Multi-UAV Assisted Data Gathering in WSN: A MILP Approach For Optimizing Network Lifetime

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**Abstract**—In this paper, we study the problem of gathering data from large-scale wireless sensor networks using multiple unmanned air vehicles (UAVs) to gather data at designated rendezvous, where the goal is to maximize the network lifetime. Previous proposals often consider a practical approach where the problem of determining a data gathering scheme is decomposed into 2 sub-problems: i) partitioning the networks into clusters for determining the rendezvous as these obtained cluster heads; and ii) determining the paths for a set of a given number of UAVs to come gathering data at these rendezvous which have been harvesting data within each local clusters, respectively. We try to deal with this as a whole optimization problem, expecting a significant increase in computation complexity which would bring new challenge in creating practical solutions for large-scale WSNs. We introduce two alternatives mixed-integer linear programming (MILP) formulations and we show that our best model could solve the problem instances optimally with up to 50 sensor nodes in less than 30 minutes. Next, we propose a heuristic idea to reduce the number of variables in implementing the 3-index model to effectively collect data at network size in hundreds. The experiment results show that our heuristic approach significantly prolongs the network lifetime compared to existing most efficient proposals.

I. INTRODUCTION

Recently, the Unmanned Aerial Vehicles (UAVs) technology has seen rapid growth with application in various fields such as military, emergency rescue, transportation, surveillance and monitoring. This technology has also emerged as a flexible and convenient approach to collect the harvested info data in large-scale WSNs because of their advantages such as low cost, simple deployment and faster moving speed. In addition, the ground-to-air communication links between sensor node (SN) and UAVs typically exploit the line-of-sight (LoS) propagation, thus the data transmission is more reliable and also provides a higher data rate compared to ground vehicles. However, the critical issue in this technology is that the UAVs usually have limited endurance due to the practical physical constraints and need to be collected for battery swap or recharging, e.g., the endurance time can be 30 minutes for a typical rotary-wing UAV [1].

Similar to other kinds of mobile collector, recent research works [2]–[7] in UAV-assisted data gathering can be classified into two basic approaches: rendezvous-less and rendezvous-based. The former approach requires the UAVs to visit every SN neighborhood at least once so that each SN can send its data directly to a UAV via single-hop transmission. Although the rendezvous-less approach improves the communication reliability and energy conservation of SNs, the length of UAV trajectory becomes excessively long thus this approach is often infeasible for large-scale WSNs. This challenging issue can be resolved by using the rendezvous-based approach, where the UAVs only visit a subset of predefined nodes called rendezvous nodes to gather data from their nearby SNs.

Several works [4], [7]–[9] on the rendezvous-based data gathering have been proposed and most of them follow a common idea of decomposing the main problem into two sub-problems which will be solved one by one: (P1) designing a clustering scheme wherein the cluster head (CHs) take the responsibility as rendezvous nodes to gather data from each cluster; (P2) determining UAV trajectories for collecting the data at the CHs and transporting to the base sink. These subproblems are easier to deal with since they can be formulated into well-known problems: the set-covering problem and the multiple Traveling Salesman problem (mTSP). In [8], an energy-efficient data gathering scheme is proposed using the reduced k-means algorithm for (P1) and Christofides algorithm for (P2). Later, the author [9] proposed another version of the k-means clustering with aiming to perfectly balance the number of SNs in each cluster as require in the compressed sensing technique. Then this work used a nearest-neighbor algorithm for the UAV trajectory subproblem. However, both works in [8] and [9] only deal with the single-UAV scenario. Consider the use of multi-UAV, the authors in [4] also applied the k-means algorithms combined with a genetic algorithm for the mTSP, but the objective is to minimize the average data collection time of the UAV. Different than the above works that sequentially solve the (P1) then (P2), the author in [7] firstly determine the UAV trajectories by a geometrical method with a simulated-annealing adjustment. Then the SNs are divided into clusters regarding their residual energy. The proposal in [7] is the closest to our work since they both target to prolong the network lifetime and able to handle the case of multi-UAV.

