Optimized Drone Data Collection in WSNs: An ILP and mTSP Framework

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Abstract*— The growing deployment of wireless sensor networks (WSNs) in remote and challenging environments demands efficient data collection methods that minimize energy consumption while ensuring comprehensive coverage. Traditional data collection approaches face limitations when sensors are sparsely distributed across large areas, creating a critical need for optimized aerial collection strategies. This study addresses these challenges by exploring the deployment of multiple unmanned aerial vehicles (UAVs) for data collection tasks through an innovative hybrid approach. We combine multiple traveling salesman problem (mTSP) methodology with Integer Linear Programming (ILP) to substantially reduce energy requirements while maintaining complete sensor coverage. Our two-phase optimization methodology first employs ILP to establish strategic Access Points (APs) that cluster sensors according to transmission capabilities, followed by mTSP to generate efficient flight paths between these APs rather than individual sensors. We tested this methodology through comprehensive simulations across diverse network configurations and drone fleet sizes. Results consistently show performance gains, with our hybrid strategy cutting travel requirements by up to 32% compared to standard mTSP implementations. We've developed a novel sparsity indicator to measure clustering effectiveness, revealing that ILP-based grouping advantages become more substantial as sensor density increases. This approach not only decreases computational complexity by breaking the problem into manageable components but also enhances operational flexibility, allowing independent reconfiguration of AP placement or drone routing as field conditions change. Applications span from environmental monitoring to emergency response and agricultural intelligence, where resource-conscious data collection proves essential. Upcoming work will investigate dynamic reconfiguration mechanisms and predictive optimization through machine learning integration.

***Keywords*— Path planning optimization; Drone path planning; ILP; mTSP; Access Points.**

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I. INTRODUCTION

Efficient data collection in large-scale sensor networks remains a critical challenge, particularly in environments where traditional infrastructure is impractical. Wireless Sensor Networks (WSNs) [1] are increasingly deployed across various applications including environmental monitoring [2], precision agriculture [3], and disaster response [4]. A fundamental challenge in these networks is the efficient collection of data, especially when sensors do not feature mobility capabilities, with limited communication range and energy resources. As noted by Balbal et al. [5], efficient data collection strategies can significantly impact the overall network performance.

Unmanned Aerial Vehicles (UAVs) or drones have emerged as a promising solution for data collection in WSNs, particularly in large, sparsely populated areas. However, optimizing both the locations that allow for the collection of data, also known as Access Points (APs), and the routing of drones is essential to minimize energy consumption and ensure timely data collection.

This paper explores the deployment of multiple UAVs for data collection tasks using a hybrid approach that combines Integer Linear Programming (ILP) [6] and the multiple Traveling Salesman Problem (mTSP) [7], [8]. We aim to minimize total energy consumption across all UAVs while ensuring complete sensor nodes' coverage.

A. Motivation & Contribution

The integration of unmanned aerial vehicles for the collection of data from ground sensors is a rapidly evolving field, particularly with respect to operational efficiency and resource optimization. The challenges of aerial data collection require innovative approaches that can address both coverage and routing problems simultaneously.

To this end, the contributions of this work can be summarized as follows:

- Propose a two-phase optimization strategy that utilizes (a) Integer Linear Programming for defining Access Points to efficiently group sensors according to their coverage range, and (b) Multi-Traveling Salesman Problem to minimize drone travel distances by visiting the APs instead of individual sensors.
- Perform simulated experimentation in order to present the effectiveness of the proposed methodology

This approach not only minimizes the number of APs required but also optimizes drone paths, leading to significant improvements in energy efficiency and scalability. The primary benefit of separating the problem into two phases is the reduction in computational complexity. The combined problem of determining optimal AP locations and drone paths simultaneously would be NP-hard and practically unsolvable for large networks.

By using ILP first to determine AP locations that minimize their number while ensuring each sensor is covered, we effectively create a clustering of sensors. This reduces the subsequent mTSP problem's complexity since drones only need to visit APs rather than all individual sensors.

The remainder of this paper unfolds as follows: Section II examines relevant contributions, covering foundational work of mTSP formulations and ILP techniques, alongside recent developments in hybrid approaches that merge clustering mechanisms with mobile collection strategies. Section III elaborates on our proposed methodology, detailing the two-phase optimization process where ILP determines optimal access point placement followed by mTSP route planning. Section IV encompasses our experimental methodology, describing the test environment, presenting the various network configurations examined, and analyzing performance outcomes through comparative distance metrics and clustering efficiency indicators. The paper concludes in Section V with a synthesis of our findings and suggestions for extending this research in emerging Internet of Things (IoT) [9] contexts.

