2025 International Conference on
Unmanned Aircraft Systems (ICUAS)
May 14-17, 2025. North Carolina, USA

Energy-Aware Coverage Path Planner for Multirotor UAVs

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***Abstract*— Coverage Path Planning (CPP) is crucial for UAV applications such as inspection and surveying. While existing CPP methods often focus on minimizing distance or time, energy consumption remains a critical, relatively unexamined constraint, especially for multirotor drones. This paper proposes a novel CPP approach that directly incorporates an energy model into the path-planning process. By utilizing a Mixed Integer Linear Programming (MILP) framework and an energy model, the proposed method aims to minimize energy consumption while ensuring complete coverage of the target area. Simulations and experimental results demonstrate that the proposed approach gives optimal solutions, and using this richer cost function reduces the processing time for the MILP problem, opening the door for faster online CPP planners.**

I. INTRODUCTION

There has been continuous and fast growth in robotics applications over the years. A prominent area has been the deployment of flying agents to survey, scan, inspect, or record assigned areas. To deploy any robot, there is the need for an offline path planner, which pre-computes the path before the robot starts moving [1], and an online motion planning system [2], which allows the robot to plan its path during motion.

Traditional path planners aim to optimize the robot's movement from a starting point to a goal in the most effective way [3]. However, these approaches cannot be directly used when visiting a set of points in a given order. This is where the necessity and value of Coverage Path Planning (CPP) becomes apparent. CPP, as defined by Galceran and Carreras [4], is the task of determining a path that passes over all points of an area or volume of interest while avoiding obstacles. This is crucial for various robotic applications, such as vacuum cleaners, underwater vehicles, lawnmowers, and mobile or flying robots for agriculture and inspection.

There is a permanent appeal in improving solutions for CPP algorithms. A complete survey on methods that tackle this problem is presented in [5]. These methods are usually divided into Decomposition methods, Multi-Robot strategies, Unmanned Aerial Vehicles (UAV) CPP Methods, Multi-UAV CPP Methods, and Energy-Saving Algorithms [5]. Decomposition is the most popular class of methods [6]. For the decomposition method, the basic concept is to divide the inspection area into cells (rectangular, hexagonal). Each cell area is usually divided based on the Field of View (FOV) of the sensor used, and then using the center of each cell, an algorithm to visit all these waypoints generates a trajectory to be implemented with a UAV. An example of such an approach is to use a wavefront algorithm to visit all cells in a given area [7], [8]. The Multi-Robot Strategies are usually an extension of the Decomposition methods, with the addition of multiple agents to cover the area in a shorter period, with the same constraints. An example, of using a Graph-Based algorithm with a cellular decomposition with a multi-robot approach can be found in [9].

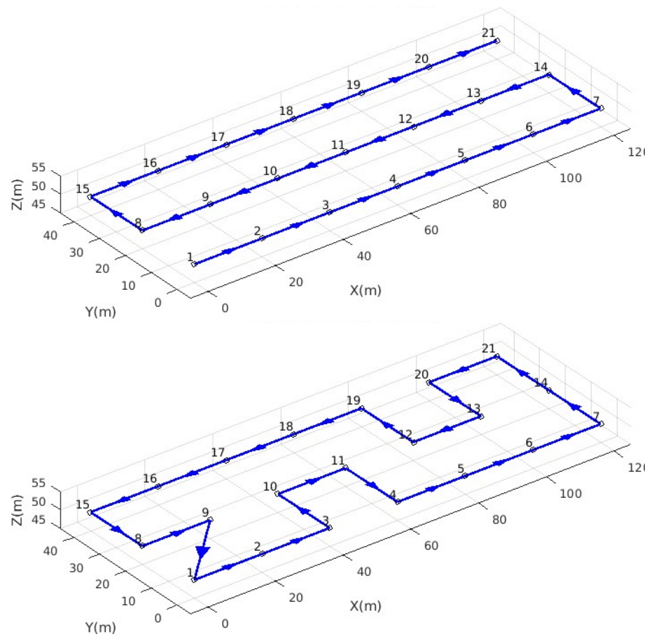

Fig. 1: Leveled flight coverage methods: The traditional back-and-forth path (top) measures 526.49 meters and consumes 4,201.69 J, while the path generated by an energy optimizer (bottom) measures 428.28 meters and consumes 3,417.93 J, achieving nearly a 20% reduction in energy consumption.

This paper is especially interested in energy-saving CPP algorithms. Fevgas et al. [5] present a comparison of methods that optimize energy consumption for the CPP problem. Most of the presented studies maintain cell decomposition and focus on energy optimizing by improving curves [10], smoothing trajectories [11], and taking into account the wind for a fixed-wing model [12], to mention a few. Di Franco and Buttazzo [13], present a data-based energy model for a specific UAV. The energy model is used to calculate an

This research is funded by the Alpha Foundation for the Improvement of Mine Safety and Health, Inc., under grant number AFCTG22r2-159. The views, opinions, and recommendations expressed herein are solely those of the authors and do not imply any endorsement by Alpha Foundation, its directors, and its staff.

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optimal speed to minimize the energy consumed on a straight flight. After calculating the speed, the authors use a standard algorithm to find a back-and-forth trajectory that covers the entire area and minimizes turns with the most efficient speed.