In this paper, we address at the same time the optimization problem of both the network clustering and UAV trajectory designing, thus can achieve a more optimal solution compared to the decomposing approach. The optimization problem is
solved in each data collection period (or a round in other words) to obtain both cluster configuration and UAV tours. Our objective is to maximize the network lifetime, which can be employed in each round by using an alternative objective function of SN energy. To sum up, our contributions are as follows:

- We introduce two formulations of the optimization problem under a mixed-integer linear programming model, namely the 2-index and 3-index models. Then we show that our best model can solve the problem instances optimally with up to 50 sensor nodes.
- We propose a heuristic model that reduces the number of variables in the 3-index model to solve the problem instance representing a practical larger-scale network with size in hundreds.
- We conduct experiments to demonstrate our heuristic model’s effectiveness in extending network lifetime compared to a recent existing proposal.

The rest of this paper is organized as follows. Section II describes the system model. Section III presents two proposed MILP formulations for the problem. Section IV discusses our numerical and experimental results. Section V concludes the paper.

### II. SYSTEM MODEL

We consider a sensor network consisting of a sink node \( s_0 \) and a set of \( n \) sensor nodes (SNs) \( S = \{s_1, ..., s_n\} \). Assume that the data of all sensors must be collected at the sink periodically and each period of data collection is called a round. There are \( m \) rotate wing UAVs deployed to collect data from sensors, all fly at a fixed altitude \( h \). In each round, the network is partitioned into clusters and each SN transmits its data to an associated CH in a multi-hop fashion. Then each UAV departs from the sink, sequentially visits some specified CHs to collect data and finally return to the sink. Assume that the residual energy of SN \( s_i \) after the \( r \)th round is \( E_i^r \) the amount of data to collect at \( s_i \) is \( b_i \). We need to find a data collection scheme in the \( (r + 1) \)th round including \( k \geq 1 \) cluster trees and \( m \) UAV trajectories satisfying the following:

- Each cluster tree is rooted at the CH and spans all cluster nodes.
- Each SN is included in exactly one cluster tree.
- Each UAV trajectory is a ring that contains the sink.
- Each CH is included in exactly one UAV trajectory.
- Each UAV trajectory has length less than a given value \( L_{\text{max}} \).

We utilize the same radio model as discussed in [10]. In this model, the free space (\( d^2 \) power loss) model is used if the distance between the transmitter and the receiver is less than a \( d_0 \) threshold, otherwise the model of multi-path (\( d^4 \) power loss) is used. Thus, the energy spent to transmit a \( l \)-bits packet over distance \( d \) is:

\[
E_{\text{Tx}}(l, d) = \begin{cases} 
  lE_{\text{elec}} + l\epsilon_{fs}d^2, & d < d_0 \\
  lE_{\text{elec}} + l\epsilon_{mp}d^4, & d \geq d_0 
\end{cases}
\]  

(1)

### TABLE I: Summary of parameters

| Parameters | Description |
|------------|-------------|
| \( V \)    | Set of all sensors |
| \( V^* \)  | Set of all sensors without sink node |
| \( b_i \)  | Amount of data to collect at node \( s_i \) |
| \( d_{ij} \) | Euclidean distance between \( s_i \) and \( s_j \) |
| \( E_{\text{Rx}} \) | Per-bit receiving energy |
| \( E_{\text{Rx}}^{ij} \) | Per-bit transmitting energy from \( s_i \) to \( s_j \) |
| \( E_{\text{Tx}}^{ij} \) | Per-bit transmitting energy from \( s_i \) to UAV |

The energy spent by the radio to receive \( l \)-bits of data is:

\[
E_{\text{Rx}}(l) = lE_{\text{elec}}
\]  

(2)