II. Background and Related Work

A. WSN Data Collection Approaches

Research in WSNs' data collection has evolved significantly over the past two decades [10], following several distinct but interconnected paths focusing on mobile collection, clustering approaches, and integrated methodologies.

1) *Mobile Data Collectors (MDCs)*: The concept of mobile elements for WSN data collection emerged in 2003 when Shah et al. introduced "Data MULEs" [11]. This seminal work established a new paradigm for employing mobile nodes to gather information from stationary sensors, addressing the power constraints inherent in long-range transmissions. Several researchers subsequently expanded this foundational work.

Gatzianas and Georgiadis [12] developed sophisticated linear programming models for resource allocation in WSNs with mobile access points. Their work emphasized network lifespan maximization while accounting for collector movement patterns. Chakrabarti et al. [13] investigated fundamental trade-offs between energy consumption and data latency in mobile collection scenarios. Their study established practical boundaries that continue to influence systems' architecture decisions. These pioneering efforts collectively shaped our understanding of mobile data collection in wireless sensor environments.

2) *AP/Cluster Head Selection*: The selection of optimal cluster heads or access points in wireless sensor networks remains a crucial research challenge that has attracted considerable attention. In [14], Heinzelman et al. developed the LEACH (Low-Energy Adaptive Clustering Hierarchy) protocol, now recognized as a pioneering and influential protocol for WSN clustering. The innovation of LEACH lay in its approach to spreading energy consumption across the network through periodic rotation of cluster head responsibilities among nodes.

Building on LEACH's foundation, Younis and Fahmy [15] introduced HEED (Hybrid Energy-Efficient Distributed clustering), which advanced clustering methodology by incorporating both remaining energy levels and communication costs as determining factors in the cluster's head selection process. This strategy notably extended networks' operational time compared to previous methods. Gupta and Younis [16] specifically tackled the challenging issue of fault-tolerant clustering, developing techniques to bounce back from cluster heads' failures and sustain network connections despite losing nodes.

3) *Combined Approaches*: Various researchers have investigated methods combining clustering elements with data collection, resembling the two-phase strategy under examination. One of the main differences between our method and previous approaches lies in how APs are conceptualized and used. Typically, related work treats APs - or cluster heads - as logical nodes within the network that gather sensor data and forward it using multi-hop communication, without the need for physical access. Our approach, however, takes a different route by treating APs as real-world locations that drones must physically visit. This redefinition turns APs from passive communication hubs into active data collection points, directly tying their placement to the drone's travel route. This role of APs - as both clustering anchors and compulsory drone checkpoints - marks a significant shift from established practices and is central to the performance gains demonstrated in our experiments.

Gandham et al. [17] presented an early dual-stage approach employing ILP for determining base station locations followed by route enhancement. Their work demonstrated the benefits of breaking down complicated problems into more manageable components.

Roberti and Ruthmair [18] created a mixed-integer linear program (MILP) framework that synchronizes truck and drones' logistics, leveraging the speed of drones alongside the capacity of trucks. Their methodology reflects a broader trend within the literature that recognizes the importance of co-deployment strategies involving different vehicle types, as it serves to optimize delivery processes in various operational settings. By aligning routing plans through ILP techniques [19], significant efficiency enhancements can be achieved, making it feasible for drones to cover greater distances with optimized energy usage.

Similarly, Meskar and Ahmadi [20] in their study integrate a realistic, load-dependent energy consumption function into a mixed-integer linear programming framework, allowing precise calculation of drone operational costs across various flight phases. By comparing different routing strategies and addressing demand uncertainty, the researchers therein provide a comprehensive method for determining optimal drone's launching centers and delivery routes, demonstrating the significant advantages of an integrated approach over traditional sequential planning methods.

Moreover, the integration of advanced algorithms and computational techniques within the ILP framework can further enhance its applicability in dynamic environments. For instance, adaptive algorithms that adjust to changing environmental conditions can be developed to optimize AP's placement and routing strategies in real-time [21].

4) *Specific Work on ILP + mTSP*: Several research teams have examined the particular combination of ILP for selecting APs followed by mTSP for planning collection paths. Castaño et al. [22] put forward a comparable approach explicitly developed for urban monitoring using IoT devices. Their methodology employed ILP to determine the most effective gateway locations before addressing the mTSP for vehicles collecting data, demonstrating notable success in dense city environments.

Gu et al. [23] introduced a two-phase optimization solution for industrial WSNs, utilizing mixed-integer programming for relaying nodes' placement followed by route enhancements. Their research addressed the specific constraints found in industrial settings, including interference and reliability demands.

