ENERGY MINIMIZATION IN WIRELESS SENSOR NETWORKS: AN EFFICIENT HEURISTIC FRAMEWORK FOR DATA COLLECTION THROUGH UAV TRAJECTORY PLANNING AND POWER ALLOCATION

Dang Thien Binh[1]*, Tran Anh Kiet[2], Vo Trung Hung[3]

[1]*The University of Danang - University of Science and Technology, Vietnam*
[2]*The University of Danang, Vietnam*
[3]*The University of Danang - University of Technology and Education, Vietnam*

*Corresponding author: dtbinh@dut.udn.vn

(Received: April 15, 2025; Revised: June 18, 2025; Accepted: June 22, 2025)

DOI: 10.31130/ud-jst.2025.23(10B).638E

Abstract - Wireless Sensor Networks (WSNs) play a vital role in modern technology by providing real-time data collection in hard-to-reach areas. Energy efficiency is critical for the sustainability of WSNs, especially in remote environments where maintenance is costly. This paper presents a solution to enhance the energy efficiency of WSNs by integrating Unmanned Aerial Vehicles (UAVs) for data collection. To extend the lifespan of WSNs, UAVs function as mobile data aggregators, minimizing the requirement of energy-intensive long-distance transmissions from sensors. The paper proposes an optimization framework using convex optimization techniques to optimize UAV trajectory and power allocation. Numerical results demonstrate the effectiveness of the proposed solution in reducing power consumption and improving the longevity of sensor networks.

Key words - Convex optimization; trajectory optimization; UAV; WSN

1. Introduction

Wireless sensor networks (WSNs) are crucial in modern technology due to their ability to monitor and collect data in real-time from remote or hard-to-reach locations. They enable continuous surveillance and provide valuable insights across various industries, including healthcare, agriculture, environmental monitoring, and smart cities [1], [2]. With wireless communication, these networks eliminate the need for extensive wiring, making them more cost-effective, flexible, and easier to deploy [3]. The data gathered by WSNs can be used for decision-making, early detection of problems, and improving efficiency [4]. Their scalability and adaptability make them an essential component in the Internet of Things (IoT), contributing to advancements in automation and real-time data-driven solutions [5].

Saving sensor energy and prolonging the lifetime of wireless sensor networks (WSNs) are critical for maintaining the efficiency and sustainability of these systems. Since sensors are typically deployed in remote or inaccessible locations, frequent maintenance or battery replacement is costly and often impractical [6]. By optimizing energy consumption, sensors can operate for extended periods without requiring intervention, reducing operational costs and ensuring continuous monitoring. Techniques such as energy-efficient data transmission, sleep modes, and low-power sensor designs help minimize energy use, allowing WSNs to remain functional longer. Prolonging sensor lifetime also contributes to environmental sustainability by reducing electronic waste and the need for frequent replacements. Overall, energy-efficient design is key to the long-term viability and effectiveness of sensor networks in real-world applications.

Utilizing Unmanned Aerial Vehicles (UAVs) to collect data can significantly enhance the energy efficiency of wireless sensor networks (WSNs). UAVs can be deployed to gather data from multiple sensor nodes over large areas, reducing the need for continuous or long-distance transmissions by individual sensors, which can be energy-intensive. By acting as mobile data aggregators, UAVs can gather and transmit data to a central base station, thus minimizing the energy consumption of the sensors themselves. This not only extends the operational life of the sensors but also optimizes the overall energy usage of the WSN [7]. Furthermore, UAVs can be programmed to operate on-demand, flying only when necessary to collect data, further improving energy efficiency and reducing unnecessary communication overhead. This integration of UAVs with WSNs offers a promising solution to enhance both the energy sustainability and performance of sensor networks.

Despite the promising potential of Unmanned Aerial Vehicles (UAVs) in enhancing the performance of Wireless Sensor Networks (WSNs), several gaps remain in their effective integration for data collection. While UAVs can significantly reduce the need for energy-intensive long-distance transmissions, their deployment presents challenges in terms of optimizing their flight paths and ensuring efficient power management across a large sensor network [8]. Current methods often rely on static UAV trajectories or predetermined flight patterns, which do not adapt to the dynamic conditions of the sensor field, such as varying sensor densities or environmental changes. Additionally, the power consumption of both UAVs and sensor nodes remains a concern, as existing solutions fail to sufficiently balance energy usage between the UAV and the sensors. Moreover, many solutions do not fully exploit the mobility of UAVs to adaptively optimize data collection based on real-time network conditions [9]. Therefore, there is a need for more advanced algorithms that optimize UAV trajectories and power allocation, ensuring both energy efficiency and system scalability in diverse deployment scenarios.

