From Inspection To Asset Management With UAV Integration In Utility-Scale Solar PV Systems

Designing PV Insight

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“My first visual memories are of this framed poster above my crib. […] *The Garden of Earthly Delights*, by Hieronymus Bosch. It was painted around the 15th hundred, and if you look at those panels long enough, they start to tell a story.

In the first panel, you have Adam and Eve, and the Garden of Eden; birds flying off in the distance, elephants and giraffes and a lot of religious iconography. The second panel it’s where it starts to become more interesting, the deadly sins start to infuse their way into the painting; there’s overpopulation, there’s the butchery and excess. In the last panel, which is the most nightmarish one –specially from a young child’s perspective-, is this: a twisted decade burnt landscape; a paradise that has been degraded and destroyed.”

Leonardo di Caprio, *Before the Flood*

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Resume

This document is the master thesis of the author submitted inside the Master's Degree in Energy Engineering and Management by Instituto Superior Tecnico (IST), Universidade de Lisboa. It is accounted as well as master thesis for the Master's Degree in Energy Engineering by Universitat Politècnica de Catalunya (UPC), as part of the double degree program Master of Science in Renewable Energy by Innoenergy, powered by the European Institute of Innovation and Technology (EIT).

The thesis is an internship-based work at Pro-Drone, a startup from Lisbon (Portugal) which develops UAV technology for the inspection of renewable energy assets. Basing the work on a business case suggested by the company, the author goes through the essential steps inside the process of turning an innovative idea into a real solution, passing through the design, development and real field testing, basing the overall process on a constant validation through direct contact with key players in the Portuguese solar PV market.

Abstract

This work analyzes the design and first stages of development of an innovative solution for utility-scale solar PV plants inspections with UAVs, based on in-house inspections and stronger data processing that simplify the work of the plant operators. The work is structured in three different blocks that have been developed simultaneously during the project, but that have been separated in the final report for a better understanding of the results. The three blocks are the solution design, the technical development and the financial analysis, introduced and concluded at the beginning and the end of the work, respectively.

The solution design goes through the methodology followed in the design thinking of the solution, reflecting the different customer validations in the features of the solution and explaining in full detail the final design. The technical development describes the calculations for data collection and the part of data processing developed by the author of the master thesis, which is the temperature data analysis model in Python. The financial analysis takes a look the economics behind the solution from the point of view of a technology developer.

Main conclusions on the work done are that the solution is technologically possible and financially feasible. By using the solution, the value added by UAVs in the O&M of solar PV systems is increased significantly, which states a step forward in the integration of drone technology into renewable energy.

Keywords: Solar PV, UAV, O&M, customer validation, temperature data analysis.

Resumo

Este trabalho descreve o projecto e a avaliação de uma soluçao inovadora para a inspecção de centrais solares fotovoltaicas com "drones" (UAVs), baseada em inspecções "in-house" e um processamento mais intensivo dos dados que simplificam o trabalho dos operadores da central. O trabalho é estruturado em três blocos distintos : definição do projecto, o desenvolvimento técnico do mesmo e a análise financeira, introduzidos e concluídos no início e fim da tese, respectivamente.

A definição do projecto descreve a metodologia seguida no processo de "design thinking" da solução, reflectindo as diferentes solicitações do cliente perante a natureza dos dados e a parte do processamento de dados que foi desenvolvida pelo autor da tese, que é o modelo de análise dos dados de temperatura dos paineis, programado em Python. A análise financeira estuda a rentabilidade do projecto na perspectiva do projectista.

As principais conclusões do trabalho são que a solução avaliada é tecnologicamente possível e financeiramente rentável. Utilizando esta solução, "drones" no O&M das centrais fotovoltaicas, a mesma traduz-se num valor acrescentado e avanço tecnológico na manutenção de sistemas de produção de energia renovável.

Palavras clave: *solar PV, drones, O&M, validaçao, análise de temperatura.*

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iii. Acronyms

IEA – International Energy Agency

CAPEX – Capital Expense

OPEX – Operational Expense

UAV – Unmanned Aerial Vehicle

US – United States (of America)

R&D – Research and Development

IR - Infrarred

PV - Photovoltaic

LCOE – Levelized Cost of Electricity

AI – Artificial Intelligence

PPA – Power Purchase Agreement

RGB – Red-Green-Blue (visual spectrum)

D-DP – Depth in Data Processing

CI-DC – Customer Independence in Data Collection

STC – Standard Test Conditions

PID – Potential Induced Degradation

EVA – Ethylene Vinyl Acetate

UK – United Kingdom

EL – Electroluminescence

E2P – Energias Endrogenas de Portugal

ROI – Return of Investment

MVP – Minimum Viable Product

R (in sensors) – Radiometric

FAQs – Frequently Asked Questions

GSD – Ground Sample or Sampling Distance

GIS – Geographic Information System

CSV – Comma-Separated Values (file type)

IV – Intensity-Voltage

BSD – Berkeley Software Distribution

Pandas – Panel Data-s (Python library)

TAM – Total Addressable Market

SAM – Served Addressable Market

FC – Fixed Costs

VC – Variable Costs

EU – European Union

PT – Portugal

Qn – Quarter or trimester n

iv. Variables

Data collection - Optics

GSD – Ground Sampling Distance [cm/pixel]

S_w – Sensor width [mm]

H – Flight height [m]

F_R – Focal length [mm]

Im_w – Image width [pixels]

Im_H – Image height [pixels]

FOV_H – Horizontal Field of View [rad]

D_w – Horizontal distance covered [m]

D_H – Vertical distance covered [m]

b – Blur [pixels]

v – Flight speed [m/s]

t – Shutter speed [s]

Data processing – Python code

P_c – Panel consumed power [W]

P_u – Panel useful power [W]

η_{panel} – Panel efficiency [-]

$P_{u,max}$ – Maximum useful power [W]

η_{max} – Maximum efficiency [-]

η_{STC} – Efficiency at STC [-]

T_{min} – Minimum temperature [°C]

T_{STC} – Temperature at STC [°C]

TC – Temperature Coefficient [-/°C]

$P_{u,real}$ – Real useful power [W]

η_{real} – Real efficiency of the panel [-]

T_{avg} – Average temperature [°C]

P_{los} – Power loss [W]

$P_{los,cum}$ – cumulated power losses [W]

P_{loss}^{i} – Power loss in panel *i* [W]

$P_{u,cum}$ – Cumulated useful power [W]

P_{u}^{i} – Useful power in panel *i* [W]

P_{w} – Minimum warrantied power [W]

f_{W} – Warranty coefficient [-]

Classification – Binary variable [0, 1]

C_{f} – Capacity factor [-]

p_{el} – Price of electricity [€/kWh - €/Wh]

h_{year} – Total time in the year [h]

L_{system} – System's yearly monetary losses [€]

L_{system}^{rel} – System's relative losses [-]

R_{system} – System's yearly revenues [€]

P_{loss}^{plant} – PV plant's losses [W]

n_{panels} – Total number of panels [-]

P_{u}^{plant} – PV plant's useful power [W]

$P_{loss,rel}^{plant}$ – PV plant's relative losses [-]

L_{plant} – PV plant's yearly monetary losses [€]

$B_{O\&M}$ – O&M's yearly budget [€]

$L_{O\&M}^{rel}$ – PV plant's relative losses to O&M budget [€]

<u>Financial analysis</u>

$C_{ct,trim}$ – Cost of commercial trips per trimester [€]

$P_{new,trim}$ – New online power capacity [MW]

P_{trip} – Capacity covered in one trip [MW]

$n_{persons}$ – Number of persons in the trip [-]

C_{person} – Cost per person [€]

$c_{dc,mw}$ – Cost of data collection [€/MW]

c_{equip} – Cost of equipment renting [€]

c_{car} – Cost of car rental [€]

c_{meals} – Cost of the meals [€]

c_{trip} – Cost of the trip [€]

$P_{covered}$ – Power covered per data collection [MW]

$n_{h,trim}$ – Human processing hours per trimester [h]

n_h – Time required per MW [h]

P_{trim} – Power online at a given trimester [MW]

n_{pers} – Persons required [-]

r_{insp}^i – Total inspections revenue at trimester *i* [€]

P_{online}^i – Power online at trimester *i* [MW]

p_{insp} – Price per inspection [€/MW]

R_{trim} – Trimestral revenue distribution coefficient [-]

r_{upl}^i – Revenue from data upload in trimester *i* [€]

p_{upl} – Price for data upload [€/MW]

f_{insp} – Frequency of inspection [-/trimester]

r_{sig}^i – Total signup revenue at trimester *i* [€]

p_{sig} – Price per signup [€/MW]

r_{TOTAL}^i – Total trimestral revenues [€]

C_{TOTAL}^i – Total trimestral costs [€]

FC_i – Total trimestral fixed costs [€]

VC_i – Total trimestral variable costs [€]

B_i – Total trimestral balance [€]

$B_{i,cum}$ – Total cumulated balance [€]

1. Introduction: Innovation in the Energy Transition

Climate change has evolved from theory to reality in the last decades. According to the NASA, the current situation of greenhouse gases emissions and global warming has already reached a point of no return: the planet is already changing and will keep doing so, being the magnitude of the changes directly proportional to the amount of greenhouse gases emitted globally [1].

Some of the changes already spotted and forecasted to last during this century are global temperature rising, frost-free and growing season lengthening, changes in precipitation patterns, increase of droughts and heat waves, stronger and more intense hurricanes, increase of the sea level up to 1.4 meters in 2100 and the Arctic completely melted in summer before mid-century. Not only will this affect the whole ecosystem of the planet, but it will also severely affect human life. Moreover, 1 every 9 deaths all around the world are due to air pollution [2]. The big challenge of the XXI Century stands then in the fight against pollution and global warming.

One of the main causes of pollution and global warming is energy generation. The energy sector has grown during the last century thanks to a strong carbonization of its activities. Coal, oil and natural gas have settled in the mix of electricity generation and facilitated the electrification and growth of the global economy. China, whose main source of generation in 2017 was coal with a 58% of the share [3], has grown from 621 TWh generated in 1990 to 6.529 TWh in 2017 [4], multiplying the energy generation by 10 in less than 30 years. That trend is expected to happen as well in other countries that are now in an electrification phase, increasing the global electricity demand. Figure 1 depicts the forecasted growth in electricity demand by the International Energy Agency (IEA).

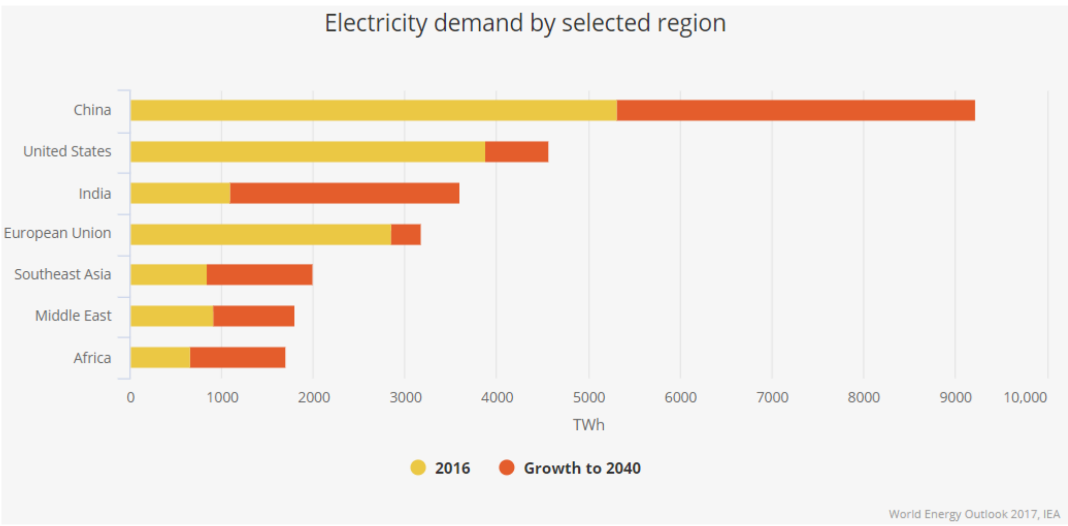


Figure 1. Electricity demand by selected region [5].

Renewable Energy accounts nowadays for 24% of the electricity generation worldwide. The strong development of hydro power in the XX Century together with the boost of wind and solar in the beginning of the XXI depict a promising scenario for these technologies to take more importance in the electricity generation mix in the future. Adding nuclear power, which is also a sustainable energy source, 0-emission sources will cover 50% of the electricity demand in 2040 as can be observed in Figure 2, extracted from the World Energy Outlook 2017 of the IEA.

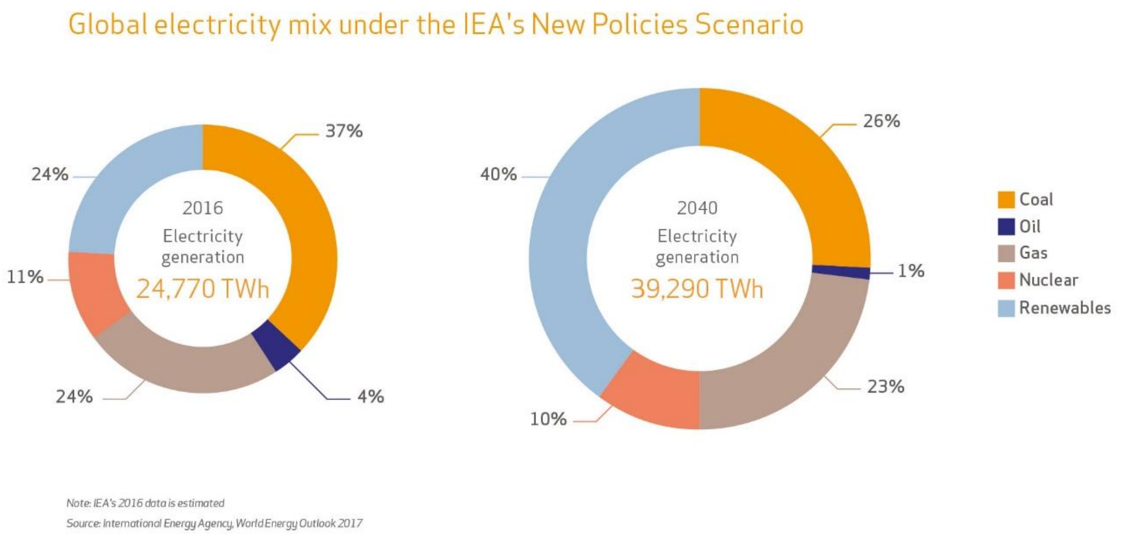


Figure 2. Global Electricity mix under the IEA's New Policies Scenario [6].

This scenario forecasts the extension of an already existing evolution in renewable energy technologies. In order to cut down costs of generation and ensure security of supply, renewable energies are maturing to a cheap and reliable technology. From centralized to stand-alone systems, the solutions that this technology brings are beneficial for both the environment and human health.

Innovation is taking an important role in dealing with the challenges that these technologies bring. From storage solutions that help to deal with the discontinuity of generation to software for asset management or new business models for electrifying rural areas in development countries, entrepreneurs are starting to occupy a significant part of the market of renewable energy. The fast development of technology is bringing many solutions on the table that help to reduce both the CAPEX and OPEX costs of renewable energy systems.

An important focus of innovation in the energy sector is digitalization. The digital era has reached the energy generation as well and new technologies are seeing its dawn in this challenging ocean, such as digital tools to perform the control on centralized renewable energy generation, or Blockchain solutions for distributed energy generation. The problem of digital tools is that they require uniform data, and in the case of renewable energy assets that is not always possible. However, there is a technology that is starting to help mitigate the inconsistency of rudimentary data and modernizing the inspections of renewable energy assets: drones or, as they are called by the sector, UAVs (Unmanned Aerial Vehicles).

1.1 UAV Inspections in Renewable Energy

UAV solutions are strongly influenced by their fast technology evolution. Drones have experienced significant upgrades during the last years and are now used in different solutions for many different sectors. In the US, the number of UAVs is already over 170.000 and it is forecasted to evolve in the future years, reaching more than 700.000 in 2022, as can be seen in Figure 3.

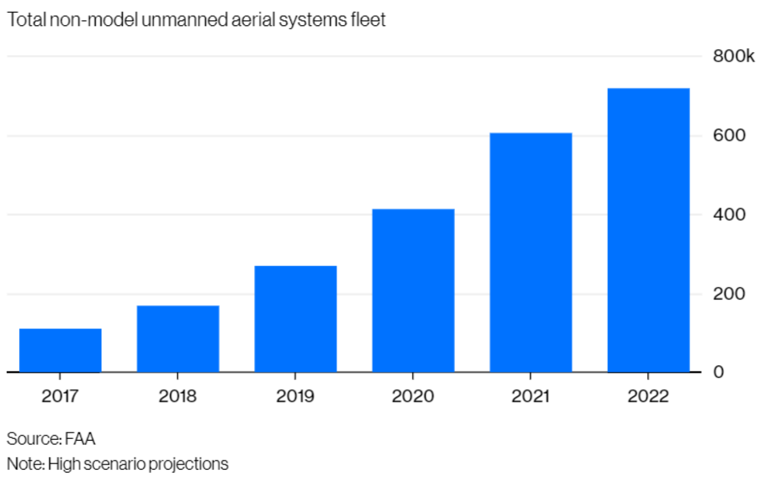


Figure 3. Total non-model unmanned aerial systems fleet in the US [7].

In the last years, the Chinese manufacturer DJI has been boosting the market by performing key characteristics of the machine (like battery capacity or payload supported) as well as developing user-friendly intuitive interfaces that help to facilitate the piloting experience. With massive investments in UAV R&D, the technology is getting simpler, safer and more reliable to use.

In renewable energy, drones are cheaper and more effective in monitoring infrastructure applications by avoiding to send workers to remote and dangerous terrain [7]. There are already some applications applied in the sector; in wind power, UAVs are used to inspect the blades of wind turbines, performing the previous man-made inspections with technicians hanging with ropes from the nacelle. Thanks to the drone, the inspection is faster, cheaper and safer, and the data is homogeneous and of better quality.

UAVs are also used in the energy sector to inspect power lines and in the growth of biofuels. In the first case, the drone is equipped with an IR sensor that enables the detection of hot areas in the power line that reflect a power transmission higher than usual and that could end up in a failure. In biofuels, drones are used for six different purposes: soil and field analysis, planting, crop spraying, crop monitoring, health assessment and irrigation surveys with hyperspectral, multispectral and thermal sensors [8].

In solar PV, UAVs help in the maintenance of the solar PV plants by inspecting the solar field with a thermal camera. What was traditionally done by on-site technicians on foot can be done in a much lower amount of time by a drone. According to UAS Vision, the use of drones in solar PV inspections reduce significantly the time spent at the same time that cuts the cost by a half [9]. Moreover, the quality of the data is optimum since the thermal picture is taken perpendicular to the panel. Figure 4 depicts the costs of drone inspections in comparison with traditional inspections:

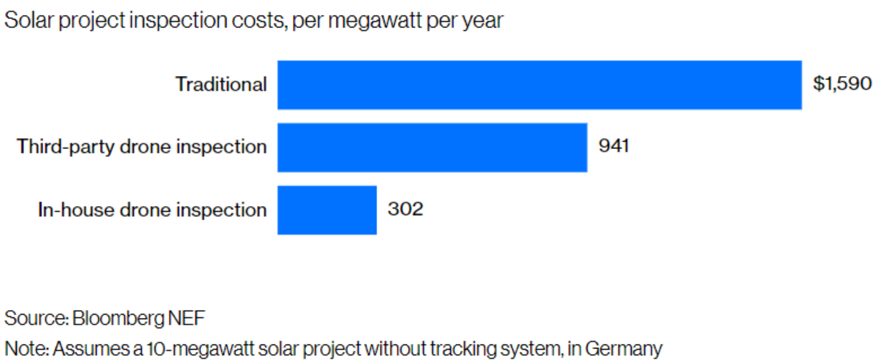


Figure 4. Solar project inspection costs, per megawatt per year [7].

This figure states two important facts about the use of drones in solar PV: first, that drone surveys can cut by a factor of up to 5 the costs of inspection; and second, that in-house inspections can be 3 times cheaper than third party-ones. However, to carry in-house inspections with the current technology, a qualified technician is needed to pilot the aircraft in the data collection and lots of pictures will need to be checked in the data analysis. UAV technology developers play a very important role in this aspect: putting in-house drone inspections easier to be carried in both the data collection and the data analysis could maximize the profits of this technology for the renewable energy sector.

Moreover, drones play a very important role in the digitalization of solar PV systems, which reduces significantly its operational costs. By facilitating homogeneous data, the image processing is simplified significantly performing the digitalization of the inspection. Digitalization is forecasted to make solar more cost-effective by lowering both the up-front costs and the levelized cost of electricity (LCOE) and by increasing the system availability and reliability, enhancing its competitiveness [10].

1.2 Introduction to the Business Case

Pro-Drone has been developing technology for wind blade inspections for more than 3 years. The business is based on the drone collecting data on the blade of the wind turbine and this data being processed and uploaded into a cloud platform, where the customer can access it online. The automatization of the drone flight allows the company to trust third party licensees to carry on the survey. In Portugal, inspections are being done by the team of Pro-Drone itself, while in Brazil a licensee is using the technology to carry inspections in their customer's facilities.

With more than 1.000 wind turbines inspected successfully in Portugal and Brazil, the solution developed for this market is reaching a maturity stage and the company is looking for new areas to expand the business. The first logical way to expand is by bringing the technology to other countries following the licensee approach. The different but complementary way that motivated this work is to replicate its technology in different markets, such as solar PV.

The core of the idea came from a customer in Portugal. Having its wind turbines inspected by the company, he liked the way they were carried out and the easiness of access to the results. Having as well solar PV plants in Portugal, he wanted to have them inspected by the same company so he would be able to access the information in a similar way. He trusted the company and saw the value on the technology, so he suggested to try to go for it.

