UAV-Driven Robust and Energy-Aware Data Collection in Robotic Wireless Sensor Networks

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***Abstract*—Optimising data collection while considering energy consumption is vital for robotic and wireless sensor networks. Although static sink-aided cluster-based protocols provide energy-efficient possibilities, unmanned aerial vehicle (UAV)-aided procedures are considered superior solutions for lowering energy consumption during data collection compared to static sinks. Several existing UAV-based systems have overlooked the practical constraint of the UAV's battery capacity. This study investigates the data collection process in robot network clusters by considering energy efficiency. Each cluster contains a cluster head (CH) robot that assigns collaborative tasks to each cluster member (CM) robot and collects data from the CMs. Simultaneously, a UAV gathers information from the CH robots by selectively visiting a constrained portion of them, due to its limited battery endurance. The decision-making process for unmanned aerial vehicles (UAVs) to visit specific CHs is constrained by numerous factors to improve the existing technology. These criteria encompass the remaining battery capacity of the UAV, together with the positions of all the CH robots. Unvisited CH robots employ CH robots as intermediate nodes to transmit data. The simulations illustrate that the proposed strategy effectively attains a total joint cost of zero, whereas the current state-of-the-art methods result in significantly higher total joint costs. Furthermore, the proposed policy achieves an efficient solution much faster than the conventional approaches.**

***Index Terms*—energy efficient routing, cluster-based routing, robotic network, WSN, IoT, UAV**

I. Introduction

The Internet of Things (IoT) idea holds great promise for bridging the digital and physical realms. In an IoT framework, wireless sensors [1] are often put on every device to enable effective data gathering and transport [2]. Wireless sensor network (WSN) has various applications in domains including agriculture, smart cities, frost monitoring, ambient air monitoring, health monitoring, and others [3], [4].

WSN and robots have been the focus of in-depth independent research for a number of decades. There are several research opportunities at the junction of robotics and WSN, known as the robotic wireless sensor network (RWSN) [5], to help offset personal drawbacks of robots and WSN. Robots can help WSNs with sensor repair and battery recharging [6]. Robots can also act as data mules, however this could cause data to travel across large distances. To shorten these wait periods, a grouping technique among data mules is suggested by the study in [7]. WSN can be used in robotic to enable robot localisation, planning, mapping, and path sensing. Numerous application domains, such as autonomous driving, military use, mining, healthcare, search and rescue, traffic monitoring, weather forecasting are made possible by the combination of WSNs and robots [5].

In an attempt to lower overall energy consumption, researchers have lately examined the energy-aware data collecting problem with mobile sinks [8]- [10]. Many studies in the literature address these issues in terms of travelling salesman problem (TSP) [11], where the mobile sink has sufficient energy to visit a fixed percentage of CH nodes to acquire data. Nonetheless, it cannot visit a set percentage of CH nodes because the battery capacity varies based on positions of CH robots. By tackling problem of a UAV's battery residual capacity constraint and offering a heuristic solution, the work in [12] bridges this gap; nevertheless, such evolutionary algorithm-based methods are slow. For this reason, we require trustworthy and effective ways to address this problem.

We investigate data gathering problem where UAV with battery capacity visits the network of clustered robots, where each cluster is composed by sensors, CM robots, and CH robots. Each of CM robots is given one mission by a CH robot. Even with a fully charged battery, a UAV's limited remaining energy may prevent it from visiting every CH robot, depending on each robot's location. In these conditions, the energy needed to visit each CH robot exceeds the UAV's battery life. Our problem is battery-limited, i.e., the UAV cannot truly have sufficient battery capacity for visiting every CH robot, unlike celebrated NP-hard TSP [11] architecture. We also include overall energy consumption by CH robots that are not visited.

Because its battery life prevents it from visiting every CH robot, the UAV uses data hopping to transfer data from one nonvisited CH robot to another. A UAV visits a group of CH robots (which may differ from all CH robots or half of them, contrary to related literature), to decrease overall energy consumptions by CH robots whose locations, and battery life are considered by UAV when deciding which robots to visit.

In this paper, our novel approach based on nearest neighbour algorithm not only achieves the similar total energy consumption but also performs nearly thirty times faster than genetic algorithm-based approaches.

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A. Main Contributions

This work contributes to the literature as follows:

- This paper considers each robot's position within the data collection problem and the UAV's residual energy constraint.
- This article proposes a solution based on locations, and intention for UAV to visit a subset of CH robots. It is demonstrated that this method also includes the optimal data sending protocols for each nonvisited CH robot. This also discusses how well the proposed approach works when a UAV visits a group of CH robots to reduce overall energy consumption.