2. Preliminaries

2.1. System model

We consider data collection for WSN where a UAV successively visits the sensors and the sensors send the sensing data. As illustrated in Figure 1, N single-antenna sensors are scheduled to transfer the data to the UAV as the uplink transmission. In this way, the trajectory of UAV to travel all sensors is searched as the optimal order. To improve the EE of WSN, the UAV equipped with M antennas is controlled to fly and collect the data in the multiple time slots. In which, each time slot corresponds to a coherent block where the channel response is considered as flat fading.

To fully leverage the mobility property of UAV, the data center is enabled to compute the trajectory of UAV along with the time slots, while the data transmission is retrived adapting to the channel instances. This strategy helps to effectively overcome the conflict in designing both trajectory and immediate receiver. We suppose that the UAV supported by global positioning system (GPS), where a device in the WSN at the time t can be located as

$$\mathbf{c}^D[t] = \left[x_D[t], y_D[t], z_D[t]\right], \tag{1}$$

where the device $D \in \mathfrak{D} \triangleq \{U, \{S_n\}_{n\in \mathcal{N}}\}$, with the set of sensor-node indices denoted by $\mathcal{N} \triangleq \{1,2,\dots,N\}$. U and S_n represent the UAV and sensor node n. Without loss of generality, we assume that all sensor nodes is the terrestrial devices, and thus the altitudes of all nodes can be set as $z_{S_n}[t]=0, \forall n$.

2.2. Channel model

Before considering the channel state information (CSI) of WSN, we introduce the distance formula between UAV and sensor node n at the time t as the Euclidean norm, i.e., $d_n[t]=\|\mathbf{c}^U[t]-\mathbf{c}^{S_n}[t]\|$ with A and B being the certain different nodes in D.

Considering the time slot t (with $t \in \mathcal{T} \triangleq \{1,2,\dots,T\}$), the CSI of the link between UAV and sensor node n is formulated as

$$\mathbf{g}_n[t]=\sqrt{\beta_n[t]}\ \mathbf{h}_n[t], \tag{2}$$

where $\beta_n[t]$ denotes the large-scale fading from U to sensor Sn, that is expressed in dB as

$$\beta_n[t]=PL_n^0[t]+\mu_{LoS}P_{LoS}+\mu_{NLoS}P_{NLoS}, \tag{3}$$

with the pairs of (μ_{LoS},P_{LoS}) and (μ_{NLoS},P_{NLoS}) stands for the average loss along with its probability in case of line-of-sight (LoS) and non-LoS (NLoS), respectively. The free-space path loss, $PL_n^0[t]$, is given as

$$PL_n^0[t]=10\alpha_n \log_{10}((4\pi f_c d_n[t])/c), \tag{4}$$

where α_n, f_c and c denote the path loss exponent for the links from U to Sn, the carrier frequency (in Hz) and speed of light (in m/s), respectively. Finally, the component of $\mathbf{h}_n[t]$ specifies the small-scale fading, of which each entry follows the symmetric circular complex distribution, known as $\sim \mathcal{CN}(0,1)$.

2.3. Data transmission

Now, we consider the data transmission from the sensor Sn to the UAV at the time slot t. By letting $x_n[t]$, with $E[|x_n[t]|^2]=1$, be the transmit signal from S_n intended to the UAV. The signal received at the UAV can be expressed as

$$\mathbf{y}_n[t]=\mathbf{g}_n[t]\sqrt{p_n[t]}\ x_n[t]+\mathbf{z}_n[t], \tag{5}$$

where each entry of $\mathbf{z}_n[t]$, with $\mathbf{z}_n[t]\sim CN(0,\sigma^2\mathbf{I})$, denotes the additive white Gaussian noise (AWGN). Herein, the square roots of power coefficients are exploited to derive the linear form in the data rate expression. After applying the matched filter, the post-processing signal at UAV can be expressed by

