Photovoltaic plant monitoring and inspection through synergic integration of UAVs and IoT

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ABSTRACT

Photovoltaic (PV) panels play a crucial role in renewable energy generation. Ensuring their optimal performance and longevity requires regular inspection. Traditional methods rely on scheduled inspections with manual, offline path planning. Our system employs a dynamic online planning algorithm that allows for real-time task allocation and inspection on a per-panel basis. In this paper, we propose a new approach where each panel is embedded with IoT sensors that communicate inspection requests to a sensored UAV swarm. This allows to create a specific inspection plan for each UAV, adapting to panel conditions and requests. Our approach contributes to the advancement of sustainable energy systems by focusing on individual panels when demanded, reducing overall inspection time and enhancing accuracy. We present the design, implementation, and evaluation of this system. [1]

1 INTRODUCTION

The transition to a sustainable energy future necessitates innovative solutions to maximize the efficiency and effectiveness of renewable energy sources. In this context, solar photovoltaics (PV) has been the fastest growing power generation technology in the world over the last decade [1]. All the scenarios towards a climate neutral energy assign a central role to PV. The widespread adoption of photovoltaic installations holds immense promise, but also presents unique challenges. To fully unlock the potential of solar energy, it is crucial to optimize the economic and energy performance of PV plants while ensuring seamless integration with existing grid infrastructure.

Another major challenge is how to carry out the monitoring and maintenance of photovoltaic plants. Many of these plants are too large, making their inspection very time-consuming if it has to be done by workers. To address this issue, various proposals have emerged, among which the use of drone fleets offers an efficient and novel solution [2]. To accomplish this mission, drones are equipped with cameras and various types of instruments [3], as shown in Figure 1. While thermal cameras mounted on UAVs can detect most PV issues [4], additional PV mounted sensing is needed, as not every issue in PV panels manifests itself in form of temperature increase, depicted in Figure 2. Additionally, it is worth noting that early fault detection is crucial in the maintenance of photovoltaic plants to ensure adequate performance and prevent defects from spreading to healthy areas. Furthermore, detecting the different aging mechanisms that can also affect photovoltaic modules is important, as a mismatch phenomenon can occur between them [5].

Figure 1: DJI M300 inspecting a PV plant.

The primary objective of this work is to integrate state-of-the-art communication technologies and autonomous UAV capabilities to streamline the control and monitoring of PV plants.

To do that, we use autonomous swarm planning algorithm for drone fleets tailored specifically for solar park inspection. These plans are generated by an online planning system that uses information coming from low-cost IoT systems for digitalized solar panels capable of self-assessment and communication in order to ensure efficient and comprehensive monitoring of PV plants.

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[1] System validation video

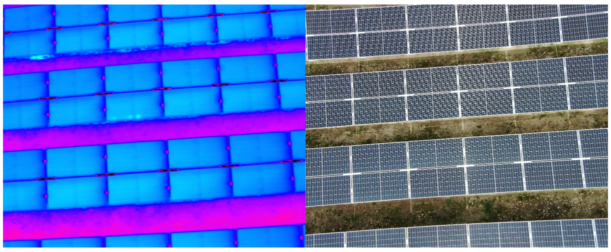

Figure 2: Image capture during the inspection process, with the thermal and RGB images.

This planning approach is swarm-oriented, meaning that each generated plan takes into account specific factors to determine which drone is assigned to which plan, along with the corresponding parameters.

We have also integrated computer vision and deep learning algorithms that work with the imaging sensors mounted on the drones to perform real time detection and evaluation of rgb and thermal images.

By pursuing this objective, we aspire to contribute to the advancement of solar energy technologies and facilitate the transition towards a more sustainable energy future. Our findings not only hold the potential to enhance the performance and reliability of PV installations but also play a crucial role in mitigating the effects of global warming by maximizing the utilization of renewable energy sources.

Concisely, the main contributions of this work are as follows:

1. Design of a novel IoT architecture that integrates solar panels and UAV swarm in a PV plant.
2. An innovative swarm-oriented online-planning algorithm to optimize on demand PV inspections.
3. An onboard real-time visual inspection and evaluation pipeline for rgb and thermal images.
4. Experimental evaluation of the system in a real photovoltaic plant, providing precise and efficient inspections.

