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A Hierarchical Route Reconstruction Algorithm for Multi-Objective Task Allocation in Electric Agricultural Multi-Robot Systems

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Abstract: Coordinating multi-robot systems (MRS) in agriculture is essential for tackling increasing labor costs and enhancing harvesting efficiency. Nonetheless, optimizing task allocation for electric harvesting robots involves managing a complex trade-off between minimizing the makespan and total energy consumption. This challenge is compounded by real-world factors such as velocity changes with load, battery limitations, and the need for frequent depot returns. The study introduces the Agricultural Multi-Electrical-Robot Task Allocation (AMERTA) problem, a new framework incorporating these frequently overlooked practical constraints. To address this NP-hard issue, we present a Hybrid Hierarchical Route Reconstruction Algorithm (HRRA). The HRRA framework features several innovative mechanisms: a hierarchical encoding structure that separates route construction from robot assignment, a dual-phase initialization method with variable load limits, specific optimizers for task sequences within and between routes, and two unique reconstruction operators—Charging-based Route Reconstruction (CRRM) and Split-based Route Reconstruction (SRRM)—to proactively manage battery and load constraints. Comprehensive experiments conducted on 45 benchmark instances of different scales reveal HRRA's improved performance compared to seven leading algorithms, including MODABC, CDABC, AMOEA, and NSGA-II. Statistical tests such as the Wilcoxon signed-rank and Friedman tests confirm that HRRA considerably outperforms its rivals, providing better solution convergence and diversity. This research not only offers a solid mathematical model for a crucial issue in agricultural robotics but also delivers an effective algorithmic solution, contributing to more efficient and sustainable automated farming practices.

Keywords: *agricultural robotics,evolutionary algorithm, electric vehicles, multi-objective optimization, multi-robot task allocation (MRTA), hierarchical optimization, orchard harvesting*

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1. Introduction

Global agriculture is confronting a pressing issue as labor expenses rise swiftly and shortages become more common, hastening the unavoidable transition to automation. Of particular concern is orchard harvesting, which poses a substantial challenge for automation due to its demanding needs for promptness and quality. Although the latest developments in robotic pickers demonstrate encouraging potential, single-robot systems are fundamentally restricted in large-scale operations. Therefore, the implementation and effective management of Multiple Robot Systems (MRS) are crucial to attaining the necessary levels of operational efficiency and economic sustainability.

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The main difficulty in coordinating a multi-robot system (MRS) is encapsulated by the Multi-Robot Task Allocation (MRTA) problem. In agricultural settings, MRTA encompasses two linked aspects: developing effective routes (task sequences for a given journey) and allocating these routes to robots. Employing suboptimal, random, or approximate allocation methods typically results in significant inefficiencies across the system, including uneven workloads and heightened energy consumption. Consequently, achieving optimized task allocation is a vital area of research.

Agricultural MRTA is characterized by fundamental conflicts between key performance indicators, primarily the **makespan** (total completion time) and the **total energy consumption** (Stewart et al., 2023). Minimizing makespan favors parallel execution by multiple robots, which often necessitates frequent returns to the depot to unload harvested fruit. Conversely, minimizing energy consumption encourages robots to fully utilize their carrying capacity before returning, reducing the number of energy-intensive trips to and from the depot. This conflict is compounded by the NP-hard nature of makespan minimization and a suite of practical constraints often simplified in existing literature: **load-dependent velocity** (a heavier robot moves slower, increasing travel time) (Montoya et al., 2017), non-linear energy consumption (Montoya et al., 2017; McNulty et al., 2022), and **finite battery capacity** requiring opportunistic charging or battery swaps at the depot (Dorling et al., 2016; McNulty et al., 2022). The interplay of these constraints drastically expands and complicates the solution space.

