A Hierarchical Cooperative Multi-Robot Path Planning Algorithm Based on TSP Encoding

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***Abstract*—Multi-robot path planning problems (MRPP) in practical applications usually involve multiple optimization objectives simultaneously, such as path length, task balance, and cooperative efficiency. This problem typically requires task allocation to be performed first, followed by path optimization for each subtask. These two processes together form a mutually coupled nested optimization structure. Most existing algorithms find it difficult to efficiently handle both task allocation and path optimization simultaneously within a unified framework. To address these challenges, this paper establishes a multi-objective MRPP model and proposes a hierarchical cooperative multi-robot path planning algorithm based on TSP encoding (HCMRPP-TE). The proposed algorithm solves the MRPP using a hierarchical optimization framework. At the upper level, the overall task is formulated as a Traveling Salesman Problem (TSP) model, where global tour optimization is performed to obtain a high-quality path structure. At the middle level, a TSP-tour-based task allocation encoding mechanism is designed to decompose the global tour into an encoding suitable for multi-robot path planning, enabling reasonable task allocation and coordinated path assignment among multiple robots. At the lower level, based on the obtained task allocation results, further local optimization is performed on each robot's route to enhance the multi-objective performance. Experimental results demonstrate that the proposed method consistently outperforms the comparison methods in terms of overall multi-objective performance. Moreover, the proposed model and algorithm effectively improve the global optimization capability of multi-robot path planning and exhibit strong effectiveness and robustness in complex multi-robot scenarios.**

***Index Terms*—Multi-robot path planning, multi-objective optimization, genetic algorithm**

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I. Introduction

With the rapid development of robotics, automatic control, and intelligent optimization techniques, multi-robot path planning (MRPP) [1]–[4] have been widely applied in fields such as warehouse logistics [5], wireless sensor networks [6], and emergency rescue [7]. Compared with single-robot systems, multi-robot cooperative operations can significantly improve system efficiency and overall task completion capability through parallel task execution. However, in practical engineering applications, multi-robot systems are often constrained by limited energy capacity, restricted operation time, and complex, dynamic working environments. How to achieve efficient and energy-saving path planning while ensuring safe cooperation has therefore become one of the key challenges that urgently need to be addressed.

In practical engineering scenarios, the total energy consumption of robots directly affects the operating cost and endurance of the system, while the execution time of the robot with the longest task completion time determines the overall operational efficiency. Therefore, optimizing MRPP based solely on path length or a single performance metric is often insufficient to meet real-world application requirements. As a result, MRPP problems typically exhibit pronounced multi-objective optimization characteristics [8]–[10].

MRPP problems are typically addressed in two stages. The first stage focuses on assigning task locations to individual robots, while the second stage performs path optimization based on the given task allocation results. Since task assignment directly affects the feasibility and optimization potential of subsequent path planning, the problem inherently exhibits a nested optimization structure. If the task allocation is unbalanced or improperly designed in the assignment stage, even highly effective path optimization algorithms may fail to produce solutions with satisfactory overall performance.

To address the aforementioned challenges, a variety of approaches for MRPP and task assignment have been proposed. Yu et al [11]. proposed a multimodal multiobjective evolutionary algorithm (MMOEA-DL) that integrates deep reinforcement learning and large neighborhood search for multirobot task allocation problems. By solving task allocation at the upper level and TSP at the lower level via an end-to-end DRL–LNS approach, the original bi-level optimization problem is transformed into a single-level one, significantly improving computational efficiency and practicality. Li et al. [12]. proposed a multimodal multiobjective evolutionary algorithm (MMOEA-DL) transformed the single-objective multirobot task allocation problem into a multiple traveling salesman problem. Subsequently, the K-means clustering algorithm was employed to cluster task target points, decomposing the MTSP into multiple TSPs. In addition, a distributed cooperative task allocation strategy based on an improved gray wolf optimizer (IGWO) was proposed, in which the Kent chaotic map is used for population initialization and an adaptive control-parameter adjustment strategy is adopted to balance global exploration and local exploitation. Hari et al. [13]. proposed a multimodal multiobjective evolutionary algorithm (MMOEA-DL) proposed an approximation algorithm that combines a multiple traveling salesman algorithm with a greedy heuristic, aiming to minimize the maximum task completion time among all robots. Milad et al. [14] proposed a hybrid approach that integrates an Artificial Potential Field (APF) method with an Enhanced GA for multi-mobile robot path planning in continuous environments, where feasible initial paths are first generated and then refined through continuous-space optimization to obtain high-quality solutions.

