The Unmanned Aerial Vehicle Routing Problem with Recharging

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Abstract

The application of Unmanned aerial vehicles (UAVs) in both civilian and military domains is drawing increasing attention recently. This paper investigates a new routing problem of small UAVs for information collection, where UAVs can be recharged at platforms (ground vehicles or stations) distributed in the area. Different from the previous works on UAV routing, the UAVs are allowed to partially recharge their batteries according to the requirement in the following route. A mixed integer nonlinear programming model is developed to formulate the problem, where both the overall time for completing all targets' observation and the number of UAVs are minimized. An improved adaptive large neighborhood search (ALNS) algorithm with simulated annealing criterion is designed, and a recharging platform insertion heuristic is developed to determine the recharging strategy and construct feasible solutions. To verify the effectiveness of the proposed ALNS algorithm, a set of new benchmark instances are designed based on the well-known Solomon dataset and solved. The computational results are compared with those obtained by the ant colony optimization and variable neighborhood search, which shows that ALNS performs significantly better and stable. Furthermore, analysis of the experimental results indicates that many advantages can be obtained through introducing the recharging strategy for small UAVs.

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Preamble

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The Unmanned Aerial Vehicle Routing Problem with Recharging

Huiting Mao, Jianmai Shi, Zhongbao Zhou and Long Zheng

Abstract– The application of Unmanned Aerial Vehicles (UAVs) in both civilian and military domains is drawing increasing attention recently. This paper investigates a new routing problem for small UAVs conducting information collection missions, where UAVs can be recharged at platforms (ground vehicles or stations) distributed throughout the operational area. Unlike previous works on UAV routing, the proposed framework allows UAVs to partially recharge their batteries according to the requirements of subsequent route segments. A mixed-integer nonlinear programming (MINLP) model is developed to formulate the problem, with objectives to minimize both the overall time for completing observation of all targets and the number of UAVs employed. An improved Adaptive Large Neighborhood Search (ALNS) algorithm with simulated annealing criterion is designed, and a recharging platform insertion heuristic is developed to determine the recharging strategy and construct feasible solutions. To verify the effectiveness of the proposed ALNS algorithm, a set of new benchmark instances is designed based on the well-known Solomon dataset. Computational results compared with those obtained by ant colony optimization and variable neighborhood search demonstrate that ALNS performs significantly better and more stably. Furthermore, analysis of the experimental results indicates that substantial advantages can be obtained by introducing recharging strategies for small UAVs.

Index Terms– Unmanned aerial vehicle, routing, heuristic, recharging

I. INTRODUCTION

Small Unmanned Aerial Vehicles (UAVs) or drones play an increasingly important role in both civilian and military applications, including agriculture monitoring, disaster relief, battlefield reconnaissance, border patrol, and logistics delivery. In civilian applications, UAVs have demonstrated great market potential, leading to significant cost savings in last-mile package delivery, information collection, wild search and rescue, and agriculture monitoring [1]. Many companies worldwide, including UPS [2], DHL [3], Alibaba [4], and Amazon [5], have adopted UAVs for "last-mile delivery" to reduce logistics costs and increase distribution efficiency. Since UAVs can access targets in dangerous environments without risking human lives, they are widely used in military operations. Small UAVs can fly at low altitudes and hover over targets to collect accurate information, and their advantages in miniaturization, strong concealment, easy maintenance, and low cost facilitate their application in Intelligence, Surveillance, and Reconnaissance (ISR) missions.

Due to limited battery capacity, small UAVs have relatively short endurance ranges, which represents a primary barrier to their application in large-area ISR missions. When a small UAV must operate over a large area, it needs to recharge its battery during the flight. Many studies have focused on extending the endurance range of small UAVs, including new energy-supported designs and solar power systems [7], automated battery swapping and recharging [8], and efficient power allocation [9].

