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The Economic Value of Photovoltaic Performance Loss Mitigation in Electricity Spot Markets

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Abstract

Photovoltaic (PV) performance is affected by reversible and irreversible losses. These can typically be mitigated through responsive and proactive operations and maintenance (O&M) activities. However, to generate profit, the cost of O&M must be lower than the value of the recovered electricity. This value depends both on the amount of recovered energy and on the electricity prices, which can vary significantly over time in spot markets. The present work investigates the impact of the electricity price variability on the PV profitability and on the related O&M activities in Italy, Portugal, and Spain. It is found that the PV revenues varied by 1.6× to 1.8× within the investigated countries in the last 5 years. Moreover, forecasts predict higher average prices in the current decade compared to the previous one. These will increase the future PV revenues by up to 60% by 2030 compared to their 2015-2020 mean values. These higher revenues will make more funds available for better maintenance and for higher quality components, potentially leading to even higher energy yield and profits. Linearly growing or constant price assumptions cannot fully reproduce these expected price trends. Furthermore, significant price fluctuations can lead to unexpected scenarios and alter the predictions.

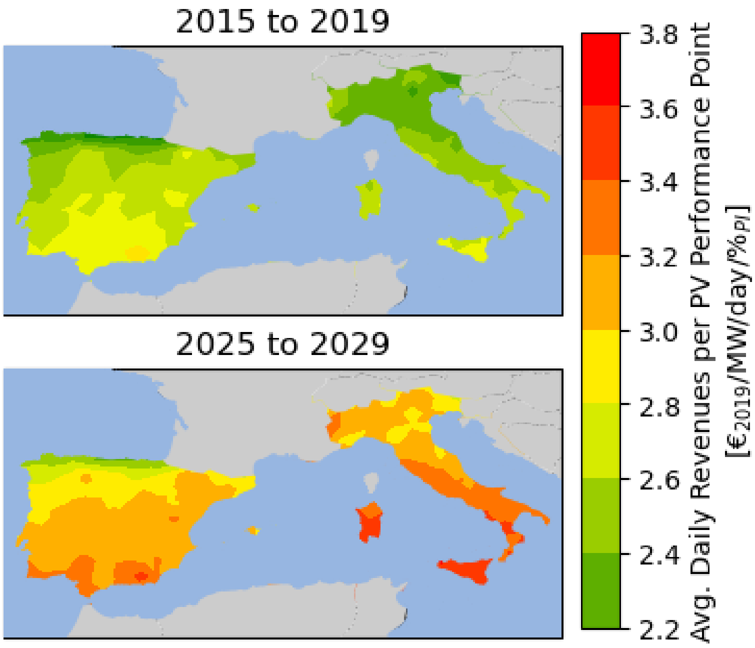
Keywords

Photovoltaics; maintenance; electricity price; soiling; performance loss; forecast.

Highlights

- PV losses in Portugal, Spain and Italy are analyzed from an economic standpoint.
- The main factor influencing the annual revenues of PV is the electricity price.
- The seasonal variation of the revenues is mainly due to yield seasonality.
- A linear performance loss rate might result in a nonlinear economic loss trend.

Graphical Abstract



1. Introduction

Several factors can affect photovoltaic (PV) performance. These include both reversible and irreversible losses, which affect the financial return of PV projects [1], as they lower the energy production and increase the uncertainty in the estimation of PV yield. Identifying these losses in advance is essential for minimizing the financial risks and optimizing the operation and maintenance (O&M) schedule of a PV plant.

Methods and systems to estimate the energy losses are being widely investigated by the community. For example, several methods exist to monitor the impact of soiling on the PV energy yield [2]. Specific soiling stations and optical sensors are available in the market to constantly measure the electrical losses of field systems [3–5]. Alternatively, these can also be estimated from environmental parameters [6,7] or directly from PV performance data [8,9], without the need of specific devices. Similarly, there are several methods available for degradation and performance loss analysis [10]. Aiming for better loss prevention, recent works have highlighted the potential non-linear profiles of performance losses in PV, showing their significant impact on the PV economics [11–13]. However, the energy loss is only part of the information needed to implement an accurate loss mitigation or prevention strategy. Indeed, any preventive or corrective solution addressing performance issues has to generate revenues higher than its cost to be profitable [14]. The gross revenues can be generally calculated as the product of the recovered energy and the electricity price. Therefore, an accurate analysis of the performance loss must consider both these aspects.

Estimates of the economic value of the lost energy have typically relied on simple approximations, which do not reflect the complex nature of electricity prices. For example, Mani and Pillai presented a list of cleaning recommendations based on regional climates and conditions [15]. While still useful, these did not take into account the electricity price and its variability. Since then, different cleaning optimization models have been proposed, mostly based on fixed electricity price assumptions [16–18]. In some cases, the effect of the variability of different electricity prices on the cleaning strategy has been evaluated, even if still modelling fixed electricity prices over time [19–21].

In reality, however, the hourly and daily electricity prices can vary significantly if the electricity is sold in a spot market. Spot electricity markets are common across Europe [22]. In these cases, the electricity price changes depending on the difference between supply and demand, and on the sources and costs of the available energy. This variability has to be taken into account when the economics of PV performance and losses is analyzed, during both the operation and the design of PV systems. However, it has been limitedly considered in the existing literature. Luque et al. [23] took into account the temporal variability of Chilean electricity prices, applying historical monthly prices in their cleaning optimization study. In an attempt to analyze the impact of losses over the lifetime of a PV system, Micheli et al. [24] assumed a linear variation in electricity prices. They found that the impact of system degradation and soiling vary significantly with the electricity price, which is one of the main factors governing the profitability of the loss mitigation strategies.

Nevertheless , the actual prices do not even follow linear trends; instead, they change depending on a number of conditions. Multi-year electricity price forecasts are nowadays commercially available [25,26]. These are generated taking into account long-term and seasonal trends of different factors that impact the electricity price, such as the fuel costs and the expected shift toward renewable energy sources. Using this type of time series, instead of constant or linear assumptions, can provide a better understanding of the future O&M trends in the PV market. In addition to assessing the profitability of corrective actions, these forecasts can also help to better evaluate the total performance losses over the PV system lifetime. This way, site designers and operators can calculate the return of different loss prevention strategies while operating or even designing the system.