Evolutionary computation methods, represented by genetic algorithms, employ population-based evolutionary mechanisms to explore promising solutions in complex search spaces and have been widely applied in path planning and scheduling optimization. However, existing methods often lack effective coordination among global path structure optimization, rational task allocation, and fine-grained single-robot path refinement, making it difficult to simultaneously optimize key performance metrics such as system energy consumption and completion time.

To address the aforementioned challenges, this paper establishes a multi-objective MRPP model and, based on this model, proposes a hierarchical cooperative multi-robot path planning algorithm based on TSP encoding (HCMRPP-TE). To avoid the task imbalance and structural bias that may be introduced by directly performing task assignment, the proposed algorithm first models all task locations as a unified TSP and obtains a high-quality global tour with favorable structural properties through overall tour optimization. On this basis, a TSP tour-based task assignment encoding mechanism is designed, in which the global tour is effectively decomposed into robot-specific subpaths by rational subpath partitioning and robot position insertion encoding, thereby achieving coordinated task and path assignment for multiple robots. Subsequently, given the fixed task allocation results, the classical NSGA-II is employed to perform secondary optimization on individual robot paths, further improving the overall system performance with respect to multiple objectives such as energy consumption and completion time.

It should be noted that for the first-stage TSP tour optimization and the third-stage multi-objective optimization using NSGA-II after task assignment, a large number of mature and efficient solution methods already exist. In this work, relatively basic yet representative optimization strategies are adopted as solvers, with the primary focus placed on constructing a unified, clear, and extensible algorithmic framework. Experimental results demonstrate that, despite the use of relatively fundamental optimization methods, the proposed hierarchical cooperative multi-robot path planning algorithm exhibits strong competitiveness and superior performance in terms of multi-objective optimization and overall solution quality.

II. Preliminaries

A. Basic Concept of Multi-objective Optimization Problems

Multi-objective optimization problems (MOPs) [15] refers to the problem of simultaneously optimizing two or more conflicting objective functions. Unlike single-objective optimization, multi-objective optimization problems generally do not have a unique global optimal solution. Instead, it is necessary to balance multiple objectives and obtain a set of representative trade-off solutions.

In general, the multi-objective optimization problem can be mathematically formulated as:

$$\min \mathbf{F}(\mathbf{x}) = \big(f_1(\mathbf{x}), f_2(\mathbf{x}), \ldots, f_m(\mathbf{x})\big), \quad \mathbf{x} \in \Omega \subseteq \mathbb{R}^n \tag{1}$$

where $\mathbf{x} = (x_1, x_2, \ldots, x_n)$ is an n-dimensional decision variable vector, Ω denotes the feasible solution space, $f_i(\mathbf{x})$ represents the i-th objective function, and m is the number of objective functions. The objectives usually impose mutual constraints or conflicts, making it difficult to achieve their individual optimal values simultaneously.

B. MRPP Problem

In the process of multi-robot path planning and task execution, a mathematical model is established under ideal conditions to characterize the temporal and energy consumption characteristics of the system. It is assumed that the robots are not affected by payload variations or environmental disturbances during task execution, and thus their traveling speed remains constant. According to the relationship between driving power and motion, the robot traveling speed v is defined as