As seen in the literature about CPP [?], [5], the most accepted approach to tackle the problem is to use a cellular decomposition and then a standard path that visits all the cells, usually back-and-forth, being beneficial for fixed-wing UAVs, but not as much for multirotor UAVs. Mier et al. [14] have published a state-of-the-art library using this standard approach, considering the application of surveillance robots, lawnmowers, and agricultural vehicles. This library contains four modules. The first one generates a headland field, which is the limit of the area to be covered. The second module is the swath generator, which covers the field with the longest parallel paths to optimize distance and coverage. The third module creates a route with different patterns (snake, spiral, or custom), and finally, the fourth module is a path planner, where Dubins [15] or Reeds-Sheepp's curves [16] can be added. This state-of-the-art library shows a gap to be covered, particularly in more complicated 3D environments, such as inspection or scanning or using the omnidirectional capabilities of multirotor UAVs.

With the growing need for multirotor UAV applications and the proven benefits of deploying this kind of robot to unravel the CPP problem, the most critical constraint and barrier to the wider acceptance of this application is its energy consumption constraint, which is also connected directly to the mission and deploying time. Examples of up-to-date studies regarding drone energy consumption and how this energy is affected by missions are [17], [18], and [19]. The key aspects of these studies and the most relevant conclusions are that energy models are still complex and depend on external and internal factors. The most accurate methods are data-based but rely on the operated drone, data quantity, and data quality. Besides, the inclusion of energy in the CPP problem is commonly addressed indirectly, trying to minimize curves, acceleration, and deacceleration sections [5]. A more direct way to include the energy limitations is to insert a constraint related to the battery consumption, which commonly relates to a maximum flight distance [20] or maximum flight time [21] that a UAV can cover with a single charge. A method that includes an energy measurement to visit a set of waypoints is presented in [19]. The authors show that a straight path is not always the most energy-efficient for multirotor UAVs, especially when climbing or descending. They also evaluate their proposed optimization approach using the aircraft dynamics and mention that, on average, the optimized paths are 1.6% – 3.3% more efficient than the shortest distance.

Given the current literature, to the authors' knowledge, energy has not been used as a cost function to solve the CPP problem for drones in inspection missions using a Travelling Salesman Problem (TSP) method, where the main objective is to guide the UAV to reach all the waypoints by following trajectories that minimize the consumed energy. Thus, the main contribution of this paper is to propose a technique

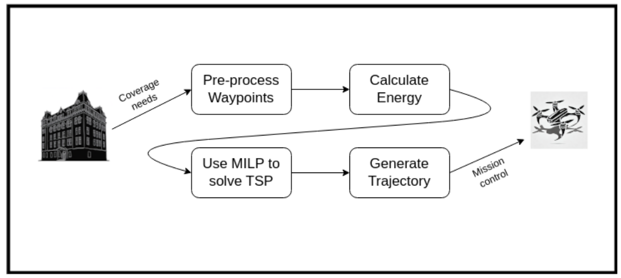


Fig. 2: Proposed approach: 1) using previous information, a set of waypoints is computed; 2) a cost matrix is generated to represent the energy cost between each pair of waypoints; 3) MILP is used to find the minimum energy path that visits each waypoint once; 4) the path is converted into a feasible trajectory.

that includes energy estimation on the optimization problem and compare it to a more traditional approach. The method contained in this paper is a step forward in the inspection of 3D environments using real-life drone constraints.

II. PROBLEM STATEMENT

Current UAVs inspection methods prefer time constraints over energy consumption, limiting the adoption and efficient use of multirotor UAVs. This paper addresses this gap by integrating an energy-aware approach into the inspection planning process. Specifically, given a predefined set of three-dimensional (3D) waypoints covering a target area or structure, this study focuses on determining the optimal path that minimizes energy expenditure while ensuring all waypoints are visited. The provided waypoints are assumed to be strategically selected to ensure proper orientation, complete coverage, and sufficient image overlap for photogrammetric 3D reconstruction. As this study focuses exclusively on energy optimization, the waypoint selection process is considered a separate, pre-established step. By isolating energy efficiency from data acquisition concerns, this approach aims to develop a robust and adaptable energy-aware method that can be applied to various inspection scenarios, improving effectiveness.

III. PROPOSED APPROACH

Our proposed approach has four steps, as shown in Fig. 2. The first step receives a set of waypoints to be visited and a desired speed to accomplish the mission. The second step is to use an energy consumption estimate of the paths between waypoints and generate a cost matrix using all of them. The third step uses a Mixed Integer Linear Programming (MILP) algorithm to solve the Traveling Salesman Problem (TSP) by visiting the waypoints and minimizing the accumulated energy. The fourth step generates the drone's trajectory using the sequence from step three.

A. Waypoints

Several methods can be used to obtain the coverage waypoints necessary to complete an inspection mission. A

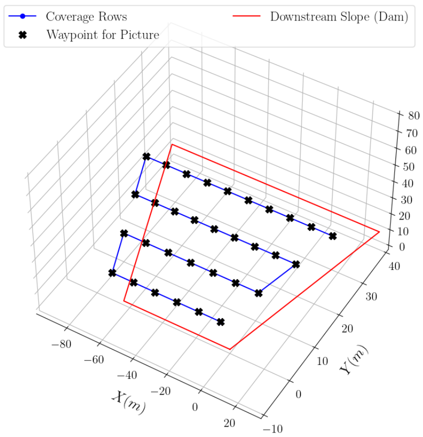


Fig. 3: Back-and-forth method and generated waypoints to inspect a dam for photogrammetry reconstruction.

traditional back-and-forth method described in [22] is used when the drone records a video and obtains a continuous feed of consecutive images. The presented approach will not assume continuous video but photos taken at each waypoint. Each image covers an area with sufficient overlap with neighboring pictures. However, we still use the back-and-forth method to generate our waypoints, which will be samples of the coverage lines. Figure 3 shows an example of the coverage lines used to inspect a dam, which was obtained with the traditional back-and-forth method proposed in [22]. The figure also shows the dots representing the waypoints used in our methodology.