Looking at the complexity of both a wind blade inspection and a solar PV panel's, and taking into account the technology available and experience already acquired during the development of the solution for wind, it looked feasible to develop the solution from a technical point of view. Taking into account the significant revenue stream that this could add to the company, the option was considered as very interesting.

Moreover, the company would be positioning itself in a strategic point: having solutions for asset inspection for wind and solar would more value to those customers having assets of both technologies. In the energy market, asset owners and managers with wind turbines and solar PV plants are very common, specially among the big multinational companies.

This document describes the design and first development stages of the solution to inspect solar PV plants. Starting with the business approach through market research and validated learning, continuing with the technical development of the code for temperature data analysis in the panels and ending up with the financial analysis of the solution in a 4-years horizon, the aim of the work is to understand:

1. How UAVs can help best in the O&M of solar PV plants.
2. How to read the temperature data and translate it into useful insights on the panel status.
3. How attractive would it be to develop this solution for a UAV technology developer specialized in renewable energy asset inspections, like Pro-Drone.

2. Solution Design

An essential step towards the final solution is the design of it. In this case, the solution's design is linked to the design thinking and validated learning process, explained in this section. Starting with the market analysis and literature review, followed by the design thinking process with constant customer validation and ending with the final design of the solution, this chapter is meant to make clear all the decisions taken during the design thinking process, as well as stating the final features and business model of the solution.

2.1 Market Analysis

The first step in the process is to analyze the market to make clear if it's interesting for any company to develop technology for it. This section explains the market analysis and literature review done to understand what is the status of the market and its forecast for the following years, get to know the technical aspects of the technology and its most common failures and, finally, assess the way drones can help in dealing with these failures.

2.1.1 Solar PV Market Status and Forecasts

Taking a look at data from the latest reports of Solar Power Europe regarding the market of Solar PV [11], it can be appreciated that the trend in yearly capacity installed in the last records is to increase. According to the estimations, the global capacity installed of solar PV will grow up from 404,5 GW in 2017 to a value in between 813,3 GW (low scenario) or 1270,5 GW (high scenario) in 2022 [11]. This forecasts that the market will at least duplicate and could triplicate in the following 5 years. Figure 5 shows the forecast of solar PV cumulative installed capacity worldwide.

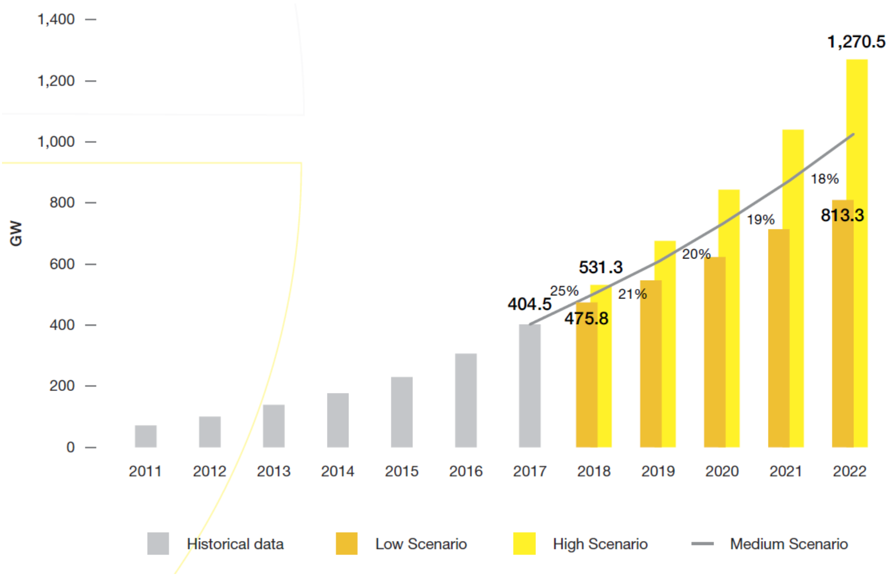


Figure 5. World total solar PV market scenarios 2018-2022 [11].

This market growth, which has been already happening during the last years, is related with the drop in prices of solar PV technology. In residential scale, it is facilitating consumers to install their own systems whereas utility-scale power purchase agreements (PPAs) are going down very fast and registering low price records constantly -a PPA is an agreement in which a buyer agrees to purchase a fixed amount of power at a fixed price over a fixed number of years [12], and it’s the most common contract used now for PV plant owners to sell electricity-.

The market segment that seems more attractive to try to develop the solution is the utility-scale PV market, which accounted for 59,38% of the total PV capacity worldwide in 2016 [13]. It englobes all systems with capacity equal or higher than 1 MW, and it is considered more attractive due to simplicity in logistics and higher OPEX budgets.

Figure 6 takes a look at the trend in the market of O&M for utility-scale solar PV systems. The capacity expressed is the installed utility-scale for different regions in the world and forecasted for different years.

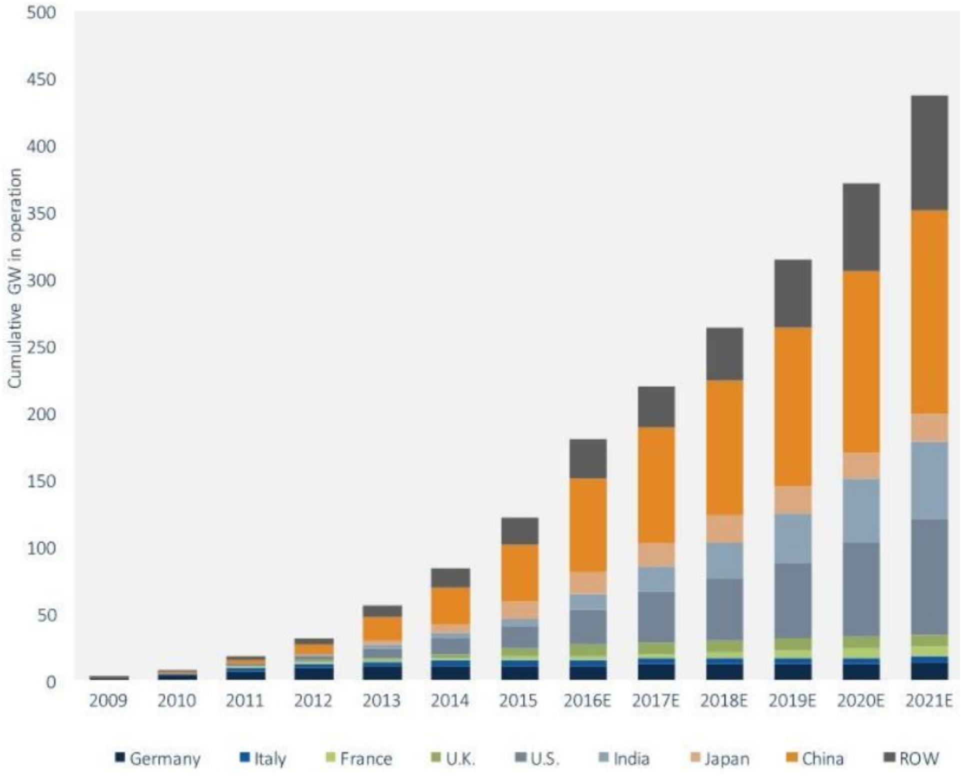


Figure 6. Cumulative megawatt-scale PV O&M Market, 2009-2021E [13].

As can be observed, the core of the growth is located in China followed by the US and India. The worldwide capacity installed in 2016 was of 182GW and it is expected to pass 450 GW at the end of 2021. As can be appreciated, utility-scale PV is not an exception inside the overall growth of solar PV.

Inside this market, the sector where UAVs can potentially add more value is in O&M. TÜV Rheinland carried out a survey for workers in Chinese photovoltaic solar plants and enterprises related to the PV industry, in order to clarify the status of the market for enterprises [14]. Some interesting results of this survey that state the potential of improvement are the following:

- 23% of the interviewees believe that stability and reliability of equipment and materials is the main factor affecting the continuous operation of PV stations. It's the most voted factor.
- 20% of the interviewees identify O&M after completion of the projects as the biggest internal problem facing distributed power stations from development to operation, occupying the second place in the survey after quality problems of key equipment and spare parts, which got a 22%.
- 31% of the interviewed enterprises believe that equipment failure is the most common case of unexpected power station shutdown, setting that case as the most voted in the survey.

The results of the survey state that there is a strong concern in the Chinese market about the quality of the equipment and its potential failures affecting the continuity of power production, which is key for the revenue streams of the power plant. Taking into account that China is the biggest PV panel manufacturer in the world, accounting for about 50% of the solar panel demand in 2017 [15], these trends could easily extend to other markets in the world. Having such concerns for the state of the equipment, and having O&M such a strong importance in the value chain of solar PV electricity generation, it is clear that the market has a clear margin of improvement and UAVs could add more value there.

Given the results of the PV market analysis, it can be stated that it is a growing market and a very interesting context to develop UAV technology. There are already some companies offering services with UAV technology for solar PV, so the focus now sets on analyzing the state and features of these already existing solutions. The next section describes the competitors' analysis.

2.1.2 Competitors' Analysis

The competors' analysis takes a look at the main existing drone solutions for solar PV worldwide and compares them. The main questions to answer are: how developed are drone surveys so far? How much value do their results add to the O&M of the plant? Is there a real margin of improvement?

The common pattern shared among the existing companies is to offer the service as a one-time-payment in exchange of an IR and sometimes also RGB scan over the field. The deliverable of this service is a report that details the failures identified in the panels during the inspection, which in some cases can be accessed online. Aeroprotechnik (Portugal), PrecisionHawk (US) or Ucair (Germany) are companies that are already offering those services with UAVs.

Another role in the market is software developers to facilitate UAV operations to the inspectors. DroneDeploy, for example, provides a software that generates flight plans for the UAV to autonomously collect pictures over a given large surface, and creates a map out of the different georeferenced pictures, which can be RGB or IR. Pix4D and RaptorMaps develop similar software. Overall, the use of UAVs in solar PV inspections is getting simpler every year and tools to facilitate those operations are already on the market.

Taking into account that the goal of solar PV inspections is to keep a better control over the solar PV panels, companies developing power monitoring technologies could also be considered as competitors. However, those technologies offering monitoring up to a panel level are far too expensive which causes a very low penetration in the market, targeting now residential systems. Hence, they have not been considered in the competitors' analysis.

The results of the main competitors' analysis are summarized in Table 1:

Name	Solution	Origin	Markets	Data collection	Data processing	Deliverable
Aeroprotechnik	Drone surveys	Portugal	Solar PV, power lines	Own automated drone with own pilot	Fault detection in cloud platform	Report and data on the cloud
Precision Hawk	Drone surveys	US	Many	Automated	End-to-end aerial data platform	Report and online data
Ucair	Drone surveys	Germany	Solar PV	3rd party pilots	In-house fault detection	Report
Raptor Maps	Drone technology	US	Solar PV	Automated flight	Thermal maps	Online data

Table 1. Competitors' analysis results.

In an initial research, many more drone companies have been spotted. However, the ones shown on the table are those that have been identified as most important given their location, size or application. Other companies spotted in the analysis but not included in the table are: Analist Group (Italy), Sharper Shape (US), Team UAV (UK), HUVR Data (US), Enertis (US) and Cleandrone (Spain). Others have been spotted but not analysed in detail due to different particular reasons.

The following points describe the deep analysis of the main comptetitors, displayed in Table 1.

Aeroprotechnik

Given the location of its headquarters in Portugal, Aeroprotechnik is a strong competitor to take into account. Started in 2015, they have partnered with Intel to develop a semi-automated UAV solution that inspects solar PV panels in utility-scale systems. Their business model is simple: they own the drone and they provide surveys to the PV plant, for which they deliver a report with information about the damaged panels, such as the location of the damage and the severity.

They have inspected a total of 1050 MW in Portugal, France, South Africa and the US, according to their webpage [16]. It is stated there that they use a drone designed and developed by themselves to collect the data and AI to detect the faults automatically. The resulting report is accessible on the cloud. The price for their survey is of around 400 € per MW inspected, and it takes around 1 week to collect the data in a 10

MW PV plant, plus 2-3 weeks to process it. The quality of their imaging is not so good, but enough to detect failures.

The advantages are the semi-automation of the drone and the AI cloud computing tools for fault detection, which allow for a faster data collection and processing, respectively. The disadvantage is the high price they charge, which does not allow customers to do more than one survey per year. Their business model is pretty locked and it does not look like changing soon, which is a clear disadvantage in such a changing environment.

Figure 7. Aeroprotechnik's automated drone in a solar PV plant [16].

Precision Hawk

Funded in 2010, Precision Hawk is set in the US and has a deep variety of services associated with drone technology. It acquired recently two important players in the US market, HAZON and Inspectools, becoming the leading provider of drone technology in the US [17]. Right now, they are present in Canada, Australia, Argentina and the UK. To date, Precision Hawk aloneit has raised more than 100 M$ in funding, which have been used to accumulate a total of 8.000 hours of flight in 13.000 inspections.

Precision Hawk covers the industries of agriculture, construction, energy –including solar PV-, insurance and government. Their presence in different markets gives them the chance of accumulating more flight time but limits their level of specialization; their products are universal, designed to add value in each one of those industries, not going in full detail in any of the markets.

Being reached through email, they state to offer both a service and a product that allows the customer to use the technology on its own. A report obtained directly from them of solar PV inspections shows some thermal maps on the field but no reliable summarized information. Conclusions on the contact with them state that they are big, they have good products that work for very different markets at the same time but their focus in each one of them is low. In the case of solar PV, the level of processing in the data is still in a very early stage, and much more value can be added on top. Regarding the data obtained, the quality of the thermal map has a big margin of improvement.

Ucair

With a kind of "Uber" approach to drone services, Ucair offers inspections of solar PV panels in both roof-top and big systems, as a third party survey. They connect customers looking for drone surveys with drone pilots that can go and collect the data for them, and send it to Ucair to be processed. The deliverable for the customer is a report with failures identified, an overview of the financial impacts of their current problems and the proof for possible warranty claims.

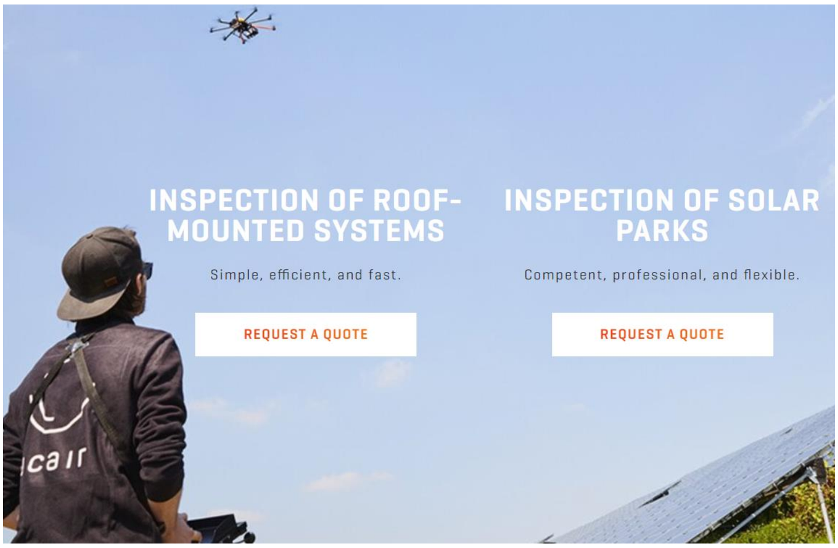


Figure 8. Vision on Ucair website [18].

Ucair has done operations outside of Germany and even in Portugal. The way they operate is: frist they receive a request for an inspection in a determined PV plant and then they contact pilots in the area that can carry the survey and give them instructions on how to do it. Afterwards, the collected information is shipped to Ucair where it is processed and delivered to the customer as a result. It is deduced that in case the customer has any preference on drone pilot it does not mean any problem for Ucair, as long as the quality of the data is enough for the processing. Their price is similar to Aeroprotechnik's.

Raptor Maps

Raptor Maps is probably the most technology-oriented company found in the analysis. They don't offer services, but they develop tools for carrying on solar PV inspections easier, basing their data processing on end-to-end artifficial intelligence and machine learning. Theay announce to have more than 115 global partners, including Enel Green Power. Their webpage specifies that they allow to fly, detect, localize and analyze failures in the panels and present a report as deliverable. Their technology has been used in the inspection of 2 GW of capacity so far [19].

Through more online research and attending to webinars of them, it was found out that they provide flight path generation tools and data processing algorithms for the data collected. Through some videos found online about customer experience in their tool, it can be observed that the output of their processing is a thermal map of the field.

Competitors' graph

The competitors' graph shows the positioning of the main companies already involved in the development of solutions for solar PV inspections by two different criterion selected as key based on the overall analysis: Depth in Data Processing (D-DP) and Customer's Independence in Data Collection (CI-DC).

- Depth in Data Processing (D-DP): it describes how far the data collection goes; a company which processes the data in full detail for solar PV applications will be ranked at the highest and a company that does simply not process the data will be ranked the lowest.
- Customer's Independence in Data Collection (CI-DC): it analyses how much freedom does the company give to their customers to perform the data collection on their own; a company that gives tools to the customer to perform the data collection completely on its own will be high ranked and a company that is locked to its own pilots to collect the data will be low ranked.

Figure 9 shows the positioning of the companies according to the analysis of those parameters:

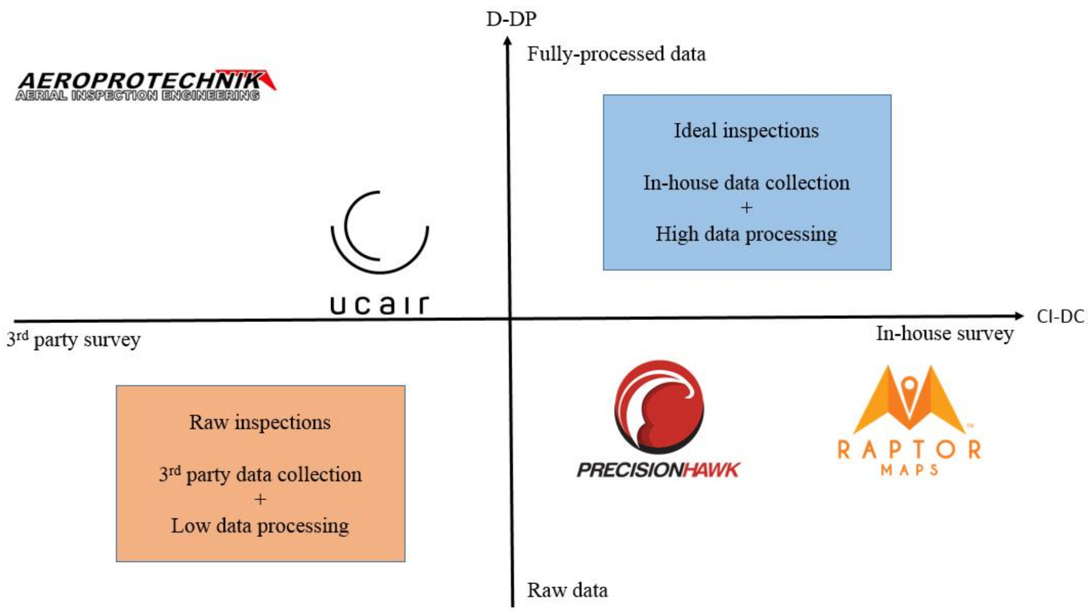


Figure 9. Competitors' analysis positioning.

As can be observed in Figure 9, the ideal area for a drone survey company is the top-right corner. There, the customer can save costs by collecting the data in-house at the same time that the data is fully processed for solar PV, delivering the most reliable results and saving time in manual data analysis. The bottom-left area is the less likely for the final customer since it basically has the high costs of 3rd party surveys plus the low processing on data, which will cost the final customer a significant amount of time and resources.

No company identified in the section is yet positioned in the top-right area; Precision Hawk and Raptor Maps are on the bottom-right and Ucair and Aeroprotechnik are on the top-left. It is more likely to happen that the ones on the bottom-right pass to the top-right rather than the ones on the top-left, since developing a company on the top-left locks the business model on the surveys. For example, the high development invested in the drone of Aeroprotechnik makes it difficult for customers to perform the inspection by themselves; only by having the same drone they could collect the data with the same reliability as done by Aeroprotechnik. In case they would like to do that jump, their business model would have to experience a pivot which, looking at the data at their webpages and acceleration of their business, does not look likely to happen. However, Ucair is more centered since the independence on drone and pilot that the customer has puts it a bit closer to the jump, but their level of processing is pretty low.

The problem for Precision Hawk to do the jump is that its products are meant to satisfy very different sectors. The only way they could do the jump is by creating a specific product for solar PV inspections, which would give them the freedom to spend more resources in data processing. With the recent acquisitions, the company could change a bit the strategy and go for more specific software for each one of the sectors that it serves, but that has not yet happened according to the information that has been published.

In the case of Raptor Maps, their mission is to create a product that serves drone pilots in the data collection, but they are not so focused on the data processing. Basing on information at their webpage and webinars, it is more similar to a data collection consultancy and support than to a full value chain technology developer for solar PV. Checking online videos it can be stated that the value they provide is a thermal map of the results with temperature records, which puts them far away from the optimum data processing.

The potential for a new solution to be developed in this competitive market relies in the fact that none of the existing companies in UAV solutions for solar PV plants are covering the whole data processing specialized for solar PV plants at the same time as allowing the customer to collect the data on its own. A solution positioned at the top-right corner of the chart would optimize the overall inspection process for the solar PV plant, including the data gathering, data processing and data display.

Regarding the data collection, the best way to make the customer independent on the flight is to provide it with the automated flight plants, which reduce the expertise required in drone piloting at the same time as ensuring the quality of the data collected. There are already tools in the market that create plans for automated flights, which need to be uploaded on an application which controls the flight. These tools are usually developed by companies focused on thermal imagery stitching, such as Pix4D and Drone Deploy. There are also open source tools like Mission Planner that can generate automated flight plans for mapping.