$$v = \frac{D_p}{\mu \times S_w \times g}, \tag{2}$$

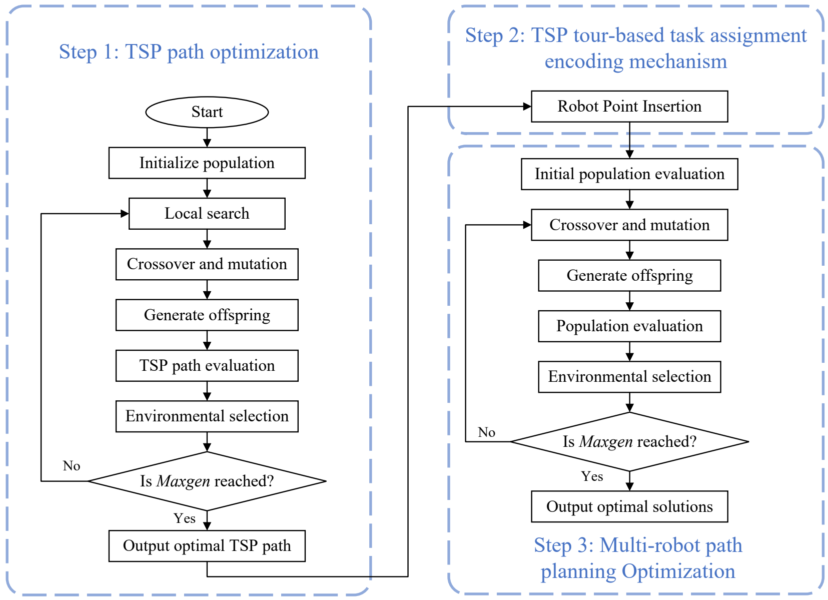

Fig. 1. Flow Chart of HCMRPP-TE Algorithm.

where D_p denotes the maximum driving power of the robot, reflecting the upper limit of the robot's propulsion capability. S_w represents the self-weight of the robot, μ is the ground friction coefficient, characterizing the interaction between the robot and the terrain surface. And g is the gravitational acceleration.

Suppose that the task path assigned to the i-th robot consists of n_i task points. The total traveling time t_i required for the robot to complete its assigned path is given by

$$t_i = \sum_{j=1}^{n_i-1} \frac{y(j, j+1)}{v} + \frac{y(n_i, 1)}{v}, \tag{3}$$

where $y(j, j+1)$ denotes the path length between task points j and $j+1$. The last term represents the time required for the robot to return to its initial position after completing all assigned tasks.

Based on the above formulation, the energy consumed by the i-th robot during task execution is defined as

$$energy_i = t_i \times D_p. \tag{4}$$

From a system-level perspective, the total energy consumption of all robots for completing all task points in the scenario can be expressed as

$$W = \sum_{i=1}^{r} energy_i, \tag{5}$$

where r denotes the number of robots involved in task execution.

On the basis of the above model, a multi-objective optimization problem is formulated by considering both energy consumption and completion time. The first objective is to minimize the total energy consumption of the system:

$$\min f_1 = \min W. \tag{6}$$

The second objective is to minimize the overall task completion time, which is defined as the completion time of the most time-consuming robot:

$$\min f_2 = \min \max(t_i), \quad i = 1, 2, \dots, r. \tag{7}$$

Through the above formulation, the multi-robot path planning and task allocation problem is transformed into a multi-objective optimization problem with the objectives of minimizing total energy consumption and minimizing completion time, thereby providing a unified mathematical foundation for subsequent algorithm design and solution.

III. Proposed Algorithm

A. Framework of Algorithm

Fig. 1 illustrates the overall framework of the hierarchical cooperative multi-robot path planning algorithm based on TSP encoding (HCMRPP-TE). The proposed algorithm consists of three main stages. In the first stage, the global path optimization of all task points is formulated as TSP problem. By incorporating the 2-opt local search operator together with genetic operators such as crossover and mutation, the TSP tour is continuously optimized. Once the maximum number of iterations is reached, the algorithm terminates and outputs a set of TSP tours. In the second stage, the obtained TSP tours are decomposed, and task points are assigned to individual robots accordingly, while the route of each robot is optimized simultaneously. To address this problem, a task assignment encoding mechanism based on TSP tours is proposed. The initial population generated by this encoding scheme can undergo arbitrary crossover and mutation operations, enabling the simultaneous optimization of task assignment and sub-route planning within a unified evolutionary framework. As a result, the nested nature of the problem does not impose restrictions on the optimization process, thereby avoiding potential resource waste caused by performing task assignment prior to sub-task route optimization. In the third stage, the NSGA-II [16] algorithm is employed to further optimize the overall task solution. Under the proposed encoding mechanism, the population can be subjected to arbitrary crossover and mutation operations. Both task assignment and sub-route optimization participate in the evolutionary process with certain probabilities, which effectively improves the overall population quality and ultimately yields the optimal cooperative path planning solution for multiple robots. The design principles and implementation details of each component of the proposed algorithm are introduced in detail in the following sections.