To address UAV endurance limitations, we propose a new operational mode for small UAVs where their batteries can be recharged at platforms distributed throughout the area. Recently, Dynamic Wireless Charging (DWC) technology [10] has been applied as a novel method for recharging electric vehicles, enabling EV batteries to be recharged remotely while staying near infrastructure equipped with DWC. With the miniaturization and intelligence of wireless charging equipment, fast wireless charging devices can be installed on many stations and ground vehicles, enabling them to serve as recharging platforms for small UAVs. When a small UAV' s battery power becomes insufficient, it can visit a nearby recharging platform to recharge and then continue its mission. In this scenario, UAV routing must consider decisions regarding recharging platform selection and battery recharging levels.

The UAV routing problem with recharging shares similarities with the Electric Vehicle Routing Problem (EVRP) in the commercial domain [11]. An important characteristic of EVRP is that EVs need to visit recharging stations during their routes to extend their endurance range and complete all delivery tasks. The main difference is that EVs do not consume battery power while waiting and serving customers, whereas small UAVs consume battery power both when waiting and when collecting information above targets, with power consumption typically being faster during information collection due to additional sensor power requirements.

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II. LITERATURE REVIEW

This section reviews two streams of relevant literature: UAV routing problems and the Electric Vehicle Routing Problem (EVRP).

UAV routing problems have been investigated in both military and civilian application domains. Shetty et al. [13] proposed a tactical routing problem for a team of UAVs conducting attack missions based on target priorities, where UAVs carry ammunition to attack different targets. Ceccarelli et al. [14] investigated a micro-UAV routing problem for reconnaissance and conducted simulation experiments to find robust solutions in the presence of randomly perturbed wind. Mufalli et al. [15] considered simultaneous sensor selection and routing of UAVs where payload affects endurance range, constructing a new mathematical model to solve the problem. Avellar et al. [16] routed a group of UAVs for area coverage to minimize coverage time, where intelligence collection can be carried out in fixed areas considering specified target time windows. Evers et al. [17] studied the routing problem of multiple UAVs for reconnaissance missions, accounting for uncertainty in fuel usage. Mahmud and Cho [18] investigated UAV routing problems where UAVs need to avoid enemy prediction, while Vanegas et al. [19] considered UAV routing under environmental uncertainty.

In civilian applications, UAVs can be used for logistics delivery [20], medical material transportation [21], efficient road detection and tracking [22], and disaster relief operations [23]. Kevin et al. [24] investigated the vehicle routing problem for drone delivery scenarios that minimize both cost and overall delivery time considering an energy consumption model. Sawadsitang et al. [25] proposed a joint ground and aerial delivery service framework considering optimization and planning uncertainty for drone package delivery, formulating a three-stage stochastic integer programming model with a decomposition method to solve the problem. In [26], UAVs were used for dynamic wildfire tracking since they can operate in hazardous fire environments instead of humans, and a distributed control framework was proposed for UAV teams.

However, due to the limited endurance range of small UAVs, their operational radius is restricted, which greatly limits their applications in large areas. To overcome this difficulty, Liu et al. [6] and Luo et al. [20] proposed a novel two-echelon ground vehicle (GV) and UAV cooperative routing problem (2E-GUCRP) for ISR missions, where the GV serves as a mobile platform carrying UAVs and recharging their batteries. In this mode, UAVs can extend their endurance range through multiple launches from GVs. In recent years, UAV applications in civilian operations have drawn increasing attention, with many commercial logistics companies using UAVs for "last-mile delivery" to save distribution costs. Chiang et al. [27] proposed a GV-UAV cooperative system where GVs serve as mobile platforms for UAV launch and landing, with both capable of delivering packages during the route. To overcome limited UAV endurance, Sungwoo and Ilkyeong [28] investigated a truck-drone system with a fixed drone station containing drones and recharging equipment, employing a truck to connect the station and logistics distribution center. Liu et al. [29] designed a Simulated Annealing algorithm to solve the 2E-GUCRP for package delivery. In these studies, ground vehicle assistance effectively extends UAV endurance range; however, UAVs can only visit targets constrained by GV paths.