Figure 10 shows the overview of Mission Planner for designing an automated flight over an agriculture field [20]. As can be observed, the area that wants to be inspected has to be selected in the central map. At the right part of the screen, some flight parameters such as the altitude or the flight speed can be modified. At the bottom, the expected output parameters such as the flight time or the ground resolution of the images can be consulted. In the map, the drone path is shown with yellow lines, marking the turns with numbered green pointers and the limits of the area to map with red pointers.

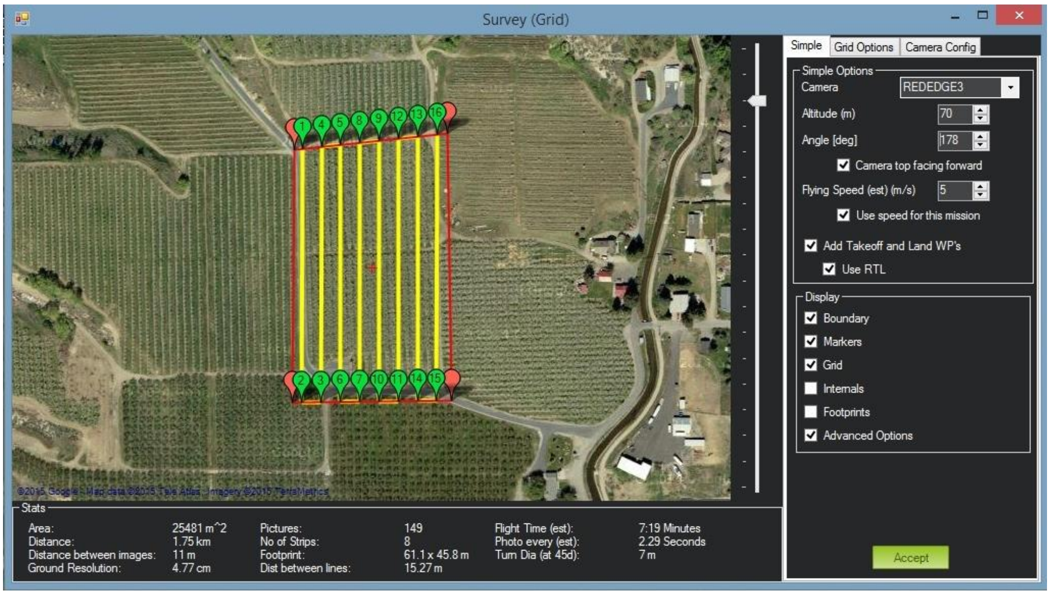


Figure 10. Mission Planner overview for an automated flight plan [20].

Regarding the data processing, the main point to understand is which data brings value to the customer. Two ways have been identified for these purpose: doing a scientific research on failures in PV panels and detection methods compatible with UAV operation, and directly contact the customer to hear it firsthand. Since the options are not exclusive, it is set that first a research is carried to win some expertise and build up assumptions and then those assumptions are validated through direct contact with the customer.

The following section describes the scientific research, which has the goal of understanding which are the most common failures in solar PV panels, how much they affect in power production – which in the end is the main important point in solar PV systems - and how can they be detected.

2.1.3 Scientific Research

The common pattern in between the different failures in solar PV panels is that they generate a temperature difference due to extra energy losses. As the temperature in the cell increases, the performance of it decreases; the electrical efficiency and the power output of a PV module are linearly dependent on operating temperature [21]. The phenomenon comes from the fact that, typically, PV cells convert 6-20% of the irradiation received into electricity, and the rest is converted into heat.

Solar irradiation and wind are the two natural phenomenon affecting the temperature of the cell; as irradiation increases so does the temperature of the cell whereas as wind increases, the temperature of the cell decreases [22]. Both are measurable with meteorological meters, and its impact on the power production can be estimated through mathematical equations.

The effect of the cell temperature on the power output is strengthened by the fact that the Standard Test Conditions (STC) of the cells, at 25 °C and 1 atm, do not reflect the real operating temperatures. Atmospheric factors like solar irradiance and ambient temperature affect severely the PV panel temperature distribution and contributes to a negative impact on the output performance of the panel [23]. Figure 11 shows power-voltage curves at different temperature values.

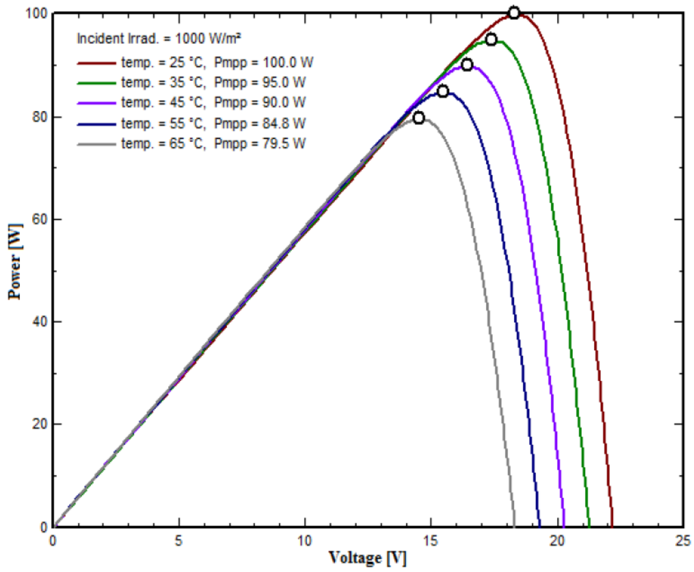


Figure 11. Output power at the maximum power point for different cell temperatures [23].

A drone can detect a difference in temperatures inside a solar PV cell by using a thermal sensor, which reads visual data in the infrared spectrum; that's why they are also called infrared or IR sensors. Some specialized companies, such as FLIR, are already developing IR sensors specially for UAVs [24].

The IR data is clearly a way to detect and quantify a failure in a solar PV cell, and that's why most of the surveys carried out nowadays by UAVs are based on this technology. The thermal differences inside a solar cell reflect a failure in the cell and are the so-called hot spots. It is possible to classify some of the failures in the cell by looking at the patterns of the hot spots in IR imaging, as can be seen in Figure 12.

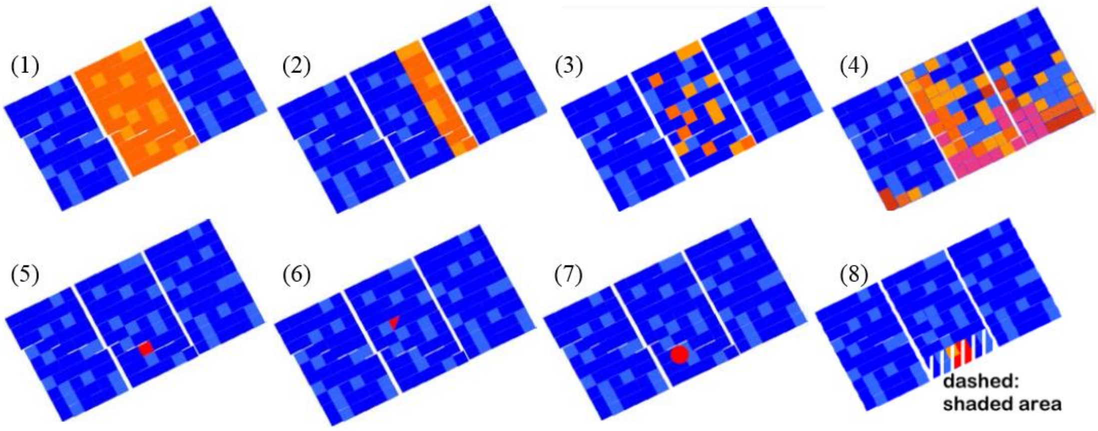


Figure 12. IR imaging patterns inside a PV panel [25].

Each one of these configurations represent different failures. Those are: open-circuited module (1), short circuited or open sub-string (2), whole module short-circuited (3), massive shunts caused by potential induced degradation –PID- and/or polarization (4), shadowing defects or defect/delaminated cell (5), broken cell or disconnected string interconnect (6), artifact or partly shaded by e.g. bird dropping, lightning protection rod (7) and sub-string with missing or open-circuit by-pass diode (8). The impact on power production depends on the area covered by the failure and the intensity of the hot-spot, which will determine the margin of the temperature difference.

As can be observed, some of the failures are related to broken cells, shadowing or objects on the glass of the panel. RGB imaging can complement the IR imaging to help identify these issues in a determined solar cell. In fact, there are some sensors for UAV that integrate both an IR plus an RGB sensor so the drone collects visual and thermal pictures over the field; they are the so-called dual sensors.

The goal of doing an inspection with both image types is to be able to identify which panels are defective and with which severity of damage through the IR and then analyzing the cause of the problem with the RGB, in case it's possible. For some failures, the minimum quality of the RGB is very high for a drone to identify it from a high altitude, but there are some others that are easy to identify since they affect a big part of the panel or their color difference with the healthy part is significant. Figure 13 shows the failures that can be identified with ab RGB camera.

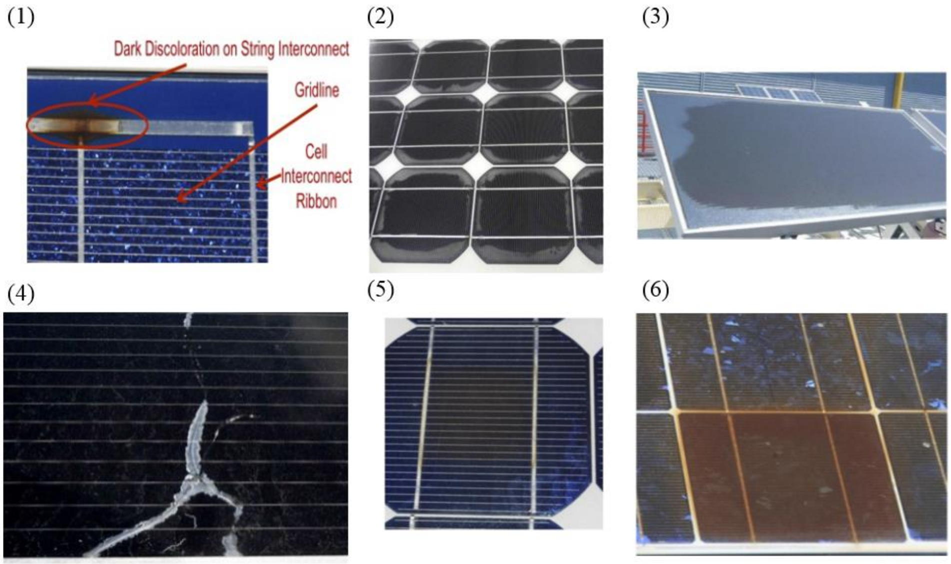


Figure 13. Failures in PV panels identified through RGB imaging [25].

The most common failure types are: burn marks at the front, discoloration of the encapsulated (1), delamination of a c-Si module (2), electrochemical corrosion of a thin-film module and associated delamination (3), thin-film glass breakage (4), slightly browned EVA –ethylene vinyl acetate- at the center of the cell (5) and a single cell browned much faster than the others due to a higher temperature (6). Failures that do not require high quality in the RGB image would be (3) and (6), whereas (1), (2), (4) and (5) generally require either a high definition sensor or a closer flight to the panel.

Micro cracks in solar PV cells

One phenomenon affecting power production, identified in several solar PV cells is micro cracks. Usually, micro cracks origin in the transport of the modules from the factory to the installation point. Also, some natural phenomenon such as snow, strong winds and hailstorms help to make them grow bigger and create significant cracks on the PV modules. These cracks could origin the disconnection of cell parts, which drops the power production of the panel significantly [26].

A very effective way of detecting micro cracks in the cells is by applying electroluminescence (EL) imaging. For shooting EL imaging, it is necessary to remove the IR filter of a camera and substitute it with a full spectrum one, which makes the camera extremely sensible to sun light. Hence, totally dark conditions are needed to get a good quality in the EL image and be able to see the cracks without damaging the sensor. Once shot, EL imaging allows a very easy and fast identification of micro cracks. Figure 14 shows EL imaging on a PV panel with cracks.

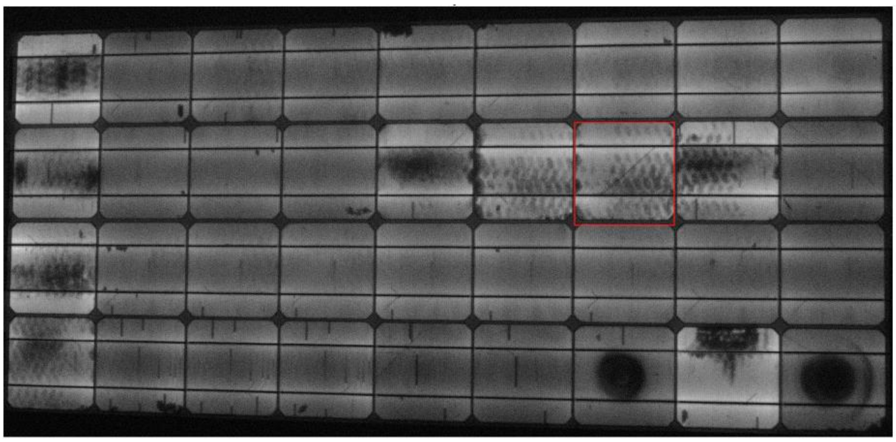


Figure 14. High quality EL imaging on a PV module [27].

The effect of micro cracks on power production depends on the size but also on the type of micro crack. Multiple directions cracks tend to affect more on the cell performance than parallel or perpendicular to bus bar ones. Figure 15 shows the average drop in output power efficiency for cells affected by multiple directions cracks.

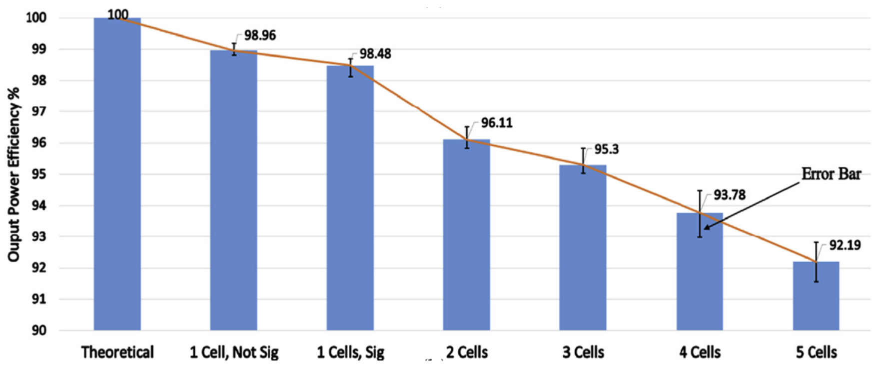


Figure 15. Output power efficiency according to the number of cells affected by the crack [26].

As can be observed, micro cracks can reduce up to an 8% the output power efficiency, which is considered as a significant drop in power performance. However, it is very difficult for UAVs to apply EL imaging despite they can carry the sensors required, since EL requires totally dark conditions. The darkest conditions in which drones could collect data would be during the night, but in most of the countries it is not allowed to perform drone flights in night hours due to the lack of visibility on the machine.

In any case, micro cracks can also be seen on RGB imaging through very high resolution sensors. For wind blade inspections, for example, a point-millimeter precision with RGB imaging is required to spot the less critical cracks in the blade. In the case of micro cracks in solar panels, those that really affect power production are on the millimeter scale; this states that, despite it would be hard to acknowledge, it could be possible to detect micro cracks through RGB imaging with drones.

Introducing the analysis of micro cracks on the UAV surveys would add more value in the asset management of the PV plant since it would allow the managers to keep a track on the cracks and check the evolution, which would be very helpful for both warranty claims on panels and preventive maintenance on the field. Moreover, the power loss generated from the crack could be calculated basing on the experiments carried out. Now the issue stands on the importance of micro crack detection for solar PV plant managers.

2.1.4 Summarized Results

Overall, the results of the market analysis state that solar PV is a very interesting market for UAV technology developers to enter: it's big, it's growing and it is forecasted to keep growing in the following years. Moreover, there seems to be a lot of margin of improvement in the O&M of PV plants and interest in the managers of PV plants to get them improved, but a new solution for UAV inspections would need to distinguish itself among the already existing competitors. In order to acknowledge that, it is key to try to position itself as close as possible to the up-right corner of Figure 9, being it capable of supporting in-house surveys and having the tools for a fully-processed output data, optimized for solar PV inspections.

For the data collection, it is very important to combine RGB and IR imaging so not only the failure itself can be detected, but also the cause of it. Different patterns can be observed in IR and RGB imaging, and the analysis of the images can be automated to identify them. Micro cracks are one of these patterns that affect in power production and no other competitor seems to be focusing on.

With these conclusions, the market analysis phase is concluded and the design phase of the solution is started. The main methodology followed in the design phase is validated learning, and the overall process is explained in the following section.

2.2 Design Thinking through Validated Learning

Validated learning is a methodology of business creation which is based in a constant process of building, measuring and learning from lean products through a constant interaction with the potential customer [28]. The goal of it is to make sure that the fraction of time and resources spent in developing useful products for the customer is maximized, maximizing as well the market impact of the product. In order to develop a good solution for PV plant inspections with UAVs, an initial design was built up basing on the results from the market analysis. Then, different companies and experts were approached through cold calling in order to stablish the network needed for the validation of the solution. Afterwards, two rounds of interviews with the contacts reached were organized, including personal meetings with operators and owners of PV plants in Portugal. This section explains the overall design thinking process of the solution through validated learning.

2.2.1 First Solution Design

Through the technical research it has been possible to identify some patterns that could be interesting to spot in the inspections, such as the IR patterns, the RGB faults and the micro cracks. It is realistic to think that those failures could be identified automatically by running classification models and fault detection algorithms on the IR and RGB images.

This context shapes the design of the very first raw idea of the solution. The vision of it relies on a PV plant manager activating its drone, set and ready to use in the same PV plant, to collect data on the solar PV field. With one click, the drone would fly over the field through automated flight planning, collecting IR and RGB images with a dual sensor. Automated flight planning means that the drone would be following a preset optimized flight plan generated by the platform according to the parameters desired for the data collection. The images collected could be uploaded in the platform to be processed and get a feedback on which panels are default. Then, a lower flight on those panels, with a higher resolution, would be set with the aim of detecting more detailed issues such as micro cracks. In the end, the data collected would be uploaded in the cloud, processed, and given back as the overview of the field with the failures identified in each one of the panels. The algorithms would identify IR and RGB patterns as well as micro cracks on the panels, and could provide an assessment on how much power is being lost in each panel due to the failures identified in the inspection. Moreover, different surveys on the plant could be carried out for other purposes, such as quick surveys for fast assessment on the plant after a natural phenomenon or a more detailed survey on those panels selected as defect to claim for warranty. And, most important, this process could be repeated many times in the same year improving the current control on the panels.

The mission of the solution relies then in providing technological support for the activity described and making sure that the price of the solution does not keep the customer from using it frequently. On one hand, guaranteeing the easy, fast, reliable and in-house data collection through automated flights is necessary. On the other hand, the cloud tools would need to process automatically in a relatively short time frame the images collected during the flights to ensure a fast and reliable diagnostic on the panels.

The tool would have then two main components: the drone for the data collection and the cloud platform for the data processing and display. This platform would provide the flight plans for the drones to fly autonomously and would be the main interaction with the customer. Through the platform, the customer would be able to select which kind of flight does he want to perform and in which area of the plant, and then check the results online after the data is uploaded and processed. Figure 16 depicts the scheme of this initial solution design.

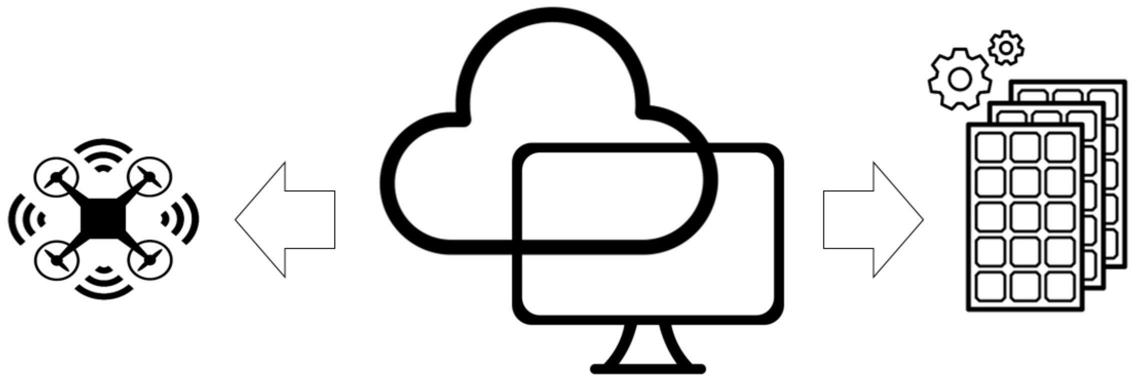


Figure 16. Scheme of the initial solution design.

This new tool would be moving UAVs from asset inspection services to asset management tools. Obviously, however, this is the initial raw vision that does not take into account the technical constraints on drone usage in the data collection or image analysis in the data processing, neither the preferences of the customer. It is merely a merge of all the assumptions taken during the market analysis phase that will need to be validated through direct contact with potential customers and pilot tests on data collection and data processing.

Sections 2.2.2 to 2.2.4 describe the validation of this initial design through direct contact with potential customers. The aim of the process it to shape the solution towards the optimum for UAVs, with the goal of adding the most value possible on the O&M of solar PV plants.

2.2.2 Cold Calling Round

The first steps towards the validation of the solution was to actually get the contacts to validate it with. The initial consideration was to contact the customers of the company's solution for wind blade inspections that also had assets in solar PV. Taking a look at the data base of Energias Endrogenas de Portugal (E2P) [29], which gathers all the non-residential renewable energy systems installed in Portugal, it could be observed that there were many other reachable companies that were not in the list. A cold calling round was set to contact them with the goal of speaking with high-ranked personnel that could help us knowing better about the O&M of PV plants and the whole of UAVs. The contacts were found online, mainly through their websites.