B. Energy Estimate

Our method assumes that an energy model estimates the energy spent between waypoints. Among the relevant models shown in [17] the best energy estimator was shown to be the one based on data. As our goal is to obtain a practical energy model rather than a highly accurate approximation, we adopt the method proposed by Kirschstein in [23].

In Kirschstein's [23] method, the power consumed by a multirotor drone is composed of five components as:

$$P_{\text{UAV}} = P_{\text{air}} + k \cdot P_{\text{lift}} + P_{\text{profile}} + P_{\text{climb}} + P_{\text{int}} \,, \tag{1}$$

where P_{air} is the power to overcome body drag, k is a lifting power markup, P_{lift} is the power to lift the UAV, $P_{profile}$ is the power to overcome rotors drag, P_{climb} is the power needed to climb, and P_{int} is the necessary power for the inner electronics. It is important to note that P_{climb} is the component that strongly influences the energy consumption and will change depending on the drone's climb and descending rate.

The first component of equation (1), P_{air}, is calculated as:

$$P_{\text{air}} = \frac{1}{2} \cdot \rho \cdot v^3 \cdot A \cdot C_{\text{air}} \,, \tag{2}$$

where ρ is the air density, v is the drone speed relative to the wind (if any), A is the UAV frontal surface area, and C_{air} is the Air drag coefficient.

The term P_{lift} from equation (1) is calculated as follows:

$$P_{lift} = w \cdot T \,, \tag{3}$$

where w is the downwash coefficient and T is the thrust, which is calculated as:

$$T = \sqrt{m^2 \cdot g^2 + D_{\text{body}}^2 + 2 \cdot D_{\text{body}} \cdot \left(\frac{P_{\text{climb}}}{v}\right)} \,,$$

where m is the UAV mass, g is the gravitational acceleration, and D_{body} is the air drag force:

$$D_{\text{body}} = \frac{1}{2} \cdot \rho \cdot v^2 \cdot A \cdot C_{\text{air}} \,.$$

The third component of equation (1), P_{profile}, is given by:

$$P_{\text{profile}} = n_{rotors} \cdot \rho \cdot R \cdot v_t^3 \cdot \left(1 + 3\left(\frac{v}{v_t}\right)^2\right) \cdot \sigma \cdot \frac{C_{\text{bd}}}{8} \,, \tag{4}$$

where n_{rotors} is the number of rotors, R is the rotor radius, C_{bd} is the blade drag, v_t is the blade tip speed, and σ is the rotor solidity ratio.

The fourth component of equation (1) is calculated as:

$$P_{\text{climb}} = m \cdot g \cdot v \cdot \sin(\gamma) \,, \tag{5}$$

where γ is the climbing angle.

Finally, the fifth component of the total power, P_{int}, is the necessary power for the inner electronics and depends directly on each UAV consumption.

Using (1) the energy can be calculated by:

$$E_{\text{total}} = P_{\text{UAV}} \cdot t_{\text{travel}} \,, \tag{6}$$

where t_{travel} is the time of flight.

To compose the cost matrix necessary for our optimization, we build a $n \times n$ matrix C, where n is the total number of waypoints to be visited, and each cell C_{ij} represents the necessary energy to travel from waypoint i to waypoint j at a desired speed. To calculate this energy estimation, we initially calculate the time to travel from i to j, then calculate the power consumption using (1). Finally, we multiply the power by time to calculate the energy using (6).

C. TSP solution

There has been extensive research on how to solve the TSP problem. A compilation of methods is summarized in [24]. Since the objective of this research is to generate UAV trajectories using energy estimation, we choose an Exact Method that guarantees to find the true optimal. Thus, we use Mixed-Integer Linear Programming (MILP). The primary issue with this method is the exponential increase in computer power and time required to solve NP-hard optimization problems. However, its main advantage is that it finds the true optimal instead of an approximation, as other faster methods such as heuristic or metaheuristic algorithms.

In our MILP solution, we used [25] as the base to create our optimization problem. However, we performed several modifications, including removing the constraints related to the multi-robot coverage and modifying the constraints to consider energy as the optimization objective. Our final optimization problem can be posed as:

Find the route that minimizes the maximum energy spent by a UAV when visiting all the waypoints:

$$\text{Minimize} \quad V_{\max}\,, \tag{7}$$

Subject to:

$$V_{\max} \geq \sum_{i \in \mathrm{N}, j \in \mathrm{N}} C_{ij} \cdot X_{ij} + d \tag{8}$$

$$\sum_{i \in \mathrm{N}, j \in \mathrm{N}} C_{ij} \cdot X_{ij} \leq L, \tag{9}$$

$$\sum_{i \in \mathrm{N}} X_{ij} = 1, \quad \forall j \in 2..N \tag{10}$$

$$X_{ii} = 0, \quad \forall i \in \mathrm{N} \tag{11}$$

$$\sum_{i \in \mathrm{N}} X_{ip} - \sum_{j \in \mathrm{N}} X_{pij} = 0, \quad \forall p \in \mathrm{N} \tag{12}$$

$$u_i - u_j + 1 \leq N \cdot (1 - X_{ij})\,. \quad \forall i, j \in 2..N \tag{13}$$

The objective function that minimizes the energy for the entire path is shown in (7). This minimizes the total cost of the TSP such that the energy is at least enough to visit all the waypoints, as shown in (8). The variable X is a boolean value the optimizer needs to select; a true value corresponds to an active segment from waypoint i to waypoint j. A battery constraint (9) is used to limit the maximum energy available. A constraint is implemented to ensure that each waypoint is visited only once in (10), except for waypoint 1. To prevent the UAV from starting and finishing at the same waypoint, we established the condition outlined in (11). Constraint (12) guarantees that the same drone arrives and departs from the same node. The Miller-Tucker-Zemlin formulation for subtour elimination is given by (13).