For more convenient, let \( E_{\text{Tx}} = E_{\text{elec}} + \epsilon_{fs}d_{ij}^2 \) be the per-bit transmitting energy from a SN and \( E_{\text{Tx}}^{ij} = E_{\text{elec}} + \epsilon_{fs}d_{ij}^2 \) be the per-bit transmitting energy from node \( s_i \) to \( s_j \), respectively. Thus, if node \( s_i \) has to relay \( B_i \) bits of data from the descendants in its cluster tree in a round, then the total energy consumption of \( s_i \) after the round is calculated as:

\[
E_i^r = E_{\text{Rx}}(B_i) + E_{\text{Tx}}(B_i + b_i)
\]  

(3)

The remaining energy of \( s_i \) after the \( (r + 1) \)th round is:

\[
E_i^{r+1} = E_i^r - E_i^r = E_{\text{Rx}} + E_{\text{Tx}}^{ij}B_i - E_{\text{Tx}}^{ij}B_i \]  

(4)

Here, we assume that there is no packet loss and ignore the signal interference. We also assume that the energy expense for broadcast the control information is negligible.

The multi-UAVs data collection problem asks for \( m \) data forwarding trees corresponding to \( m \) clusters, each of which roots at a CH node and \( m \) UAV trajectories which start and end at the sink. The objective is to maximize the network lifetime, which is defined as the time span from deployment to the instant when the first SN run out of energy.

### III. MILP FORMULATIONS

#### A. Objective function and basic constraints

Both formulations proposed in this section used the same objective function and shared some basic variables and constraints. We will first present these fundamentals in this subsection.

In both formulations, the cluster configuration (i.e the network spanning forest) and all UAV trajectories will be defined by two types of binary variables \( x_{ij} \) and \( r_{ij} \). In particular, the variable \( x_{ij} \) where \( i, j \geq 0 \) takes value 1 when \( s_i \) and \( s_j \) are in the same cluster and \( s_i \) is the parent node of \( s_j \) in the data forwarding tree, otherwise \( x_{ij} \) is set to 0. As a convention, we use the value of \( x_{ij} \) to indicate if \( s_i \) is CH (\( x_{i,0} = 1 \)) or not (\( x_{i,0} = 0 \)). Next, the binary variable \( r_{ij} \) takes value 1 if \( s_i \) and \( s_j \) are two CHs visited by the same UAV and \( s_j \) is visited right after \( s_i \) on the trajectory, or \( r_{ij} = 0 \) if one of these above conditions is violated.

Since we aim to maximize the network lifetime, the objective function in the MILP model must be relevant to the residual energy of SNs. Thus, we define \( n + 1 \) real variables \( e_1, e_2, ..., e_n, e_{\text{min}} \) where the first \( n \) variables equal to \( n \) values
of SN’s residual energy, respectively and the \((n+1)th\) variables that will take the minimum value among these former.

With these above variables, the problem objective and basic constraints are given as follow

**Objective:** \( \max f = \alpha e_{\min} + (1 - \alpha) \frac{1}{N} \sum_{i \in V} e_i \) \( (O) \)

**Constraints:**

\[
\sum_{j \in V \setminus \{i\}} x_{ij} + \sum_{j \in V \setminus \{i\}} r_{ij} = 1 \quad \forall i \in V^* \quad (B.1)
\]

\[
\sum_{j \in V \setminus \{i\}} r_{ij} = \sum_{j \in V \setminus \{i\}} r_{ji} \quad \forall i \in V^* \quad (B.2)
\]

\[
x_{i0} = \sum_{j \in V \setminus \{i\}} r_{ij} \quad (B.3)
\]

\[
\sum_{j \in V \setminus \{i\}} r_{ij} \leq m \quad (B.4)
\]

\[
x_{ij} = 0 \quad \forall i, j \in V^* \quad \text{and} \quad d_{ij} > R \quad (B.5)
\]

\[
e_{\min} \geq 0, e_i \geq e_{\min} \quad \forall i \in V \quad (B.6)
\]

\[
e_{\min} \geq 0, e_i \geq e_{\min} \quad \forall i \in V \quad (B.7)
\]

As shown in (O), the objective of the MILP model is to maximize a weighted sum of \( e_{\min} \) and \( \frac{1}{N} \sum_{i \in V} e_i \) that are respectively the minimum and the average residual energy of SNs. Intuitively, since the network lifetime is equal to the respective the minimum and the average residual energy of SNs.

