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METHODOLOGY FOR THE OPTIMIZATION OF PREVENTIVE MAINTENANCE STRATEGIES FOCUSED ON LARGE-SCALE SOLAR PHOTOVOLTAIC PLANTS

TESIS PARA OPTAR AL GRADO DE
MAGÍSTER EN CIENCIAS DE LA INGENIERÍA, MENCIÓN ELÉCTRICA

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RESUMEN DE LA TESIS PARA OPTAR AL GRADO DE MAGÍSTER EN CIENCIAS DE LA INGENIERÍA, MENCIÓN ELÉCTRICA
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METODOLOGÍA PARA LA OPTIMIZACIÓN DE ESTRATEGIAS DE MANTENIMIENTO PREVENTIVO ENFOCADO EN PLANTAS FOTOVOLTAICAS DE GRAN ESCALA

En las últimas décadas, la energía solar fotovoltaica ha crecido a ritmos increíblemente rápidos en cuanto a posicionamiento global y escalabilidad, sin embargo, actualmente faltan mecanismos estandarizados para evaluar las políticas de mantenimiento preventivo. Este trabajo propone una metodología para la optimización de políticas de mantenimiento de plantas fotovoltaicas de gran escala basado en simulaciones de Monte Carlo y Algoritmo Genético. La metodología establece un modelo que depende del uso y no del tiempo, creando indicadores de estado de salud en función de la degradación acumulada inducida por factores de estrés; estos últimos son producidos por la operación y las variables meteorológicas. El objetivo es encontrar el máximo beneficio que equilibre los ingresos esperados de la generación y los costes esperados de las inspecciones y el mantenimiento preventivo y correctivo.

Los resultados muestran que el plan óptimo puede producir un mayor beneficio que un plan basado en las mejores prácticas; sin embargo, esta mejora es a costa de sub mantener algunos elementos y sobre mantener otros. Además, no es rentable aumentar el nivel de mantenimiento de por vida para compensar el aumento de las fallas en los últimos años; adicionalmente, el plan óptimo puede adaptarse a una periodicidad de mantenimiento fija. Algunas divergencias en los resultados mostraron que es necesario incorporar limitaciones operativas adicionales, como el inventario, la logística y el cumplimiento de los contratos.

ABSTRACT OF THE THESIS TO OBTAIN THE DEGREE OF MAGISTER OF SCIENCE IN ELECTRICAL ENGINEERING
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METHODOLOGY FOR THE OPTIMIZATION OF PREVENTIVE MAINTENANCE STRATEGIES FOCUSED ON LARGE-SCALE SOLAR PHOTOVOLTAIC PLANTS

In recent decades, solar PV has grown at incredibly fast rates in global positioning and scalability, yet there is a lack of standardized mechanisms to evaluate preventive maintenance policies. This work proposes a methodology for the optimization of large-scale PV plants maintenance policies built upon a Monte Carlo simulation and Genetic Algorithm. The methodology establishes a model depending on usage rather than time, creating health state indicators as a function of cumulative degradation induced by stress factors; the latter are produced by the operation and meteorological variables. The objective is to find the maximum profit that balances the expected revenue of generation, and expected costs of inspections, preventive, and corrective maintenance.

The results show that the optimal plan can produce a greater profit than a plan based on best practices; however, this improvement is at the cost of under-maintaining some elements and over-maintaining others. Moreover, it is not cost-effective to increase the level of lifetime maintenance to compensate for the increase in failures in recent years; additionally, the optimal plan can be adapted to fixed maintenance periodicity. Some divergences in the results showed that additional operating constraints such as inventory, logistics, and contract fulfillment need to be incorporated.

"Si tú no trabajas por tus sueños, alguien te contratará para que trabajes por los suyos"

Steve Jobs

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1 Introduction

1.1 Motivation

The development of renewable energies (REs) in the last decades especially solar photovoltaic (PV) and wind contribution has prompted important changes worldwide, both in terms of energy and regulatory policies. On the one hand, renewable energy production has increased enormously thanks to its accelerated cost reduction and the attractive downward trends presented by entities such as the International Energy Agency (IEA) and the International Renewable Energy Agency (IRENA). Renewable energy production has not only become competitive but even more profitable in some large-scale applications. IRENA states that the global weighted-average LCOE of utility-scale solar PV fell 82% between 2010 and 2019 [1], where PV technology had the best learning rate. On the other hand, due to both climate change and the beneficial features of REs, global governments have created ambitious programs for the renovation of their energy matrixes towards the next decades, where REs are obvious protagonists. According to the chilean energy policy, at least 70% of electricity production must come from REs by 2050 [2], while in more ambitious countries, like Germany and Denmark, 100% must come from REs in the same time frame. This has motivated an extensive project portfolio, which has driven entities, like IEA and consortiums like Solar Bankability (SB), to participate in studies to evaluate the risks and impacts of PV projects from a technical and economic point of view.

Additionally, there has been a trend towards increasing the size of photovoltaic plants. This implies that centralized actions, like the maintenance plan, can significantly reduce the energy yield if optimal decisions are not taken, and consequently an important profit reduction would be perceived by investors. Along with the above, the advance in inverter technology has allowed incorporating new possible connection topologies by means of string inverters, multi-string inverters, and micro-inverters, in a market where the dominant technology has been central inverter for decades. These new topological options expand the possibilities of maintenance schedules because the failure impact can be widely different among these inverter technologies [3].

It is widely accepted by stakeholders that quality operation and maintenance (O&M) services mitigate potential risks, reduce the LCOE, improve the PPA prices, and have a positive impact on the return of the investment. Likewise, an effective O&M program enhances the likelihood that actual production and costs will approach projected values, thereby strengthening confidence in the long-term performance and earning capacity of the asset. This concept is reinforced if we consider that the life cycle of a PV project can be divided into four stages: development, construction, O&M, and dismantling or repowering. According to Solar Power Europe [4] in their last best practices guidelines (2018), the first stage lasts between one and three years; the second normally a few months; the third around 25-30 years; and the last a few months [4]. Moreover, the IEA and SB report that maintenance costs can reach 70% of the total annual operational expenditures (OPEX) [5]. It should be noted that the growth of solar PV technology has been accelerated, and given the continued growth in the size of large-scale PV plants, construction durations and dismantling (which depend on the installed capacity) are also tending to increase.

Additionally, although it may seem logical to establish the specifications of PV systems, topology, installation sites, and requirements in general, there is confusion or lack of clarity and knowledge on the part of many asset owners and funding entities regarding the minimum requirements to be considered [4]. Currently, solar PV plants mainly incorporate only the two most essential types of maintenance, which are preventive and corrective maintenance. The current knowledge and technology make possible the arising of new maintenance types like predictive maintenance (PdM), which uses condition-based information and risk models to predict the future behavior of a facility. Industries like aeronautics have studied for decades the optimization of their processes, including maintenance, which contrasts strongly with the current PV status. One reason for this maintenance development delay is due to no international standards have been created to support investor decision-making and risk mitigation.

With the presented above, we understand that maintenance activities are one of the most preponderant factors in the long-term yield and the profitability of PV projects. In this context, as the PV technology advances, maintenance strategies must also advance with it, otherwise, risk assessment becomes increasingly difficult. Therefore, we consider it necessary to develop mechanisms for the evaluation of the impact of maintenance policies considering the technical and economic characteristics of PV plants, intending to generate an orderly and systematic structure that allows the optimization of the maintenance process.

1.2 Research hypothesis

At present, the maintenance policies in the PV industry have not advanced at the same level of technological development observed in recent decades. Given the above, the following hypothesis is proposed to provide a useful tool for evaluating and implementing optimal preventive maintenance policies:

"It is possible to generate a maintenance policy evaluation methodology for large-scale solar PV plants that maximizes the profit and improves the energy production of a PV plant that operates under a maintenance plan based on best practices, subjected to the same conditions, and considering uncertainty in meteorological variables and maintenance procedures".

It should be clarified that there is no international definition for considering a PV plant as large-scale, so, inspired by chilean law [6], large-scale PV plants will be considered to be all those that exceed 9 MW of capacity and are directly connected to the transmission system (see section 4.2 for more details). Nevertheless, emphasis is placed on the scalability of the methodology to any size of solar PV plant without further discussion of what specific value is considered large-scale.

1.3 Objectives

1.3.1 General objective

The general objective of the thesis is to generate a methodology to optimize the preventive maintenance policy of large-scale solar photovoltaic plants through cumulative degradation models based on stress factors induced by operation and meteorological variables.

1.3.2 Specific objectives

1. Investigate the operation mechanism and failure modes of a large-scale photovoltaic plant.
2. Perform state-of-the-art optimization strategies in photovoltaic plants and compare them to other areas.
3. Formulate mathematical degradation models that allow coupling meteorological and energetic variables to form degradation models that allow the application of maintenance policies.
4. Design a preventive maintenance optimization methodology using mathematical degradation models.

5. Analyze a large-scale solar photovoltaic plant using the proposed methodology and provide recommendations based on the results obtained.

1.4 Structure of the thesis

This document is organized as follows. Chapter 2 starts with the global context of solar photovoltaic energy where are reviewed installed capacities, cost evolution, projections, etc. This is followed by a complete characterization of the photovoltaic plant, breaking down its components and associated failure modes. Thirdly, it is carried out a review of the state of the art in relation to maintenance optimization strategies in solar photovoltaic plants and other industries. Chapter 3 presents the proposed methodology, where all the elements and criteria adopted are developed in detail. The application of the methodology and the pertinent analyses are carried out in Chapter 4, where a large-scale solar photovoltaic plant is analyzed. Finally, the relevant conclusions are compiled in Chapter 5, where the advantages and disadvantages of the methodology are clearly stated, together with future work.

1.5 Scope of the thesis

The development of this work is focused on the creation of a methodological proposal to optimize the maintenance policies of large-scale solar plants. The objective is that this methodology is based on usage and not on time, so degradation models that represent the stress factors produced by the climate and the operation of the plant must be created. As this work explores a new area, there are no points of comparison, so the methodology is based on giving the model the freedom to find the best solution with the least number of external factors that can modify the results.

Therefore, among the simplifications taken is not to consider the auxiliary consumptions; that is, the model will focus exclusively on the production and performance of the plant and the energy it injects to the system. In addition, it is assumed that there is an energy contract that values the energy at a constant price, and the injection and retirement of energy are performed at the same node. Penalties for non-compliance with the contract, both for energy and maintenance periods, are not considered. Neither are economic, structural, or stochastic dependencies between the modeled elements considered. It is part of the scope of the thesis to analyze the results incorporating uncertainty in the maintenance procedures. Moreover, logistics and inventory are not considered in the modeling. For validation of the proposed methodology, actual historical average failure rates and costs are used, while for missing information like maintenance plan, criteria based on best practices are used.

2 Global context and state of the art

2.1 Introduction

To provide the basis for a proper understanding of this thesis, chapter 2 starts by presenting the technical, climatic, and economic context regarding the operation and maintenance of solar PV plants. It is followed by a general review of the state of the art associated with the optimization of preventive maintenance, showing the different approaches and applications followed in the literature. Finally, different preventive maintenance optimization methodologies in solar PV plants are presented, where the findings in the literature are discussed and contrasted with the scope of this thesis.

2.2 Climate change

Taking action to reduce the impact of climate change is crucial to combat global warming. The consequences of rapidly rising global temperatures will be far-reaching and devasting for humans and the environment unless urgent actions are taken globally to curb emissions [7]. In this context, for almost three decades, world governments have met every year to forge a global response to the climate emergency. Under the 1992 United Nations Framework Convention on Climate Change, every country on earth is treaty-bound to “avoid dangerous climate change”, and find ways to reduce greenhouse gas emissions globally in an equitable way [8].

Since the first Conference of Parties (COP1) of Berlin in 1995, two conferences have been the most important: Kyoto (COP3) and Paris (COP21). At the COP3 summit, the signatory governments of these countries agreed to reduce polluting emissions by 5 % on average between 2008 and 2012, taking as reference the 1990 levels. At the COP21 summit, two important points can be highlighted. First, the Paris agreement was characterized by the consensus of non-binding commitment, and the lack of enforcement mechanisms. It recognizes the need for global emissions to reach a ceiling as soon as possible, assuming that this task will take more time for developing countries. In addition, it includes the importance of achieving a path of reduction of emissions in the medium and long term, consistent with a scenario of carbon neutrality in the second half of the century. Second, COP21 limited the global increase of the temperatures below 2°C and to try that the rise is not superior to 1.5°C [9].

2.3 Renewable energies worldwide

Implicit in the goals agreed in COPs is the need for a transition to a low-carbon energy sector, which accounts for two-thirds of global emissions. Renewable Energy (RE), coupled with energy efficiency gains, can provide 90% of the CO2 emissions reductions needed by 2050 [10]. Additionally, IRENA's analysis demonstrates that doubling the share of renewables in the global energy mix by 2030 is possible with existing technologies, and this, combined with improved energy efficiency, would put the world on track to keep global warming under 2°C [7]. Also, a key pillar of several countries' mitigation strategies is the decarbonization of the energy sector through renewable energy deployment [7], which in combination with cost reduction, has motivated an accelerated development and integration of REs.

2.3.1 Installed capacity

At the end of 2021, global renewable generation capacity amounted to 3064 GW. Wind and solar energy reached 849 GW and 825 GW, respectively. Other renewables included 143 GW of bioenergy and 16 GW of geothermal, plus 524 MW of marine energy. Renewable generation capacity increased by 257 GW (+9.1%) in 2021. Solar energy continued to lead capacity expansion, with an increase of 133 GW (+19%), followed by wind energy with 93 GW (+13%). Hydropower capacity increased by 19 GW (+2%) and bioenergy by 10 GW (+8%). Geothermal energy increased by just under 1.6 GW. Solar and wind energy continued to dominate renewable capacity expansion, jointly accounting for 88% of all net renewable additions in 2021 [11]. Figure 1 shows the evolution in the installed capacity of renewable energies in the last decade.

With the sustained increase in solar capacity worldwide, installed solar capacity has now outgrown installed wind power capacity. Expansion in Asia was 76 GW in 2021 (compared to +77 GW in 2020), with major capacity increases in China (+53.0 GW) and India (+10.3 GW). Japan also added 4.4 GW and Republic of Korea expanded solar capacity by almost 3.6 GW. Outside Asia, the United States added 19.6 GW of solar capacity in 2021, Brazil and Germany respectively added 5.2 GW and 4.7 GW, and the Netherlands and Spain added more than 3 GW [11].

Regarding the renewables forecast, the IEA states that the growth of renewable capacity is forecast to accelerate in the next five years, accounting for almost 95% of the increase in global power capacity through 2026. They declare that, globally, renewable electricity capacity is forecast to increase by over 60% between 2020 and 2026, reaching more than

4800 GW, which is equivalent to the current global power capacity of fossil fuels and nuclear combined [12].

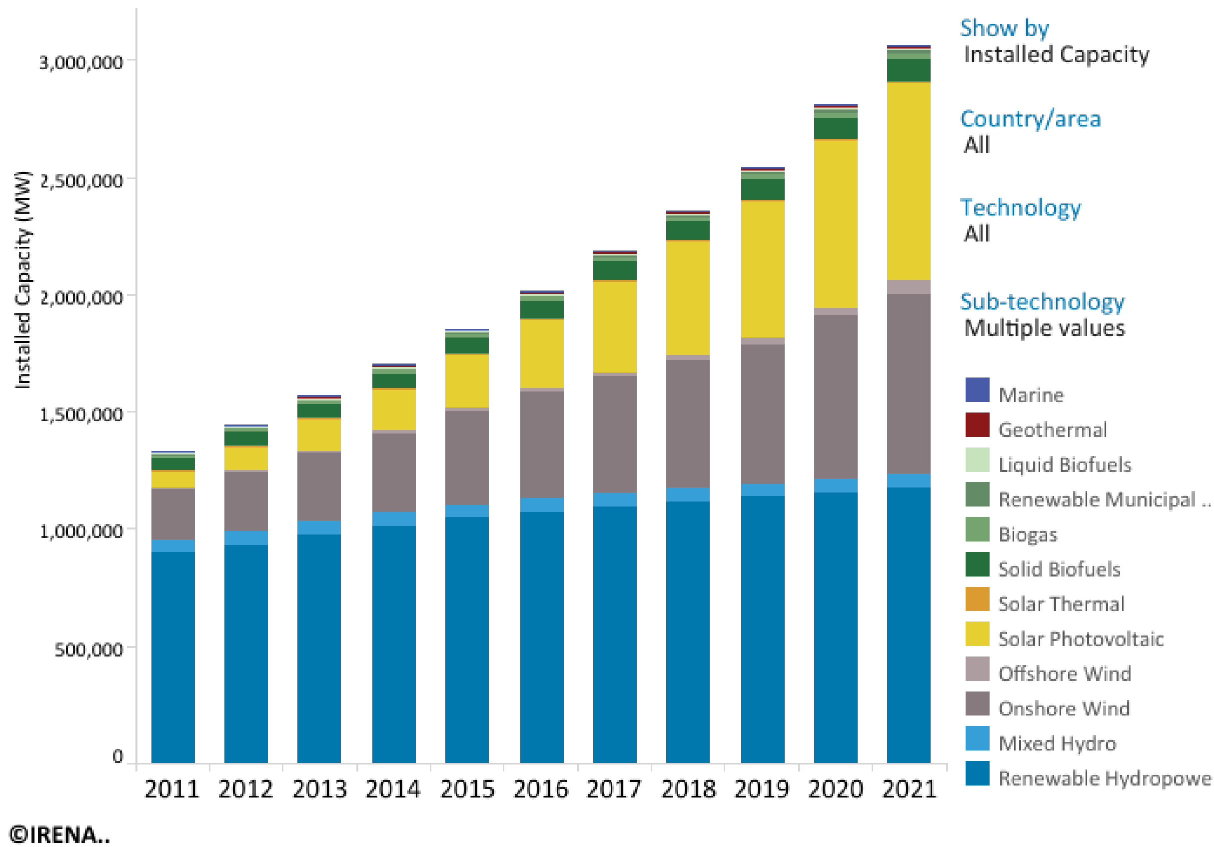

Figure 1 Installed capacity of renewable energies worldwide in the last 10 years [13].

2.3.2 Renewable generation

Of all energy sources in the electricity sector, only the use of renewables expanded in 2020, despite economic disruptions caused by Covid-19. Renewables-based electricity generation increased by 7.1% (a record 505 TWh) – almost 20% higher than the average annual percentage growth since 2010; solar PV and wind each accounted for about one-third of total 2020 renewable electricity generation growth, with hydro representing another 25% and bioenergy the remainder. The share of renewables in the global electricity supply reached 28.6% in 2020, the highest level ever recorded [14].

Despite these favorable numbers, renewable power deployment as a whole still needs to expand significantly to meet the Net Zero Emissions (NZE) by 2050 Scenario share of more than 60% of generation by 2030; yearly generation must increase at an average rate of nearly 12% during 2021-2030, almost twice as much as in 2011-2020. In fact, record generation growth in 2020 and the expected increase in capacity additions in upcoming years will not be sufficient to ensure Net Zero levels. Enlarging annual capacity additions from 134 GW in 2020 to 630 GW in 2030 will require considerable effort [14].

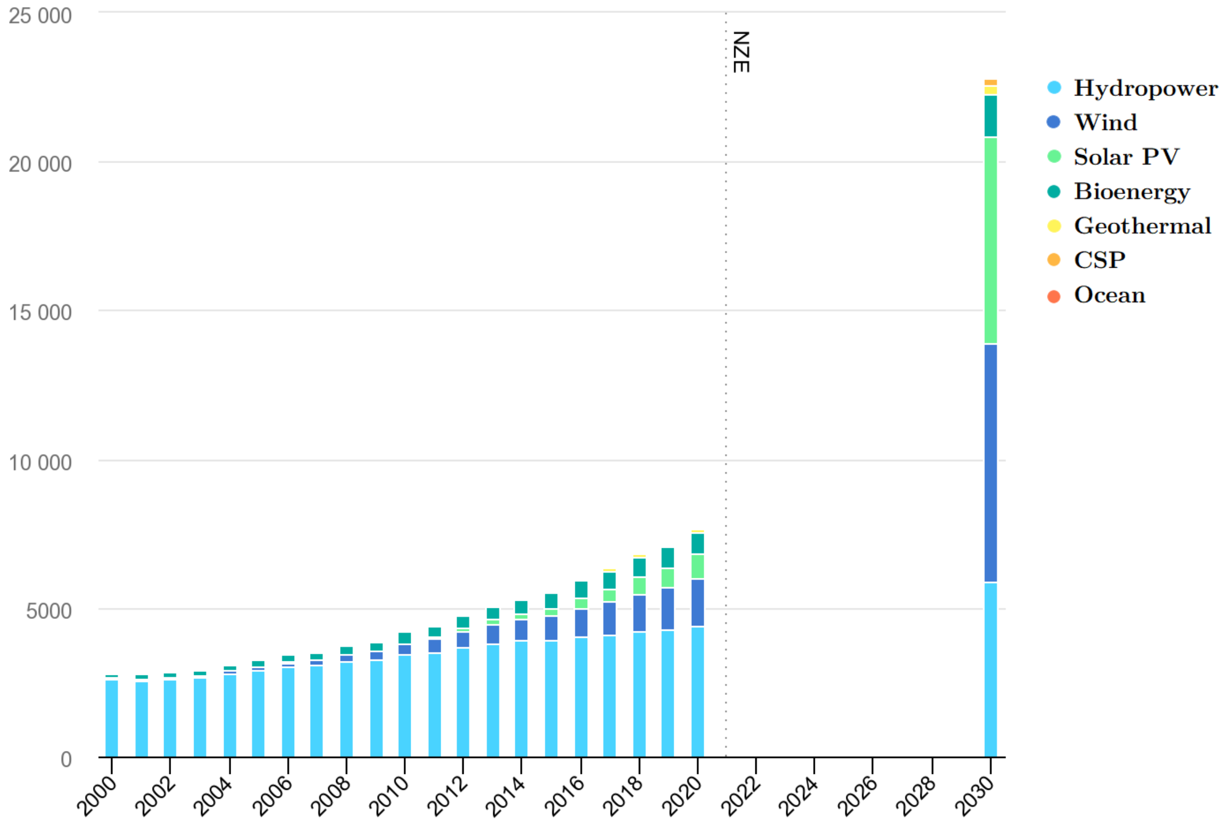

Figure 2 Renewable power generation by technology, historic, and in the Net Zero Scenario 2000-2030 [14].

2.3.3 Costs evolution

Electricity costs from renewables have fallen sharply over the past decade, driven by improving technologies, economies of scale, increasingly competitive supply chains, and growing developer experience [1]. This trend is projected to continue, smacking renewables increasingly competitive with fossil fuels in countries across the world and the least-cost option in a growing number of markets. In this framework, renewable technologies now represent the most economical solution for new capacity in a growing number of countries and regions and are typically the most economical solution for new grid-connected capacity where suitable resources are available [15].

According to the latest cost data from the IRENA [1], the global weighted-average LCOE of utility-scale solar PV fell 85% between 2010 and 2020, while that of concentrating solar power (CSP) fell 68%, onshore wind 56%, and offshore wind 48%. Electricity costs from utility-scale solar PV fell 7% year-on-year in 2020, reaching USD 0.057 per kilowatt-hour (kWh), which is lower than the 13% experienced in 2019. The global weighted-average LCOE of the onshore and offshore wind both reached USD 0.039/kWh and USD 0.084/kWh, respectively. Costs for CSP - still the least-developed among solar and wind technologies - fell 1% to USD 0.108/kWh [1]. Figure 3 shows the cost reduction of global weighted-average LCOE from principal utility-scale renewable technologies for 2010 and 2020. Figure 4 shows the evolution of total installed costs, capacity factor, and LCOE for solar PV technology between 2010 and 2020.

It should be noted that these values reported are based on global statistics, so the data may not coincide for areas of high radiation. Regarding the capacity factor, both systems with a fixed structure and tracking devices are considered in the study. It can be appreciated that the presence of PV plants in high radiation areas with tracking systems is not predominant in the global average; consequently, the global weighted average resembles values characteristic of plants with fixed structures in areas without high radiation, as is the case in most of Europe.

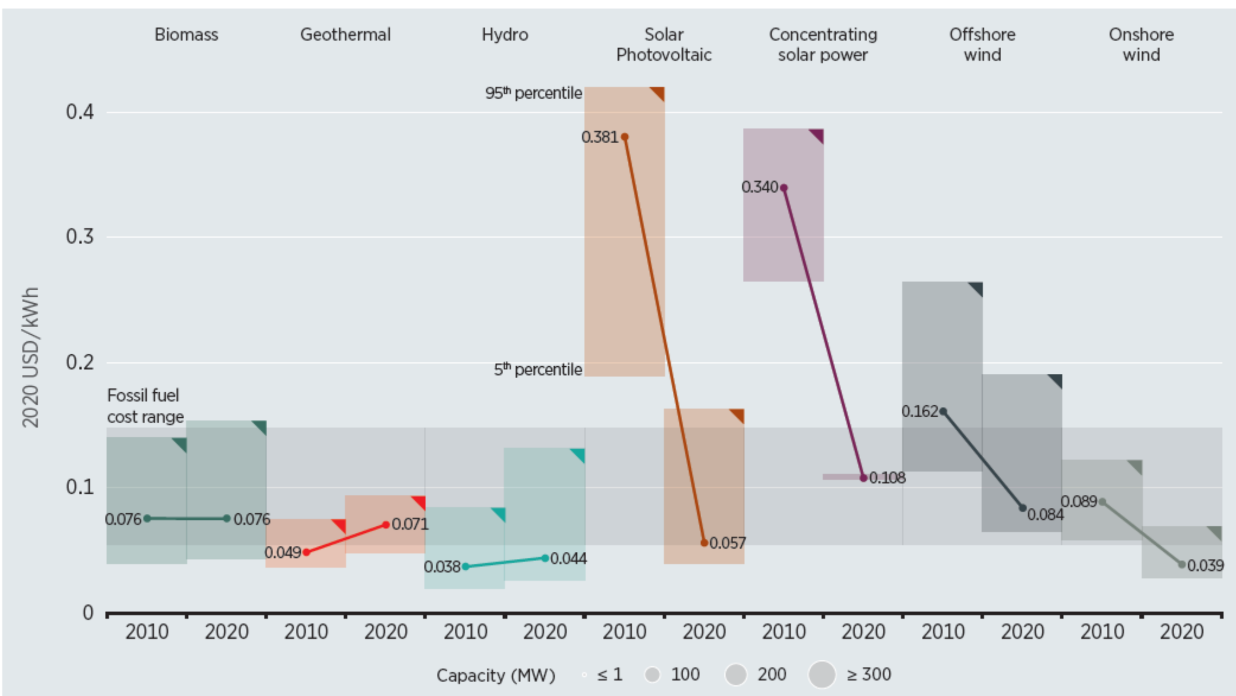

Figure 3 Global weighted-average levelized cost of electricity from utility-scale renewable power generation technologies, 2010 and 2020 [1].

Furthermore, solar and wind power still have impressive "learning rates[1]" since 2010. For the period 2010 to 2020, the LCOE learning rate was 39% for solar PV, 36% for CSP, 36% for onshore wind, and 15% for offshore wind.

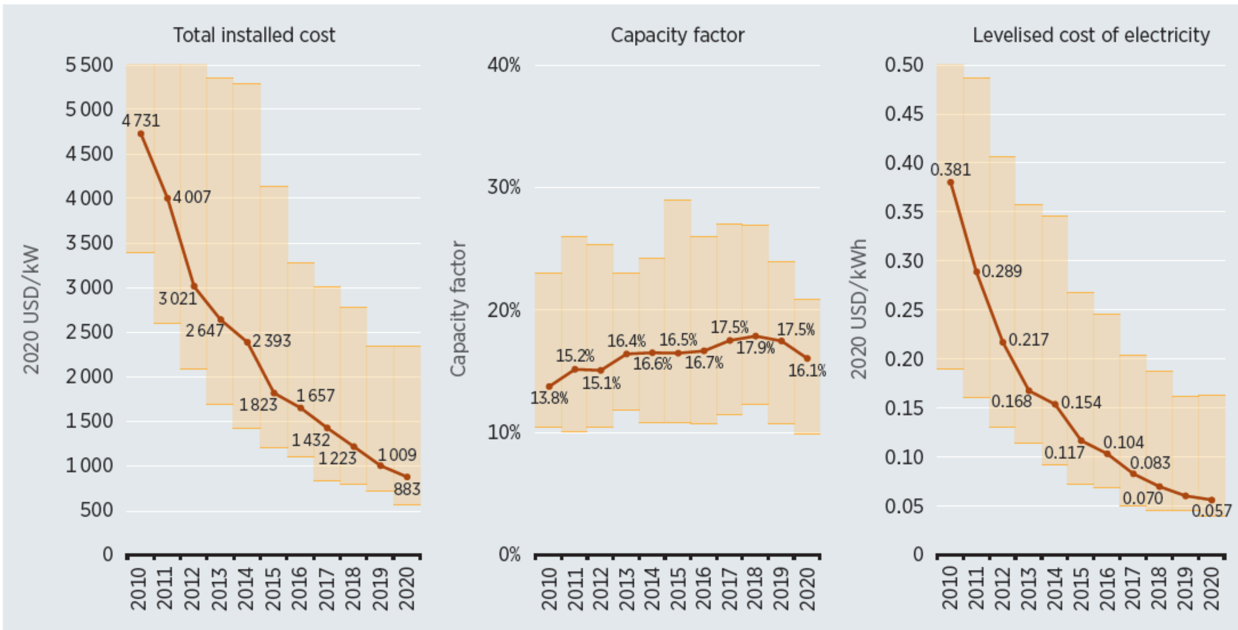

Figure 4 Global weighted-average total installed costs, capacity factors, and LCOE for solar PV, 2010-2020 [1].

2.3.3.1 Operation and maintenance costs for solar PV

The operation and maintenance (O&M) costs of utility-scale solar PV plants have also declined in recent years. These declines have been driven by module efficiency improvements, that have reduced the surface area required per MW of capacity. At the same time, competitive pressures and improvements in the reliability of the technology have resulted in system designs optimized to reduce O&M costs and improved O&M strategies that take advantage of a range of innovations - from robotic cleaning to "big data" analysis of performance data to identify issues and preventative interventions ahead of failures - to drive down O&M costs and reduce downtime [1].

For the period 2018-2020, O&M cost estimates for utility-scale plants in the United States have been reported at between USD 10/kW and USD 18/kW per year. Average utility-scale O&M costs in Europe have been recently reported at USD 10/kW per year, with historical data for Germany suggesting O&M costs came down 85% between 2005 and 2017, to USD 9/kW per year. Recently, costs seem to be dominated by preventive

[1] The "learning rate" is the percentage reduction in costs that is achieved for every doubling of cumulative installed capacity.

maintenance and module cleaning, with these making up as much as 75% and 90% of the total, depending on the system type and configuration. The rest of the O&M costs can be attributed to unscheduled maintenance, land lease costs, and other component replacement costs [1] [3] [16].

2.4 Chilean scenario

Chile has extraordinary radiation conditions, which could supply all chilean consumption with solar energy about 60 times or 20% of global energy consumption [17]. According to Climatescope 2019 elaborated by BlombergNEF, Chile is in second place in the global ranking of most attractive nations for investment in renewable energies. Chile stands out as the only emerging market where the government and utilities have made a serious commitment to phase out coal generation [18].

2.4.1 Installed capacity and generation of renewables

In Chile, there are three independent electric systems: *Sistema Eléctrico Nacional* (SEN), *Sistema Eléctrico de Aysén* and *Sistema Eléctrico de Magallanes*; where the SEN account for more than 99% of the total installed capacity of the country. The installed capacity of the SEN to March 2022 was 32399 MW, where 12331 MW corresponds to non-conventional renewable energies[2] (NCRE). Solar PV amounts to 20.7% of the total installed capacity, wind 12.8%, geothermal 0.2%, CSP 0.3%, and hydropower 27% [19]. Figure 5 shows the increase in NCRE installed capacity in the last 13 years.

In concordance with the global climate scenario, chilean regulation established that at least 20% of the cumulative annual energy must be generated by NCRE in 2025. In this context, to March 2022, the total installed capacity of NCRE reached 38.1%, where 34.5% of the cumulative annual energy was generated by NCRE [19]. The development of renewable energies, the chilean energy policy and cost reduction have also allowed NCRE to have an accelerated penetration in the chilean energy market.

[2] The non-conventional renewable energies are defined by chilean regulation as wind, solar, bioenergy, geothermal, marine and mini hydropower (less than 20 MW) [91].

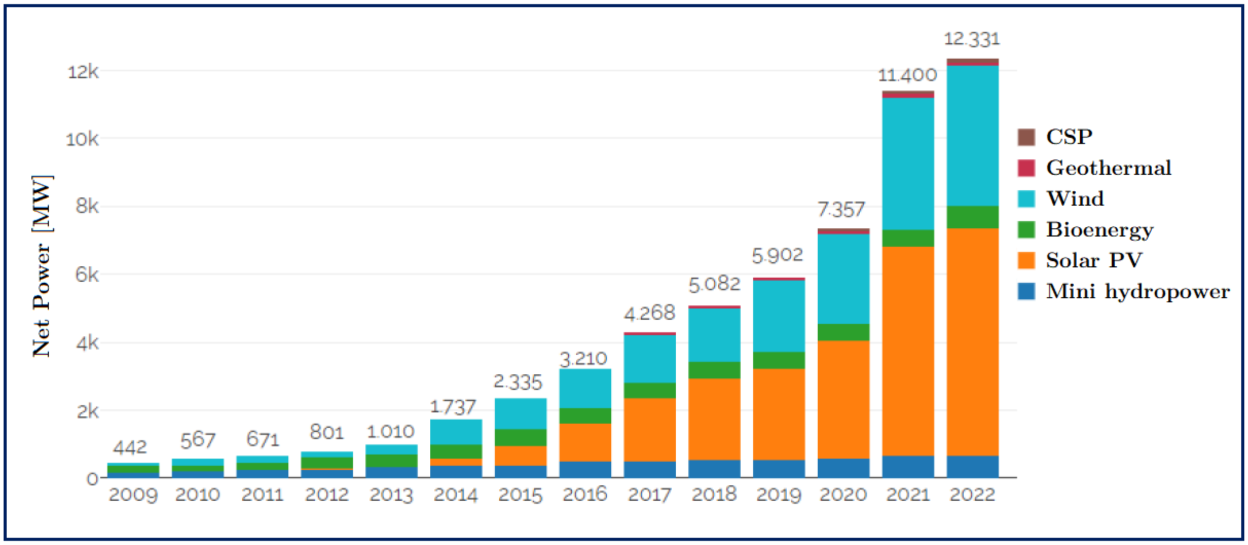

Figure 5 Evolution of chilean installed capacity of non-conventional renewable energies, March 2022 [19].

2.5 Solar PV plants

As we observed in previous sections, solar PV is one of the most promising technologies to face global warming and support the decarbonizing process. It is the interest of this work to understand the processes involved in solar PV maintenance; therefore, the next subsections present the components, topologies, and maintenance associated with solar PV plants.

2.5.1 Components of solar PV plants

As we know, photovoltaic technology has increased enormously in the last decades with a varied number of applications. Its versatility allows solar PV plants to work alone or in cooperation with other technologies such as energy storage, wind, fuel cell, hydro turbines, and diesel generators [20] (see Figure 6). Since our interest is in large-scale PV plants, we will focus on grid-connected PV systems without considering any storage system. A simple schematic view of a large-scale PV system is shown in Figure 7, where the basic chain of operation is composed of PV panels (or PV modules), a combiner box, an inverter, a transformer, and the electrical grid; however, there are other important components present in the generation process that can affect the PV performance such as supporting structures (fixed or tracked), grounding, wires, switches, breakers, fuses, and the monitoring and communicating system.

For simplicity purposes, we organized the main components of the PV system into five categories: generation system, conversion system, transmission system, transformation system, and monitoring and communicating system. Each system is organized as follows:

- **Generation system:** contains all components that participate directly or indirectly in the electric generation (i.e. PV modules, supporting structures and grounding).
- **Conversion system:** contains the inverters, which convert the energy of PV strings from DC to AC. Depending on the topology, the generation and conversion system can be just one system (i.e. when using micro-inverters).
- **Transmission system:** contains the elements that participate in the transmission of the AC or DC energy (i.e. AC/DC wiring, combiner box, switches, breakers and fuses); this system connects all other systems described.
- **Transformation system:** contains the LV/MV/HV transformers, which transform energy from the low voltage (LV) to medium/high voltage (MV/HV) for the injection to the grid.
- **Monitoring and communicating system:** contains all elements that allow the supervision of the PV system (energy and safety) and the communication needed to the correct functioning (i.e. sensors for electrical and meteorological monitoring, energy measurement for reporting to the authority and energy valuation, communication systems, security cameras, and intruder alarms for mitigating risks like theft and vandalism).