For all these reasons, the present study analyzes the impact that electricity prices can have on the economic profitability of PV systems and on the loss mitigation strategies. Historical and forecasted electricity price trends are investigated in three of the largest European electricity markets: Italy, Portugal and Spain, which at the end of 2019 represented ˜26% of the EU28 PV capacity [27]. This is done by modelling the PV energy yields across these three countries and by analyzing the actual performance and soiling losses of two Spanish PV systems. The economic value of the PV energy between now and 2030 in Southwestern Europe is investigated and future O&M trends are outlined. Four electricity-pricing trend scenarios are used for this purpose and are compared with the typical assumptions of linear or no price escalation. In addition, the impact that exceptional and unexpected events, such as the COVID-19 outbreak or the current energy crisis, can have on the electricity market is also discussed.

2. Methodology

The approach used in the present analysis is shown in Fig. 1. The first step consists of the estimation of the PV energy yields over the investigated region using a PV performance model. Using the predicted yields, revenues and losses with country-specific electricity prices are calculated. Future daily electricity prices are estimated for each country by merging forecasts and seasonal trends extracted from historical time series. Two case studies from southern Spain are also reported. Finally, discussions of the software packages used for the analysis and the modelling uncertainties are presented.

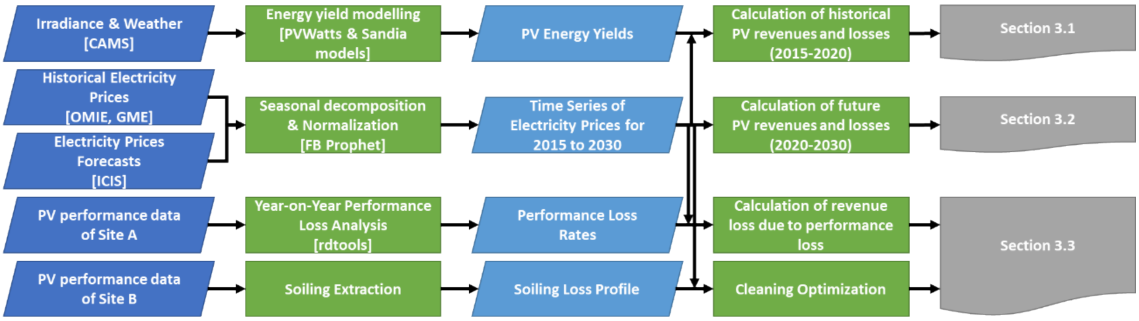


Fig. 1. Schematic of the procedures employed in this work and organization of the results. Data sources: CAMS - Copernicus Atmosphere Monitoring Service [28–30]*; OMIE – OMI-Polo Español S.A. (Spanish and Portuguese electricity market operator)* [31]*; GME - Gestore dei Mercati Energetici SpA (Italian electricity market operator)* [32]*; ICIS - Independent Commodity Intelligence Services* [25]*.*

2.1. PV performance and economic assessment

The first part of this work uses satellite-derived irradiance and weather data as inputs to PV performance and temperature models to estimate the PV yields and revenues across Italy, Portugal, and Spain. In particular, the economic assessment of the PV performance and losses in these countries is conducted through the development of an energy yield map, based on a 0.75°×0.75° grid. The output of a crystalline silicon mono-facial module on each grid point is estimated using the PVWatts DC power model [33]. The model is run with 2015 to 2020 hourly irradiance and temperature data from Copernicus Atmosphere Monitoring Service (CAMS) [28–30]. The cell temperature is calculated using the Sandia model [34], assuming an open-rack mounting structure and a glass-polymer backsheet module. A fixed configuration is modeled, with panels mounted at the optimal tilt angle and southward orientation. The optimal tilt is determined by modeling for each location all the tilt angles in between 30° and 50° and selecting the angle returning the maximum yield. Since the goal of this work is to understand the economic value of PV losses, these are not simulated at this stage; therefore, a perfect "lossless" operation is assumed.

The economic analysis is conducted by quantifying the revenues generated per percentage point of performance index. The performance index (PI) expresses the ratio of the measured energy output to the expected energy output of a system and has a value of 1 when the system has no losses (e.g., soiling, snow, degradation, failures, etc.). The revenues per point of PV performance index can be calculated as:

$$€_{PV}(i) = E(i) \cdot EP(i) \cdot 1\%_{PI} \tag{1}$$

where E(i) is the energy yield on day *i*, in kWh/kWp/day, estimated with PVWatts, and EP is the electricity price, in €/kWh. The revenues are expressed in €/kWp/day per percent of performance index ($\%_{PI}$) and can be interpreted from either a loss or a profit perspective. They represent the gross revenues made/lost by increasing/decreasing the performance index by $1\%_{abs}$. A system operating at the 90% of the performance index will be generating total revenues equal to $90 \cdot €_{PV}(i)$, as shown in Fig. 2, and experiencing a loss in revenues equal to $(100 - 90) \cdot €_{PV}(i)$. From a loss mitigation perspective, the $€_{PV}(i)$ corresponds to the maximum expenditure allowed to profitably improve the performance index by $1\%_{abs}$.