Out of 16 companies reached, 4 agreed to collaborate by having a Skype call and sharing some of their experience with solar PV and UAV inspections; that stated a 25% of success in the cold calling round. In the end of the round, a total of 10 potential customers were available for Skype calling or doing personal meetings at their offices, including industry experts, entrepreneurs and managers of solar PV systems in Portugal, from a commercial to a utility scale.

2.2.3 First Round of Interviews

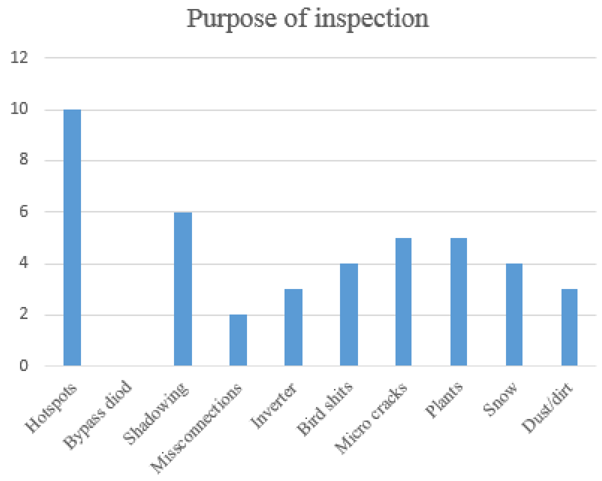
The first round of validation had the objective of understanding from a direct point of view the most common issues in the O&M of solar PV plants. Some questions regarding the assumptions taken during the validation round were prepared, but the core of the conversation was to give a freedom of speech to the interviewed. During the call, a short introduction of both companies was given followed by an open question on what are the issues that worry them most on O&M of solar PV plants. Then, the interviewed were asked about previous experiences on UAV inspections and the features that they identified that could be performed to add more value. In the end, if some specific information was missing, more detailed questions were asked.

Notes on the interviews were taken during the calls and meetings, so the feedback from the interviewed was stored digitally. The answers were then compared to previously designed statistic values so each one of the interviews could be qualified and quantified. From the statistic results, some figures were extracted that helped to understand the point of view of the market on the O&M of the plants and the role of UAVs.

Some of the most important results were the following:

- 64% of the interviewed preferred a tool over a service as a solution for the inspections.
- 0% of the interviewed monitored power production up to a panel level.
- The most important failure to identify in the inspections were the hot spots (100%).
- Disaster assessments raised few interest.
- It would be interesting for most of the interviewed to be able to inspect the full plant or only part of it.
- 88% of the interviewed wanted to have both RGB and IR imaging on the results.
- Desired output is online data in 90% of the interviewed, with the option of extracting a report as well for 60% of them.

Note that most of the percentages are not multiples of ten, despite being 10 the population of the survey. This is because the topics covered on the interview depended on the insight of the customer. The charts on the purpose of inspection and the current monitoring system are represented in Figure 17:



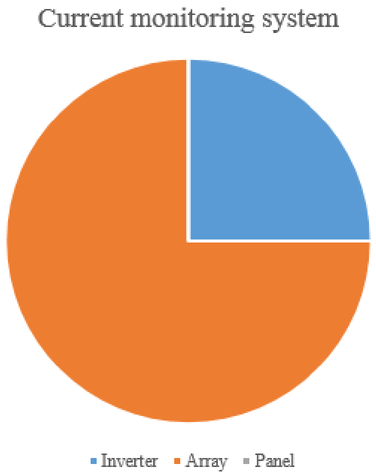


Figure 17. Main statistic results of round 1.

As can be observed in the right chart, power production is mostly monitored at an array level. Current technologies of per-panel power monitoring involve huge CAPEX costs in purchasing and installing sensors in the panels at utility-scale level, and are hence targeting domestic systems. Taking a look at the left chart, it can be seen that most of the interest in the inspections is in identifying that there is a failure through hot-spotting, but it is not so critical to really know what it is exactly going on in the panel. In case there is a major failure, it will be reflected in the IR image and the personnel at the plant will go and check the default panel with metering equipment.

Conclusions extracted from the results of the interviews state mostly positive facts. First, it is validated that UAV inspections have a big margin of improvement since the experts in the sector see these technologies as still raw and immature. Second, the drone-as-a-tool approach is valued by the sector and the view is shared by some of the players. The main drawback in having the drone as a tool is the high investment in the system, which might not fit in all OPEX budgets. This fact made the core of the initial idea shift from drones living in the plant to drones owned by the company and operated in different plants, so the cost of the equipment is shared among the plants.

One negative conclusion is that it was very hard to find a manager who wanted to inspect his/her plants more than once per year. One of the initial assumptions was that if the price was lower in drone surveys, managers would order more inspections. According to their point of view, the main drawback for spending more time in panels' inspections is that problems do not evolve so fast in solar PV panels and it is not so critical to keep such a strong control on the panels since the power is monitored for each array. Hence, the role of the drone in the O&M is mainly identifying which panels are causing the problems by getting a scan of the whole solar PV field.

Another conclusion that meant a change in the initial vision is the fact that high quality RGB imaging is not so critical. Interviewed often answered about the micro cracks with indifference, stating that the main thing to identify for them was the hotspot through IR, since the size and intensity of it already reflects the magnitude of the damage. RGB is highly appreciated for understanding the cause of the problem, but it is not needed up to a point-millimeter level if that makes the flight significantly longer. This stated IR imaging as first priority in image quality parameters and, most important, in image processing.

The shape of the solution at the end of the first round showed a different picture: it would still keep the roots of being a tool to be used for the local team, with the automated flight and the cloud data processing as main pillars, but the focus on both the data collection and the data processing changed. Now, IR was set as most important data to collect and process, which opened the door for temperature data analysis inside the panels as automated failure detection.

2.2.4 Second Round of Interviews

After the results gathered in the first round, some changes in the design of the solution were made to re-adapt it to the market needs and make it more attractive. With the output design, some financial models were made and a key question popped up: which would be the right price for the solution? And, moreover; how should it be priced?

It was obvious that the high equipment cost would have to mean a lower operational cost compared to the competitors' solutions; otherwise, it would not make sense for the customers to go for our solution. Basing on existing hardware, the equipment cost was set as 20k€ for a dual sensor and a gimbal that could attach it to and control it from the drone, plus a drone capable of carrying that payload without lowering significantly the flight time.

The marginal costs for the company to have this solution up and running were not so high: mainly personnel salaries and trips for testing and for sales. Hence, we were left with a comfortable margin to offer a much lower price than the market price. A price of 100€ per MW was set, being it a 66% cheaper than the cheapest one found, of 300-350€ per MW in the UK. The return of investment for the customer on the equipment purchase was depending now on the installed capacity that would be inspected, most important, on the frequency of inspection.

The main purpose of round 2 was to understand the frequency parameter directly from the customer. With that goal in mind, two different price scenarios were designed: one with the variable price per MW inspected, of 100 € per MW, and another one with a fixed monthly fee per MW online, set at 17 € per MW online and month – with unlimited number of inspections. The monthly fee was designed for having the same yearly cost as inspecting the whole capacity of a single customer twice. Hence, the fixed fee would be more interesting for those customers willing to do more than two inspections per month whereas for the more conventional customers, the fixed would be fine. The goal of the round was to present both prices to the customer and make them decide one, so we could estimate how often were they really willing to use the solution. Excel sheets were prepared, which calculated the ROI given the capacity and number of inspections per year for each one of the pricing scenarios, so the customer could play with them before stating its preference. The population interviewed this time were those customers who showed more interest during round one.

The results of the second round were different than expected. It was not possible to validate the price assumptions since the solution was not yet in a commercial stage. The main drawback for this was that being asked for price models created confusion in the customer about the aim of the call.

However, the round served to validate the actual design of the solution, shaped after the first round. Since the solution needed to be presented before introducing the prices, the customer was asked for feedback and gave valuable insights on it. The main drawback identified was that the cost of the equipment was very high. That kept the customer from ensuring to take the upfront cost of the drone in exchange of savings in the inspections and ROIs of 1-2 years. The fact that the solution that had not been tested yet and that the team accumulated 0 minutes of flight time in data collection and 0 MW of data processed were key factors for not trusting it enough and not seeing the investment as feasible, despite the significant savings.

This helped to understand that the solution needed two small changes, both related with the target market. First, it was clear that residential and commercial systems needed to be put out of the scope of the initial solution, since their few capacity put the feasibility of the solution far away from their position. Second, it stated that targeting only the internal teams of O&M companies was a wrong and actually unnecessary assumption: having such a low margin, the solution could be offered to licensees and still keep the overall price competitive. The internal team would get satisfied, being the value of the solution designed specially for solar PV, the licensees would gain a reliable solution to work with desired by their customers and the company would be keeping a margin on each inspection. Hence, small customers were discarded and licensees were added in the customer segment.

The most positive output from the second round is that some important players showed a lot of interest in the design of the solution and that opened doors for future development agreements and access to PV plants for testing. This fact pushed to start the development phase of the solution, which stated the design acquired at that point as the optimum design to aim for in the development of the solution. Section 2.3 describes the features and key business strategy of this final solution.

2.3 Final Solution – PV Insight

PV Insight is the chosen name to reflect the features of the solution for inspecting utility-scale solar PV systems with UAVs. Overall, the solution follows a do-it-yourself approach for data collection combined with an automated data processing. Section 2.3.1 explains the main design of the solution, analyzes it through the Business Model Canvas chart and explains the workflow of the solution.

2.3.1 Solution design

PV Insight is a cloud platform that supports autonomous solar PV plant inspections with drones. On one hand, it provides automated flight plants with optimized parameters for Solar PV inspections to the drone, so the data collection is optimized and can be carried by someone without extensive knowledge on UAV piloting. On the other hand, it processes all the data collected during the flight to narrow it down to easily-accessible and trackable data that helps in the asset management of PV plants. Overall, it facilitates a better control on the panels' maintenance by facilitating an assessment on their state, using both IR and RGB imaging.

The features of PV Insight can be divided in two main blocks: the data capturing and the data processing. The main tool for the data capturing is the drone: with different payloads accepted by PV Insight, the drone can fly safely and autonomously over the solar field and collect the data needed for the inspection. The solution is capable of supporting images taken with different sensors as long as they are taken with its flight plans and following some guidelines to ensure minimum data standards. This adaptability to different payloads is thanks to the fact that, in automated flight planning, the flight parameters can be adjusted in order to ensure the same quality in the images for different sensors. The customer can then choose to do an RGB or an IR flight, or both at the same time in case he/she has a dual sensor or a drone that can support two sensors at the same time. It is also possible to select different types of flights with different data quality and flight time outputs: higher and faster flights for more general issues and closer and slower flights for specific ones. Also, the customer can select to inspect the whole plant or only a single sector, row or even panel in the plant.

For the data processing, the main tool is the cloud platform. It which integrates the algorithms that narrow down and convert all the data collected by the drones to reliable and easy-accessible key information for the decision making process of the PV plant management. The overall functionality of the platform is narrow down all the IR and RGB pictures of solar PV panels into useful information for the plant manager, such as the failure identified, the severity of the damage or which panel is having that failure (georeferenced and with an ID). All this data baked by an easy-to-navigate IR and RGB map of the plant that allows the customer to check and compare the results online with visual support, being able to change from one inspection to another to compare the results.

Regarding the ownership of the drone, a small variation has been taken into account. During the initial stages of the solution, the customer does not have to purchase the equipment since the data collection will be done by the company. This will mean a higher fee per MW for the customer during the initial inspections, but will release them from purchasing the equipment until the solution is robust enough. This is explained in more detail in the economic analysis, but its' mention is needed to understand the business model.

2.3.2 Business Model Canvas

The Business Model Canvas is a tool that helps to understand the principles behind a business. It is a visual chart that contains the essential elements to describe a firm or product's value proposition, infrastructure, customers, and finances [30]. The Business Model Canvas of PV Insight is represented in Figure 18. PV Insight Business Model Canvas. Developed with Strategyzer [31] .Figure 18.

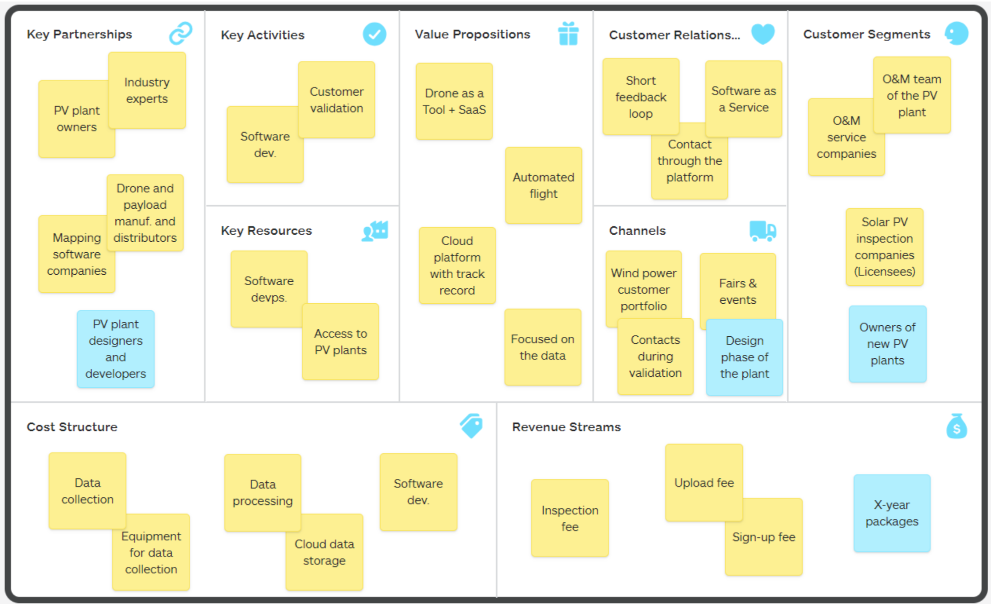


Figure 18. PV Insight Business Model Canvas. Developed with Strategyzer [31] .

The labels in yellow represent the key features of the solution. The labels in blue represent an optional business model that could be added on top of the original one in a more mature stage, and that would add a lot of value to the solution. These last labels will be explained at the end of the section, in the sub-section called *New PV Plants*.

As can be appreciated, the customer segments are the O&M team, the O&M service companies and the inspection companies. The first two are the final customers that would get access to the results of the inspection in any case. The inspection companies would do the inspections as 3rd party for any of the first two, and they could access the results as well.

The value proposition is based on the value brought to the O&M team – internal or external - of the PV plant, which is the final customer in any case. The focus on the data combined with the access to the inspections results with track record allows the customer to get a quick and effective understanding on the state of the panels and the evolution of the failures. Having the drone as a tool allows a cheaper data collection, at the same time that the software offered as a service ensures the optimum functioning of it for the application of solar PV inspections. The automated flight allows a fast and homogeneous data collection independently on the pilot. For the licensees, working with a solution that adds more value to their customer is adding value for themselves as well.

The customer relationships are based on a short feedback loop and an initial contact through the platform. The short feedback loop is meant to keep improving the features of the solution. Regarding the contact through the platform, the idea is to have a section of FAQs regarding the operation of the solution for those customers which are not yet familiar with it. In case of not being enough, a contact of the licensee or the developer – depending on the case - is also guaranteed online to be reached by phone call. The main priority is to keep the customer comfortable with using the solution by getting him supported any time it's needed.

The channels to reach new customers are diverse. First, we have the company's existing wind power customer portfolio, in which most customers also have assets in solar PV. Second, all the contacts done during the validation are useful and it's possible to already distinguish which ones are more fitted for being the early adopters of the solution and which are better to be reached once the solution is robust. Finally, fairs and events related with solar PV and O&M are always a good chance to expose the solution and awake curiosity.

The revenue streams come at the first stages of the solution from the inspection fees, which will turn into signup and upload fees as the solution matures. For the licensees, the margin to be charged will be equivalent to the upload fee. The signup fee has two means: first, to get a revenue for the time and resources spent in signing up the customer's profile online and in the first inspection where more processing needs to be done; and second, increase the customer's fidelity (if the customer has already payed to be online it's more probable that it will use the tool in future surveys).

The key partnerships are divided in those valuable for the development of the solution and those valuable for the commercialization. For the development, industry experts and PV plant owners are key for understanding the market and testing our solution in real field. For the commercialization, the mapping software companies are key in case we don't manage to do the mapping with open-source tools and the manufacturers and distributors of drones and sensors can be very useful partners for lowering costs of equipment in exchange of expanding their market.

The most important key activity is the customer validation. It is first priority to keep feeding the validation loop even when the solution is robust, and keep flexible to the experience that the customers are getting with it. Software development is key for building up the solution, as well as for innovating and applying the feedback loop. Key resources are then software developers and the access to PV plants; first one for developing the software and second one for testing it.

The cost structure is divided into costs for data collection in the initial stage and the costs of data processing all-through the business plan. The costs for data collection are basically the operational costs plus the cost of the equipment needed. The costs for data processing are mainly for processing the images of the data collection, plus a small part related to the cost of having the solution and the data on the cloud. Software development costs are very important to keep innovating in the solution.

New PV plants

The business model for targeting new projects of PV plants in a design or development stage is the same but needs some components to be added on top. The motivation for going to this market as well is basically being able to fit the solution inside the CAPEX of the PV plant as temporary agreements, since the budgets for CAPEX are much bigger than those for OPEX. This idea was actually introduced by an expert in solar PV that works in the design phase of solar PV plants.

The first main component to be added is the new customer segment, owners of new PV plants, which will be reached in the development stage of the PV plant. A key partnership to reach them are companies focused on the design and development of solar PV plant projects. This new business model will add an extra revenue stream that will be the packages of x years of usage of the solution of Pro-Drone with a discount in the price in exchange for the fidelity.

2.3.3 Solution workflow

The business model explained is backed on a workflow that ensures the well-functioning of it, specifying the tasks done by the developer and the tasks done by the customer. Figure 19 shows the workflow chart for the final solution, without taking into account the initial stage in which the developer does the data collection as well.

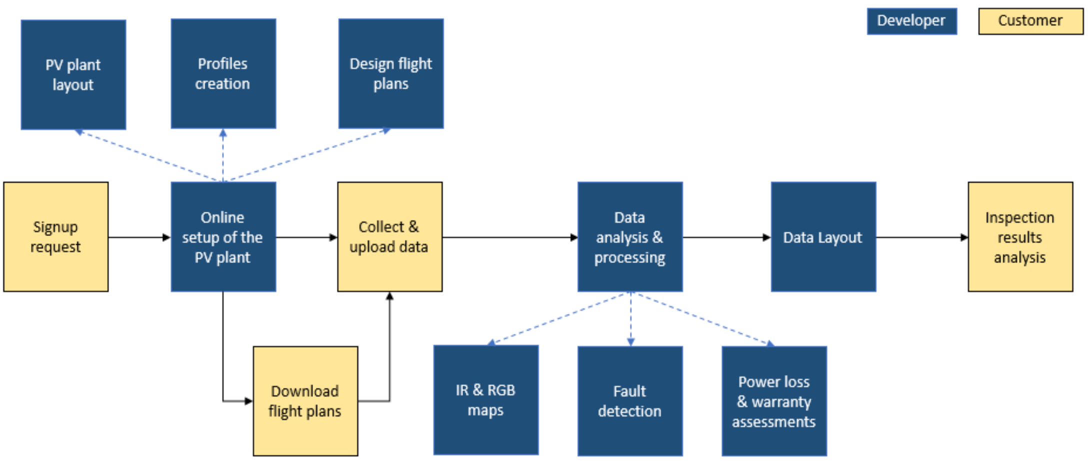


Figure 19. PV Insight workflow.

The business workflow starts with the customer requesting to sign up its PV plants in the platform. The team of Pro-Drone develops then the digital display of the plant and generates the flight plans to inspect it. Once the plant is online, the customer can download the flight plans and use them on the drone to collect the IR and RGB pictures, which will later be uploaded on the platform to be processed, synthesized and displayed. The revenue stream comes from a signup fee plus a fee per data processed on the platform. Both fees are based on a per MW price: in the case of the signup fee, the base is the PV capacity that is requested to be signed up online; in the case of the upload fee, the base is the PV capacity that has been inspected and is uploaded and processed.

For the initial stage of the solution in which the developer carries the data collection, the signup request is an inspection request and the steps of downloading flight plans and collecting and uploading data are done by the developer. The only part done by the customer is the analysis of the results.

Having clarified final solution design, the design thinking phase of the solution is over. The next chapter describes the technical development of this solution, explaining the main reasoning behind the data processing and showing the results of the first tests of data collection and processing in a PV plant in Portugal.

3. Technical Development

This part of the thesis describes the technical structure of the solution, based on the concepts described in the design phase. The solution to develop is a cloud platform that generates flight plans and processes the images to provide the customer directly with the important information to be analyzed. This section explains the reasoning behind the technical design of the solution for data collection, and the data processing developed by the author of the thesis, which is the temperature data analysis model developed in Python.

3.1 Data Collection

For data collection, as explained in the business part, automated flights are used. This means that the drone will be flying autonomously over the solar field, collecting pictures of the panels. In this case, the drone is a mere carrier of the most important component of the data collection: the sensor. As has been discussed previously in the document, this sensor can be IR, RGB or dual.

For ensuring an appropriate use of the sensor during the automated flight, some important flight parameters need to be calculated and set. Section 3.1 describes the optic and flight calculations that need to be done to set an automated flight. From these variables, and the area in that needs to be mapped, the software can extract the flight paths and the details regarding the flight, such as the number of pictures taken, the total flight time…etc. At the end of the section, an automated flight with the calculated parameters is simulated with Mission Planner.

Those calculations depend on the characteristics of the sensor. In our case, the chosen sensor for the calculations is the FLIR Duo Pro R, which is a dual sensor (RGB and IR) and is shown in Figure 20.

Figure 20. FLIR Duo Pro R [32].

3.1.1 Sensor Optics

The first step towards defining the parameters for the automated flight is related with the sensor optics. The principles behind the math have to do with the dimensions of the sensor projected to the ground through the lens from a given height and with a given angle. Figure 21 shows the main dimensions playing a role in the calculations.