B. Organization

The remainder of this paper is organised as follows. Section II gives pertinent literature. Section III explains the problem and its system model. In Section IV we show a novel method that considers both the energy consumed by UAVs and CH robots. We assess strategies given in Section V in terms of their numerical performance. Section VI presents the paper's conclusion and recommendations for further work.

II. Related Work

Energy-aware data collection problem with a static sink was tackled first time in the work [31], where a wireless sensor network is first clustered by electing a cluster head to collect data from sensors and forward to the static sink. The work [17] presents different variants of the LEACH protocol. The works in [18], [19] and [20] are three recent works which consider the energy aware data collection problem in underwater wireless sensor networks.

A group of CH robot send data toward a UAV with a finite amount of battery life. As a result, we give a summary of the key methods used for routing with mobile sinks that take energy efficiency into account. Our formulation of the problem is similar to the classical orienteering problem (OP) [21], where the objective is to maximum reward while taking into account a path length constraint. As some research studies also take into account the differences in data quality that different CH robots obtain, we review other research that study OP.

In [22], the authors provide a data collecting technique that makes use of EAPC algorithm whereby mobile sink can choose one or more sites and begin data collection there thanks to trajectory planning. Salar (2014) asserts that EAPC is less energy-intensive than the weighted rendezvous points (WRP) approach.

The study [24] presents a technique for energy-efficient trajectory planning (EETP) that balances the load of rendezvous sensors and shortens the route using multiple-objective particle swarm optimisation. Salar (2014) reported that EETP uses less energy and has a longer network lifetime than WRP.

A solitary mobile sink visits rendezvous sites (RP) to gather sensor data, in [25]. It presents PSO-based RP selection method with a lower trajectory length than current approaches. Using a similar paradigm, the authors of [26] suggest a high-level heuristic to increase network lifetime.

[27] suggests WSN- and UAV-focused solutions for this issue. Sensors use a WSN-oriented method to send data to its CH. UAV then gathers data by moving from CH to CH. By sending information to sink, the UAV-oriented strategy functions. As a result, the UAV only visits the sink, saving flight time but raising the system's overall energy consumption.

The majority of literature's solutions to this issue involve mobile sinks with unlimited battery capacity. According to conventional models, the sink may visit all CH nodes or half of them, depending on a predetermined selection. That being said, for UAV to reach the same number of CH nodes, different networking topologies result in varying energy requirements. If the UAV's energy requirement is more than its battery capacity, the UAV may not be able to finish its mission due to the remaining energy constraint. The prior work in [12] fills a hole in the literature by also addressing limited battery capacity for UAVs to limit this problem. The similar issue is addressed in [14] by taking into account several CH robot priority lists. The issue is subsequently addressed in the publication [13] by taking into account various data qualities for various CH robots. Subsequently, [15] examines the same problem with distinct hop constraints.

A joint optimisation problem of aircraft cruise control and data gathering for preventing network data loss is addressed in [28], where the UAV functions as POMDP that does not know any IoT node's condition. That research offers deep Q-network-based technique to schedule data, and UAV optimisation in the case that the network states are not up to date.

In this study, we take into account a restriction on the UAV's battery capacity and the energy that CH robots spend, with the same data quality for all CH robots during data collection. If data qualities were different for different CH robots, the investigated problem would be comparable to the classic OP, also referred to as the reward maximisation problem with restricted path length and first presented in [21]. The shortest path between a given set of nodes is determined after those nodes are chosen. OP [29] combines these two processes. The objective is to maximise the overall reward by selecting specific nodes when the mobile sink does not have enough time to visit every node that is reachable.

In the most recent study [30], by treating the UAV trajectory design problem as OP, UAV flies over many locations for serving maximum users in limited time. It formulates this problem as mixed-integer linear programming problem; then, it offered a greedy solution. We demonstrate how quickly and almost perfectly the suggested method performs.

Our limited-capacity battery-powered UAV employs an innovative and robust technique to choose a cluster of CH robots to visit, thereby reducing the overall energy used of nonvisited CH robots that transfer data to another nonvisited CH robot until it reaches a visited CH robot. This paper considers battery capacity, locations of each CH robot, and their data qualities when deciding which CH robots to visit. We consider multiple hop limits in addition to optimising overall energy consumption.

III. System Model and Problem Description

This section offers a more thorough exposition of the original model of the RWSN.Subsequently, the essential concepts are clearly defined and the problem is subsequently formulated with enhanced precision.