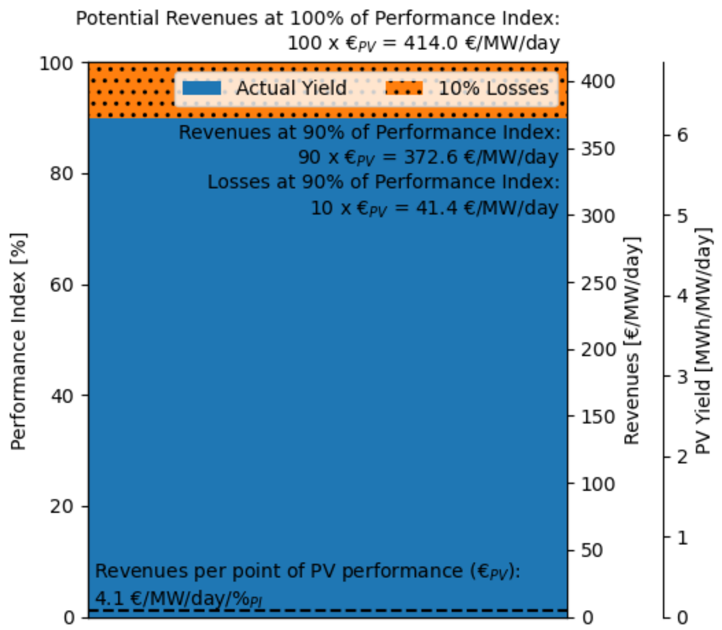


Fig. 2. Example of the revenues per point of PV performance index. A lossless yield of 6.9 MWh/MW/day is modeled for a PV module in Jaén, Spain on June 21st in this example. At an electricity price of 60 €/MWh, the revenues per point of PV performance index ($€_{PV}$) correspond to 4.14 €/MW/day/$\%_{PI}$. This means that an ideal performance index of 100% would generate a revenue of 414 €/MW/day. At a performance index of 0.9, the energy yield and the revenues per point of PV performance index would be 6.2 MWh/MW/day and 373 €/MW/day, respectively. In this condition, the losses would be 0.7 MWh/MW/day, or 41 €/MW/day.

2.2. Electricity price

In European countries, most of the electricity is sold through daily markets [22]. This means that the electricity price depends on the amount and sources of available energy and the demand at each hour. The present work considers the day-ahead electricity market prices, sourced from the Iberian and Italian market operators' websites [31,32]. Portugal and Spain share the same electricity market (Iberian Electricity Market, MIBEL) and operator (OMIE). On 68% of days since 2015, average day-ahead electricity prices in these two countries were the same. On the other days, the average deviation between 2015 and 2020 has been 0.25 €/MWh (< 1% of the mean price).

Several factors affect the electricity prices. The average daily prices in the three investigated countries are shown in Fig. 3A. Dissimilar values can be registered in different countries, as a result of different energy mixes, capacities, and demand profiles. The plot in Fig. 3A also shows that electricity prices can significantly fluctuate with time. Factors influencing the temporal variability of the prices can have effects on different timescales. A decomposition analysis was run to understand these various temporal components. This was done with an open-source forecasting library, Facebook Prophet [35], fed with the daily 2015-2020 data. The deseasonalized and seasonal trends are shown in plots B and C of Fig. 3 respectively. The long-term electricity price trends are typically driven by the installation of new electrical capacities, and by the aging of the existing capacity. The variability in fuel prices and the availability of the various renewable and non-renewable sources can cause short-term fluctuations from these trends.

In addition, electricity prices also have seasonal trends, influenced by the seasonality of some sources, such as PV, and of the demand, which is not constant over the year. Fig. 3C shows the seasonal component of the electricity price, which is found to be typically lower in the first half of each year for the investigated countries.

Last, one has to take into account that exceptional events, can also influence price of electricity. For example, a significant fall in electricity price can be seen in the first half of 2020 in Fig.3a. In that period, monthly average prices as low as 22 €/MWh in Italy and 18 €/MWh in Spain and Portugal were registered. These were , due to the drop in electricity demand that followed the lockdowns imposed at the start of the COVID-19 pandemic in 2020 [36]. These unexpected events can lead to unforeseen fluctuations.

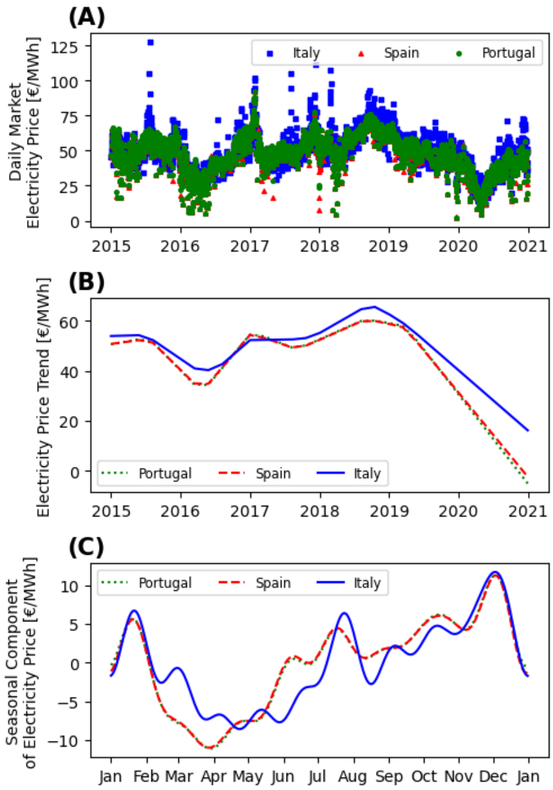


Fig. 3. A) Wholesale daily electricity prices in Italy, Portugal, and Spain since 2015. B) Deseasonalized trends of electricity prices since 2015. C) Seasonal trends. Yearly and Seasonal electricity analysis conducted on data from January 2015 and December 2019 using Facebook Prophet (fed with changepoint_range=1 and default inputs) [35].