B. TSP Path Optimization

For the TSP tour optimization task in the first stage, numerous mature and efficient optimization algorithms [17]–[20] have been proposed in recent years. Therefore, this work does not redesign a new algorithm for the TSP optimization problem, but instead adopts and improves existing methods based on prior studies. Specifically, HCMRPP-TE first incorporates the classical 2-opt local search operator to preliminarily optimize the initial population, thereby enhancing individual solution quality. Subsequently, the crossover operator proposed in the hierarchical genetic algorithm (HGA) [20] by Yue et al. is employed to further optimize the TSP tours. HGA introduces a hierarchical evolutionary framework, in which the second stage is designed to achieve fast optimization of TSP paths, which is highly consistent with the optimization objective of HCMRPP-TE at this stage. Therefore, the crossover operator and the generation operator from HGA are incorporated into the first stage of HCMRPP-TE to enhance the efficiency of path optimization. The details of the adopted operators are introduced in the following.

2-opt operator: The 2-opt operator is a classical and efficient local search method that has been widely applied to path optimization in the TSP. Its core idea is to select two non-adjacent edges from the current tour, remove them, and reconnect the path by reversing the intermediate segment, thereby eliminating crossings and reducing the total path length. By repeatedly performing such exchange operations and determining whether to accept the new path after each update, the 2-opt operator can gradually improve the quality of the solution.

Crossover operator: HCMRPP-TE adopts the crossover operator proposed in HGA Algorithm, and its basic principle is illustrated in Fig. 2. Specifically, two parent individuals, denoted as P_1 and P_2, are randomly selected from the current population for crossover. For each parent path, two crossover points are randomly determined, thereby dividing the complete

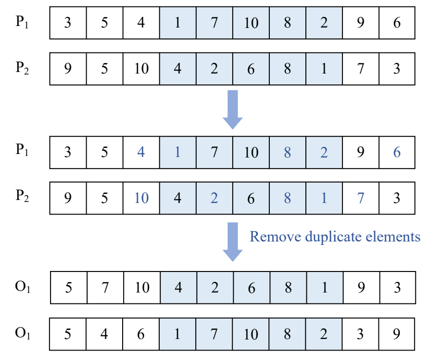

Fig. 2. Crossover operator.

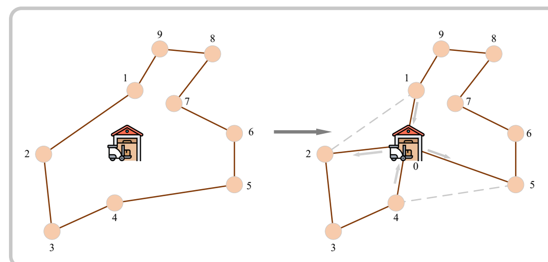

Fig. 3. Encoding mechanism.

path into three segments. During the crossover process, the middle segment of each parent is directly inherited by the offspring: the middle segment of P_1 is inherited by offspring O_2, while the middle segment of P_2 is inherited by offspring O_1. To ensure that the generated offspring paths satisfy the constraint of the TSP, namely that each task point is visited exactly once, conflict elimination and completion operations are required after inheriting the middle segment. Specifically, after inheriting the middle segment from P_2, offspring O_1 removes the task points that are duplicated with this segment from P_1, and then sequentially fills the remaining task points into the vacant positions of the offspring path according to their original order, thereby constructing a feasible and complete TSP tour. The generation process of offspring O_2 is similar.

Individual generation operator: The individual generation operator identifies common path segments from a subset of elite individuals in the current population and preserves these segments unchanged during offspring generation, while the remaining unassigned positions are filled according to a greedy strategy. This operator is able to retain high-quality path structures while guiding the search toward more promising regions of the solution space. The detailed implementation can be found in [20].

C. TSP tour-based task allocation encoding mechanism

The primary purpose of the proposed encoding mechanism is to transform the TSP path representation into a multi-robot path planning representation. By introducing a new encoding form, task allocation and sub-task route planning can be jointly optimized within a unified representation framework. From a graph-theoretic perspective, the core idea of this encoding mechanism lies in decomposing a single TSP tour and distributing task points among n robots. Specifically, the multi-robot task allocation process can be equivalently regarded as breaking n edges in the TSP tour and reconnecting the breakpoints to the starting positions of the robots, thereby forming n mutually independent sub-tours. The task allocation result is directly related to the selection of the broken edges. As shown in Fig. 3, when an optimized TSP tour is decomposed and assigned to two robots, two edges need to be removed from the original tour. In the example shown in the figure, edges $1-2$ and $4-5$ are removed. Different edge-breaking strategies correspond to different task allocation results.