2 Industry Drone-Based Inspection Techniques and PV monitoring

The rapid expansion of PV markets has spurred the development of large-scale solar power plants, intensifying the need for more advanced inspection and monitoring tools. Traditionally, manual inspections have been the norm [6], but there's a growing shift towards employing more dynamic systems, particularly drones, for these tasks. Drones are increasingly recognized as a fitting solution for the solar industry due to their diverse surveillance and monitoring capabilities, long-range inspection potential, and ease of control. Over recent years, they have gained popularity for their ability to swiftly monitor expansive solar parks more efficiently than human inspection teams. Equipped with sensing technology, drones efficiently gather essential data and transmit it to the cloud for analysis, significantly reducing time and enhancing accuracy.

Current state of the art usage of drone-based PV plant monitoring suggests having an experienced drone pilot to remotely manipulate the drone [7]. However, for a fully autonomous drone, the focus and range (i.e., correct temperature range set on thermal camera) of the cameras, as well as the flying distance are difficult to dynamically reconfigure, and they require proper settings during image capture.

During an automated aerial infrared thermography operation, the UAV navigates through a series of waypoints, ensuring comprehensive coverage of the solar plant's modules [8]. Consequently, the deployment of a refined path-planning algorithm is crucial to achieve the most efficient route in terms of time and battery usage [9].

Moving on to fully autonomous UAVs, we can clearly differentiate between a planning phase and a navigation phase.

When focusing only on planning of UAVs, a semi-supervised remote control system is proposed in [10], where there is no planning needed as it is integrated in the human pilot control loop. In [11] a GUI is integrated with the capacity of defining waypoints for more specific curvilinear terrain shapes or polygons in case the layout allows it, to then create a grid shaped path within that polygon. A sequence of georeferenced waypoints is introduced in the system prior to navigation phase in [12], which implies user having to look up to exact GPS coordinates with a third party tool. A form of semi-automated planning is performed in [13] in which the boundary information can be gained from design drawings of the photovoltaic plant, GPS, and aerial images together with Geographic Information Systems. A polygon is then built and path is created using back and forth algorithm. A previously designed trajectory is used in [14], being unspecified the way of creating it. In [15], travelling salesman shortest path algorithm to devise a route encompassing a random assortment of modules that collectively depict the entire photovoltaic (PV) plant, thus optimizing battery utilization is utilized. In [16] a strategy is developed utilizing density clustering, boustrophedon motion planning, and Bezier curves. Similarly, path planning optimization algorithm using Bezier curves is crafted in [17], in conjunction with particle swarm optimization. This approach also factors in the dynamics of flight attitude, the constraints of the gimbal, and the overall path distance.

All of previously mentioned autonomous or semi-autonomous UAVs PV inspection systems have one thing in common, planning is made offline, which means there would be a limitation in time and workload if the inspection zone layout changes and planning needs to be reconfigured.

Motivated by this scarcity, we present a solution that addresses the problematic of offline planning by enabling specific panel and drone communication in order to perform online per-panel planning.

3 AUTOMATED ONLINE INSPECTION SYSTEM

The main problem addressed in this work is the implementation of an on-demand panel inspection system that is able to integrate PV intelligent monitoring system with an aerial inspection system.

3.1 IoT Architecture Overview

The pipeline of the automated online inspection is composed by three main components, depicted in Figure 3. Alongside, we propose a communication scheme to connect these components. Moreover, we develop a two-step swarm-oriented planning strategy, approach and inspection, to adapt to on-call PV panel inspections. The three main components of the system are:

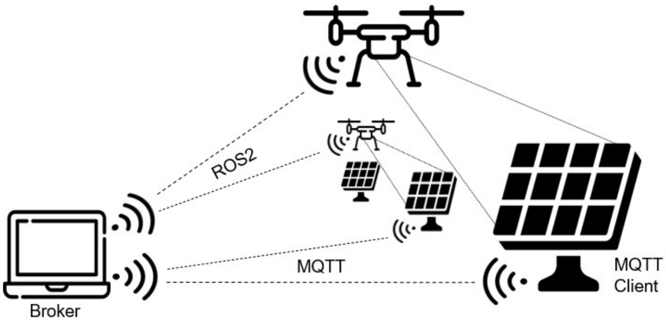

Figure 3: Overview of the inspection system components. It is composed by the PV plant intelligent monitoring subsystem, with the IoT integrated within every panel, the aerial inspection subsystem, with a swarm of UAVs, and a ground station, acting as a manager.