In this work, the electricity price forecasts have been downloaded from [25], where four possible long-term scenarios for various EU countries (Fig. 4), assuming different coal and gas trends, are available. In all scenarios, the electricity price is expected to increase until 2024-2025, before either decreasing or stagnating. A similar forecast was proposed in [37], with electricity prices slowly increasing up to an interquartile range of 50 to 80 €/MWh by 2030, pushed by the increasing fossil fuel prices and by the ageing of the conventional power plant fleet. It is important to highlight that the forecasts available at the time of the study were produced before 2020. Since then, the aforementioned COVID-19 pandemic and the following energy crisis have led to an unprecedented drop and raise in electricity price. The exceptional growth is still occurring at the time this paper is written and has led the electricity prices to values as high as 240 €/MWh and 228 €/MWh for Italy and the Iberian peninsula's countries, respectively. At the present time, it is difficult to predict if the prices will drop soon and remain high for a long time. A forecast presented in January 2022 depicted different scenarios, expecting prices to remain above historical levels in the worst case at least until the end of that year [38]. The best scenario predicts them to drop to historical levels by the end of the year. A more recent forecast [39] predicts that the average European prices will drop below 100 $€_{2020}$/MWh around 2025, even in the worst case scenario. For this reason, the present analysis is conducted by assuming that long-term trend will behave as predicted in the forecasts presented in [25]. However, the current prices have not been neglected in this study and their effect on PV has been discussed in Section 3.4.

Each country's specific long-term price trend from [25] has been adjusted through the addition of the seasonal price component (see Fig. 3C). This was extracted from the historical electricity price time series using Facebook Prophet [35]. Because of the lack of forecasts for the Portuguese price trends, these have been assumed equal to the prices forecasted for Spain. If not otherwise stated, the present work utilizes the baseline scenario shown in Fig. 4. The other three scenarios, labelled as B, C, D, have been processed in a similar manner. Scenario B depicts more favorable conditions for electrical generation from coal over gas. On the other hand, Scenario C considers more favorable conditions for gas over coal. In Scenario D, a smaller carbon market is modelled.

To understand the real changes experienced by electricity prices over the investigated period, these must be expressed in constant monetary units. This is done by normalizing the actual electricity price to a baseline value. In this work, 2019 was selected as base year and the electricity prices are therefore reported in $€_{2019}$/MWh. The conversion is conducted by taking into account the "Harmonised Indices of Consumer Prices (HICPs)-Inflation rates" [40].

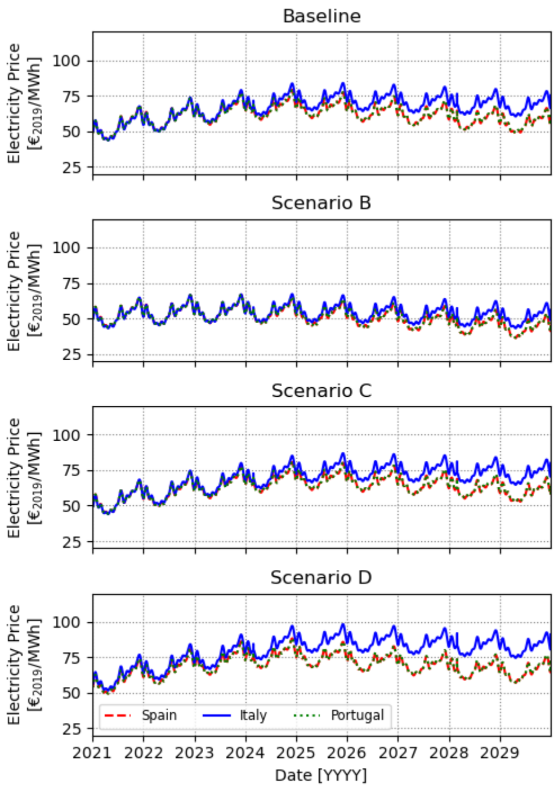


Fig. 4. The four-electricity price forecasts for Italy, Portugal, and Spain. The long-term trends are sourced from the electricity price forecasts reported in [12] and corrected using the seasonal component modeled with Facebook Prophet [35]. *Electricity prices in $€_{2019}$/MWh.*

2.3. PV sites for case studies

The variability in electricity prices affects both proactive and reactive loss mitigation strategies. In this light, the evolution of the economic impact of performance and soiling losses measured at two actual PV sites is calculated and presented. This makes it possible to show how also loss prevention and mitigation could change depending on the electricity prices.

The analysis makes use of data from two PV systems installed in Andalucía, the southernmost region of peninsular Spain. Spain has seen its national capacity grow by more than 200% since 2018 [41] and more than 30 additional GW are expected to be installed in the current decade [42]. Andalucía is one of the regions with the highest irradiation and hosts about 20% of the national PV capacity [43]. The proximity to the African continent makes Andalucía occasionally exposed to Saharan dust intrusions, which can lead to significant soiling losses. Both the investigated systems, here named Site A and Site B, are mounted on a fixed structure, facing southward at a tilt angle of 30 degrees.

Site A is a test installation mounted in 2011 on the rooftop of one of the University of Jaén buildings. The university is located in Jaén, a town in Southern Spain subject to an average global horizontal irradiance of 1847 kWh/m^2/year and a mean ambient temperature of 15°C [44]. The highest mean irradiance and temperature values are typically recorded in July, averagely > 8 kWh/m^2/day and > 25°C. The minimums are generally experienced in between December and January, with mean values as low as 2.5 kWh/m2/day and <6°C. The system in Site A consists of 5 parallel strings of 3 series-connected 60Wp a-Si modules. The modules are connected to a SMA™ Sunny Boy SB1200 grid-tied inverter. Electrical and weather data (temperature and wind speed) are provided as 15-minute averages for the 2012 to 2020 period. The in-plane irradiance was measured with a Kipp&Zonen CMP 21 pyranometer. A previous study on this system reported performance loss rates between -1.0 and -1.5%/year [45]. In this work, the linear performance loss rate was determined through the year-on-year approach [46]. The normalized PV power was calculated using PVWatts [47] and the procedure described in rdtools [48]. Default rdtools filters have been applied; global plane-of-array irradiance in between 200 and 1200 W/m^2, and cell temperatures in between -50 and 110 °C have only been accepted. The Sandia model was employed to estimate the cell temperature from ambient temperature, wind speed and irradiance, assuming an open rack glass-glass configuration [34].