To extend endurance range and reduce UAV dependence on GVs, Coelho et al. [30] designed a two-level routing problem model where UAVs can be recharged at given stations to complete their tours. Li et al. [31] proposed a mission planning method considering both UAV routing and recharging station location, assuming fixed recharging times. Ribeiro et al. [32] studied UAV application for belt conveyor inspection systems in the mining industry where UAVs must be fully charged at recharging stations. To extend mission coverage, Noureddine et al. [33] utilized public land transport vehicles to carry UAVs during part of their routes to save energy consumption, with recharging power set as a fixed parameter. Yu et al. [34] studied UAV route planning by allowing visits to fixed recharging stations with unmanned ground vehicles (UGVs) serving as mobile stations.

The routing problem with recharging has also been studied in EVRP. Schneider et al. [12] studied the EVRP with Time Windows (EVRPTW), applying a full fast recharging strategy and designing a metaheuristic integrating VNS with Tabu search, tested on instances generated from the Solomon dataset. Ding et al. [35] studied EVRP where partial recharging for electric vehicles is allowed and recharging station capacity is considered. Keskin and Çatay [36] investigated EVRPTW where EVs are also allowed partial recharging. More works on EVRP can be found in the comprehensive review by [37].

From the related literature, it is evident that investigating different recharging strategies to enlarge UAV endurance is an important research topic. The mode of UAVs being recharged by smart wireless recharging platforms is a new research area requiring more efficient models and algorithms.

III. PROBLEM FORMULATION

The initial motivation for the UAV routing problem with recharging comes from reconnaissance missions in battlefield scenarios, where multiple small UAVs start from a base and collect information at a set of targets. A certain number of ground (combat) vehicles distributed across the battlefield are configured with fast wireless charging devices and act as recharging platforms for UAVs. Before a UAV' s battery powers off, it can fly to any of these platforms for recharging and then continue visiting subsequent targets. Fig. 1 [Figure 1: see original paper] presents an illustrative example of the problem. Different battery icons denote the power level after visiting each target. The UAV starts from the unique base with a fully charged battery; after visiting target T3, the battery power cannot support travel to the next target T4, so the UAV finds nearby recharging platform P2 for partial recharging. After recharging, the UAV continues its tour to visit T4 and T5, then returns to the base. Furthermore, UAVs are allowed to visit recharging platforms multiple times.

Although the UAV routing problem with recharging is initially inspired by military applications, many potential civilian applications exist, such as information collection in wild areas, wild search and rescue, and agriculture monitoring. The main factors and constraints are as follows:

1) UAVs: Small UAVs are driven by lithium batteries with limited capacity. Battery consumption is divided into three parts. First, UAVs consume power during flight between targets, with consumption speed related to flying speed and distance. Second, when collecting information at a target, sensors on the UAV consume battery power; the consumption rate is related to reconnaissance accuracy and duration. Third, power consumption still occurs when the UAV hovers above a target while waiting, though sensors are turned off. In this paper, UAVs start from the base and must return after completing all reconnaissance missions within specified time.

2) Recharging Platforms: Many ground vehicles in the battlefield are equipped with wireless charging devices that can recharge UAVs quickly. The recharging level is related to recharging time. The locations of these platforms and the base are known.

3) Targets: A set of targets are located at different positions, each detectable only within a specified time window. If a UAV arrives earlier than the earliest start time, it must hover and wait. Time windows and location information for all targets are given before mission planning.

The objective is to minimize total mission time and the number of UAVs utilized by optimizing flight routes for reconnaissance and recharging.