From an encoding perspective, the starting position of each robot is uniformly encoded as node 0. Suppose that the optimized TSP tour obtained in the first stage is given by $1-2-3-4-5-6-7-8-9$. Breaking a specific edge in the tour is essentially equivalent to inserting the robot node 0 at the corresponding position in the encoding. For example, when edges $1-2$ and $4-5$ are removed, the resulting re-encoded sequence becomes $1-0-2-3-4-0-5-6-7-8-9$. Under this encoding mechanism, each robot departs from its starting position, executes its assigned tasks, and then returns to the start, thereby forming two preliminary and independent robot routes, namely $0-2-3-4-0$ and $0-5-6-7-8-9-1-0$. Consequently, the proposed encoding naturally achieves a unified representation of initial multi-robot task allocation and path planning. Based on this encoding strategy, the multi-robot path planning problem can be transformed into a single-sequence combinatorial optimization problem, which allows most classical genetic algorithm operators (e.g., crossover and mutation) to be directly applied, thereby significantly enhancing the generality and scalability of the proposed method.

For the selection of edge-breaking positions in the TSP tour, namely the robot node insertion strategy, HCMRPP-TE adopts two simple yet effective approaches: 1) Breaking the n longest edges in the TSP tour, so as to mitigate the adverse impact of long edges on path quality. 2) Randomly breaking n edges, in order to enhance the diversity of task allocation results.

D. Muti-robot path planning optimization

Since the TSP tour has been globally optimized in the previous stage, the decomposed sub-paths already exhibit favorable structural properties and solution quality. Therefore, the initial population generated through the proposed encoding mechanism can directly participate in subsequent crossover and mutation operations while maintaining feasibility. On this basis, HCMRPP-TE employs NSGA-II as the multi-objective optimizer to further optimize the multi-robot task allocation and path planning problem. The overall procedure of the algorithm is illustrated as Step 3 in Fig. 1, and the detailed steps are omitted here for brevity.

IV. Experiment and Analysis

A. Experimental Setup

To verify the effectiveness and superiority of the proposed HCMRPP-TE algorithm in solving multi-robot path planning problems, a series of comparative experiments are conducted under various representative multi-robot path planning scenarios. All experiments are performed in a two-dimensional planar environment. The test instances consist of task sets with 20, 50, 100, 200, and 500 task nodes. For each problem scale, two configurations are considered, where 3 and 6 robots are assigned to each task node, resulting in a total of ten benchmark problems. The task nodes are randomly distributed within a predefined workspace. All robots start from the same initial location and return to the starting point after completing their assigned tasks.

To comprehensively evaluate the overall performance of the proposed algorithm, three representative multi-robot path planning methods are selected for comparison, covering combinatorial optimization algorithm [21], TSP-based path planning algorithm [22], and classical multi-objective optimization algorithm [16]. All algorithms are executed under the same experimental environment and constraint conditions. The population size of each algorithm is uniformly set to 100, and the maximum number of fitness evaluations is fixed at 200,000. To ensure statistical significance, each algorithm is independently run 21 times, thereby guaranteeing the fairness and comparability of the experimental results.

B. Analysis of Experimental Results

To further analyze the overall performance of the proposed HCMRPP-TE algorithm, the HV (Hypervolume) indicator is employed to evaluate the comprehensive performance of all algorithms. The HV metric is widely used to assess the convergence and diversity of solution sets in the objective space. A larger HV value indicates that the obtained solutions are closer to the true Pareto front (PF). Accordingly, Table I summarizes the HV results of all algorithms across different test instances, where the gray shading denotes the best performance for each instance. As can be observed in Table I, the HCMRPP-TE algorithm achieves the highest HV values in the majority of test instances, demonstrating stable overall performance with clear advantages. These results indicate that HCMRPP-TE is capable of maintaining a good balance between convergence and distribution in multi-objective optimization, thereby more effectively and uniformly covering the PF.