Site B is a commercial 1MW PV power plant, also located in Southern Spain. The system is installed in province of Granada, subject to an average global horizontal irradiance of 1903 kWh/m2/year and a mean ambient temperature of 16°C [44] The highest mean irradiance and temperature values are typically recorded in July, averagely > 8 kWh/m^2/day and > 27°C. The minimums are generally experienced in between December and January, with mean values as low as <3 kWh/m2/day and <7°C. Previous analyses [21,24], conducted on the 2019 data from one of the inverters of Site B, showed that it is exposed to significantly seasonal soiling. The power drops toward the end of the summer can be higher than 20% and can lead to a 3 to 4% loss in annual energy yield. The same data generated previously [24] were employed to analyze how the revenue losses due to soiling would have changed over the years in different economic scenarios. In that work [24], the normalized power output was extracted using the Sandia model [49] and weather data downloaded from [50]. As recommended by the standards [51], only central hours of the day were considered. The soiling profile was built by fitting the normalized performance in between natural and/or artificial cleaning events using Theil-Sen regression [8]. A change in the soiling accumulation rate, attributed to the arrival of a dust-laden wind, occurred in mid-June during the longest dry period [52]. As in previous studies [21,24,53], the present work assumed that, after each artificial cleaning, no soiling was left and no change in soiling rate occurred. In addition, the seasonality of the location allowed the assumption of a repetitive soiling profile every year [54].

2.4. Analysis tools and uncertainty

All the analyses have been implemented in Python 3.7. pvlib python has been employed for the PV performance analysis [55] and rdtools for the performance loss rate extraction [48]. The influence of electricity price and PV energy yield on the PV revenues has been estimated using a feature importance analysis based on Extremely Randomized Trees [56], implemented in the Python's Scikit-learn tool [57]. This assigns to each variable a value between 0 and 1 with the sum over all variables equal to 1. The greater its value, the more important the variable is. Maps were generated using the Cartopy package [58].

The first part of the analysis uses satellite-derived data and performance models to estimate lossless yields of PV over a grid of locations. According to a recent report of the IEA [59], the estimation of the available solar resource is the main source of uncertainty in PV yield assessments. The insolation data for this study were downloaded from CAMS, which has been validated using measurements from 19 stations in the Baseline Surface Radiation Network [60]. Of these, only one station is in one of the three investigated countries (Spain). For this station, the root-mean-square errors in the estimated hourly global horizontal irradiance (GHI) and direct normal irradiance (DNI) are approximately 20% and 30% respectively. However, these errors are lower for daily (10% and 17%) and monthly averages (4% and 7%). The present work makes use of hourly irradiance data to estimate the daily time series of energy yields, which are then used to calculate the monthly and annual PV outputs over multiple years. Since the results are plotted in monthly or annual terms, the overall uncertainty of the yield estimation is expected to be in line with the lowest reported errors. In addition, the energy models employed in this work are used only to estimate the effects of irradiance, temperature, and angular and reflection losses on PV performance. The IEA report estimates them to introduce uncertainties of 1.0%, 0.8% and 0.5% respectively. Therefore, considering the long-term irradiance estimation and the energy modeling uncertainties, an overall uncertainty of ±9% is expected for the generated yields in this work.

3. Results and Discussion

3.1. Spatial distribution and variability of PV revenues

The revenues of the PV energy generated in Italy, Portugal, and Spain from 2015 to 2020 are shown in Fig. 5. PV in these countries provided average gross revenues of 2.4 $€_{2019}$/MW/day per point of performance index. However, these values vary by factors of 1.6× to 1.8× depending on the specific location within each country. As expected, the highest revenues occur in the South, with a maximum mean of 2.7 $€_{2019}$/MW/$\%_{PI}$ per day in Sicily (Italy) and Andalucía (Spain). The lowest values, with daily averages of 1.9 $€_{2019}$/MW/$\%_{PI}$, are in northern Italy and Spain. This means that the PV revenues and performance gains achievable through energy loss mitigation are not the same everywhere. Therefore, loss mitigation activities that might be economically feasible in the southernmost locations are not necessarily feasible in the northern regions.

The correlation between climate and performance losses is already a topic of interest for photovoltaics. It is understood that the same materials and components can suffer from different degradation and performance losses when exposed to different weather conditions [61,62]. In addition, causes of energy loss such as soiling and snow are also intrinsically site-specific, as their occurrence and intensity are related to the local conditions. Because of this, loss mitigation actions are already tailored to the site-specific conditions. However, the result shown in Fig. 5 proves that an additional site-specificity exists and must be considered: PV does not produce the same revenues everywhere, and its value can change even within the same country. This is due to both the variability in electricity prices experienced by the different spot markets as well as the regional variations in solar resource. For these reasons, each percentage point of performance index in the southern regions has a higher economic value than in the north. The higher revenues therefore justify higher spending for O&M in the south. While these results might sound obvious from a "local" or qualitative perspective, they provide, for the first time, a quantitative and systematic estimation of the economic value of PV performance in various sites. In addition, the reasons for these differences are also presented, as they are not limited only to the magnitude of the energy losses but are also strongly influenced by economic factors.

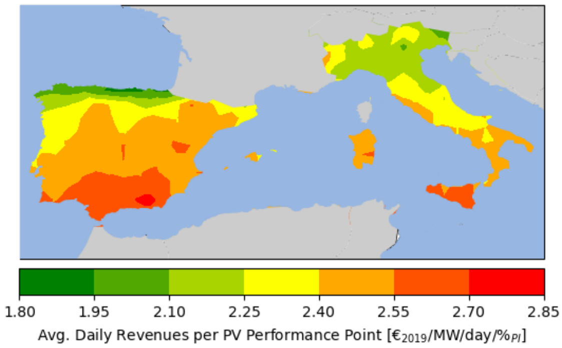


Fig. 5. Average revenues per point of PV performance index in Portugal, Spain, and Italy over the 2015 to 2020 period. Electricity prices in €$_{2019}$/MWh.