The notations used in the model formulation are summarized in TABLE I:

TABLE I NOTATIONS USED IN THE MODEL

Parameters	
V	set of targets
F	set of recharging platforms and their copies
0	the starting base
$n+1$	the ending base
V^+	set of targets, recharging platforms and the starting base, $V^+ = V \cup F \cup \{0\}$
V^-	set of targets, recharging platforms and ending base, $V^- = V \cup F \cup \{n+1\}$
V^0	set of all vertices
d_{ij}	the travel distance between node i and j
t_{ij}	the travel time between node i and j
g	the battery charge rate
s_i	the reconnaissance time of target i
e_i	the earliest starting time of reconnaissance at target i

Parameters	
l_i	the latest starting time of reconnaissance at target i
Q	the capacity of the UAV' s battery
α	the weight coefficient of unit UAV
β	the weight coefficient of total reconnaissance time, and $\alpha + \beta = 1$
c_d	the power consuming rate of UAV for travelling
c_r	the power consuming rate of UAV for reconnaissance
c_w	the power consuming rate of UAV for waiting
c_{uav}	fixed cost of a UAV

Decision variables	
u_i	the starting time of reconnaissance target i, $i \in V$
y_i	the remaining power level when the UAV arrives at node i, $i \in V^+$
q_i	the recharging quantity at recharging platform i, $i \in F$
Y_i	the power level when the UAV leaves the recharging platform i, $i \in F$
δ_i	the waiting time of the UAV at target i, $i \in V$
x_{ij}	1, if a UAV travels from node i to node j; otherwise 0; $i \in V^+, j \in V^-, i \neq j$
z_i	1, if the recharging platform i is selected for recharging; otherwise 0; $i \in F$

The mathematical model of the UAV routing problem is formulated as follows:

Objective function:

$$\min \Pi = \alpha \cdot \sum_{j \in V^-} c_{uav} x_{0j} + \beta \cdot \left(\sum_{i \in V} s_i + \sum_{i \in V} \delta_i + \sum_{i \in V^+} \sum_{j \in V^-} t_{ij} x_{ij} + \sum_{i \in F} \frac{q_i}{g} \right) \quad (1)$$

Subject to:

$$\sum_{j \in V^-, j \neq i} x_{ij} = 1, \quad \forall i \in V \quad (2)$$

$$\sum_{i\in V^+, i\neq j} x_{ij} \leq 1, \quad \forall j \in F \tag{3}$$

$$\sum_{j\in V^-, j\neq i} x_{ij} - \sum_{j\in V^+, j\neq i} x_{ji} = 0, \quad \forall j \in V^0 \tag{4}$$

$$u_j \geq u_i + s_i + \delta_i + t_{ij} - M(1 - x_{ij}), \quad \forall i \in V, j \in V^-, i \neq j \tag{5}$$

$$u_j \geq u_i + \frac{q_i}{g} + t_{ij} - M(1 - x_{ij}), \quad \forall i \in F, j \in V^-, i \neq j \tag{6}$$

$$e_j \leq u_j \leq l_j, \quad \forall j \in V \tag{7}$$

$$y_j \leq y_i - c_d \cdot d_{ij} - c_r \cdot s_i - c_w \cdot \delta_i + Q(1 - x_{ij}), \quad \forall i \in V, j \in V^-, i \neq j \tag{8}$$

$$y_j \leq y_i - c_d \cdot d_{ij} + Q(1 - x_{ij}), \quad \forall i \in F, j \in V^-, i \neq j \tag{9}$$

$$Y_i = y_i + q_i, \quad \forall i \in F \tag{10}$$

$$Y_i \leq Q, \quad \forall i \in F \tag{11}$$

$$x_{ij} \in \{0, 1\}, \quad \forall i \in V^+, j \in V^-, i \neq j \tag{12}$$

$$z_i \in \{0, 1\}, \quad \forall i \in F \tag{13}$$

$$q_i \geq 0, \quad \forall i \in F \tag{14}$$

Objective (1) minimizes a weighted sum of the total number of UAVs and the overall time for completing all targets' reconnaissance missions, where the weighted coefficients are determined by the planner. Constraint (2) ensures each target is visited exactly once, while constraint (3) handles connectivity between nodes (targets and recharging platforms). Constraint (4) guarantees flow conservation at each vertex. Constraints (5) and (6) enforce time flow feasibility. Constraint (7) ensures compliance with target time windows. Constraints (8) and (9) balance residual battery level after visiting a target or recharging platform and ensure it is always non-negative. Constraint (10) determines the battery level after recharging at a platform. Constraint (11) ensures the battery level at recharging platforms does not exceed UAV recharging capability. Constraints (12)-(14) define the decision variables.