Cornejo-Acosta et al. [24] presented innovative methods for solving routing challenges across various mTSP variants by developing compact mathematical models with reduced computational complexity. Their proposal of integer programming formulations offer flexible solutions for real-world routing scenarios, demonstrating significant theoretical and practical advantages in handling multiple salespersons' routes without traditional depot constraints.

B. Benefits of Using Integer Linear Programming

ILP is particularly effective for problems involving discrete variables, such as the placement of APs. Its primary benefit is yielding optimal solutions for complex combinatorial problems [25]. By formulating AP placement as an ILP, each sensor can be covered by exactly one AP while minimizing the total number of APs used [25].

ILP allows for the exploration of multiple objectives, such as minimizing the number of APs while maximizing coverage and connectivity. This multi-objective optimization is particularly relevant in scenarios where environmental conditions may vary, necessitating adaptive deployment strategies [26]. The flexibility of ILP in accommodating different constraints and objectives makes it a powerful tool for network design and optimization [27], [28].

The findings of Kara and Bektas [29] suggest that solving the mTSP directly using their ILP formulations is more efficient than transforming it into a standard TSP. Similarly, Wang et al. [30] provide a comprehensive framework for aerial data collection in large-scale wireless sensor networks, supporting the notion that effective AP placement leads to significant improvements in data collection efficiency.

As researchers continue to bridge ILP with drone routing complexities, it becomes evident that these methodologies present a promising avenue for enhancing logistical efficiencies across varied applications, from disaster relief to commercial deliveries. In summary, the integration of Integer Linear Programming within the paradigms of Access Points' placement and multi-Traveling Salesman Problem analysis for drones' routing reveals a powerful capability for enhancing operational efficiencies.

III. Proposed Method

As mentioned previously we propose a two-phase optimization strategy.

A. Phase 1: ILP for APs' Placement

This phase entails the modeling of the Access Points' placement challenge as an Integer Linear Programming problem. This approach enables the efficient clustering of sensors based on their transmission capabilities.

In order to enhance the legibility of the work, we present it by employing an example scenario: As illustrated in Fig. 1, the initial configuration of the scenario consists of 20 static sensor stations (S_1 ... S_{20}) distributed across a field. These stations continuously collect data that must be retrieved. At the designated launchpad (H), three drones are stationed for deployment to collect the data from the distributed sensors.

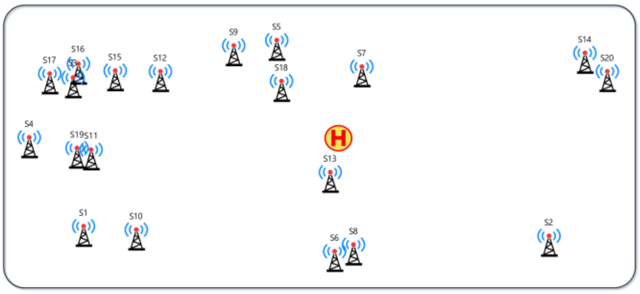

Fig. 1 A random placement of sensor stations in a field.

By applying the ILP algorithm, we have grouped stations according to their data transmission range capabilities. The results of this optimization are depicted in Fig. 2, where distinct clusters have been formed. These newly established groups, designated as Access Points, are clearly demarcated with circular boundaries in the illustration, wherein the center of the boundary is identified by the ILP and the radius is 100 units.

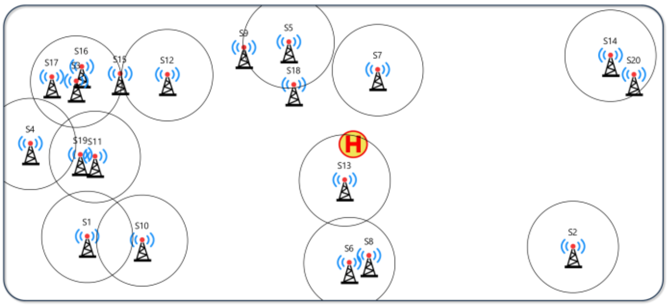

Fig. 2 Application of ILP for APs' definitions.

These optimized Access Points now serve as consolidated collection locations, significantly streamlining the flight paths required for the drones to retrieve all sensors' data. Rather than visiting each individual sensor, the drones now need only visit these strategically positioned Access Points.