$$r_n[t]=\mathbf{a}_n[t]\ \mathbf{g}_n[t]\sqrt{p_n[t]}\ x_n[t]+\mathbf{a}_n[t]z_n[t], \tag{6}$$

where $\mathbf{a}_n[t]=\mathbf{g}_n^H[t]\in C^{1\times M}$ represents the receiver vector for decoding the signal from S_n. Therefore, the data rate can be determined as

$$R_n[t]=B\log_2(1+\gamma_n[t]),\ \text{(bits/s)} \tag{7}$$

where B is the system bandwidth and the signal-to-interference-plus-noise ratio (SINR) at the UAV for decoding the signal from S_n at the time t, denoted by $\gamma_n[t]$, is given as

$$\gamma_n[t]=\rho_n[t]|\mathbf{a}_n[t]\ \mathbf{g}_n[t]|^2, \tag{8}$$

with the power coefficient determined as

$$\rho_n[t]=p_n[t]/\sigma^2, \tag{9}$$

2.4. Energy consumption model and problem formulation

Let Δt be the duration of one time slot. The energy consumption for S_n to send the data can be formulated as

$$E_n=E_0+\Delta t\sum_{t=1}^{T} p_n[t], \tag{10}$$

where E_0 is the energy required to maintain the operation of sensor S_n (remaining the on mode and data processing). To prolong the operation of WSN, the lifetime of every node should be guaranteed, and then an optimization problem for the energy comsumption fairness is considered as follows.

$$\underset{\mathbf{p},\mathbf{c}}{\text{minimize}} \quad \max_{n\in\mathcal{N}} E_n \tag{11a}$$

$$\text{subject to} \quad p_n[t]\le P_n^{max},\ \forall n\in\mathcal{N}, \tag{11b}$$

$$\Delta t\ \sum_{t=1}^{T} R_n[t] \ge F_n, \forall n\in\mathcal{N}, \tag{11c}$$

$$\|\mathbf{c}^U[t]-\mathbf{c}^U[t-1]\|\le V_{max}\Delta t,\ \forall n\in\mathcal{N}, \tag{11d}$$

$$\|\mathbf{c}^U[T]\|\le V_{max}\Delta t, \tag{11e}$$

where P_n^{max} and V_{max} represent the maximum power budget at sensor n and maximum velocity of UAV, respectively. Constraint (11b) ensures that the transmit power remains within the maximum power budget of the sensors, while constraint (11c) guarantees that all data from each sensor is fully collected by the UAV. Constraints (11d) and (11e) capture the mobility characteristics of the UAV.

3. Proposed Solution based on Convex Optimization

To effienciently solve (11), this section presents how to apply the convex optimization framework to problem (11). First, problem (11) can be transformed into an equivalent form as follows.

$$\underset{\mathbf{p},\mathbf{c}}{\text{minimize}} \quad \theta, \tag{12a}$$

$$\text{subject to} \quad p_n[t]\le P_n^{max},\ \forall n\in\mathcal{N}, \tag{12b}$$

$$\Delta t \ \sum_{t=1}^{T} R_n[t] \geq F_n, \forall n \in \mathcal{N}, \quad (12c)$$

$$\|\mathbf{c}^{\mathrm{U}}[t]\text{-}\mathbf{c}^{\mathrm{U}}[t\text{-}1]\| \leq V_{max}\Delta t, \ \forall n \in \mathcal{N}, \quad (12d)$$

$$\|\mathbf{c}^{\mathrm{U}}\ [T]\| \leq V_{max}\Delta t. \quad (12e)$$

$$E_0 + \Delta t \sum_{t=1}^{T} p_n[t] \leq \theta, \forall n \in \mathcal{N} \quad (12f)$$

where θ is newly introduced as a variable. It can be observed that problem (12) is still hard to be solved due to the non-convex constraint (12c).

To ease the implementation complexity of constraint (12c), we replace (12c) with the following equivalent equations:

$$(12c) \Leftrightarrow \begin{cases} \sum_{t=1}^{T} \log_2(1+\gamma_n[t]) \geq \frac{F_n}{\Delta t\, B} \\ \gamma_n[t] = \rho_n[t]|\mathbf{a}_n[t]\mathbf{g}_n[t]|^2 \end{cases} \quad (13)$$

To reduce the complexity of solving problem (12), we propose two-step algorithm: (i) the first step is to determine the trajectory of UAV using the travelling salesman algorithm; and (ii) the convex optimization is applied to find the power allocation. After completing the first step, we obtain the solution for variable **c**, and then, the problem for power allocation is expressed as

$$\underset{\mathbf{p}}{\text{minimize}} \ \theta, \quad (14a)$$

subject to (12b), (13), (12f). (14b)

This problem can be directly solved using convex tool, e.g., cvxpy in PYTHON program.