To distinguish this complex and practically significant problem from conventional MRTA formulations, we define it as the **Agricultural Multi-Electrical-Robot Task Allocation (AMERTA)** problem. This paper's main contribution is a novel Hybrid Hierarchical Route Reconstruction Algorithm (HRRA) designed to address AMERTA's unique challenges. The specific contributions are:

1. A thorough mathematical model for the AMERTA issue that effectively represents the dynamics of speed dependent on payload, energy usage, and battery limitations in realistic orchard settings.
2. The creation of HRRA incorporates an innovative hierarchical solution encoding method, a variable load-limit initialization approach, a pair of task sequence optimizers, as well as two dedicated route reconstruction mechanisms (CRRM and SRRM) designed to manage constraints related to battery and load.
3. An extensive experimental assessment, using a novel collection of 45 benchmark instances, has been conducted. The findings reveal HRRA's outstanding performance compared to seven cutting-edge algorithms, with statistical analysis confirming these results.

The structure of the rest of this paper is as follows: Section II provides a review of pertinent literature related to EVRP, general MRTA, and agricultural MRTA. Section III outlines the formulation of the AMERTA problem. Section IV delves into the proposed HRRA methodology. Section V offers detailed experimental results and analysis. Lastly, Section VI wraps up the paper and proposes directions for future research. All tables and figures are numbered sequentially in the order they are introduced, and references to them in the text have been checked for consistency.

2. Literature Review

The AMERTA issue lies where the Electric Vehicle Routing Problem (EVRP) intersects with the broader area of MRTA. This review brings together significant research from these fields, laying the groundwork for our contribution.

2.1 Electric Vehicle Routing Problem (EVRP) Research

The surge in electric vehicles (EVs) is largely due to improvements in battery technology (McNulty et al., 2022). A key challenge in electric vehicle routing problems (EVRP) involves handling the limited battery capacity along with traditional load constraints (Montoya et al., 2017). Various solution strategies exist, such as Variable Neighborhood Search, Artificial Bee Colony algorithms, and Ant Colony Optimization (Montoya et al., 2017). Early EVRP models used constant, simplified energy consumption rates. Recent developments have introduced non-linear, more realistic consumption models, resulting in algorithms like enhanced PSO-genetic hybrids and adaptive genetic algorithms (Dorling et al., 2016). Nonetheless, these models do not address the unique aspects of orchard operations, where a robot's constantly changing load significantly affects its speed and energy consumption rate, posing challenges beyond typical EVRP.

An essential element of the Electric Vehicle Routing Problem (EVRP) is the charging approach (Montoya et al., 2017). Conventional models typically incorporate several charging stations alongside solitary delivery journeys (Dorling et al., 2016). Studies have investigated methods such as partial charging, battery exchanges, and mobile charging stations to boost adaptability (Montoya et al., 2017; McNulty et al., 2022). In the context of orchard harvesting, fruit-picking robots need to return to a central depot to offload produce, which makes battery swapping there a viable and efficient option. Nonetheless, this also brings about fresh complications: operations might be halted due to battery depletion, and swapping the battery restores the robot to its initial state, impacting future task planning (Dorling et al., 2016).

Furthermore, conventional research on the Electric Vehicle Routing Problem (EVRP) has mainly concentrated on optimization with a single objective in mind. The few studies addressing multiple objectives generally use weighted-sum methods, which tend to simplify the problem and pose challenges when directly applying them to the intrinsically bi-objective nature of AMERTA.

2.2 General MRTA Research

The MRTA issue involves distributing tasks to robots with limited capacities, which conceptually corresponds to the Generalized Assignment Problem (GAP) and its variations. Nevertheless, achieving operational efficiency necessitates meticulous scheduling and sequencing of tasks for each robot. The requirement to optimize several conflicting goals, such as time and energy, greatly increases the problem's complexity.