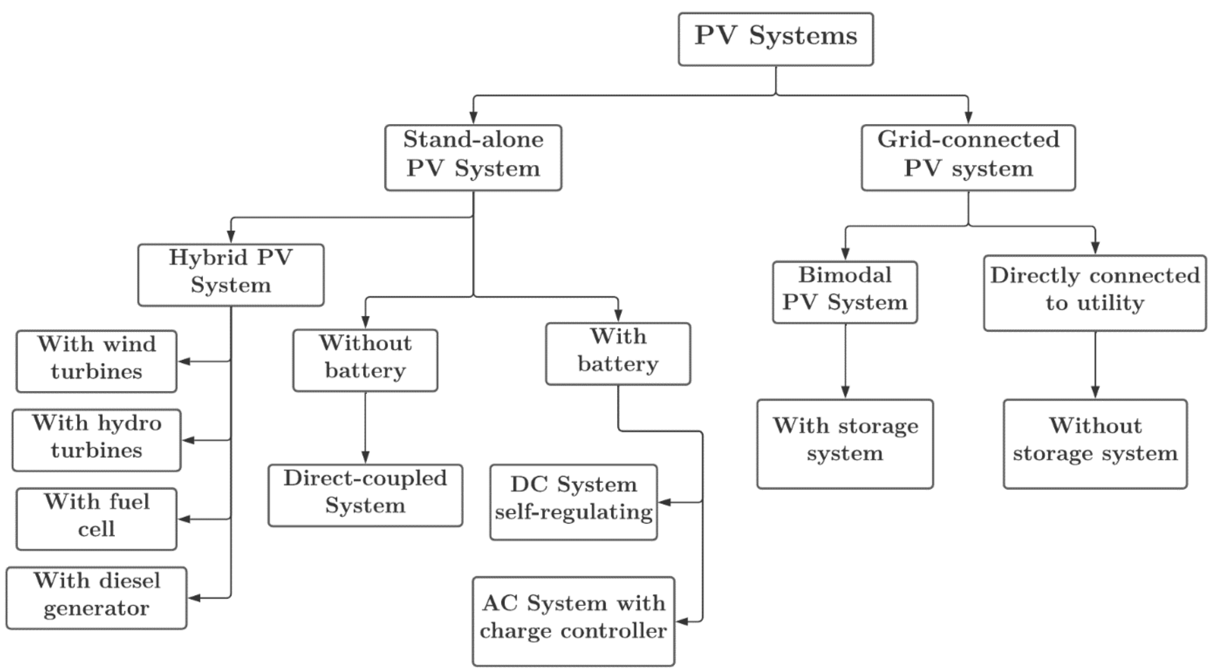

Figure 6 Applications of the photovoltaic sector (image reconstructed from [20]).

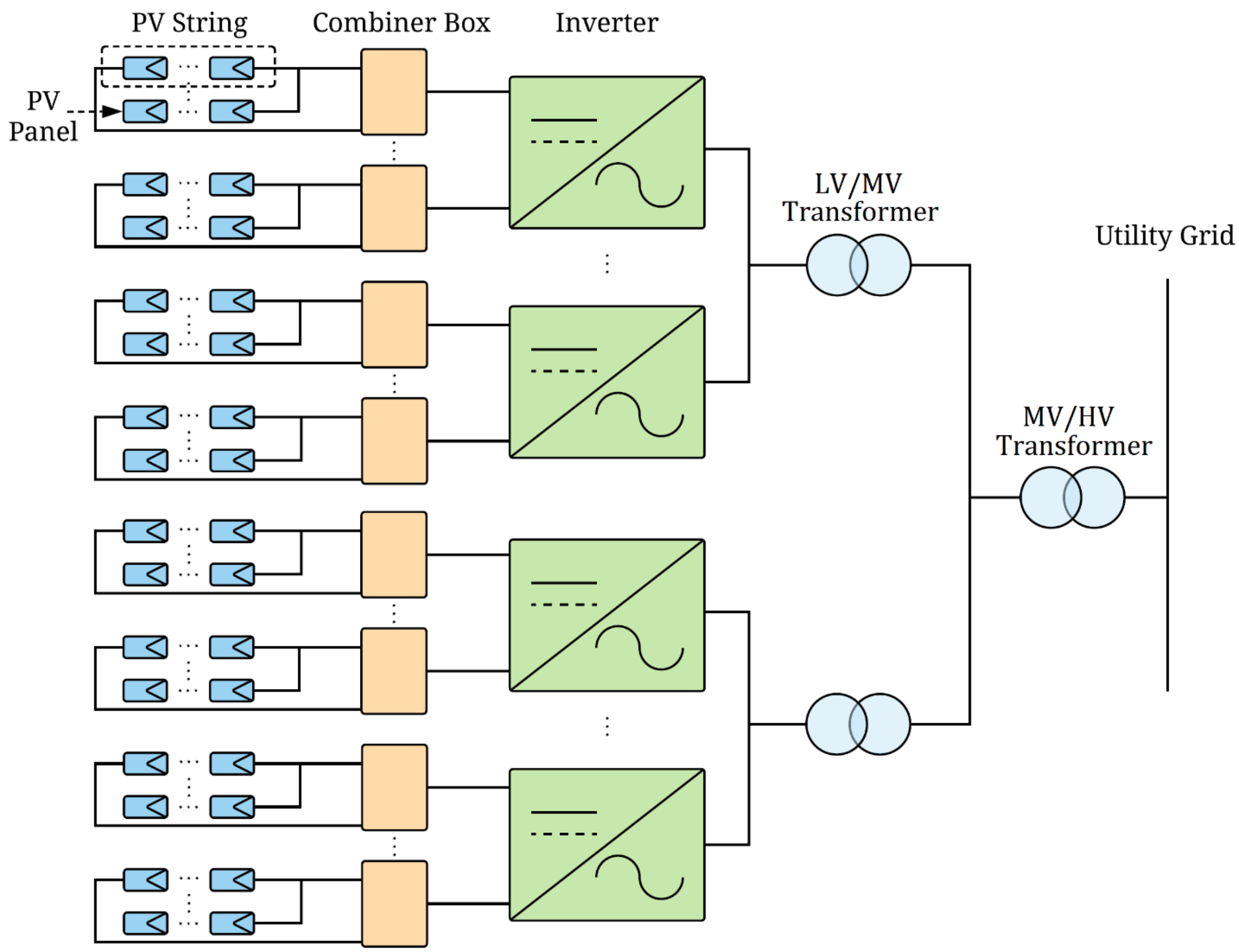

Figure 7 Simplified diagram of a grid-connected large-scale PV system (edited from [21]).

2.5.1.1 Generation system

2.5.1.1.1 PV panels

The basis unity of PV panels is the solar cell, which converts solar energy into electrical energy. Each panel is constructed with numerous solar cells, which are connected in series, and then encapsulated in a special frame. Some known solar cell materials are crystalline silicon (c-Si), multi-crystalline silicon (m-Si), and amorphous silicon thin film (a-Si), where the first two have dominated the utility market during the last years. [22].

2.5.1.1.2 Supporting structures

The supporting structures place the PV panel in the correct orientation for maximizing the PV generation. In large-scale applications, it is usually used ground-mounted structures, which can be either fixed tilt or track the movement of the sun, either in one axis or two axes [3] [23].

2.5.1.1.3 Grounding

In all electrical systems, grounding is a mechanism for ensuring the safety of the public during the installation's decades-long life. In this period, the basic PV module can produce potentially dangerous currents and voltages. Metal enclosures containing electrical components may become energized as a result of insulation or mechanical failures. Energized metal surfaces, including the metal frames of PV modules, can present electrical shock and fire hazards [24].

2.5.1.2 Conversion system

2.5.1.2.1 Inverter

The inverters are electronic devices that permit the conversion from DC to AC power, which can be done through different topologies. Depending on the topology, its participation in the PV system can be more or less critical. The main topologies known are the central inverter, string inverter, multi-string inverter, and AC module integrated inverter (micro-inverter) [3] [22].

2.5.1.3 Transmission system

2.5.1.3.1 AC/DC wiring, switches, breakers, and fuses

These elements are presents in both the AC and DC sides; they permit the correct transmission of the energy, and proper handling and protection of the PV system. The criticality of AC and DC elements relies on the topology used in the PV system (i.e. if a central or multi-string inverter is used, a fault in DC-side wiring is less critical than in AC-side wiring because less energy is lost).

2.5.1.3.2 Combiner box

The combiner box joins the output of multiple strings of the PV modules with the inverter; its principal purpose is to protect the inverter from the DC side. Therefore, a combiner box usually contains overcurrent protection devices, disconnectors, and surge protective devices; depending on the application, combiners can be equipped with monitoring devices to measure current, voltage, and temperature [25].

2.5.1.4 Transformation system

2.5.1.4.1 Transformer

In large-scale PV plants, two types of transformers are used. The first one (Tn) raises the voltage from the PV inverters to the range of 13.8–46 kV. The second one (T-HV) has two functions: *(i)* to provide galvanic isolation for the PV plant from the electrical grid and *(ii)* to raise the voltage from the PV plant to the electrical grid voltage [22].

2.5.1.5 Monitoring and communicating system

The main purposes of a monitoring and communicating system are to measure the energy yield, provide the information requested by the authority, assess the PV system performance, and quickly identify design flaws or malfunctions. Many large PV systems use analytical monitoring to prevent economic losses due to operational problems [26]. Besides, the monitoring system can include safety aspects (i.e. security cameras, intruder alarms, etc.) to protect the facility against theft and vandalism [3].

2.5.2 Topologies for PV plants

As shown in Figure 7, in a solar farm, a large number of PV panels are connected hierarchically; meaning that multiple PV panels are connected into a PV string, and multiple PV strings are connected together to a combiner box [21]. The number of PV panels connected into a PV string and the number of strings connected into a combiner box can change depending on the inverter design, which defines the topology used.

In PV plants, there are four basic topologies [3] [22]: *(i)* central inverter, *(ii)* string inverter, *(iii)* multi-string inverter and *(iv)* AC module integrated inverter (micro-inverter). Topologies *(i)*, *(ii)* and *(iii)* are commonly used in large-scale applications; *(iv)* is still in development. The correct choice of the topology according to the power output, location, reliability, cost, and efficiency is quite important because the power produced by the different topologies is affected by solar radiation and the shading effect [22]. A simple illustration of the mentioned topologies is shown in Figure 8.

The central inverter topology (see a 2-string central inverter in Figure 8.a) interconnects several thousands of PV panels to one inverter through combiner boxes. The disposition of these PV panels is clustered into PV arrays. Each array has hundreds of PV strings connected in parallel, and each string has hundreds of PV panels connected in series. Finally, the combiner boxes gather the arrays and connect them to the inverter input. The string inverter topology (see Figure 8.b) connects one PV string with one inverter; it usually includes a DC-DC converter for the MPPT of the system and does not need combiner boxes. The multi-string inverter topology (see Figure 8.c), as in the last point, connects one PV string to a DC-DC converter; but then, 4 or 5 DC-DC converters are connected to one inverter, which may or may not be closed to the DC-DC converter. The AC module integrated inverter topology (see Figure 8.d) has one inverter per each PV panel [22]. The typical electrical characteristics related to the technology of the four kinds of inverters are shown in Table 1.

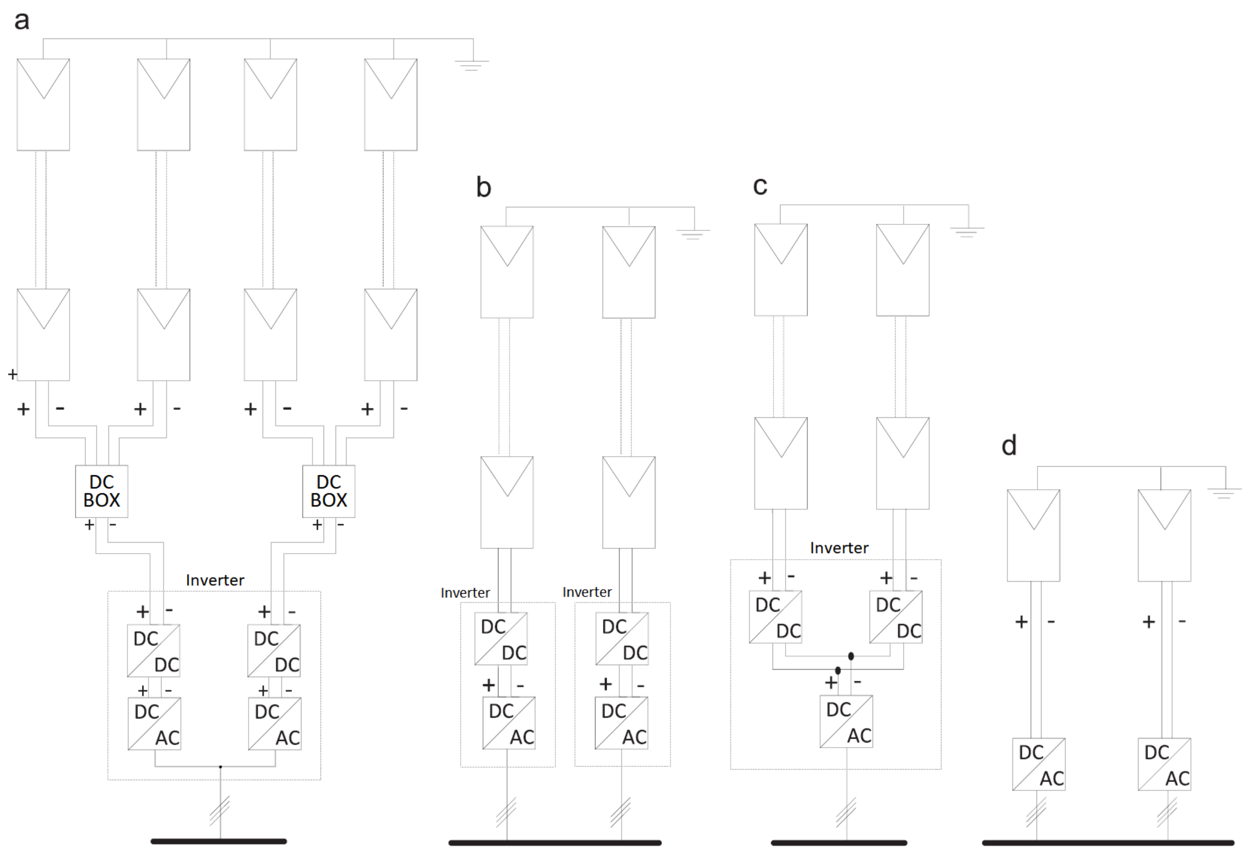

Figure 8 PV inverter topologies. (a) central inverter, (b) string inverter, (c) multi-string inverter, and (d) AC module integrated inverter (edited from [22]).

Table 1 Typical electrical characteristics of PV inverter topologies [22].

Inverter topology	P [kW]	V_{in} MPPT DC [V]	V_{out} AC [V]	f (Hz]
Central	100 - 1500	400 - 1000	270 - 400	50, 60
String	0.4 - 5	200 - 500	110 - 230	50, 60
Multi-string	2 - 30[3]	200 - 800	270 - 400	50, 60
Module integrated	0.06 - 0.4	20 - 100	110 - 230	50, 60

[3] In 2022, there are already inverters reaching 100 kW.

2.5.3 Failure modes of PV plants

Regardless of the degree of sophistication of a system, all systems fail at some time. The failure modes and frequency of failures transform maintenance operations into a problem specific to each area of study. A thorough understanding of the failure modes of a system can make the difference between an adequate maintenance program or an ineffective one. More specifically, the optimal maintenance plan for one system may be quite inefficient in another.

The study of failure modes in PV plants has received much attention in recent decades, where PV panels and the inverter have been clear protagonists. The following is a general review of the main failure modes present in solar PV plants focused on their impact on the generation. For a more comprehensive understanding, please refer to the references cited below. The structure adopted is the same as defined in 2.5.1.

2.5.3.1 Generation system failure modes

2.5.3.1.1 PV panels

Photovoltaic panels are probably the most studied elements in the entire generation chain. Numerous studies address the physics to the reliability of the panels, providing a complete characterization of this element. Our interest is to understand the failure mechanisms of photovoltaic panels and their impact on power generation. According to the literature [27] [28] [29] [30], the most characteristic and significant failure modes are listed below:

1. Delamination
2. Discoloration
3. Busbar/Frame corrosion
4. Cell cracks and Broken glass
5. Hot spots
6. Defective by-pass diode
7. Bubble formation
8. Potential induced degradation (PID)
9. Weld ribbons failure
10. Snail tracks
11. Broken interconnections and weld ribbons

Failures in photovoltaic panels can be caused by environmental factors, human intervention, factory defects, aging, etc. In general, a panel failure is not considered critical because of the large number of panels involved, and this causes minimal energy losses in the short term; moreover, the repair is simple and fast. In this context, hot spots, PID, and by-pass diode faults produce the highest performance losses in this time frame. All other failure modes generally lead to accelerated aging in the long term. For a more specific review, please refer to [27] [28] [29] [30].

2.5.3.1.2 Supporting structures

Supporting structures are the least failed elements in the entire system; they have especially low failure rates and generally do not have a major impact on PV generation. Supporting structures can have structural, mechanical, control, or electrical failures. Among the most reported failures are the following [31] [32]:

1. Wind damage
2. Tracker failure
3. Misalignment (ground instability)
4. Structural torsion
5. Control system
6. Corrosion
7. Oil leakage (tracker)
8. Broken structure

As mentioned above, supporting structure failures have a low impact on the generation and repair is simple and quick in most cases; although failures can be aggravated by improper design. These failure modes are caused by factors such as dust, humidity, solar exposure, etc. The most common and short-term failures are usually in the mechanical and control area; such as tracker failures and control systems. Long-term failures mostly affect the structural part, producing structural torsion, structure breakage, corrosion, etc.

2.5.3.1.3 Grounding

Grounding is a fundamental element in any electrical system. In the photovoltaic system, a properly installed grounding system provides stability and a correct reference for the operation of the electronic equipment, including the inverter, and also protects the operators from abnormal operating conditions. Faults associated with grounding are mainly due to improper installation or design. These can cause corrosion problems, neutral currents, instability conditions of the neutral reference, safety problems, among others. Corrosion can be considered a long-term failure, however, under certain conditions, corrosion can appear even within a year [33]. The remaining failure modes are due to improper installation or external factors (such as phase-to-ground fault) and can occur at any time; their identification is mainly limited to the detection capability of the operators.

2.5.3.2 Conversion system failure modes

2.5.3.2.1 Inverter

The inverter is among the most studied and characterized elements of the entire photovoltaic system since it is also used in systems like wind power and other power electronics applications. The more complex an element, the more forms it can fail. A long list of failure modes evidences this in the researches and reports found in the literature [31]

[32] [34] [35] [36] [37] [38]. In this sense, a fairly representative classification of the inverter failure modes is presented in [38], shown below (complemented with the literature found):

1. Power semiconductors Module
    a. IGBT
        i. Thermal runaway
        ii. Ceramic substrate to base plate solder fatigue
        iii. Emitter wire bond fatigue
        iv. Partial discharge in insulation gel
    b. Freewheeling diodes
        i. Static high voltage breakdown
        ii. Rising leakage current
        iii. Snappy recovery
        iv. Reverse recovery dynamic avalanche
        v. High power dissipation
2. DC link capacitator
    a. Aging
    b. Overvoltage
    c. Overheating
    d. Humidity
    e. Radiation
    f. vibration
3. AC/DC contactor
    a. Fails to open or open late
    b. Open by mistake
    c. High resistance contactor
    d. Fails to close
4. Cooling systems
    a. Mechanical
        i. Cage damage
        ii. Bearing failures
        iii. Lubrication deterioration
        iv. Pollution
    b. Electrical
        i. Cracks on printed circuit board the fan
        ii. Wiring errors
        iii. Electrical overstress
5. Printed circuit board (PCB)
    a. Delamination between PCB's layers (due to overheating, soldering repairs)

    b. Cracks in the boards
    c. Ion immigration (due to high humidity and electrical potential)
    d. Component soldering
6. Control software
    a. Launch failure
    b. Loss of monitoring data
    c. Grounding issues
    d. Firmware issues
    e. Maximum power point tracker failure
    f. Communication failure

Of this extensive list, failures associated with control, pollution, electric protection systems, and human intervention are the most common and short-term. The rest of the failure modes appear as the elements age and fatigue due to operation and environmental factors. It should be noted that inverter parts can be replaced to a greater or lesser magnitude depending on the type of inverter and the maintenance strategy. The two most common maintenance strategies are total replacement at the end of the inverter's lifetime and reconditioning to extend the inverter's lifetime to the total project period. Each project decides the path to follow and consequently its most appropriate maintenance plan.

2.5.3.3 Transmisión system failure modes

2.5.3.3.1 Combiner box, AC/DC wiring, switches, breakers, and fuses

Transmission system failures can be divided mainly into two categories: DC side and AC side. Failures on the AC side produce higher generation losses as they carry several times the power of the DC side (depending on the plant configuration); however, a failure on the DC side is not negligible at all. In most cases, the failure is significant but its repair is quick and simple. Among the main failure modes of the transmission system are the following [32] [34] [39]:

1. Improper installation
2. Wrong/absent cables connection
3. Broken/burned connectors
4. Damaged/corroded cables
5. Broken, missing or corroded cover
6. Broken cable ties
7. Conduit failure
8. Wrong connection, isolation and/or setting of strings
9. UV aging
10. Cables undersized
11. Wrong wiring
12. Theft cables
13. Animal intervention
14. Vandalism

15. Strong wind
16. Pulled cables
17. Insulation failure

Of these failure modes, operational failures such as burned connectors are difficult to predict and can occur throughout the life of the project, but since they are quick and simple to repair, good inventory management is sufficient. Environmental factors and human intervention are the major contributors to failures in this system, where weather affects long-term failures, while humans can induce failures at any time.

2.5.3.4 Transformation system failure modes

2.5.3.4.1 Transformer

Transformers are another well-known element used in all electrical systems. A failure at this level can already represent a considerable loss and it depends on the maintenance contract the response times depending on the failure rate of the plant and the severity of failures [4]. The transformer failures mode can be mainly categorized into mechanical, electrical, and thermal failures. Among the main failure modes are the following [32] [34] [40] [41]:

1. Connection problems
2. Overheating
3. Oxidized or degraded parts
4. Broken parts
5. Improper/inadequate installation
6. Broken transformer
7. Wrong transformer configuration
8. Soiling
9. Open/short circuit
10. Insulation failure
11. Manufacturing defects
12. Overloading
13. Line surge
14. Improper maintenance
15. Lightening
16. Sabotage
17. Moisture
18. Oil contamination

From the presented failure modes, insulation and line surge failures are the most preponderant [40], where these failures can be caused by electrical, mechanical, or thermal stress. These failures are within the long term and are mainly due to operation and aging. The human factor, besides being capable of inducing failures, can accelerate aging when maintenance is defective or insufficient and when the transformer is operated under overload. These bad practices can also aggravate failures produced by environmental factors, such as oxidation and soiling.

2.5.3.5 Monitoring and communicating system failure modes

In general, monitoring and communication system failures are of low occurrence and can be easily resolved. Often the reason for a failure is unknown and in many cases, it is resolved by simply rebooting the system. The main failures occur in the servers, communication with the PV plant, software, presence of animals, problems with the service provider, Power Plant Control (PPC), among others. In many cases the problem is external, but it directly affects the PV plant, so the problem must be solved by the responsible parties within the contractual framework [4] [26] [31].

2.5.4 PV plants maintenance based on current best practices

As a natural consequence of age or exposure to environmental factors, industrial systems are affected by degradation, which leads to system failures; a system is said to fail when it is no longer capable of delivering the designed outputs. These failures could generate safety and quality issues, equipment damage, and unexpected machine unavailability; some failures can be catastrophic in the sense that they can result in serious economic losses, affect human lives, and do serious damage to the environment. The degradation can be controlled, and the likelihood of catastrophic failures reduced through maintenance actions [42] [43]. Overall, maintenance can be described as a combination of all technical and administrative actions including supervision and actions intended to retain or restore the system into a state in which the system can perform a required function [44].

As the plant becomes older, operation and maintenance (O&M) become more and more important for improving the performance of the plant. An effective O&M program will enhance the likelihood that a system will perform at or above its projected production rate and cost over time. It, therefore, reinforces confidence in the long-term performance and revenue capacity of an asset [32].

Currently, it is widely acknowledged by all stakeholders that high-quality O&M services mitigate potential risks, improve the LCOE and Power Purchase agreement (PPA) prices, and positively impact the return on investment. This can be highlighted if one considers the lifecycle of a PV project which can be broken down into the 4 phases below. The O&M phase is by far the longest [4]:

- Development (typically 1 - 3 years)
- Construction (a few months)
- Operation & Maintenance (typically 20 - 35 years)
- Dismantling or repowering (a few months)

It is worth mentioning that the information mentiond above is based on European statistics from the last version of Solar Power Europe Best Practices guidelines (2018), which are still changing from year to year as PV technology and projects evolve, and as more global experience is gathered; thus, these amounts have been changing to date. For instance, given the increasing size of solar plants, the construction period may be longer than 1 year; the lifetime may be reduced in the presence of highly demanding desert environments; and the economic and ecological effects of decommissioning a PV plant may impact project lifetime and costs more than expected, as empirical evidence for large-scale projects is still lacking.

Therefore, increasing the quality of O&M services is important, and in contrast, neglecting O&M is risky. The PV industry - a "young" industry that evolves also in the services segment - offers a wide range of practices and approaches. Although this is partly logical, reflecting the specificities of each system, topologies, installation sites, and country requirements, there is a confusion or lack of clarity and knowledge of many Asset Owners and funding authorities (investors or/and banks) of what the minimum requirements should be.

A reason for this lack of clarity is due to O&M practices and approaches, historically, have not been standardized, and instead, they were implemented in various proprietary methods. This approach can increase the cost to projects and portfolios, as well as raise the perception of risk from investors [3]; current standardization still does not fill in the gaps or clarify the requirements and their implementation. Consequently, although several technical international standards can be followed in maintenance, in operations, which also covers planning, scheduling, and administrative tasks, there are many shortcomings [4].

2.5.4.1 Components of PV maintenance

The O&M for any profitable project is planned to earn sufficient returns over the investment. Consequently, the proper management (O&M) of the assets incorporated into the existing infrastructure, for the operational continuity of the photovoltaic plant, results in an efficient use of the economic resources [23].

In general terms, all kinds of maintenance actions are related to corrective and preventive maintenance [45]. For example, when a component fails, independent of the maintenance policy used, it is necessary to make corrective actions to replace or restore the component to an acceptable operating condition; condition-based maintenance uses continue monitoring for analyzing the system in real-time status and activating alarms to announce that preventive maintenance is required; predictive maintenance utilizes historical data and the information generated with condition-based maintenance for learning the behavior of a system and elaborating prognostics useful for establishing the correct time to realize preventive maintenance. Thus, the main components of a maintenance plan are corrective maintenance (CM), preventive maintenance (PM), condition-based maintenance (CBM), and predictive maintenance (PdM). In the next sub-sections, it is given a detailed description of maintenance types focused on PV plants.

2.5.4.1.1 Corrective maintenance

Corrective maintenance is the most elemental maintenance, which was the natural protocol for the first industries. It covers the activities performed by the maintenance team to restore a failed PV solar plant, equipment, or component to a status where it can perform the required function. The CM takes place after a failure detection either by remote monitoring and supervision or during regular inspections and specific measurement activities [4]. While a system is down or when output is reduced, lost revenue accrues; however, only if there is an opportunity to repair more efficiently shortly, repairs should be delayed [3]. According to Solar Power Europe [4], corrective maintenance includes three activities:

- **Fault diagnosis:** also called troubleshooting to identify fault cause and localization.
- **Temporary repair:** to restore the required function of a faulty item for a limited time, until a repair is carried out.
- **Repair:** to restore the required function permanently.

Also, corrective maintenance can be divided into three levels of intervention:

- **1st level:** intervention to restore the functionality of a device without the need for substituting a component.
- **2nd level:** intervention to restore the functionality of a device that requires the substitution of a component.
- **3rd level:** intervention to restore device functionality with a necessity to intervene on the software of the device.

Corrective maintenance requires man-hours to identify, analyze, and fix the fault, or rectify the failure. The cost of the activity varies depending on the nature of the fault or failure and the quality of the preventive maintenance program. Effective corrective maintenance requires good detection capabilities, starting with the monitoring system that detects the error and can supply plant production and condition data that aid in troubleshooting the problem. A “smart monitoring” system can be especially effective in this way. The speed with which the personnel rectifies the problem is a function of the tools at their disposal [5].

One of the most difficult tasks of the corrective maintenance is the spare parts management because it is an inherent and substantial part of O&M that should ensure the spare parts are available promptly for CM to minimize the downtime[4] of (a part of) a solar PV plant while minimizing the costs of spare parts storage [4].

2.5.4.1.2 Preventive Maintenance

Preventive Maintenance activities are the core element of the maintenance services to a PV plant. It comprises regular visual and physical inspections, as well as verification activities conducted with specific frequencies of all key components, which are necessary to comply with the operating manuals and recommendations issued by the Original Equipment Manufacturers (OEM); PM must also maintain the equipment and component warranties in place and reduce the probability of failure or degradation. This maintenance is carried out at predetermined intervals or according to prescribed OEM and O&M manuals [4]. Also, PM ought to be balanced by financial cost to the project; therefore, the goal is to manage the optimum balance between the cost of scheduled maintenance, yield, and cash flow through the life of the system [3].

One major O&M issue is related directly to improper maintenance protocols, either from the perspective of maintenance frequency or the maintenance procedure itself. In general, the maintenance works should follow the PV component manufacturer guidelines. A failure to do so could cause not only damage to the component but is also likely to result in the voiding of the manufacturer's warranty [5].

Preventive maintenance protocols depend on system size, design, complexity, and environment [3]. Meteorological conditions that affect the maintenance include humidity, high thermal gradients, snow, pollen, effects of animals, high-UV radiation, marine environments, high-speed winds, industrial pollution, soiling due to agriculture or building construction, among others [23]. Some typical activities that PM includes are visual inspections, housekeeping of components, cleaning PV panels, vegetation control, wires tightening, adjusting parameters, re-calibration of sensors, and replacement of defective components [5]. The larger the PV plants become, the higher the impact of preventive maintenance in O&M costs and energy yield. Hence, it is useful to have advanced tools for monitoring and predicting the PV plant’s performance.

[4] Downtime: time when the PV system cannot provide power to the load, expressed either in hours per year or as a percentage.

2.5.4.1.3 Condition-based maintenance and predictive maintenance

Condition-based maintenance is the practice of using real-time information from data loggers to schedule preventive measures such as cleaning or to head off corrective maintenance problems by anticipating failures or catching them early. Because the measures triggered by conditions are the same as preventive and corrective measures, they are not listed separately. Rather, condition-based maintenance affects when these measures occur, with the promise of lowering the frequency of preventive measures and reducing the impacts and costs of corrective measures [3, 37] [23]. In recent decades, research on CBM has been rapidly growing due to the rapid development of computer-based monitoring technologies. Research studies have proven that CBM can be effective in improving equipment reliability at reduced costs if it is planned properly [45].

Predictive Maintenance is a special service provided by O&M contractors who follow best practices principles. It is defined as a CBM carried out following a forecast derived from the analysis and evaluation of the significant parameters of the degradation of the item (according to EN 13306). In this context, it is necessary to acquire “intelligent” equipment set with sufficient sensors, and an appropriate monitoring software system that should be able to provide basic trending and comparison (timewise or between components and even between PV sites) functionality [4].

The operations team of the O&M contractor does predictive maintenance through continuous or regular monitoring, supervision, forecast, and performance data analysis (e.g. historical performance and anomalies) of the PV plant (at the DC array, transformer, inverter, combiner box, or/and string level). This can identify subtle trends that would otherwise go unnoticed until the next circuit testing or thermal imaging inspection and that indicate upcoming component or system failures or underperformance [4]. In general, predictive maintenance does not avoid preventive maintenance; though, to avoid unnecessary costs, it can extend the PM period and establish when maintenance can be done without generating a worse condition.

Big data analytics permit the handling of the analysis from observation of collected information to fault detection, fault diagnosis, and optimization through recommendations issued from the advanced monitoring system. Today different approaches are proposed, whereas classic artificial intelligence (AI) proposes an advanced diagnostic through knowledge-based models, unsupervised and supervised learning methods offer different approaches (e.g. neural networks) using statistical approaches [4].

Both the CM and PM are the basis of any PV plant maintenance program; however, predictive maintenance is still a tool in development in the PV area. In studies made for consortiums like Solar Bankability and entities like IEA, no PV plant surveyed had predictive maintenance implemented [5] [46]. Nevertheless, predictive maintenance is becoming more relevant in large-scale PV plants.

2.6 Maintenance optimization

Maintenance is a topic present in all types of deteriorating systems, independent of the discipline. Over the last few decades, the maintenance of systems has become more and more complex. One reason for this is that systems consist of many components that depend on each other. Interactions between components complicate the modeling and optimization of maintenance; however, interactions also offer the opportunity to group maintenance which may save costs [42]. Nowadays, manufacturing industries are aiming for higher operation efficiency, effectively, and economically to survive in the fiercely competitive global economy.

Proper maintenance has been drawing more and more attention in contributing industries towards prolonging the system's effective operational lifetime and also improves the reliability and availability of the system to ensure the delivery of high-quality products to customers on time [44]. This leads to more preventive maintenance actions that are also better aligned with other business functions, such as production scheduling and spare parts control [43].

Maintenance of deteriorating systems and replacement problems have been studied extensively in many fields, especially in mechanical, electrical, aerospace, and civil engineering. In addition to several books on operation research, there is a vast amount of papers related to maintenance [47]. Also, there exists a high variety of approaches depending on the specific topic tackled, and various reviews have been made to give a general overview of maintenance optimization. The reviews made in [42], [43], [44], [47], [48], [49], [50] and [51], provide us with a multidisciplinary approach based on academic literature. Although there are some differences among the authors in classifying optimization models, the main purpose of this section is to give an overview and not to discuss the correct classification. In this case, we have adopted the approach given in [44]. The next sub-sections give a general sight of maintenance optimization referencing to some representative works.

2.6.1 Model definition for maintenance optimization

In [44] the authors give a general definition of what elements maintenance optimization models usually include. In this context, they first define optimization as finding a balanced maintenance solution that closes to the objective under certain criteria by using the preferred approach. Second, they state that a model in maintenance policy optimization aspects is a description of a process to model, analyze, and determine the optimal maintenance policy under predetermined maintenance objectives and criteria. Following the above, models used to derive optimal maintenance policy generally cover four main aspects:

- A description of the system being maintained.
- A model on how the system deteriorates and the consequences thereof.
- A description of the available information on the system and the available response options.
- An objective function and an analytical framework (or tools) according to which the optimal maintenance policy is to be derived.

In the general framework developed by Wang [52], he details more specific inputs: maintenance policies, system configuration, maintenance effectiveness, maintenance costs, optimization criteria, modeling tools, planning horizon, dependence, and system information.

2.6.2 System configuration and information

When describing a system, different configurations are possible: single-unit, multi-unit, series, parallel, k-out-of-n, standby, etc. A single-unit system consists of either one component or multiple components. By contrast, multiple or multi-unit systems consist of several system units with several components. Furthermore, the elements of each system state are arranged mechanically into two configurations, namely the serial and the parallel. In a serial configuration, the entire system fails if any one of the system's components fails. By contrast, for a parallel configuration, the entire system works as long as not all the systems or components fail [50]. A k-out-of-n system is a system composed of n elements, which functions if at least k components function. If k=1, then it is a parallel system; if k=n, then it is a series system [42]. In literature, several optimization models have been developed for each type of system configuration. The review papers [43], [44], and [51] all address single-unit, multi-unit, and k-out-of-n systems.

Describing the function and importance of the technical system is necessary to understand the working principle and determine the criticality and system configuration of the equipment at hand. Analyzing data without knowing the underlying mechanisms can lead to wrong decisions, which stresses the importance of having the proper system information [51]. A proper system information will reveal dependencies between components (when present) of a multi-component system. If there no exists dependence between components, then the problem reduces to an optimal policy for each component.

Traditionally, three types of dependence between components are distinguished: economic, structural, and stochastic dependence [43] [51].

2.6.2.1 Economic dependence

Economic dependence exists when the cost of maintaining or inspecting multiple units simultaneously is different from the cost of maintaining or inspecting these units separately (e.g. due to a fixed setup cost) [43]. In [42] authors extend this definition to positive and negative economic dependence.

Positive economic dependence implies that costs can be saved when several components are jointly instead of separately maintained; economies of scale and downtime opportunity can promote positive economic dependence. "Economies of scale" is often used to indicate that combining maintenance activities is cheaper than performing maintenance on components separately. The work developed in [53] considers a condition-based maintenance policy for a two-unit deteriorating system under a stochastic process, with economic dependence and non-periodic inspections; here, joint maintenance of components saves costs. In [54] the authors develop a model of a condition-based maintenance policy for a two-component system with both stochastic and economic dependencies.