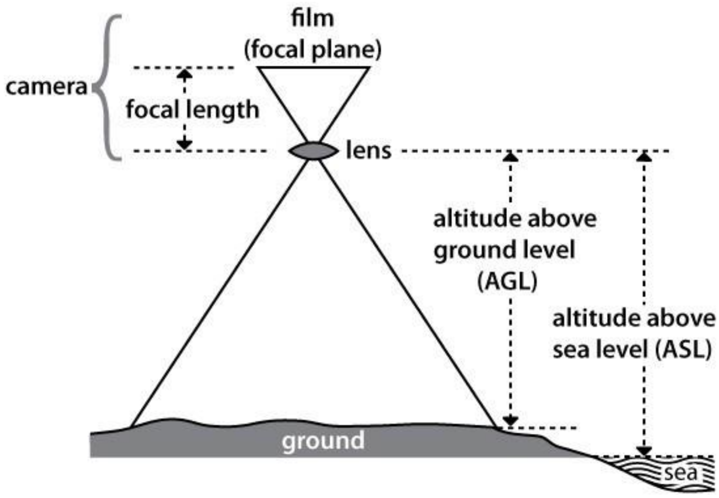


Figure 21. Optic scheme of an aerial image [33].

The focal plane is commonly referred as sensor width. The angle attached to the lens is the field of view (FOV), which has a horizontal and a vertical component – it must be taken into account that the picture is a square on the ground and not a line, like projected in the image. In our case, the height that has been taken into account is directly the altitude above the ground level and the elevation that the solar panels can have in comparison to the ground level has been neglected. In case there is any, the object will be closer and the resolution of the image will be better so it is not a limiting factor.

Sensor Dimensions

The first step in calculating parameters for data collection is determining the dimensions of the sensor, which are the focal length, the sensor width and the field of view. They are all usually provided by the manufacturer, but in some cases the sensor width needs to be calculated with trigonometry. Equation (1) describes de calculation [34]:

$$S_w = 2 * F_R * \tan\left(\frac{FOV_H}{2}\right) \quad (1)$$

Where S_w is the sensor width in millimeters, F_R is the focal length of the camera in millimeters and FOV_H is the horizontal field of view in radians.

Another parameter that plays a role in the optics of the data collection is the image resolution of the sensor, which specifies the amount of pixels that are disposed inside an image. For the sensor selected, there are two different resolutions, each of them offering different configurations of focal length and field of view. Table 2 disposes the optic parameters for every configuration of the sensor. Since the sensor width was not given in the data sheet, it has been calculated using equation (1).

Image resolution [pixels]	F_R **[mm]**	FOV_H **(°)**	S_w **[mm]**
336 x 256	9	35	5.7
	13	25	5.8
	19	17	5.7
640 x 512	13	45	10.8
	19	32	10.9
	25	25	11.1

Table 2. Sensor characteristics.

Ground Sample Distance (GSD)

Once the dimensions of the camera are specified, the dimensions on the ground need to be analyzed. This is a key parameter to select a configuration of the sensor and determine a height at which the drone will be taking the pictures. The flight speed is also affected by the GSD.

First step is defining the minimum size to be visualized in the images; in other words, the smallest failure that needs to be identified. In this case, there are two different sizes of default: the size of the defaults in the IR imaging and the size of the defaults in the RGB. As explained previously, the type of sensor selected in this case is a dual sensor and, hence, RGB and IR imaging will be collected in the same flight. Considering that IR sensors usually have a lower resolution than RGB – specially in dual cameras -, it can be stated that the flight parameters for IR will be the limiting factor in a dual data collection, which is the case selected. Being considered so, the first step is to assess what's the minimum sample size of a failure detected in IR.

According to the different configurations of hotspots failures shown in Figure 12, the smallest hotspot to be detected in an IR image has the size of part of a solar cell. In other words; the minimum thing that would need to be seen in an IR picture is that half of a cell is at a different temperature than the other half. Hence, the size of the smallest default is half of a solar PV cell. Knowing that the standard measures of a solar cell are 15 per 15 centimeters, we can consider that the size of the minimum failure to see is a square of 7.5 per 7.5 centimeters.

The size of the minimum failure determines the area covered by one pixel in the image. In terms of imaging, this parameter is called Ground Sampling Distance (GSD), and in our case it needs to have a value of maximum 7.5 centimeters per pixel. The equation to calculate the GSD is described below [35].

$$GSD = \frac{100 * S_w * H}{F_R * Im_w} \tag{2}$$

Where GSD is the ground sample distance in centimeters per pixel, S_w is the sensor width in millimeters, H is the height in meters, F_R is the focal length of the camera in millimeters and Im_w is the width of the image, in pixels, which is the horizontal component of the image resolution.

As can be appreciated, the equation of GSD depends directly on the sensor used and the height from which the picture is taken. Knowing already the sizes of the sensor, the only parameter left to calculate the GSD is the flight height. This calculation is explained in the section of flight parameters.

3.1.2 Flight Parameters

The equations for calculating sensor characteristics and image resolution are needed for calculating the most important part of our data collection: the flight parameters. By determining the flight altitude and the flight speed, we can already assess with automated flight software how much time will the flight take and how many pictures will be required to be taken. This will determine the logistics for the data collection.

Flight altitude

The first flight parameter to estimate is the maximum flight altitude at which the drone can fly to acquire the GSD desired. The flight altitude for UAVs has a legal limit of 121 meters in most of the countries and the methodology to estimate it is by trying different values of height and seeing the different GSDs for each one of the values, choosing then the closest value to the preset maximum. It has to be taken into account that less GSD means a better resolution in the image but at the same time means a lower flight, which enlarges the distance covered by the drone and the duration of the flight. Another consideration to take into account for this calculation is that the dimensions of the sensor affect the value of the GSD, so there will be different GSDs for different sensor dimensions at the same height.

The height at which the picture is taken influences as well the coverage in meters of ground surface inside the picture. The rectangular area that the image is covering on the ground can be calculated with equations (3) and (4).

$$D_w = \frac{GSD * Im_W}{100} \tag{3}$$

$$D_H = \frac{GSD * Im_H}{100} \tag{4}$$

Where D_w and D_H are the horizontal and vertical distances covered in the image in meters, respectively, GSD is the ground sample distance in centimeters per pixel and Im_w and Im_H are the width and height of the image in pixels, respectively –which is the same as the horizontal and vertical component of the resolution.

To cover all this calculations, different heights have been tried for different sensor configurations. The results are summarized in Table 3. Highlighted in green are those values that are under the GSD limit of 7.5 cm per pixel.

Image resolution [pixels]	**Height [m]**	**F_R [mm]**	**GSD [cm/pixel]**	**D_w [m]**	**D_H [m]**
336 x 256	25	9	4.7	16	12
		13	3.3	11	8
		19	2.2	7	6
	50	9	9.4	31	24
		13	6.6	22	17
		19	4.4	15	11
	75	9	14.0	47	36
		13	9.9	33	25
		19	6.7	22	17
	100	9	18.8	63	48
		13	13.2	44	34
		19	8.9	30	23
640 x 512	25	13	3.3	16	12
		19	2.2	14	11
		25	1.7	11	9
	50	13	6.5	22	17
		19	4.5	29	22
		25	3.5	22	18

	75	13	9.7	62	50
		19	6.7	43	34
		25	5.2	33	27
	100	13	12.9	83	66
		19	9.0	57	46
		25	6.9	44	35

Table 3. GSD and distances in the image for different heights and resolutions.

The table shows that the low resolution only allows to fly up to 75 meters, whereas the high one allows flights up to 100m. The question stays there on which resolution to choose, the high one flying high or the low one flying closer to the panels. Of course, a higher resolution means a higher price of the sensor, but it has some key advantages, related with the dimensions covered by the image on the ground.

The size of the image captured is a way of computing how many images will the drone need to take to cover a given area. This can imply two different limiting factors, for two different cases. First, if the drone needs to stop every image – the so called flight with hovering - it will take a lot more time to carry a flight that requires a large quantity of images. Second, the smaller the image is, the faster the camera needs to shoot to cover a determined area – feature known as shutter speed -; this is a common limiting factor when deciding for one sensor or another, since it’s usually in the limit of the minimum. Hence, it is highly appreciated not only that the resolution is enough, which is of course the most important parameter, but also that the sensor does not need to shoot too fast. Another reason that plays an important role in this decision is that the higher the flight, the lower the distance covered by the drone and the lower the flight time –with or without hovering.

This reasons state that it is more interesting to choose the 640 per 512 resolution, despite the higher price. With this resolution, the height at which the drone can fly is somewhere between 50 and 100 meters, depending on the focal length. The focal length of 25 millimeters offers a higher flight at more or less the same GSD, but that configuration is strange to find in distributors and usually needs to be shipped from the headquarters of FLIR, in the US, increasing the shipping costs. Also, the sensor itself is more expensive than the one of 19 millimeters. Hence, a focal length of 19 millimeters is chosen.

To sum up, the chosen sensor is the FLIR Duo Pro R with a resolution of 640 per 512 and a focal length of 19 millimeters, which will allow the drone to capture data from a 75m height with an expected GSD of 6.7 centimeters per pixel. Given the fixed value of the GSD, the maximum flight speed can be calculated.

Flight speed

Another input to give for calculating the flight plan of the automated flight is the speed at which the drone is going to be flying. As the speed increases, the quality of the images taken is lower but the flight time is lower as well. A too fast speed might also interfere with the shutter speed of the sensor, the speed at which a picture is taken.

Equation (5) reflects the calculation [36]:

$$v = \frac{b * GSD}{t} \tag{5}$$

Where v is the flight speed in centimeters per second, b is the blur in pixels, GSD is the ground sample distance in centimeters per pixel and t is the shutter speed of the sensor in seconds.

It is recommended that the blur does not exceed a value of 0.5 pixels. Over this value, the data collected could be distorted; hence, the value of the blur is fixed at 0.4. Regarding the shutter speed, the value for the given sensor is of 10 milliseconds, which is equivalent to 0.01 seconds. Given a value of the GSD of 6.7 centimeters per pixel, the flight speed value is of 268 centimeters per second, which is equivalent to 2.68 meters per second.

Flight altitude and speed are not the only parameters needed to be fixed in order to ensure a good data collection. Other parameters, such as the angle from which the sensor is taking the pictures, are required as well. These parameters depend on different factors and different recommendations have been found regarding the configurations that should be used for a good data collection. Hence, these parameters will require to be tested on the field, as is explained in Section 3.3 Real Data Collection and Processing – Field Tests.

The wind is another parameter that affects data collection. Drone systems, however, are designed to be able to fly under certain wind conditions, and set maximum values for wind speed at which the drone can carry the data collection. Drones operated with automated flight paths automatically correct path deviations due to wind, but high values of wind – even if under the maximum values - can affect the quality of the images, since the sensor might shoot when the drone is correcting and, hence, moving.

3.1.3 Flight Simulation

Once fixed the initial parameters, it is possible to simulate the flight and estimate how much time would it take a multi-copter drone to collect data over a PV field. To do that, the open source tool MissionPlanner has been used. The input parameters are resumed in Table 4.

Height [m]	Sensor Resolution [pix]	Sensor Focal length [mm]	Blur [pix]	Speed [m/s]
75	640 x 512	19	0.4	2.68 ~ 3

Table 4. Flight simulation input values.

The speed is considered as 3 m/s since the software does not allow decimal numbers. The plant selected for the simulation is located in Portugal and has a capacity of 6.2 MW and an approximated area of 20 hectares. It's the PV plant of Porteirinhos, property of the Portuguese utility Generg. Figure 22 shows an image of the grid created for the automated flight with these parameters.

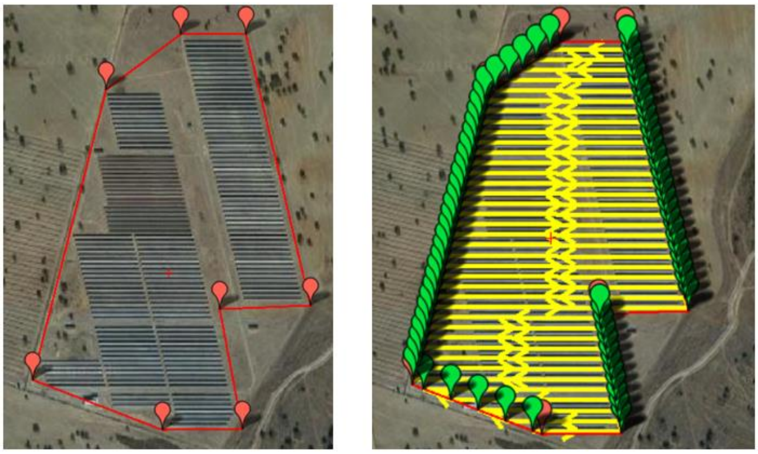


Figure 22. PV plant without and with flight grid. Extracted from MissionPlanner [37].

The grid shows the way that the drone will follow during the flight with those parameters. The red points are the delimiters of the area, the green points indicate where the drone will turn and the yellow lines are the path. The output does not take into account the model of drone used and, hence, the time for battery swapping is not taken into account. The results of the simulation are summarized in Table 5.

Flight time	GSD [cm/pix]	Number of pictures	Picture every [s]
1h 24min	6.71	670	5.73

Table 5. Flight simulation results.

With these results, it can be stated that the calculations done previously regarding the GSD are correct; with this sensor resolution and focal length, the GSD is the same as the value in Table 3. Taking a look at the time, it can be estimated that, in this case, every MW of data collected would take around 13 minutes of flight time; that is, the time that the drone would be in the air. This time is obviously bigger for the overall data collection, since this value does not take into account all the time spent in logistics for preparing the flight and swapping/charging batteries. This parameters require field testing for a proper valorization but the results of the simulation suggest that, overall, the data collection for this specific PV plant could be carried out in one morning.

3.2 Data Processing

The technical development of the solution for data processing involves many different aspects:

- Development of the cloud platform, which is the main working interface for the company, for an inspector that uses the solution to provide a survey and for the final customer, considered as the O&M team of the PV plant.
- Mapping applications and classification model. The mapping applications are used to generate the IR and RGB maps from the images collected. There is open-source software for mapping -such as ODM- and payed licenses from private companies, like Pix4D or DroneDeploy. The classification model is based on a QGIS model that runs on top of the IR and RGB maps to identify and classify the panels inside the image, reading the temperature data in the IR map and generating tables of temperature values that can be extracted in a CSV file.
- In the end, there is the analysis of the temperature data provided by the classification models, through data science integrated in a Python code that analyzes the statistical temperature values, such as maximum, minimum and average, for the different panels in the given CSV file, extracted directly from the QGIS model.

The three parts of the technical development are developed by different members of the team. Given the focus of this master thesis on fault detection in PV panels and the influence of temperature in its power production, the part that has been developed by the author regarding the data processing is the analysis of the temperature data to assess the inspection results with Python. The other two parts are developed by others and are then out of the scope and analysis of this master thesis.

3.2.1 Temperature Data Analysis With Python

The goal of the temperature data analysis is to check the numerical temperature data inside each panel and transform it into valuable insights for solar PV managers. In order to do this, the scripts developed in Python work on three different aspects:

1. Estimate if the panel has a defect or not. This is checked by comparing the maximum temperature and the average temperature of the panel. If the difference is over a given parameter, the panel is set as defect.
2. Assess the power lost due to thermal differences inside the panel. By taking a look at the minimum temperature of the panel, which represents the lowest temperature value at which the panel can work, and comparing it with the average temperature, the average electric loss of the panel due to temperature gradients inside can be estimated. This takes into account that the average is higher than the minimum due to severe or moderate hotspots that have an effect on the average temperature of the panel.

3. Assess which panels could be exceeding warranty conditions of power production. By knowing the power losses in the panels, it is possible to estimate which panels could be producing power under the warranty conditions. The warranty conditions of the panels are published online by the manufacturers.

It is important to state that all three outputs are given as assessments and not as final diagnostics. In this case, it is important to understand that the scripts do not provide absolute truths but estimations that need to be validated by a human being in order to give the final diagnostic. The overall goal of the script is to save time in human data analysis, not to eliminate it.

The first aspect adds value to the inspector of the IR map, who has to define which panels are defect and which not. By having a first estimation of the ones that have temperature inconsistencies, it sets the first filter on the panels that might be having defects.

The second aspect identifies the overall power losses of the data set due to inconsistencies in temperature values inside a panel. By having an estimation on the power lost by each one of the panels it is easy to identify which panels might be causing power production drops in a given array. Taking into account that a technician on foot will have to go to the location of the panel, this could save time by directing him/her directly to the panels that are suspicious to be losing power. Once there, he/she will be able to measure the power losses of the panels with and I-V meter and check if the predictions are correct or not. In any case, a huge amount of time can be saved by avoiding to analyze as well all the panels that seem to be alright.

In the third aspect, the model combines the results of the other two to assess which modules could be presenting significant defects that drop down power production under the minimum value warranted per module. In case the panel production is not according to the values set by the warranty conditions, the manufacturer should provide a new panel for free.

Section 3.2.1 Temperature Data Analysis With Python explains the way the model developed reads the data, processes it with mathematical equations based on physical principles, and overwrites the original document to feed it with the results. The model is written in Python.

Introduction to Python and pandas for data science

Python is a programming language that has won popularity in the recent years due to its intuitive structures, extensive libraries and easiness to use. This quote from its website defines it perfectly:

“Python is an easy to learn, powerful programming language. It has efficient high-level data structures and a simple but effective approach to object-oriented programming. Python’s elegant syntax and dynamic typing, together with its interpreted nature, make it an ideal language for scripting and rapid application development in many areas on most platforms” [38].

In the scope of this work, Python has been identified as a very interesting language for developing the automated analysis of tabular temperature data through data science. For the data analysis, the *pandas* library has been used. The following quote defines this library:

> "*Pandas* is an open source, BSD-licensed library providing high-performance, easy-to-use data structures and data analysis tools for the Python programming language" [39].

This library has been very useful since it has functions specifically designed for reading data from CSV files in an organized and intuitive way for the user, as well as functions for overwriting the file with the results of the analysis. In the code, *pandas* helped to iterate through the CSV file to read the temperature data, and then overwrite the file with the results.

Raw data

For all the different analysis, the raw data is a CSV file with the temperature data in a tabular format. The document is structured as follows: the rows are panels analyzed and the columns are the different data in the panel, such as temperature maximum, minimum and average. The code analyzes the information in the file, processes it and writes the results on the same document, in new columns at the right of the existing ones.

Model architecture

The model for the temperature data analysis is structured to iterate through each row in the file to check each one of the aspects explained; so to say, check if each one of the panels is defect or not, how much power could it be losing due to the thermal phenomenon and, in case the panel is set as defected, if this power loss could infringe warranty conditions. Then, it moves to the next row, summing up the values of power losses and real useful power for that row into cumulative variables. Once the iteration is over, the final results are given.

Figure 23 depicts the architecture of the Python code.

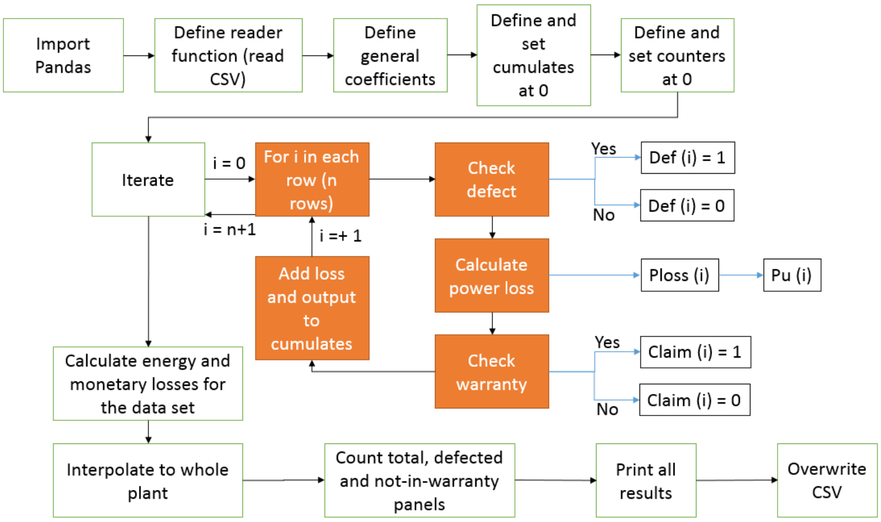


Figure 23. Python code architecture.

As can be observed, the *pandas* function to read the CSV is defined at the beginning as a variable. From then on, every time that data from the CSV needs to be read, the variable is called and, hence, so is the *pandas* function to read the data. The model works with the data that is reading, creating a table inside the console that does not overwrite on the CSV file until the end, when another *pandas* function to overwrite the CSV is called.

Fault detection estimation

For detecting faults in the panels, the model analyzes the temperature records in the panel and follows the same logic as in visual inspections of IR imaging on solar PV panels: look for the hot spots. A hot spot is a part of the panel that is operating at a higher temperature than the rest of it, called so because it appears as hotter in the IR image.

A hot spot creates a distortion in the temperature distribution of the panel. Usually, most of the panel temperature values are grouped around the average, following a normal distribution profile. However, when a hot spot appears in the panel, the distribution is doubled and catches two different means in the plot: one around the operating temperature and one around the hot spot temperature.

Figure 24 depicts this phenomenon. It is based on a fictitious IR image on two different panels, being panel 1 healthy and panel 2 defected. The figures are created artificially with distribution curves in Python but depict reasonably how the temperature distribution in the panels would look like, basing on the number of pixels at given temperature values in the IR image.