In addition to the spatial variation, the average PV revenues changed significantly over the years (top plot of Fig. 6). Factors of 1.6× to 1.8× exist between the annual maximum and minimum values experienced by each country. The maximum revenues were reached in 2018, while minimums occurred in 2016 and 2020. This is the same trend seen in the electricity price and suggests that the yearly PV profitability is mostly a result of the electricity price variability. Indeed, while the standard deviation of annual revenues ranged between 16%$_{rel}$ and 19%$_{rel}$, the standard deviations of the energy yields were limited to only 2 - 3%$_{rel}$ in the same years. This conclusion is also confirmed by the extremely randomized trees analysis, which returned feature importance > 0.8 for electricity price and < 0.2 for the PV yields when compared with the daily revenues.

From a seasonal perspective, the highest economic revenues for PV are typically registered in the summer months (bottom plot of Fig. 6). In July and August, the median daily revenues are almost twice as high compared to January and December. In this case, the result of the feature importance analysis is the reverse of the previous one: the importance of the energy yield is significantly higher than that of the electricity price (> 0.8 vs. < 0.2 respectively). This means that the seasonal trend of the PV profitability is mainly the result of the seasonality in energy yield, while the seasonal behavior of the electricity prices (Fig. 3C) has only a limited effect.

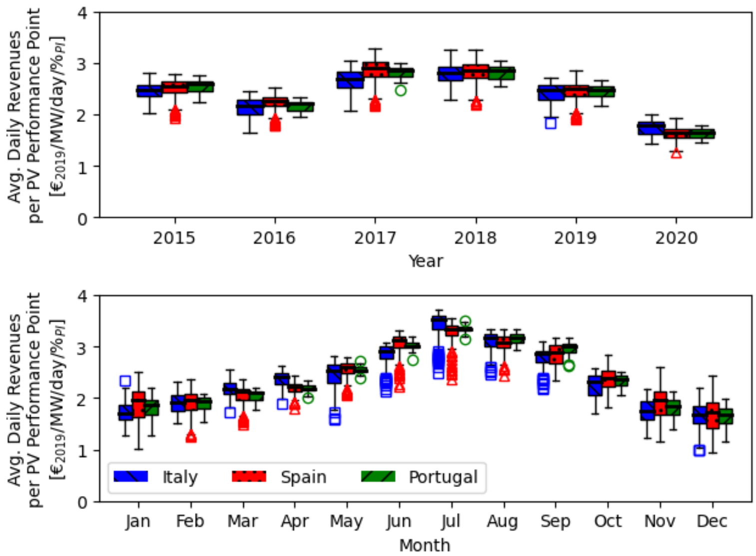


Fig. 6. Top: Yearly PV revenue trends. Bottom: Distribution of PV revenues by month. The black bold horizontal lines represent the median values. Electricity prices in €$_{2019}$/MWh.

3.2. Perspectives

Using the electricity price forecasts presented in Fig. 4 makes it possible to also get an estimate of the future PV revenue trends. The left plot of Fig. 7 shows that these are expected to follow similar trends in Spain and Portugal. They will increase until 2025 up to a maximum value of 3.2 - 3.3 €$_{2019}$/MW/day/%$_{PI}$. Then, they will start decreasing at a rate of -0.13 €$_{2019}$/MW/day/%$_{PI}$ per year. Even Italian revenues are expected to reach a similar peak (3.3 €$_{2019}$/MW/day/%$_{PI}$) in 2025. After that year, the revenues will decrease at a rate of -0.06 €$_{2019}$/MW/day/%$_{PI}$ per year. Because of the limited drop, higher PV revenues are forecasted for Italy in 2029 compared to the other investigated countries: 3.1 €$_{2019}$/MW/day/%$_{PI}$ vs. 2.7-2.8 €$_{2019}$/MW/day/%$_{PI}$. In all cases, the PV revenues will be higher in 2030 compared to the 2015-2020 period; Italy will experience a rise in revenues of 32%, whereas this will be limited to 13-15% for Spain and Portugal.

It is important to highlight that the predicted PV revenues can change significantly depending on the electricity price scenario (right plot of Fig. 7). In most cases, however, they are expected to achieve higher values in 2030 compared to the 2015-2020 period. At most, in the highest prices' scenario (D), revenues in Italy and in the Iberian countries in 2029 will be respectively ˜60% and ˜33% higher than in the 2015-2020 period. The only exception occurs for Scenario B, which depicts conditions that are more favorable for coal generation over gas. In this case, the PV revenues by 2030 in Italy will be in line with those of the last 5 years (-2.1%), whereas Spain and Portugal will experience revenues in between 11 and 12% lower compared to the 2015-2020 period.

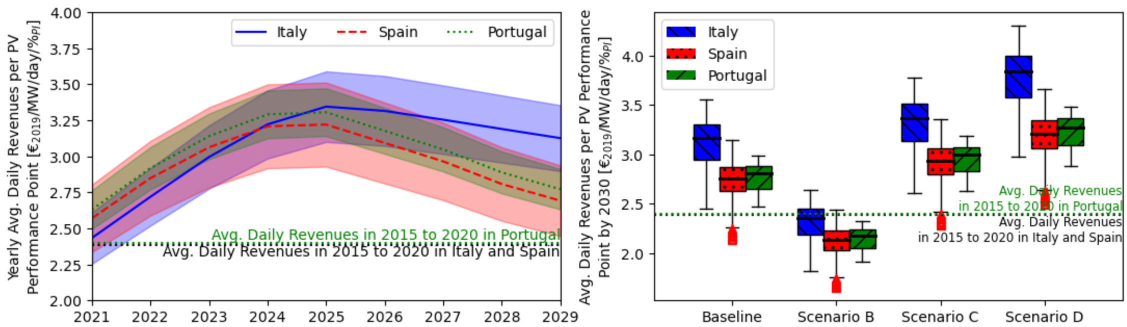


Fig. 7. Left: Prediction of the economic impact of PV performance losses in between 2020 and 2030, using the baseline scenario. Right: Economic value of PV by 2030 for four different scenarios. Electricity prices in €$_{2019}$/MWh

Estimating the future PV revenues is essential to maximize the profitability of systems that are required to operate for 25+ years. Corrective actions, such as cleaning or PV repowering, can be typically scheduled year after year depending on current electricity prices and shorter-term predictions. On the other hand, preventive actions require the estimation of long-term effects. For example, in higher price scenarios, it might be worth investing in more expensive PV modules and components if they have lower performance loss than others. In this light, Fig. 8 shows the average economic loss in the first five years of operation for systems installed in 2015, 2020 and 2025 and experiencing the same -1%/year performance loss rate. As expected, the same performance loss rate will cause, in a system installed in 2025, economic losses in between 20% and 30% higher than those experienced by an identical PV system installed in 2015. This growth is driven by the rise in the electricity price.