Downtime of a system is an opportunity to combine preventive and corrective maintenance. This is especially true for series systems, where a single failure results in a system breakdown. Group maintenance policies and opportunistic maintenance policies are given in [52]. In [55] is developed opportunistic maintenance approaches for an entire wind farm considering imperfect maintenance. The authors propose three opportunistic maintenance optimization models, where preventive maintenance is considered perfect, imperfect, and two-level action, respectively.

Negative economic dependence between components occurs when maintaining components simultaneously is more expensive than maintaining components individually; that is, the shortage of resources. Some reasons to produce that are manpower restrictions, safety requirements, redundancy or production-loss, maintenance facility, and spare parts [42] [49]. For example, maintenance results in a peak in manpower needs; there are often restrictions on the usage of equipment when executing maintenance activities simultaneously; maintenance of components in systems in which some kind of redundancy is available may not be beneficial. In [56] a model for preventive maintenance scheduling of power plants including wind farms is given; a restriction of manpower is also included.

2.6.2.2 Structural dependence

Structural dependence occurs when an intervention of a component requires that other components be intervened (either replaced or dismantled) at the same time. In other words, structural dependence between components indicates that they cannot be maintained independently. Recently, the resource dependence was introduced in [48]. The authors explain that resource dependence arises for example when several components are connected through a shared, limited set of spares. As a consequence, maintenance optimization is required on the system level rather than on the component level. Moreover, they extend the definition of structural dependence by further classifying this into technical and performance dependence.

A system is considered technically dependent when intervention activities for certain components are restricted by those of other components; the negligence of this dependence inevitably results in an infeasible maintenance strategy. Performance dependence is applied when an intervention activity, deterioration, and failure of a component affects the performance of other components and the overall system [49]. According to [52], this dependence is also referred to as system configuration. An example of structural dependence is developed in [57], where authors use selective maintenance on multi-state systems. Here, each component can be in one of multiple working levels and several maintenance actions are possible to a component in a maintenance break.

2.6.2.3 Stochastic dependence

According to [42], stochastic dependence, also referred to as failure interaction or probabilistic dependence, implies that the state of components can influence the state of the other components. Here, the state can be given by the age, the failure rate, state of failure, or any other condition measure. They mention three different types of failure interactions in a two-component system.

Type I failure interaction implies that the failure of a component can induce a failure of the other component with a given probability. This means that there are two types of failures: natural and induced. The natural failures are modeled by random variables and the induced failures are characterized by the given probabilities. Type II failure interaction establishes that the failure of component *2* can induce a failure of component *1* with a given probability, whereas every failure of component *1* acts as a shock to component *2*, without inducing an instantaneous failure, but affecting its failure rate. Type III failure interaction states that the failure of each component affects the failure rates of the other component, i.e. every failure of one of the components acts as a shock to the other component [42].

Generally, when considering stochastic dependence in the literature, the maintenance policies considered are focused on opportunistic nature since the failure of the components represent prejudicial for the rest of the components. For example, in [58] is developed a dynamic opportunistic condition-based maintenance strategy for multi-component systems. The strategy is based on real-time predictions of the remaining useful life under the simultaneous consideration of economic and stochastic dependence. Authors in [59] deal with the problem of maintenance optimization of a two-component system with stochastic dependence when components are heterogeneous regarding their degradation model. Components are dependent in such a way that the lifetime parameters of components subject to shocks depend on the degradation level of the gradually deteriorating component.

2.6.3 Classification of maintenance policy optimization model

The following classification is given in [44], which adopts the certainty theory to characterize the maintenance policy optimization model. Here, the model is classified in terms of the degree of certainty: certainty, risk, and uncertainty. This classification has a direct relation to the quantity of information available. Figure 9 shows the certainty theory continuum.

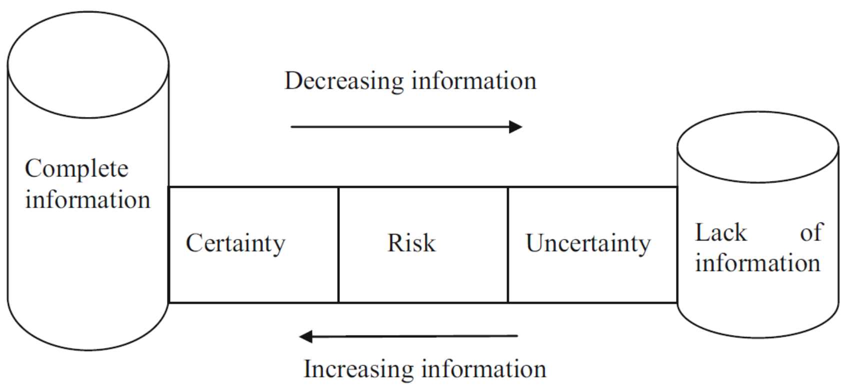

Figure 9 Certainty theory continuum [44].

2.6.3.1 Certainty category

In the presence of certainty, there is only one state of nature for each strategy. That is, perfect knowledge is assumed and the probability of a specific state of nature is one. It is generally simple and does not require complicated optimization procedures. A graphical based model uses graphs or figures to denote the optimal maintenance policy according to the value of a predetermined criteria. In [60] is used fuzzy maintenance and decision-making grid to specify what maintenance action must be done on the system based on the equipment's criticality and reliability properties. The graphical model is simple but may be less accurate because it is considered limited criteria. For example, in [61] downtime and failure frequency were the only two criteria involved. In practical terms, a policy must consider several different aspects like safety and environmental problems. Moreover, the possibility to have complete information in the optimization process is quite low.

2.6.3.2 Risk category

When risk is present in models, the states of nature are known and can be described stochastically through the probability of failure of the components as a function of time. Typical models under risk category are mathematical, simulation, and artificial intelligence. The mathematical model is the most used optimization model in the literature. It is consisting of an abstract model that describes a system through mathematical language. It is likely to predict the possible condition including the system itself and variables that influence the system by using the stochastic principle; thus, the optimization process can be conducted along with the predicted information. One of the methods used in mathematical models is the proportional hazard method (PHM). When using PHM it is possible to model system variables, external factors that included environmental conditions and working conditions, and age of the system. In the real environment, it is usually difficult to specify the quality of maintenance precisely and the failure times of system always affected by different covariates; in this context, PHM uses the proportional age reduction factor to the baseline of hazard rate or to operation time. One example can be found in [62] where authors model the reparable system reliability with various indicators included accumulated operating time and state of a system depending on its age and degree of repair; The indicators may be used as covariates in a proportional intensity model (PIM), or as reduction factors in a virtual age process model.

The simulation model is a computable method for running an abstract model over time, where the model can be implemented using computational techniques such as mathematical formalism that used different algorithms. It is useful for observing the behavior of a complex system when obtaining a solution based on a mathematical method is infeasible. One of the most popular methods for calculating optimal policies is Monte Carlo simulation. Researches adopting Monte Carlo simulation in the maintenance optimization usually focus on identifying the cost-effectiveness maintenance policy. In [63] the authors develop meta-heuristics for the specific problem in conjunction with an evolutionary particle swarm (PSO) algorithm; they incorporate Monte Carlo simulation to study the problem of balance between preventive and corrective maintenance as a multi-objective optimization problem.

Between the various definitions for artificial intelligence (AI), the most relevant is: AI is a field in science and engineering concerned with the computational understanding of what is commonly called intelligent behavior and with the creation of artifacts that exhibit such behavior. Among the AI methods, genetic algorithm (GA) is the most popular optimization method adopted in the maintenance policy optimization area. GA is well-known due to its robust search capabilities that help reduce the computational complexity of large optimization problems. Among the topics where GA has been implemented successfully is industrial engineering, including maintenance optimization, where its potential for resolution complex systems has attracted the attention of researchers. An example of the use of GA is given in [64], where authors proposed RAM+C (reliability, availability, maintenance and cost) models to address the effect of human and material resources.

2.6.3.2.1 Modeling deterioration

The modeling of the deterioration process of components and systems is truly important for obtaining the basic information on which all decisions about when to perform maintenance or inspection are made [51]. Understanding deterioration mechanisms, which is key in defining a maintenance program, requires modeling the time-dependent changes of the structural properties and its uncertain nature [47]; consequently, this deterioration process description should match as close as possible with the real deterioration of the system.

A deterioration process can be modeled with a discrete or continuous state space. Models with a discrete state space have a countable, generally finite number of states; that is, when modeling with discrete state space, two (functioning or failed), three (functioning, defective, failed), or more states can be used. The deterioration in models with a continuous state space level can take any value within a particular interval [43]. The deterioration process is frequently divided into progressive and shock based. In progressive deterioration, the structure's performance degrades gradually and slowly over time. Shock-based degradation damage accumulates as a result of successive shocks (e.g., effect of earthquakes) [47].

Models that assume discrete-state deterioration are usually modeled by Markov processes. This is commonly used when precise measurements of the degradation states of the system cannot be obtained, and sometimes, it is a technical requirement since there is no need to work on every discrete value individually – from an engineering practice viewpoint. Instead, the degradation states are categorized into several deterioration levels [45]. In [65] the authors consider systems that deteriorate stochastically and exhibit multi-state failures and model their state evolution using Markov chains and directed graphs. Although Markov processes are used regularly to model deteriorating components, this approach also has some disadvantages. The analytical resolution is difficult in complex cases, the classification of states is arbitrary, and the transition probabilities are difficult to estimate and may not be elaborate enough in complex cases. A more realistic approach is to model deterioration by a stochastic continuous state process, though this has the disadvantage of mathematical complexity when modeling complex systems.

Continuous state processes, for example, have been widely implemented in CBM since more conditions or health information can be obtained through sensors that monitor the deterioration process. Some of the most common approaches use Wiener, Gamma, and Inverse Gaussian process. The Wiener process is appropriate in describing a degradation that shows increment or decrement of deterioration over time (non-monotonic), while the Gamma process is more suitable in modeling monotonically increasing (or decreasing) degradation. Gamma process has a monotonic degradation path and has been studied extensively in CBM models for continuously deteriorating systems [45].

The Inverse Gaussian process is a limiting compound Poisson process that is suitable for modeling heterogeneous degradation of systems deteriorating in a random environment, i.e. it is flexible in incorporating random effects and covariates that account for heterogeneities. Similar to the Gamma process, the Inverse Gaussian process is also suitable in modeling monotonic degradation but is more flexible in incorporating random effects compared to the Gamma process [45]. Also, the degradation process can be modeled with random proportional changes in time, as in [66]. The authors develop a continuously monitored deteriorating systems by using Monte Carlo simulation to find the optimal degradation threshold for performing preventive maintenance.

2.6.3.3 Uncertainty category

In the presence of uncertainty, future conditions and their corresponding probabilities are unknown; therefore, the necessary information must be determined based on judgment and utilization via subjective probabilities. We can subdivide this category into three sub-categories: heuristic, criticality, and multi-criteria.

Heuristic is a "rule-of-thumb"-based problem-solving approach that uses logic, experience, and knowledge derived from observation. When an exhaustive search is infeasible, the heuristic-based model can speed up the process of finding a satisfactory solution. In this context, a common tool used is a decision tree, which is a friendly tool for supporting decisions. Also, the justification of decisions usually is made according to the knowledge and experience of experts. For example, in [67] is carried out a study on selecting the optimal maintenance policy with the aid of a decision tree. In the selection process using the decision tree, two types of questions - technical and economic - would be sequentially asked for each proposed maintenance policy.

Hazard usually means the potential to cause harm either tangible or intangible. Papers under this approach emphasizes mainly in solving failures effectively rather than just focusing on economic aspect; the main concern is on improving maintenance quality in terms of safety, as well as reliability without drastically increasing the cost by assigning maintenance policy. Due to growing awareness on hazard and safety issues either human or environmental has brought about the rising of development on the hazard-based model in determining the optimal maintenance policy especially in heavy industry or high-risk industry. Some main approaches in the literature are failure mode, effect, and criticality analysis (FMECA); multi-criterion classification of critical equipment (MCCE); risk matrix; fault tree analysis; root cause analysis. In [68] authors applied FMECA to a fossil-fired power station for effectively preventing failures and finding the optimal policy.

Multi-criteria decision making (MCDM) is also one of the popular methods adopted in the maintenance policy optimization models. The |advantage of the MCDM is that it can include the multiple, usually conflicting, objectives into the decision-making process; therefore, it is useful in maintenance policy optimizations for conflicting objectives such as maximizing availability at the lowest cost. There are three main steps in adopting any kind of MCDM. The initial step of implementation is to determine the relevant criteria and alternatives, followed by attaching numerical measures to the relative importance (i.e. weight) of the criteria and the impacts (i.e., relative performance) of the alternatives on these criteria. Finally, process the numerical values to determine the ranking of each alternative, in this case, the optimal maintenance policy. Several MCDM method has been proposed in the literature such as analytic hierarchy process (AHP), weighted sum method (WSM), elimination and choice translating reality (ELECTRE), a technique for order preference by similarity to ideal solution (TOPSIS), among others. Among the developed MCDM methods, AHP is the most widely used in the maintenance selection. An implementation of AHP has been suggested [69] to measure the health, safety, environmental awareness, as well as costs issues in selecting a maintenance policy. Validation of the methodology was carried out in a case study on the oil and gas industry.

2.6.4 Maintenance effectiveness

The maintenance effectiveness is an important factor that must be considered in the optimization process. Maintenance effectiveness is the degree to which the operating conditions of an item are restored after a maintenance action is performed [51]. The main purpose of the O&M operators is to restore a component to an improved definite state; however, the human error cannot be neglected, especially in large-scale applications. Some common causes of human error are bad setting, damage during maintenance, replacement with failed or damaged parts, perform maintenance out of the established schedule, perform maintenance with damage equipment, bad calibration, prognosis error, bad decisions based on wrong prognosis, among others [47] [70]. An overview of the different possible degrees of restoration is given below [47] [51]:

- **Perfect repair or perfect maintenance:** the operating condition of the system is restored to an as-good-as-new state, which means that the lifetime distribution, degradation level, and failure rate are the same as for a new component.
- **Minimal repair or minimal maintenance:** the failure rate of the system is restored to the one the system had before the maintenance action was performed, which is referred to as-bad-as-old state.
- **Imperfect repair or imperfect maintenance:** the operating condition of the system is restored to somewhere between as-good-as-new and as-bad-as-old state.
- **Worse repair or worse maintenance:** the system failure rate or actual age of the system increases by performing a maintenance action, but the system does not break down.
- **Worst repair or worst maintenance:** the system will certainly fail by performing a maintenance action.

2.6.5 Maintenance policies

As we have seen, there are a vast number of maintenance models inspired by the high variety of systems' characteristics. Ideally, a specific system should have a personalized-suitable maintenance model and policy to obtain better outputs. Given the large number of approaches in maintenance policies as well, Wang [52] summarizes, classifies, and compares various existing maintenance policies for both single-unit and multi-unit systems.

According to Wang, maintenance can be categorized into two major classes: corrective (CM) and preventive maintenance (PM). CM means all actions performed as a result of a failure, to restore an item to a specified condition. PM means all actions performed in an attempt to retain an item in a specified condition by providing systematic inspection, detection, and prevention of incipient failures.

Thousands of maintenance and replacement models have been created; however, all these models can fall into some categories of maintenance policies: age replacement policy, random age replacement policy, block replacement policy, periodic preventive maintenance policy, failure limit policy, sequential preventive maintenance policy, repair cost limit policy, repair time limit policy, repair number counting policy, reference time policy, mixed-age policy, preparedness maintenance policy, group maintenance policy, opportunistic maintenance policy, etc. [52]. A brief description (based on [52]) of the most used policies for both single-unit and multi-unit systems is given below.

2.6.5.1 Single-unit systems policies

2.6.5.1.1 Age-dependent PM policy

This is one of the most common and popular maintenance policies. Under this policy, a unit is always replaced (or maintained) at its age T or failure, whichever occurs first, where T is a constant. Depend on the approach, both PM and CM can be perfect, imperfect, minimal or worse. Some variations were made as a better understanding of minimal and imperfect maintenance emerged. For example, a random-age-dependent maintenance policy is used when a unit has a variable work cycle so that a fixed T is impractical; under this policy, T is a random variable and, consequently, the policy would have to be a random one, taking advantage of any free time available to perform maintenance. Other results and extensions like *T-N policy*, *periodic replacement with minimal repair at failure*, *repair replacement policy,* and *mixed-age PM policy* can be found in [52].

2.6.5.1.2 Periodic PM policy

In the periodic PM policy, a unit is preventively maintained at fixed time intervals kT ($k = 1,2,\ldots$) independent of the failure history of the unit, and repaired at intervening failures where T is a constant. In some early research, the *block replacement policy* was examined in which a unit is replaced at prearranged times kT ($k = 1,2,\ldots$) and at its failures. The block replacement policy derives its name from the commonly employed practice of replacing a block or group of units in a system at prescribed times kT ($k = 1,2,\ldots$) independent of the failure history of the system and is often used for multi-unit systems.

2.6.5.1.3 Failure limit policy

Under the failure limit policy, PM is performed only when the failure rate or other reliability indices of a unit reach a predetermined level and intervening failures are corrected by repairs. This PM policy makes a unit work at or above the minimum acceptable level of reliability; for example, a maintenance cost policy where PM is performed whenever a unit reaches the predetermined maximum failure rate, and failures are corrected by minimal repair. An interesting approach is developed by [71], where authors investigate a failure limit policy in which replacement policies are based on measurements of some increasing state variable, e.g., wear, accumulate damage or accumulated stress; the proneness to failure of an active unit is described by an increasing state-dependent failure rate function. The optimal replacement rule in terms of average long-run maintenance cost rate is shown to be a failure limit rule, i.e., it is optimal to replace either at failure or when the state variable has reached some threshold value, whichever occurs first.

2.6.5.1.4 Sequential PM policy

Unlike the periodic PM policy, a unit is preventively maintained at unequal time intervals under the *sequential PM policy*. Usually, the time intervals become shorter and shorter as time passes, considering that most units need more frequent maintenance with increased ages. Under sequential PM, the next PM interval is selected to minimize the expected expenditure during the remaining time. Thus, this policy does not specify at the beginning of the original period each future PM interval; rather, after each PM, it specifies only the next PM interval.

2.6.5.1.5 Repair limit policy

When a unit fails, the repair cost is estimated and repair is undertaken if the estimated cost is less than a predetermined limit; otherwise, the unit is replaced. This is called the *repair cost limit policy* in the literature. A disadvantage of the repair cost limit policy is that the replacement or repair decision depends only on the cost of a single repair. An extension of this policy is the *repair time policy*, where a unit is repair at failure under a condition: if the repair is not completed within a specified time T, it is replaced by a new one; otherwise, the repaired unit is put into operation again; T is called *repair time limit*.

2.6.5.1.6 Repair number counting and reference policy

In the *repair number policy*, a unit is replaced at the kth failure. The first (k-1) failures are removed by minimal repair. Upon replacement, the process repeats. The policy decision variable is k. Later, this policy is extended by introducing another policy variable T *critical reference time* which is a positive number. Under this extended policy, all failures before the kth failure are corrected only with minimal repair. If the kth failure occurs before an accumulated operating time T, it is corrected by minimal repair and the next failure induces replacement. But if the kth failure occurs after T, it induces replacement of the unit.

2.6.5.2 Multi-unit systems policies

2.6.5.2.1 Group maintenance policy

The main topic that addresses this policy is the clustering of the elements that should be maintained after a failure depending on which dependencies exist among them. In this category, there are three main types of policies. The first policy, referred to as a T-age group replacement policy, calls for a group replacement when the system is of age T. A second policy, referred to as an m-failure group replacement policy, calls for a system inspection after m failures have occurred. The third policy combines the advantages of the m-failure and T-age policies. This policy, referred to as an (m, T) group replacement policy, calls for a group replacement when the system is of age T, or when m failures have occurred, whichever comes first.

2.6.5.2.2 Opportunistic maintenance policy

When exists economic dependence in multi-systems, it is possible to do PM to non-failed components at a reduced additional cost while failed components are being maintained. When exists failure dependence or correlated failures, upon a component failure the other component, as well as the failed one, may be also maintained o replaced by a new one if its age exceeds a predetermined control limit L. An extension of this is such a policy: both units are replaced either when one of them fails and the age of the other unit exceeds the critical control limit L, or when any of them reaches a predetermined critical age S. A unit is replaced at age T or at failure, whichever occurs first.

2.6.6 Maintenance optimization criteria

Optimization is always performed by minimizing or maximizing an objective function. In most of the maintenance optimization models, the objective function only takes into account one criterion (e.g., cost, availability, reliability). Although most of the works develop a single-objective optimization, in practical terms, a multi-objective optimization should be more suitable [51]. Despite the vast analysis of the researchers in maintenance topics like optimization models, maintenance policy optimization, or deterioration models, there is a lack of studies focused on the correct choice of the maintenance optimization criteria; it is evident that a wrong criteria optimization results in wrong outputs. Different opinions about the most important criteria for maintenance optimization are recommended in the literature, where the choice is regarding the specific phenomena of the real case. The following list [51] contain all possible maintenance optimization criteria found in literature and some additional added by authors:

- Maintenance costs (discounted)
- Maintenance quality
- Personnel management
- Availability
- Reliability
- Maintainability
- Inventory of spare parts
- Safe/risk
- Logistics
- Output quantity
- Output quality
- Environmental impact
- Overall equipment effectiveness
- Number of maintenance interventions
- Capital replacement decisions
- Life-cycle optimization

It is important to note that each element in the list represent the main topic; thus, additional related sub-elements can be incorporated. Also, to better model a system, some of the criteria listed can be mixed as a function of the problem addressed.

2.7 Solar PV maintenance optimization

The pronounced worldwide growth of solar photovoltaics is beginning to steer greater industry attention towards operation and maintenance planning and execution strategies. Lately, there is merit in the industry to more comprehensively incorporating O&M strategies into PV system planning, design, and asset management activities to increase lifecycle PV. It is becoming more apparent to the participants of the PV sector, that increasing the reliability is the most effective way to reduce the LCOE of PV technology [34] [72]. In contrast, although plenty of research has been done in the literature regarding maintenance optimization, there is a lack of works in PV maintenance optimization; besides, most of the works focused on individual elements of PV plants and not to tackle the complete system. On the other hand, the PV industry bases its maintenance schedules on best practices and heuristics, and practitioners tend to not share the policies. In this context, PV maintenance topics have been addressed by literature through reliability and fault analysis in simple components or sub-systems, with considerable attention to PV panels [34] (in monofacial and bifacial), where some authors make suggestions and improvements in maintenance.

For example, in [73] and [74] authors develop an FMECA analysis methodology to classify the occurrence, the severity, and the impact of all possible mechanisms on the PV system. Their principal focus is to characterize PV failure modes to improve reliability and maintainability of PV panels. In [75] is studied how the degradation of individual components affects the state of the PV inverter to effectively replace marginal components with more reliable ones, increase the lifetime and efficiency of the inverter and decrease the cost per watt. In [76] authors focuses on how to ensure high reliability and long service life of photovoltaic PV inverters in the design phase; also, they discuss maintainability for long-term reliability of the PV inverter. Zini et. al. [77] present a method for assessing the reliability of large-scale grid-connected photovoltaic systems using fault tree and probability analysis to compute the reliability equation. They conclude that the only likely way to figure out faults occurring in PV modules and string protections is to use automatic monitoring and diagnostic systems to capture reduced power output from small defaults which can result, if not detected, in potential sources of serious economic losses; also, periodical verification and policies of preventive substitution of string protections (if present) and inverters can greatly improve energy conversion output.

Another focus has been on the detection and mitigation of faults. In this respect, various works in condition-based and predictive PV maintenance, and condition monitoring have been developed. In [78], Ventura and Tina introduce a new indicator for on-line monitoring and fault detection of inverters that compares the inverter's efficiency and detects anomalies even when the overall PV system efficiency is in acceptable values. In [79] authors adapt reliability models to incorporate monitoring data on operating PV assets, as well as information on their environmental conditions, in their calculations. The main purpose is to predict failure modes and forecast energy to assist maintenance based on an artificial neural network (ANN) model; with this tool, they can improve the on-line diagnosis and potential asset degradation prediction. Riley and Johnson [80] develop a novel model-based prognostics and health and management (PHM) system to monitor the health of a PV system, measure degradation, and indicate maintenance schedules. Their method is based on ANN which eliminates the need for *a priori* information by teaching the algorithm "good" performance behavior based on the initial performance of the array. Similar works can be found in [81] and [82]; in the first, authors apply convolutional neural networks (CNN) for monitoring the operation of PV panels based on the power curves of the neighboring panels and predict accurately the power curve of a functioning power; in the second, authors present a solution for fault prediction based on data collected from supervisory control and data acquisition (SCADA) system. Prediction is offered at two-level: generic fault prediction and specific fault class prediction, using two different modules based on machine learning. Results demonstrate that the proposed methodology effectively anticipates high-frequency inverter failures up to almost 7 days in advance, with sensitivity up to 95% and specificity of almost 80% and guarantees early detection for unpredictable failures.

Until now in this section, works reviewed present useful tools for enhancing the performance and maintainability of PV systems; however, none of them establish periodicity or policies of maintenance and they only assert their models' suitability for maintenance assistance. Regarding PV soiling, there is vast literature addressing this topic from the point of view of characterization and evaluation of PV soiling performance; several reviews are available in the literature [83] [84] [85] [86] [87] [88] [89] [90] [91]. Also, some works tackle maintenance through cleaning schedule optimization.

In this context, papers estimate optimal cleaning intervals using different methods. For example, authors in [92], [93] and [94] develop mathematical approaches based on a linear-solar-irradiation model fitted with real data and cleaning costs; In [94] authors extend the optimization to various tilt angles and bifacial PV modules. Other researchers [95] [96] utilized particle swarm optimization (PSO) in non-linear empirical models to minimize the cleaning interval. In [95] authors also incorporate the effect of installation azimuth angle and make a comparison of PSO with analytical method, where PSO performance is shown more efficiently. In [96] the focus is on daily and monthly soiling ratio variations and its influence in energy loss; it is revealed the non-uniformity and meteorological dependence of soiling. Another approach [97] uses mixed-integer linear programming and simulation for evaluating different cleaning strategies in bifacial PV modules and finding the optimum cleaning schedule. Some other interesting approaches are given in [98] and [99]; in first one, authors develop ANN and extreme learning machine (ELM) models to estimate system conversion efficiency based on experimental data to determine an optimal cleaning frequency; the second one is similar but the comparison is between multivariate linear regression (MLR) and ANN models.

Concerning to preventive maintenance optimization, the following three papers address this topic in a distinct form. In [100] authors tackles the optimization of a stand-alone hybrid photovoltaic-batteries-hydrogen (PV-hydrogen) system, using an evolutionary algorithm. They state two optimization problems: the first one consists in the obtention of the optimal number, distribution, and disposition of the PV panels in the facility; the second one addresses the same problem but scheduling a maintenance visit per year. Although the authors optimize the size considering preventive maintenance, they do not optimize frequency or policy of PM at all; besides, the system studied is a stand-alone power system for feeding a remote telecommunications facility, so that it is a small system. Villarini et al. [34] present a complete and new assessment of reliability centered maintenance carried out using an FMEA approach to photovoltaic systems. The analysis is extended to include the whole PV system, without limiting the focus to issues of a single component as presented in previous studies. The authors develop a complete characterization of failure modes based on the opinions of technicians who are experts in the functioning of a PV system and suggest numerous improvements in preventive maintenance. Although this work is concerning to PM, it focuses principally on mitigation risks and optimization of PM procedures, not policy; also, this approach is highly dependent on the researcher's criteria. The most allusive paper in preventive maintenance optimization is done by Baklouti et al. [101]. Here, authors develop a PM strategy for a solar system composed of solar panels functioning as a series system; the strategy suggests systematically replacing n panels with their respective wiring system every time units T over a finite operating period H. Authors model and minimize the expected total maintenance cost over a finite operating time horizon H for a different combination of input parameters; the model is based on the reliability theory and is solved analytically. This is the first version of the work, so that the model proposed develops a basic modeling. For example, the system considered includes only series PV modules; the system is considered in a failed state whenever its efficiency drops below a predefined threshold; only perfect maintenance is considered.

2.8 Discussion

In general terms, it is evident that a vast number of works have addressed maintenance optimization from different approaches and purposes; however, there are still some challenges that have not been tackled and that are necessary to resolve. A latent problem is the evident gap between industry and academics. On the one hand, the academia has developed hundreds of works addressing maintenance optimization. On the other hand, maintenance policy managers and engineers often make decisions heuristically in the industry based on their experience and common sense due to the difficulties in finding models that suit the practical realistic issues of actual projects [47]. Several authors [43] [44] [50] [51] agree that the gap between theory and practice is due to two main reasons:

- **Models complexity:** Most of approaches and methods in maintenance optimization tend to develop complex mathematical models. Industry has management time, resources, and knowledge (specific academic knowledge) limitations that difficult the adaptation of the models to their specific business context; this can lead to the industry disinterest [44] [51].
- **Academy focus:** In literature, many works are written for mathematical purposes only and case studies are often only used to demonstrate the applicability of a developed model, rather than finding an optimal solution to a specific problem of interest to a practitioner. In general, case studies are not well presented, although maintenance is something that should be done in practice and not in theory. A clear example of this is that most of the works focus on single-unit systems, which is an unrealistic scenario in practice. There exist many that are theoretically advanced in determining optimal maintenance policies, but these are limited to very specific problems, and few are applied to solve real-life problems [43] [44] [51] [102].

Another limitation of academic models is that most of the models focus on only one optimization criterion (mostly focus on variable costs and reliability), making multi-objective optimization models an underexplored area of maintenance optimization; single-objective optimization can be attractive for modeling, yet this approach does not capture all important aspects of a real-life situation [44] [51]. Moreover, the formulation of optimization problems including choosing the objective function, decision variables, and constraints is rarely discussed in the literature; also, there are poor analysis of the elements surrounding maintenance operations and their effect on the desired output.

Further, modeling multi-unit systems is a better approach for a real-life situation; however, the complexity of the problem increases, and alternatives methodologies are required; for instance, commonly used methodologies in multi-unit systems are simulation to compare various (heuristic) policies, simulation-based optimization, genetic algorithms, and heuristic algorithms specified by the authors [43]. In this context, simulation delivers an advantage over mathematical approaches because many maintenance policies are not analytically traceable. Furthermore, it allows experimentation and a better understanding of complex systems [102].

Comparing the risk category models with uncertainty category models, the latter involved less complex algebraic formulation. It tends to adopt logic thinking-based approaches rather than using complicated algebraic formulation to perform probability analysis. Despite this kind of model is capable of providing more reliable analysis, it is still facing difficulties in collecting quality data because these models tend to utilize experience and knowledge which is not well documented [44].

Regarding PV maintenance optimization, the concerning works are even more scarce. Although there are plenty of works related to reliability, soiling, failure modes, and performance of PV systems, literature has studied the phenomena separately and only a few works address maintenance optimization. In fact, we could not find an approach that encompasses the complete PV plant to calculate the optimal preventive maintenance policy. Thus, considering the accelerated increase of photovoltaics in the industry, we observe an inherent necessity of developing new strategies for addressing the optimization of PV preventive maintenance to a real-life case. In this regard, Horenbeek et al. [51] state an interesting noteworthy concept: *Maintenance optimization should not start with developing a maintenance model and trying to fit an application to it, but it should start with an application and try to fit a maintenance optimization model to it.* This is the central idea that we aim to apply in the present thesis.

3 Proposed methodology

3.1 Introduction

This chapter begins with a complete general presentation of the proposed methodology, explaining in global terms the type of methodology, the elements that compose it, the modeling mechanism, modeled variables, and optimization criteria. After that, all the elements that compose the methodology are explained and developed graphically, together with the mathematical expressions and the level of detail modeled. Finally, the complete mathematical optimization model is presented, explicitly defining the decision variables and their scope in the model.

3.2 Presentation and definition of the methodology

The proposed methodology represents an empirical model for large-scale preventive maintenance optimization. In this context, our approach models the degradation phenomena occurring in the elements of PV plants by representing health state (HS) curves and stress factors (SF); i.e., degradation is modeled as a function of usage, not time. Thus, the degradation suffered by an element due to SF is represented by an HS curve as a function of duty cycles (expressed with the variable k), where the HS curve is defined in the range [0,1], and the duty cycle (k) is defined as the cumulative work performed in a 24-hour day[5]. In an ideal case, the HS is equal to 1 at $k = 0$; after that, the HS decreases with degradation caused by each new duty cycle.

As an element is affected by stress factors, the health state drops, and then a failure may occur. The maintenance policy sets thresholds on the value of HS curves at which inspections and preventive maintenance are performed in order to avoid failures. Once the maintenance has been performed, the health state is restored to the theoretical value of 1; however, due to maintenance error, this value is randomly varied by a value less than 1.

The determination of the optimal preventive maintenance policy is carried out through Monte Carlo simulation and Genetic Algorithm, where the decision variables are inspection spacing (in duty cycles), inspection threshold (in the range [0,1]), and preventive maintenance threshold (in the range [0,1]), for each element modeled. The objective function

[5] A 24-hour cycle is assumed because solar radiation, wind speed and ambient temperature have daily cycles that are reasonably comparable to a duty cycles.

is the expected profit composed of the difference between the expected energy revenue and the total expected maintenance cost. Figure 10 shows a general scheme for the entire proposed methodology, and the following sub-sections show its full breakdown.

This methodology integrates the different elements present in a solar PV plant into a single model, modeling the phenomenology of the elements by employing health state curves. In the literature, these curves have been used to model simple and independent elements, so it is of interest to this thesis to evaluate the behavior and robustness of the methodology when integrating several health state curves in a single problem.

Assumptions and considerations: This methodology contemplates a multi-unit configuration. The PV plant information available is collected through inspections and the monitoring system. There is no economic, structural, or stochastic dependence between the modeled elements of the PV plant. All activities performed by the human team are subject to procedural errors, which directly impact the different health states. Auxiliary consumption is not considered in the economic and energy balance. Full availability of spare parts is assumed. The logistics required to carry out the different types of maintenance are not modeled.

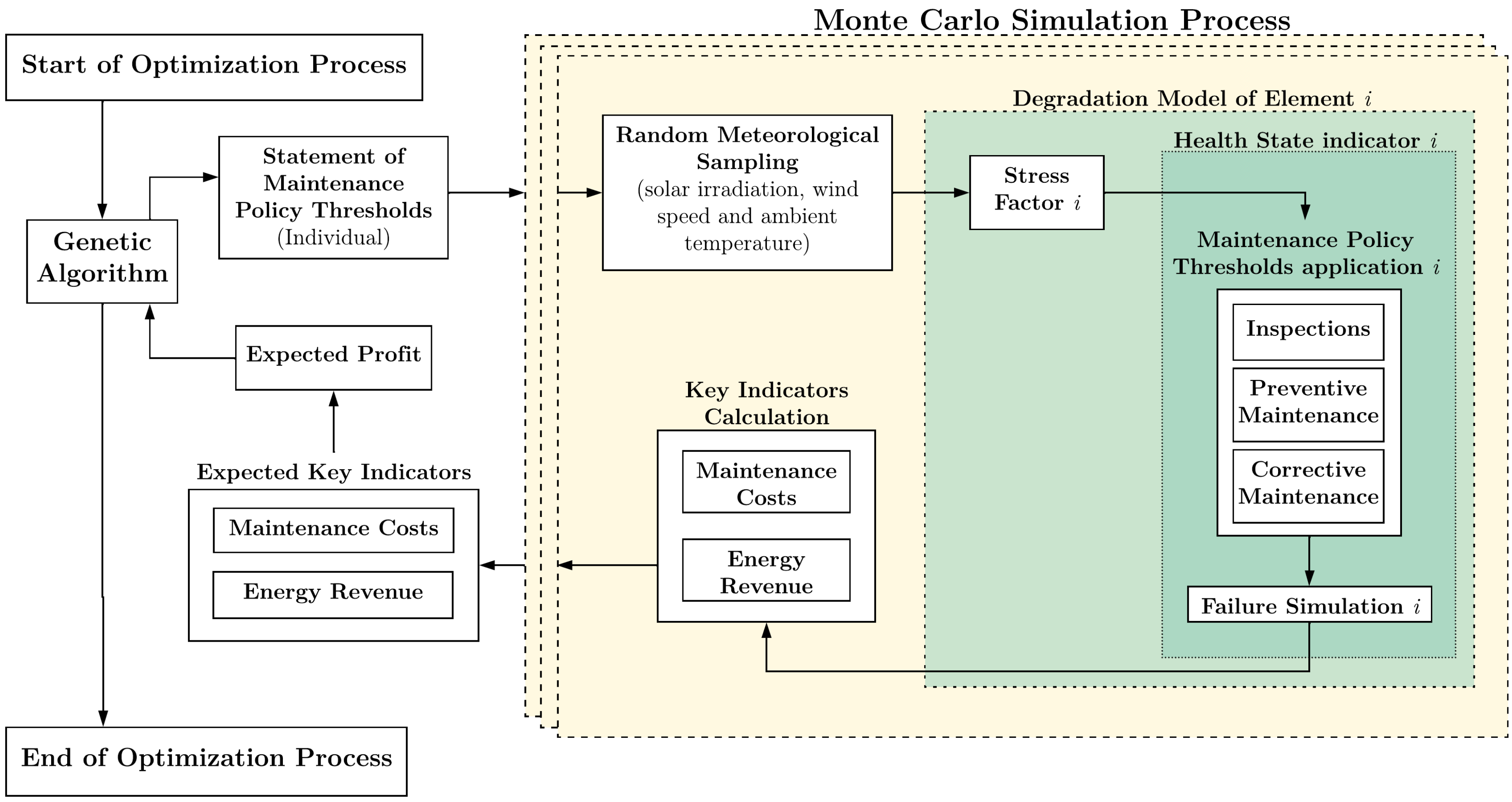

Figure 10 General scheme of the proposed methodology.