A. System Model

This paper deals with a M-clustered robot network and a single UAV with limited battery capacity. Sensor nodes in this network collect data by monitoring alterations in their immediate surroundings.

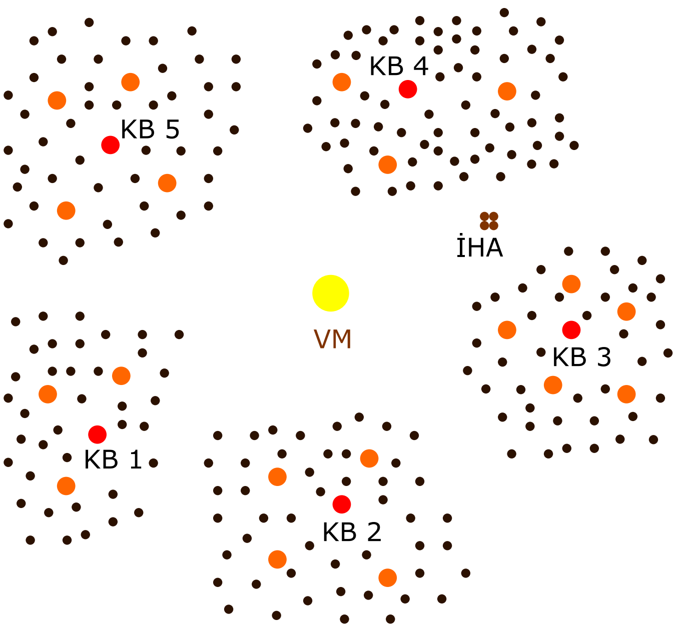

Fig. 1. The RWSN is composed of five robot clusters, a base station (BS), and a UAV. Red dots designate CH robots, whereas orange dots show cluster members. The UAV starts its trajectory at BS. UAV collects data from CH robots and then returns to BS to deliver it. It also charges its batteries for the next trajectory there.

Figure 1 shows an example of RWSN. A cluster head (CH) robot delegated tasks to cluster member (CM) robots. Once the CM robots have completed the duties given to them, they forward the processed data to the relevant CH robot. Depending on placements of CH robots, and battery capacity, UAV makes visits to them. Data from CM robots must first be gathered by CH robots. Every nonvisited CH robot transfers its data over many hops to one nonvisited neighbour CH if a UAV does not visit every CH robot. $S \triangleq \{1, 2, \cdots, M\}$ represents index set of CH robots, and B denotes the UAV's remaining battery life.

CH robots have to spend a lot of energy collecting and transmitting data to other CH robots or to other CH robots nearby if the UAV doesn't visit. When a CH robot behaves like a CM robot, its battery life quickly drops below a critical point, which may result in repeated CH elections that consume needless time and energy. As a result, when they give CM robots tasks that they can perform very well, CH robots may soon give up on behaving as a CH.

Assumption 1. *Every CH robot has an identical amount of data, which may be instantaneously transmitted to UAV or to another CH robot.*

Initial location of UAV is indicated by $\xi_0 \triangleq (x_0, y_0)$, while position of CH robot i is shown by $\xi_i \triangleq (x_i, y_i)$. The definition of its energy usage from CH robot i to j is

$$E_{UAV}(i,j) \triangleq C_{UAV}\sqrt{(x_i - x_j)^2 + (y_i - y_j)^2} \tag{1}$$

where C_{UAV} is the fixed quotient of the distance travelled and energy used by the UAV. Energy consumption of CH robot i during data transmission to CH robot j is explained as

$$E_{CH}(i,j) \triangleq C_{CH}\left[(x_i - x_j)^2 + (y_i - y_j)^2\right] \tag{2}$$

where C_{CH} is ratio of energy consumed by one CH robot over square of that hop distance.

Every pertinent study presumes that every CH node has enough energy to transmit information to UAV's base station. Even if it doesn't visit the CH robot during this inquiry, the UAV may pass near to it on its route. In the worst case scenario, data from unvisited CH robots could be sent to the UAV during its takeoff phase from BS.

B. Problem Formulation

Our goal is to schedule the path a UAV with limited battery capacity has to go. *The whole energy consumption minimisation is the aim of UAV path planning.* The definitions 1–2 are used to define problems.

Strategy of UAV, π, is the trajectory followed by UAV to gather data.