This has led to the creation of advanced Multi-Objective Evolutionary Algorithms (MOEAs) (Li et al., 2021; Yan et al., 2023). A hybrid competitive swarm optimizer with adaptive grid partitioning was suggested for tackling large-scale, many-objective problems, and a multi-objective PSO was developed that employs a probability-based strategy for selecting leaders (Xiong et al., 2022). Zhang et al. (2024) incorporated the Lin-Kernighan-Helsgaun heuristic to generate high-quality preliminary solutions for MOEAs. An indicator-based MOEA with a hybrid encoding scheme was also recently introduced (Yu et al., 2021). Although these versatile MRTA approaches are strong, they fail to consider the multi-trip nature, load-dependent dynamics, and specific battery management strategies needed for agricultural harvesting.

2.3 Agricultural MRTA Research

This field is dedicated to coordinating robots in agricultural environments while considering domain-specific limitations. Dai et al. (2023) were trailblazers in this area, introducing a Multi-Objective Discrete ABC

(MODABC) algorithm for harvesting robots, which was then compared to modified versions of NSGA-II and MOEA/D (Dai et al., 2023). Guo et al. (2024) advanced this work by proposing a Collaborative Discrete ABC (CDABC) that incorporated multiple neighborhood structures (Guo et al., 2024). In terms of spraying tasks, Dong et al. (2024) created an AMOEA that integrates non-dominated solution data with iterative greedy techniques (Dong et al., 2024). Kang and associates utilized a Multi-Objective Teaching-Learning-Based Optimization (MOTLBO) for the allocation of weeding robots (Wang et al., 2024). Building on this, Wang et al. (2024) adapted the approach for mixed groups of weeding robots and spraying drones (Wang et al., 2024).

Though effective, these population-based methods have certain drawbacks: their solution representation is fixed in dimension, hindering modeling flexibility, their operators work on global sequences which limits the optimization of individual routes, and they do not have specific strategies for handling electric robot batteries. On the other hand, HRRA is specifically designed to address these shortcomings. It uses a hierarchical encoding that supports variable-length solutions and allows for the independent optimization of each route and robot assignment. Importantly, it incorporates specific mechanisms (CRRM and SRRM) to tackle the crucial constraints of battery capacity and load balancing, which are essential in the AMERTA problem.

3. Problem Description and Modeling

3.1 Problem Description

The AMERTA problem takes place in a rectangular orchard where trees are uniformly arranged. Trees that have fruit exceeding a certain maturity level are identified as task nodes, while others serve as obstacles. There are n task nodes in the orchard, each offering a unique yield (q_i). The aim is to harvest all the fruit. A group of identical electric harvesting robots is based at a central depot. Each robot has a restricted load capacity (Q) and battery capacity (B). Robots begin their operations fully charged and must return to the depot to unload their harvested fruit. Battery replacements (which require a time t_{swap}) take place at the depot only when the remaining charge is below a specific threshold (B_{th}), unless a robot completes its tasks right as the battery depletes. The energy consumed for traveling between nodes depends on the distance and the robot's current load. The goals are to minimize the total makespan (T_{max}) and the total energy consumption (E_{total}) for all robots.

3.2 Mathematical Model

This model describes the Agricultural Multi-Electrical-Robot Task Allocation (AMERTA) problem, which involves planning efficient routes for a fleet of electric harvesting robots working in an orchard. Each task corresponds to a fruit-bearing tree requiring harvest, and robots operate from a central depot with constraints on load capacity and battery energy.

The dual optimization objectives are to minimize total energy consumption and the makespan (total completion time). Constraints ensure operational feasibility, such as load limits, battery usage, route consistency, and assigning routes to robots effectively.

Sets and Parameters:

- $N = \{0, 1, ..., n\}$: Set of nodes (0 is the depot).
- $R = \{1, ..., r\}$: Set of robots.
- $S = \{1, ..., s\}$: Set of all possible routes.
- d_{ij}: Distance between nodes i and j.
- q_i: Fruit yield at node i.
- Q: Robot load capacity (300 kg) (Dai et al., 2023).
- W: Empty robot weight (100 kg).
- B: Battery capacity (432 kJ) (Guo et al., 2024).