D. Generate Trajectory

The last step of our methodology is to generate a trajectory for the drone. From the optimization problem, we get matrix X, which stores the sequence of waypoints to be visited. Using this sequence (path), we will employ two methodologies. The first involves a path follower trajectory that only uses the edges as waypoints to change direction and tries to maintain constant speed the whole time, no stop is considered on each waypoint. The second involves the use of methodology proposed in [26], which is based on creating minimum snap trajectories [27] between the waypoints to maintain control over the drone's speed and minimize energy usage.

IV. EXPERIMENTAL RESULTS

In all simulations and experiments of this paper, we assume the use of the Parrot ANAFI USA drone, which is able to fly for around 30 minutes with a single battery. The complete specifications of this drone can be found in [28].

Several experiments were performed to evaluate the proposed approach. We first simulate the energy consumption model with the parameters of our drone to highlight and understand its characteristics. Second, we compare our proposal with the traditional back-and-forth method in a dam coverage problem. Third, an evaluation with random waypoints in a 3D scenario was conducted to test the limits of the MILP solver. Fourth, we compare, in simulation, a minimum snap trajectory against the original path for the back-and-forth method and the energy-optimized paths found by our method. Finally, we used our method in a real-life experiment to create a 3D map of a water dam.

A. Energy evaluation

This section simulates the energy estimation model proposed in [23] with the parameters of the Parrot Anafi USA drone, presented in I. We first simulate a leveled flight for a straight segment with different lengths. Each curve in Figure 4 represents the change in energy for different segments as a function of the speed. It is evident and anticipated that greater distances require more energy. Additionally, the smaller the segment, the less important the speed is. Also, observe that an optimal speed (the one that results in minimum energy) is associated with each scenario.

A similar trend is shown in Figure 5 related to the climbing angle. As the climbing angle increases, so does the energy required. Once again, it is clear that an optimal speed can be identified for any continuous flight. Furthermore, this plot indicates that energy consumption continues even during descent (negative angles).

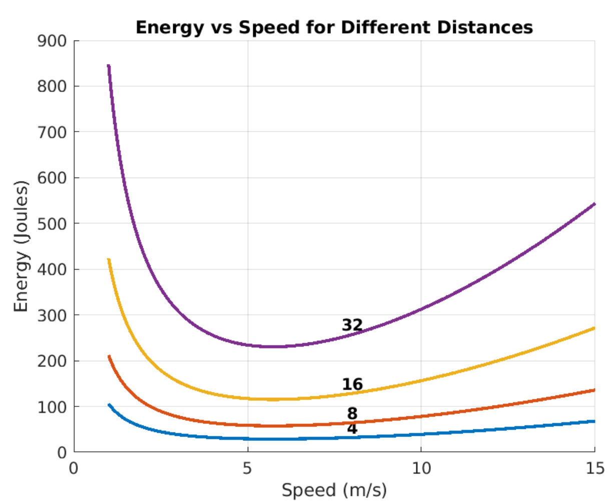


Fig. 4: Required energy for a leveled flight for different distances evaluated at speeds from 1 to 15 m/s.

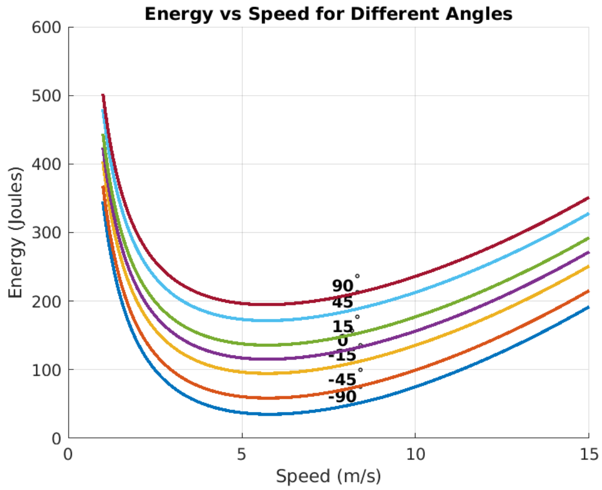
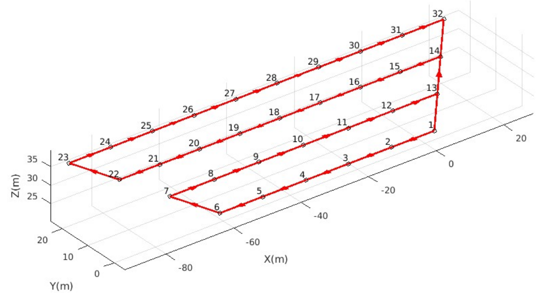


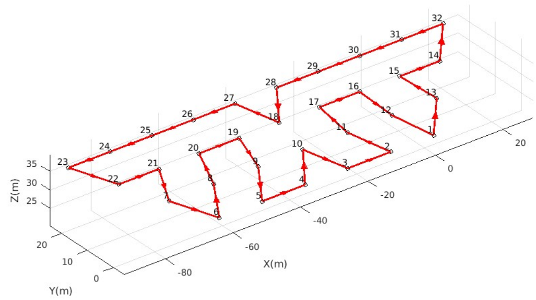
Fig. 5: Required energy for climbing or descending the same distance evaluated at speeds from 1 to 15 m/s.

TABLE I: Model parameters used in simulations.