Definition 1. ***Energy consumed by UAV with policy*** π*,* E^{π}_{UAV}*, is*

$$E^{\pi}_{UAV} \triangleq \left[\sum_{j=1}^{M}\sum_{i=1}^{M} C_{UAV}\|\xi_i - \xi_j\| I_{\{p(\xi_i,\xi_j)\in\pi\}}\right], \tag{3}$$

where $I_{\{X\}} = 1$ *if* X *is true. Otherwise,* $I_{\{X\}} = 0$*.*

The set of nonvisited CH robots under strategy is denoted by π, S^{π}_{nv}. Energy consumed to forward data of CH robot i under strategy π, u_i, is denoted by $E^{\pi}_i(u_i)$.

Definition 2. ***Total energy consumption of CH robots under strategies*** π*,* u*,* ***denoted by*** $E(u,\pi)$*, is*

$$E(u,\pi) \triangleq \sum_{i\in S^{\pi}_{nv}} \left(\eta_i \times E^{\pi}_i(u_i)\right). \tag{4}$$

The problem is defined precisely as follows.

Problem 1. *Minimizing total energy consumption of nonvisited CH robots via UAV with limited-capacity battery*

$$\begin{aligned} \underset{\pi, u\subseteq P}{min} \quad & E(u,\pi) \\ s.t. \quad & E^{\pi}_{UAV} \leq B \end{aligned}$$

IV. Robust and Energy Consumption Minimization Problem

We formulate this problem as TSP and find minimum battery capacity required for visiting all CH robots as our first step in solving it. The nearest neighbour technique (NN) is employed to ascertain this capacity.

By deciding which CH robots to visit, UAV aims to limit the sum energy consumed by nonvisited CHs. These robots will transmit data to a visited CH node by making numerous hops via other non-visited CH.

The next subsection looks at the data forwarding plan of each nonvisited CH robot.

A. Data Forwarding Strategies for CH Robots

Since it does not need data forwarding, a visited CH robot i doesn't use any of them. However, a single non-visited CH robot i needs to figure out the quickest route to each and every visited CH robot. After then, it must decide which of all the shortest paths is the least expensive. Squares of the distances between CH robots are used for determining the shortest pathways between them (from Equation (2).) They can therefore learn the most effective data forwarding strategies. Be aware that all visited CH robots are seen as potential targets by all nonvisited CH robots.

B. Optimal Strategy for UAV

The UAV's energy consumption should be kept to a minimum, as should overall energy consumed by all nonvisited CH robots.

B_{TSP} should reflect the minimum battery capacity required to visit each CH robot. A UAV with a battery capacity of $B < B_{TSP}$ must avoid certain visits from CH robots. Therefore, our task becomes determining which CH robots to leave unattended to decrease overall energy consumed by unvisited CH robots while maintaining a low battery capacity for the UAV.

Definition 3 gives a motivation for describing Algorithm 1.

Definition 3. ***K-element combinations of the CH robots, denoted by*** S_a^K***,*** *is K-element subset of the M-element set of all CH robots, i. e., $S_a^K \subseteq S$ and $|S_K^a| = K$ for $1 \leq a \leq \binom{M}{K}$. $S^K(B)$ denotes set of all feasible K-element combinations that UAV with battery capacity B can visit.*

Algorithm 1 Robust and Energy-Aware Data Collection Strategy (READCS)

if $B \geq B_{TSP}$ **then**
  Solve the problem at hand by considering it as TSP.
  Output: π^{READCS} is a nearest neighbour algorithm-based policy whereby UAV visits all CH robots.
  #Comment: UAV has insufficient battery capacity to visit all CH robots, i.e., $B < B_{TSP}$.#
else
  for $K = (M-1) : 1$ **do**
    Find all $\binom{M}{K}$ combinations of CH robots.
    for $a = 1 : \binom{M}{K}$ **do**
      if $\min_{\pi} E_{UAV}^{\pi} \leq B$ for S_a^K **then**
        $S_a^K \subset S^K(B)$
        Apply minimum-energy shortest path strategy for each CH robot $i \in S - S_a^K$. Find $\sum_{i \in S - S_a^K} \gamma_i^{\pi}$.
      else
        # Comment: S_a^K is an infeasible set in which UAV with B cannot visit all CH robots. #.
        $S_a^K \not\subset S^K(B)$
      end if
    end for
    if $S^K(B) \neq \emptyset$ **then**
      Find $\min_{S_a^K \in S^K(B)} \sum_{i \in S - S_a^K} \gamma_i^{\pi}$
    end if
  end for
  Find $\min_{K} \left[\min_{S_a^K \in S^K(B)} \sum_{i \in S - S_a^K} \gamma_i^{\pi} \right]$.
  Output: π^{READCS} is a nearest neighbour algorithm-based strategy for TSP where UAV visits CH robots in the combination S_a^K found on previous step.
end if