In this model, the UAV's battery can be partially recharged, so only the required battery power for the following route is recharged to save time and energy.

IV. ADAPTIVE LARGE NEIGHBORHOOD SEARCH ALGORITHM

This section proposes an improved Adaptive Large Neighborhood Search (ALNS) algorithm embedded with a recharging platform insertion heuristic. The ALNS framework was first proposed by Pisinger and Ropke [38-40] and has been widely used for solving VRP [41-43] and EVRP [44-45]. The basic idea of ALNS is to employ different combinations of destroy and repair operators to obtain new neighborhood solutions while adaptively updating each operator' s utilization probability based on its weight, which is related to its performance during the search process.

A two-stage constructive heuristic generates an initial feasible solution. First, the nearest neighborhood heuristic constructs a solution without considering battery capacity constraints. In this stage, each UAV' s route satisfies time window constraints, though battery capacity may be insufficient to complete the route. In the second stage, a recharging platform insertion heuristic optimizes where to recharge the UAV and how much energy to replenish to make the route feasible. The detailed insertion heuristic process is described in Subsection A.

During ALNS search, any change to targets in a route could affect recharging decisions. To improve search efficiency, destroy and repair operations are conducted on the Non-Charged (NC) solution where all recharging platforms are removed from UAV routes. When an NC solution is generated after destroy and repair operations, the recharging platform insertion heuristic makes it feasible. Thus, each neighborhood search operation follows a "Search First, Insertion Afterwards" rule. The new feasible solution is accepted with the SA criterion, and the main ALNS procedure is shown in Algorithm 1.

A. Recharging Platform Insertion Heuristic

Due to battery capacity limitations, UAV endurance range is restricted. If total energy consumption exceeds battery capacity, the UAV must visit a recharging platform to recharge before visiting subsequent targets. A recharging platform insertion heuristic optimizes recharging decisions regarding where and how much to recharge. The main steps are shown in Algorithm 2.

For an NC route where total travel distance violates maximum battery capacity, the UAV starts from the base and travels along the route until reaching a target that cannot be visited with remaining battery power. The nearest reachable recharging platform is then found and inserted after the current target. To find the best insertion position, all possible insertions between adjacent targets are compared. Considering routes (a) and (b) in Fig. 2 [Figure 2: see original paper] as an example, both are feasible routes after inserting recharging platforms into the same NC route at different positions. Although the UAV in route (b) needs recharging twice, total time is slightly shorter than route (a) due to recharging platform distribution. In this case, route (b) would be selected.

After determining the insertion position, the UAV can be partially recharged, with the recharging level determined by required battery power for the subsequent route. Once recharging levels at each platform are known, target time windows after the recharging platform may be affected and must be checked for feasibility. If any target' s time windows are violated, those targets should be removed into the list $V_{unvisit}$. As shown in Fig. 3 [Figure 3: see original paper], after inserting P4 between target 3 and target 4, target 4' s time window is violated due to long recharging time at P4, so target 4 must be removed from the route. For targets in $V_{unvisit}$, the two-stage constructive heuristic is iteratively applied until a feasible solution is generated. Finally, many feasible routes are generated based on the same NC route after inserting recharging platforms at different positions, and the best route is accepted—preferring routes that retain more targets and consume less time.

B. Neighborhood Structures

Given an initial feasible solution, all platforms are removed to generate an NC solution. Neighborhood search is applied through different destroy and repair operators on the NC solution. First, a removal operator is selected and a certain number of targets are removed based on the corresponding removal rule. Then, an insertion operator repairs the destroyed NC solution by inserting removed targets. Finally, the recharging platform insertion heuristic inserts recharging platforms into the NC solution to generate a feasible solution.