B. Phase 2: mTSP for Drone Path Planning

The second phase leverages the mTSP methodology, applying it to the newly established Access Points (AP_1...AP_{12}) from Fig. 2 rather than addressing each sensor individually. With the same deployment plan as stated before, i.e. three drones, Fig. 3 demonstrates the optimized results, with the drones flying a total distance of 4,805 units. Drone 1 flies the orange route (H, AP_{12}, AP_2, AP_6, AP_{11}, H) covering 1,767 units. Drone 2 flies the blue route (H, AP_9, AP_4, AP_1, AP_8, H) covering 1,571 units and drone 3 flies the green route (H, AP_7, AP_5, AP_{10}, AP_3, H) covering 1,467 units.

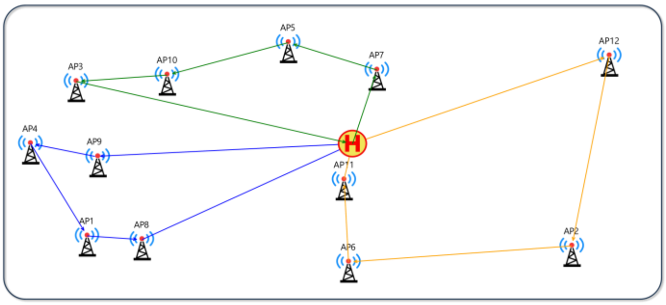

Fig. 3 Application of mTSP on the APs.

To evaluate the effectiveness of this strategic approach, we conducted a parallel analysis applying mTSP directly to the original configuration illustrated in Fig. 1, i.e. before the application of the ILP and the formation of the clusters / APs. Using identical parameters - the same number drones and identical launch location - Fig. 4 displays these results, showing a total required travel distance of 5,054 units. Drone 1 flies the orange route (H, S_{13}, S_6, S_8, S_2, S_{20}, S_{14}, S_7, H) covering 1,894 units. Drone 2 flies the blue route (H, S_{10}, S_1, S_4, S_{19}, S_{11}, S_9, S_5, H) covering 1,770 units and drone 3 flies the green route (H, S_{18}, S_{12}, S_{15}, S_{16}, S_{17}, S_3, H) covering 1,390 units.

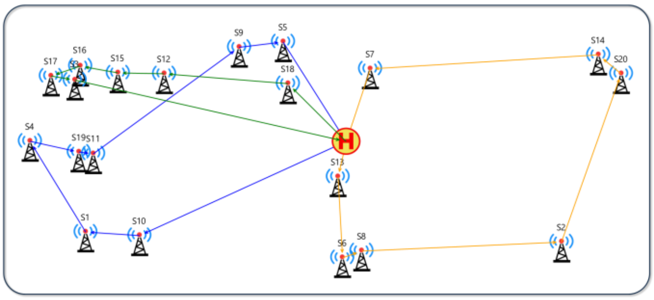

Fig. 4 Application of mTSP on the stations without use of ILP / APs.

A comparative examination of both approaches reveals significant operational benefits. The optimized approach in Fig. 3 requires navigation to only 12 collection points, whereas the conventional approach in Fig. 4 necessitates visits to all 20 original locations. This strategic consolidation translates to considerable reduction on the required travel distance when implementing the Access Point methodology.

This efficiency improvement on travel distance units demonstrates the tangible operational advantages of the hierarchical routing strategy through intermediate aggregation points.

C. Benefits of the Two-Phase Approach

After determining optimal APs' locations through ILP in the first phase, the second phase uses the mTSP framework to optimize drone routing for data collection. This approach treats the previously determined APs as nodes in a graph, with drones functioning as multiple salesmen tasked with visiting these nodes. The objective is to reduce the overall journey length or duration while guaranteeing that each AP receives exactly one visit from exactly one drone.

By formulating the problem this way, we can generate efficient flight paths for multiple drones, balancing workload across the fleet while minimizing energy consumption.

This methodology scales well with network expansion. When new sensors are introduced, the number of required APs may not increase proportionally, particularly if these sensors are positioned within the communication range of existing APs as it will be shown in the experimentation section herein.

In addition, a significant advantage of this decoupled two-phase approach is its adaptability to dynamic field conditions. Modifications in sensor deployment or operational status can be addressed by reconfiguring APs' placements while maintaining existing drone paths, where feasible. Conversely, changes in drone fleet composition or availability can be managed by adjusting routing solutions without necessitating alterations to the established AP infrastructure.

Finally, this sequential approach significantly reduces computational complexity compared to attempting to optimize both APs' placement and drones' routing simultaneously.