In section IV, we will do the experiment to find the optimum weight value \( \alpha \) so that the network lifetime is maximized.

Next, consider the basic constraints, constraint (B.1) means that a SN must be either forward data to its parent node if it is not a CH or else forward data to a corresponding UAV.

Constraints (B.2) and (B.3) require that number of UAVs that arrive and leave a SN must be the same and equal to 1 if \( s_i \) and equal to 0 otherwise. The maximum number of UAVs is met due to (B.4). Finally, constraint (B.5) indicates that a SN \( s_i \) could send data to \( s_j \) only if the Euclidean distance \( d_{ij} \) between them is not exceed the maximum range \( R \).

In the next two subsection, we present two completed MILP formulations for the multi-UAV data collection problem by adding other constraints on SN energy and trajectory length of UAV.

**B. 2-index formulation**

The 2-index formulation for the data collection problem with multiple UAVs is given as follow by using the big-M notation:

**Objective** \( \max f \) \( (F1) \)

subject to \( (B.1) - (B.7) \) and \( (F1.1) - (F1.6) \)

\[
\sum_{j \in V} B_{ij} = B^n_i \quad \forall i \in V^* \quad (F1.1)
\]

\[
B^n_i + b_i \leq B^c_{ij} + M(1 - x_{ij}) \quad \forall i \in V^*, j \in V \quad (F1.2)
\]

\[
E^n_i - E_{Rx} B^n_i - \sum_{j \in V \setminus \{i\}} E^c_{ij} B^n_{ij} \geq e_i \quad \forall i \in V^* \quad (F1.3)
\]

\[
E^n_i - E_{Rx} B^n_i - E^{UAV}(B^n_i + b_i) \geq e_i - M(1 - x_{i0}) \quad \forall i \in V^* \quad (F1.4)
\]

\[
L_i + d_{ij} \leq L_j + M(1 - r_{ij}) \quad \forall i,j \in V \quad (F1.5)
\]

\[
L_i + d_{i0} r_{i0} \leq L_{max} \quad \forall i \in V \quad (F1.6)
\]

**C. 3-index formulation**

Although the above formulation is compact which only has \( O(n^2) \) variables and constraints, however it is based on the big-M notation. It is known that the big-M constraint typically yields a very poor lower bound in the search trees and thus leading to a slower solving time. Thus, in this subsection, we present a novel MILP formulation that can exclude the big-M notations.

This formulation is inspired by the multi-commodity flow formulation for the Ring-Tree problem in [11]. Here we introduce two types of commodity flows. The first one is called the intra-cluster flows. Each of them originates from a SN, traverses the cluster tree’s edges to a CH, and finally terminates the sink by directly sending from the CH. We define the continuous flow variable \( g_{ij} \) \( \in \{0, 1\} \) to model the amount of the \( k^{th} \) intra-cluster flow that is transferred from \( s_i \) to \( s_j \). All these flow variables must be satisfied the following constraints:

\[
0 \leq g_{ij} \leq x_{ij} \quad \forall i,j,k \in V \quad (F2.1)
\]

\[
\sum_{j \in V \setminus \{i\}} g_{ij} - \sum_{j \in V \setminus \{i\}} g_{ji} = \begin{cases} -1 & i = 0 \\ 1 & i = k \quad \forall k \in V^* \\ 0 & \text{else} \end{cases} \quad (F2.2 - F2.4)
\]

Constraint (F2.1) means that a commodity flow can only be transferred through a tree edge. Constraints (F2.2), (F2.3) and (F2.4) are the flow conservation constraints at the sink node, the source node and the transit nodes, respectively.