1) Removal operators: The destroy mechanism consists of nine removal operators grouped into two types: Route Removal (RR) and Target Removal (TR). In RR, an entire UAV route is selected and removed. In TR, a subset of targets is selected and moved into the removal list $V_{unvisit}$. The number of removed targets is determined according to the overall number of targets, generated from a uniform distribution. All removal operators are introduced below.

- **Random Route Removal:** A route is randomly chosen from all routes, and all its targets are removed and added to $V_{unvisit}$. This strategy extends search range and increases probability of finding global optimum.
- **Shortest Route Removal:** This operator selects the shortest route in the current solution and removes all its targets, maximizing UAV utility and reducing the number of UAVs.
- **Random Target Removal:** A set of targets is randomly removed from different routes to diversify and enlarge the search space.
- **Worst-Distance Target Removal:** Targets with the worst distance are removed iteratively. Here, a target' s distance is the sum of distances from the current target to its preceding and succeeding targets in the route.
- **Worst-Time Target Removal:** This operator calculates, for each target, the difference between reconnaissance start time and earliest start time, then iteratively removes the target with the largest difference. The purpose is to avoid long waiting or delayed reconnaissance to satisfy time windows for more targets.
- **Modified Shaw Removal:** This operator removes a set of targets according to a specified rule, adapted from Shaw Removal [1998]. The difference is that UAV routing does not consider load capacity but considers reconnaissance time since duration affects power consumption. The operator starts by randomly removing a node. Let $l_{ij}^* = \arg\min\{|s_i - s_j|\}$ if targets

i and j are both detected by the same UAV in the same route, where $\Phi_1, \Phi_2, \Phi_3, \Phi_4$ are weight parameters.

- **Proximity-based Target Removal:** The first target is randomly selected, then the nearest target to the previously selected one is chosen. This process continues, always selecting the target nearest to the former one. Fig. 4 [Figure 4: see original paper] illustrates this operator.
- **Time-based Target Removal:** Similar to Proximity-based Removal, this operator selects targets with proximate time windows and removes them from the current solution.
- **Zone Removal:** This operator first randomly defines an area with predefined size in the Cartesian coordinate system, then randomly selects targets located in that area for removal. If fewer than λ targets are found, it reselects an area with the same size and repeats until λ nodes are removed. As Fig. 5 [Figure 5: see original paper] shows, the green rectangular box represents the selected area, with targets T4, T5, T6, T7, and T9 randomly selected for removal. The pseudocode is given in Algorithm 3.

2) Insertion operators: Five insertion operators insert removed targets back into routes to generate a new NC solution. During insertion, time window constraints must be satisfied while battery capacity is not considered.

- **Greedy Insertion:** This operator calculates the insertion cost of each removed target at its best insertion position, repeatedly inserting the node with the least insertion cost into its best feasible position. Insertion cost is calculated as increased distance.
- **Regret-2 Insertion:** Let Δf_i^1 represent the objective function value difference after inserting target i in the best feasible insertion place, and Δf_i^2 the difference after inserting target i in the second-best insertion place. The operator inserts the target with the largest regret value $\max\{\Delta f_i^2 - \Delta f_i^1\}$.
- **Regret-3 Insertion:** Similar to Regret-2 Insertion, let Δf_i^3 represent the difference after inserting target i in the third-best insertion place. The operator inserts the target with the largest regret value $\max\{\Delta f_i^3 - \Delta f_i^1\}$.
- **Time-based Insertion:** This operator originates from Greedy Insertion, with the unique difference being insertion cost calculation. The cost is defined as the change in route finish time.
- **Zone Insertion:** This operator selects removed targets using the Time-based Insertion criterion but only considers routes in a specific zone rather than investigating all routes in the current destroyed solution.