Therefore, the same energy losses could result in greater economic losses in the upcoming years because of the increase in forecasted prices (Fig. 8). This confirms that there could be even more incentive to invest in module technologies with lower degradation. For example, investments in higher quality modules that could have not been economically worth in 2015 could become profitable in the upcoming years. Similar analyses could be made, for example, to evaluate the profitability of preventive soiling mitigation solutions, such as the anti-soiling coatings [63]. In addition to preventive solutions, the additional revenues could also justify more frequent corrective actions, e.g., cleanings. Examples of the correlations between electricity prices, economic losses and potential mitigation investments are presented in the following section using data from the two field PV systems.

It is important to highlight once more that, while the growth will occur for all the investigated locations, this will not affect the spatial non-uniformity of the loss distribution. The highest values will still be recorded in the southern locations with the higher solar resource. In addition, it should be noted that, in agreement with the trends shown in Fig. 7, the Iberian Peninsula would reach the maximum values in the 2020-2024 period, while Italy would experience the peak in the following years. As such, electricity price trends will drive the inter-annual variations and the inter-country differences, while solar resource will be responsible for the spatial variations within each country.

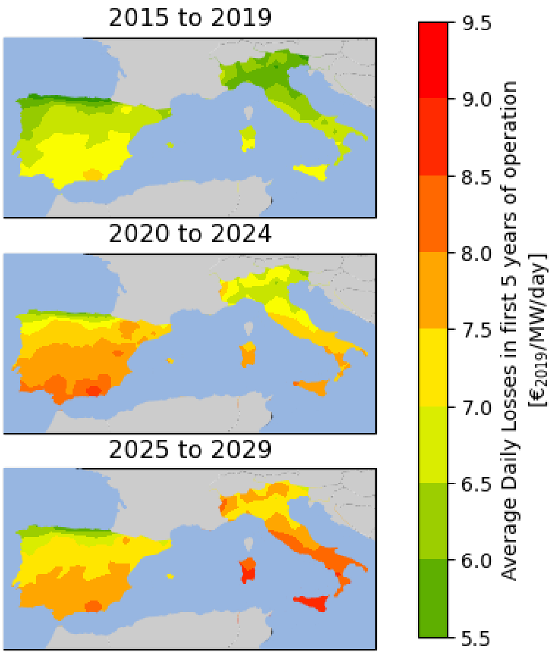


Fig. 8. Total cumulative economic losses due to a -1%/year performance loss over the first 5 years of life of a PV system installed in 2016 (top plot), 2020 (mid plot), 2025 (bottom plot). Electricity prices in €$_{2019}$/MWh. Despite the same performance loss trend, the system experience different economic losses.

3.3. Case Studies

This section presents the analysis of the losses at two PV sites in Southern Spain. In the first part, the variable economic impact of a linear performance loss rate over the 2012-2020 period is investigated. The second part focuses on soiling, and the perspectives for cleaning optimization in an increasing electricity price scenario.

Site A experienced a linear performance loss rate of -0.9%/year in between 2012 and 2020 (top plot of Fig. 9). Because of this, the energy losses increased linearly over the years, with small deviations due to each year's specific irradiation. On the other hand, this linear energy loss translated into a variable economic loss (lower plot of Fig. 9). The highest economic losses occurred in 2018, when the electricity price also reached its maximum. Since then, however, lost revenues have been gradually declining, despite the continuously increasing losses in yield. In 2020, the economic losses reached the minimum since 2017, pushed down by the significant reduction in price due to the COVID-19 crisis related demand drop [64].

If performance loss rates are projected in the future and merged with the electricity price forecasts, one could potentially estimate the economic impact of performance loss over the PV system lifetime. In this light, the present analysis suggests that the value of lower performance loss rates might be greater in the future due to the expected increase in electricity prices. Therefore, it may be worthwhile to invest upfront in module technologies that can lead to lower performance loss rates.

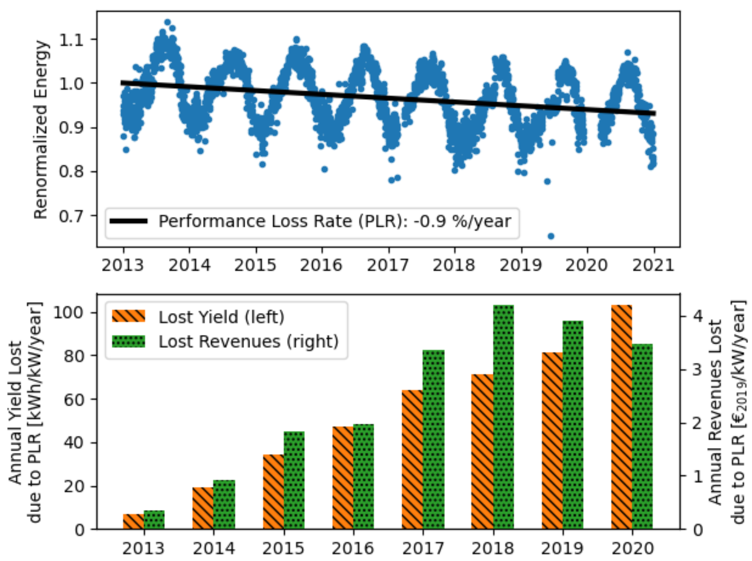


Fig. 9. Performance loss rate (PLR) of Site A (top) and its corresponding energy and economic losses (bottom). The calculation is based on electricity prices in €$_{2019}$/MWh.