- **Intelligent PV plant monitoring subsystem**. The intelligent PV plant monitoring is composed by IoT boards that have been wired to the electrical system of the panels, along with self-diagnosing tools capable of generating different types of alerts. These alerts reach to the ground station in form of request. Additionally, aerial inspection results are sent back from the ground station to the panels as responses in form of hot-spot location within the panel.
- **Ground station**. The ground station serves as central node, responsible for processing the information received from the panels and managing the aerial inspection subsystem. It acts as a broker between both subsystems, assigning PV panel request to UAVs in the swarm and monitoring inspections in progress.
- **Aerial inspection subsystem**. The aerial inspection system consists of a swarm of UAVs capable of capturing and processing thermal images of the PV panels. The swarm is homogeneous, carrying all UAVs the same payload formed by a gimbal and an hybrid RGB-IR camera.

3.2 Communication Scheme

The communication scheme is responsible for connecting the PV plant's intelligent monitoring subsystem with the aerial inspection subsystem through the ground station.

To achieve this, two communication protocols are used. On one hand, the communication between the PV plant and the ground station is carried out using the MQTT protocol. On the other hand, the connection between the ground station and the agents of the aerial swarm is established using ROS 2, as depicted in Figure 4.

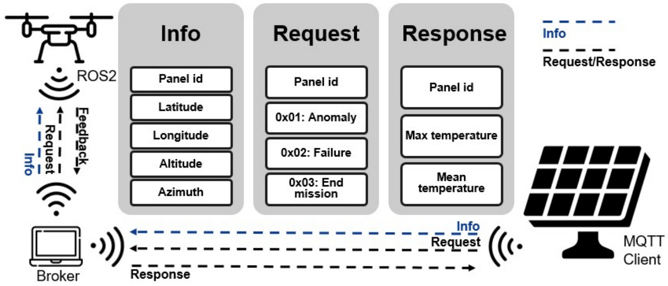

Figure 4: Communication scheme layout. Blue dashed lines stands for *info* interface, while black dashed lines for *request/response* interfaces. Boxes on top show fields of each message for every communication interface.

We establish a link between each PV panel and each UAV using three different types of message interfaces: *info*, *request*, and *response*. Table 1 summarizes these interfaces on both sides, PV plant and UAVs systems.

Interface	Direction	Trigger Event
Info	PV $\rightarrow$ UAVs	Panel initialize
Request	PV $\rightarrow$ UAVs	Panel failure
Response	UAVs $\rightarrow$ PV	Image processed

Table 1: The defined communication interfaces between the intelligent PV plant monitoring system and the aerial inspection system, along with their respective trigger events.

In the MQTT side, the *info* interface is used to send positioning information of each PV panel that is needed for the ground station to build a custom plan for that panel. The *request* interface is utilized by the panel to request an inspection when an alarm is triggered by the self-diagnosing tool of the IoT board connected to the panel sensors. The *response* interface is employed to receive the requested inspection results taken by the aerial subsystem, mainly the maximum, minimum and mean measured temperature.

In the ROS 2 side, the *info* interface is utilized to localize the positions of the PV panels relative to the swarm coordinate system. The *request* interface is employed to assign and define the mission that the UAV must perform to inspect the panel. The *response* interface is used to transmit the temperature information of the panel, which results from image processing by the UAV.

3.3 Swarm-oriented Online Planning Algorithm

The planning algorithm is in charge of translating from request to missions, assigned to UAVs. These inspection missions are managed by the ground station. For every request sent, the ground station assigns a new mission to a specific UAV, and then monitors its inspection. The UAV assignment is based on the distance to the panel position where the request came from, aiming to optimize flight time and, consequently, energy consumption. When the mission reaches the UAV, it is added to its inner First In First Out (FIFO) queue. The UAV will perform each inspection in the queue sequentially, and once the queue is empty, it will land in the safety zone waiting for new inspection requests.

The ground station defines two phases of the mission: approaching to the panel and performing the inspection.

1. **Approach phase:** The approach maneuver is done at a different height for each UAV in flight, and different from the inspection height, to avoid collisions in case of trajectory crossing. If the UAV starts from the ground, the maneuver will require a prior takeoff to the specified height, and if it is already in the air, it will perform a vertical movement only. The approach point is located at a distance from the perpendicular to the panel, using the position and elevation information of the panel.