Variable	Value	Unit	Description
ρ	1.225	kg/m^3	Air density
A	0.15	m^2	Frontal surface area
C_{air}	0.65	-	Air drag coefficient
w	0.2	-	Downwash coefficient
m	0.5	kg	Mass
g	9.81	m/s^2	Gravity
n_{rotors}	4	-	Number of rotors
R	0.0324	m^2	Rotor area
C_{bd}	0.075	-	Body drag coeff.
v_t	20.3575	m/s	Blade tip speed
σ	1.2	-	Rotor solidity ratio



(a)



(b)

Fig. 6: Coverage methods: (a) Back-and-forth path; (b) Minimum Energy and Minimum Distance (same path).

TABLE II: Distance and energy cost functions evaluated in a dam inspection (Fig. 6).

CPP path	Distance (m)	Energy (J)
Back-and-forth	423.6993	3381.42
Distance cost function	372.1059	2969.57
Energy cost function	372.1059	2969.57

B. Dam inspection

For the dam inspection, we present simulations of a drone flying over the dam using different coverage methods. We compare three different coverage methods: a standard back-and-forth method; TSP solved using MILP with distance as a cost function; and TSP solved using MILP with an energy cost function, which is the proposal of this paper. Trajectories are not computed for these approaches, and only paths are compared. To ensure a fair comparison among these three scenarios, they all operate under ideal conditions with no wind, and it is assumed that the UAV can fly at a constant speed while maintaining the same starting and ending positions. We use 32 waypoints arranged at a constant distance to the dam, those waypoints are obtained as discussed in Section III-A.

The results of the back-and-forth method are in Fig. 6a while the ones related to optimization using the distance cost function, and the energy cost function are in Fig. 6b. Notice that the optimization of both cost functions resulted in the same path. Table II summarizes the results of this experiment.

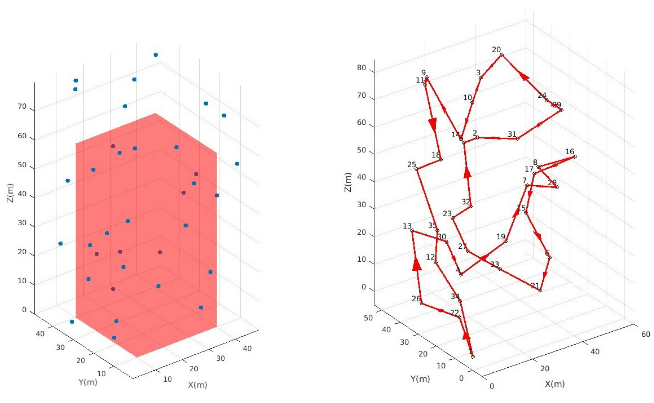
Our results show that the optimal path using the Energy cost function is the same as the optimal path using the Distance cost function for the conditions of our simulation. Since our method assumes that the paths between two waypoints are straight lines and does not consider other constraints, such as wind and drone acceleration, this is an expected result. However, recent research [19] has shown that a straight-line path is not always the most efficient path, especially if the drone's acceleration is considered.

Some studies attempt to optimize the path length when performing 3D reconstruction using drones [29], [30], [31]. From our results (assuming no wind, straight-line paths, and constant velocity), it is unclear when using an energy model over a distance cost function is better. To clarify this, we performed the experiment shown in the next section, which considered less structured sets of waypoints.

C. Energy versus Distance cost function

We used multiple scenarios with an increasing number of random points to test the performance of the optimization using energy and distance cost functions. Fig. 7a and 7b, respectively, present an example of this scenario and its optimized solution.

The main finding from this experiment is the significant improvement in efficiency offered by the energy cost function compared to the distance cost function, particularly when the problem increases in size and complexity. As shown in Fig. 8, energy optimization can enhance performance remarkably. This substantial efficiency gain emphasizes the advantages



(a) (b)

Fig. 7: Random points scenario: (a) The generated points around an inspection structure and (b) The generated minimum energy path.

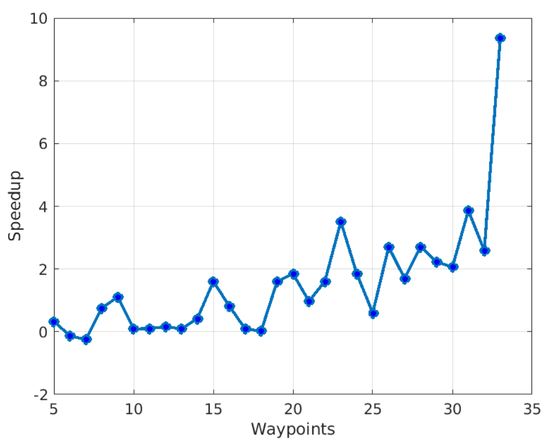


Fig. 8: Speedup for the Energy cost function against the Distance cost function.

of employing the Energy model, particularly as the scenario grows.

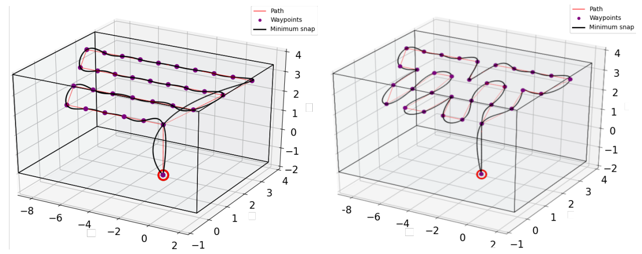
D. Trajectory generation

In this section, we evaluate the entire proposed approach, including the trajectory generation step, which was not considered in the previous section. The simulations use a scaled version of a real-life dam inspection problem. We compare our method with the back-and-forth method with and without a trajectory generation. The trajectories for back-and-forth and our method are shown in Fig. 9. As proposed before, the trajectory is generated using the minimum snap approach proposed in [27].