V. Numerical Results

Varied numbers of CH robots and varied degrees of residual battery are used to test the strategies. A static sink benchmark for this problem shows that optimal fraction of CH nodes should be between 3% and 5% [31]. A second study [32] utilises a 1%–5% range for the CH node fraction in the network to handle this problem utilising a mobile sink. [33] state that ratio of CH nodes is 6%. Consequently, roughly 5% of nodes in relevant studies are selected for serving as CH. We analyse two scenarios with 5-CH and 10-CH robots. The units C_{UAV} and C_{CH} are considered as one to preserve the parametric value.

In our simulations, every CH robot has same data quality. We use $\eta_i = 1$ for CH robot i to produce same data qualities. In these situations, it is discovered that the UAV's total trajectory length for visiting each CH robot is fewer than fifty units. Put differently, the maximum amount of battery capacity required for visiting all CH robots is $50 \times C_{UAV}$. We evaluate the performances of our previous works: QEADCS in [13], [15], GAMEDFS in [12], READCS (the proposed technique in this study), and the UAV-oriented approach in [27].

A. 5-CH case

Figure 2 shows link weights between CH robots and their positions which are $(\xi_1, \xi_2, \xi_3, \xi_4, \xi_5) = ((-7,6),(3,3),(7,11),(-1,-2),(-4,-4))m$.

1) UAV-Oriented Strategy: UAV visits just CH robot 2 ($\xi_2 = (2,2)$) and collect all data of CH robots from there if $B \approx 5.66 \times C_{UAV}$, by which $J(u, \pi^{UAV-O}) = 328 \times C_{CH}$. It may not be applicable for $B = 5$.

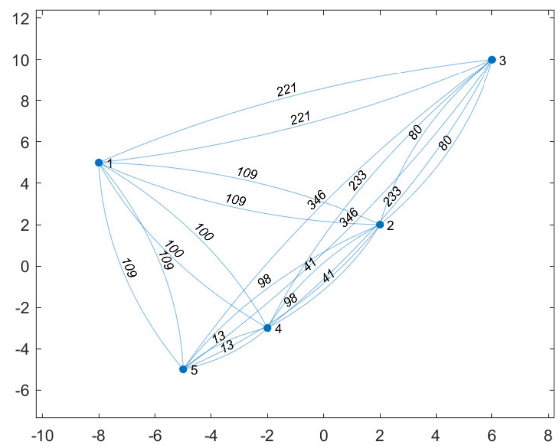

Fig. 2. Nodes show that the locations (positions) of the 5 CH robots. The weight of a link shows square of distance between two nodes connected via that link.

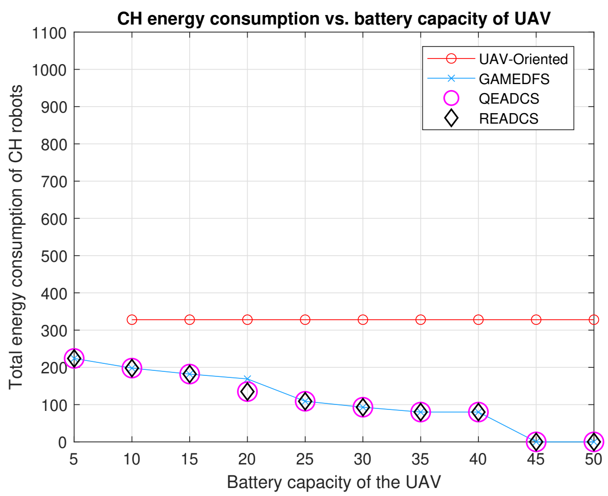

Fig. 3. The total energy consumption of the 5 CH robots in Figure 2 under the strategies, UAV-Oriented and Optimal for varying battery capacities of the UAV from $B = 5 \times C_{UAV}$ to $B = 50 \times C_{UAV}$

2) *GAMEDFS:* Performance findings for GAMEDFS [12] are displayed in Table II, where battery capacities in the configuration depicted in Figure 2 vary from $B = 5$ to $B = 50$. By using GAMEDFS, i.e., $J(u, \pi^{GAMEDFS}) = 0$, the UAV with $B = 45 \times C_{UAV}$ or $B = 50 \times C_{UAV}$ may visit all CH robots in Figure 3. In the configuration depicted in Figure 2, the energy required by a UAV to visit each CH robot is $E_{UAV}^{\pi^{GAMEDFS}}(u) \approx 44.29 \times C_{UAV}$.