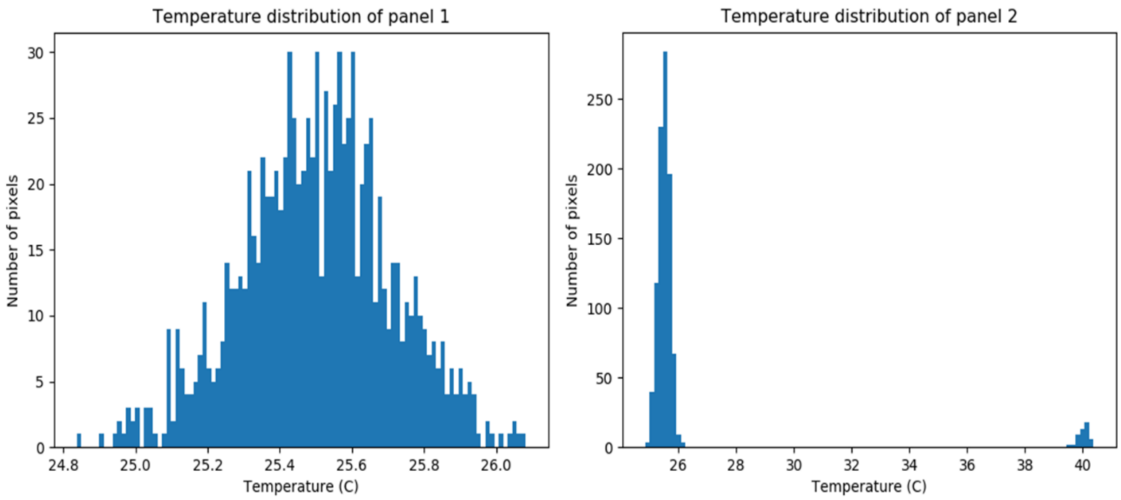


Figure 24. Temperature distributions for different PV panels. Plotted in Python.

The causes of a hot spot are diverse, but they all express a power loss inside the solar cell that creates a temperature gradient with the other cells inside the panel. In some cases, the hot spot can be inside a single cell, dividing it in different temperatures. Equations (6) and (7) define the criterion used for detecting defected panels.

$$T_{max} - T_{avg} > 1°C \tag{6}$$

$$T_{max} > 35°C \tag{7}$$

In the model, a panel is considered as defect if the difference between the maximum temperature and the average temperature of the panel is higher than 1°C (meaning it has a hot spot), or the panel registers a maximum temperature higher than 35°C (meaning it's overheated). The reason for the hot spot detection is based on real image analysis during our field tests: the minimum temperature gradient found in panels with hotspots in the data set analyzed was of 1°C. When a panel is selected as defect, the variable of defect is set as 1; otherwise, it is set as 0. The variable is printed as an extra column at the end of the csv table.

Figure 25 depicts the criterion followed in equations (6) and (7):

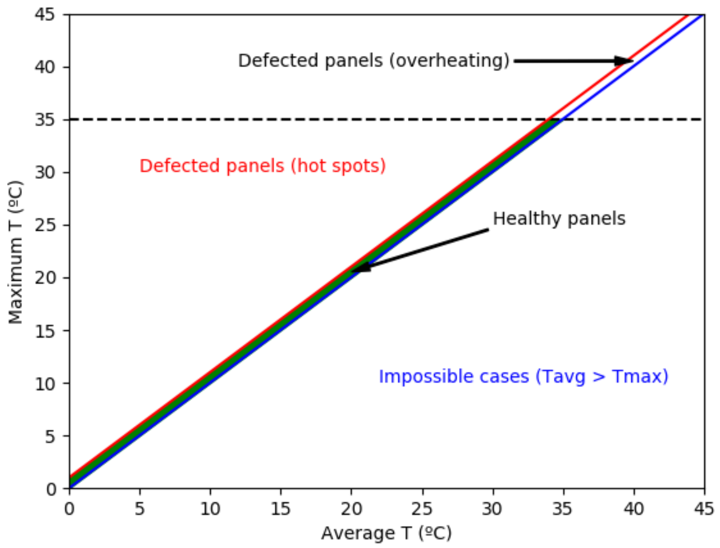


Figure 25. Panel classification by maximum and average temperature values. Plotted in Python.

As can be observed, all cases at the right of the blue line have been discarded since the average value of the panel can never be higher than the maximum. All panels located on top of the dotted line are also considered as defected (overheating criterion), as well as all panels left of the red line (hot spot criterion). The healthy panels are those located in the green region between these three lines.

Power production loss assessment

Apart of detecting which panels are defect, it is important to assess how much power is being lost due to the temperature gradients inside the panels. In this analysis, all panels – defective and healthy - have been considered in order to get to know the impact of this phenomenon in all the panels of a given system.

The photovoltaic temperature coefficient of power indicates the dependence in between the PV array power output and the cell temperature, measured at the surface of the PV array [40]. This coefficient depends on the model and manufacturer of the module [41]. For every Celsius degree over the STC (25°C, 1 atm) the efficiency of the PV panel decreases and, hence, so does the power output.

To calculate the power loss due to temperature gradients, the maximum power at which a specific panel can be producing energy and the real useful power at which the panel is actually producing energy need to be calculated, all based on the statistic temperature data of the panel. The first step is to calculate the power consumed by using equation (8).

$$P_c = \frac{P_u}{\eta_{panel}} \tag{8}$$

Where P_c is the power consumed in watts, P_u is the useful power in watts and η_{panel} is the efficiency of the panel, at a unit base. The values taken into account here are the useful power and the theoretical efficiency of the panel, both given by the manufacturer at Standard Test Conditions (STC) in the datasheet or specs sheet of the panel. This power consumed is needed to calculate the maximum useful power, as explained in equation (9).

$$P_{u,max} = P_c * \eta_{max} = P_c * [\eta_{STC} + (T_{min} - T_{STC}) * TC] \quad (9)$$

Where $P_{u,max}$ is the maximum useful power that a given panel can produce – given its minimum temperature - in watts, P_c is the power consumed in watts and η_{max} is the maximum efficiency of that panel at a unit base. To calculate η_{max}: η_{STC} is the efficiency at STC at a unit base, T_{min} is the minimum temperature of the panel in °C, T_{STC} is the temperature at STC in °C (25 °C) and TC is the temperature coefficient in units per °C.

Once the maximum useful power is calculated, it is possible to calculate as well the real useful power of that panel, basing on the temperature difference between the minimum and the average, as shown in equation (10).

$$P_{u,real} = P_c * \eta_{real} = P_c * \left[\eta_{max} + \left(T_{avg} - T_{min}\right) * TC\right] \quad (10)$$

Where $P_{u,real}$ is the real useful power in watts, P_c is the power consumed in watts and η_{real} is the real efficiency of the panel at a unit base. To calculate η_{real}: η_{max} is the maximum efficiency of that panel at a unit base, T_{avg} is the average temperature of the panel in °C, T_{min} is the minimum temperature of the panel in °C and TC is the temperature coefficient in units per °C.

Once we know the maximum useful power of the panel and the real useful power of that panel, the power loss is a very simple operation. It is expressed in equation (11).

$$P_{los} = P_{u,max} - P_{u,real} \quad (11)$$

Where P_{los} is the power loss in watts, $P_{u,max}$ is the maximum useful power that a given panel can produce in watts and $P_{u,real}$ is the real useful power in watts.

Once these calculations are done for a given panel, the values of P_{los} and $P_{u,real}$ are added to the cumulated variables for analyzing the overall losses and useful power of the data set. At the end of the iteration, those variables express the power losses in the data set, and the theoretical useful power given those power losses.

For calculating the cumulated losses and cumulated useful power of a data set, equations (12) and (13) are used.

$$P_{los,cum} = \sum_{i=0}^{n} P_{loss}^{i} \quad (12)$$

$$P_{u,cum} = \sum_{i=0}^{n} P_{u}^{i} \quad (13)$$

Where $P_{los,cum}$ are the cumulated power losses in watts, P_{loss}^{i} are the power losses of a given panel in watts, $P_{u,cum}$ is the cumulated useful power in watts and P_{u}^{i} is the useful power of a given panel in watts. n is the total number of panels in the data set.

Warranty assessment on defected panels

Once calculated the power lost, it is possible to assess if a defected panel is covering warranty conditions or not. For that, some previous calculations need to be done regarding the warranty conditions from the manufacturer. For the data found, the usual way of giving those conditions is by giving the minimum power output of the panel as a percentage of the theoretical useful power expressed at the specs sheet. This percentage usually decreases along the lifetime of the PV panel, and this decrease is reflected in the warranty minimums. Hence, the minimum power output given by the warranty differs depending on the age of the panel.

Equation (14) expresses how to calculate this minimum useful power under warranty conditions.

$$P_w = P_u * f_W \quad (14)$$

Where P_w is the minimum warrantied power in watts, P_u is the useful power in watts and f_W is the coefficient of the warranty at a unit base.

Once P_w is calculated, it is compared to $P_{u,real}$ to check if the power losses inside the panel could be affecting the warranty conditions of the panel. The criterion to identify panels that are not covering warranty conditions is expressed in equation (15).

$$[\mathit{Classification} = 1] \text{ AND } [P_w > P_{u,real}] \quad (15)$$

The variable *Classification* expresses if the panel has been set as defected (=1) or not (=0) by the automatic inspection. Since the default classification is done before the warranty assessment, it is possible to do both in the same iteration. The reason why this variable is set as a premise for the warranty analysis is because the goal of the assessment is to identify those panels not covering warranty conditions due to hot spots.

In case both premises in equation (15) are true, then the panel is set as claimable for warranty conditions by setting the binary variable at 1. Otherwise, the binary variable stays at 0.

Final calculations

After iterating through all the panels in the dataset, the next step is no analyze the results of the inspection. For that, the model takes the cumulated variables of power lost and useful power and computes the financial impact of these losses, assessing the fraction of revenues that is lost due to thermal inconsistencies in the panels.

For doing these calculations, some parameters need to be fixed previously regarding the electricity market price, the type of technology and the model of solar PV panel used. Table 6 resumes these parameters.

Parameter	**Variable**	**Depending on**	**Value**
Capacity factor	C_f	Type of technology (solar PV)	0.2
Price of electricity	p_{el}	Country	0.05 € / kWh
Total hours in the year	h_{year}	-	8640 hours

Table 6. Parameters for final calculations.

The price of electricity has been estimated by looking at different PPA prices in the last years, and taking into account that most of the PV plants in Portugal are around 10 years old [29][42]. Knowing these values, the calculations done to estimate the economic losses are described in equations (16) and (17).

$$L_{system} = P_{los,cum} * h_{year} * C_f * p_{el} \tag{16}$$

$$L_{system}^{rel} = \frac{L_{system}}{R_{system}} = \frac{P_{los,cum} * h_{year} * C_f * p_{el}}{P_{u,cum} * h_{year} * C_f * p_{el}} = \frac{P_{los,cum}}{P_{u,cum}} \tag{17}$$

Where L_{system} are the yearly monetary losses of the system in euros, $P_{los,cum}$ are the cumulated power losses in watts, h_{year} is the number of hours in a year, C_f is the capacity factor on a per unit basis, p_{el} is the electricity price in euros per Wh, L_{system}^{rel} are the relative losses of the system on a per unit basis, R_{system} are the yearly revenues of the system in euros and $P_{u,cum}$ is the cumulated useful power of the system in watts.

Once the losses of the system analyzed are known, those are extrapolated to the whole PV plant. For that, it is taken into account the average loss per MW installed in the plant and multiplied per the total power capacity installed in the plant. Equations (18), (19) and (20) are used.

$$P_{loss}^{plant} = \frac{P_{los,cum}}{n_{panels} * P_u} * P_u^{plant} \tag{18}$$

$$P_{loss,rel}^{plant} = \frac{P_{loss}^{plant}}{P_u^{plant}} = \frac{P_{los,cum}}{n_{panels} * P_u} \tag{19}$$

$$L_{plant} = P_{loss}^{plant} * h_{year} * C_f * p_{el} \tag{20}$$

Where P_{loss}^{plant} are the losses in the PV plant in watts, $P_{los,cum}$ are the cumulated power losses in watts, n_{panels} is the total number of panels in the data set, P_u is the useful power of one panel in watts, P_u^{plant} is the useful power of the plant in watts, $P_{loss,rel}^{plant}$ are the relative losses of the plant on a per unit basis, L_{plant} are the yearly economic losses of the plant in euros, h_{year} is the number of hours in a year, C_f is the capacity factor on a per unit basis and p_{el} is the electricity price in euros per Wh. For estimating the number of panels in the set, the code reads and counts the number of rows in the CSV file, subtracting one for the indexes.

Once the yearly economic losses of the whole plant are calculated, these are compared with the yearly budget that the PV plant has for O&M, which is estimated to be around 20€ per kW installed [43]. The equations used are (21) and (22).

$$B_{O\&M} = P_u^{plant} * \frac{20}{1000} \tag{21}$$

$$L_{O\&M}^{rel} = \frac{L_{plant}}{B_{O\&M}} \tag{22}$$

Where $B_{O\&M}$ is the yearly budget for O&M in euros, P_u^{plant} is the useful power of the plant in watts, $L_{O\&M}^{rel}$ are the relative losses in comparison to the O&M budget and L_{plant} are the yearly economic losses of the plant in euros.

Output

The output of the script is divided in two different blocks: on one hand, there are the values calculated for each one of the panels, and on the other hand the analysis of the system and extrapolation to the whole PV plant. Each one of them is expressed in a different output:

- Values for each panel: they are printed in the CSV as new columns at the right of the last column of data, adding the values of the defect and warranty classifications as binary variables (1 positive, 0 negative), and the values of power output and power loss as integers.
- Results of the system and PV plant assessment: they are shown in the console as printed lines, customized with text to make the results understandable.

Validation of the code

In order to validate that the code was working properly, it needed to be validated with a data set. Since the real data set was not available until the end of July 2018, a fake data set was created with Python as well, creating a CSV that had panels as rows and whose temperature values were ranged random integers. Once the code was tested with that data set and proved to work correctly, it was ready to be tested with a real data set.

3.3 Real Data Collection and Processing – Field Tests

3.3.1 Real Data Collection

In July 2018, real IR and RGB images of panels in a solar PV plant in Portugal were collected. The plant was property of a company reached during the validation of the solution interested in collaborating in the development of it. Some tests to carry on the plant regarding the logistics of data collection were planned, with the goal of obtaining the first piece of reliable data to process. The equipment used for this first real data collection is not the same as considered in the optics calculations, since it was decided to be rented to mitigate financial risks and the those components are not available for renting in Portugal at the moment. The drone and sensor used are described in Table 7.

Drone model	DJI Inspire 1
Weight (without payload)	2.845 kg
Maximum Takeoff Weight	3.5 kg
Maximum Flight Time (without payload)	Approx. 18 min
IR Sensor Model	DJI Zenmuse XT
Resolution	336 x 256
Focal length	9 mm
Weight	0.27 kg
Expected New Flight Time	Approx. 15 min
Max. Height for IR GSD < 7.5 cm	40 m
RGB Sensor Model	DJI Zenmuse X4s

Table 7. Characteristics of the equipment rented [44][45].

The disadvantages of this equipment in comparison with the equipment selected in the calculations for data collection are significant. First, the sensor is not dual so different flights for IR and RGB need to be carried. Second, the characteristics of the IR sensor do not allow a high flight, which would cut down significantly the flight time. For this gamma of sensors, the selected one has the lowest resolution and a short focal length. However, the drone supports automated flight plans so the different parameters calculated were tested.

Figure 26. Real data collection over a PV plant.

The tests were carried on and the data collected after one day of testing. The flight parameters were tested, some corrections were done, and the first piece of IR and RGB data over a solar field was acquired. The IR images were taken at a height of 25 meters, whereas the RGB were taken at 40 meters.

3.3.2 Real Data Processing

After the data collection, the first step in the processing is to process the images into RGB and IR maps. On top of those, the classification model is run and the temperature data is extracted from the IR map. Figure 27 shows the visualization of the map with the temperature data in the software used for the image classification model. Despite the model shown is not inside the scope of this master thesis and has not been developed or used by the author of this work, it was considered interesting to show it in order to get a visual picture of the results on image processing, and help to understand the overall process.

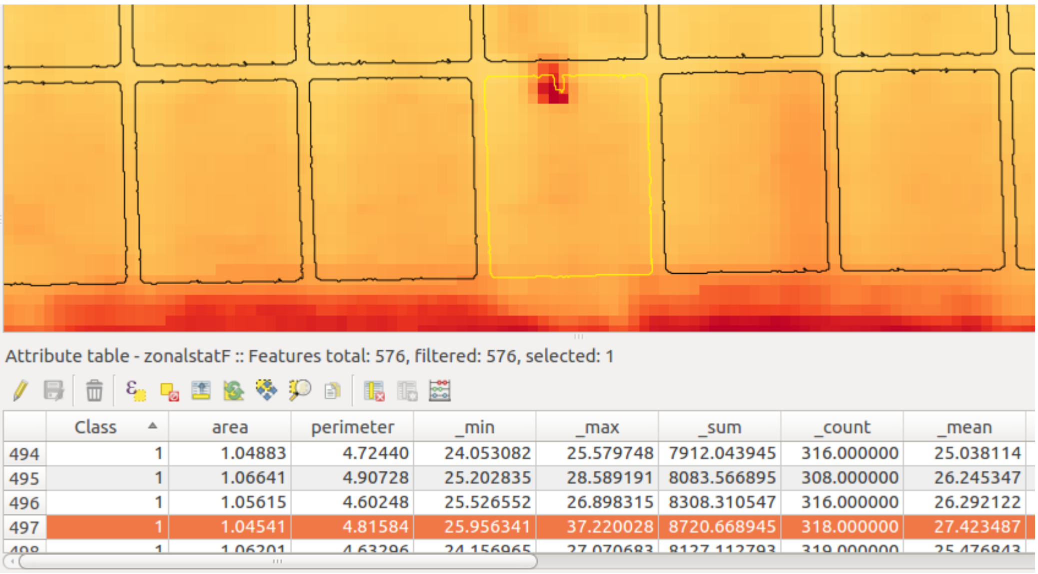


Figure 27. IR map with temperature data. Developed with internal software.

Next step was exporting the statistical data to a CSV and use the temperature data model to process it. After changing some parameters in the code to adapt it to the CSV that came from the image classification model, the console could run the file successfully. The numerical results of the classification model are shown in Table 8.

Variable	**Result**
Total number of panels	576
Defected panels	353
Panels claimable for warranty	179
Theoretical useful power	120,960 W
Practical useful power	117,477 W

Cumulated losses	3,483 W
Data set economic losses	300.87 € / year
PV plant economic losses	15,421 € / year
Relative to O&M budget	12.44 %

Table 8. Results of the automatic inspection.

Classification results

The first results to analyze from running the model on the temperature data are the classification results; so to say, the results on classifying the panels as defected and claimable for warranty basing on the temperature data. Taking a look at the defected panels, it is noticed that more than half of the data set is set as defected. Parallel to the automatic inspection of the assets, a visual inspection on the IR map was done. A member of the team analyzed all the panels one by one and changed a variable of defect manually to 1 in case a hot spot was seen. Figure 28 shows the results of the panel classification.

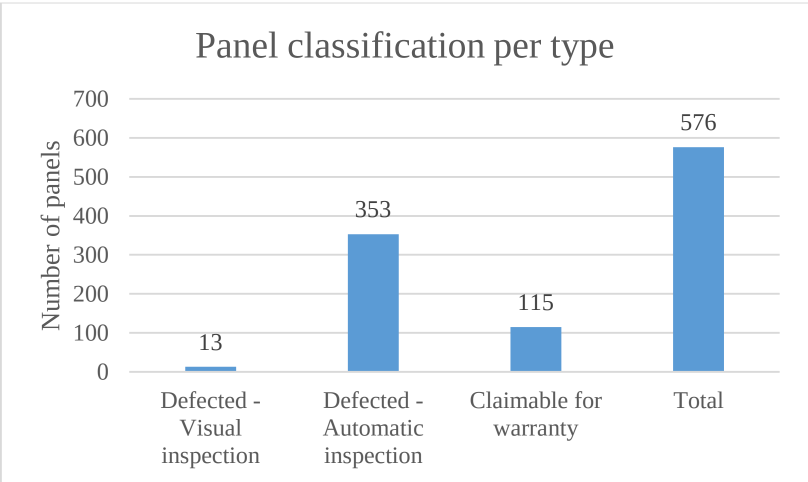


Figure 28. Panel classification per type, not exclusive.

In total, the visual inspection identified 13 defected panels out of 576 whereas the code detected 353, which was a significant difference to take into account. The first reasonable reaction is to think the criterion is wrong, it needs to be tighter to not select so many panels as defected. However, the criterion of 1°C difference between the maximum and the average had been fixed according to the minimum difference seen in the hotspots identified by visual inspection; if this criterion would be tighter, being the temperature difference higher, then some panels set as defected in the visual inspection would not appear in the automated. The criterion followed in this case was to prioritize the appearance of false positives (defect seen but not true) over the appearance of the false negatives (true defect not seen). The issue to look into then is the considerable amount of false positives appearing.

Checking the raw data (the IR map), and going through the panels that were seen as false positive by the automated survey, a common defect was observed: the panels showing false positives were catching pixels from the ground, which was warmer than the modules. These pixels were increasing the value of the maximum temperature considered inside the panel, so they were counted as having hot spots despite the silicon material in the picture was alright.

The inconsistency in the IR map was due to the low quality of the images. Since the pictures were having low resolution and there were also some issues with the calibration of the sensor, the maps were created with deviated lines and that made the classification model confuse the pixels and get temperature records from the ground. Overall, the conclusion was that, in order to get reliable results in the automated analysis, it is of key importance to have high quality raw data.

Taking a look at the number of panels claimable for warranty, 115 panels were set as claimable basing on the power losses of each one of them. All results from the inspection are considered to be affected by the anomaly in the IR maps.

A part of a numerical analysis of the classification of panels, a graphical analysis is also built in order to analyze the distribution of the panels with the criterion fixed, based on maximum and average temperatures and depicted previously in Figure 25. The goal is to see if the criterion stablished is respected by the results obtained from the code. The results are shown in Figure 29.