4. Numerical Result

4.1. Parameter Settings

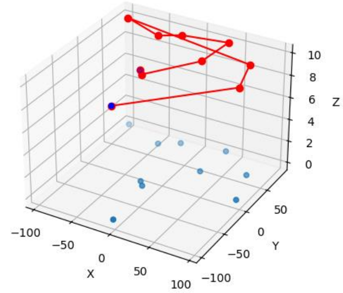
To evaluate the system performance, we use Python to establish the UAV-assisted WSN where a UAV equipped with multiple antennas is controlled to fly and collect the data from multiple sensors deployed in various configurations to cover a sensing area. The primary objective of the UAV is to efficiently navigate the environment while maintaining optimal coverage of the sensor points in the sensing area. The data collected by one sensor is given at 1 Kb. The system bandwidth is set to 1 MHz while the power density of background noise is -174 dBm/Hz. The other parameters is described in Table 1.

Table 1. *Parameters for Simulation*

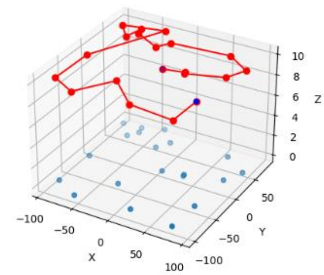
Parameters	Values
Maximum power budget, P_n^{max}	10 dBm
Maximum velocity of UAV, V_{max}	20 m/s
Number of time slots, T	N

4.2. Adaption of UAV Trajectory Computation

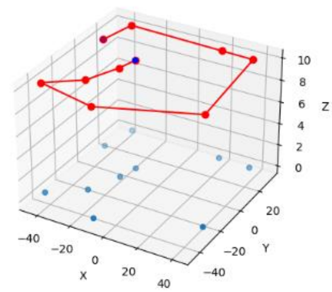
Figure 1 represent different UAV trajectories with varying sensor densities and changes in the sensing area. The levels of sensor employment vary as (a) sparse with 10 sensors allocated in area of 200mx200m, (b) moderate with 20 sensors allocated in area of 200mx200m, (c) dense with 10 sensors allocated in area of 100mx100m and (d) very dense with 20 sensors allocated in area of 100mx100m. This investigation demonstrates the relationship between sensor density and trajectory, showing how the UAV adapts its flight pattern based on the number of sensors available and the need to cover a larger or more precise sensing area.



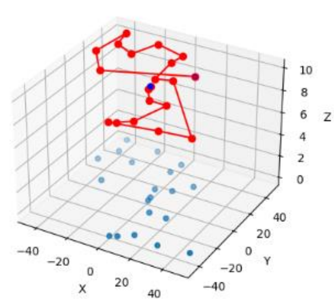
(a) Sparse



(b) Moderate



(c) Dense



(d) Very dense

Figure 1. *UAV trajectory versus the change of sensing area and number of sensors*

4.3. Performance Evaluation

The Figure 2 presents a CDF (Cumulative Distribution Function) plot of the min-max power consumption for the sensors under the different UAV trajectory scenarios. Three key lines are investigated to verify the effectiveness of the proposed schemes:

- Proposed Joint Optimization of Trajectory and Power Allocation (JO-TPA, Red Solid Line): This line represents the CDF for the power consumption when using the JO-TPA method.

- Fixed UAV Position (Blue Dashed Line): This line shows the CDF for a fixed UAV position at the center of examined area (0,0), where the UAV's position does not change over time.

- Fixed UAV Trajectory (Black Dotted Line): The black dotted line represents the CDF for a UAV that follows a predefined trajectory.

As illustrated in Figure 2, the proposed algorithm consistently outperforms the others across all percentile points. Notably, at the median percentile, it achieves gains of 2.5×10^{-4} mW and 4×10^{-4} mW over the fixed-position and fixed-trajectory baselines, respectively. These gains further increase to 3×10^{-4} mW and 5×10^{-4} mW at the 95th percentile. These results highlight the effectiveness and robustness of the proposed algorithm under varying channel conditions.