Relevant results are presented in Table III. Notice that the

TABLE III: Performance comparison of different methods.

	Method	Distance (m)	Avg. speed (m/s)	Max. Accel. (m/s^2)	Energy (J)
Back and Forth	Path	48.74	0.50	1.49	2568.42
	Trajectory	49.37	0.51	0.81	2559.43
Energy Opt.	Path	45.05	0.52	2.16	2296.29
	Trajectory	45.06	0.52	0.52	2271.19



(a) (b)

Fig. 9: Simulated paths and trajectories: (a) Back-and-forth method; (b) Minimum energy method. The dimensions are in meters.

minimum energy method reduces energy needs by around 10% when compared to the back-and-forth approach. Also, in each case, an average speed of 0.5 m/s^2 is maintained. Finally, for the paths, the maximum required acceleration is approximately four times larger than the acceleration required by the minimum snap trajectory.

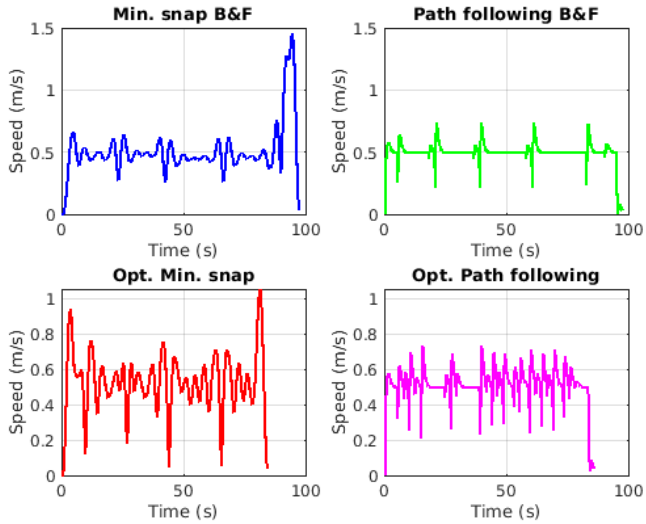
By comparing the speed and energy in Fig. 10, we observe that the minimum snap trajectory shows more variability in speed but experiences fewer abrupt changes. These differences become apparent in the energy plots where the drone following the original path suffers from sudden changes, while the one following the minimum snap trajectory displays a more continuous pattern. These abrupt speed changes are related to large accelerations that, in real life, are difficult to be followed by the UAV.

E. Real life evaluation

In this section, we show a result where the proposed methodology was used to create a 3D map of a water dam, given hardware and software limitations at this time we did not use any trajectory generation in this experiment since the commercial drone only follows waypoints. After the flights, we processed the data using the photogrammetry software Colmap [32] and obtained a point cloud. For comparison, the ANAFI drone was programmed to execute two missions: first, the drone records a video following a traditional back-and-forth trajectory; second, the drone uses the method presented in this paper by visiting each waypoint in the order provided by the energy-based MILP optimizer and taking pictures at each waypoint.

The top view of the sparse point clouds overlaid by the camera positions for the back-and-forth and the minimum energy cost function are presented in Fig. 11. The point clouds obtained with both methodologies are visually similar, although the one obtained by our method is larger, given that the photos have more resolution than the video. Fig. 12 shows the dense point cloud obtained with the minimum energy cost function.

A major drawback of our methodology, which we observed during our experiments, was that our mission time was longer than that of a traditional back-and-forth method despite the shortest distance of our path. The back-and-forth method took 1 minute and 48 seconds, while the proposed



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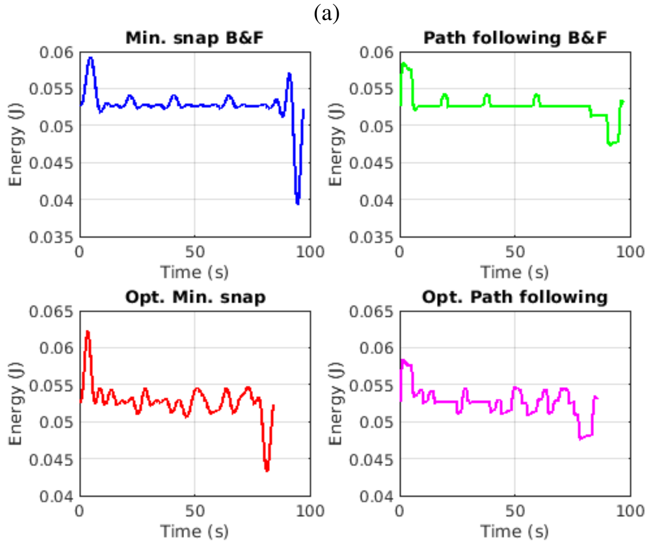


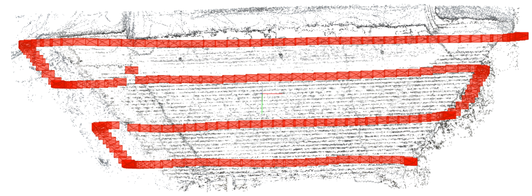
(b)

Fig. 10: (a) Speed and (b) Energy plots for computed trajectories: The top images correspond to the back-and-forth method, and the bottom images represent the minimum energy method. The left side shows the minimum snap trajectory and the right side shows the path.