3.3 Characterization of the PV system

3.3.1 System breakdown

As described in section 2.5.1 and following the same characterization, we organize the main components of the PV system into 5 categories: generation system, conversion system, transmission system, transformation system, and monitoring and communicating system. From these sub-systems, we identified 8 principal elements that could be modeled: PV panels, supporting structures, grounding, inverter, wiring, transformer, sensors, and communicating system. Figure 11 shows a schematic with the breakdown of the *"representative system"*; the latter can be understood as a subsystem containing all elements of the power plant upstream of the LV/MV transformer (from the PV module arrays to the LV/MV transformer itself), which works as a minimum representative system, that if replicated n times could achieve the desired power output.

Of these 8 main elements, grounding is not modeled as an individual element, rather the faults caused by grounding are considered as part of the failure modes of other elements such as PV panels and inverters. Also, the sensors and the communication system are not considered within the methodology because they do not belong to the direct generation chain and a stress-based model might not be suitable. The remaining elements have their own degradation model.

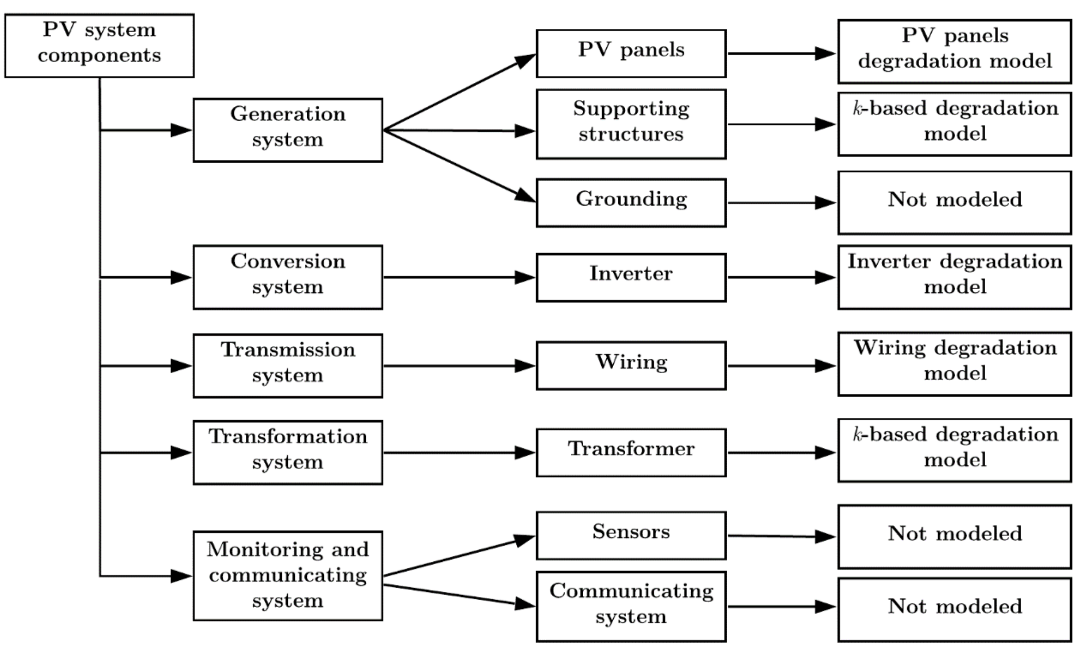

Figure 11 Representative solar PV plant breakdown.

3.4 Methodology breakdown

3.4.1 Monte Carlo Simulation

The proposed methodology incorporates two main sources of uncertainty: meteorological variables and maintenance error. In the first case, weather conditions induce degradation and aging in the components, which are affected to a greater or lesser extent by the stochastic behavior of the meteorological variables. In the second case, human error together with component failures also behaves as stochastic elements. In addition, Monte Carlo is a robust method for evaluating multiple scenarios, which allows obtaining a general approximation of all possible solutions. Therefore, the stochastic nature of the proposed methodology leads us to use Monte Carlo simulation as a consistent alternative for solving our high complexity stochastic problem.

The Monte Carlo method consists of creating a mathematical model that simulates a real system to which a large number of random samples of the model are applied, and which produces a large number of random samples of the model results. The method is based on running the model many times, as in random sampling. For each sample, random variants are generated for each input variable. Since each input is random, the results are random [103]. By generating numerous simulations, the results may converge to a known distribution depending on the nature of the model representing the developed phenomenon.

In the proposal, the simulated model corresponds to the performance of the PV plant when random weather variables are applied to the input; each sample of random weather variables and maintenance policy thresholds represents a possible scenario. Within each realization, the methodology defines different items involved in the performance of the PV plant. These items are referred to as "work items", which are described below.

3.4.2 Work items

For producing a possible scenario, the methodology is designed using independent work items that operate sequentially. These items are as follows: Random meteorological sampling, degradation models, and calculation of key indicators. As each item is independent, it can be refined and improved without changing the methodology.

3.4.2.1 Random meteorological sampling

The purpose of this work item is to generate the meteorological random variables that will serve as input variables for the Monte Carlo simulation. The meteorological variables modeled are solar irradiance, wind speed, and ambient temperature. These variables are established based on the degradation models described in section 3.4.2.2.

The first thing is to find a function that correctly represents the data, for which there are different methods and strategies to generate data fits depending on the nature of the data and the purpose of use. There are parametric and non-parametric fits. When the distribution of a data set does not fit any known parametric function, it is necessary to use nonparametric methods, which can describe any distribution and are not limited to known functions. The second is sampling the data maintaining daily and seasonal correlation conditions. In this regard, there is sufficient literature that allows us to find the most appropriate model. It is not the purpose of this thesis to find the best way to fit and sample the data, rather, we are more interested in finding a fast method with acceptable results; further work can improve the accuracy of this section.

For practical purposes and computational speed, we propose a simplified empirical method of a random sampling of meteorological variables that allows running multiple samples maintaining daily and seasonal correlations within the available computational time and enough accuracy. The proposed method is based on sampling the data using normal distributions having as mean a moving central vector $\overrightarrow{\mu_i}$ and standard deviation σ_i obtained from the monthly variability. For each hour of the day, the three variables are sampled together following three different Gaussians (taking advantage of highly optimized Python libraries) with the mean the central vector, and the given standard deviation. Each variable has a central vector of 8760 data obtained from a typical year, which allows preserving the daily and seasonal correlation between the variables (since all three variables are sampled at the same time following the central vector). The standard deviation is calculated for each hour of the day in every month as the difference between the extreme values divided by 6; this assumes 3 standard deviations with 99.6% of the data within the distribution, therefore, the data belong to the interval $\overrightarrow{\mu_i} \pm 3\sigma_i$. Figure 12 to Figure 14 show the three variables for a typical meteorological year compared to the variables sampled; these are normalized so they represent probability density functions. For more details on the reasons for the choice of this empirical method, see Annexed A.

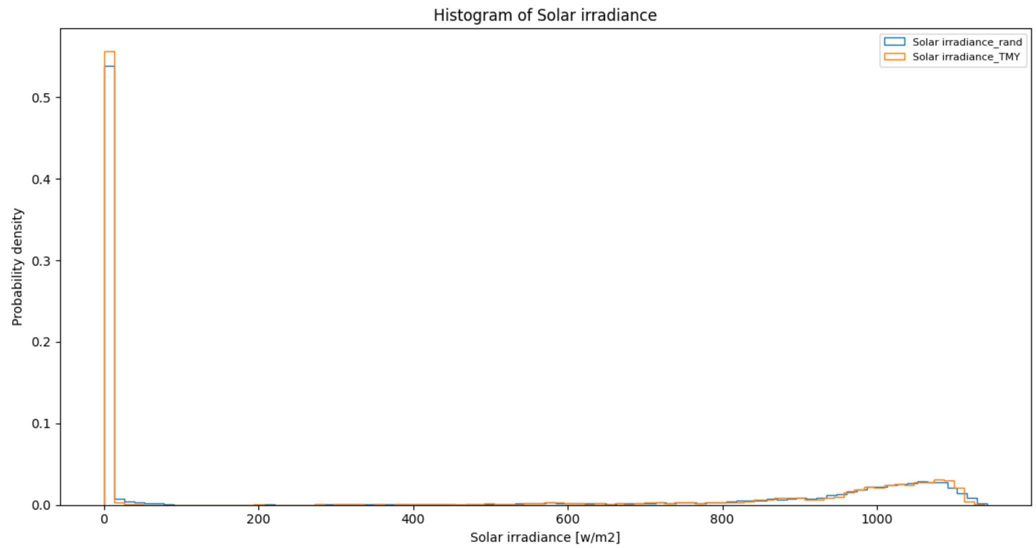

Figure 12 Histogram for sampled solar irradiance vs. typical year solar irradiance.

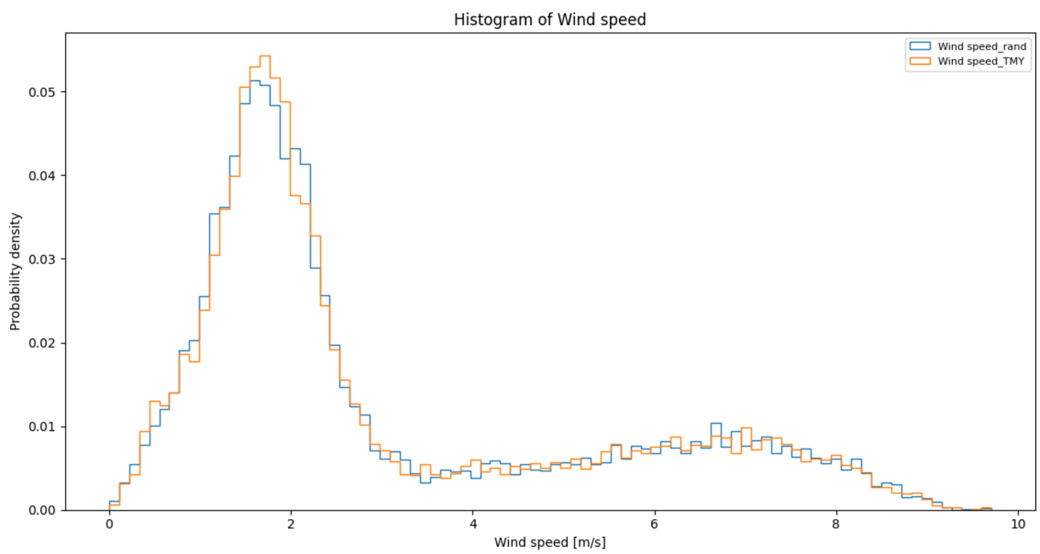

Figure 13 Histogram for sampled wind speed vs. typical year wind speed.

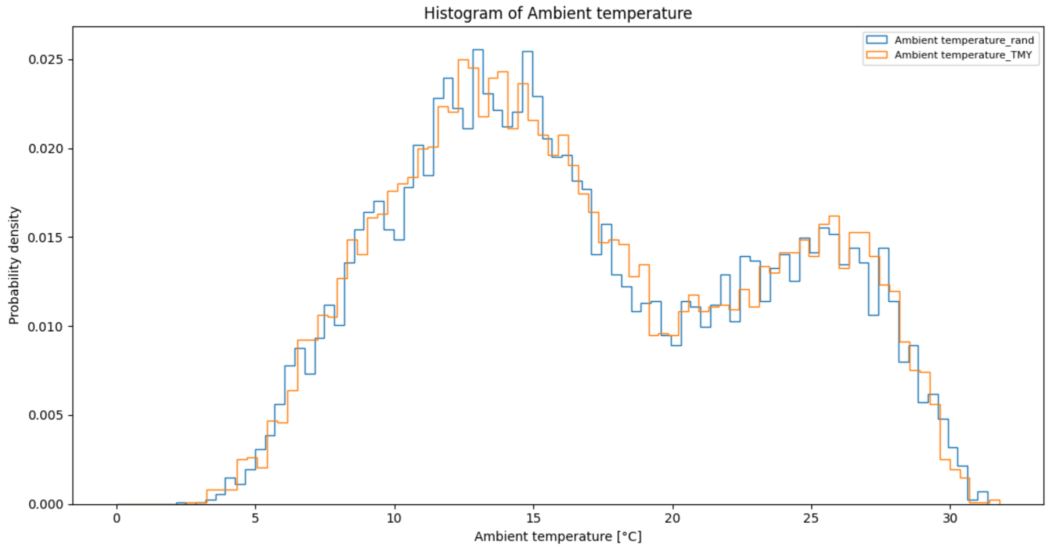

Figure 14 Histogram for sampled ambient temperature vs. typical year ambient temperature.

3.4.2.2 Degradation models

The proposed degradation models are a graphical and mathematical illustration of device life, depicted in health state (HS) curves. It represents a stochastic and usage-based model. This approach is based on the cumulative degradation caused by stress factors in a duty cycle k, where the degradation in each duty cycle is added to the degradation of the previous cycle k - 1. A duty cycle is conveniently defined as the work performed on a 24-hour day given the natural cyclical characteristics of the meteorological variables. This cumulative degradation causes the HS, initially equal to 1 (ideally) and defined in the range [0,1], to decrease progressively over the duty cycles forming a naturally decreasing curve. In conclusion, the HS curve proposed is a mathematical abstraction that represents graphically the evolution of the life of an element throughout its useful life. This allows us to generate cycles to estimate maintenance intervals; it also represents the inverse of degradation.

Degradation curves can behave in several forms depending on the variables modeled and the characteristics of the elements. Sometimes, degradation presents a characteristic curve type inherent to a certain phenomenon. For instance, several degradation models for solar panels as a function of failure modes are presented in [28] [104] [105]. These models generate characteristic curves as a function of the modeled physical variables; Figure 15 and Figure 16 show an example of the degradation characteristic curves for different specific failure modes modeled in the literature. However, we are not modeling specific phenomena, but rather, a set of phenomena per element. Therefore, we can assume a joint degradation characteristic curve type, which is fitted by historical failure rate data. This simplification is necessary because it is extremely complex to model a complete PV plant in detail using analytical methods and extremely computationally expensive using simulation-based methods. This is important because it defines the mathematical expression of the degradation model and how the stress factor is defined to produce degradation.

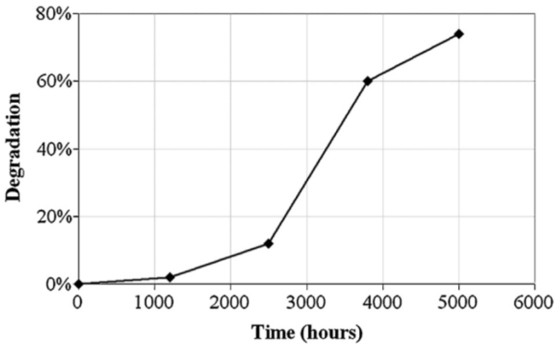

Figure 15 Photovoltaic panel power degradation curve based on Pan's model considering corrosion and discoloration as failure modes [28].

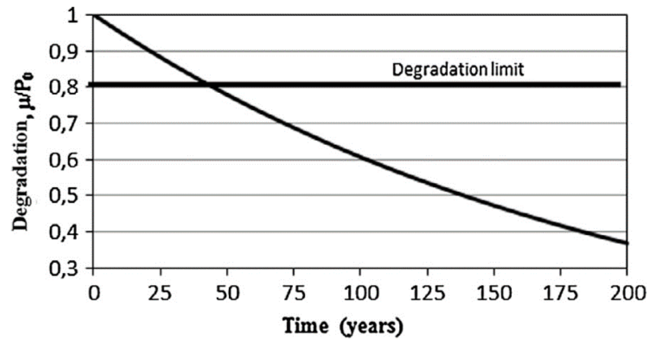

Figure 16 UV stress degradation curve as a function of the variation of the short-circuit current of the photovoltaic panel [28].

To create the degradation of a new duty cycle, the previous HS is affected by a stress factor (SF), which is defined for each particular element in section 3.4.2.2.1; a stress factor can be constructed based on electrical o meteorological parameters. Additionally, as the work cycles progress, the HS is further limited by an aging curve, which causes the HS to be restored to a lower value after maintenance. Finally, in general, the proposed degradation models are based on the original health state curve, which is affected by the stress factor and the aging curve. A graphical example of a generic degradation model is shown in Figure 17.

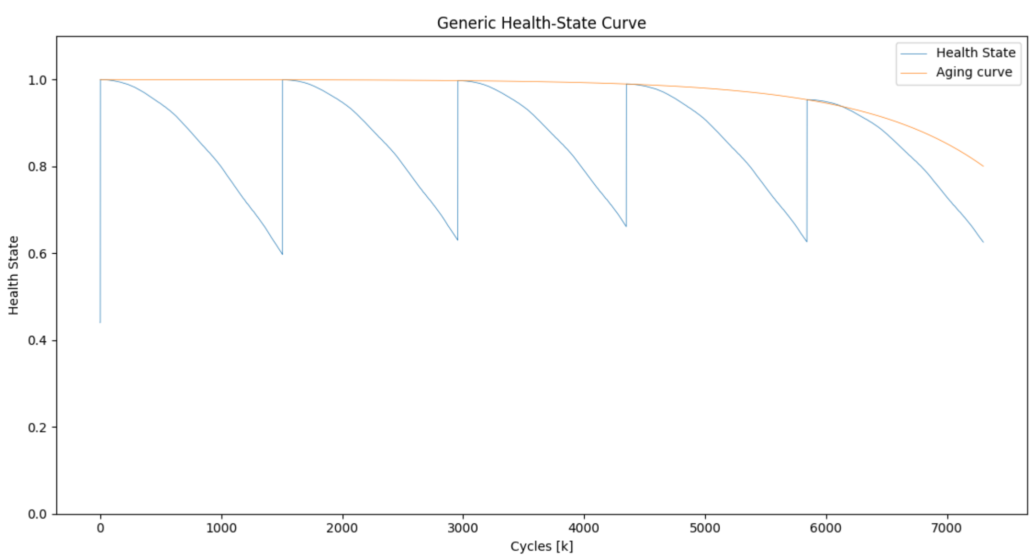

Figure 17 Health-State curve for a generic element.

The cyclic patterns observed in the HS in Figure 17 relate to the moments when the HS is restored to its initial value after preventive (programmed) or corrective (by failure) maintenance. This is an explanatory example; however, for each element, there are some variations. The formal definitions of the equations and the specific degradation models for each element are presented in section 3.4.2.2.1.

3.4.2.2.1 Types of degradation models

As mentioned above, we assume a joint curve type for estimating the HS. This curve is a decreasing sigmoidal type, which is obtained in general form employing (1),

$$H_k = H_{k-1} \cdot (1 - \alpha_k)^k \tag{1}$$

where H_k is the current health state at cycle k, H_{k-1} is the previous health state at cycle $k-1$, and α is the element stress factor. This expression produces the curve in Figure 18.

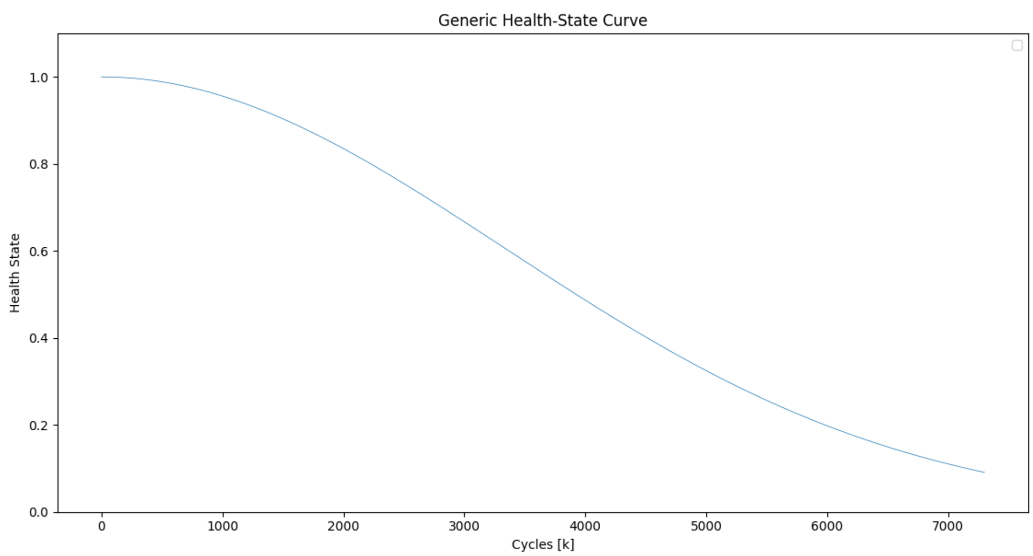

Figure 18 Type of generic curve for health state.

This type of curve is assumed for all modeled elements, except for soiling, which is a special case (see 3.4.2.2.1.1.2.). Equation (1) makes it possible to generate the curve in Figure 18 for all cases where the stress factor represents a small portion of daily degradation (modeling based on meteorological or electrical variables). A variation of this equation occurs when the stress factor depends directly on the duty cycles and not on external variables (see the case of supporting structures and transformers). In this case, the health state curve is calculated through equation (2), resulting in the same type of curve as in Figure 18. The detailed modeling for each element is shown below.

$$H_k = H_{k-1} \cdot \alpha_k \tag{2}$$

3.4.2.2.1.1 PV panels degradation model

3.4.2.2.1.1.1 Degradation due to physical stress

There is extensive literature where the degradation of photovoltaic panels is modeled and evaluated [27] [28] [105] [106] [107] [108] [109] [110] [111] [112]. Since our interest is in modeling joint degradation, we must formulate an expression consistent with the proposed methodology. In this respect, experience has shown that the performance of a PV plant can vary considerably depending on the area in which it is located, and consequently its lifetime; here are some examples in the literature [113] [114] [115]. If we assume that climatic conditions directly affect PV degradation, then it is logical to propose a model based on these variables. In this regard, Sandia [116] [117] has developed for decades a simple model that relates solar irradiance, wind speed, and ambient temperature to cell temperature. Equations (3) and (4) are used to calculate the PV module and cell temperature, respectively. It should be noted that this modeling can be made as complex as desired (see some examples in [118]), but in terms of availability of information, Sandia's model is satisfactory; furthermore, Sandia acknowledges that the model originally developed was unnecessarily complex.

$$T_m = G \cdot (e^{a+b \cdot v}) + T_a \tag{3}$$

$$T_c = T_m + \frac{G}{G_{STC}} \cdot \Delta T \tag{4}$$

In equation (3), T_m is the module temperature [°C], G is the incident radiation [w/m^2], a and b are parameterized statistical constants, v is the wind speed [m/s], and T_a is the ambient temperature [°C]. In equation (4), T_c is the PV cell temperature [°C]; G_k is the incident radiation [w/m^2]; G_{STC} is the reference radiation in standard test condicionts STC (1000 [w/m^2]); and ΔT is the temperature difference between the module and the cell at 1000 [w/m^2].

With these expressions, it is possible to calculate the cell temperature at any time. On the other hand, we know from the manufacturer's specifications that the PV module is designed to operate at a nominal temperature. By putting these two elements together, we can create a stress factor that relates the average cell temperature over a cycle to the nominal temperature. Thus, expression (5) shows the stress factor in cycle k of PV panels due to meteorological variables.

$$\alpha_{1_k} = \frac{1}{365 \cdot af1} \cdot \left[\frac{T_{c_k}}{T_{NOCT}}\right] \tag{5}$$

Here α_{1_k} is the PV panel stress factor at cycle k, T_{c_k} is the average cell temperature at cycle k for the daylight hours [°C], T_{NOCT} is the nominal cell operating temperature [°C], and $af1$ is an adjustment factor. The adjustment factor of this expression permits modifying the degradation rate of the elements to calibrate the curve according to the reported failure rates; this factor is present in all the elements. Although $af1$ can take any positive value, the equation (5) is normalized annually to give a practical and intuitive sense.

The aging curve in Figure 17 applies to all elements and is calculated as shown in equation (6),

$$\delta_{i_k} = 1 - e^{fi \cdot \left(k - \left(365 \cdot fy - \frac{ln\,(1-fv)}{fi}\right)\right)} \tag{6}$$

where δ_{i_k} is the aging state in cycle k for element i, fi is the shape factor i of the curve for PV panels, k is the cycle evaluated, fy is the final year of the project's life for which the curve is projected, and fv is the final value that the curve will have in year fy (in the range [0,1]). This expression allows maintaining a different type of aging curve for each element if desired, but for this thesis, we will assume for all elements $fy = 25$ years, $fv = 0.8$, and $fi = 0.01$. With these parameters, a curve like the one in Figure 17 is obtained.

Finally, the health state of the PV panels due to meteorological variables in cycle k ($H_{1_k}^{MV}$) is obtained by the expression (7), where H_{1_k} is calculated by means of the expression (8), which follows the general form shown in (1).

$$H_{1_k}^{MV} = H_{1_k} \cdot \delta_{1_k} \tag{7}$$

$$H_{1_k} = H_{1_{k-1}} \cdot \left(1 - \alpha_{1_k}\right)^k \tag{8}$$

It should be noted that the factors of the expression (7) are independent of each other and must be calculated separately.

3.4.2.2.1.1.2 Degradation due to soiling

Soiling is another highly studied topic in the literature due to its high incidence on PV plant performance; numerous reviews provide a complete characterization of soiling (see 2.7, paragraph four). Several factors influence soiling deposition according to the literature; Jamil et al. [119] summarize them in wind speed, tilt angle and orientation, dust properties (chemical, biological, electrostatic, size, shape, and weight), glazing characteristics, site characteristics (local vegetation, pedestrian and vehicular traffic, air pollution), ambient temperature and humidity. Researchers, in their attempt to model soiling, have developed different methods based on regression models, neural networks, empirical models, among others (see 2.7, paragraph five), which use various meteorological variables to model dust deposition. These models are highly dependent on the data of the geographical location, so they must be adjusted for each study area.

There is no consensus on which model is more suitable to model soiling, so based on the methodological proposal, we propose a simplified model that allows us to construct a characteristic health state curve. Our argument is based on the main parameter affected by soiling that reduces plant performance: transmittance; the more dust deposition, the less light the solar panel receives. For this special case, the HS curve assumed is not the one presented in Figure 18, since this indicator will be treated slightly differently in our model.

In this case, we will take the concept of the soiling ratio (SR). This value is defined as the ratio between the power generated with soiling and the power with a clean panel. This ratio varies in a decreasing exponential form as the dust concentration density increases [120] [121] (see Figure 19 and Figure 20). Although in some works a linear behavior of the soiling is observed [92] [95] [97] [98] [99] [122], a linear approximation is valid for the beginning of the curve where the dust concentration density is low; the literature shows that with periodic cleanings (natural or scheduled), the SR remains in the linear zone. However, we will use the exponential curve as a reference for more general modeling.

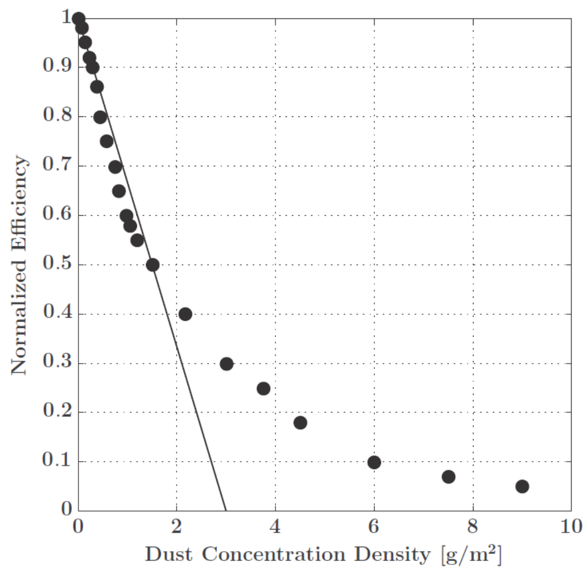

Figure 19 Normalized efficiency vs dust concentration density [120].

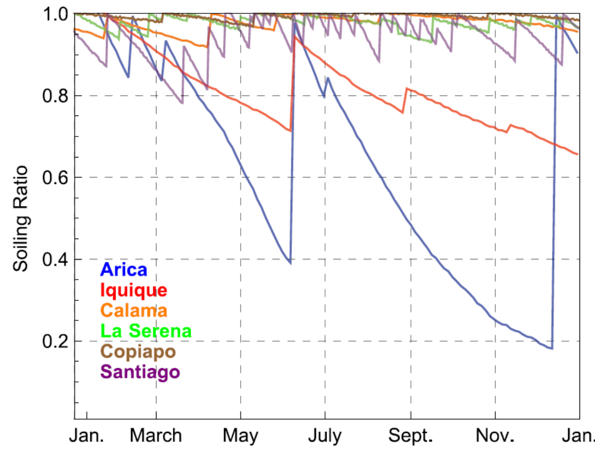

Figure 20 Soiling Ratio measurements over 12 months in chilean cities (from sea level up to 2500 m.s.n.m) [121].

That said, the model that allows us to calculate the stress factor due to soiling is given by the equation (9),

$$\alpha_{2_k} = \frac{1}{365 \cdot af2} \cdot \left[\frac{v_k}{v_m}\right] \tag{9}$$

where α_{2_k} is the stress factor due to soiling, v_k is the average wind speed in cycle k [m/s], v_m is the annual average wind speed [m/s], and $af2$ is the adjustment factor of soiling. This expression establishes a direct relationship between wind speed and the level of dust deposition (except for storms and abnormal weather conditions). Then, to obtain the decreasing exponential health state curve, a variant of equation (1) will be used, from which the exponent k is removed. With this, the health state for soiling in cycle k ($H_{2_k}^S$) can be calculated by the expression (10), generating the curve in Figure 21.

$$H_{2_k}^S = H_{2_{k-1}} \cdot \left(1 - \alpha_{2_k}\right) \tag{10}$$

Since this HS is constructed based on the SR and is normalized in the range [0,1], the same behavior is obtained, therefore the HS of the soiling will be weighted by the power generated by the PV panel. This means that the maximum power of the solar panel P_{max} at the output is given by $P_{max} \cdot H_{2_k}^S$. This is the only case in which the health state represents a real operating condition because it relates to a single phenomenon.

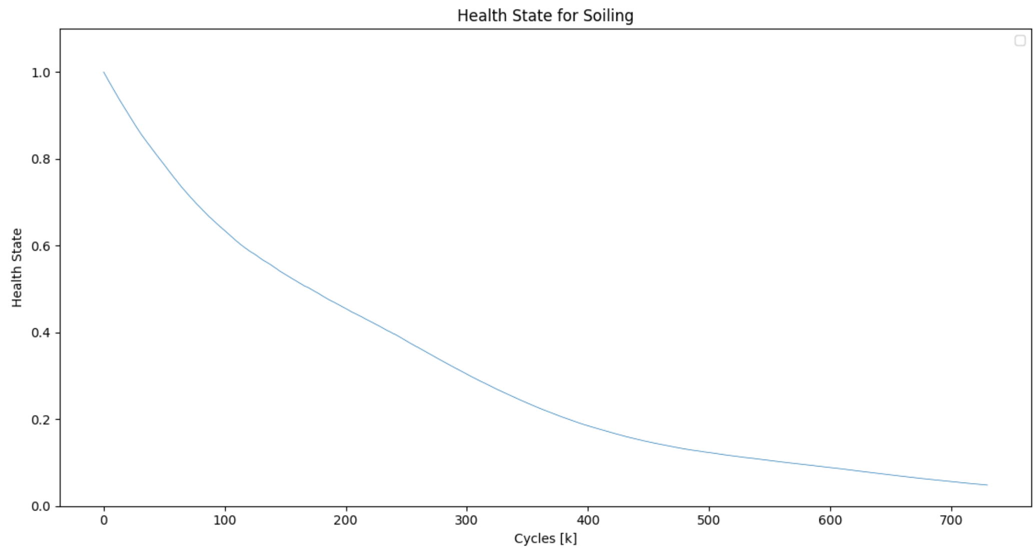

Figure 21 Health state for soiling.