In the two small-scale instances, Instance-20-3 and Instance-20-6, the performance of HCMRPP-TE is slightly inferior to that of DNEA-TSP. To further analyze the underlying reasons, Fig. 4 presents the distributions of the first PF obtained by different algorithms on problems with varying dimensionalities. From the experimental results on Instance-20-3, it can be observed that all four algorithms are able to converge to similar PF locations. However, the solution set produced by DNEA-TSP exhibits a more uniform and diverse distribution in the objective space. This advantage can be mainly attributed

TABLE I

RESULTS FOR HV ON THREE COMPARED ALGORITHMS AND HCMRPP-TE

HV	NSGA-II	DNEA-TSP	MOEA/D-ACO	HCMRPP-TE
Instance-20-3	3.16e+06±2.20e+05(+)	**3.64e+06±1.05e+05(-)**	3.54e+06±1.92e+04(=)	3.49e+06±1.51e+05
Instance-50-3	9.94e+06±7.14e+05(+)	1.36e+07±4.87e+05(+)	1.21e+07±2.42e+05(+)	**1.48e+07±1.82e+05**
Instance-100-3	1.63e+07±2.95e+06(+)	2.64e+07±3.13e+06(+)	3.04e+07±6.85e+05(+)	**4.43e+07±5.99e+05**
Instance-200-3	2.51e+07±5.55e+06(+)	2.38e+07±7.66e+06(+	9.04e+07±2.83e+06(+)	**1.58e+08±1.54e+06**
Instance-500-3	5.55e+08±4.50e+07(+)	2.81e+08±2.08e+08(+)	1.69e+09±4.79e+07(+)	**2.50e+09±6.33e+06**
Instance-20-6	5.69e+06±1.80e+05(+)	**6.44e+06±6.57e+04(-)**	5.99e+06±2.97e+04(+)	6.16e+06±1.60e+05
Instance-50-6	8.86e+06±8.10e+05(+)	1.22e+07±6.74e+05(+)	1.14e+07±2.46e+05(+)	**1.35e+07±3.88e+05**
Instance-100-6	1.46e+07±3.27e+06(+)	1.46e+07±2.36e+06(+)	2.48e+07±7.17e+05(+)	**3.64e+07±5.40e+05**
Instance-200-6	2.71e+07±5.97e+06(+)	8.47e+06±3.96e+06(+)	6.23e+07±2.69e+06(+)	**1.19e+08±1.69e+06**
Instance-500-6	1.90e+08±3.30e+07(+)	1.56e+07±8.88e+06(+)	7.04e+08±7.91e+06(+)	**1.28e+09±5.80e+06**
+/=/-	10/0/0	8/0/2	9/1/0	

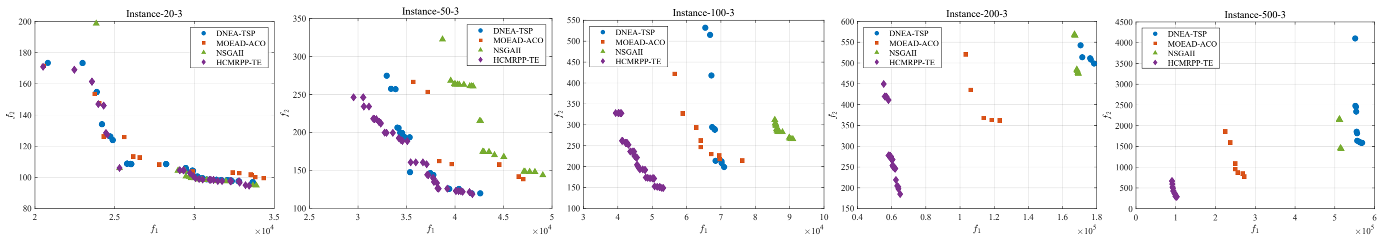

Fig. 4. Distribution of solutions on the first Pareto front obtained by four comparative algorithms across five test problems.

to the environmental selection strategy based on dual sharing functions adopted in DNEA-TSP, which simultaneously preserves diversity in both the objective space and the decision space, thereby effectively enhancing the coverage of the final solution set for small-scale problems. By jointly examining Table I and Fig. 4, it can be observed that when the problem dimensionality reaches 100 or higher, DNEA-TSP is no longer able to achieve effective convergence, and both the quality and stability of its solution sets deteriorate markedly. In contrast, HCMRPP-TE maintains satisfactory convergence performance and solution diversity on medium and large-scale problems, demonstrating strong scalability and robustness in tackling complex multi-objective MRPP optimization problems.