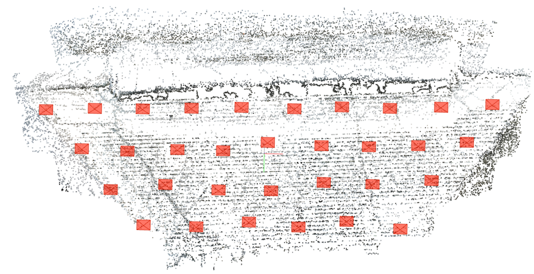
method took 8 minutes and 52 seconds. The difference in time mainly occurred because the drone halted for approximately 12 seconds at each waypoint to take a picture, which were not considered in the minimum energy evaluation, and waypoint-based navigation caused the drone to accelerate and decelerate to reach each waypoint.

V. DISCUSSION

The experimental results in the previous section show that the proposed approach is beneficial and can further improve the solution for the CPP. The most significant finding is the drastic reduction in processing time as the complexity of the problems increases. From our analysis, we found that this behavior corresponds to the richer information contained in the energy cost function when compared to the distance one.



(a)



(b)

Fig. 11: Sparse point cloud with different methods: (a) Back-and-forth method; (b) Minimum energy method.

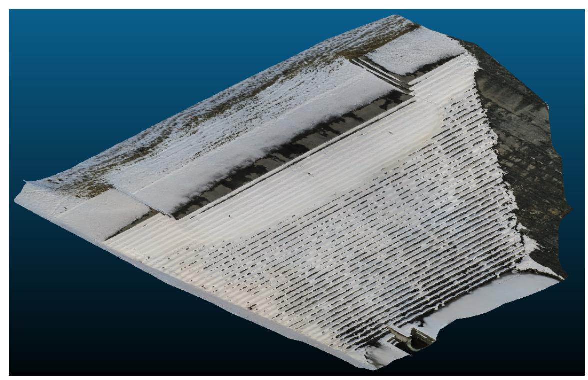


Fig. 12: Point cloud generated for a Water dam using the minimum energy method.

This becomes explicit when we analyze the MILP solver, which uses a branch-and-bound algorithm. We noticed that the energy-based optimizer eliminates branches faster than the one relying on distance.

As we observed in the real-life experiment, implementing the optimized paths has limitations for commercial UAVs, which traditionally follow waypoints and need to stop at each one to take a picture, there is the option to consider this into the optimizer, or work with different lower-level controllers to guarantee that the UAV can follow optimized trajectories, and take pictures at the desired position and orientation.

VI. CONCLUSIONS AND FUTURE WORK

This paper presented a coverage-path planning methodology that optimizes the path taken by an inspection drone using an energy cost function. The paper describes the methodology and evaluates its behavior through several simulations and a real-world experiment. The energy model used in this paper is a practical approach for optimizing UAV paths without requiring complex dynamic or data-based methods. Its versatility and adaptability make it suitable as the cost function for our optimization problem. The use of Mixed-Integer Linear Programming (MILP) demonstrated that a feasible solution exists. Additionally, incorporating an energy cost function improved processing time. Although this approach may not be suitable for online planning, it can serve as a valuable resource for preparing inspection missions using multirotor UAVs.

While the minimum-energy trajectory with minimum snap has been recognized as the most efficient approach for energy consumption, implementing it practically on commercial UAVs remains difficult. Barriers such as constraints from standard flight controllers, limited onboard computational resources, and the need for precise control adjustments hinder its widespread adoption.

It is well-known that real-life inspection problems are significantly larger than those analyzed in this paper. Therefore, after showing the benefit of using an Energy cost function, adopting a metaheuristic approach could yield good results in a shorter time frame, making it more suitable for online planning. Methods proposed by [30] and [29] could benefit from this approach with minor adjustments by replacing the minimum distance with the minimum energy cost function.

Furthermore, [25] has shown that MILP is adequate for multi-robot systems. Our future work will explore more complex problems by implementing a similar technique to address multiple inspection areas with various drones.

ACKNOWLEDGMENT

The authors thank Paulo V. G. Simplicio for his support with the real-life experiments, and waypoint generation based on a real-life inspection problem.

REFERENCES

[1] S. Mittal and K. Deb, "Three-dimensional offline path planning for uavs using multiobjective evolutionary algorithms," in *2007 IEEE Congress on Evolutionary Computation*, 2007, pp. 3195–3202.

[2] S. Karaman, M. R. Walter, A. Perez, E. Frazzoli, and S. Teller, "Anytime motion planning using the rrt*," in *2011 IEEE International Conference on Robotics and Automation*, 2011, pp. 1478–1483.

[3] J. D. Gammell, T. D. Barfoot, and S. S. Srinivasa, "Batch informed trees (bit*): Informed asymptotically optimal anytime search," *The International Journal of Robotics Research*, vol. 39, no. 5, pp. 543–567, 2020.

[4] E. Galceran and M. Carreras, "A survey on coverage path planning for robotics," *Robotics and Autonomous systems*, vol. 61, no. 12, pp. 1258–1276, 2013.

[5] G. Fevgas, T. Lagkas, V. Argyriou, and P. Sarigiannidis, "Coverage path planning methods focusing on energy efficient and cooperative strategies for unmanned aerial vehicles," *Sensors*, vol. 22, no. 3, 2022.

[6] H. Choset, "Coverage for robotics–a survey of recent results," *Annals of mathematics and artificial intelligence*, vol. 31, pp. 113–126, 2001.

[7] A. Barrientos, J. Colorado, J. d. Cerro, A. Martinez, C. Rossi, D. Sanz, and J. Valente, "Aerial remote sensing in agriculture: A practical approach to area coverage and path planning for fleets of mini aerial robots," *Journal of Field Robotics*, vol. 28, no. 5, pp. 667–689, 2011.