C. Adaptive Adjustment of Operators' Weight

Selection of removal and insertion operators is governed by a roulette-wheel mechanism. With k operators having weights w_i, operator j is chosen with probability $p^j_{select} = w_j / \sum_{i=1}^{k} w_i$. Initially, all removal and insertion operators have equal probability. With nine removal operators and five insertion operators, initial weights are set to 1/9 and 1/5, respectively. During search, weights are updated as:

$$w_i^{t+1} = w_i^t \cdot (1 - \pi) + \pi \cdot \frac{\omega_i}{r_i}$$

where w_i^t is the weight of operator i in iteration t, π is the roulette-wheel parameter, ω_i is the score of operator i, and r_i is the number of times it was used. If a new global best solution is obtained, the operator score σ_i is increased by σ_1. If the new feasible solution is not global best but better than the current solution, the score is increased by σ_2. If the solution is worse than current but accepted within a certain probability, the score is increased by σ_3.

D. Acceptance and Stopping Criteria

Simulated annealing is adopted as the acceptance criterion. During search, Ψ_{best} is the global best solution, $\Psi_{current}$ is the current solution before iteration begins, and Ψ_{new} denotes the feasible solution after iteration. Let $c(\Psi)$ be the objective function value of solution Ψ. A solution Ψ_{new} is always accepted if $c(\Psi_{new}) < c(\Psi_{current})$. If $c(\Psi_{new}) > c(\Psi_{current})$, it is accepted with probability $\exp(-(c(\Psi_{new}) - c(\Psi_{current}))/T)$, where T is temperature. In the iteration process, temperature is gradually decreased at a constant rate h $(0 < h < 1)$. The algorithm returns the global best solution after reaching the maximum number of iterations.

V. COMPUTATIONAL EXPERIMENTS

As the first work investigating UAV routing with recharging, no benchmark dataset exists. To analyze ALNS performance, we designed a new benchmark set based on the well-known Solomon dataset. All algorithms were programmed in Visual C++ and experiments conducted on a laptop with Intel Core i5 processor (3GHz) and 8GB RAM. Detailed data is presented in the supplement [53].

A. Experiment Design

A set of 56 large instances was designed, each with 100 targets and 21 recharging platforms. The distribution of targets and platforms follows the dataset in [12], which is based on the Solomon dataset. Instances are divided into three classes according to target geographical distribution: Random (R), Clustered (C), and a mixture of both (RC). Instances with narrow time windows are classified as groups R1, C1, and RC1, while those with wide time windows are groups R2, C2, and RC2. Detailed node information for all 56 instances is available in the supplement.

UAV battery capacity is constant at 150. Battery power consumption rates are set to 1 when flying en-route, 0.5 when hovering above targets and waiting, and 2 when collecting information (higher than travel due to sensor power requirements). Average UAV velocity is 1, and inverse recharging rate is 0.33, meaning complete recharging from zero requires 50 minutes.

B. Algorithm Performance

To analyze ALNS performance, it is compared with two widely used metaheuristics: Ant Colony Optimization (ACO) and Variable Neighborhood Search (VNS). ACO was first proposed by Dorigo et al. [46] and widely applied to VRP and EVRP [47-49]. VNS performs local search on large neighborhoods with effectiveness verified in previous works [12, 50-51]. This experiment applies ACO and traditional VNS frameworks from [52].

All 56 instances were solved by ALNS, ACO, and VNS. TABLE II-IV report the best objective function values from 10 runs. Relative gaps between ALNS and ACO ($\Delta_1\% = (Obj_{ALNS} - Obj_{ACO})/Obj_{ALNS}$) and between ALNS and VNS ($\Delta_2\% = (Obj_{ALNS} - Obj_{VNS})/Obj_{ALNS}$) are calculated. Negative values indicate relative improvement by ALNS.

The 23 R-type instances are divided into R1 (narrow time windows) and R2 (wide time windows). TABLE II shows ALNS achieves better solutions than other algorithms for all R instances. For R1 instances, objective values are reduced by an average of 19.81% compared to ACO and 18.27% compared to VNS. For R2 instances, reductions average 24.58% compared to ACO and 24.99% compared to VNS.