3.4.2.2.1.2 Wiring degradation model

The wiring of a PV plant is essential to ensure power transmission. Its operation is quite intuitive and suggests a model based on the level of utilization. This can be achieved by modeling the stress factor through power transmission. Thus, we propose that the stress factor of the wiring is as shown in equation (11), which is a function of the DC power transported. This equation has a variation for the AC side, which is shown in equation (12).

$$\alpha_{3DC_k} = \frac{1}{365 \cdot af3_{DC}} \cdot \left[\frac{E_{DC_k}}{E_{DC0}}\right] \tag{11}$$

$$\alpha_{3AC_k} = \frac{1}{365 \cdot af3_{AC}} \cdot \left[\frac{E_{AC_k}}{E_{AC0}}\right] \tag{12}$$

In equation (11), α_{3DC_k} is the stress factor at cycle k for the DC side, E_{DC_k} is the DC energy produced at cycle k [MWh], E_{DC0} is the DC energy at rated power of the PV plant [MWh], and $af3_{DC}$ is the adjustment factor; E_{DC_k} can be estimated using equation (13) by calculating the sum of the P_{DC_t} in cycle k, where t are the hours of the day; E_{DC0} is the DC energy at rated power of the PV plant in cycle k; P_{DC_t} can be calculated by (15).

$$E_{DC_k} = \sum_{t=1}^{24} P_{DC_t} \tag{13}$$

The same reasoning is maintained in equation (12); α_{3AC_k} is the stress factor at cycle k for the AC side, E_{AC_k} is the AC energy produced at cycle k [MWh], E_{AC0} is the AC energy at rated power of the PV plant [MWh], and $af3_{AC}$ is the adjustment factor. E_{AC_k} can be estimated using equation (14) by calculating the sum of the P_{AC_t} in cycle k, where t are the hours of the day; E_{AC0} is the AC energy at rated power and rated inverter efficiency of PV plant in cycle k. P_{AC_t} is calculated by (20), defined in 3.4.2.2.1.3 below.

$$E_{AC_k} = \sum_{t=1}^{24} P_{AC_t} \tag{14}$$

$$P_{DC_t} = \frac{G_t}{G_{STC}} \cdot P_{DC0} \cdot \left(1 + \gamma \cdot \left(T_{c_t} - T_{STC}\right)\right) \tag{15}$$

Equation (15) is used in the "Explorador Solar" [123] and comes from the PVWatts [124] software developed by NREL, where P_{DC} is the rated DC power produced by the PV plant, G_t is the solar irradiance in hour t [w/m^2], G_{STC} is the solar irradiance under Standard Test Conditions (STC) [w/m^2], P_{DC0} is the rated power of the PV plant [MW], γ is the cell temperature coefficient for maximum power [%/°C], T_{c_t} is the temperature of the PV cell in hour t [°C], and T_{STC} is the rated operating temperature of the PV cell [°C]. The calculation of G_t changes as a function of irradiance, which is defined in the expression (16).

$$G_t = \begin{cases} 0.008 \cdot G_t^2 & if \;\; G_t < 125\ [w/m^2] \\ G_t & if \;\; G_t \geq 125\ [w/m^2] \end{cases} \tag{16}$$

Finally, equation (17) shows the health state of the wiring at cycle k ($H_{3_k}^W$) in general form, which follows the type shown in Figure 18, and where H_{3_k} is calculated by the expression (18). The aging curve δ_{3_k} is calculated by the expression (6).

$$H_{3_k}^W = H_{3_k} \cdot \delta_{3_k} \tag{17}$$

$$H_{3_k} = H_{3_{k-1}} \cdot \left(1 - \alpha_{3_k}\right)^k \tag{18}$$

3.4.2.2.1.3 Inverter degradation model

Inverters are the most common failure element in the entire PV plant. For this reason, literature has made great efforts to understand and model their phenomena. The literature has studied the inverter mainly from the point of view of the reliability of its main elements. Inverter degradation is associated with the nature of these components, most of which are electronic. In this scenario, the degradation of the inverter is mainly due to the aging of its components, which results in increased failure rates throughout its useful life. It should be noted that the large majority of failure modes are due to control problems and component failure (see 2.5.3.2.1), for which the form of repair is the spare replacement or simple software reset. In this sense, we propose a simplified stress factor model based on the energy produced, which is a measure of inverter utilization. Equation (19) describes the stress factor of the inverter,

$$\alpha_{4_k} = \frac{1}{365 \cdot af4} \cdot \left[\frac{E_{AC_k}}{E_{\eta_{nom}}}\right] \tag{19}$$

where α_{4_k} is the inverter stress factor at cycle k, E_{AC_k} is the AC energy produced at cycle k [MWh], $E_{\eta_{nom}}$ is the AC energy at rated inverter efficiency [MWh], and $af4$ is the adjustment factor; E_{AC_k} can be estimated from the expression (14). Equation (20) is used in the "Explorador Solar" [123] and is inspired by the PVWatts software [124], which is estimated by calculating the sum of the P_{AC_t} in cycle k; P_{DC_t} can be calculated from the expression (15). The inverter efficiency is given by the expression (21), which is used in PVWatts software [124] and has been obtained statistically from a large set of inverters.

$$P_{AC_t} = \begin{cases} \eta \cdot P_{DC_t} & if \;\; P_{DC_t} < P_{DC0} \\ \eta_{nom} \cdot P_{DC0} & if \;\; P_{DC_t} \geq P_{DC0} \end{cases} \tag{20}$$

$$\eta = \frac{\eta_{nom}}{0.9637} \cdot \left(-0.0162 \cdot \frac{P_{DC_t}}{P_{DC0}} - 0.0059 \cdot \frac{P_{DC0}}{P_{DC_t}} + 0.9858\right) \tag{21}$$

In equations (20) and (21), η is the inverter efficiency as a function of P_{DC_t} and η_{nom} is the inverter rated efficiency. This allows us to construct a health state curve following the guidelines set in this work. Equation (22) shows the health state of the inverter at cycle k ($H_{4_k}^{inv}$), which follows the form shown in Figure 18, and where H_{4_k} is calculated by the expression (23). The aging curve δ_{4_k} is calculated by the expression (6).

$$H_{4_k}^{inv} = H_{4_k} \cdot \delta_{4_k} \tag{22}$$

$$H_{4_k} = H_{4_{k-1}} \cdot \left(1 - \alpha_{4_k}\right)^k \tag{23}$$

3.4.2.2.1.4 *K*-based degradation model for other components

For elements that have low failure rates and can maintain a good performance with an adequate maintenance plan, a model based exclusively on duty cycles is proposed. This model is inspired by elements such as the support structures and the transformer since they satisfy the characteristics just mentioned. On the one hand, support structures tend to fail few times, and when they do, their impact on generation is quite low. On the other hand, transformers are present in all electrical systems, so they are well studied and maintenance protocols are well known. Thus, the stress factor based on duty cycles is given by the equation (24),

$$\alpha_{i_k} = 1 - (m_i \cdot k) \tag{24}$$

where, α_{i_k} is the stress factor for element i in cycle k, m_i is the slope of element i, and k is the duty cycle. In this case, i refers to the supporting structures and the transformer. Finally, equation (25) shows the health state based on duty cycles at cycle k ($H_{i_k}^{k-based}$), which follows the type shown in Figure 18. In this case, no aging curve is applied, since failure rates are low and the effect is negligible.

$$H_{i_k}^{k-based} = H_{i_{k-1}} \cdot \alpha_{i_k} \tag{25}$$

3.4.2.2.2 Failure simulation

The health state H_k decreases as degradation increases; degradation can also be defined as the complement $H'_k = 1 - H_k$. As degradation increase, the probability of element failure increases. At each duty cycle, there is a probability of failure that is calculated using the generalized logistic function or Richards' curve [125], shown in (26). This curve was initially developed to be used in population growth to provide empirical fits; however, given its great flexibility, its use has been extended to other areas such as economics, social media, neural networks, among others.

$$Y(t) = A + \frac{K - A}{\left(C + Qe^{-B(t-M)}\right)^{1/v}} \tag{26}$$

This equation allows generating a very versatile and flexible sigmoid curve. For this thesis, we will call it the failure probability curve (FPC). In our case, we are interested in generating a soft transition of the failure probability of the elements instead of imposing a rigid threshold for which the element fails if it exceeds this value. This transforms the problem into a stochastic problem, which adds uncertainty and variability, in addition to meteorological variability. Thus, an element can fail at any cycle depending on its probability of failure; moreover, an element can degrade and fail due to different failure modes, which have different durations and impacts on generation (see Annexed B). For our purposes, equation (26) is modified according to our parameters, resulting in equation (27),

$$PFC(H_k) = \frac{H_{max} - H_{min}}{1 + e^{-B\cdot(\,(1-H_k)\,) - M)}} + H_{min} \tag{27}$$

where $FPC(H_k)$ is the probability of failure as a function of health state H_k, H_{max} is the superior asymptote, H_{min} is the inferior asymptote, B is the growth rate, and M is the maximum growth value when $Q = v = 1$. The parameters C, Q, and v take value 1. Equation (28) shows the final form of the FPC for $H_{max} = 1$, $H_{min} = 0$, $B = 30$, and $M = 0.5$. The B and M values were arbitrarily chosen to achieve the shape of Figure 22.

$$PFC(H_k) = \frac{1}{1 + e^{-30\cdot(\,(1-H_k)\,) - 0.5)}} \tag{28}$$

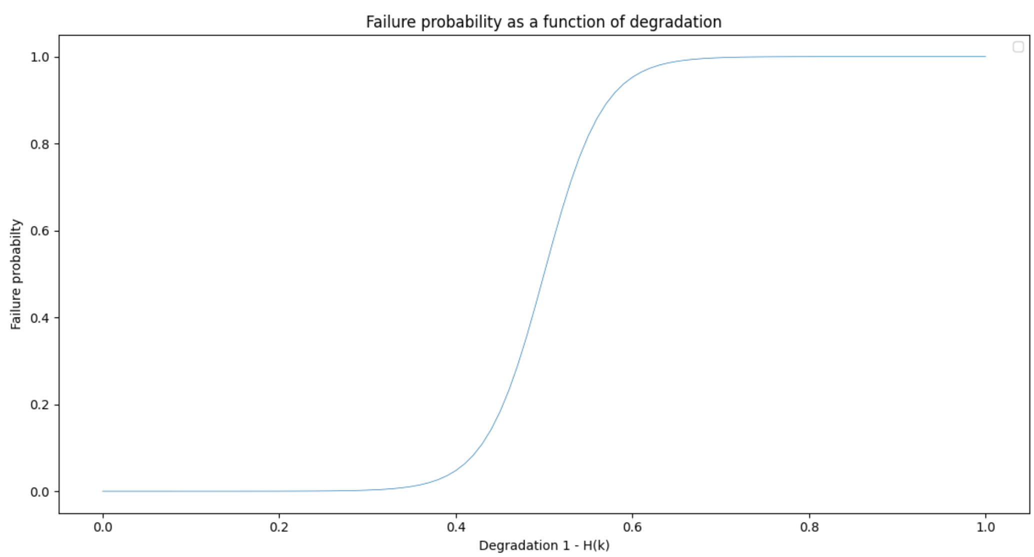

Figure 22 Sigmoid curve of failure probability for an element as a function of degradation.

Once an element fails, the energy associated with that element may decrease for a certain period. In this case, the energy generated is penalized proportionally by the failure factor (FF_{ij}), which is a factor in the range of [0,1] for element i and failure mode j that directly affects the generation associated with a fault. We show the energy penalization in the equation (29), where FF_{ij} can be calculated with equation (30).

$$E_k = E_{ref_k} \cdot FF_{ij_k} \tag{29}$$

$$FF_{ij_k} = 1 - FI_{ij_k} \cdot FTF_{ij} \tag{30}$$

In equations (29) and (30), E_k is the energy generated in cycle k, E_{ref_k} is the reference energy in cycle k (see 3.4.2.2.3), FF_{ij_k} is the failure factor of element i in cycle k, FI_{ij} is the failure impact of the element i with failure mode j in cycle k, and FTF_{ij} is the fault time factor of the element i with failure mode j. We define failure impact (FI_{ij}) as the ratio of failed energy to the total energy associated with that element, and failure time factor (FTF_{ij}) as the proportion of failure duration (FD_{ij} in hours) compared to the total hours of the cycles associated with the failure; a failure may last more than one cycle, so in this case, the value of FTF_{ij} takes value 1 until the number of hours of the failure is completed in the respective number of cycles. Both parameters are normalized to the range [0,1]. The values of FI_{ij_k} and FTF_{ij} depend on the failed element and the nature of the failure. For more details on the failure modes considered for the modeling, see Annexed B.

3.4.2.2.3 Energy linkage

The assumptions stated in 3 establish that the elements modeled through the health state curves are technically independent. This means that a technical failure in element A cannot induce a technical failure in element B, even if they are in the same series branch; for example, a technical failure in the inverter does not induce a technical failure in the supporting structures. This is justified by the fact that all elements are physically independent and are not part of a complete system as could be the elements of a motor. However, there is an electrical dependency in all the elements, which could induce electrical faults in each other; for example, a ground fault on the inverter. Nevertheless, this type of failure is attributable to external factors and is not modeled, while within the PV plant, some protections electrically separate the elements, isolating sections in case of failure.

Thus, the only connection between the elements is the transmission of energy. This means that as a result of a technical failure in A, the transmitted energy does not reach B, therefore the whole series branch and upstream elements are affected energetically. This is done simply.

First, before the Monte Carlo simulation, n reference energy vectors E_{ref} are defined as a function of the n modeled PV panel degradation; for instance, assuming an installation that has two inverters of three strings, there would be six reference energy vectors; each string has its own reference vector. These represent the ideal generation of the panels, with no failures (aging is still considered). The sum of all the E_{ref} vectors result in the total reference energy (E_{Tref}), equivalent to the energy that would ideally be injected into the system if there were no failures.

Once the E_{ref} vectors are defined, maintenance policies and fault simulations are applied within the Monte Carlo cycle. These possible scenarios will cause the real generation to be lower than the ideal E_{ref_k}. Thus, we define the lost energy for element i and failure mode j in cycle k (LE_{ij_k}), which is calculated by the equation (31).

$$LE_{ij_k} = E_{ref_k} - E_{ref_k} \cdot FF_{ij_k} \tag{31}$$

This expression is applied to all modeled elements, which makes it possible to calculate the energy lost by all PV plant elements. Thus, equation (32) shows the total energy lost,

$$TLE_k = \sum_{i=1}^{NE} \sum_{j=1}^{NFM_i} LE_{ij_k} \tag{32}$$

where TLE_k is de total energy lost due to all elements in cycle k, NE is the number of modeled elements, and NFM_i is the number of failure modes of element i.

3.4.2.2.4 Maintenance policy

To establish the maintenance policy to be used, three types of maintenance are modeled: inspections, preventive maintenance, and corrective maintenance; actually, inspections are part of preventive maintenance, however, we separate them for academic purposes. First, we divide the PFC into two parts: no maintenance zone and maintenance zone (see Figure 23). No maintenance zone represents the range of the health state where the probability of failure is approximately zero; otherwise, it corresponds to the maintenance zone. The limit between these two zones is named maintenance limit (ML); an element can fail at any cycle once it crosses the ML. Once the element has failed, corrective maintenance is performed.

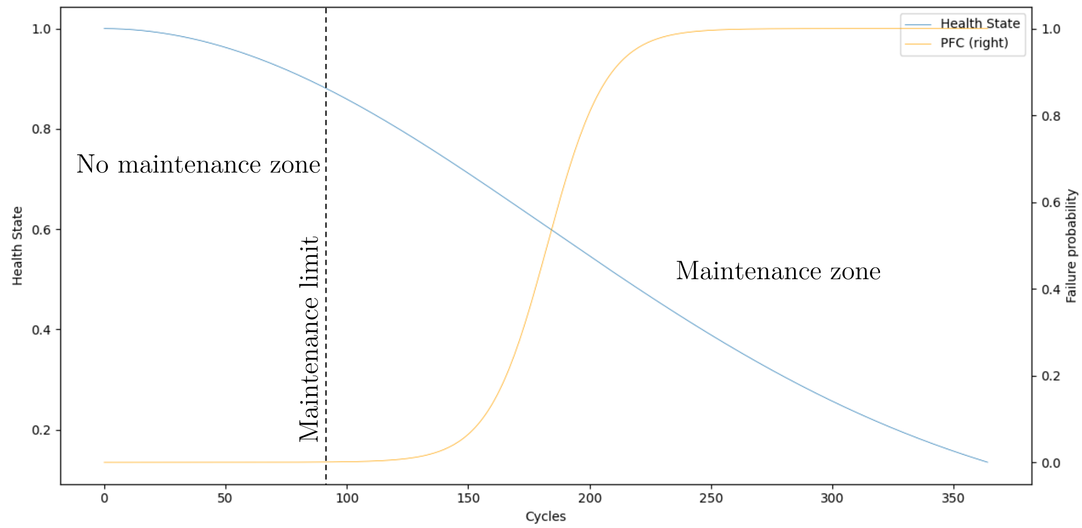

Figure 23 Health state and PFC in maintenance policy.

3.4.2.2.4.1 Inspection modeling

Inspections are modeled with a threshold I_i in the health state (represented by the red line in Figure 24), defined by the policy (decision variable). When the health state falls below I_i an inspection is carried out. During an inspection, the operator can or cannot find a defective status of a certain component with a given detection probability (DP); in the absence of precise information, we arbitrarily define DP with value 0,5. Defective status is understood as a status that cannot affect the operation (no corrective maintenance is needed) but represents a potential of failure.

We define arbitrarily for this thesis the potential of failure (PF), which is a random value in the range [0,1]. If the operator finds a defective status and PF is less than 0.5, palliative maintenance is carried out (see Figure 24); in our case, palliative maintenance means that the health state is set at the maintenance limit (where the probability of failure is approximately zero and starts to grow significantly with each new cycle). In other words, not expensive maintenance is carried out while the period of preventive maintenance arrives; the cost of palliative maintenance is equivalent to a simple inspection. Some examples of palliative maintenance can be minor adjustments, the re-setting configuration of some components, correct alarms, retighten connectors, some minor cleaning, etc. If the operator finds a defective status and PF is equal to or more than 0.5, preventive maintenance is carried out.

This approach intends to incorporate the diverse cases present in operation. Additionally, once the first inspection is carried out, the number of cycles to the next inspections is modeled with another decision variable TI_i. That is, once the health state falls below I_i, the variable TI_i indicates how frequently the next inspection should be performed, as long as the health state remains below I_i.

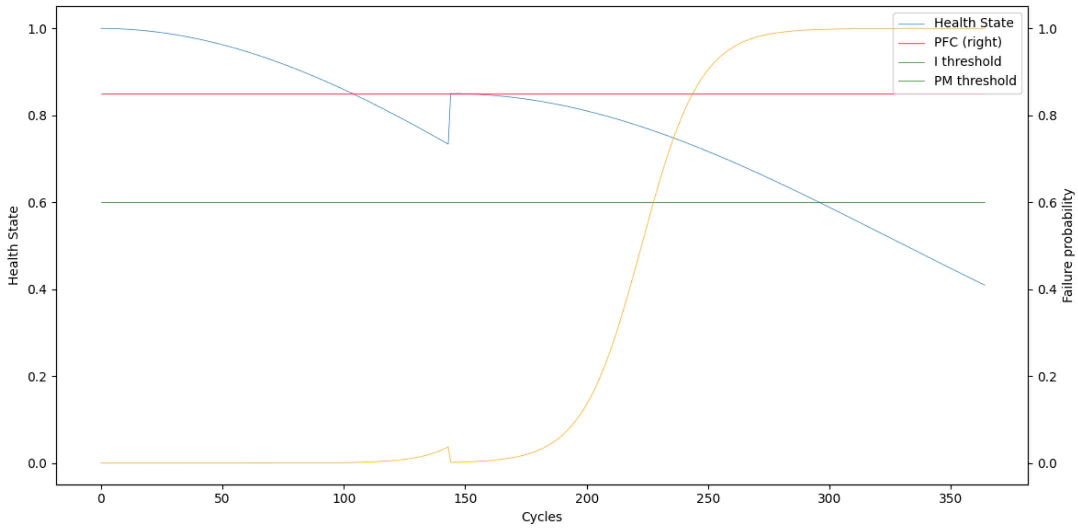

Figure 24 Health state after palliative maintenance due to an inspection.

3.4.2.2.4.2 Preventive maintenance modeling

Preventive maintenance is modeled with a threshold PM_i, in the health state (represented by the green line in Figure 25), defined by the policy (decision variable). When the health state falls below PM_i, preventive maintenance is carried out. This means that the health state is set with value one (ideally); recall that the health state is affected by the aging curve. The cost of preventive maintenance is higher than inspection costs because additional costs are incurred for repair of elements, spare parts, cleaning, etc.

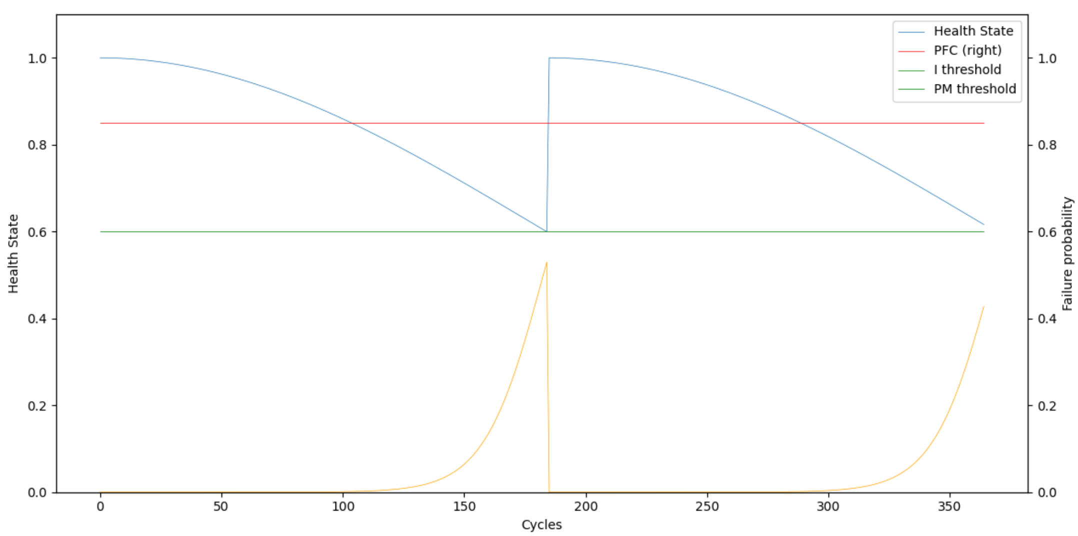

Figure 25 Health state after preventive maintenance.

3.4.2.2.4.3 Corrective maintenance modeling

When degradation rises and enters into the maintenance zone, the probability of failure increases gradually. If the operator does not find a defective status and no preventive maintenance is carried out, the system eventually will fail. When this occurs, the health state is set in value zero meanwhile corrective maintenance eliminates the failure, as shown in Figure 26.

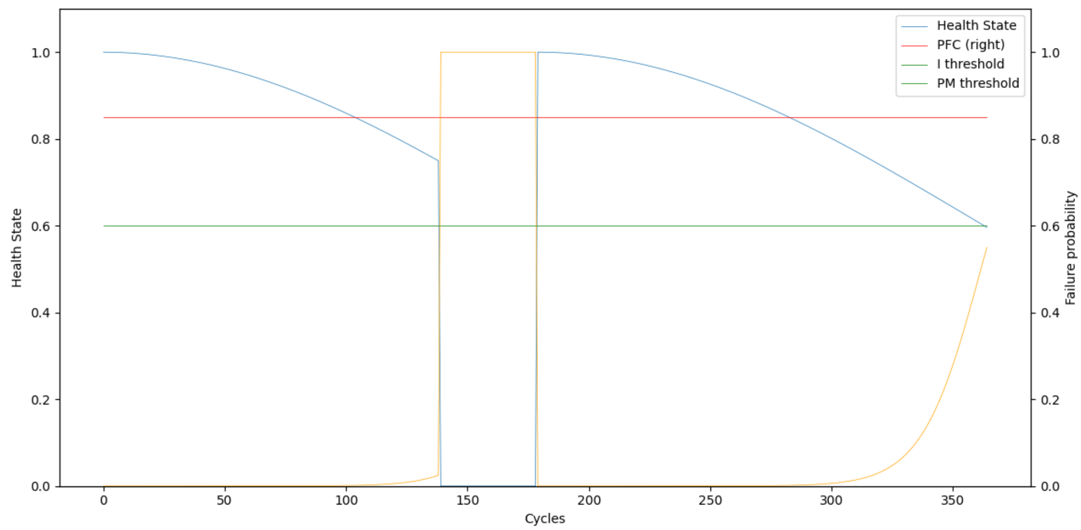

Figure 26 Health state after corrective maintenance.

The health state will remain at zero for the number of cycles the fault lasts, after which it will be restored to value 1 (ideally). Failures can occur as long as the health state of an item is above the preventive maintenance threshold and below the inspection threshold. Outside this range, the probability of failure is negligible (over inspection threshold) or preventive maintenance has already been performed.

3.4.2.2.4.4 Error in inspections and maintenance

Whether in inspections, preventive or corrective maintenance, the chance that the inspection or maintenance will not be effective is considered. When inspection or maintenance is performed, there may be errors due to human mistakes, defective or degraded spare parts, or other factors. This does not allow the health state to return to its ideal values (1 in the case of preventive maintenance). Therefore, the health state may be restored to value 1, less than 1, the same as before maintenance, worse than before maintenance, or it may even fail due to maintenance.

To incorporate this effect, the ideal value of health state restoration is multiplied by a random variable with beta distribution ($\alpha = 30$, $\beta = 4$), as shown in Figure 27; the parameters α and β of this distribution were chosen on the assumption that perfect maintenance cannot always be performed, but high levels of maintenance effectiveness are highly expected. Thus, if palliative maintenance is performed, the health state is fixed at the maintenance limit affected by the random sample. If preventive or corrective maintenance is performed, that random sample is multiplied by 1.

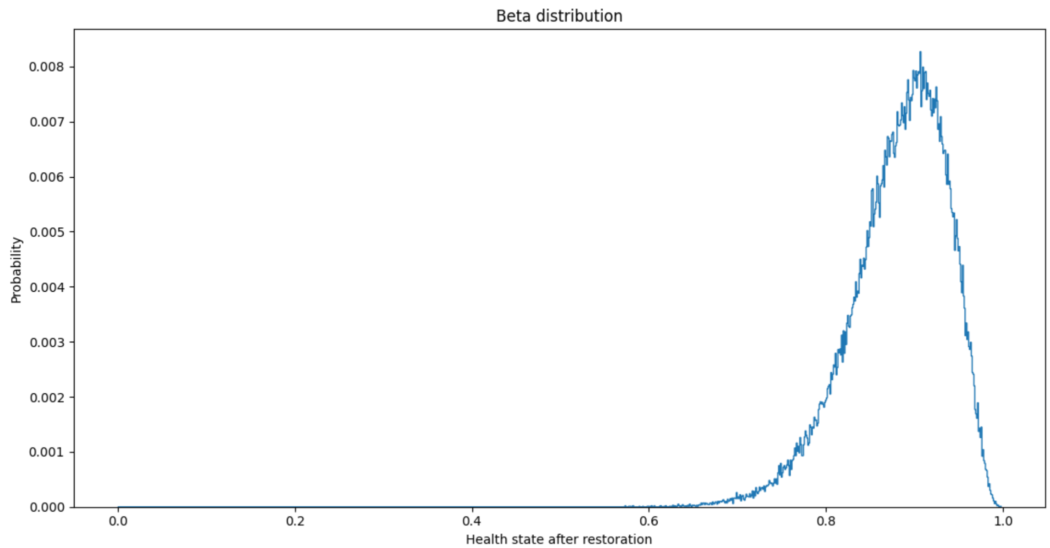

Figure 27 Beta distribution for random variable sampling in health state restoration error.

3.4.2.3 Key indicators and optimization criteria

There is flexibility about the optimization criteria and the key indicators needed to find an optimal point. In our case, we are interested in a slightly more realistic view, so based on economic criteria, the logical option is to minimize maintenance costs.

In this sense, lowering the thresholds of our decision variables implies lower maintenance periodicity and an increase in failures, which directly affects the performance of the PV plant through energy penalties. Therefore, given that the only technical constraints of our model are the upper and lower bounds of the decision variables, the balance between maintenance costs and economic revenues from energy sales seems to be the most appropriate criterion.

Thus, by maximizing the net profit (energy sales revenue minus maintenance costs), a trade-off between maintenance level and energy yield of the PV plant can be found. It should be noted that in our approach, we are not considering contractual requirements of minimum uptime or other criteria; we are only relying on economic criteria.

3.4.3 Optimization problem definition

Once the methodology has been broken down, the formal definition of the optimization problem is shown in equation (33), where the profit is maximized as a function of the decision variables $\vec{x}$,

$$\max\left\{\sum_{k=1}^{TC}\left(R(\vec{x})_k - MC(\vec{x})_k\right)\right\} \quad ; \quad \vec{x} = [x_1, x_2, \dots, x_{19}] \tag{33}$$

subject to

$$\begin{aligned} &1 \leq x_r \leq 365; \quad \forall\, r \;;\; r = 1,2,3,\dots,6 \\ &0 \leq x_s \leq \;1 \;\;; \quad \forall\, s \;;\; s = 7,8,9,\dots,19 \\ &x_r \in \mathbb{N} \;;\; x_s \in \mathbb{R} \end{aligned}$$

with:

x_1 = IT_1: Threshold associated with spacing between PV panel inspections $H_{1_k}^{MV}$ [cycles]
x_2 = IT_{3DC} : Threshold associated with spacing between DC wiring inspections $H_{3DC_k}^{W}$ [cycles]
x_3 = IT_{3AC}: Threshold associated with spacing between AC wiring inspections $H_{3AC_k}^{W}$ [cycles]
x_4 = IT_4: Threshold associated with spacing between inverter inspections $H_{4_k}^{inv}$ [cycles]
x_5 = IT_{SS}: Threshold associated with spacing between supporting structures inspections $H_{SS_k}^{k-based}$ [cycles]
x_6 = IT_{T}: Threshold associated with spacing between transformer inspections $H_{T_k}^{k-based}$ [cycles]
x_7 = I_1: Threshold associated with PV panel inspections $H_{1_k}^{MV} \in [0,1]$
x_8 = I_{3DC}: Threshold associated with DC wiring inspections $H_{3DC_k}^{W} \in [0,1]$
x_9 = I_{3AC}: Threshold associated with AC wiring inspections $H_{3AC_k}^{W} \in [0,1]$
x_{10} = I_4: Threshold associated with inverter inspections $H_{4_k}^{inv} \in [0,1]$
x_{11} = I_{SS}: Threshold associated with supporting structures inspections $H_{SS_k}^{k-based} \in [0,1]$
x_{12} = I_{T}: Threshold associated with transformer inspections $H_{T_k}^{k-based} \in [0,1]$
x_{13} = PM_1: Threshold associated with PV panel preventive maintenance $H_{1_k}^{MV} \in [0,1]$
x_{14} = PM_2: Threshold associated with PV panel cleaning $H_{2_k}^{S} \in [0,1]$
x_{15} = PM_{3DC}: Threshold associated with DC wiring preventive maintenance $H_{3DC_k}^{W} \in [0,1]$
x_{16} = PM_{3AC}: Threshold associated with DC wiring preventive maintenance $H_{3AC_k}^{W} \in [0,1]$
x_{17} = PM_4: Threshold associated with inverter preventive maintenance $H_{4_k}^{inv} \in [0,1]$
x_{18} = PM_{SS}: Threshold associated with supporting structures preventive maintenance $H_{SS_k}^{k-based} \in [0,1]$
x_{19} = PM_{T}: Threshold associated with transformer preventive maintenance $H_{T_k}^{k-based} \in [0,1]$

where $R(\vec{x})_k$ is the expected revenue from energy sales in cycle k [USD], $MC(\vec{x})_k$ is the expected total maintenance costs in cycle k [USD], and TC are the total simulated cycles. $R(\vec{x})_k$ and $MC(\vec{x})_k$ can be calculated by equations (34) and (35), respectively,

$$R(\vec{x})_k = PPA \cdot E(\vec{x})_k \tag{34}$$

$$MC(\vec{x})_k = IC(\vec{x})_k + PMC(\vec{x})_k + CMC(\vec{x})_k \tag{35}$$

where PPA is the power purchase agreement [USD/MWh], $E(\vec{x})_k$ is the expected energy generated in cycle k [MWh], $IC(\vec{x})_k$ is the expected inspection costs in cycle k [USD], $PMC(\vec{x})_k$ is the expected preventive maintenance costs in cycle k [USD], and $CMC(\vec{x})_k$ is the expected corrective maintenance costs in cycle k [USD]. $E(\vec{x})_k$ can be calculated by the expression (36),

$$E(\vec{x})_k = \frac{1}{NMI} \cdot \sum_{m=1}^{NMI} \left(E_{Tref_{k_m}} - TLE(\vec{x})_{k_m} \right) \tag{36}$$

where $E_{ref_{k_m}}$ is the total reference energy in cycle k in iteration m, $TLE(\vec{x})_k$ is the total lost energy in cycle k in iteration m, and NMI is the total iterations of Monte Carlo simulation. Expected total inspection costs ($IC(\vec{x})_k$) can be calculated using equation (37),

$$IC(\vec{x})_k = \frac{1}{NMI} \cdot \sum_{m=1}^{NMI} \left(P_{DC0_s} \cdot 10^3 \cdot \sum_{i=1}^{NE} \left(IV(\vec{x})_{i_{k_m}} \cdot a_i \right) \right) \quad ; \quad IV(\vec{x})_{i_{k_m}} \in \{0,1\} \tag{37}$$

$$PMC(\vec{x})_k = \frac{1}{NMI} \cdot \sum_{m=1}^{NMI} \left(P_{DC0_s} \cdot 10^3 \cdot \sum_{i=1}^{NE} \left(PMV(\vec{x})_{i_{k_m}} \cdot b_i \right) \right) \quad ; \quad PMV(\vec{x})_{i_{k_m}} \in \{0,1\} \tag{38}$$

$$CMC(\vec{x})_k = \frac{1}{NMI} \cdot \sum_{m=1}^{NMI} \left(P_{DC0_s} \cdot 10^3 \cdot \sum_{i=1}^{NE} \left(CMV(\vec{x})_{i_{k_m}} \cdot c_i \right) \right) \quad ; \quad CMV(\vec{x})_{i_{k_m}} \in \{0,1\} \tag{39}$$

where $IV(\vec{x})_{i_{k_m}}$ is a binary vector of inspections for element i in cycle k in iteration m, a_i is the average annual cost of inspections for element i [USD/kW-year/inspection], and P_{DC0_s} is the rated power of the PV plant per string [MW]. The binary vector $IV(\vec{x})_{i_{k_m}}$ is a vector of zeros initially, to which a 1 is placed at position k each time an inspection is performed; the sum of $IV(\vec{x})_{i_{k_m}}$ results in the number of whole-plant inspections performed on element i for all cycles in iteration m. The same is done for expected preventive ($PMC(\vec{x})_k$) and corrective ($CMC(\vec{x})_k$) maintenance costs, in equations (38) and (39), respectively, where $PMV(\vec{x})_{i_{k_m}}$ is a binary vector of preventive maintenance, b_k is the average annual cost of preventive maintenance for element [USD/kW-year], $CMV(\vec{x})_{i_{k_m}}$ is a binary vector of corrective maintenance, and c_k is the average annual cost of corrective maintenance [USD/kW-year].

3.4.4 Optimization process

The proposed methodology has three determining characteristics when choosing an optimization algorithm: it is represented by a non-derivable function, it is highly non-linear and it is multidimensional. The health state indicators are built based on the previous state of an element, so that a simple linear model depending on the previous state, generates an exponential form; also, the multidimensionality of the problem presupposes a multioptimality condition. This characteristic makes the model highly nonlinear, which added to the high dimensionality of the modeled independent elements, turns infeasible the resolution by traditional methods.

As a result of the above, it is necessary to use an optimizer according to our requirements. In this sense, considering the nature of our model, evolutionary algorithms represent an intuitive choice. Genetic algorithms (GA) are one of the best known and most widely used heuristic methods available, with great versatility and adaptability to all types of high complexity problems. It is not the aim of this thesis to discuss the best algorithm for this type of problem, thus, based on literature, genetic algorithms fully satisfy our requirements. For a deeper and more specific understanding of GA, see [126].

Genetic algorithms, as well as all evolutionary algorithms, are based on natural phenomena. In this regard, GA simulates the natural selection of species, where only species capable of adapting can survive, reproduce and form a new generation. This algorithm is based on 4 main elements: individual, population, crossover, and mutation.

In practical terms, the individual, also called a gene, is an array containing the decision variables of the problem. For our case, considering that for each element we have modeled inspections, spacing between inspections, and preventive maintenance, our individual contains 19 decision variables.

The population is a set of N individuals. There must be an initial population, which is usually generated randomly. To achieve this, uniformly distributed random samples of the variables within each individual are generated, keeping within the limits of each variable. This generates the initial base for moving to the next step.

To perform the crossover, it is first necessary to select the individuals. There are several methods to do so, among which the most commonly used are the traditional, ranking, tournament, and elitism; each of them has particular characteristics, which must be chosen appropriately according to the type of problem modeled. In our case, we will use the tournament for selection without considering elitism since we presuppose a problem with numerous local optima, so the selection process must go through as much variety as possible to avoid premature convergence. Then, the crossover is performed. To do so, two individuals (parents) are chosen, from which variables are swapped among them. The number of swapped variables and the positions are simulated randomly with probability P_c. This results in two new individuals (offspring) that will be added to the population of a new generation. In this form, the offspring inherit the characteristics of their parents.

Finally, the mutation is applied to the new generation. This is performed to provide variability to the evolution and to prevent the algorithm from converging prematurely. The mode of mutation varies according to whether the GA is modeled in binary or real variables. In our case, the modeling is in real variables, so the mutation is performed by adding to the mutated variables of each individual a positive or negative random sample from a uniform distribution. The number and position of the mutated variables of each individual are randomly simulated with a probability P_m. In this form, a search beyond the characteristics inherited by the parents is stimulated.

It is important to note that the genetic algorithm must be tuned specifically for each problem, where population size, crossover probability, and mutation probability are highly sensitive to the performance of the algorithm. Although there is no universal rule for fitting the genetic algorithm, there are approximation methods that suggest values within certain ranges [127]; however, the fit is unique to each problem. Not choosing the right parameters of the genetic algorithm can lead to convergence problems, premature convergence, over-utilization of computational resources, etc.

3.4.5 Model calibration

3.4.5.1 Calibration of health state curves

The calibration of the proposed methodology follows an iterative process. The adjustment factors af_i for stress factors α_i modify the health state curves to decay slower or faster (see Figure 28). In this way, an element can fail more or fewer times in the same number of cycles.

To fit each curve, the health indicators for each element i are simulated and the average number of failures per year is calculated based on a typical maintenance plan. This plan should ideally be the maintenance plan of the plant to be evaluated; however, as this information is difficult to obtain, we assume a maintenance plan based on best practices (see section 2.5.4). Then, the af_i factors are modified to increase or decrease the average annual failure rate according to literature and industry reports [31] [36] [76] [77] [128] [129] [130]. To achieve a reliable and consistent fit, it is necessary to use the same number of iterations used in the Monte Carlo simulation.

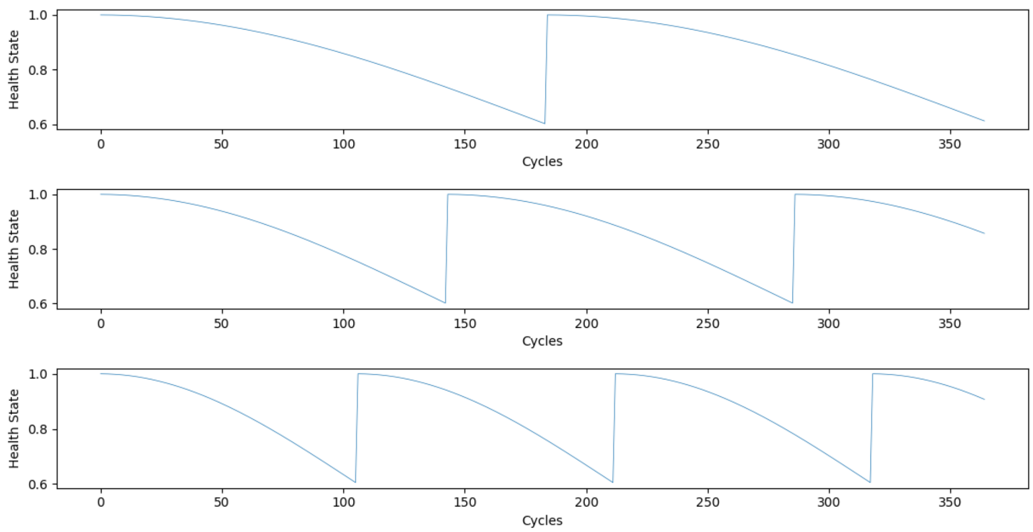

Figure 28 Health state for different values of af_i.