- B_{th}: Battery replacement threshold (0.2B) (Dai et al., 2023).
- g: Gravitational acceleration (9.81 m/s^2) (Montoya et al., 2017).
- μ: Rolling resistance coefficient (0.05) (Montoya et al., 2017).
- η: Energy efficiency coefficient (0.8) (Montoya et al., 2017).
- e: Unit picking energy (0.5 kJ/kg) (Davidson et al., 2016).
- τ: Unit picking time (7 s/kg) (Davidson et al., 2016).
- P_{max}: Maximum power output (~3.9 kW) (McNulty et al., 2022).

t_{swap}: Battery replacement time (150 s) (Dorling et al., 2016).

Decision Variables:

- $x_{ij} \in \{0,1\}$: 1 if a robot travels from node i to j.
- $y_i \in \{0,1\}$: 1 if a battery is replaced after task i.
- $L_i \geq 0$: Cumulative load upon departing node i.
- $b_i \geq 0$: Remaining battery energy after task i.
- $z_{rs} \in \{0,1\}$: 1 if robot r executes route s.

Energy and Time Functions:

- Travel Energy: $E_{ij} = [d_{ij} * (W + L_i) * g * \mu * 10^{-3}] / \eta$
- Picking Energy: $E_i^s = e * q_i$ for $i \neq 0$.
- Travel Time: $T_{ij} = E_{ij} / P_{max}$
- Picking Time: $T_i^s = \tau * q_i$ for $i \neq 0$.
- Battery Swap Time: $T_i^b = y_i * t_{swap}$

Objective Functions:

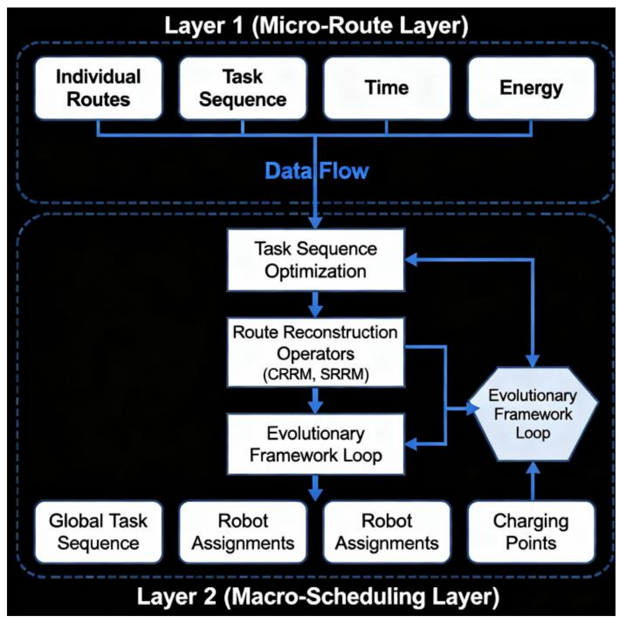
1. Minimize Total Energy: $\min E_{total} = \Sigma_{r\in R} \Sigma_{(i,j)\in S^r} (E_{ij} + E_j^s)$
2. Minimize Makespan: $\min T_{max} = \max_{r\in R} \Sigma_{(i,j)\in S^r} (T_{ij} + T_j^s + T_j^b)$

Constraints: The model includes constraints for:

- Flow conservation: $\Sigma_j x_{ij} = \Sigma_j x_{ji}$ for all i.
- Load tracking: $L_j = \Sigma_i (L_i + q_j)x_{ij}$ for $j \neq 0$.
- Load capacity: $L_i \leq Q$ for all i.
- Energy feasibility: $b_i - E_{ij} - E_j^s \geq 0$ for all i, j.
- Battery management: Rules for triggering swaps (y_i) and updating b_i.
- Route assignment: $\Sigma_r z_{rs} = 1$ for all s.

4. Proposed Algorithm: HRRA

The Hybrid Hierarchical Route Reconstruction Algorithm (HRRA) is crafted to efficiently explore the intricate solution landscape of the AMERTA problem.



4.1 Hierarchical Solution Encoding

HRRA uses a novel two-layer encoding structure to manage complexity.