[8] A. Pérez-González, N. Benítez-Montoya, Jaramillo-Duque, and J. B. Cano-Quintero, "Coverage path planning with semantic segmentation for uav in pv plants," *Applied Sciences*, vol. 11, no. 24, 2021.

[9] K. Easton and J. Burdick, "A coverage algorithm for multi-robot boundary inspection," in *Proceedings of the 2005 IEEE International Conference on Robotics and Automation*. IEEE, 2005, pp. 727–734.

[10] J. F. Araujo, P. Sujit, and J. B. Sousa, "Multiple uav area decomposition and coverage," in *2013 IEEE symposium on computational intelligence for security and defense applications (CISDA)*. IEEE, 2013, pp. 30–37.

[11] O. Artemenko, O. J. Dominic, O. Andryeyev, and A. Mitschele-Thiel, "Energy-aware trajectory planning for the localization of mobile devices using an unmanned aerial vehicle," in *2016 25th international conference on computer communication and networks (ICCCN)*. IEEE, 2016, pp. 1–9.

[12] N. Lawrance and S. Sukkarieh, "Wind energy based path planning for a small gliding unmanned aerial vehicle," in *AIAA Guidance, Navigation, and Control Conference*, 2009, p. 6112.

[13] C. Di Franco and G. Buttazzo, "Energy-aware coverage path planning of uavs," in *2015 IEEE international conference on autonomous robot systems and competitions*. IEEE, 2015, pp. 111–117.

[14] G. Mier, J. Valente, and S. de Bruin, "Fields2cover: An open-source coverage path planning library for unmanned agricultural vehicles," *IEEE Robotics and Automation Letters*, vol. 8, no. 4, p. 2166–2172, Apr. 2023.

[15] L. E. Dubins, "On curves of minimal length with a constraint on average curvature, and with prescribed initial and terminal positions and tangents," *American Journal of mathematics*, vol. 79, no. 3, pp. 497–516, 1957.

[16] J. Reeds and L. Shepp, "Optimal paths for a car that goes both forwards and backwards," *Pacific journal of mathematics*, vol. 145, no. 2, pp. 367–393, 1990.

[17] C. Muli, S. Park, and M. Liu, "A comparative study on energy consumption models for drones," 2022.

[18] P. Beigi, M. S. Rajabi, and S. Aghakhani, "An overview of drone energy consumption factors and models," 2022.

[19] N. Michel, A. Patnaik, Z. Kong, and X. Lin, "Energy-optimal planning of waypoint-based uav missions - does minimum distance mean minimum energy?" in *2024 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS)*, 2024, pp. 10 362–10 369.

[20] J. Xie, L. R. G. Carrillo, and L. Jin, "An integrated traveling salesman and coverage path planning problem for unmanned aircraft systems," *IEEE Control Systems Letters*, vol. 3, no. 1, pp. 67–72, 2019.

[21] F. Zhang and X. Zhang, "Cooperative area coverage path planning for multiple uavs over large areas," in *2022 9th International Conference on Dependable Systems and Their Applications (DSA)*, 2022, pp. 346–352.

[22] P. V. G. Simplicio and G. A. S. Pereira, "Mission planning for photogrammetry-based autonomous 3d mapping of dams using a commercial uav," in *2024 International Conference on Unmanned Aircraft Systems (ICUAS)*, 2024, pp. 464–471.

[23] T. Kirschstein, "Comparison of energy demands of drone-based and ground-based parcel delivery services," *Transportation Research Part D: Transport and Environment*, vol. 78, p. 102209, 2020.

[24] P. C. Pop, O. Cosma, C. Sabo, and C. P. Sitar, "A comprehensive survey on the generalized traveling salesman problem," *European Journal of Operational Research*, vol. 314, no. 3, pp. 819–835, 2024.

[25] G. S. Avellar, G. A. Pereira, L. C. Pimenta, and P. Iscold, "Multi-uav routing for area coverage and remote sensing with minimum time," *Sensors*, vol. 15, no. 11, pp. 27 783–27 803, 2015.

[26] N. Kreciglowa, K. Karydis, and V. Kumar, "Energy efficiency of trajectory generation methods for stop-and-go aerial robot navigation," in *2017 International Conference on Unmanned Aircraft Systems (ICUAS)*, 2017, pp. 656–662.

[27] D. Mellinger and V. Kumar, "Minimum snap trajectory generation and control for quadrotors," in *2011 IEEE international conference on robotics and automation*. IEEE, 2011, pp. 2520–2525.

[28] Parrot Drones, "Technical specifications ANAFI USA," Available: https://www.parrot.com/us/drones/anafi-usa/technical-specifications, accessed in January 2025.

[29] E. M. Lee, S. Jung, S. Song, D. Choi, D. Lee, S. Lee, S. Kim, and H. Myung, "Ceo-mlcpp: Control-efficient and obstacle-aware multi-layer coverage path planner for 3d reconstruction with uavs," in *Robot Intelligence Technology and Applications 7*. Springer International Publishing, 2023, pp. 27–36.

[30] S. Jung, S. Song, P. Youn, and H. Myung, "Multi-layer coverage path planner for autonomous structural inspection of high-rise structures," in *2018 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS)*, 2018, pp. 1–9.

[31] H. Wang, H. Li, C. Zhang, S. He, and J. Liu, "A 3d coverage path planning approach for flying cameras in nature environment under photogrammetric constraints," in *2017 36th Chinese Control Conference (CCC)*. IEEE, 2017, pp. 6761–6766.

[32] J. L. Schönberger and J.-M. Frahm, "Structure-from-motion revisited," in *Conference on Computer Vision and Pattern Recognition (CVPR)*, 2016.