2. **Inspection phase:** The goal of this phase is to capture a image of the panel and obtain its temperature data. To achieve this, initially, the UAV positions itself at the relative image capture distance from the panel. Subsequently, it adjusts the gimbal to center the panel in the image. Next, the image is captured and processed, with the results being sent to the ground station. Finally, the UAV returns to the approach point, with the security height, awaiting a new request of this panel inspection, or concluding it to proceed with the next task in its queue.

We have used the behavior-based interface of Aerostack2 [18] for mission definition. A mission is formed by tasks, and each task correspond to a behavior from Aerostack2. Figure 5 shows a description of an inspection mission when a panel makes a request, while a visual example of the generated mission is depicted in Figure 6.

3.4 Onboard Real-Time Visual Inspection

During the aerial inspection phase, there are two key points in our strategy to extract the temperature data from the panel. First, centering the panel in the image, and second a three-step onboard image processing pipeline.

The camera gimbal is used for centering the panel in the image, which is important for a better analysis later. To

```
{"takeoff": {"z": approach_height, "frame_id": "earth"}},
{"go_to": {"position": [current_pos_x, current_pos_y,
    approach_height], "frame_id": "earth"}},
{"go_to": {"position": [0.0, 0.0, approach_height], "
    frame_id": "panel_x"}}
```

```
{"go_to": {"position": [0.0, 0.0, capture_distance], "
    frame_id": "panel_x"}},
{"gimbal": {"frame_id": "panel_x"}},
{"image_process": {}},
{"go_to": {"position": [0.0, 0.0, approach_height], "
    frame_id": "panel_x"}}
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Figure 5: Approach (top) and inspection (bottom) of a panel inspection mission definition using behavior-based tasks from the Aerostack2 standard.

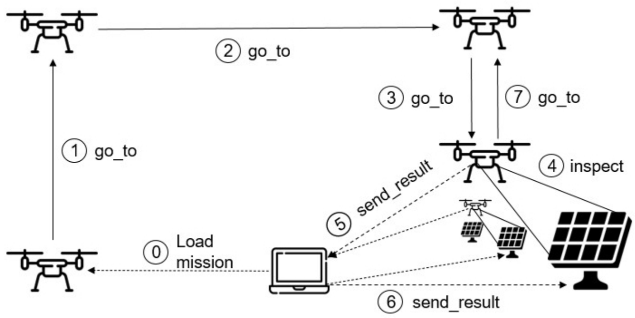

Figure 6: Planned mission relative to PV panel: step 0, 1 and 2 constitute approaching phase, being step 1 executed only if the UAV is landed first. Inspection phase are formed by steps 3 to 7, both included.

achieve this, we introduce a multi-frame coordinate system, as shown in Figure 7. The variables to be controlled are the translation of the UAV with respect to the Earth ($\mathbf{T}^{\text{UAV}}_{\text{earth}}$) and the rotation of the gimbal with respect to the UAV ($\mathbf{R}^{\text{camera}}_{\text{UAV}}$). The desired reference is the camera's translation ($\mathbf{T}^{\text{camera}}_{\text{panel}}$), defined by the desired image capture distance, and its orientation ($\mathbf{R}^{\text{camera}}_{\text{panel}}$), which should be perpendicular to the panel, as shown in Equation 1. The UAV's frame positioning uses its localization system, while the panel's frame positioning uses the information received from the panel.

$$\begin{aligned} \mathbf{T}^{\text{UAV}}_{\text{earth}} &= \mathbf{T}^{\text{panel}}_{\text{earth}} \cdot \mathbf{T}^{\text{camera}}_{\text{panel}} \cdot \mathbf{T}^{\text{UAV}}_{\text{camera}} \\ \mathbf{R}^{\text{camera}}_{\text{UAV}} &= \mathbf{R}^{\text{earth}}_{\text{UAV}} \cdot \mathbf{R}^{\text{panel}}_{\text{earth}} \cdot \mathbf{R}^{\text{camera}}_{\text{panel}} \end{aligned} \tag{1}$$

Once the PV panel to capture is centered in the image, a picture is shot and the onboard image processing pipeline starts. The pipeline's objective is to measure the maximum, average, and minimum temperature of the panel, for transmission to the intelligent monitoring subsystem. Our approach is optimized for embedded platforms and to fulfill real-time capabilities. To achieve this, we propose a three-step strategy. First, we perform a keypoint-based (vertices) panel detection using the framework described in [19]. Subsequently, the