The intra-cluster flows are used to measure the amount of data that a SN receives and transmits. Consequently, we can model the constraints on SN energy as in (F2.5):

\[
E^n_i - E_{Rx} \sum_{j \in V \setminus \{i\}} \sum_{k \in V^*} b_k g_{ki} - \sum_{j \in V \setminus \{i\}} \left( E^c_{ij} \sum_{k \in V^*} b_k g_{ki} \right) \geq e_i \quad \forall i \in V^* \quad (F2.5)
\]

Our second type of commodity flow is the inter-cluster flow. In particular, each CH will produce a second flow that follows the remaining trajectory of the UAV to reach the sink. The amount of the \( k^{th} \) inter-cluster flow sent from \( s_i \) to \( s_j \) is denoted as \( f_{ij}^k \). The flow conservation constraints for \( f_{ij}^k \) are given as follow

\[1\text{For consistency in notation, we use the value } E_{Rx}^O \text{ equal to } E_{Rx}^{UAV} \text{ since a CH will transmit data to a UAV instead of directly sending it to the sink.} \]
The tour length constraint for UAV can be conveniently formulated by using the length of the inter-cluster flow as in (F2.10)

\[ d_{0k}x_{k0} + \sum_{j \in V \setminus \{i\}} d_{ij}f_{ij}^k \leq L_{max} \quad \forall k \in V^* \]  

(F2.12)

To sum up, the proposed 3-index formulation is as follow:

Objective \( \max \ f \)  
subject to (B.1) - (B.7) and (F2.1) - (F2.10)

D. Heuristic model

Through the experiment, we find that our best MILP model can only deal with problems of moderate size, namely up to 50 SNs hence, it is insufficient to apply in a large-scale network of several hundred or thousands of nodes. Thus we propose a simple heuristic to reduce the number of variables in the MILP model. Since our objective is to prolong the network lifetime, the selected CHs in a round should be the nodes with higher residual energy. Therefore, we restrict the set of potential nodes to become CHs to the set of \( P \) percent of nodes with the highest energy in the network \( N_P \). As a result, the number of variables \( r_{ij} \) can be reduced from \( n^2 \) to \( |N_P|^2 \) because \( r_{ij} = 0 \) if either \( i \) or \( j \) is not in the set of potential CHs \( N_P \) and the number of variables \( f_{ij}^k \) can also be reduced from \( n^3 \) to \( |N_P|^3 \).

IV. EXPERIMENTS

In this section, we first compare internally between two proposed MILP models and the heuristic implementation regarding the computation time and optimality. Later we evaluate the network lifetime performance when applying the heuristic model in comparison with a recent relevant proposal. Table II sums up the experiment settings and parameters.

All MILP models were solved by using the commercial MIP solver CPLEX in version 20.10. The experiments were run on a computer with an Intel(R) Core(TM) i7-4770 CPU @ 3.40GHz and 8 GB of RAM. For each test instance, the relative MIP gap tolerance is set to 0.1%. We also set a solving time limit of 30 minutes in CPU time. Other configuration parameters of the CPLEX solver are left as default.

A. Impact of the weight parameter \( \alpha \)

Firstly, we examine the most efficient value of the weight factor \( \alpha \) in the objective function that would induce the longest network lifetime. In particular, we experiment on a random WSN with 30 SNs and the value \( \alpha \) is varied from 0.1 to 1. Fig 1 depicts the experiment results of network lifetime with different value of \( \alpha \). As can be seen, the value \( \alpha \) equal to 0.6 achieved the longest lifetime, namely approximately 2000 rounds. Accordingly, we will use the value \( \alpha = 0.6 \) in the next experiments.