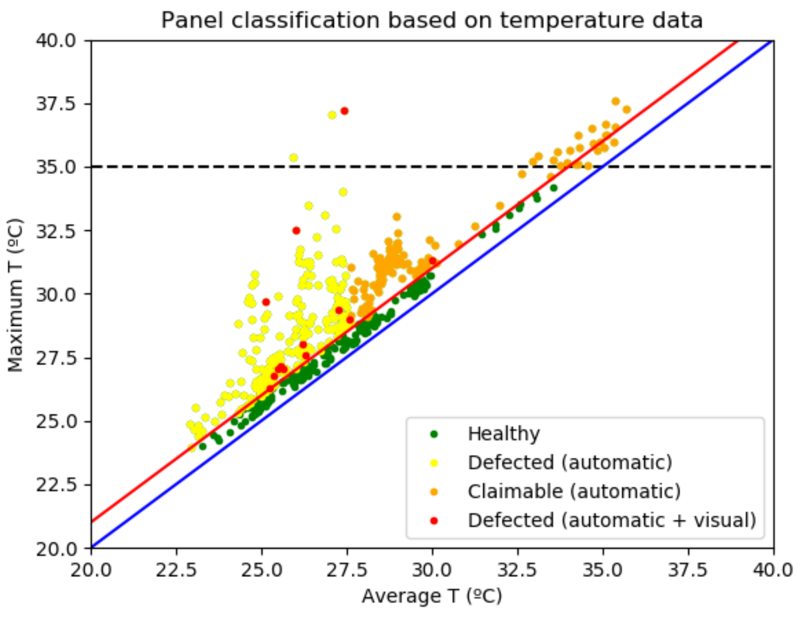


Figure 29. Inspection graphical results. Plotted in Python.

The graph has been plotted in Python with a model that reads the CSV file of the raw data overwritten with the inspection results. The figure orders the different failures identified in the automatic and visual inspections by a color code that depicts the order of importance of the defects. In green appear the healthy panels, in yellow those who have been set as defected and in orange those who have been set as claimable for warranty, all diagnostics given by the automatic analysis. Finally, in red appear those panels that have identified as defected by a human being with a visual inspection on the IR imaging. It is important to state that in case of not painting those points in red, they appear as yellow or orange but not in green, since the criterion was fixed for false negatives – in comparison to the visual inspection - not to happen.

The results of the graph depict the following conclusions:

1. The data analyzed is reliable. No panel is positioned under the blue line, which would have meant inconsistency of data (the average can never be higher than the maximum); hence, this fact states that the temperature data extracted from the IR maps is following a logic reasoning, which states a good data processing from IR pictures to temperature data.
2. The temperature data model runs the classification criterion perfectly, since no healthy panel is out of the graphical limits of the healthy zone, or vice versa.
3. There happens to be a common trend in the panels set as claimable for warranty: it seems to be a vertical differentiation between those who are defected and claimable and those who are defected but not claimable, positioned at around an average temperature of 27.5°C. It is important to remind that the criterion for stating if a panel is claimable or not is based on the power losses, which are based on temperature data; in this case, in the minimum and the average temperature values of the panel. Hence, it is normal that some patterns regarding temperature values appear in the warranty classification.
4. Only one of the panels selected as claimable for warranty has been identified as defected in the visual inspection. This could be due to the low quality of images that distorted the results, a bad criterion on identifying panels claimable for warranty or, most interesting, an incapability for visual inspections to find these anomalies. It would be positive for the model to compare the power losses calculated for those panels with real power losses measured on-site with I-V meters in order to help in estimating the cause.

Power loss results

Taking a look at the power loss calculations, the code gave as an output that the cumulated power losses of the data set, which had a rated power of 121 kW, were of 3.48 kW; that is, 2.87% of the rated power was lost due to thermal inconsistencies. That is a significant value to take into account, even more when it's extrapolated to the whole plant capacity. There, we can see that the losses are equivalent to the 12.44% of the whole budget in O&M, estimated in 124,000€ per year. In case of this assessment being true, the plant would be experiencing significant losses in power production due to thermal inconsistencies inside the panels.

Figure 30 shows the power losses of the plant in comparison with the O&M budget, both data in a yearly basis.

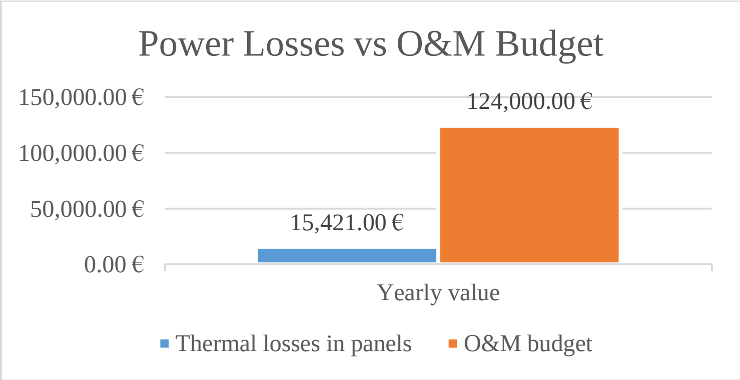


Figure 30. Power losses of the plant in comparison with its O&M budget.

3.3.3 Real Tests Conclusions

After carrying successfully the first real data collection and data processing, some balance was done on the conclusions extracted regarding the processes run in the scope of the thesis.

Regarding data collection, the results were satisfactory in the logistics but insufficient in the quality of the data collected. On one hand, it was a fast and easy to carry inspection, despite not counting on a dual sensor and having to carry the flights separately. This stated that the in-house inspection by PV plant technicians is be feasible. On the other hand, however, the quality of the IR images draw some problems in the data processing, which have been linked to the characteristics of the sensor.

Regarding data processing -for the part that is included in the scope of this thesis- in general terms the results of running the scripts on the real data set are positive. The model not only managed to apply the criterion fixed and run the classification of the panels successfully, but also gave an insight on the effect of the thermal inconsistencies in the power production of the system. Moreover, an important conclusion to be drawn from the results is that, in order to run the code properly, a high quality data collection needs to be ensured.

In any case, it is important to remember that the output of the model is an assessment and not a final verdict. In order to validate the diagnostic, more in-detail methods should be carried out in the panels identified as defected and on those identified as claimable for warranty. For those identified as defected, an efficient method to validate the results has been the visual inspection by a human being on the IR map, while as for those identified as claimable for warranty it is recommended to analyze them with electric meters before claiming to the manufacturer.

3.3.4 MVP and Validation With The Customer

The results of processing successfully the first set of real data opened the door to build a Minimum Viable Product (MVP) and validate the results with the customer. Given the lack of resources to build directly the online platform to dispose the results, an offline tool was created and a personal meeting was scheduled with the customer, so the members of the team could show the results via personal computers. It was key for this decision to identify that the development of the cloud platform was not needed to validate the results with them, and an offline solution was hence enough.

The open-source software used for running the image classification models is appropriate for the purpose since it disposes the thermal maps plus all the temperature records and statistical data, such as maximum or average temperatures, on them. The problem is, it is too complex to use for an unexperienced user and has too many features that could confuse the customer. In order to simplify it, the software was personalized to show only those features that could enhance the exposition of the results, such as the buttons to navigate through the map or a table that showed the temperature data of the selected panels. Summing up, the development tool turned into a user-friendly interface where the customer was be able to understand the results with personal help to navigate through them.

The overall outcome of the meeting is considered as very positive. The customer was very impressed with the quality of the data processing and understood that the inconsistencies in the maps were due to the issues with the sensor. They suggested to process the temperature data before getting introduced to the processing that had already been done, and the procedures they suggested were following the same reasoning as the temperature data model. Furthermore, the customer checked the detailed reasoning behind the model and agreed on the criterion used. Further development agreements were stablished, which stated the validation as very successful.

Overall, the MVP was considered as a very useful tool with a very low initial budget to test, validate and learn from the different assumptions that were taken previously. Together with the validation of the solution design done previously, it created the interest desired in the customer to pull for the solution instead of the company trying to push it to them, which is considered as a very positive feedback from this design and initial technical development stage.

With the design of the MVP it was also stated that the solution is technically possible to develop. Having a clear picture of the final design of the solution, it was left to analyze its profitability for the technology developer, which is explained in Section 4.

4. Financial Analysis

This part describes the economic feasibility of the solution designed for Pro-Drone to expand to the market of Solar PV inspections. It analyzes the cash flows in the project in a 4 years horizon starting at October, 2018 taking into account the costs of development and the revenues associated.

4.1 TAM, SAM and Target Market

Cumulative solar PV capacity installed worldwide accounted for 404.5 GW in 2017, and it's meant to grow in the following years [11]. Taking into account the average market price of UAV inspections, of 350 € per MW, and a frequency of 1 inspection per year, the Total Addressable Market (TAM) for UAV inspections in solar PV plants at the end of 2017 was of 142 million €. However, the price of the solution taken into account for this economic analysis is of 50 € per MW, as it is explained in detail in the financial analysis below. With this price of 50€ per MW and a frequency of inspection of once per year, the TAM at the end of 2017 for PV Insight is of around 20 million € per year. Following an average of the scenarios forecasted for 2018, the new TAM could be of 25 million € per year at the end of this one. Following the same reasoning, the TAM could be of 52 million € per year in 2022. Table 9 resumes these numbers.

	Current market price (350€ per MW)	**License price (50€ per MW)**
TAM 2017	142 M€	20 M€
*TAM 2018**	176 M€	25 M€
*TAM 2022**	365 M€	52 M€

*Table 9. TAM per year for inspections and licenses. *: forecast.*

The market segment where PV Insight adds more value is the segment of utility-scale installed capacity, or systems with capacity equal or over 1 MW. Taking into account that, in 2016, 59.38% was utility-scale capacity [13], the total cumulative solar PV utility-scale capacity worldwide can be estimated of 240.19 GW in 2017. With a price of 50€ per MW and a frequency of inspection of 1 per year, the Served Addressable Market (SAM) at the end of 2017 for PV Insight would be of 12 M€ per year. Following an average of the scenarios forecasted for 2018, the new SAM could be of 15 M€. It would be of 31 M€ per year in 2022. Table 10 shows the SAM for inspections and licenses in different years.

	Current market price (350€ per MW)	License price (50€ per MW)
SAM 2017	84 M€	12 M€
*SAM 2018**	105 M€	15 M€
*SAM 2022**	217 M€	31 M€

*Table 10. SAM per year for inspections and licenses. *: forecast.*

Following a realistic approach, the financial models take into account a share of the market equal to 10% of the European utility-scale capacity at the end of a 4-year horizon, which equals now to 4 GW. With these numbers, the Target Market of PV Insight at the end of the 4th year is of 400.000€ per year. The financial analysis has been performed taking into account the target market and does not take into account the growth in PV capacity in the future years, which would increase the TAM and the SAM every year.

4.2 Financial Analysis

The financial analysis reflects the economic balance of the solution in a 4 years horizon, with the goal of having by that time capacity online equal to the target market. In order to estimate the economic feasibility of the solution designed, a financial model has been built taking into account the potential costs and revenues linked to the development and commercialization of the solution. This analysis does not take into account the taxes associated to the costs and revenues.

The model is structured in four different stages, which reflect the evolution of the solution along the time line. The capacity signed up online increases progressively during the stages, and so does the team. The stages are resumed in Table 11:

Stage	**0**	**I**	**II**	**III**
Name	Testing	Developing	Switching	Expanding
Duration	6 months	6 months	1 year	2 years
Milestone	80 MW	160 MW	780 MW	4.000 MW
Area	Portugal	Portugal	Europe	Worldwide

Table 11. Stages in the financial model.

Every stage implies different strategies and costs. Stages 0 and I are testing and developing the solution, taking only into account revenues coming from full inspections. At stage II, the business adapts the licensing part and at stage III it expands. Sections 4.2.1 and 4.2.2 explain the cost structure and revenue streams of each stage, respectively. Sections 4.2.3, 4.2.4 and 4.2.5 show different results of the model.

4.2.1 Cost Structure

Equipment (FC)

It is considered in the model that the equipment for the data collection will be bought at the end of stage 0. The equipment is the following:

- Drone Matrice M600 Pro
- Gimbal for FLIR Duo Pro R (various models available)
- Sensor FLIR Duo Pro R 640 19mm
- Repairs and other costs

Overall, the equipment cost is estimated in 20.000 €. In the financial model, the equipment cost also includes the purchase of laptops and PCs every time a new one is needed for processing information. The price of one PC/laptop is fixed at 1.000 €, and the reasoning behind the purchase is to support the data processing, explained in detail at the part *VC – Software License.*

Team (FC)

In order to meet the capacity requirements, the team increases along the project. There are three categories of members: full-timers, PT interns and EU interns. Both types of interns are supported by public scholarships from the government of Portugal (partly supported) or from the EU (fully supported).

The number of members and the salaries of the members differ in every stage. Table 12 shows the number of members and monthly salaries in euros for each stage (number / salary). It is taken into account that 2 people are needed for data collection and the number of people for data processing varies.

	Stage 0		**Stage I**		**Stage II**		**Stage III**	
	Number	Salary	Number	Salary	Number	Salary	Number	Salary
Full timers	1	900€	1	900€	3	1.000€	5	1.200€
PT Interns	1	100€	1	100€	2	100€	3	100€
EU Interns	2	0€	2	0€	2	0€	2	0€

Table 12. Number of members and salaries per stage.

Commercial trips (VC)

Another cost associated to the solution is the cost of the commercial trips for business meetings. The trip costs take into account the expenses for car renting and gasoline for the first two stages and plane tickets for the last two, plus the expenses for housing and meals. Table 13 sums up those costs.

	Stage 0	Stage I	Stage II	Stage III
Power per trip (MW)	30	30	200	500
Number of persons	2	2	2	2
Cost per person	150€	150€	500€	1.500€

Table 13. Costs of commercial trips.

The increase in both the power per trip and the cost of the person at stages II and III is due to the distance covered in the trips. In Stages 0 and I they are meant to be done entirely in Portugal, whereas for Stage II the trips are in Europe and for Stage III they are anywhere in the world. It is supposed that the more the solution evolves, the bigger the customers that will be attracted.

As can be observed, each trip has an amount of MWs associated. Commercial trips are variable costs that depend on the amount of power capacity added every month to the platform, by following equation (23):

$$C_{ct,trim} = \frac{P_{new,trim}}{P_{trip}} * n_{persons} * C_{person} \tag{23}$$

Where $C_{ct,trim}$ is the cost of commercial trips per trimester, $P_{new,trim}$ is the new online power capacity in MW, P_{trip} is the capacity covered in one trip in MW, $n_{persons}$ is the number of persons in the trip, and C_{person} is the cost per person in euros. All costs are in euros and the power in MW.

Cost of data collection (VC)

Each data collection carried out by the company has some costs associated to the logistics of the operation. These costs include the transport, the housing nearby the PV plant and the meals that the team needs to have during the days of the data collection. In Stage 0 the sensor will be rented and it's included in the variable costs of collection, taking as reference the prices payed for the real tests. Figure 31 shows the variable costs for data collection per MW collected for the case of renting sensor (Stage 0) and owning the sensor (stages I and II), taking into account as well that the trips are longer for data collection in Stage II. It is taken into account that no data will be collected by the company in Stage III.

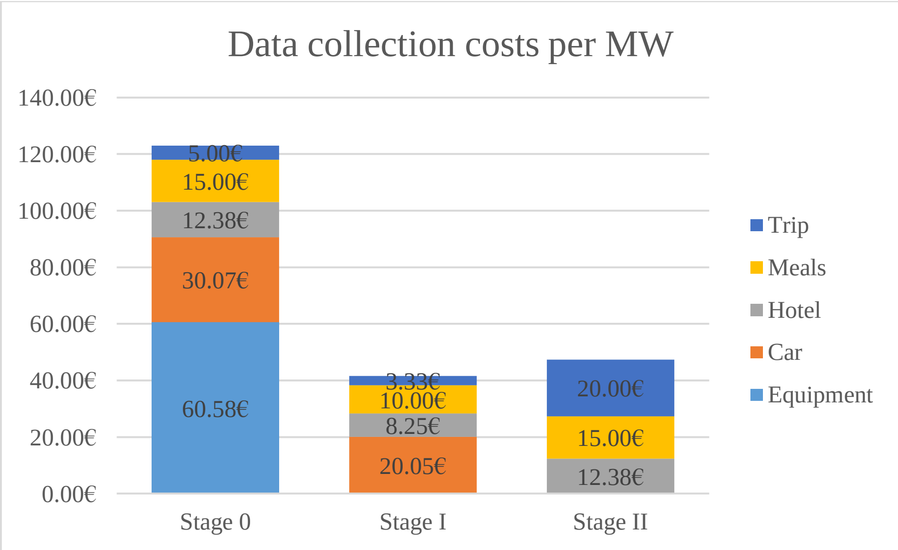


Figure 31. Data collection costs per MW.

As can be noticed, the costs of the personnel are not included in the data collection costs since they are already computed as fixed costs. Equation (24) is followed:

$$c_{dc,mw} = \frac{c_{equip} + c_{car} + c_{meals} + c_{hotel} + c_{trip}}{P_{covered}} \tag{24}$$

In which $c_{dc,mw}$ is the cost of data collection per MW, c_{equip} is the cost of renting the equipment, c_{car} is the cost of renting a car, c_{meals} is the cost of the meals, c_{hotel} is the cost of the hotel, c_{trip} is the cost of the trip – road or plane tickets - and $P_{covered}$ is the power covered in each data collection, considered to last 1 week. All costs are in euros and the power is in MW.

The variable costs of data collection are based on the real costs for data collection during the field test carried out in July. It has been considered that the same equipment would be rent in Stage 0. For car rental and hotel, the costs are based on the real ones as well but they have been adjusted to the requirements of future tests; for example, in those tests there were 4 persons collecting data, and only 2 are needed. The cost of the meals has been estimated as 15 € per person and meal and the price of the trip has been taken by estimating an average price from different trips by car in Portugal through Via Michelin [46] for stages 0 and I, and an average price of 600 € for stage II, taking into account European flights plus transport in the country. The costs of the hotel and meals have been multiplied by 1.5 for stages II and III considering that those costs will be higher outside of Portugal.

The costs for data collection take into account that the power collected per week of collection will increase with the purchase of the dual sensor. This is shown in Table 14.

	Stage 0	Stage I	Stage II
Power collected	20 MW	30 MW	30 MW

Table 14. Power collected in a week of collection per Stage.

Software License (VC)

In order to process the images collected, a software license of a mapping software might have to be purchased. It might be possible to do it with an open source tool, but the criterion followed in this case has been the worst-case scenario; so to say, purchasing a payed license of software to process the images into maps. In order to get to the total cost of the software license, some previous calculations need to be done. The first one is to estimate how many hours of processing data are needed for each trimester, which is done with equation (25).

$$n_{h,trim} = n_{h,mw} * \frac{1}{4} * P_{trim} \tag{25}$$

Being $n_{h,trim}$ the amount of hours per trimester, n_h the amount of hours required for each MW in that stage, and P_{trim} the power online in that trimester, in MW. As can be appreciated, it is multiplied by a factor of ¼; the reason behind this is that each MW of capacity is meant to be inspected once per year and, hence, that's equivalent to a quarter of that MW inspected every trimester.

To calculate the number of hours needed per trimester ($n_{h,trim}$), a minimum amount of hours per MW ($n_{h,mw}$) has been estimated according to the time it took us to process the data in the first tests. It has been considered that this amount of time per MW for processing data will be reduced as the project advances, optimizing the process. Table 15 resumes the hours needed per MW for each stage.

	Stage 0	Stage I	Stage II	Stage III
$n_{h,mw}$	8	4	2	1

Table 15. Hours needed per MW of data processed.

The reduction in processing time is understood from two different aspects: first, an organization through optimization of the processes carried out the first time would help to reduce the time; and second, development of open source tools for data processing would add an extra reduction. Overall, a minimum time of human intervention or supervision is considered in any case.

Once the amount of hours per trimester is calculated, the number of persons needed to cover those hours (n_{pers}) needs to be calculated. For this, it is taken into account that a regular worker works 8 hours per day during 22 days in the month, dedicating 100% of the time to process data. Equation (26) shows the calculation.

$$n_{pers} = \frac{n_{h,trim}}{3 * 22 * 8} \tag{26}$$

Where n_{pers} the number of persons required and $n_{h,trim}$ the amount of hours per trimester.

It has been considered that for every person working in the processing of data, a laptop or PC is required. This is analyzed in the excel and the cost of this equipment added automatically every time the number of people dedicated to processing increases, taking into account the cost of the equipment described above, in the section *FC – Equipment.*

Now, the cost of the licenses can be calculated. The license elected -Pix4D Desktop- costs 216 € per month and covers the use of a PC and a laptop. The cost of the license per trimester has been estimated according to the number of computers needed for processing the data. It has been taken into account that a license needs to be payed for every two persons working in data processing, as can be seen equation (27).

$$c_{softw} = 216 * 3 * \frac{n_{pers}}{2} \tag{27}$$

Where c_{softw} is the cost of the software in euros and n_{pers} the number of persons required. The cost of the software is computed directly in the financial model as a variable cost.

As extra note in the software license costs, it must be said that some other desktop licenses have also been taken into account. In the end, the chosen one has been this one since it’s the one that gave us best results at a reasonable price. Some other types of licenses such as cloud-integrated automatic map generation have also been taken into account, but discarded due to the extremely high prices that made impossible the feasibility of the project. The goal in this aspect is to adapt the open-source available ones to make them suitable for our solution, and use desktop license until that goal is achieved.

Cloud storage (VC)

Having data online has a cost, even if it's stored on the cloud. Basing on the cost of having data on the cloud for the company's solution for wind blade inspections, the cost has been estimated as 35 cents per MW online. The variable costs for having data in the cloud are calculated multiplying that price per the amount of MW online in that trimester, taking into account that during Stage 0 the solution is not yet online.

4.2.2 Revenue Streams

As revenue streams we have inspections, signups and data uploads. Not all the revenue streams are present in all the stages, so a coefficient is multiplying the total revenues to reflect the final revenues in that trimester (R_{trim}). Table 16 shows the value of this coefficient for each one of the stages.

	Stage 0	**Stage I**	**Stage II**	**Stage III**
Inspections	1	1	0.5	0
Signups	0	0	0.5	1
Uploads	0	0	0.5	1

Table 16. Revenue distribution coefficients in every stage.