3) *QEADCS:* For all battery capacity levels between $B = 5$ and $B = 50$, QEADCS and GAMEDFS have reached the same findings, as shown in Figure 2.

Because CH 4 transfers data from CH 5, UAV decides to visit CH 4 with lesser battery capacities. For $B = 10$, UAV chooses to forego CH 4 in favour of CH 2, as CH 4 visits result in a lower total energy consumption by CH robots than CH 2 visits.

Take note that if CH 4 were located at $(-1, -1)$ instead of $(-1, -2)$, then CH 4 and CH 2 would have the same distance to the origin.

4) *READCS:* READCS and QEADCS have reached the same conclusions for every battery capacity value between $B = 5$ and $B = 50$ in Figure 2. On the other hand, READCS provides this solution 26.9 times faster than GAMEDFS and QEADCS.

5) *Performance Comparison:* Table I displays the indices of the nonvisited CH robots in Figure 2. Table II displays the overall energy usage for the CH robots that are not visited. Based on battery capacity, the UAV in Figure 2 determines whether or not to visit a subset of CH robots, as shown in Tables I and II. Additionally, as the UAV's remaining energy varies, so does the overall energy utilised by nonvisited CH robots, which influences its decision-making. Furthermore, overall energy consumed by nonvisited CH robots are influenced by their positions.

B. 10-CH case

Figure 4 shows link weights between CH robots and their positions which are $(\xi_1, \xi_2, \xi_3, \xi_4, \xi_5, \xi_6, \xi_7, \xi_8, \xi_9, \xi_{10}) = ((7, -6), (-4, 4), (3, 5), (-3, 8), (-1, 3), (3, -6), (0, -1), (5, -7), (0, 6), (8, -5))m$.

1) *UAV-Oriented Strategy:* Only CH 7 ($\xi_7 = (0, -1)$) is reached by the UAV using a UAV-Oriented approach, and all CH robot data is collected from that point if $B \approx 4.47 \times C_{UAV}$. Thus, $J(u, \pi^{UAV-O}) = 491 \times C_{CH}$.

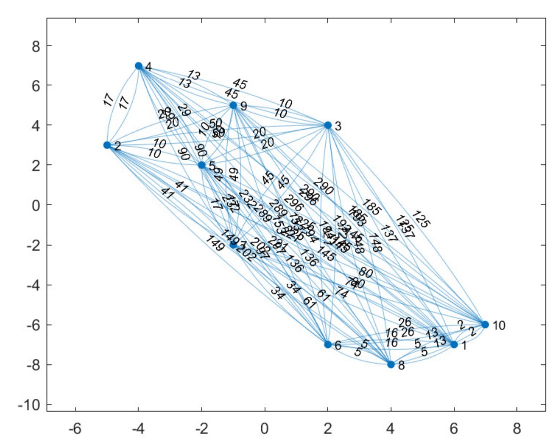

Fig. 4. Nodes show that the locations of the 10 CH robots. The weight of a link shows the square of distance between the two nodes connected via that link.

2) *GAMEDFS:* Table IV displays the performance findings of GAMEDFS [12] with battery capacity ranging from $B = 5$ to $B = 50$ in Figure 4. By employing the optimal strategy, that is, $J(u, \pi^{GAMEDFS}) = 0$, the UAV with $B = 45 \times C_{UAV}$ or $B = 50 \times C_{UAV}$, may visit each CH robot in Figure 5. In the setup depicted in Figure 4, the minimum energy needed for a UAV to visit every CH robot is $E_{UAV}^{\pi^{GAMEDFS}}(u) \approx 42.02 \times C_{UAV}$.

TABLE I
INDICES OF NONVISITED CH ROBOTS VS. BATTERY CAPACITY OF UAV IN FIGURE 2. "NONE" IMPLIES THAT UAV CAN VISIT ALL CH ROBOTS.

Battery level	**5**	**10**	**15**	**20**	**25**	**30**	**35**	**40**	**45**	**50**
UAV-Oriented	Infeasible	1,3-5	1,3-5	1,3-5	1,3-5	1,3-5	1,3-5	1,3-5	1,3-5	1,3-5
GAMEDFS	1-5	1-3,5	1,3,5	2-5	2,3,5	3,5	3	3	None	None
QEADCS	1-5	1-3,5	1,3,5	2-5	2,3,5	3,5	3	3	None	No
READCS	1-5	1-3,5	1,3,5	2-5	2,3,5	3,5	3	3	None	None

TABLE II
TOTAL ENERGY CONSUMPTION NON-VISITED CH ROBOTS VS. BATTERY CAPACITY OF UAV IN FIGURE 3.