| Network | Area                | Sink location     |
|---------|---------------------|-------------------|
| 15/20/30 SNs: 50m × 50m | 50 SNs: 75m × 75m |
| 100 SNs: 100m × 100m | Center of the square area |

| Number of UAVs | Max. trajectory length | Packet size | SN energy | Communication range |
|----------------|------------------------|-------------|-----------|--------------------|
| 2              | 100m                   | 100Kb       | Random in [20J, 40J] | 40m |

| Radio | 
|-------|
| \( P_{elec} \) | 50 nJ/bit |
| \( \epsilon_f \) | 10 pJ/bit/m² |
| \( \epsilon_{mp} \) | 0.0013 pJ/bit/m² |

Fig. 1: Impact of the weight \( \alpha \) to the network lifetime

B. Comparison between models

In this second experiment, we will compare the performance of two proposed MILP models and the heuristic implementation in terms of solving time and optimal gap. Here, we test each model on several network instances where the number of SNs and there are 20 network instances randomly generated for each network size. In this experiment, we also consider two different energy settings. In particular, for each network size, there are only 10 instances that take the default energy setting as presented above. With the 10 remaining network instances, each SN will take a random energy value from a more narrow interval [10J, 12J]. This second energy setting reflects the situation in a later round when the SN energies are gradually balanced through multiple previous rounds.

We provide the comprehensive results in Table III. In this table, the solving time and the best relative gap to the optimal solution, including the average and the worst case value, are respectively presented in the column "time" and "gap". Besides, the column "\( P_{opt} \)" shows the percentage of instances that can be solved optimally over 20 instances. Especially, a cell in column "gap" or "\( P_{opt} \)" is left blank in case that all test instances are solved optimally.

According to the results, the 2-index model has a significantly shorter solving time than the 3-index model due to the lower number of variables. Also, the 2-index model can solve the problem instances of size 50 SNs optimally, while the 3-index model can only handle the network with less than 30 nodes. However, with \( N = 100 \) nodes, both models cannot find the feasible solution for some problem instances, so we omit the results at 100 nodes of these models in the table.

We can also see that the computation time using the heuristic implementation is much faster than the complete model.
TABLE III: Comparison between models

| N   | Model | \( P_{opt} \) | Time (s) | Gap (%) |
|-----|-------|--------------|----------|---------|
|     |       | avg | max | avg | max |
| 15  | 2-index | 0.50 | 2.05 |
| 3-index | 2.83 | 7.75 |
| Heuristic 50% | 0.13 | 0.20 |
| Heuristic 20% | 0.02 | 0.14 |
| 30  | 2-index | 5.38 | 20.23 |
| 3-index | 1026.02 | 1800.00 | 2.07 | 9.24 |
| Heuristic 50% | 2.63 | 7.17 |
| Heuristic 20% | 0.37 | 0.67 |
| 50  | 2-index | 256.66 | 1800.00 | 0.05 | 0.10 |
| 3-index | 1800.00 | 1800.00 | 8.94 | 28.25 |
| Heuristic 50% | 38.62 | 122.77 |
| Heuristic 20% | 5.82 | 12.17 | 0.04 | 0.11 |
| 100 | Heuristic 50% | 367.07 | 1436.12 |
| Heuristic 20% | 126.61 | 360.09 | 0.06 | 0.12 |

![Fig. 2: Network lifetime in multi UAV scenario](image)

while the solutions are still close to optimal. In particular, all test instances are solved optimally by using the heuristic model with 50% of potential CHs out of all. When the percentage is 20%, the probability of achieving optimal solution using the heuristic model is still 95% with 50 nodes and 90% with 100 nodes. Moreover, the worst-case relative gap of a non-optimal solution is also relatively small, namely 0.11% and 0.12% with N = 50 and 100, respectively.

