Large language models for autonomous driving—concept, review, benchmark, experiments, and future trends," *Proceedings of the IEEE*, pp. 1–36, 2026.

[38] G. Zhang, W. Li, Q. Qian, J. Wang, D. Zhao, S. Lu, and R. Xu, "On the generalization capacities of mllms for spatial intelligence," *arXiv preprint arXiv:2603.06704*, 2026.

[39] H. Zhao, Z. Guo, C. Zhang, Z. Zhou, and Z. Hu, "Structuthink: Reasoning with task transition knowledge for autonomous llm-based agents," in *Findings of the Association for Computational Linguistics: EMNLP 2025*, 2025, pp. 24 489–24 506.

[40] Z. Xu, Z. Wang, X. Jiang, D. Li, D. Cheng, and N. Wang, "Reasoning-driven multimodal llm for domain generalization," *arXiv preprint arXiv:2602.23777*, 2026.

[41] R. Han, S. Chen, S. Wang, Z. Zhang, R. Gao, Q. Hao, and J. Pan, "Reinforcement learned distributed multi-robot navigation with reciprocal velocity obstacle shaped rewards," *IEEE Robotics and Automation Letters*, vol. 7, no. 3, pp. 5896–5903, 2022.

[42] Z. Li, X. Meng, X. He, Y. Zhang, and W. Yin, "Large-scale model-enhanced vision-language navigation: Recent advances, practical applications, and future challenges," 2026.

[43] A. Gómez-Espinosa, J. B. Rodríguez-Suárez, E. Cuan-Urquizo, J. A. E. Cabello, and R. L. Swenson, "Colored 3d path extraction based on depth-rgb sensor for welding robot trajectory generation," *Automation*, vol. 2, no. 4, pp. 252–265, 2021.

[44] C.-C. Tran and C.-Y. Lin, "An intelligent path planning of welding robot based on multisensor interaction," *IEEE sensors journal*, vol. 23, no. 8, pp. 8591–8604, 2023.

[45] J. Wei, X. Wang, D. Schuurmans, M. Bosma, F. Xia, E. Chi, Q. V. Le, D. Zhou *et al.*, "Chain-of-thought prompting elicits reasoning in large language models," *Advances in neural information processing systems*, vol. 35, pp. 24 824–24 837, 2022.

[46] C. Duan and S. Luo, "Research on welding robot path planning based on genetic algorithm," in *2023 IEEE International Conference on Control, Electronics and Computer Technology (ICCECT)*. IEEE, 2023, pp. 1401–1407.

[47] M. Dobiš, M. Dekan, P. Beňo, F. Duchoň, and A. Babinec, "Evaluation criteria for trajectories of robotic arms," *Robotics*, vol. 11, no. 1, p. 29, 2022.

[48] D. B. Dangi, B. B. Dangi, and O. Steinbock, "Evaluation of gpt-4o and gpt-4o-mini's vision capabilities for compositional analysis from dried solution drops," *ACS omega*, vol. 10, no. 18, pp. 18 955–18 959, 2025.

[49] C. Wu, J. Li, J. Zhou, J. Lin, K. Gao, K. Yan, S.-m. Yin, S. Bai, X. Xu, Y. Chen *et al.*, "Qwen-image technical report," *arXiv preprint arXiv:2508.02324*, 2025.

[50] W. Wang, Z. Gao, L. Gu, H. Pu, L. Cui, X. Wei, Z. Liu, L. Jing, S. Ye, J. Shao *et al.*, "Internvl3. 5: Advancing open-source multimodal models in versatility, reasoning, and efficiency," *arXiv preprint arXiv:2508.18265*, 2025.

[51] X. An, Y. Xie, K. Yang, W. Zhang, X. Zhao, Z. Cheng, Y. Wang, S. Xu, C. Chen, D. Zhu *et al.*, "Llava-onevision-1.5: Fully open framework for democratized multimodal training," *arXiv preprint arXiv:2509.23661*, 2025.