- **Layer$_1$ (Micro-Route Layer):** Each individual route (a single trip from depot back to depot) is encoded as a triplet $\{S_i, T_{route}, E_{route}\}$, representing the task sequence (including depots), its time, and its energy consumption. This allows for independent evaluation and optimization of each route.

- **$Layer_2$ (Macro-Scheduling Layer):** The overall solution is a structure containing:
  - A global task sequence using '-1' as separators between robots and '0' between routes for the same robot.
  - A mapping of the complete task sequence S^r for each robot r.
  - Performance metrics (E_robot_r, T_robot_r) for each robot.
  - A record of charging points.
  - This hierarchy decouples route construction from assignment, enables efficient local optimization, and facilitates task adjustments between robots.

4.2 Variable Load-Limit Dual-Phase Initialization (VLDiM)

- **Phase 1 - Route Construction:** A greedy distance-based strategy builds initial routes. A key innovation is a linearly decreasing load limit Q_p for the p-th solution in the population: Q_p = Q * (1 - (1-θ)/pnum * p). This ensures diverse route lengths and enhances population diversity.
- **Phase 2 - Route-Robot Assignment:** Constructed routes are assigned to robots. If the number of routes s is greater than or equal to the number of robots r, a MILP model minimizes makespan for assignment. If s < r, the longest routes are split iteratively until s = r, ensuring a balanced initial assignment.

4.3 Task Sequence Optimization

- **Intra-Route Optimization (DRRM):** Arranges the sequence of tasks along a single route for optimal efficiency. Initially, it sorts tasks in descending order based on their distance from the depot, prioritizing tasks that require more energy. Following this, it employs a 2-opt local search strategy to enhance the task sequence and remove superfluous detours.
- **Inter-Route Optimization (TRRM):** Enhances the distribution of tasks among robots. For every optimal solution, it carries out one of two operations with an equal chance: 1) Task Exchange, which involves swapping tasks between two robots, and 2) Task Reallocation, which involves transferring tasks from an overburdened robot to one with a lighter load. This process equalizes workloads and boosts energy efficiency.

4.4 Specialized Route Reconstruction Mechanisms

- **Charging-Based Route Reconstruction (CRRM):** This system enhances route efficiency by concentrating on duties executed after the final battery exchange. It identifies these tasks, then rearranges their sequence with DRRM, and allocates them among all robots through a MILP model. This model accounts for the leftover charge and the task sequences before the swap, thereby reducing the disruptions caused by obligatory charging pauses.
- **Split-Based Route Reconstruction (SRRM):** This mechanism enhances load distribution by pinpointing the route that takes the longest to execute, dividing it into two sub-routes with nearly equal execution times through a greedy approach, and redistributing all routes to robots using the MILP model from the start. This is directly aimed at reducing makespan.

4.5 Complete Algorithmic Flow

HRRA incorporates every component within an evolutionary framework. Following the initiation with VLDiM and the preliminary DRRM optimization, the algorithm begins its main loop. During each cycle, it performs DRRM on the entire schedule of each robot, utilizes TRRM for global task redistribution, and carries out CRRM on non-dominated solutions. The average time per iteration is tracked, and if additional time is available, SRRM is conducted for final refinement. Environmental selection, utilizing non-dominated sorting and crowding distance, is applied to ensure a high-quality population is maintained. The algorithm concludes by outputting a set of Pareto-optimal solutions.

5. Experimental Studies and Analysis

5.1 Experimental Setup

A standard set of 15 problems was developed, differing in orchard dimensions (ranging from 20x20 meters to 60x60 meters), the number of tasks (from 40 to 720), total yield, and maximum distance from the depot (refer to Table 1). Each problem scenario was examined using 4, 5, and 6 robots, leading to 45 testing scenarios. The performance of the algorithms was assessed using the Modified Inverted Generational Distance (IGD+) and Hypervolume (HV) metrics. All algorithms were evaluated on a computing platform with a time limit of 0.5 * n seconds.