C. Performance of the heuristic model

To illustrate our heuristic MILP approach's effectiveness, we compare it with a relevant proposal that showed the most effective, namely the Convex-Hull-based protocol (CHP) in [7]. This protocol firstly divides the network into multiple sectors with the same percentage of energy decrease, and each mobile collector (UAV) is associated with a unique sector. A UAV trajectory is constructed inside its sector at initial by a geometrical method. Then a simulated-annealing adjustment is adopted to improve the trajectories in terms of total network energy consumption.

Fig. 2 presents the minimum residual energy after each round when applying our heuristic model and the CHP in a network with 100 SNs. As can be seen, our algorithm has a lower rate of energy reduction. As a result, the network lifetime when applying the heuristic model is 150 rounds, higher than 36% compared to 110 rounds as in the CHP.

V. CONCLUSION

This paper introduced two mixed-integer linear programming formulation for the rendezvous-based data gathering problem in WSNs using multiple UAVs. We proposed a heuristic idea to reduce the number of variables in the MILP model thus can handle the larger-scale WSNs. The experiment indicated that our best MILP model could optimally solve the problem instances with up to 50 sensor nodes, while the heuristic model can deal with the network with size in hundreds. These tests also show that our proposal can extend the network lifetime by 36% compared to the most efficient previous scheme. In the future, we will focus on improving the heuristic model and exploiting an extended problem where the cluster reconfiguration cost in each round is considered.

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REFERENCES

[1] X. Xu, Y. Zeng, Y. L. Guan, and R. Zhang. Overcoming endurance issue: Uav-enabled communications with proactive caching. *IEEE Journal on Selected Areas in Communications*, 36(6):1231–1244, 2018.
[2] C. Zhan, Y. Zeng, and R. Zhang. Energy-efficient data collection in uav enabled wireless sensor network. *IEEE Wireless Communications Letters*, 7(3):328–331, 2018.
[3] Mianxiong Dong, Kaoru Ota, Man Lin, Zunyi Tang, Suguo Du, and Haojin Zhu. Uav-assisted data gathering in wireless sensor networks. *The Journal of Supercomputing*, 70(3):1142–1155, Dec 2014.
[4] S. Alfattani, W. Jaafar, H. Yanikomeroglu, and A. Yongacoglu. Multi-uav data collection framework for wireless sensor networks. In *2019 IEEE Global Communications Conference (GLOBECOM)*, pages 1–6, 2019.
[5] Qiuyue Wu, Peng Sun, and Azeddine Boukerche. Unmanned aerial vehicle-assisted energy-efficient data collection scheme for sustainable wireless sensor networks. *Computer Networks*, 165:106927, 2019.
[6] C. Zhan and Y. Zeng. Completion time minimization for multi-uav-enabled data collection. *IEEE Transactions on Wireless Communications*, 18(10):4859–4872, 2019.
[7] Charalampos Konstantopoulos, Nikolaos Vathis, Grammati Pantziou, and Damianos Gavalas. Employing mobile elements for delay-constrained data gathering in wsns. *Computer Networks*, 135:108 – 131, 2018.
[8] Amar Kaswan, Kumar Nitesh, and Prasanta K. Jana. Energy efficient path selection for mobile sink and data gathering in wireless sensor networks. *AEU - International Journal of Electronics and Communications*, 73:110 – 118, 2017.
[9] D. Ebrahimi, S. Sharafeddine, P. Ho, and C. Assi. Data collection in wireless sensor networks using uav and compressive data gathering. In *2018 IEEE Global Communications Conference (GLOBECOM)*, pages 1–7, 2018.
[10] W. R. Heinzelman, A. Chandrakasan, and Balakrishnan. Energy-efficient communication protocol for wireless microsensor networks. In *Proceedings of the 33rd Annual Hawaii International Conference on System Sciences*, pages 10 pp. vol.2–, 2000.
[11] Alessandro Hill and Silvia Schwarze. Exact algorithms for bi-objective ring tree problems with reliability measures. *Comput. Oper. Res.*, 94(C):38–51, June 2018.