Battery level	**5**	**10**	**15**	**20**	**25**	**30**	**35**	**40**	**45**	**50**
UAV-Oriented	$\times$	328	328	328	328	328	328	328	328	328
GAMEDFS	224	198	182	135	109	93	80	80	0	0
QEADCS	224	198	182	135	109	93	80	80	0	0
READCS	224	198	182	135	109	93	80	80	0	0

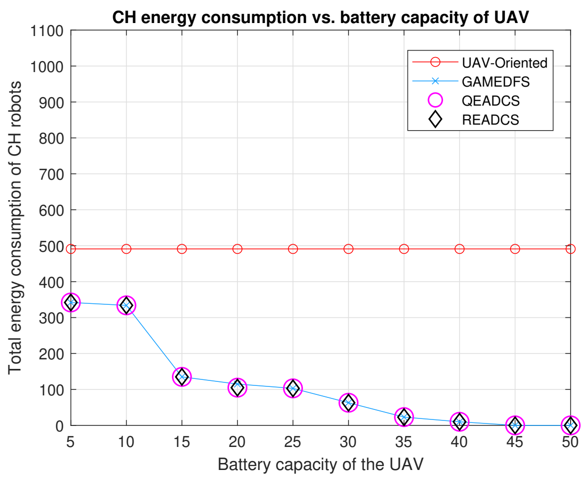

Fig. 5. The total energy consumption of the 10 CH robots in Figure 4 under the strategies, UAV-Oriented and Optimal for varying battery capacities of the UAV from $B = 5 \times C_{UAV}$ to $B = 50 \times C_{UAV}$

3) QEADCS: QEADCS and GAMEDFS have reached the same conclusions for all battery capacity values between $B = 5$ and $B = 50$, with exception of $B = 20$ in Figure 4.

The result of UAV with $B = 20 \times C_{UAV}$ not visiting CH robots 1-5, 9, and 10 is $E(u, \pi^{GAMEDFS}) = 135 \times C_{CH}$. Furthermore, considering GAMEDFS, UAV with $B = 25 \times C_{UAV}$ disregards CH robots 2-5, 9, and 10; this results in $E(u, \pi^{GAMEDFS}) = 109 \times C_{CH}$. As a result, $E(u, \pi^{QEADCS}) = 135 \times C_{CH}$ for $B = 20 \times C_{UAV}$ and $E(u, \pi^{QEADCS}) = 109 \times C_{CH}$ for $B = 25 \times C_{UAV}$ since QEADCS makes the same decision as GAMEDFS.

Under QEADCS, UAV with $B = 25 \times C_{UAV}$ does not visit CH robot 1-4, 8, 9 and 10 which results in $J(u, \pi^{QEADCS}) = 69.40 \times C_{CH}$ and $E_{UAV}^{\pi^{QEADCS}}(u) \approx 24.80 \times C_{UAV}$.

UAVs prefer to visit CH 6&8, even if their battery capacities are lower due to their proximity to CH 1 and CH 10, which enables CH 6 and CH 8 to transmit their data. Even a single visit to CH 6 reduces energy consumed by each CH robot since UAV acquire data from CH8, CH1, and CH 10 at CH6. UAVs with smaller battery capacities do not visit CH 2 and CH 3. This is because, in contrast to CH 6&8, CH 2&3 forward no data by other CHs.

UAV prefers to visit CH 5 and CH 7, even under their lower battery capacities. With $B = 10$, since CH 5 and CH 7 are significantly closer to the origin than others.

For $B = 5$, visiting CH 7 is the only feasible course. It should be noted that CH 3 would communicate its data to CH 5 instead of origin if UAV does not visit CH 3 and CH 5 were located at $(-1, 2)$ instead of $(-2, 2)$. Data from CH 2 would be forwarded by CH 5 to CH 4, CH 9, and CH 3, and data from CH 6 to CH 8, CH 1 to CH 10, and so on, if $B = 5$. In comparison to visiting no CH robot, the UAV would visit just CH 5 at the point $(-1, 2)$, reducing energy consumption $5 \times C_{CH}$. Similarly, the UAV would lower energy consumption $5 \times C_{CH}$ by just visiting CH 7 at the point $(-1, -2)$. Therefore, UAV with $B = 5$ would choose CH 5 over CH 7 to decrease total energy consumed by CH robots.