The performance of MOEA/D-ACO and NSGA-II is relatively weak. Specifically, NSGA-II fails to obtain the best HV values across all test instances, exhibiting generally low HV levels, which indicates its limited capability in simultaneously maintaining convergence and diversity of the solution set. Although MOEA/D-ACO can achieve suboptimal results in some test instances, in large-scale instances, its HV value is significantly lower than that of HCMRPP-TE. Moreover, the performance varies greatly among different instances, and the performance is not stable enough. This indicates that MOEA/D-ACO still has room for improvement in terms of search efficiency and algorithm stability for high-dimensional and complex problems.

Fig. 5 illustrates the differences in convergence performance of different algorithms on the HV metric for Instance-100-3. It can be observed that MART consistently achieves the highest HV values throughout the optimization process and converges rapidly in the early stage, demonstrating superior search efficiency and solution quality. DNEA-TSP shows slow improvement at the beginning but gradually improves as the number of evaluations increases, reaching a competitive level in the later stage. In contrast, MOEA/D-ACO converges quickly at the early stage but exhibits limited improvement in the middle and later stages, indicating a tendency to stagnate. NSGAII has the slowest convergence speed and the lowest final HV value, resulting in relatively poor overall performance. Overall, MART outperforms the other algorithms in both convergence speed and solution quality, highlighting its stronger global optimization capability.

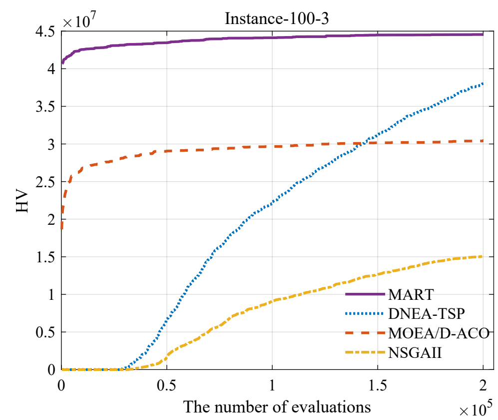

Fig. 5. Convergence comparison of HV.

From the statistical results, it can be further observed that HCMRPP-TE outperforms the comparative algorithms on the majority of test instances, verifying its superior overall performance. Across test instances of different scales, HCMRPP-TE demonstrates stronger adaptability in terms of solution quality, stability, and scalability, effectively enhancing the optimization performance for multi-objective MRPP problems and thereby validating the effectiveness of the proposed method.

V. Conclusion

This paper focuses on the multi-robot path planning problem in practical engineering scenarios and formulates a multi-objective multi-robot path planning model with the objectives of minimizing the total energy consumption and the maximum completion time. The proposed model is analogous to the multiple traveling salesman problem and is capable of realistically characterizing the key performance requirements of cooperative multi-robot task execution. It is therefore of significant practical relevance to typical application scenarios such as warehouse logistics, unmanned inspection, intelligent manufacturing, and emergency response. A hierarchical cooperative multi-robot path planning algorithm based on TSP encoding, termed HCMRPP-TE, is proposed. The proposed method first performs global TSP tour optimization to obtain a high-quality path with favorable global structural properties. Subsequently, a TSP-tour-based task allocation encoding mechanism is designed to decompose the single TSP tour into multiple robot sub-paths, achieving a unified representation of task allocation and path planning. Finally, NSGA-II is employed to conduct secondary multi-objective optimization on the robot paths under the obtained task allocation results, further improving the overall performance in terms of energy consumption and completion time. Experimental results demonstrate that the proposed method achieves good overall performance.

In future work, the proposed approach can be further extended in several directions. Dynamic and uncertain factors, such as dynamic task arrivals and environmental disturbances, can be incorporated to enhance the robustness of the algorithm in complex scenarios. Moreover, extending the method to heterogeneous multi-robot systems by considering differences in motion capabilities and energy consumption characteristics would improve its applicability. In addition, by constructing more refined energy and motion models and integrating parallel computation or learning-assisted optimization techniques, the computational efficiency and online planning capability of the algorithm can be further enhanced, thereby better meeting the requirements of large-scale and real-time applications.

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