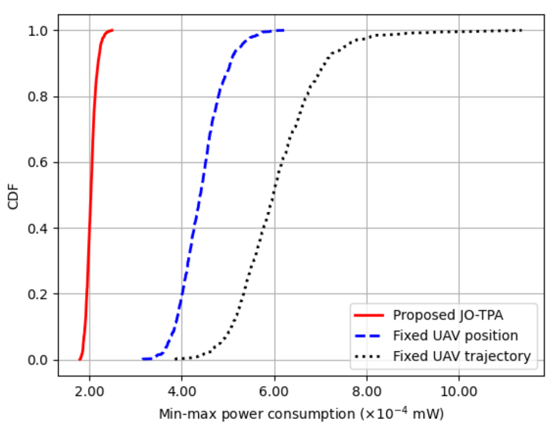


Figure 2. *The CDFs versus min-max power consumption*

5. Conclusion

In this paper, we presented a novel approach to enhance the energy efficiency of wireless sensor networks by integrating UAVs for data collection. By optimizing UAV trajectories and power allocation through convex optimization, we demonstrated significant reductions in energy consumption. The results from our simulation show that the proposed method outperforms traditional methods of fixed UAV positions or predefined trajectories, ensuring robust performance even under varying environmental conditions. The approach not only improves the operational lifetime of WSNs but also contributes to energy sustainability, making it a valuable solution for real-world applications in sectors like healthcare, agriculture, and environmental monitoring.

Acknowledgments: This research is funded by Ministry of Education and Training under project number B2024.DNA.16.

REFERENCES

[1] F. Ullah, M. A. Shah, S. Zhang, S. Y. Lee, and M. A. AlZain, “Wireless Sensor Networks for Health Monitoring Systems: A Review*”, IEEE Access*, vol. 9, pp. 112233–112254, 2021.

[2] H. M. Jawad, R. Nordin, S. K. Gharghan, A. Gharghan, and M. Ismail, “Wireless Sensor Networks in Precision Agriculture: Trends, Challenges and Applications”, *Computers and Electronics in Agriculture*, vol. 192, Art. no. 106606, 2022.

[3] M. M. Rathore, A. Paul, A. Ahmad, B. W. Chen, and W. Ji, “A Survey on Smart Cities: Architectures, Emerging Technologies, and Applications”, *IEEE Access*, vol. 8, pp. 144379–144403, 2020.

[4] A. Al-Fuqaha, M. Guizani, M. Mohammadi, M. Aledhari, and M. Ayyash, “Internet of Things: A Survey on Enabling Technologies, Protocols, and Applications”, *IEEE Communications Surveys & Tutorials*, vol. 17, no. 4, pp. 2347–2376, 2024.

[5] C. Gómez and J. Paradells, “Wireless Sensor Networks in Environmental Monitoring: Applications, Challenges, and Future Trends”, *Sensors,* vol. 21, no. 2, pp. 472–488, 2021.

[6] S. Singh and H. Bansal, “Energy-Efficient Protocols in Wireless Sensor Networks: A Review and Future Research Directions”, *Journal of Ambient Intelligence and Humanized Computing*, vol. 14, pp. 1203–1221, 2023.

[7] R. Khan, S. U. Khan, R. Zaheer, and S. Khan, “Security and Privacy Issues in Wireless Sensor Networks for Smart Cities: A Survey”, *IEEE Access*, vol. 12, pp. 19245–19266, 2024.

[8] T. T. Nguyen, L. T. Pham, and Q. H. Bui, “Energy-Aware UAV-Assisted Data Collection in Wireless Sensor Networks: A Convex Optimization Approach”, *IEEE Internet of Things Journal*, vol. 11, no. 2, pp. 1760–1774, 2025.

[9] P. X. Nguyen, V. -D. Nguyen, H. V. Nguyen and O. -S. Shin, "UAV-Assisted Secure Communications in Terrestrial Cognitive Radio Networks: Joint Power Control and 3D Trajectory Optimization*", in IEEE Transactions on Vehicular Technology*, vol. 70, no. 4, pp. 3298-3313, April 2021, doi: 10.1109/TVT.2021.3062283.