4) READCS: READCS and QEADCS have reached the same conclusions for every battery capacity value between $B = 5$ and $B = 50$ in Figure 4. On the other hand, READCS provides this solution 28.9 times faster than GAMEDFS and QEADCS.

5) Performance Comparison: Table III displays the indices of nonvisited CH robots in Figure 4. Table IV displays the total energy usage for the CH robots that are not visited. These tables show how the UAV in Figure 4 decides whether or not to visit a subset of CH robots based on its battery capacity. Moreover, UAV battery capacity affects the overall energy consumed by nonvisited CH robots, which influences UAV decision-making. Furthermore, overall energy consumed by nonvisited robots are influenced by locations of CH robots.

GAMEDFS obtains optimality when all CH robots have same data quality, as mentioned in [12]. QEADCS and READCS achieve the same performance as GAMEDFS by making the same decisions as GAMEDFS while READCS achieves this performance much faster than GAMEDFS and QEADCS.

VI. CONCLUSION

This study focuses on the difficulty of collecting data in a clustered robot network utilising UAV with constrained battery

TABLE III
INDICES OF NONVISITED CH ROBOTS VS. BATTERY CAPACITY OF UAV IN FIGURE 4. "NO" IMPLIES THAT UAV CAN VISIT ALL CH ROBOTS.

Battery level	**5**	**10**	**15**	**20**	**25**	**30**	**35**	**40**	**45**	**50**
UAV-O	1-6,8-10	1-6,8-10	1-6,8-10	1-6,8-10	1-6,8-10	1-6,8-10	1-6,8-10	1-6,8-10	1-6,8-10	1-6,8-10
GAMEDFS	1-6,8-10	1-4,6,8-10	1-5,7-10	1-5,9,10	2-5,9	2-4,9	2,4	2	No	No
QEADCS	1-6,8-10	1-4,6,8-10	1-5,7-10	1-5,9,10	2-5,9	2-4,9	2,4	2	No	No
READCS	1-6,8-10	1-4,6,8-10	1-5,7-10	1-5,9,10	2-5,9	2-4,9	2,4	2	No	No

TABLE IV
TOTAL ENERGY CONSUMPTION OF NONVISITED CH ROBOTS VS. BATTERY CAPACITY OF UAV IN FIGURE 5.

Battery level	**5**	**10**	**15**	**20**	**25**	**30**	**35**	**40**	**45**	**50**
UAV-Oriented	491	491	491	491	491	491	491	491	491	491
GAMEDFS	342	334	135	105	103	63	23	10	0	0
QEADCS	342	334	135	105	103	63	23	10	0	0
READCS	342	334	135	105	103	63	23	10	0	0

capacity, while considering energy efficiency of CH robots. A single CH robot assigned tasks to other robots inside each cluster. Once the CH robot finishes its assigned tasks, it collects data for analysis and fusion. It subsequently sends generated data to the UAV. The UAV visits either all of the CH robots or a specific selection, depending on factors such as its battery capacity, and position. Each unvisited CH robot passes its data to a distinct CH robot. The objective of UAV is to minimise total energy consumption.

To tackle this problem as TSP, this study initially eliminates constraints in UAV's battery capacity. Subsequently, UAV analyses the problem considering limitation imposed by battery capacity of UAV. If its battery capacity is insufficient to visit each CH robot, it selectively omits certain CH robot trips to ensure that its energy consumption remains within the battery's limit. We adopt an analytical method to assess the situation and identify the optimal course of action. Subsequently, the proposed methodology is compared to previously published techniques in the literature, considering different cluster quantities. Our approach outperforms previous methodologies across many configurations, including varying numbers of CH robots, UAV battery capacity, as substantiated by quantitative outcomes. UAV optimises total energy consumption of CH robots by considering factors such as battery capacity, and locations. Our novel approach based on nearest neighbour algorithm not only achieves the similar energy consumption but also performs nearly thirty times faster than genetic algorithm-based approaches.

Our current research aims to expand the proposed framework by assessing environmental ambiguities and designing UAV trajectories based on anticipated levels of ambiguity. Another contemporary research area that can enhance the presented methodology is wireless power transfer (WPT). Our immediate strategy, therefore, is advancing proposed policy to include WPT knowledge into decision-making process. Future research will also prioritise investigating the system's response to mitigate UAV failures resulting from energy deficiencies.

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