3.4.5.2 Calibration of maintenance costs

In the same manner that health state curves are calibrated using annual average failure rates, costs are calibrated using annual average maintenance costs found in the literature and industry reports [3] [16] [131] [132] [133], and based on the maintenance plan of the plant being evaluated; here we also assume a maintenance plan based on best practices.

To achieve this, once the health state curves have already been calibrated, the values a_i, b_i and c_i of equations (37), (38), and (39), respectively, are adjusted so that the value of $IC(\vec{x})_k$, $PMC(\vec{x})_k$, and $CMC(\vec{x})_k$ are in the desired order. Note that these values represent the total costs of all simulated cycles, so for obtaining the average annual costs, they should be divided by $TC/365$ when calibrating, which is the number of equivalent simulated years; TC is the total cycles simulated; here it is also necessary to use the same number of iterations used in the Monte Carlo simulation.

4 Case study

4.1 Introduction

In this chapter, the proposed methodology is validated by applying it to a large-scale case. For this purpose, the parameters of the modeled solar PV plant, its health state curves, energy price, maintenance costs, and calibration variables are presented. Subsequently, the analysis of the results is performed by contrasting 2 cases: the base case (based on best practices) and the optimized case (the result of the optimization problem).

4.2 Case study selection criteria

The proposed methodology is validated through the application of a large-scale system. To accomplish this, we have to choose a real solar plant of the Chilean electrical system. The choice of this plant follows the reasoning presented below.

Chilean law [6] establishes the figure of small resources of distributed generation (PMGD for its acronym in Spanish) as those solar photovoltaic installations of up to 9 MW, connected to the distribution or transmission system; therefore, for this thesis, plants directly connected to the transmission system larger than 9 MW will be considered large scale solar plants. This definition is relevant just for this work since there is a lack of international standards for the maintenance of large-scale solar plants. It is important to mention that the emphasis is on the scalability of the methodology for large-scale plants, since definitions of "large-scale" may vary depending on each country's regulations.

Additionally, sufficient information must be available to calibrate our model. The information we have comes primarily from two sources: the benchmarking study of solar PV plants in Chile [31] and the CEN[6] [134]; the missing information is supplemented with literature. The CEN provides public information concerning PV plant equipment, topologies, and power generation. The benchmarking study, conducted in 2017, provides valuable technical and operational information of 8 large-scale PV plants, reaching 42% of installed capacity in the country at the date of the study; the central focus of the study was on the collection of information concerning types and failure rates. In summary, the plant to be

[6] The CEN is entity in charge of coordinating the installations of the chilean electric system (National Electric Coordinator, CEN for its Spanish acronym [136]).

chosen must be of more than 9 MW capacity and must have sufficient information to calibrate our model.

4.3 Diego de Almagro PV solar plant modeling

Following the criteria described above, the chosen solar PV plant is called Solar Diego de Almagro, located 3 km northeast of Diego de Almagro, Atacama region. It is a 32 MW plant owned by Enel Green Power. It was commissioned on December 11, 2014, having about 2 years of operation at the time of the benchmarking study [31]. According to [134], its annual net generation has varied between 46.12 GWh and 73.94 GWh from 2015 to 2020.

This PV plant is composed of 49 1-string central inverters and 23 medium voltage transformers (MT), where each transformer groups 2 or 3 inverters; see Annexed C to visualize the topology. In practice, solar plants can combine more than one type of element, among the most important of which are inverters and photovoltaic panels. The chosen plant also has these variants, thus for simplicity, we use only the most common and representative type of element in the installation. All MT transformers belonging to the collector system raise the generation voltage from 0.38 [kV] to the nominal voltage of the PV plant, which is 10.5 [kV] [135]. Table 2 shows all the technical information gathered from [31], [134], and [135] required for model calibration. See Annexed D for the corresponding datasheets.

Table 2 Technical parameters of the photovoltaic system.

	Parameter	Value	Description
PV panel	Model	Sharp NA-E125L5	
	Type	Frameless thin film	
	P_{max}	125 Wp	Maximum power output
	$P_{\max\_end}$	$125 \cdot 0.8$ Wp	Maximum power output in year 25
	γ	-0.24 %/°C	Temperature coefficient of Pmax
	T_{ref}	25 °C	Reference temperature at STC[7]
	T_{NOCT}[8]	46 °C	Nominal temperature of the photovoltaic cell
I	Model	SOLEIL 660HV-TL	

[7] STC: Standard test conditions: irradiance 1000 W/m^2, AM 1.5, cell temperature 25 °C.

[8] NOCT: Module operating temperatura at 800 W/m^2 irradiance, air temperature 20 °C, wind speed 1 m/s.

	Parameter	Value	Description
	Type	Central	1 string central inverter
	P_{inv}	0.66 MW	Inverter rated power
	η_{nom}	0.972	Inverter euro-efficiency[9]

4.3.1 Health State curves

To perform the calibration of the health state curves, we use the failure rates shown in Table 3. Failure rates were decided based on the average values given in [31]; we have decided to use this study as a reference since, although it is not the most representative in contrast to the literature, it is the one that provides the most complete information. In this sense, there may be variations concerning the data reported in the literature mainly due to 2 factors: the short operation time of the PV plant and the “average” effect. Since the benchmarking study has confidentiality clauses, it is not possible to extract the data directly from the chosen plant, for this reason, we had to use the average data. Although this may distort the data if we want to have results that are close to reality, they are used only as a reference and is not an obstacle to further analysis; besides, the data are in an acceptable range for literature reports.

Table 3 Total average failure rates for model calibration.

Average failure rate for the...	**Value [failure/year]**
PV panels due to meteorological variables	56
DC wiring	13
AC wiring	16
Supporting structures	8
Inverter	78
Transformers	12

[9] Euro-efficiency [139] is a weighted operating efficiency over a yearly power distribution used to characterize inverter operation based on an efficiency profile as a function of operating power. It is a more realistic measure of operation since inverters do not always operate at maximum efficiency; it is referenced to the middle-Europe climate; there exist also the CEC-efficiency, designed for more demanding climates, but not all manufacturers provide this value.

Thus, following the proposed methodology, the adjustment factors and slopes for the degradation models that produce the failure rates in Table 3, assuming a maintenance plan based on best practices, are presented in Table 4. The aging curve is assumed to be the same for all elements, where $fi = 0.01$, $fy = 20$ (except for PV panels, which is 25), and $fv = 0.8$.

Table 4 Adjustment factors and slopes for the degradation model of the simulated element.

Adjustment factor for the degradation model of the...	**Symbol**	**Value**
PV panels due to meteorological variables	af_1	147
Soiling	af_2	15.85
DC wiring	af_{3DC}	4760
AC wiring	af_{3AC}	440
Inverter	af_4	22
Slope for the degradation model of the...		
Supporting structures	m_{SS}	$3 \cdot 10^{-8}$
Transformers	m_T	$14 \cdot 10^{-7}$

4.3.2 Prices and costs

The costs defined below are inspired by industry reports. Ideally, the defined costs must agree with the distributions described in 2.3.3.1, which estimate that the costs of inspections and preventive maintenance can vary between 70% and 90% of the total costs. In our case, given that the PV power plants described in [31] are young and the data provided contemplate the first years of operation, the failure rates are still above the average reported in the literature, so when adjusting the model, there will be an over-dimensioning of the failures. Considering this, we have decided that the inspection and preventive maintenance costs represent 55% of the total costs based on a best-practice maintenance plan according to the higher level of existing failures. This is only an adjustment criterion, which will be the basis of reference for further analysis.

4.3.2.1 Purchase Power Agreement

We assumed the existence of a Purchase Power Agreement (PPA) that values the energy at 50 USD/MWh, where energy is injected and retired at the same node. In this way, transmission losses are not included in the economic balance. This is done only for practical purposes as it is not our interest to model transmission losses. The PPA value is arbitrarily chosen from the range of existing contracts.

4.3.2.2 Inspection costs

The cost of inspections is inspired by [131], where a range between 1.4 - 5 USD/kW-year is specified for electrical inspections and 0.2 - 3 USD/kW-year for general site maintenance; these values are based on a yearly inspection and are also consistent with [132]. These ranges depend, among other factors, on the portion of the PV plant contracted for these services. In our case, we approach the lower limit since we assume that 100% of the plant will be inspected. Hence, we have defined the average annual cost per inspection for all elements as 1.5[10] USD/kW-year/inspection.

4.3.2.3 Preventive maintenance costs

Preventive maintenance costs are highly variable as they depend on factors such as maintenance plan, plant age, spare parts availability, type of technology used, among others. Therefore, inspired by [131] and [132], we have arbitrarily defined the average annual cost per preventive maintenance for all elements as 20 USD/kW-year/maintenance. The cost of cleaning the PV panels per occasion has been set at USD 1.6 USD/kW-year/cleaning.

4.3.2.4 Corrective maintenance costs

Industry and best practice reports indicate statistics on annual preventive maintenance costs, but there is not much information on corrective maintenance; however, there are ratios that are statistically true in practice as indicated in the second paragraph of 2.3.3.1. Therefore, we have arbitrarily defined the average annual cost per corrective maintenance for all elements as 50 USD/kW-year/maintenance. This value follows the reasoning that when a failure occurs, it triggers additional costs to the costs of preventive maintenance, which is usually much more economically invasive.

4.4 Computational simulation

4.4.1 Simulation on a high-performance computer

Since the methodology is based on simulation, the computational requirements of our model are quite elevated, so a laptop is not enough to obtain results in reasonable times. This requires us to apply for resources in the National Laboratory for High Performance Computing (NLHPC), where we were assigned an initial account with 88 cores and 50000

[10] When calibrating the model, it is necessary to define a number of reference years (it could be 10 for example), so all costs must be divided by the number of reference years used to calibrate; this is done for mathematical consistency since the model is implemented based on total cycles, not annual cycles.

computational hours. These resources are a fundamental limitation when adjusting the genetic algorithm since we must be as efficient as possible.

Additionally, given the architecture of our code, we cannot share memory between nodes, so to use the 88 available nodes, it is only possible to perform simulations one node ("general" partition) at a time in parallel and independent; for more information about the NLHPC, see 4.4.1.1. Due to this technical limitation, we have decided to divide the assessment horizon into 2 periods: the first one covers the first 10 years and the second one the second 10 years; this results in a total evaluation period of 20 years for the PV plant.

4.4.1.1 National Laboratory for High Performance Computing (NLHPC)

The NLHPC is the most powerful national high performance computing center in Chile and one of the most powerful in South America. It is at the service of the national scientific community, the Chilean Government, and the industry that requires high performance computing services. The NLHPC is a high performance computing infrastructure based on a distributed memory architecture. It consists of two clusters, Guacolda and Leftraru, which together have 5236 computing cores distributed in 192 nodes. The computational resources of the NLHPC are distributed in "partitions" (as shown in Table 5) with the SLURM resource manager.

Table 5 Distribution of the NLHPC partitions.

Node name	Node	Quantity	Cores per node	RAM per node	GPUs
general	sn[001-048]	48	44	192 Gb	0
largemem	fn[001-009]	9	44	768 Gb	0
gpus	gn[001-002]	2	44	192 Gb	2
slims	cn[001-128]	128	20	48 Gb	0
slims	cnf[001-004]	4	20	64 Gb	0
debug	leftraru[1-4]	4	20	64 Gb	0

4.4.2 Genetic algorithm tuning

Based on the guidelines and recommendations described in 3.4.4, we have adjusted the parameters of the genetic algorithm specifically for our case. We have decided to set the crossover probability P_c to the typical value of 0.5. Regarding population size, after several tests with a fictitious small system and with the large-scale case study, we defined it at 100 individuals (considering 1000 Monte Carlo iterations); this value is justified since, at higher values, the performance improvement grows marginally; for lower values, the dependence of the results to the initial population intensifies. Moreover, the model works better with a larger number of individuals and fewer generations than in the opposite case.

For testing population size, the probability of mutation P_m was set to a typical value of 0.01; however, by increasing the mutation probability it was possible to find better results but with a higher number of generations. To improve this, since we are aiming to maximize the search in the least number of generations due to resources limitations, we have decided to assign a variable mutation probability as a function of the number of iterations, being higher at the beginning and asymptotically decreasing to the value 0.01 at generation 10. Thus, in the first generations, the probability of mutation is high, and consequently, the search is more exhaustive; whereas as the generations progress, the probability of mutation is stable at 0.01. This allows us to adjust our model to the available computational resources by balancing good results and performance.

4.5 Results for the large-scale problem

4.5.1 Performance of the genetic algorithm

The genetic algorithm (GA) optimization was performed on the "general" partition of the NLHPC, using 44 cores per node in each period, running both periods simultaneously on different nodes. The maximum number of allowed generations was defined as 20, while the minimum was defined as 10. In addition, an early stopping criterion was implemented if the change of the best individual of the last 4 generations was not greater than 0.01%. The execution time for the first period was 10 days, 11 hours, and 50 minutes, evaluating a total of 20 generations; while the second period was executed in 9 days, 22 hours, and 16 minutes, activating the early stop at generation 19.

Figure 29 shows the evolution of the profit (blue line) for all individuals throughout the first period simulation along with the error (orange line) and a simple moving average (SMA, in red line) over the error; similar is shown for the second period in Figure 30. In these figures, it can be seen how the largest search is performed in the first half of both simulations, where the variation of the best individual is in the range of 0.1% and 0.2% between generations 10 and 20. From generation 10 onwards, the error improves marginally, so it is feasible to limit the number of maximum generations of the GA between 12 and 15, obtaining an improvement in computation times of about 25% to 40% without compromising the quality of the results.

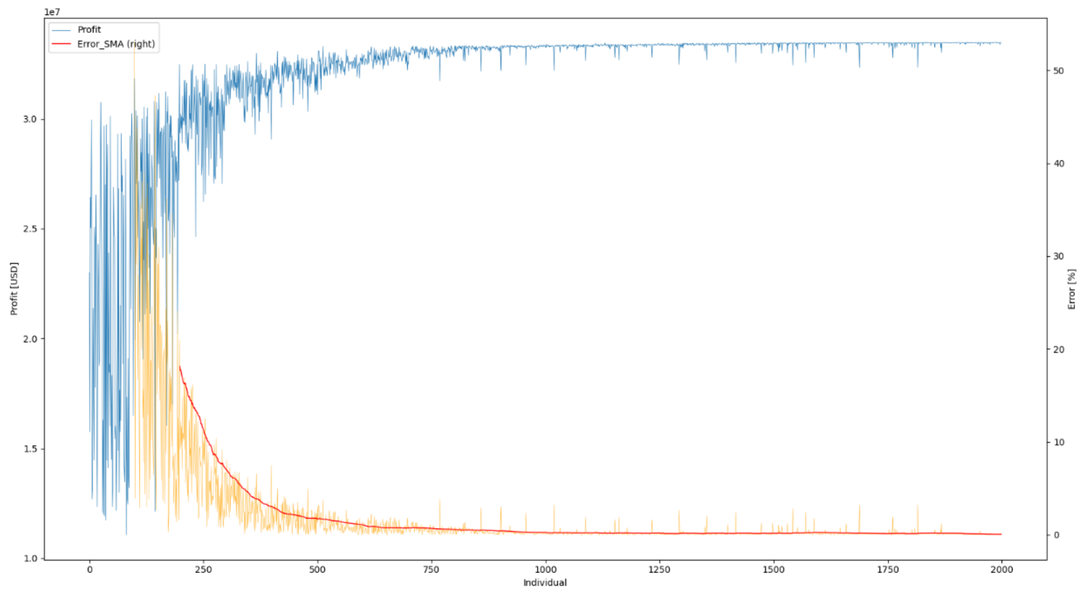

Figure 29 Evolution of profit and error for all individuals evaluated in the first period (1-10 years).

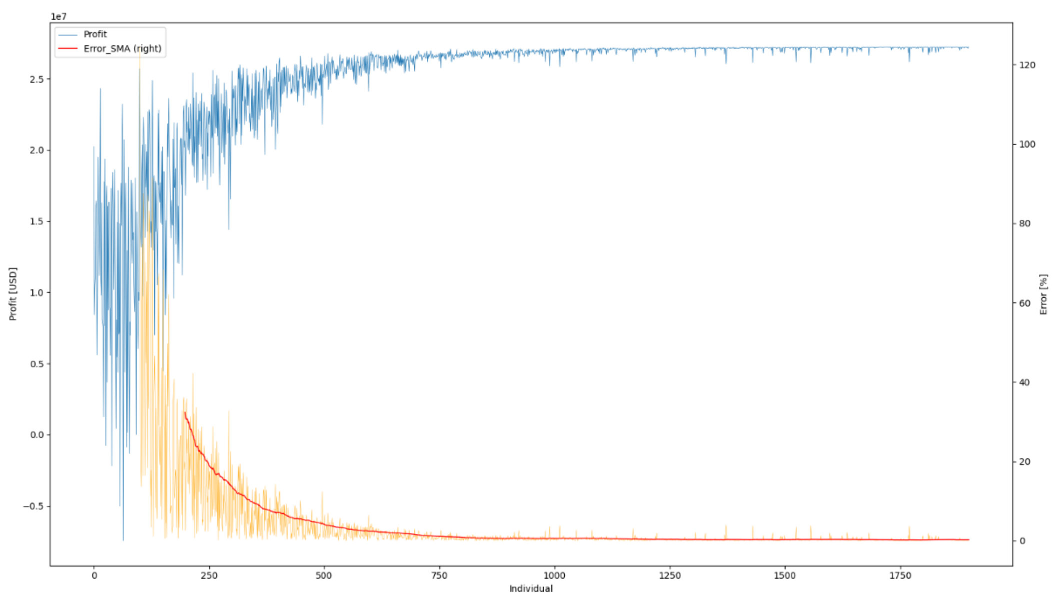

Figure 30 Evolution of profit and error for all individuals evaluated in the second period (11-20 years).

This behavior is consistent with the variable mutation probability defined above in 4.4.2. In this sense, if necessary, the number of generations at which the mutation probability stabilizes at 0.01 (defined above in generation 10) could be increased to provide a larger search space.

4.5.2 Overall results and costs analysis

4.5.2.1 Base case

The base case is the reference case, which represents the scenario in which the PV plant is maintained using a maintenance plan based on best practices (see Table 6), with fixed periodicity, and with the costs and failure rates adjusted as mentioned in 4.3. In this case, the simulated profit and cost distribution for the first 10 years are presented in Table 7, where it is shown the expected values resulting from 1000 Monte Carlo iterations for the settings described in Table 2, Table 3, and Table 4; equally, the results for years 11 to 20 are shown in Table 8.

Table 6 Maintenance plan based on best practices.

Element	**Inspection per year**	**Preventive Maintenance per year**
PV panels	2	1
Cleaning	-	3
Supporting structures	2	1
DC wiring	2	1
Inverter	12	2
AC wiring	2	1
Transformer	1	Every 5 years

Table 7 Total expected profit and cost distribution for years 1 to 10 for the base case.

Description	**Value**	**Weighting**
Installed capacity [MW]	32	
Total energy generated [GWh]	698.8	
Profit [MMUSD]	**21.35**	
Revenue [MMUSD]	**34.88**	
Inspection costs [MMUSD]	0.98	7.2% of total costs
Preventive maintenance costs [MMUSD]	6.59	48.5% of total costs
Corrective maintenance costs [MMUSD]	6.02	44.3% of total costs
Total maintenance costs [MMUSD]	**13.59**	

Table 8 Total expected profit and cost distribution for years 11 to 20 for the base case.

Description	**Value**	**Weighting**
Installed capacity [MW]	32	
Total energy generated [GWh]	632.8	
Profit [MMUSD]	**12.98**	
Revenue [MMUSD]	**31.64**	
Inspection costs [MMUSD]	0.98	5.3% of total costs
Preventive maintenance costs [MMUSD]	6.59	35.3% of total costs
Corrective maintenance costs [MMUSD]	11.09	59.4% of total costs
Total maintenance costs [MMUSD]	**18.66**	

When comparing Table 7 with Table 8, it is evident that performance is reduced at the end of life (second period), with less energy being produced (9.4% less) due to aging and increased failures; also, corrective maintenance (CM) costs increase. In the first period, the average annual capacity factor is 24.9%, while in the second period it is 22.6%.

It is important to note that, in addition to aging and the bathtub curve effect, the maintenance plan is fixed throughout the useful life, since best practices only generally recommend an annual maintenance plan, but it is not optimized for any type or age of PV plants. In this sense, each PV plant goes through a learning process, where the maintenance plan is adjusted year by year to obtain better performance.

Although only the average failure rates of the Diego de Almagro plant are known, and the maintenance plan is confidential information, the year-to-year increase in actual plant generation is likely due to the reduction of failure rates in the early years (bathtub curve) along with the adjustment of the maintenance plan to the specific conditions of the PV plant; hence, following the concept of the previous paragraph, it can be seen in the base case how a maintenance plan based on best practices is insufficient since the CM costs were increased in the second period instead of preventive maintenance (PM) costs.

A simple solution for this case under this modeling could be the implementation of several standardized plans based on best practices depending on the age of the PV plant; however, only general recommendations appear in the manuals and any necessary adjustments are the responsibility of the operator.

Table 9 Annual energy produced by the Diego de Almagro PV solar plant between 2015 and 2020 [134].

Year	Energy [GWh]
2015	46.1
2016	50.8
2017	58.9
2018	67.6
2019	71.7
2020	73.9

Naturally, the cost distribution is also different in the two periods. In the first period, inspection and PM costs represent 55.7% of total maintenance costs; in the second, this value decreases to 40.6% due to the almost doubling of CM costs. In broad terms, profit decreased by 39.2%, revenue decreased by 9.2% and total maintenance costs increased by 37.3%. The computation time for both periods was approximately 1 hour and 8 minutes on a traditional 4-core laptop with 8 logical processors (1000 iterations per period).

4.5.2.2 Optimal maintenance plan

Optimization shows that the optimal maintenance plan produces 16.2% more energy in the first period and 18% more in the second period, compared to the base case (see Table 10 and Table 11); this reveals that despite over dimensioning the failure rates, the model can find the maintenance plan that balances costs and generates better performance; this reinforces the idea that the maintenance plan based on best practices is only a basic reference guide, but that it must be adjusted according to the characteristics of each PV plant. The increase in energy production is mainly explained by the decrease in failures, which rapidly reduces CM costs; a 74.2% reduction for the first period and a 78.4% reduction for the second period, compared to the base case.

Remarkably, inspection and PM costs represent 78.3% of total maintenance costs in the first period; in the second period, this value drops to 76.2%. These values are in perfect agreement with the cost distributions reported in the literature (see 2.3.3.1, last paragraph), suggesting that the model delivers reasonable and applicable results in a real case. Additionally, we can see that the inspections and PM costs are at the lower limit of the range reported in the literature, which could be explained by the high failure rates of the plant, which forces CM to take a greater share.

Compared the first period to the base case, profit increased by 56.8%, revenue increased by 16.4% and total maintenance costs decreased by 47.5%. Compared the second period to the base case, profit increased by 109.7%, revenue increased by 18% and total maintenance costs decreased by 45.9%. Comparing the first and second periods for the optimal maintenance plan, we have that profit decreased by 18.7%, revenue decreased by 8.1% and total maintenance costs increased by 41.5%. Table 12 summarizes the percentage variations between the base case and the optimal case, taking the base case as a reference. Table 13 shows a comparison between the first and second periods for the base and the optimal case. Table 14 shows the cost distribution comparison for the first and second periods.

Table 10 Total expected profit and cost distribution for years 1 to 10 for the optimal plan.

Description	**Value**	**Weighting**
Installed capacity [MW]	32	
Total energy generated [GWh]	812.2	
Profit [MMUSD]	**33.47**	
Revenue [MMUSD]	**40.61**	
Inspection costs [MMUSD]	0.24	3.4% of total costs
Preventive maintenance costs [MMUSD]	5.34	74.9% of total costs
Corrective maintenance costs [MMUSD]	1.55	21.7% of total costs
Total maintenance costs [MMUSD]	**7.13**	

Table 11 Total expected profit and cost distribution for years 11 to 20 for the optimal plan.

Description	**Value**	**Weighting**
Installed capacity [MW]	32	
Total energy generated [GWh]	746.5	
Profit [MMUSD]	**27.22**	
Revenue [MMUSD]	**37.32**	
Inspection costs [MMUSD]	0	0% of total costs
Preventive maintenance costs [MMUSD]	7.69	76.2% of total costs
Corrective maintenance costs [MMUSD]	2.4	23.8% of total costs
Total maintenance costs [MMUSD]	**10.09**	

Table 12 Comparison between the base case and the optimal maintenance plan.

		Period 1 (1-10) optimal			**Period 2 (11-20) optimal**		
		Profit	Revenue	Total costs	Profit	Revenue	Total costs
Period 1 (1-10) base case	Profit	+56.8%	-	-	-	-	-
	Revenue	-	+16.4%	-	-	-	-
	Total costs	-	-	-47.5%	-	-	-
Period 2 (11-20) base case	Profit	-	-	-	+109.7%	-	-
	Revenue	-	-	-	-	+18%	-
	Total costs	-	-	-	-	-	-45.9%

Table 13 Comparison between the first and second periods for the base case and the optimal case.

Case	**Period 1 (1-10)**			**Period 2 (11-20)**		
	Profit	Revenue	Total costs	Profit	Revenue	Total costs
Base case	-	-	-	-39.2%	-9.2%	+37.3%
Optimal	-	-	-	-18.7%	-8.1%	+41.5%

Table 14 Cost distribution comparison between the first and second periods for the base and the optimal case.

Case	**Period 1 (1-10)**				**Period 2 (11-20)**			
	Inspection costs	PM costs	CM costs	Energy	Inspection costs	PM costs	CM costs	Energy
Base case	-	-	-	-	0%	0%	+84%	-9.4%
Optimal	-	-	-	-	-100%	+44%	+54.8%	-8%

From Table 12, it can be seen that the optimal maintenance plan generates a better profit in both periods due to improved energy production, increased revenue, and decreased CM costs. In addition, it is observed that the profit of the second period is much more effective in the optimal plan even though the decrease in costs in both periods was reduced almost the equivalent. This is explained by examining Table 14, where it is observed that the increase in CM costs in the second period is lower in the optimal plan, but PM costs are higher (CM costs are higher than PM costs). In this form, a trade-off occurs, where PM is increased and CM is decreased. This action compensates the total costs producing an equivalent reduction in the optimal plan for both periods; in brief, PM improves plant performance while reducing failures.

Table 13 ratifies the fact that the optimal maintenance plan finds a better mix as the end-of-life profit was reduced by slightly less than half of what it is reduced in the base case; however, total costs can be seen to increase. This is due to what was explained in the previous paragraph, since in the second period of the optimal plan, no inspections are carried out and only preventive and corrective maintenance are performed, which are more expensive than inspections. It is interesting to note that in the second period no inspections are performed, which is somewhat counter-intuitive. The analysis of this particularity will be made later in 4.5.3.

4.5.3 Analysis of the optimal maintenance plan

Since our model was run in two stages, there is an optimal maintenance plan for each period; the decision variables found by the optimizer are presented in Table 15. As mentioned in the methodology (in 3.4.2.2.4, specifically), the variables of inspections I_i and preventive maintenance PM_i are limits on the health state for which an inspection or PM is triggered, respectively. Variable IT_i represents the number of cycles between inspections once the health state drops below I_i.

Table 15 Outcome variables for obtaining the optimal maintenance plan.

Group element	**Type**	**Variable**	**Name**	**Value period 1**	**Value period 2**
PV panels	Spacing	x_1	IT_1 (cycles)	157	340
	Inspection	x_7	I_1	0.26	0.44
	PM	x_{13}	PM_1	0.68	0.68
Soiling	Cleaning	x_{14}	PM_2	0.81	0.81
Wiring DC	Spacing	x_2	IT_{3DC} (cycles)	330	8
	Inspection	x_8	I_{3DC}	0.35	0.53
	PM	x_{15}	PM_{3DC}	0.73	0.71
Wiring AC	Spacing	x_3	IT_{3AC} (cycles)	276	307
	Inspection	x_9	I_{3AC}	0.64	0.19
	PM	x_{16}	PM_{3AC}	0.7	0.69

Group element	Type	Variable	Name	Value period 1	Value period 2
Inverter	Spacing	x_4	IT_4 (cycles)	15	36
	Inspection	x_{10}	I_4	0.67	0.34
	PM	x_{17}	PM_4	0.66	0.66
Supporting Structures	Spacing	x_5	IT_{SS} (cycles)	2	277
	Inspection	x_{11}	I_{SS}	0.75	0.32
	PM	x_{18}	PM_{SS}	0.22	0.74
Transformer	Spacing	x_6	IT_T (cycles)	171	349
	Inspection	x_{12}	I_T	0.66	0.42
	PM	x_{19}	PM_T	0.73	0.65

It is relevant to mention that the mechanism of inspections is more complex than PM because there are decision criteria to be followed by the operator. This is reflected in the methodology by the probability of detecting a failure (DP) and the potential of failure (PF), which add uncertainty to the problem. In this regard, an inspection can trigger palliative maintenance or directly preventive maintenance. In contrast, PM is simple: once the health state drops below PM_i, preventive maintenance is performed.

In this connection, it is pertinent to state that if PM_i is greater than I_i, then no inspections are executed for element i. Not so in the opposite case: if I_i is greater than PM_i, then both can coexist; this can be corroborated in the second period of the optimal plan where the PM_i variables of all elements were greater than I_i (green cells in Table 15), and where the inspection costs were 0 (see Table 11). This occurs because an inspection has the possibility of triggering PM or not, and in the case of palliative maintenance, the probability of failure restarts at the maintenance limit, therefore, mathematically it is possible to perform an inspection before a PM. In the opposite case, if PM is performed first, the health state is reset to 1 (ideally), so mathematically it is impossible to perform an inspection since the probability of failure is in the "no maintenance zone"; however, this is not 100% certain because the maintenance error is also modeled, which implies that the health state after PM may not simply be 1, but may also take values lower, equal or even worse than the health state before PM; but this reasoning explains the trend of the results. It is important to clarify this as we observe some particularities in the results.

4.5.3.1 Particular cases of the supporting structures and the inverter

When comparing the optimal maintenance plan for each period, we noted some similarities and differences. First, it is observed that preventive maintenance PM_i was greater than inspections I_i in all elements in the second period, while in the first period it was 5 out of 7. It seems that there is an evident preference for the model to avoid inspections. In the two cases where I_i was greater than PM_i there are some observations. In the result of the supporting structures of the first period, it is clear that the model prefers a high number of inspections (every two cycles) rather than performing PM. While it is possible to perform PM when the health state reaches a value of 0.22, at this point the probability of failure is 0.999 (according to $PFC(H_k)$), so it is almost impossible to perform PM without the element having already failed.

This suggests that it is mathematically possible to carry out an over-inspection plan and ensure that the health state of the supporting structures remains stable throughout this period (remember that inspections can also trigger PM when necessary); however, in a practical sense, this scheme cannot be implemented. Common sense indicates that ideally there should be a balance between PM and inspections; however, the trend of the results is clear in indicating a preference for PM over inspections. So in this case, the result of the supporting structures would be an impractical case and the actual solution should be something similar to the case of the second period.

The second particular case is the inverter. In this case, the optimizer found a trade-off between inspections and PM that achieves mathematical stability but is again an impractical case; this solution may be a local optimum condition that the optimizer was not able to escape from. The latter makes sense if we compare the inverter solution in the second period since it is expected that at the end of the useful life the level of maintenance will increase given the higher number of failures; however, this does not occur. In the second period, it can be seen that PM_4 (0.66) is noticeably higher than I_4 (0.34), where the value of PM_4 remains constant in both periods; therefore, the most consistent approach is to take the solution of the second period as the correct and applicable reference result; this can be tested by applying the inverter maintenance plan in period 1.

The two particular cases mentioned above occur mainly for three reasons. The first is because no technical operating constraint is modeled that establishes boundaries between maintenance and inspections. Thus, the model is free to choose the operating ranges that are mathematically appropriate, but which may lead to impractical cases. To solve this problem, constraints can be added to establish minimum spacing between maintenance and inspections; however, it is necessary to define these constraints very carefully since they can condition the solution and produce biased results. The best form to do this is by modeling logistics and inventory, which requires implementing a higher level of detail and information that will have a direct impact on the model's performance.

The second reason is due to the nature of the problem. This problem presents a condition of multiple optima, in which there may be different combinations that are mathematically consistent, but practically not (see the case of the supporting structures); this reinforces the need to add operational constraints. The third reason is the nature of the genetic algorithm. It is known that the GA is quite effective in finding solutions to highly complex problems that cannot be solved with traditional optimizers, but this method is not free of weaknesses. It is common practice to perform several runs of the same problem to find a more consistent solution since this method is sensitive to the initial conditions and the tuning made, so the results may vary from one run to another. Unfortunately, given the computational cost of our problem and the limited resources, we cannot perform several runs and make a more exhaustive analysis of the solutions, so we must prioritize the systematic analysis.

4.5.3.2 Transformer case

Let us now analyze the case of the transformer maintenance plan. In both the first and second periods, inspections are not triggered and only preventive maintenance is performed. It is interesting to see how in the second period less preventive maintenance is performed than in the first period, being that at the end of the plant life failures increase (see the increase of corrective maintenance costs in Table 10). This behavior may be since the transformer is modeled in terms of duty cycles, i.e., they depend only on the number of cycles elapsed. In addition, it does not have an aging curve since the failure rates are so low that the effect of an aging curve is not noticeable; furthermore, the number of transformers is low compared to elements such as PV panels.

In this sense, the model does not observe mathematical differences in the transformer between the first period and the second, except for the increase in failures at the end of the useful life. That said, it is likely that the GA has only found a better solution in the second period, which could be perfectly applicable to the first period. This makes sense if we compare the results of the DC and AC wiring, where the PM_i values are slightly lower in the second period; also consider the PV panels and the inverter which remain constant in both periods. Also, given the number of transformers and the low failure rate, the impact of this element on the overall profit is probably low (even though this element has the most critical failures), and could be the reason why this element has the greatest difference in the solution of the first period (0.73) and the second period (0.65), being the lower value for the second period. Thus, this case could also be attributed to weaknesses in the genetic algorithm mentioned in the previous section and the modeling performed on this element.

4.5.3.3 Analysis of the decision variables of the methodology

We previously discussed what happens when inspections are not triggered. Now, let us take a further examination of what occurs to the rest of the variables in this scenario. Table 16 is analogous to Table 15 but includes the best 10 individuals (we order from worst to best, from left to right), which represent the best 0.45% of the entire simulation (top 10 individuals) for the first period; the analogous case for the second period is presented in Table 17. In green are marked the variables that are activated; in red are the variables that are not activated; we will understand that PM_i is activated when its value is greater than I_i; the same applies otherwise.

These individuals have practically the same profit (0.013% difference in profit between the best and the worst of the top 10), but there are substantial differences between them. For example, in the case of DC wiring, individual 3 has a variable of inspection spacing IT_3 equal to 31, while individual 4 has a value of 330. This enormous difference is because the variable IT_i is directly dependent on inspections I_i, so if I_i does not activate, then the variable IT_i does not activate either. This causes the inspection variables I_i and inspection spacing IT_i to be insensitive to the model when PM_i value is greater than I_i. Taking as an example the period with the most homogeneous results (period 2), it can be seen that the variation of I_i and IT_i is quite elevated considering that these are the 10 best individuals of the period over 2000 total individuals. In contrast, the variation of the PM_i variables are practically 0%. In this context, we can remark that the variability of the data is perfectly explainable given the modeling and the nature of the optimizer.

Table 16 Maintenance plan for the top 10 individuals of the first period (1-10 years).

Name	**Top 10 Individuals**										
	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**%var**
IT_1 (cycles)	157	157	152	157	244	157	157	244	244	157	25%
I_1	0.26	0.23	0.26	0.26	0.21	0.21	0.24	0.20	0.21	0.26	6%
PM_1	0.68	0.68	0.68	0.69	0.68	0.68	0.68	0.68	0.68	0.68	1%
PM_2	0.81	0.81	0.81	0.81	0.81	0.81	0.81	0.81	0.81	0.81	0%
IT_{3DC} (cycles)	330	330	31	330	248	248	31	330	26	330	83%
I_{3DC}	0.32	0.58	0.35	0.34	0.38	0.38	0.45	0.34	0.41	0.35	26%

Name	Top 10 Individuals										
	1	2	3	4	5	6	7	8	9	10	%var
PM_{3DC}	0.73	0.73	0.73	0.73	0.73	0.73	0.73	0.73	0.73	0.73	0%
IT_{3AC} (cycles)	276	276	276	280	276	130	276	275	276	276	41%
I_{3AC}	0.67	0.65	0.65	0.65	0.65	0.65	0.65	0.62	0.64	0.64	5%
PM_{3AC}	0.70	0.70	0.71	0.70	0.70	0.70	0.70	0.70	0.70	0.70	1%
IT_4 (cycles)	15	16	15	15	15	16	16	10	15	15	2%
I_4	0.67	0.67	0.67	0.67	0.67	0.67	0.67	0.67	0.67	0.67	0%
PM_4	0.67	0.67	0.66	0.67	0.67	0.67	0.67	0.67	0.67	0.66	1%
IT_{SS} (cycles)	5	4	5	5	5	5	5	5	5	2	1%
I_{SS}	0.75	0.75	0.71	0.75	0.75	0.75	0.75	0.75	0.72	0.75	4%
PM_{SS}	0.22	0.22	0.19	0.22	0.19	0.19	0.25	0.22	0.19	0.22	6%
IT_T (cycles)	290	171	290	171	171	171	290	166	171	171	34%
I_T	0.28	0.28	0.28	0.28	0.28	0.65	0.28	0.28	0.20	0.66	46%
PM_T	0.73	0.73	0.73	0.73	0.73	0.73	0.73	0.73	0.73	0.73	0%

Table 17 Maintenance plan for the top 10 individuals of the second period (11-20 years).