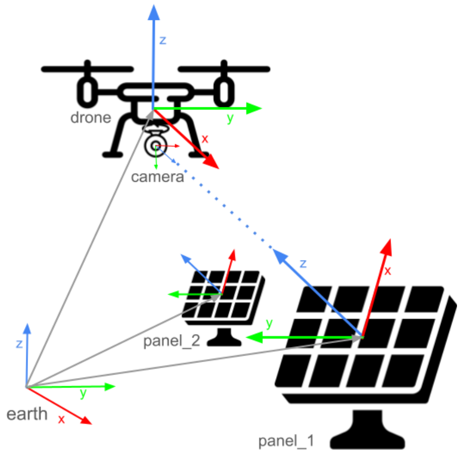

Figure 7: Multi-frame coordinate system used for calculating the positioning of the UAV relative to the panel and the orientation of the camera relative to the UAV.

central panel of the image is segmented using the vertices previously detected. Last, the thermal image is processed finding local maxima and minima over the temperature values of the segmented panel, Figure 8 shows the described image processing pipeline.

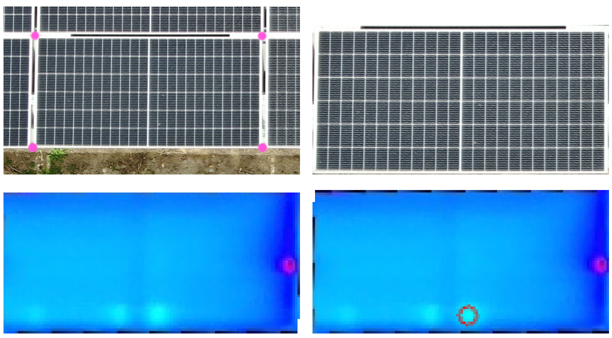

Figure 8: Sequence of the image processing pipeline, from right to left and top to bottom; panel vertices detection, panel segmentation and local maximum detected in thermal image.

4 EXPERIMENTAL VALIDATION

In order to validate our inspection strategy, we performed extensive experiments on simulation and real world environments. We first followed a simulation to real methodology in order to validate our system, then we performed a mission in a real PV plant with a swarm of two UAVs.

4.1 *Experimental setup*

To first test the algorithms, we followed the simulation to real methodology that ensures safe real deployment of the system described in [20]. During this methodology we used only one UAV in order to have a minimal setup working. We started with a simulation development phase, followed by a precise Hardware-In-The-Loop (HITL) simulation and finishing with the industrial environment validation.

After testing the system from simulation to real scenario with a minimal setup, we added one UAV to the swarm, increasing the complexity of the mission. Real scenario is located at Repsol Technology Lab in Madrid.

For performing the real missions two different UAVs form the swarm were used to inspect the PV plants, these are the DJI M300, used in the single UAV setup, and DJI M350, used in the swarm setup together with the M300. Executing Aerostack2 software onboard, NVIDIA Xavier AGX boards have been mounted on top of each UAV.

For both real missions PV panel damage is simulated with an intentional hot-spot in the cells. Then, PV panel sends a request and the closest UAV executes the inspection. The results are sent to the panels (simulated and real) and the information is then managed by them. When no more requests are planned to be sent, the UAVs perform a return to land (RTL) operation.

Table 2 presents pairs time-distance from approach phase and inspection phase, main metrics used during the experiments.

Header	Description	Unit
t_{ap}	Time for approaching phase	Seconds
d_{ap}	Distance for approaching phase	Meters
t_{ins}	Time for inspection phase	Seconds
d_{ins}	Distance for inspection phase	Meters

Table 2: Time and distance metrics used during the experiments.

Moreover, through the ground station there are certain configurable parameters in the system, these are: speed, inspection altitude and safety altitude. Choosing this parameters depends on PV plant configuration and swarm capabilities. Table 3 details the parameters set during our experiments.

Drone	Speed (m/s)	IA (m)	SA (m)
M300	2.0	15	20
M350	2.0	15	30

Table 3: Setup for parameters in the experiments below. Speed: Maximun speed for flying. IA: Inspection Altitude, SA: Safety Altitude.

4.2 *Simulation to Real Validation*

For development purposes, we have first setup a simulation using Gazebo simulator. Simulation have been set imitating every possible parameter from real experiments; GPS initial positions, PV panel GPS positions, same configured speed and altitude and same communication protocol. After this, we shifted to DJI's HITL simulation. We decoupled

Gazebo's UAV simulation and used HITL instead. We then integrated the information from simulated panels in Gazebo together with the UAV HITL. Finally, we tested our system on a industrial environment with the same configuration used before.