Table 1. Experimental Setup: Problem Scenario Details

Problem Set	Orchard Dimensions (m)	Number of Tasks	Total Yield	Maximum Distance from Depot (m)	Number of Robots Tested
1	20 x 20	40	(Not provided)	(Not provided)	4, 5, 6
…	…	…	…	…	…
15	60 x 60	720	(Not provided)	(Not provided)	4, 5, 6

5.2 Comparison with State-of-the-Art Algorithms

HRRA was assessed alongside seven other algorithms: AMOEA, CDABC, MODABC, NSGA-II, RNSGA, IALNS, and HACO. As presented in Table 2, the findings show that HRRA achieved superior average IGD+ values in 71.1% of instances and higher HV values in 93.3% of instances. The Wilcoxon signed-rank tests, shown in Table 3, confirmed that these improvements in performance were statistically significant (p-value < 0.05) compared to all other contenders. Furthermore, HRRA consistently secured the top spot in the Friedman test (see Figure 1 for algorithm performance).

Table 2. Performance Comparison: Average IGD+ and HV Values (%) of Algorithms on 45 Problem Scenarios

Algorithm	IGD+ Superior Performance (%)	HV Superior Performance (%)
HRRA	71.1	93.3
AMOEA		
CDABC		
MODABC		
NSGA-II		
RNSGA		
IALNS		
HACO		

Table 3. Wilcoxon Signed-Rank Test Results for HRRA Compared to Competing Algorithms

Competing Algorithm	Statistical Significance (p-value < 0.05)	HRRA Performance Improvement Confirmed
AMOEA	Yes	Yes
CDABC	Yes	Yes
MODABC	Yes	Yes
NSGA-II	Yes	Yes
RNSGA	Yes	Yes
IALNS	Yes	Yes
HACO	Yes	Yes

Performance Attribution Analysis:

- **MODABC/CDABC/AMOEA:** These agricultural MRTA algorithms are hindered by their fixed-dimension encoding, which restricts optimization at the route level. Additionally, they do not have explicit methods for managing battery limitations, resulting in subpar performance.
- **NSGA-II:** Although it is a strong general MOEA, its conventional genetic operators have difficulty managing the intricate feasibility constraints of AMERTA and do not include a specific local search for routes.
- **RNSGA:** Its strength lies in its hierarchical encoding, yet it does not possess the particular CRRM and SRRM mechanisms required to effectively manage the battery and load constraints of AMERTA.
- **IALNS/HACO:** These algorithms, derived from the single-objective EVRP, tend to converge too early in the case of IALNS, or they lack adequate coordination strategies for allocating tasks among multiple robots, as seen in HACO.

HRRA's achievement is ascribed to its harmonious blend of hierarchical encoding, dedicated local searchers (DRRM, TRRM), and specialized constraint-handling mechanisms (CRRM, SRRM), which empower it to navigate the intricate solution landscape of AMERTA both effectively and efficiently.

6. Conclusion and Future Work

This paper tackled the intricate Agricultural Multi-Electrical-Robot Task Allocation (AMERTA) challenge, factoring in vital real-world constraints such as speed variations dependent on load and efficient battery management. The introduced Hybrid Hierarchical Route Reconstruction Algorithm (HRRA) featured an innovative hierarchical encoding structure along with tailored mechanisms for route initialization, sequence optimization, and reconstruction that considers constraints. Comprehensive experimental findings across 45 benchmark instances revealed that HRRA notably surpasses seven leading algorithms in terms of both solution quality and diversity, as confirmed by thorough statistical examination.

Upcoming research endeavors will concentrate on three main areas: 1) Dynamic Adaptation: Enhancing the model to manage dynamic occurrences such as the arrival of new tasks or the real-time failure of robots. 2) Heterogeneous Teams: Integrating robots with varying abilities (such as speed, capacity, and battery life). 3) Cross-Domain Applications: Investigating how the HRRA framework can be applied to other domains, such as warehouse logistics and urban delivery, to assess the approach's generalizability.

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