Name	Top 10 Individuals										
	1	2	3	4	5	6	7	8	9	10	%var
IT_1 (cycles)	67	46	46	46	71	340	342	75	340	340	81%
I_1	0.44	0.41	0.44	0.49	0.59	0.4	0.44	0.59	0.44	0.44	19%
PM_1	0.68	0.69	0.69	0.69	0.68	0.68	0.69	0.68	0.68	0.68	1%
PM_2	0.81	0.81	0.81	0.81	0.81	0.81	0.81	0.81	0.81	0.81	0%
IT_{3DC} (cycles)	122	8	10	8	125	8	125	8	125	8	32%
I_{3DC}	0.53	0.31	0.49	0.49	0.62	0.43	0.49	0.43	0.53	0.53	31%
PM_{3DC}	0.71	0.71	0.71	0.71	0.71	0.71	0.71	0.71	0.71	0.71	0%
IT_{3AC} (cycles)	226	307	307	303	226	307	225	305	307	307	22%
I_{3AC}	0.19	0.19	0.19	0.19	0.19	0.19	0.2	0.62	0.19	0.19	43%

Name	Top 10 Individuals										
	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**%var**
PM_{3AC}	0.69	0.69	0.69	0.69	0.69	0.69	0.69	0.69	0.69	0.69	0%
IT_4 (cycles)	36	155	36	155	36	36	36	153	40	36	33%
I_4	0.34	0.31	0.33	0.31	0.36	0.31	0.36	0.49	0.44	0.34	18%
PM_4	0.66	0.66	0.66	0.66	0.66	0.66	0.66	0.66	0.66	0.66	0%
IT_{SS} (cycles)	277	259	37	261	37	259	40	277	277	277	66%
I_{SS}	0.26	0.32	0.26	0.32	0.32	0.19	0.59	0.25	0.25	0.32	40%
PM_{SS}	0.74	0.74	0.74	0.74	0.74	0.74	0.74	0.74	0.74	0.74	0%
IT_T (cycles)	341	349	347	341	336	347	349	332	341	349	5%
I_T	0.41	0.42	0.41	0.45	0.43	0.42	0.43	0.44	0.38	0.42	7%
PM_T	0.65	0.65	0.65	0.65	0.65	0.65	0.65	0.65	0.65	0.65	0%

Now, let us extend the analysis to the entire last generation for which we will use box plots. These diagrams help us to understand compactly the distribution and dispersion of the data. Figure 31 shows an illustrative example with the components of the box plot. The box is composed of the data above the 25th percentile (Q_1) and below the 75th percentile (Q_3), i.e., the central 50% (interquartile range). The size of the box will indicate an approximation of how dispersed the data are; the larger the box, the greater the dispersion of the data, and conversely.

The line dividing the box corresponds to the median, that is, the central value of the data. This gives us an idea about the symmetry of the distribution. If the median is located in the center of the box then the distribution is symmetrical and the mean, median, and mode coincide (this can be observed in a normal distribution); when the median approaches one of the edges of the box, then the data are asymmetrically distributed.

The continuation of two segments in the box are called whiskers that determine the limit for outlier detection. The continuation of two segments in the box are called whiskers that determine the limit for outlier detection; data exceeding the whisker limits will be referred to as outliers. The whiskers should have a maximum length, which should not exceed 150% of the interquartile range.

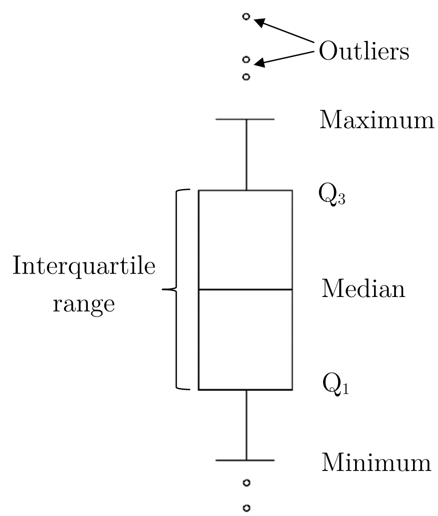

Figure 31 Illustrative example of a box diagram.

Having mentioned the above, Figure 32 shows a box plot of the last 100 individuals for period 1; the analog for period 2 is shown in Figure 33. These figures show all the decision variables of the problem, however, the range in which inspection spacing IT_i moves is different (between 1 and 365, left axis) than inspections I_i and preventive maintenance PM_i (0 to 1, right axis), therefore, for a better visualization, they will be displayed separately in Figure 34, Figure 35, Figure 36, and Figure 37.

Analyzing Figure 34, it can be seen that in general terms, almost all PM_i variables have a practically flat box plot, which shows that the optimizer has consistently decided their results. The exception to this are the supporting structures, which have a high dispersion due to PM_{SS} (supporting structures) not being activated, and instead, the inspection variable I_{SS} is activated. In general, the I_i variables show greater dispersion of the data, where there are not many outliers but they oscillate constantly until the last generation. The low dispersion of I_4 (inverter), commented in the previous section, is explained because, in the first period, both PM_4 and I_4 took the same value, so both variables are activated. In this context, low dispersion is to be expected.

Similarly, in Figure 35, IT_4 (inverter) and IT_{SS} (supporting structures) have a low dispersion since they are activated. In general, the bodies of the boxes with the highest dispersion are wide, indicating that more than 50% of the central data have variability. In the case of the second period, the data are much more homogeneous and consistent. Figure 36 shows how the boxes of the PM_i variables are flat with outliers very close to the box whiskers. It should be noted that the PV module cleaning variable PM_2 is the one with the lowest dispersion of all the variables, both in the first and second periods. This is also seen in Table 16 and Table 17, where its value was the same in both periods in all individuals. This is because soiling is directly related to the output energy of the plant, therefore, it is one of the most critical variables of the model. The boxes of the IT_i variables show large bodies with short whiskers, which indicates high dispersion mentioned above.

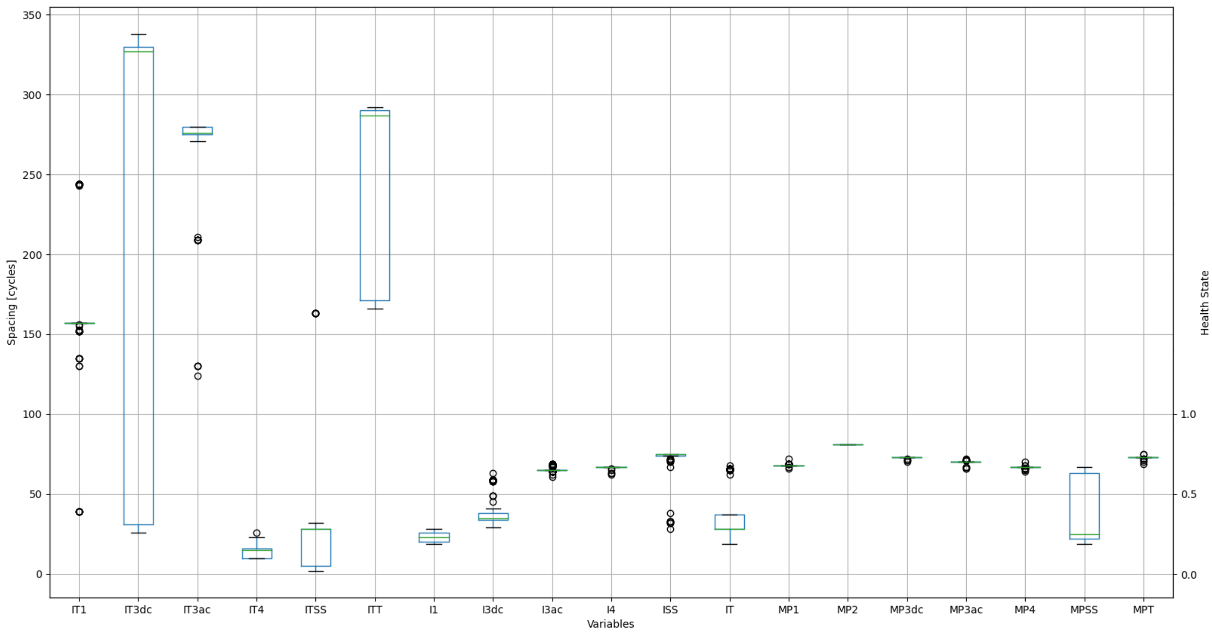

Figure 32 Boxplot of the last 100 individuals in period 1.

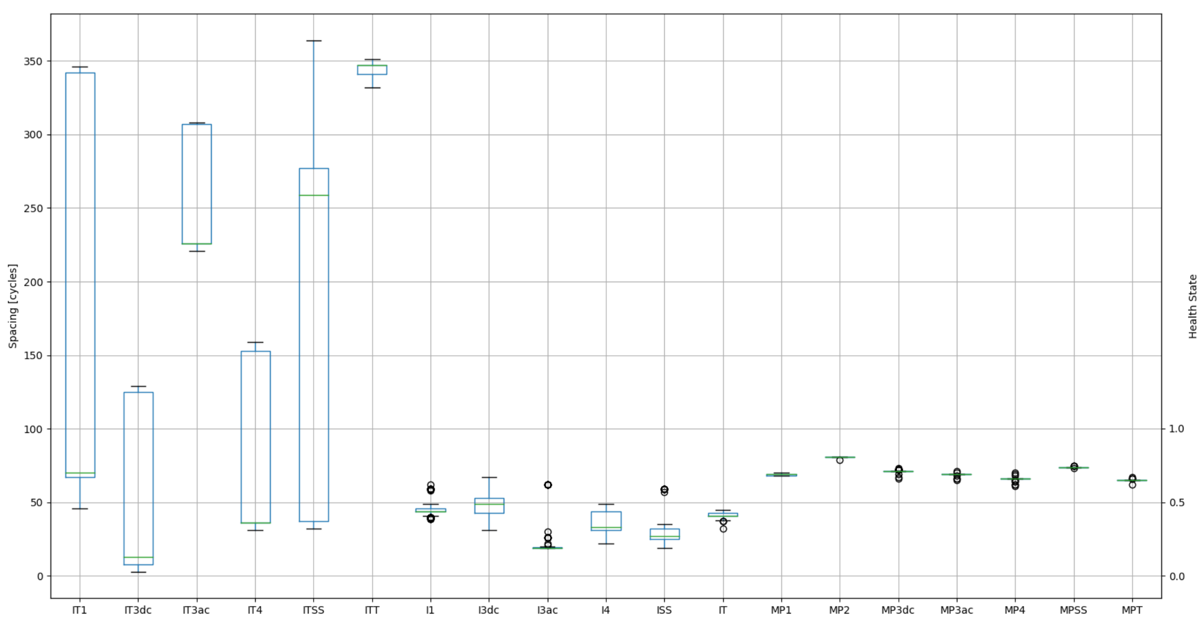

Figure 33 Boxplot of the last 100 individuals in period 2.

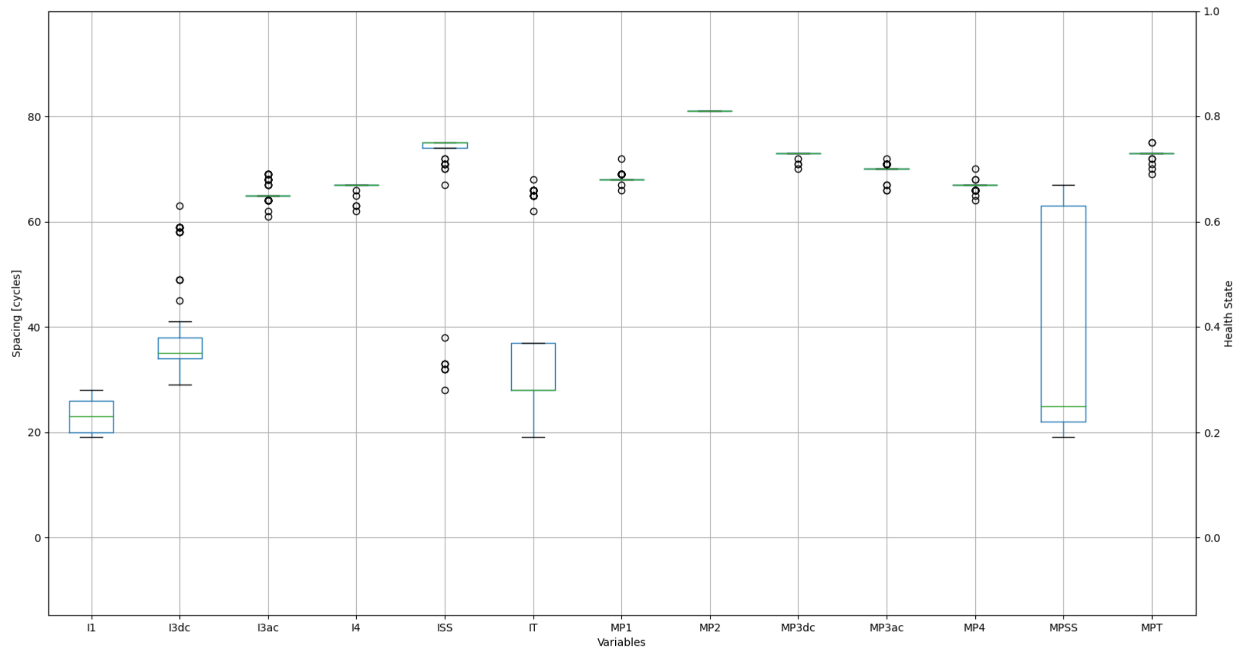

Figure 34 Boxplot of the last 100 individuals in period 1 (I_i and PM_i only).

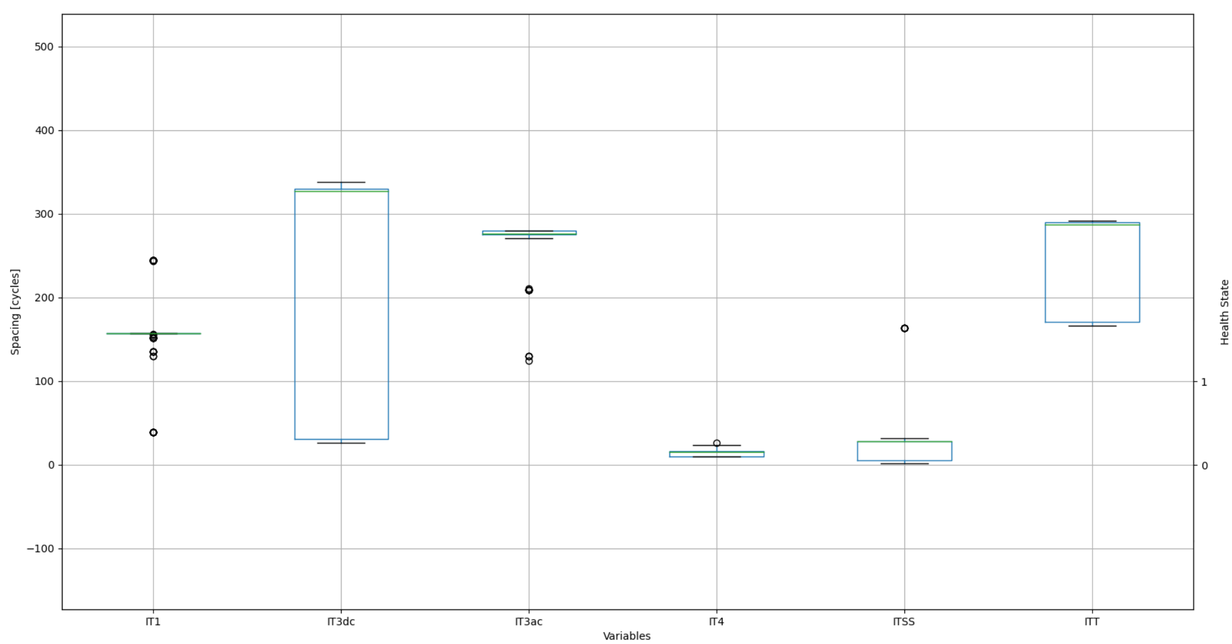

Figure 35 Boxplot of the last 100 individuals in period 1 (IT_i only).

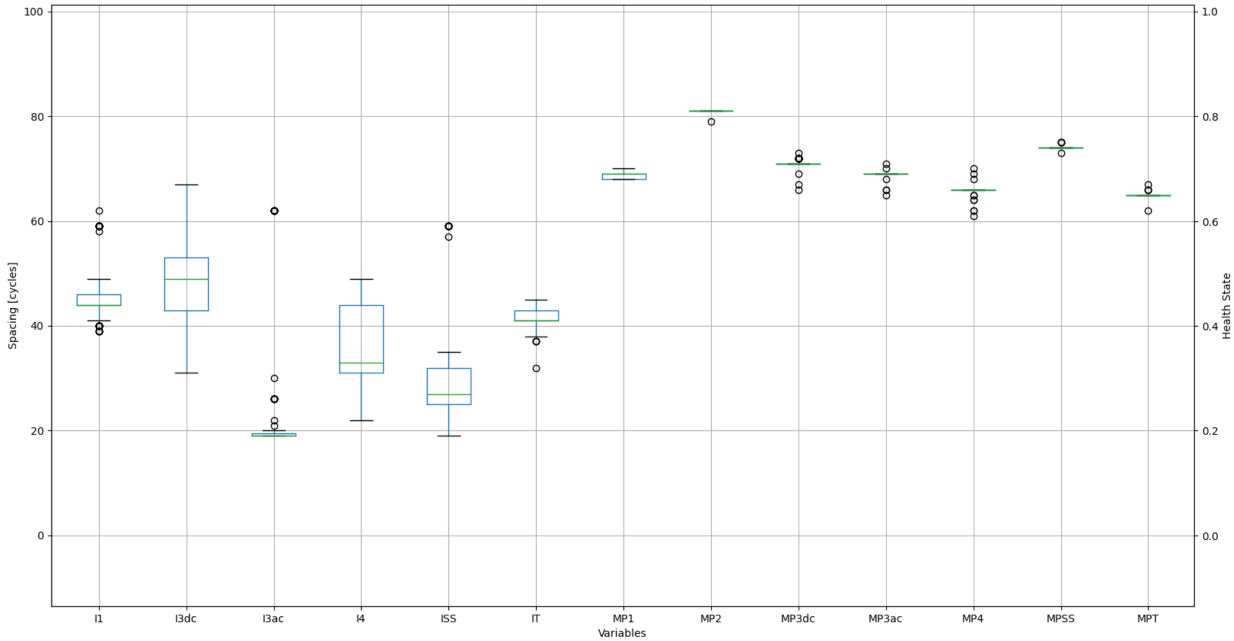

Figure 36 Boxplot of the last 100 individuals in period 2 (I_i and PM_i only).

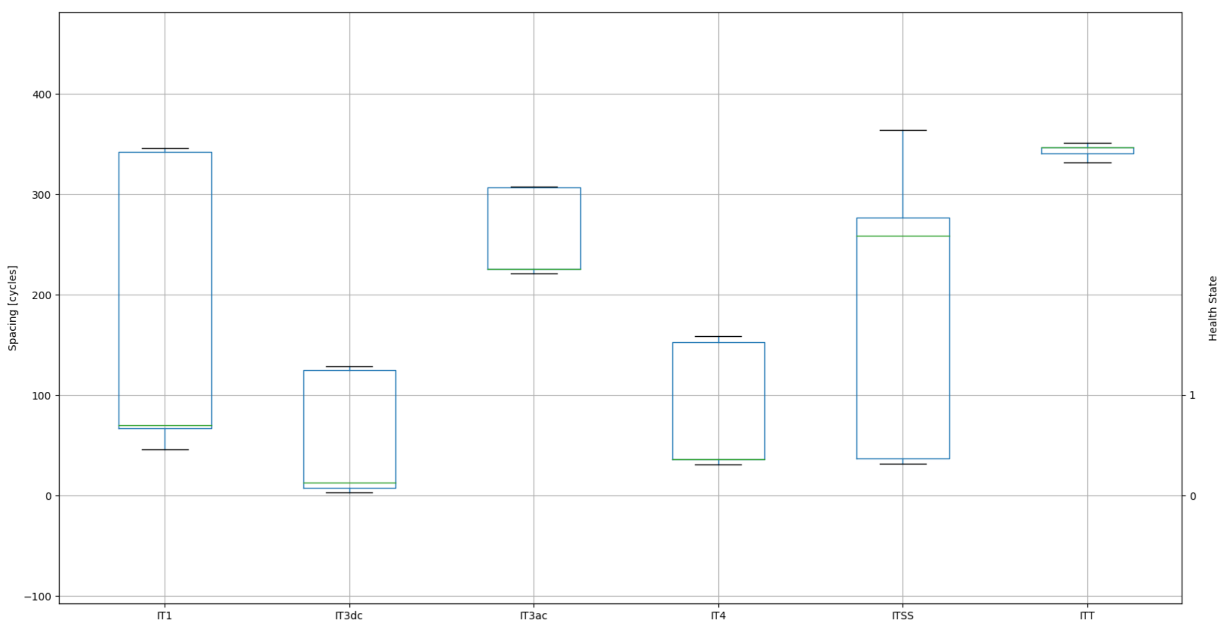

Figure 37 Boxplot of the last 100 individuals in period 2 (IT_i only).

On the other side, we are interested in knowing the incidence of the variables have on profit. For that purpose, Figure 38 shows the Pearson correlation matrix of all the variables and the profit for the first period; the analogous case for the second period is shown in Figure 39. These matrices show whether there is any degree of correlation between the variables themselves, including profit. It is important to mention that as these matrices are constructed with the individuals evaluated by the genetic algorithm, there is a conditioning of the data by the searching process. To reduce this effect, the correlation matrices were constructed only with the first 100 individuals, which represent the initial population, and therefore, the most random and less conditioned values; however, this small sample may not be sufficiently representative and still contains biases.

The data we are most interested in belong to the first line of the figures since they directly show the correlation between the variables with profit. We will not analyze the correlation between the variables themselves since the methodology does not contemplate technical couplings, structural dependencies, or opportunistic maintenance so that modifying the maintenance plan of one element cannot technically affect the maintenance plan of another. That said, the first observation we can make is quite clear: the variable that has the greatest impact on profit is the cleaning of the panels (PM_2). This is strongly reflected in both periods and ratifies what was previously commented.

Soiling (MP_2) is the most conclusive variable since in general the degree of correlation present in all other variables is quite low. In any case, it can be verified, in contrast with the box plots, that preventive maintenance of supporting structures MP_{SS} and transformer MP_T have a low incidence in the model, since the inspection I_{SS} was activated in the first period, and the transformer has very low failure rates. The second most incident variable is preventive maintenance of inverter MP_4, which coincides with being the element that fails the most, therefore, by varying the plan an improvement in the profit is perceived.

Having explained the particularities of the solutions found, we realize that the maintenance plans in both periods are more similar than they initially seemed. In fact, it makes sense to homologate a single maintenance plan for both periods without losing quality in the results given that in both periods the behavior was the same (although intuitively it was expected that in the second period the maintenance plan would be more demanding given the increase in failures at the end of the plant's useful life). Based on this premise, we can draw an important conclusion: it is not profitable to oversize the maintenance plan during the useful life to cover the increase in failures at the end; eventually, doing so would imply higher costs than simply responding with corrective maintenance.

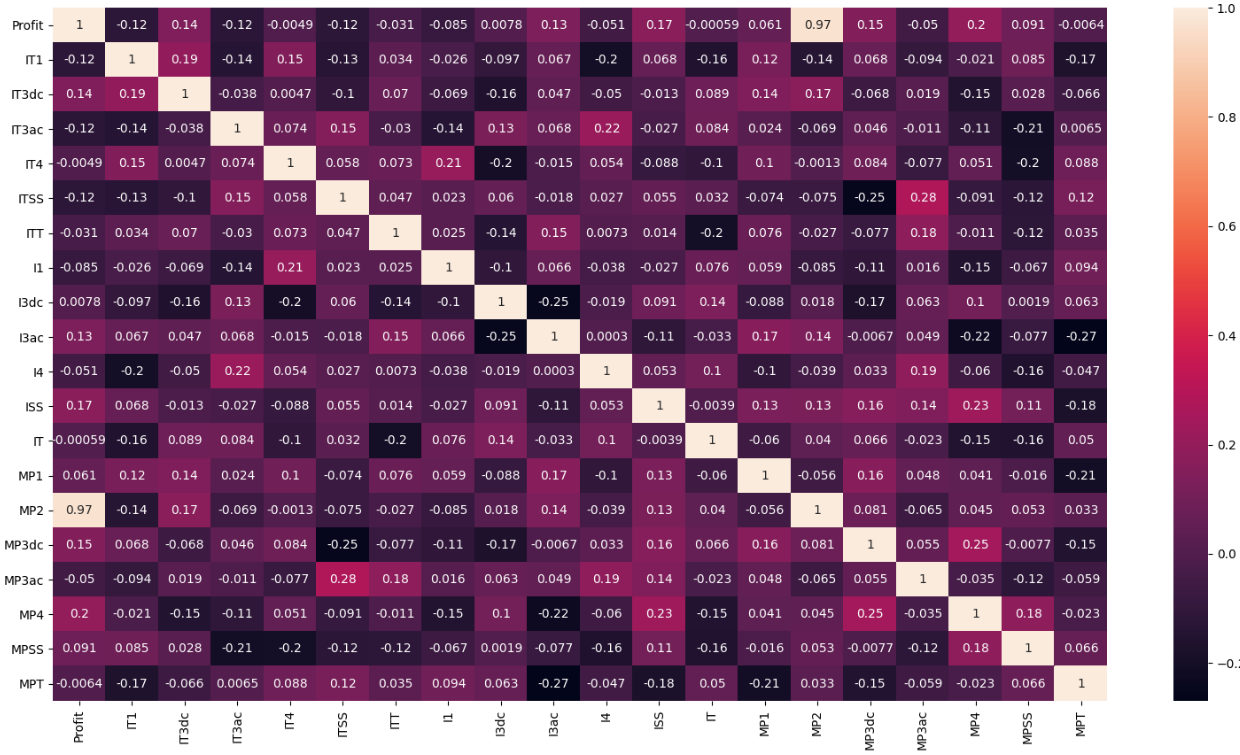

Figure 38 Pearson's linear correlation coefficient for period 1.

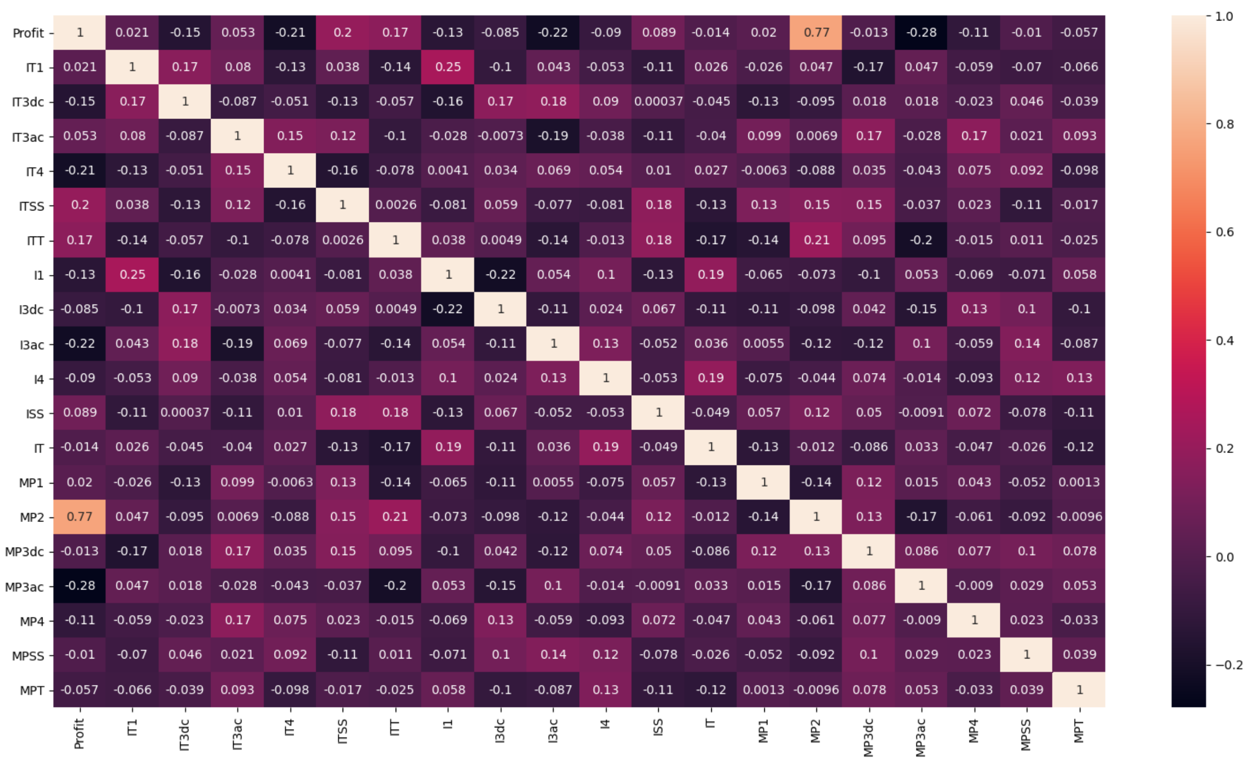

Figure 39 Pearson's linear correlation coefficient for period 2.

4.5.3.4 Optimal maintenance plan in time format.

As we stated in 3, our methodology is based on indicators of health state as a function of duty cycles. The duty cycle was defined in 24-hour periods given the daily cycles perceived in the meteorological variables. In this sense, the method to transform the 19 output variables of the model is by evaluating the optimal maintenance plan in a 1000-iteration Monte Carlo cycle and writing the cycle number in which inspections and preventive maintenance are performed. Table 18 shows the maintenance plan based on best practices as a function of the spacing between inspections and preventive maintenance. Table 19 shows a summary of the number of inspections and preventive maintenance per year for period 1; similarly, Table 20 is shown for period 2.

Strictly defined, the optimal maintenance plan depends on the meteorological variables and the accumulated degradation, therefore, the plan is variable; however, when analyzing the results, it can be seen that cycles pattern are generated between one maintenance and another with differences of a few days. Therefore, the results shown in Table 19 and Table 20 will be adapted to a fixed periodicity maintenance type for better visualization, and the spacings will be defined by the average difference between one and the other maintenance; thus, the results presented are the average optimal maintenance plan.

Table 18 Maintenance plan based on best practices.

Element	**Inspection**	**Preventive Maintenance**
PV panels	Every 183 days	Every 365 days
Cleaning	-	Every 122 days
Supporting structures	Every 183 days	Every 365 days
DC wiring	Every 183 days	Every 365 days
Inverter	Every 30 days	Every 183 days
AC wiring	Every 183 days	Every 365 days
Transformer	Every 365 days	Every 1825 days

Table 19 Average optimal maintenance plan for period 1.

Element	**Inspection**	**Preventive Maintenance**
PV panels	0	Every 183 days
Cleaning	-	Every 51 days
Supporting structures	Every 2129 days	0
DC wiring	0	Every 1202 days
Inverter	Every 93 days	Every 93 days
AC wiring	0	Every 384 days
Transformer	0	Every 670 days

Table 20 Average optimal maintenance plan for period 2.

Element	**Inspection**	**Preventive Maintenance**
PV panels	0	Every 181 days
Cleaning	-	Every 51 days
Supporting structures	0	Every 2129 days
DC wiring	0	Every 1262 days
Inverter	0	Every 90 days
AC wiring	0	Every 385 days
Transformer	0	Every 784 days

When comparing the maintenance plan based on best practices with the optimal plan, some similarities and differences can be appreciated. The PV panels are maintained once a year and inspected twice a year in the best practices plan. In the optimal plan, it is proposed to simply perform preventive maintenance twice a year, avoiding inspections; this is valid for the whole useful life. In this form, fewer but more accurate and consistent interventions are performed during the year.

As previously mentioned, the cleaning of the panels is critical, so the frequency of cleaning was doubled in the optimal plan; valid for the whole useful life. This allows for greater energy production, while increasing costs, however, this increase is offset by the decrease in the maintenance of other elements.

Supporting structures have the same maintenance periodicity as PV panels in the best practice plan; however, in the optimal plan, this is one of the elements that is sub-maintained due to its low failure rate and low impact on failures. In the first period, the optimal plan states that it should be inspected every 2129 days with a periodicity of 2 days until a potential failure is detected and preventive maintenance should be performed. As mentioned above, this is not a case applicable in practice, so it is preferable to apply the maintenance plan for the second period, which proposes preventive maintenance directly every 2129 days.

DC wiring is another sub-maintained element in the optimal plan. Best practices indicate its maintenance in conjunction with the PV panels and supporting structures, as they belong to the same system; however, the optimal plan indicates that preventive maintenance is performed in the range of every 1202-1262 days.

The inverter is another element that showed particular data in period 1. Best practices recommend monthly inspections and preventive maintenance twice a year. In the optimal case of the first period, preventive maintenance and inspections are established every 93 days. Evidently, there is a useless redundancy, so the maintenance plan for the second period, which establishes only preventive maintenance every 90 days, should be adopted.

The AC wiring found in the optimal plan is a good match to best practices, but with the inspections removed. Instead of inspecting 2 times per year and performing preventive maintenance once a year, the optimal plan states only preventive maintenance in the range of every 384-385 days.

Regarding the transformer, best practices suggest an annual inspection and preventive maintenance every 1825 days. In this case, the optimal plan finds a trade-off between the periodicity of inspections and maintenance. Considering both simulated periods, the optimal plan establishes to perform only preventive maintenance in the range of every 670-784 days.

As can be seen in the results of the case study, the increase in net profit with the optimal maintenance plan involved the under-maintenance of several elements. In practice, there are often contracts that establish minimum maintenance intervals, minimum maintenance requirements to cover manufacturer's warranties, or simply preventive measures to extend the useful life of the elements. Since the model does not incorporate these factors, two cases can be obtained from the optimal maintenance plan that are not applicable in practice; in this sense, the model lacks restrictions that allow more practical results to be obtained and that consider factors beyond the purely economic. Incorporating these factors with real data represents no minor challenge given that maintenance programs are usually handled confidentially, so access to such information is difficult. The latter is not unimportant, since it implies the possibility of adding relevant operating restrictions that will directly modify the results.

5 Conclusions

The initial hypothesis of this work has been achieved through the methodology developed and validated with the results. To achieve this, it was necessary to obtain an understanding of the solar PV plant in terms of operation mechanisms and failure modes, to find an adequate form of modeling the PV plant.

Since there are no standards that establish the proper manner to generate a maintenance plan, it was necessary to understand the mechanisms that are used in practice and the academia to find an optimal maintenance plan and evaluate the feasibility of applying these mechanisms to the developed methodology.

Once the general context was understood, the solar PV plant was mathematically characterized using a model based on health state indicators that are generated from the accumulated degradation caused by meteorological and operational variables. This model allowed the search for the best maintenance plan through Monte Carlo simulation and the Genetic Algorithm, for which it was necessary to use the resources of the NHLPC supercomputer.

Finally, the developed methodology could be validated through the application in a 32 MW solar plant, which allowed analyzing the advantages and weaknesses of the proposed model. The following subsections present the conclusions regarding the results in terms of costs, technical aspects, and recommendations for future works.

5.1 Conclusions about costs

The maintenance plan of a PV power plant is one of the most important elements since it is present during the entire service life. Best practices recommendations are an excellent starting point, but they are not sufficient as these are general recommendations and the performance of a photovoltaic plant can vary considerably depending on its characteristics, geographical location, logistics, etc. The results confirm this statement, since the profit found in the optimal maintenance plan was 56% and 109% higher than the base case, for the first and second periods, respectively; this improvement is mainly associated with a higher energy production due to the increased frequency of the panels cleaning along with a decrease in failures.

Inspection and preventive maintenance costs represented 55.7% (given the plant's high failure rate) of total costs in the first period, while in the optimal plan these values increased to 78.3% and 76.2% in the first and second periods, respectively. It is noteworthy that the optimal plan was able to balance the costs to keep the distribution in the range reported in the literature (even though it did not start within the range). This demonstrates that when a suitable maintenance plan is found for a PV plant, costs stabilize in the statistically known ranges (75% - 90%). Furthermore, being located at the lower limit, it denotes higher participation in corrective maintenance, which is consistent with the high failure rate of the plant. Therefore, the results reinforce the economic validity of the methodology.