Mission consists on using a single UAV (M300) that receives the requests from two panels multiple times. It receives a total of six requests. Panel 1 requests two times, then panel 2 make three requests, then at last, panel 1 sends one final request. The UAV then performs RTL operation. Path comparison between simulated and real mission can be seen in Figure 9. Time and distances measurements for both approach and inspection phases during the real mission can be found in Table 4.

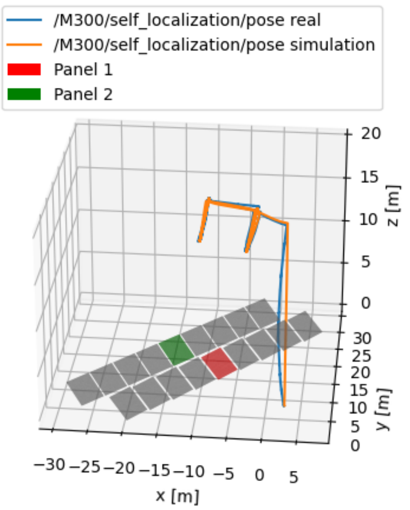

Figure 9: Path comparison between simulated path and real path. Mean square error between both paths is 0.19 meters.

Panel ID	$t_{ap}(s)$	$d_{ap}(m)$	$t_{ins}(s)$	$d_{ins}(m)$
Panel 1	30.23	29.34	15.08	10.35
Panel 1	0.41	0.11	14.27	10.87
Panel 2	5.97	10.07	21.85	10.89
Panel 2	0.53	0.09	17.12	11.22
Panel 2	0.55	0.10	15.18	11.06
Panel 1	6.05	10.36	18.15	10.99
Total	43.74	50.07	101.65	65.38

Table 4: Time and distance results from the industrial environment flights during simulation to real validation experiment. First row's approach phase includes takeoff distance and time.

Discussion

The simulation to real methodology ensured that no material or human resource was at risk. When looking at the trajectory comparison between the real and simulated mission, we see that we get a relatively low mean square error in meters ($MSE = 0.19$), increased only in the takeoff phase where the real UAV could not keep a straight path, but decreased in the rest of the mission where trajectory differences are within less than 0.1 meter error. Therefore, we conclude that simulation is reliable to test navigation and planning algorithms.

From time and distances tables, we can see that distance relates directly with time in the approach phase, however, as we can see in the first row where takeoff phase in included, the more vertical motion there is in a path, the longer it takes to reach. There is also high variability in inspection times due to variability introduced by inference times of the detection model.

4.3 PV plant swarm inspection

To validate the whole scope of our system, we increased the complexity from the previous experiments by adding an additional panel which is inspected by an additional UAV. By doing that, request management and mission planning complicate showing the strength of our system.

Mission consist on using a swarm of two UAVs (M300 and M350) and three panels making request wit no order. For this experiment, each panel requests only one inspection. Then, once inspections are finished, both UAVs perform RTL operation.

Figure 10 depicts paths followed by each UAV in this mission. Notice that the inspection altitude is the same for both UAVs, while the approach altitude differs to avoid collision if the trajectories cross each other during the approach phase. In this particular case, M350 is assigned to inspect panel 3, while M300 inspects panel 1 and 2 due to the proximity of each panel. Panel 1 is inspected first than panel 2 because its request arrived first to the ground station. Time and distances measurements for both approach and inspection phases can be found in Table. 5.

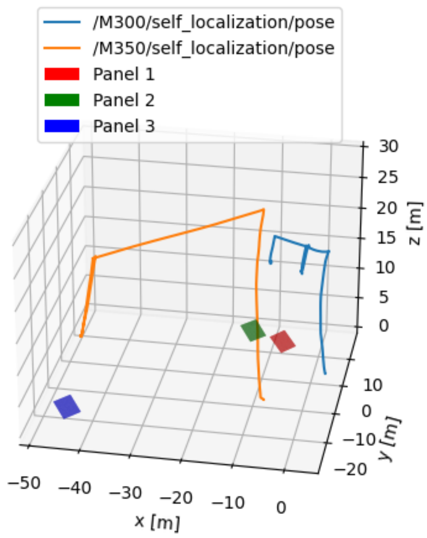

Figure 10: Swarm paths from real flights. M300 goes to panel 1 and panel 2. M350 goes to panel 3.

Panel ID	$t_{ap}(s)$	$d_{ap}(m)$	$t_{ins}(s)$	$d_{ins}(m)$
Panel 1	30.60	29.98	19.99	11.37
Panel 2	6.58	9.17	15.99	10.86
Panel 3	51.16	64.57	34.00	32.50

Table 5: Time and distance results from the swarm inspection. Panel 1 and 2 corresponds to M300. Panel 3 corresponds to M350. First and third row's approach phases include their respective UAV's takeoff distance and time.

Discussion