As can be observed, stages 0 and I have their revenues entirely from inspections and are not charging a fee for having capacity online (the fee is "included" in the price of the inspection), whereas in stage II the revenue is 50% inspections and 50% signups and data uploads. At stage III, the revenues are entirely from signups and data uploads.

Inspection revenues

The revenues coming from inspections have a price of 200€ per MW. This price is enough to cover the costs of data collection and processing, and save margin to pay back the investment in the equipment. The revenues from inspections are calculated following equation (28):

$$r_{insp}^{i} = \left(P_{online}^{i} - P_{online}^{i-1}\right) * p_{insp} * R_{trim} \tag{28}$$

Where r_{insp}^{i} is the total revenue from inspections in the actual trimester in euros, P_{online}^{i} and P_{online}^{i-1} the power online in the actual and previous trimester respectively, p_{insp} is the price per inspection in euros and R_{trim} is the revenue distribution coefficient for a given stage and revenue.

Upload / licensing revenues

These revenues reflect the use of the solution for the data collection either by the final customer or by a licensee that acts as a third party. The price in both cases is fixed at 50€ per MW, despite for the licensee it could vary depending on the agreement. The revenues from upload or licensing are calculated with equation (29):

$$r_{upl}^{i} = P_{online}^{i} * p_{upl} * f_{insp} * R_{trim} \tag{29}$$

Where r_{upl}^{i} is the revenue from data upload to the platform in trimester i, P_{online}^{i} is the power online in that trimester, p_{upl} is the price for data upload, f_{insp} is the frequency of inspection per trimester (1/4) and R_{trim} is the revenue distribution coefficient for a given stage and revenue.

Signup revenues

Signup revenues show the income from customers willing to use our service. Its price, set at 85€ per MW, is higher than the price of data upload by two reasons:

1. Cover the higher costs of data processing the first time that a PV system is inspected, plus the cost of creating all the profiles and preferences in the platform.
2. Ensure a customer lock-in. By paying a higher price at the beginning, our customers will be more susceptible to use the service again at a lower price.

The revenues from signups are quantified by following equation (30):

$$r_{sig}^{i} = \left(P_{online}^{i} - P_{online}^{i-1}\right) * p_{sig} * R_{trim} \tag{30}$$

Where r_{sig}^{i} is the total revenue from signups in the actual trimester, P_{online}^{i} and P_{online}^{i-1} the power online in the actual and previous trimester respectively, p_{sig} is the price per signup and R_{trim} is the revenue distribution coefficient for a given stage and revenue.

4.2.3 Marginal Balance

Either for inspecting directly the solar PV plant or for processing the data uploaded by someone else, the activities of the developer involve some costs that need to be fulfilled by the revenues for the solution to be sustainable. Section 4.2.3 compares the costs vs the revenues of the two different activities: full inspection of the asset (data collection and processing) or part inspection of the asset (only data processing, with the final customer or a third party uploading the data collected). These comparisons are set on a per MW basis and differ from one stage to the other, due to the different data collection and data processing costs.

Part inspection: only data processing

The costs of data processing are based on the hours spent by the personnel on processing the images. As shown in Table 15, those hours differ from stage to stage on a per MW basis. Figure 32 shows the costs and revenues per MW, as calculated in the previous sections, for the data processing.

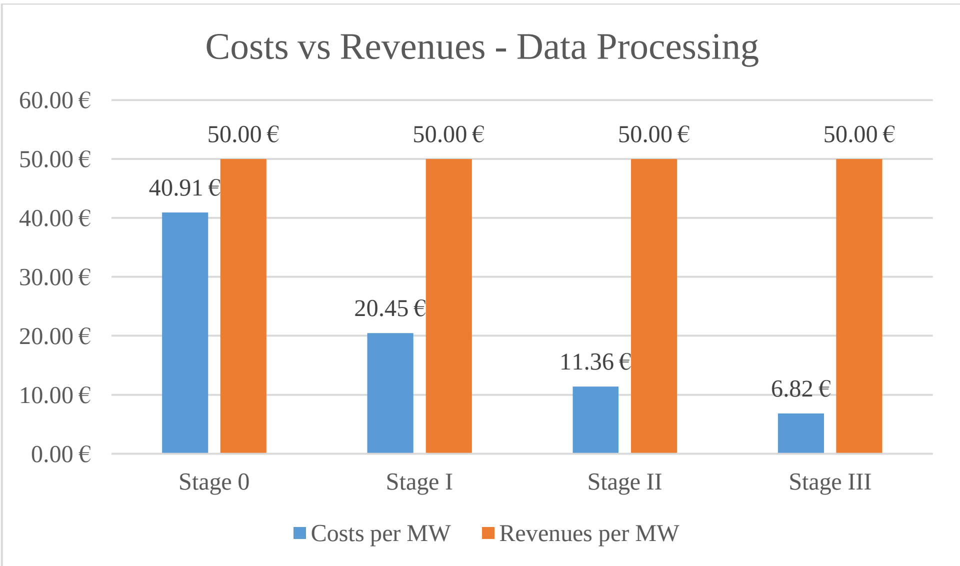


Figure 32. Costs vs Revenues for only data processing.

Figure 32 shows the reason behind pricing the data upload at 50 € per MW; this price allows the company to cover costs of data processing for each one of the stages, increasing the margin as the overall process performs. It can be considered that, despite stages 0 and I do not consider data uploaded by the customer, the part of the price charged for the full inspection that would be related to the data processing is the same as the data upload price for stages II and III.

It is important to notice that the revenues from signup fees are not included in the comparison, since the comparison takes into account an image processing after the first one of the PV plant, and the signup fee plays no role in this case.

Full inspection: collection and processing

For data collection and processing, the costs are those for data processing plus the variable costs explained in the previous section. It is important to state that no full inspections are forecasted for Stage III. Figure 33 shows the results.

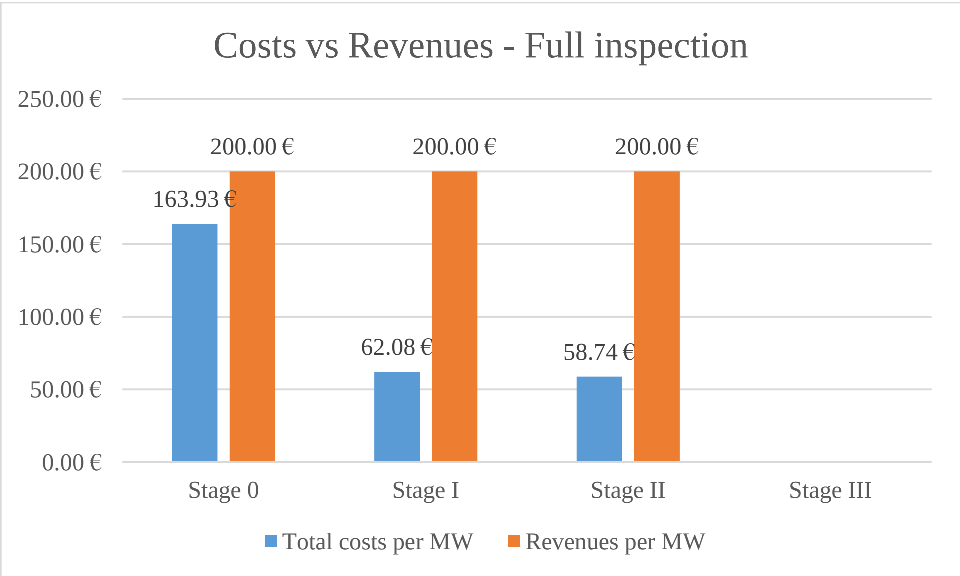


Figure 33. Costs vs Revenues for full inspection.

An important observation to make in this case is the difference between the costs of stage 0 and I, due to the purchase of the sensor and the end of the renting phase. It can be appreciated that afterwards it is harder to lower down costs in data collection, and the small reduction comes basically from data processing; actually, the costs of data collection increase from stage I to stage II.

4.2.4 Balance

From the given data, the model calculates the balances and cumulated balances for each trimester. First, it sums up the revenues and costs of each trimester by using equations (31) and (32):

$$r^i_{TOTAL} = \sum r_i \tag{31}$$

$$C^i_{TOTAL} = \sum FC_i + \sum VC_i \tag{32}$$

Where, for a given trimester, r^i_{TOTAL} are the total revenues, C^i_{TOTAL} are the total costs, FC_i are the fixed costs and VC_i are the variable costs. Once the costs and revenues are summed up, the balance and cumulated balance for a given trimester is calculated using equations (33) and (34):

$$B_i = r^i_{TOTAL} - C^i_{TOTAL} \tag{33}$$

$$B_{i,cum} = \sum_{j=1}^{j=i} r^j_{TOTAL} + \sum_{j=1}^{j=i} C^j_{TOTAL} \tag{34}$$

Where B_i is the balance for a given trimester and $B_{i,cum}$ the cumulated balance until that trimester, with the actual one included.

4.2.5 Results

The financial analysis results are summarized in three different graphs separated in trimesters or Qs: the first one depicts the revenues vs the total costs, the second one shows the balance and cumulated balance, and the third one shows a combination of the first two. For the parameters defined in the previous sections, the results are depicted in Figure 34 and Figure 35.

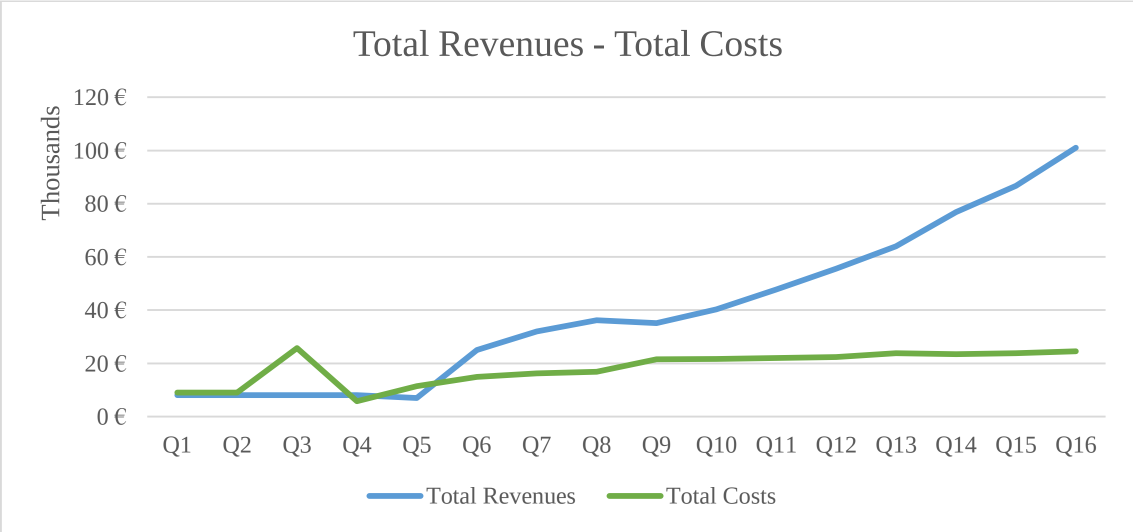


Figure 34. Total Revenues vs Total Costs

As can be observed, the costs start over the revenues for the first three trimesters. At Q3, the purchase of the equipment puts costs far over revenues but, thanks to the reduction in marginal costs, costs go under revenues in Q4. At Q5, the expansion of the team at the beginning of Stage II makes costs go over revenues again, but that is corrected before Q6 putting revenues on top of costs until the end of the time line.

Looking at Figure 34 it could be said that there are two break even points: one slightly before the end of Q3 and another one at Q5. The breakeven point is set as the second one, in the middle of Q5, since from that point on revenues are over costs. The following graph shows the balance and cumulated balance.

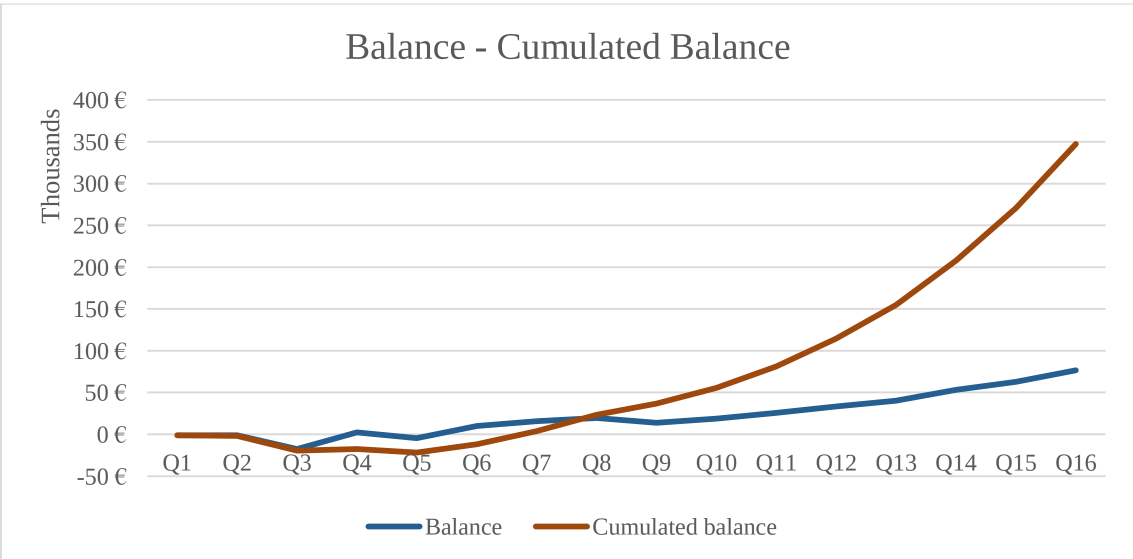


Figure 35. Balance and Cumulated Balance.

Figure 35 depicts the initial negative balances that follow the reasoning of the costs and revenues comparison. The two theoretical breakeven points are reflected as the balance curve steps over the 0 in the horizontal axis.

Figure 35 also depicts a very particular situation of the project. It can be appreciated how the reduction of full inspection activities creates a reduction in the balance as well (end of Q4 and Q8). Looking at the numbers, this could be understood as a mistake since it seems logical to keep on with inspections if the revenues that they generate are higher. However, the main value proposition of the solution is to allow data collection by the customer, lowering down their operational costs. This can be justified in two different ways:

1. From a more business-oriented point of view, lowering down the customer's operational costs is the main motivation to attract new customers on board, enlarge the market share and revenues and acknowledge the goal of online capacity set at the end of the 4th year.
2. From a purely financial point of view, continuing with the full inspection business would require larger operational costs as well, which could end up not being as profitable as it is in the beginning of the project. This assumption takes into account that the inspections in stages 0 and I are done in a relatively short distance from the headquarters.

The final results of the financial analysis are shown in Figure 36.

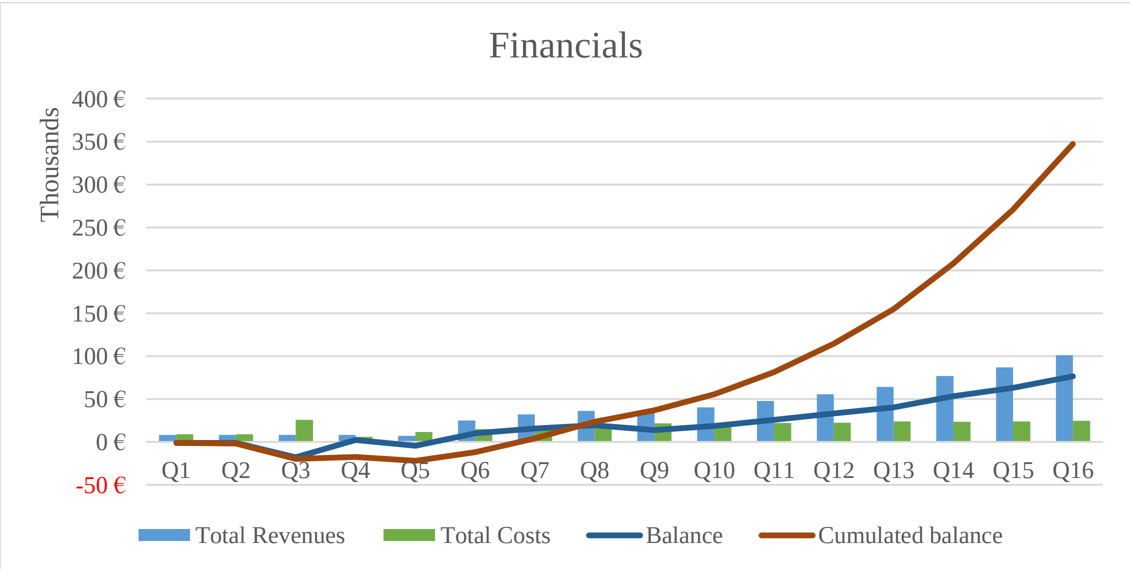


Figure 36. Financials.

As final results of the financial analysis, it can be stated:

- The breakeven point happens relatively soon. At the middle of year 2, the balance is already positive and will not go negative again.

- The investment needed on the solution is low. Looking at the cumulated balance, it can be stated that the solution will require a maximum of 25.000€ which, taking into account the financial and strategic advantages that it brings, is very attractive.
- The cumulated benefit at the end of the 4^{th} year (Q16) is of 350.000€, which is 14 times the initial investment required, of 25.000€.

5. Conclusions

In this document, the design of a solution for integrating UAVs with the O&M of solar PV plants has been described. Overall, it can be stated that the solution is technically possible and adds value to the final customer. Moreover, the financial model states its economic feasibility: with a relatively low investment, of 25.000€, it can generate significant revenues, with a cumulated balance at the end of the 4th year of 350.000€. This cumulated balance is taken into account as the Net Present Value (NPV) of the solution.

Taking a look at the business part, it can be stated that the original idea evolved successfully during the process thanks to the feedback of key players in the market. Following the process of validated learning, many assumptions were changed from the conclusions of the market analysis and the initial solution draft. In the end, the solution generated expectation in some of the customers reached through the validation process and brought on the table collaboration agreements for the development of the solution. The interest of those customers states that the solution is on the right track to be developed and implemented, but it is very important to state that it must be capable of steering and even pivoting in case the circumstances require it. In the end, the design depicted in this document is just a snapshot in this exact moment of the whole design thinking and validation process, which is basically the life time of the project in any lean startup. More feedback is meant to be gathered from future tests, and it is very important that this feedback keeps having its influence in the overall design.

Going into more details in the market and competitors' analysis, it can be stated that now is a promising time to develop the solution, given the growth in capacity installed that the market of solar PV is forecasted to have. However, it is very important to keep on with the development of the solution since UAV solutions are evolving fast as well in what is turning into a very competitive market.

Analyzing the technical part, it can be stated that the development fulfilled the initial requirements: it was possible to pass from raw IR and RGB pictures to a digital diagnostic of the solar field. The model developed in Python covered the last stage of this digitalization, which was the analysis of the temperature data. With the temperature data generated from the image classification models, the code could be tested with real data and its panel classification based on temperature data was proven to work correctly. Moreover, the code is able to estimate as an extra the power loss due to the thermal phenomenon in PV cells, which gathers more knowledge about the functioning of solar PV cells and generates more value in the data processing part of the solution.

However, the results in fault detection of running the code on real data differed a lot from the results of visual inspections by human beings. This states that if the quality of the pictures is not high, the analysis of the temperature data extracted from the maps is not reliable. Another conclusion to extract is that the way suggested is not the optimal for developing a fault analysis; instead of setting the criterion and making it run automatically on the data, it would be more appealing to develop machine learning algorithms that run on the diagnostics from professional inspectors in the pictures and can estimate the criterion by themselves. This has not been done in this work due to the lack of data, since machine learning applications require a significant amount of data and the project started with none.

Given this facts, the model can be used now to provide an initial assessment until there is enough data to apply machine learning. Moreover, the model can also be used to test the quality of the IR maps by checking the differences between the visual and automated inspections; if the difference is low, it will mean that the quality of the map is high, and vice versa. Until the volume of data gathered is big enough for machine learning to be implemented, it is a good first start for automatic fault detection, but it should not be the ideal way to proceed.

Looking at the financials, we can state that the project presents an interesting feasibility. With very low development costs, the solution can bring high revenues for the company as well as positioning it in a strategic situation with two platforms for asset inspections in two different renewable energy technologies. Moreover, the financial model is taking into account a market share of 10% of the European utility scale capacity now, which by the end of 2022 will represent less than 5% according to the market growth predictions. The goal is reasonable, and the profit involved in getting there is significant.

Future works in the project require collecting and processing more data, and eventually building up the online platform. The first version of this online platform should consist on a limited version of the final solution, so the different desired features can be tested in future validation rounds with customers. It is of key importance to remember the good results that the constant build-measure-learn loop has brought so far to the project. Overall, the feedback from the customer should keep being the main driver in the development of the final solution.

Looking at the model for temperature data analysis, it would be very interesting to measure the real I-V curves of the panels inspected in this work, and compare the real power losses with the ones calculated with the code. As an improvement of the power loss assessment stands performing the code to understand the electronics of the panel as well; those electronics usually cut down power to entire cells and panels to prevent major damages, and would increase the value of the power lost estimation – both the numerical value and the value for the customer. For future stages in the automatic fault detection, it would be interesting to develop machine learning algorithms for the fault detection that would substitute this model once their accuracy is high enough.

Taking a look at the three objectives set in the introduction of this document, it can be concluded at the end of the work that:

1. UAVs can help in a different way in the O&M of solar PV plants. They can add more value in the overall value chain of IR and RGB panel inspections at the same time as cutting down OPEX costs. The results of this work suggest that this way is going to be through in-house inspections; using PV Insight, the price of an inspection goes down from 350€ per MW to 50€ per MW.
2. Temperature data inside the IR pictures can provide useful information about the status of the panel, but requires further development in both collection and processing of data for the results to be accurate enough. The model built in this work is a reliable starting point.
3. The solution explained in the document is set as very profitable in economic terms, with an NPV of 350.000€. The decision to invest on it depends of course on the investor.

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