C-type and RC-type instances also have two classes each (C1/RC1 with narrow windows, C2/RC2 with wide windows). TABLE III reports C-type results and TABLE IV reports RC-type results. ALNS performs better than ACO and VNS for all C and RC instances. Generally, results for C2 and RC2 instances are better than C1 and RC1, showing ALNS works better for wide time window instances and can efficiently enlarge search space when time window constraints are loose.

The results verify ALNS' s significant superiority for solving the URP-RC problem, obtaining the best solution in all 56 instances. Regarding fixed vehicle costs, ALNS always reaches the minimum, contributing substantially to the best solutions.

C. Analysis on the Impact of the Recharging Strategy

A key characteristic of the investigated problem is allowing UAVs to recharge during routes, expected to expand endurance range and improve routing efficiency at lower cost. To analyze recharging strategy impact, ALNS solves all instances with recharging (URP-RC) and without recharging (URP). We analyze the number of UAVs (m), total mission completion time (TT), and objective function value (Obj). ALNS runs 10 times per instance, with best solutions reported in TABLE V-VII.

Results show the number of UAVs for URP-RC is much less than for URP. For R1 and RC1 instances, total completion time for URP-RC is also less than for URP, while for other instances, URP mode can complete tasks in less time because UAVs in URP-RC must visit multiple recharging platforms, consuming additional time. Since UAVs are critical resources in both military and civilian applications with relatively high costs compared to routing costs, the greatly reduced number of UAVs in URP-RC yields smaller objective function values overall. RC-type results in TABLE VII show URP-RC performs better in each objective aspect than URP.

TABLES V-VII demonstrate that URP-RC obtains better solutions with significantly fewer UAVs and smaller objective function values for all instances compared to URP, confirming that the recharging strategy improves efficiency and reduces UAV costs.

D. Sensitivity Analysis on Battery Capacity

Battery capacity plays a key role in UAV routing problems. To analyze different battery capacities' impact, capacity is varied from 120 to 300 while other parameters remain unchanged. The number of UAVs (m) and overall mission time (TT) are calculated under different capacities by ALNS for both URP-RC and URP. Results for R101 instance are reported in Fig. 6 [Figure 6: see original paper]; results for other instances are similar and omitted.

Fig. 6(a) shows the number of UAVs decreases sharply with increasing battery capacity in URP and decreases more gently in URP-RC. At capacity 120, the deviation in UAV count between URP-RC and URP reaches 30, verifying that URP-RC significantly reduces UAV fixed costs, especially for small UAVs with short endurance. As capacity increases, the deviation shrinks and reaches 0 at capacity 300 because UAVs can complete tasks without recharging when capacity is large enough. Fig. 6(b) shows overall mission time decreases as battery capacity increases, becoming identical for URP-RC and URP at large capacities. Since targets have specific time windows in both modes, when UAVs arrive earlier than earliest start times they must wait, making the relative deviation in mission time smaller than that for UAV count.

Fig. 6 confirms that battery capacity significantly impacts UAV routing and indicates that recharging efficiently improves small UAV routing performance when battery capacity is insufficient.

VI. CONCLUSION

To promote small UAV utilization, we investigated a UAV routing problem with recharging to extend endurance range, where recharging platforms are fixed and UAVs can recharge during routes. A mixed-integer nonlinear programming model was established and an improved ALNS algorithm with recharging platform insertion heuristic was designed. A benchmark set based on the Solomon dataset was created, and experimental results showed the proposed ALNS performs significantly better than ACO and VNS. Additionally, the recharging strategy' s advantages were verified, and sensitivity analysis on battery capacity showed that capacity affects both the number of UAVs and objective values in URP-RC and URP.

Future research directions include extending the study to dynamic environments where recharging platforms are mobile and have time windows. In many practical applications, recharging platforms are mobile (e.g., public transport) with recharging capacity and time windows, making this a meaningful and valuable model extension. Another valuable direction is developing new algorithms to solve this problem more efficiently and quickly.

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