We can conclude that the IoT architecture integrates satisfactorily the intelligent PV plant monitoring subsystem with the aerial inspection subsystem, enabling a powerful dialog to cope with PV malfunctions. We also verified that the swarm oriented online planning is able to deal with multiple request arranging collision free inspection with a swarm of multiple UAVs. Finally, our onboard visual inspection and analysis was feasible to detect and report defects on real time. Inspection phases took on average 18 seconds, including a vertical descend (and ascend back) of 5 meters, a gimbal maneuver to center the panel on image, image capture and processing and reporting the result.

Comparing both UAVs inspections, we can confirm from the values in the last row of the results table that safety distance plays an important role in the inspection time, due to the vertical motion approach to inspect the panel. Difference between t_{ins} from panel 1 and 3 differs in $\sim$14 seconds, which is noticeable for an extra path of $\sim$11 meters only.

Our system offers a per-panel inspection approach. When a panel detects a failure and sends a request to the ground station, it takes less than 60 seconds for a UAV landed within 60 horizontal meters from the panel that made the request to be flying, positioned and ready for inspecting. Plus less than 35 seconds for it to inspect the panel, given a safety altitude of 30 meters and inspection altitude of 15 meters. For a current PV plant, if a panel fails, it won't be detected until inspection is scheduled and executed. Our approach ensures a more efficient PV panel energy production by addressing failures in an on-demand manner.

5 CONCLUSIONS

In this work, we introduced an autonomous UAV-based approach for on-demand inspections of photovoltaic panels. Unlike traditional manual path planning, which often relies on predefined paths or polygons, our system adapts in real time to environmental conditions and panel requests. Our method leverages online planning algorithms to optimize inspection routes dynamically, reducing overall inspection time and energy consumption while enhancing inspection accuracy.

Rather than inspecting entire arrays uniformly, our system focuses on individual panels, optimizing the resource allocation. When a panel signals a need for inspection (e.g., due to reduced output or anomalies), the UAV autonomously adjusts its flight path to address that specific panel. This targeted approach maximizes inspection accuracy while minimizing resource usage. Panels that perform within expected parameters receive fewer visits, while those with issues receive prompt attention. So that, this resource-efficient strategy enhances overall system reliability.

Integrating additional sensors (such as thermal cameras or multi-spectral imaging) further enhance our system. These sensors provide valuable data on panel temperature, cell health, and potential defects. By fusing this information with our online planning, we can achieve even more precise inspections.

We evaluated our system on a real photovoltaic facility, previously tested on simulation, performing successful per-panel inspection. The results showed our swarm oriented online planning algorithm working for multiple requests from the intelligent PV plant monitoring tool. Our onboard visual inspection and evaluation pipeline is able to detect faults on the panels on real time.

As part of the future work, a visual information method should be integrated in the inspection pipeline for better centering the panel center on image, rather than only using RTK and odometry measurements. Also, the proposed online planning algorithm should be improved to avoid cross paths between UAVs, instead of using different approach heights to avoid collisions. Finally, we aim to optimize the assign request-to-UAV algorithm to include priority information on the requests following certain criteria like severity of the possible fault or the distance to the panel.

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