5.2 Conclusions about technical results

The results of the variables defining the optimal maintenance plan show a clear trend: avoidance of inspections. This is because the mechanism of inspections is more complex and uncertain than scheduled preventive maintenance. Inspections involve uncertainty factors such as the possibility of detecting a failure, the accuracy of that inference, and the error in human intervention. Although inspections are considerably cheaper to perform, the optimizer avoids performing them because their execution does not ensure greater effectiveness. Therefore, it is more accurate to perform preventive maintenance than inspections, keeping human intervention to a minimum.

The results showed some divergences that allowed us to reach valuable conclusions. This is reflected in 3 cases: (a) the optimizer prefers to perform a high level of inspections but no preventive maintenance in the first period for supporting structures; (b) it is established that inspections and preventive maintenance should be performed on the inverter practically at the same time in the first period; (c) the maintenance of the transformer is more demanding in the first period than in the second period.

Case (a) shows that a case is mathematically possible but practically not applicable. This is the cost of not including technical operating constraints that discriminate realistic operating conditions and rule out those combinations that are not feasible. In addition, this case can also be a sub-optimality condition, as it shows how there is mathematical consistency in over-inspecting an element but at the same time under-maintaining it. The objective is met through cost trade-offs but in an unrealistic form.

Case (b) is a variation of case (a), where inspections and preventive maintenance are performed 1 or 2 days apart; doing this in practice is infeasible. This case is also produced by the lack of technical constraints and sub-optimal constraints from which the optimizer was not able to escape.

Case (c) is a bit counter-intuitive since it is expected that at the end of the PV plant's lifetime the maintenance plan will be more demanding, however, the opposite is true. In the second period, the maintenance plan is more relaxed, resulting in a maintenance delay of more than 3 months. Although in practice this value is not much given that the transformer has low failure rates and the number of transformers present in the PV plant does not compare to elements such as panels or supporting structures, this seems to be a consequence of the sensitivity to the adjustment of the genetic algorithm and the initial conditions. It is known that the GA does not always obtain the same results, so it is a good practice to perform several simulations and compare results. Unfortunately, since our computational resources are limited, we cannot perform more than one run per period.

On the other part, when we analyzed the top 10 individuals in the simulation, we could see that there were high variations in the IT_i variables (spacings between inspections) for individuals with such a similar profit (a maximum variation of 0.013% in profit). This is because these variables depend directly on whether the I_i variables (inspection thresholds) are activated. Since in the vast majority of cases the inspections variables I_i are not activated, then the I_i and IT_i variables become insensitive to the model. This allows rethinking the modeling of the problem as the number of variables could be considerably reduced and the model performance improved.

In general terms, the box plots showed that the variables with the greatest dispersion were the IT_i variables first, followed by the I_i variables. This high dispersion of the data is explained by the insensitivity that occurs in most cases. On the other hand, a low dispersion was observed in the MP variables, which are mainly the ones that decided the optimal maintenance plan.

Pearson's correlation matrix shows that the variable with the highest preponderance of profit is panel cleaning (PM_2), as it is a variable that is directly related to the plant's energy output. In this sense, the model raises the threshold of this variable as much as it is economically feasible to improve energy production. The second most important variable is the inverter, which is to be expected since it is the element that fails the most and whose impact on failures is critical. Moreover, it is observed that elements such as the supporting structures and the transformer have a low impact on the profit. Supporting structures have a high number of elements but their impact on failures is low. On the other hand, transformer failures are more critical since they transport much more energy, but the effect is compensated with their low failure rate compensates.

Having understood and explained the divergences in the model, it can be seen that the maintenance plans in both periods are quite similar. Therefore, it is possible to homologate a single maintenance plan for the entire useful life without losing quality in the results since the behavior of the results was the same. Based on this premise, we can draw an important conclusion: it is not profitable to oversize the maintenance plan during the useful life to cover the increase in failures at the end; eventually, doing so would imply higher costs than simply responding with corrective maintenance. This conclusion is valid under the approach that the maintenance plan is optimized for the whole lifetime of the plant; however, another approach could be to optimize the annual maintenance plan to have a dynamic plan throughout the lifetime. In this respect, the maintenance plan could be more demanding at the beginning and the end, and less demanding in the middle of the lifetime, following the bathtub curve.

Although our methodology is based on finding a variable maintenance schedule based on cumulative degradation, when transferring the results to the time frame it can be observed that, effectively, the spacing between one maintenance and another is variable; however, repetitive patterns occur given the nature of the meteorological variables. In this sense, the optimal maintenance plan is not much different from a fixed spacing maintenance plan since the variability of the spacing is low. In this regard, a representation of the optimal plan in terms of a fixed spacing plan using the average of the maintenance spacings of each element is valid.

Overall, the optimal maintenance plan produces better values for profit, but compared to the best practice plan, under-maintenance occurs in PV panels and DC and AC wiring. PV panels cleaning increases the frequency to double, while in the inverter and transformer there is a trade-off, where the periodicity of preventive maintenance is between the inspections and preventive maintenance periodicity of the best practices-based plan.

Although the optimal plan produces better profit at the cost of under-maintaining some elements, in practice other important factors intervene in the process and can affect the results, such as contracts with suppliers and operators, minimum maintenance to keep up with warranties, or simply strategies to extend the useful life of the elements; in addition to factors such as logistics and inventory. These types of factors must be included in the modeling in future work to obtain more reliable results.

5.3 Future works

5.3.1 Improving code implementation

The code was programmed in Python version 3.8.6 with the implementation of parallelism through the Multiprocessing library. Python has enormous advantages over other programming languages such as being a high-level language, versatility, strong community, libraries, free open source, and low learning curve; however, there are not negligible disadvantages that directly affected the development of this work, among which is the slowness due to its versatility and dynamism and high memory consumption. Among all the mentioned qualities, the disadvantages were enough to make us request access to the NLHPC. Future work should consider a thorough evaluation of the most suitable programming environment for our problem.

5.3.2 Adding technical operating constraints

According to what has been developed in this work, there are technical operating constraints that need to be implemented. Among the most obvious ones are the inventory, which establishes the availability of spare parts and element replacement; the logistics that establishes minimum and maximum periods in which inspections and preventive maintenance can be performed; and the opportunistic maintenance that defines maintenance protocols for adjacent elements when a system or part of it fails. The aforementioned constraints can be addressed as input parameters or can even be incorporated into the optimization function. In the case of opportunistic maintenance, it is necessary a solid definition of the parallelization mechanism since there must be communication between the parallel processes.

5.3.3 Adding contractual constraints

In practice, contracts must be complied with, which may result in financial penalties in the event of non-compliance. In this sense, it would be pertinent to include compliance with minimum maintenance to maintain the guarantee in force and compliance with generation contracts (PPA). The approach to implementing these restrictions could be through a penalty in the objective function in case of non-compliance with such requirements. In the case of generation contracts, it is necessary to incorporate the remuneration of energy through energy cost profiles at the injection node to create a balance between sale and purchase to the electricity system, and the subsequent sale to the customer. In this sense, it is possible to create the scenario of buying energy from the spot market in case of not meeting the generation requirements; energy cost profiles at the retirement node should also be included, therefore, transmission losses are also incorporated.

5.3.4 Extend methodology to dynamic evaluation

Analyze the possibility of modifying the methodology to obtain an annual dynamic maintenance plan, such that the maintenance plan is adjusted as failure rates evolve. This could be achieved by performing several sequential optimizations with a shorter evaluation period, where the evaluation period is constant but the start and end year changes, so that each optimization represents a feasible result for one year (or other defined time frame). The objective of this approach is to obtain an appropriate maintenance plan for each stage of the PV plant's lifetime.

5.3.5 Analysis of the PFC sensitivity, beta function, and probabilities associated with human error

In this work, several assumptions had to be made due to the lack of information, among which are the assumed values for the PFC and beta function settings, which simulate failures and error probabilities. It is pertinent to generate a statistical study with real information about the sensitivity of these parameters in the model, to obtain a realistic and adequate calibration.

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Annexes

Annexed A - Random meteorological sampling selection

There is a major limitation when choosing the method to be used. Since the computational cost of the methodology is high, and Monte Carlo simulation and genetic algorithms are used, this work must be executed on a high-performance computer (NLHPC), which has limited resources. This requires us to privilege computational time over academic rigor based on computational speed. Although it is more appropriate to use methods such as synthetic series or Kernel-based algorithms, this simplification is necessary to run our model within the established limits.

If we plot the histograms of the three variables for the total data (see Figure 40 to Figure 43), we observe different distributions that do not fall into the category of typical distributions. This leads us to use more sophisticated non-parametric fitting methods. We tested fitting and sampling the data through a Kernel Density Estimator, but the computation times exceeded the time available at NLHPC.

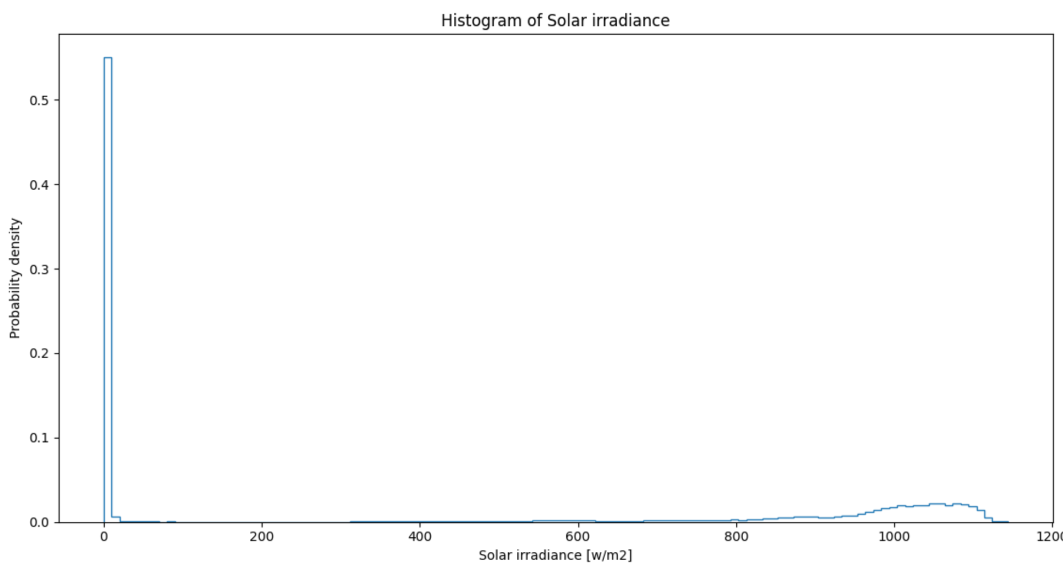


Figure 40 Histogram of solar irradiance for all data.

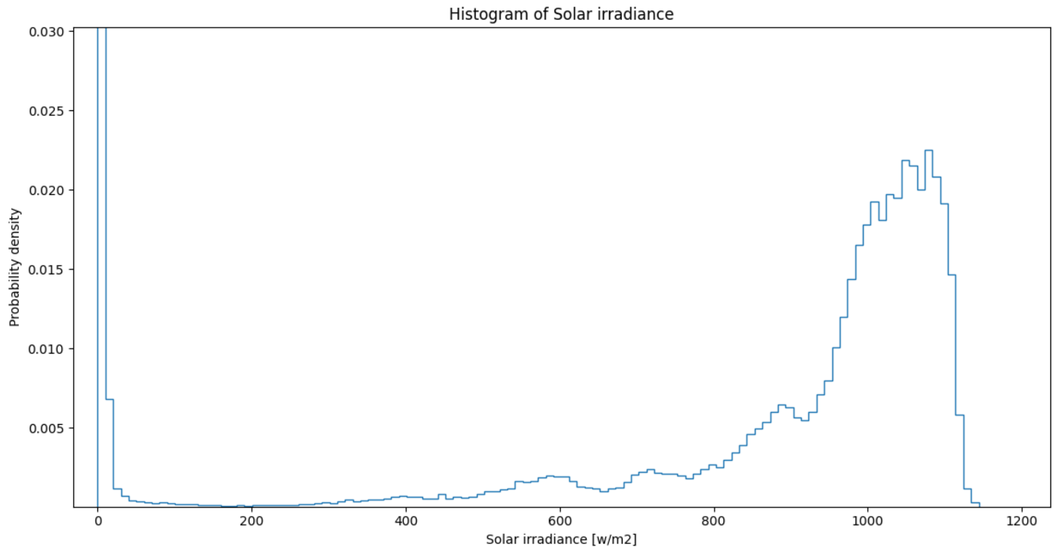


Figure 41 Histogram of solar irradiance for all data with zoom for better visualization.

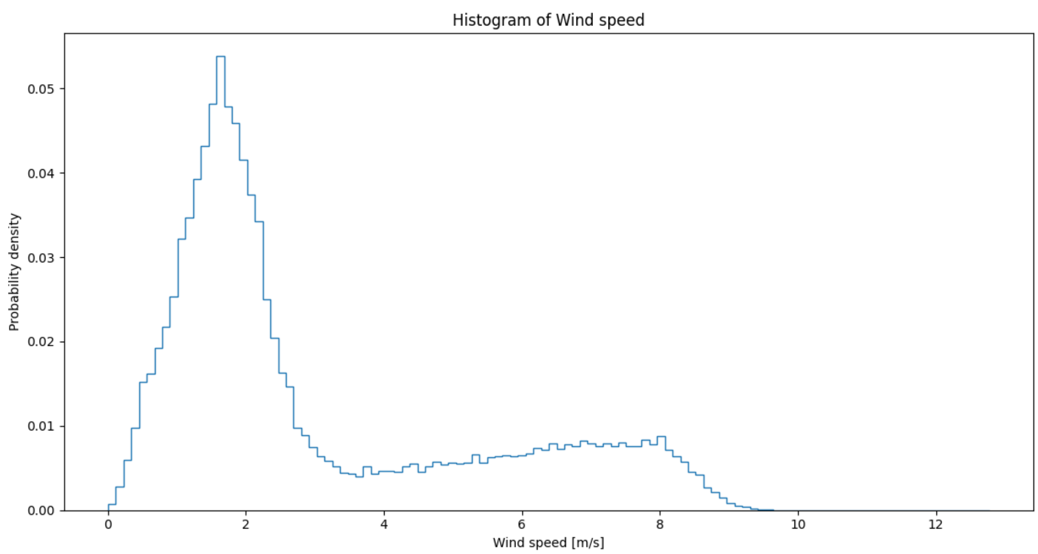


Figure 42 Histogram of wind speed for all data.

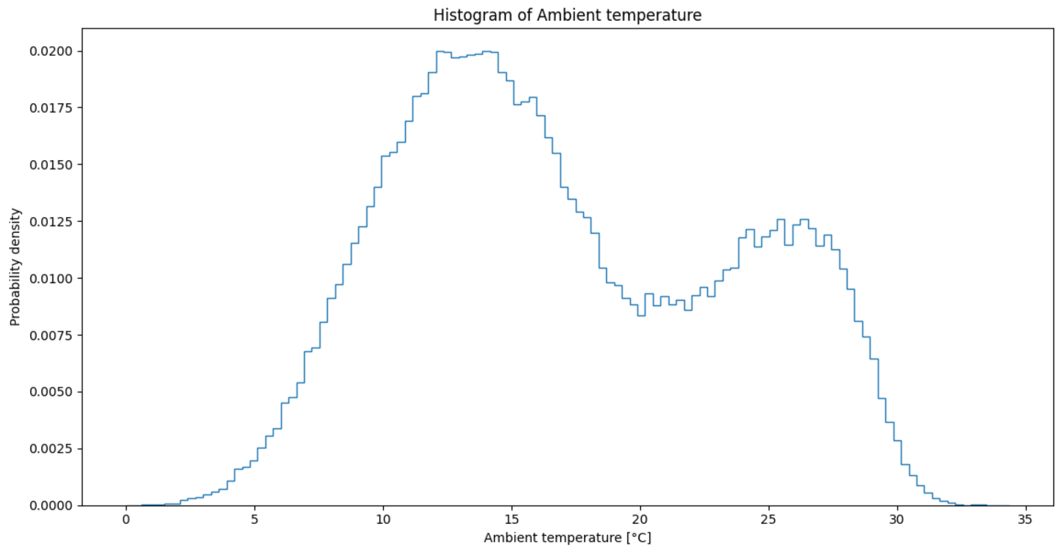


Figure 43 Histogram of ambient temperature for all data.

On the other hand, if we plot the histograms for a single hour of the day, for all days of a month, and all years, we can see that all distributions approximate a normal distribution (see Figure 44 to Figure 46); this is valid for any hour of the day in our data. Thus, simulating random numbers following normal distributions bounded to the data allows us to have a sampler with sufficient accuracy for this thesis.

It should be noted that in the case of solar irradiance, there is an additional step since there are a few low irradiance data that represent cloudy days. These data are simulated through a uniform distribution with a weighted probability equal to the cumulative probability of such data.

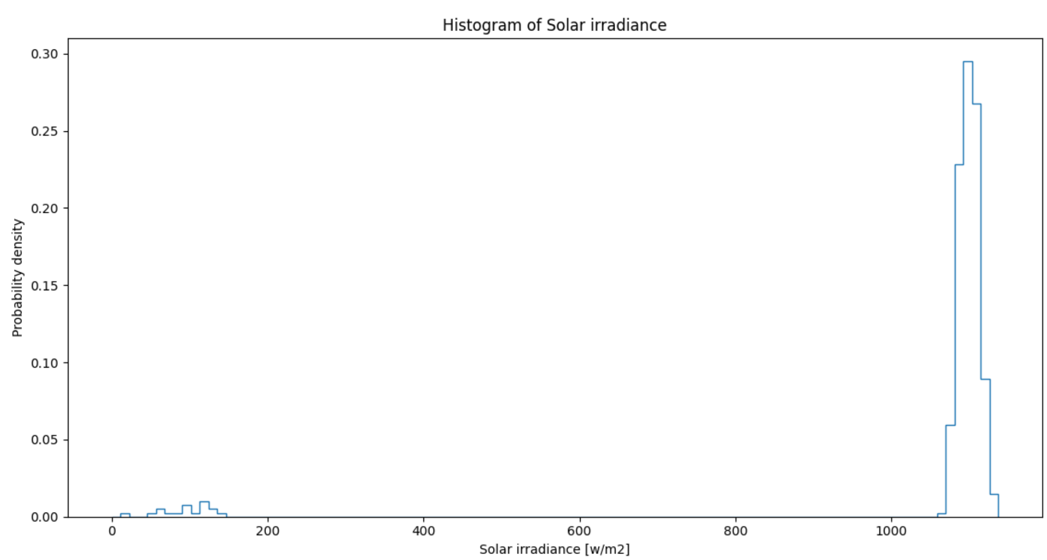


Figure 44 Histogram of solar irradiance at 12:00 for all January months of all years.

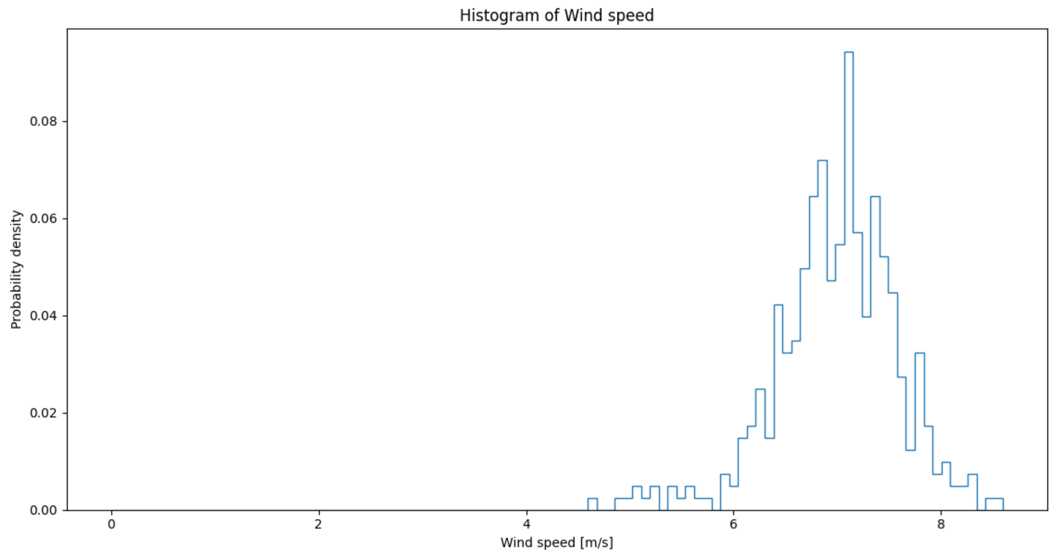


Figure 45 Histogram of wind speed at 12:00 for all January months of all years.

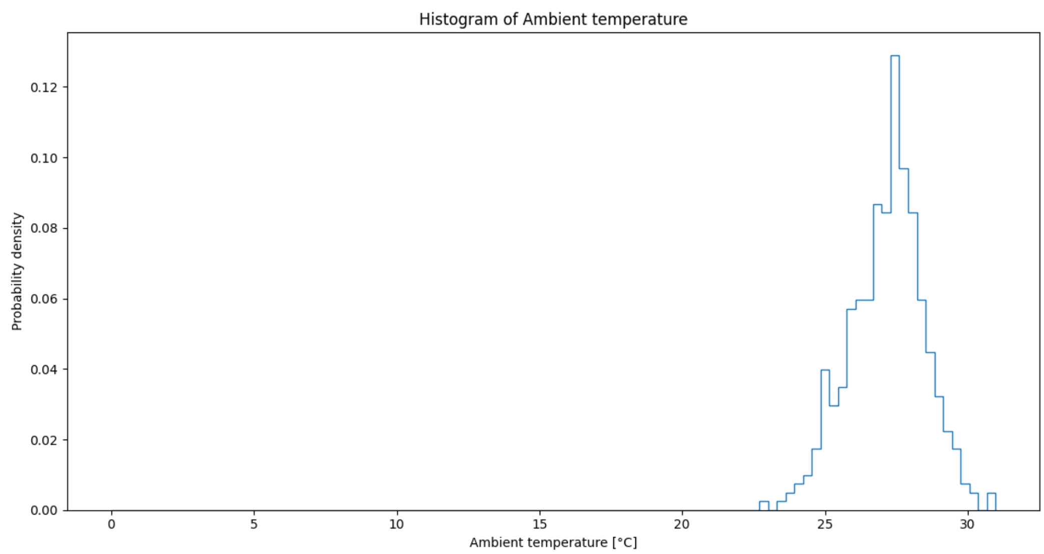


Figure 46 Histogram of ambient temperature at 12:00 for all January months of all years.

Annexed B - Failures modes modeled

As reviewed in section 2.5.3, there are numerous forms in which PV plant elements can fail with varying levels of impact on energy generation; for instance, a panel failure does not produce the same power loss as an inverter failure. Therefore, this section describes generally the modeled failure modes and their impact on generation loss. The values given in this section are inspired by literature and technical reports (see 2.5.3); however, these values may be modified for practical reasons for the purposes of this thesis. Also, note that some failure modes were weighted in the same way due to a lack of real information.

PV panels

In general, panel failures do not represent a serious problem to the PV plant since when they fail, generation is affected minimally. The most serious cases are hot spots and PID, which can directly affect the by-pass diodes and can lose 33% of the panel generation depending on the number of diodes burned (usually there are 3 by-pass diodes in each panel). Nevertheless, the loss is still small compared to the total generation. The rest of the faults only decrease their generation as time progresses. Therefore, we estimate the FI_{1j} in the range [0.01;1] and the FD_{1j} in the range [0.5;168] hours. The complete table of failure modes included in the simulation along with their FI_{1j} and FD_{1j} are shown in Table 21.

Table 21 Failure modes modeled for PV panel.

	Failure mode	**Min FD_{1j} [hours]**	**Max FD_{1j} [hours]**	**Min FI_{1j}**	**Max FI_{1j}**
1	Delamination	0.5	168	0.01	1
2	Discoloration	0.5	168	0.01	1
3	Corrosion	0.5	168	0.01	1
4	Cracking	0.5	168	0.01	1
5	Hot spots	0.5	168	0.33	1
6	By-pass diode	0.5	168	0.33	1
7	Bubbles	0.5	168	0.01	1
8	PID	0.5	168	0.33	1
9	Weld ribbons	0.5	168	0.01	1
10	Snail tracks	0.5	168	0.01	1

Supporting structures

Supporting structures tend to fail quite a few times. with tracker and control failures being the most frequent. The impact on generation is low in general but has a slightly higher priority than PV panels since a failure implies a higher portion of generation. Therefore. we estimate the FI_{SSj} in the range [0.1;0.5] and the FD_{SSj} in the range [0.5;36] hours. The complete table of failure modes included in the simulation along with their FI_{SSj} and FD_{SSj} are shown in Table 22.

Table 22 Failure modes modeled for supporting structures.

	Failure mode	**Min FD_{SSj} [hours]**	**Max FD_{SSj} [hours]**	**Min FI_{SSj}**	**Max FI_{SSj}**
1	Wind damage	0.5	36	0.1	0.5
2	Tracker failure	0.5	12	0.1	0.5
3	Corrosion	0.5	36	0.1	0.5
4	Misaligment	0.5	36	0.1	0.5
5	Oil leakage	0.5	12	0.1	0.5
6	Broken structure	0.5	36	0.1	0.5
7	Control	0.5	6	0.1	0.5

Combiner box. AC/DC wiring. switches. breakers. and fuses

As with support structures. failures of the transmission system are a higher priority than panel failures. but some wiring failures have a greater impact than supporting structure failures; for example. a connector failure that results in a branch disconnection has an FI equal to 1. Therefore. we estimate the FI_{3j} in the range [0.1;1] and the FD_{3j} in the range [0.5;4] hours. The complete table of failure modes included in the simulation along with their FI_{3j} and FD_{3j} are shown in Table 23. These values apply to both the DC and AC sides. Although the faults on the AC side are more important since they carry more energy. the impact of each fault is the same; however. since energy is penalized proportionally to the amount of energy associated with an element. the impact of an AC side fault is greater than that of a DC side fault.

Table 23 Failure modes modeled for wiring.

	Failure mode	**Min FD_{3j} [hours]**	**Max FD_{3j} [hours]**	**Min FI_{3j}**	**Max FI_{3j}**
1	Broken/Burned connector	0.5	4	0.1	0.5
2	UV aging	0.5	4	0.1	0.5
3	Conduit failure	0.5	4	0.1	0.5
4	Vandalism	0.5	4	0.1	1
5	Disconnection	0.5	4	0.1	1
6	Animal damage	0.5	4	0.1	0.5
7	Insulation	0.5	4	0.1	0.5
8	Cracks and ruptures	0.5	4	0.1	0.5

Inverter

As seen in section 2.5.3.2.1. the inverter can fail in several forms. almost all of which can be considered critical. Being a power electronics element. it needs very specific conditions for its correct operation. Therefore. a failure in any part of the inverter generates a stop of the energy conversion in most cases. As the list of failure modes is extensive. we have summarized it to the 12 most frequent cases. Therefore. we estimate the FI_{4j} in the range [0.99;1] and the FD_{4j} in the range [0.25;36] hours. The complete table of failure modes included in the simulation along with their FI_{4j} and FD_{4j} are shown in Table 24.

Table 24 Failure modes modeled for the inverter.

	Failure mode	**Min FD_{4j} [hours]**	**Max FD_{4j} [hours]**	**Min FI_{4j}**	**Max FI_{4j}**
1	Pollution	0.25	12	0.99	1
2	Firmware	0.25	4	0.99	1
3	Overheating	0.5	12	0.99	1
4	IGBT failure	0.5	12	0.99	1
5	PCB failure	0.5	12	0.99	1
6	Overvoltage/ Overcurrent	0.5	12	0.99	1

	Failure mode	Min FD_{4j} [hours]	Max FD_{4j} [hours]	Min FI_{4j}	Max FI_{4j}
7	Vandalism	0.5	36	0.99	1
8	Grounding	0.25	12	0.99	1
9	AC/DC Contactor	0.5	4	0.99	1
10	Fuses failure	0.25	4	0.99	1
11	MPPT failure	0.25	4	0.99	1
12	DC link Capacitator	0.5	12	0.99	1

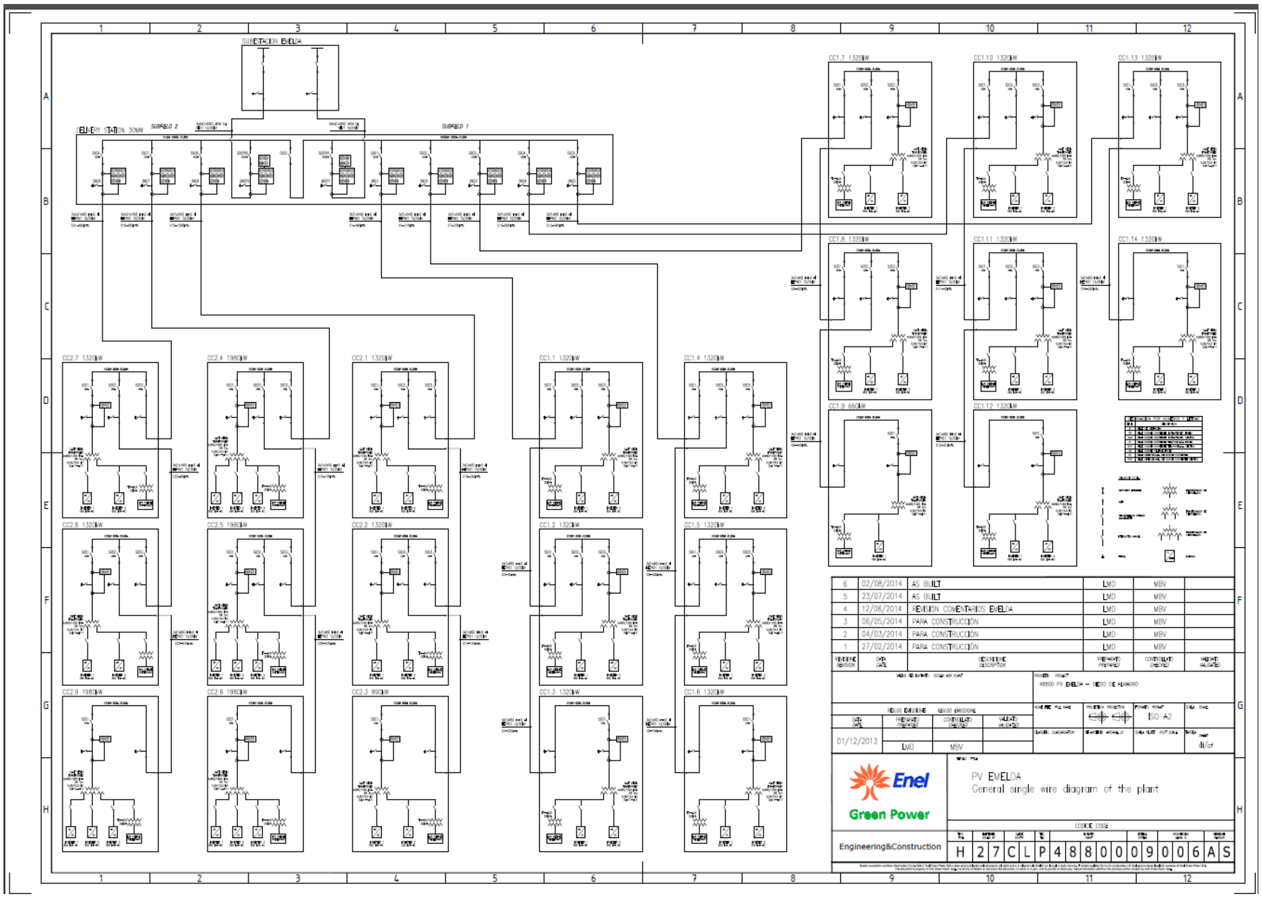
Transformer

The transformer is another element that not often fails. but when it does. it generates a major generation loss due to a large amount of energy associated with it. From the extensive list shown in 2.5.3.4.1. we have summarized the seven most significant and recurring failure modes. Therefore. we estimate the FI_{Tj} in the range [0.99;1] and the FD_{Tj} in the range [6;36] hours. The complete table of failure modes included in the simulation along with their FI_{Tj} and FD_{Tj} are shown in Table 25.

Table 25 Failure modes modeled for the transformer.

	Failure mode	Min FD_{Tj} [hours]	Max FD_{Tj} [hours]	Min FI_{Tj}	Max FI_{Tj}
1	Coonection problems	6	24	0.99	1
2	Oxidized or degradated parts	6	36	0.99	1
3	Broken parts	6	36	0.99	1
4	Insulation failure	6	36	0.99	1
5	Oil contamination	6	36	0.99	1
6	Open/Short circuit	6	24	0.99	1
7	Overheating	6	24	0.99	1

Annexed C - Case study topology



Annexed D - Datasheets

PV panel datasheet

ELECTRICAL DATA (AT STC)

		Nominal values				Initial values				
		NA-E140L5	NA-E135L5	NA-E130L5	NA-E125L5	NA-E140L5	NA-E135L5	NA-E130L5	NA-E125L5	
Maximum power	P_{max}	140	135	130	125	160.9	155.2	149.5	143.7	W_p
Open-circuit voltage	V_{oc}	61.8	61.3	60.4	59.7	62.5	61.8	61.1	60.4	V
Short-circuit current	I_{sc}	3.45	3.41	3.41	3.37	3.53	3.51	3.47	3.43	A
Voltage at point of maximum power	V_{mpp}	48.5	47.0	46.1	45.5	50.8	49.3	48.7	48.3	V
Current at point of maximum power	I_{mpp}	2.89	2.88	2.82	2.75	3.17	3.15	3.07	2.98	A
Module efficiency	η_m	10.0	9.6	9.3	8.9					%

STC = Standard Test Conditions: irradiance 1,000 W/m², AM 1.5, cell temperature 25 °C. Rated electrical characteristics of I_{sc} and V_{oc} are within ±10% of the indicated values and +7/−2% of P_{max}. The initial values are approx. 15% higher than the nominal (stabilised) values and will decline within the first weeks of operation. Afterwards the power output will stabilize around the nominal value according to the seasonal changes.

ELECTRICAL DATA (AT NOCT)

		NA-E140L5	NA-E135L5	NA-E130L5	NA-E125L5	
Maximum power	P_{max}	106.7	102.4	98.6	94.8	W_p
Open-circuit voltage	V_{oc}	57.2	56.8	55.9	55.3	V
Short-circuit current	I_{sc}	2.84	2.76	2.76	2.73	A
Voltage at point of maximum power	V_{mpp}	46.0	44.0	43.2	42.6	V
Current at point of maximum power	I_{mpp}	2.32	2.33	2.29	2.23	A
Nominal operating cell temperature	NOCT	46	46	46	46	°C

NOCT: Module operating temperature at 800 W/m² irradiance, air temperature of 20 °C, wind speed of 1 m/s.

LIMIT VALUES

Maximum system voltage	1,000 V DC
Over-current protection	6 A
Temperature range	−40 to +90 °C
Maximum mechanical load	2,400 N/m²

MECHANICAL DATA

Length	1,402 mm
Width	1,001 mm
Depth (including junction box = 23.3 mm)	6.7 mm
Weight	24 kg

TEMPERATURE COEFFICIENT

P_{max}	−0.24 % / °C
V_{oc}	−0.30 % / °C
I_{sc}	+0.07 % / °C

Inverter datasheet

MODELLO *MODEL*	Soleil 660 HV-TL
CARATTERISTICHE DI INGRESSO *INPUT PARAMETERS*	
Potenza max moduli (kWp) *Max power of modules (kWp)*	803
Tensione min / max di MPPT (V) *Min / max MPPT voltage (V)*	460 / 780
Tensione max (Voc) -10°C *Max input voltage (Voc)*	980
Corrente max moduli (A) *Max current of modules (A)*	2 x 731
n° MPPT *no. MPPT*	2
CARATTERISTICHE DI USCITA *OUTPUT PARAMETERS*	
Potenza nominale AC (kW) potenza continua *Nominal power (kW)*	660
n° fasi *no. phases*	3f
Tensione nominale AC (V) *Nominal voltage (V) AC*	280
Distorsione armonica (%) *THD (%)*	< 3
Separazione Galvanica (Trasformatore) *Galvanic isolation*	NO
Rendimento di conversione max (efficienza) (%) *Yield of max conversion (efficiency) (%)*	98,1
Euro rendimento (%) *Euro efficiency (%)*	97,2
Fattore di potenza *Power factor*	1
CARATTERISTICHE GENERALI *GENERAL FEATURES*	
Temperatura operativa (°C) *Operative temperature (°C)*	-5°C / + 45°C
Livello acustico (dBA) *Acoustic level (dBA)*	<68
Dimensioni (LxPxH) mm *Dimensions (WxDxH) mm*	
Grado di protezione *Protection degree*	
Peso kg *Weight (Kg)*	1600
CERTIFICAZIONI NAZIONALI E INTERNAZIONALI *ITALIAN AND INTERNATIONAL CERTIFICATES*	