IV. EXPERIMENTAL EVALUATION

A. The Setup

To model the Access Point selection as an ILP problem, we adapted the mTSP framework from our prior research [31], [32] and leveraged Google OR-Tools [33] to simplify the implementation of ILP-based solutions. The code was developed in C# using the .NET framework. All tests were conducted on a high-performance system with the following specifications: 512 GB of RAM, an AMD® Ryzen Threadripper Pro 5955WX processor (16 cores, 32 threads, 4.0 GHz base clock), and four NVIDIA RTX A5000 (GA102GL) GPUs.

We generated 80 distinct flight plans, each representing a different scenario. These scenarios explored a range of station densities, specifically 5, 10, 15, 20, 25, 45, 60, and 100 stations, while accommodating varying drone counts from 1 to 10. To mitigate potential statistical variations arising from randomized stations' locations, each scenario was executed 10 times, yielding 800 total test runs (80 scenarios × 10 iterations). The results were averaged to ensure statistical reliability.

B. Evaluation Results

To assess the effectiveness of our approach, we used two key metrics:

- **Performance Improvement**: Measures the gains achieved (in percentage) by the two-phase method compared to using mTSP alone
- **Sparsity Ratio**: Indicates how efficiently access points are distributed relative to the number of stations. A ratio near to 1 suggests one access point per station, while a lower ratio implies shared access points among multiple stations.

The results obtained from the experiments are depicted in Fig. 5: the graph demonstrates a clear trend that aligns well with the theoretical expectations described herein on the two-phase optimization approach involving ILP and mTSP.

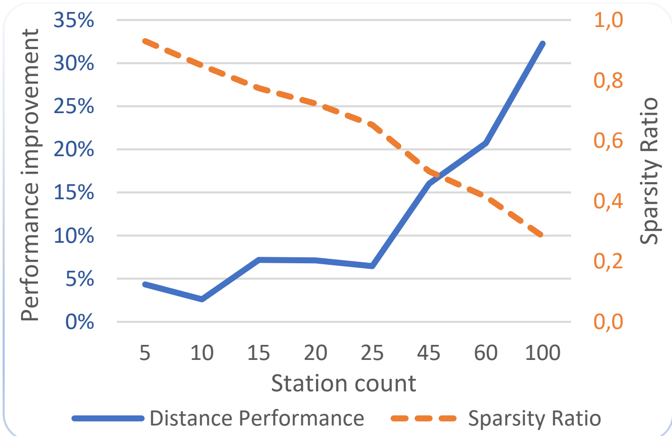

Fig. 5 Distance performance by applying ILP for APs first and then mTSP.

1) *Performance Analysis*: The performance metric, in percentage, shows consistent improvement across all tested scenarios.

The performance advantage increases substantially with network size. For small networks with 5-25 stations, the improvement ranges from 3-7%. However, for larger networks with 45-100 stations, the improvement jumps significantly to 16-32%.

The most dramatic performance gain occurs in the largest tested network of 100 stations, where the two-phase approach reduces travel distance by nearly one-third (32%) compared to the direct mTSP approach.

2) *Sparsity Analysis*: The sparsity metric reveals important insights about the efficiency of the ILP phase. The sparsity decreases steadily as the number of stations increases, from 0.9 for 5 stations to 0.3 for 100 stations. This indicates that the clustering advantage becomes more pronounced in larger networks.

In small networks with 5 stations, nearly all stations serve as Access Points (sparsity = 0.9), offering minimal clustering benefit. However, in the largest network with 100 stations, only 30% of stations need to serve as Access Points.

The inverse relationship between sparsity and performance improvement confirms the paper's theoretical framework: as more stations can be clustered under fewer Access Points, the efficiency gain of the two-phase approach increases.

V. Conclusion

Our research demonstrates that combining ILP and mTSP creates a powerful framework for drone-based data collection in wireless sensor networks. The two-phase approach - using ILP for strategic Access Point's placement first, then applying mTSP for flight path optimization - offers significant advantages over single-stage methods.

Breaking complex problems into sequential stages dramatically reduces computational demands in large-scale deployments. Our tests reveal that this hierarchical approach not only improves scalability but also extends drones' battery life through more efficient routing. The framework effectively balances energy constraints with operational requirements.

These methodologies have broad applications beyond academic interest. Environmental monitoring programs, emergency responses' coordination, and commercial delivery systems can all benefit from the efficiency gains observed herein.

Future research directions might explore dynamic reconfiguration mechanisms that adapt both APs' placement and flight paths in real-time. Incorporating predictive optimization through machine learning techniques could further enhance systems' performance.

With Internet of Things ecosystems rapidly expanding, these sophisticated optimization approaches will become increasingly vital for building sustainable data collection infrastructures capable of addressing future challenges.

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