In addition to irreversible performance losses, PV systems can also be affected by factors such as soiling, whose effect could be mitigated through O&M actions. Soiling can be significantly seasonal in the Mediterranean countries, due to the long dry periods and the more frequent dust storms occurring in summer [65,66]. Because of these conditions, Site B was found to experience an annual soiling loss of 3-4%, with power drops as high as 20% at the end of August [21]. These losses could be mitigated with one- or two-yearly cleanings, which could increase the profits of the system by 3.6%. However, previous studies only considered fixed or linearly increasing electricity prices [21,24]. As discussed earlier, historical time series clearly show that price trends do not follow linear functions (Fig. 3).

The price at which the electricity is sold is one of the two factors that determine the maximum expenditure that can be invested to mitigate the PV losses. This is particularly important for the mitigation of soiling, a reversible performance loss that can be removed through artificial cleanings. Cleaning PV modules has a price that covers the cost of resources (water, electricity, equipment, etc.) and human labor [14] and cleanings are typically performed when the revenues made through the recovered energy are higher than the cost of cleaning.

Fig. 10 shows how the maximum allowed cleaning cost has changed and will continue to change for soiling at Site B, assuming one cleaning per year; the typical scenario for the investigated location [54]. As expected, the losses, and therefore the funds available for cleaning, vary depending on the electricity price, from minimum values in between 1.0 €$_{2019}$/kW and 1.2 €$_{2019}$/kW in 2016 and 2020 to a maximum of 1.8 €$_{2019}$/kW in 2018. The average allowance in the 2010s for this site was 1.4 €$_{2019}$/kW. Scenarios A, C, D expect this allowance to increase in 2020s, with averages allowed costs ranging from 1.7 €$_{2019}$/kW to 1.9 €$_{2019}$/kW. In Scenario B, instead, this allowance is not expected to change significantly with respect to the 2010s.

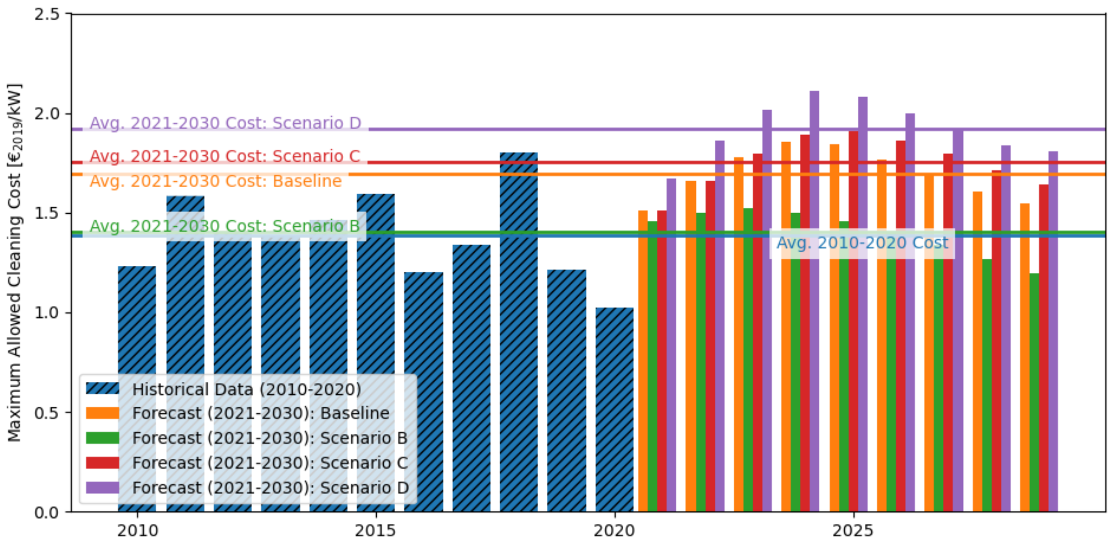


Fig. 10. Maximum allowed cleaning cost at Site B. The calculation is based on electricity prices in €$_{2019}$/MWh.

Reference [24] analyzes the various factors affecting the cleaning frequency optimization. It shows that the optimal cleaning frequency in a given year can be determined as a function of performance loss rate, variations in electricity price and cleaning costs. While higher electricity prices positively affect the cleaning frequency, this relationship becomes less significant and can even reverse as performance loss rates and cleaning costs increase.

In the present example, a linear performance loss rate of -1%/year is assumed. Three different scenarios are instead modeled for the cleaning costs: a positive +2% yearly increase (similar to the inflation rate), a negative -2% per year decrease (assuming a positive scale effect) and a 0.0%/year variation. Fig. 11 shows how the soiling mitigation profits for Site B are expected to vary in the upcoming years in these different scenarios, assuming the baseline price forecast. The profits of soiling mitigation are calculated by comparing the yearly revenues achievable through mitigation with the yearly revenues in case of unmitigated soiling. Two different schedules are modeled: one or two cleanings per year on optimal dates. The cost of each cleaning is also taken into account in the calculation of the profits made by soiling mitigation.

The blue dotted portions of the bars in Fig. 11 represent the increase in soiling mitigation profits due to the addition of a second cleaning. A switch from a 1-cleaning to a 2-cleaning scenario is always recommended in 2023 and 2024 independently of the cleaning cost escalation rate driven by the high electricity prices. However, the number of years in which two cleanings per year are recommended increases while the cleaning cost escalation rate decreases. In this case, the additional energy recovered thanks to the higher electricity prices would lead to an increase of up to 5% in cleaning profits, with a maximum per year that can be as high as 8%. Therefore, in addition to the increased revenues per kWh, higher electricity price could also potentially lead to higher energy yields, as PV owners and operators will be incentivized to maximize the energy generation thanks to the higher revenues achievable through with PV loss mitigation.

It should be noted that this example considers only cleanings as soiling mitigation solution. However, preventive actions, such as the deposition of coatings, could also be considered by plant owners for soiling mitigation and could be similarly favored by the higher expected electricity prices.

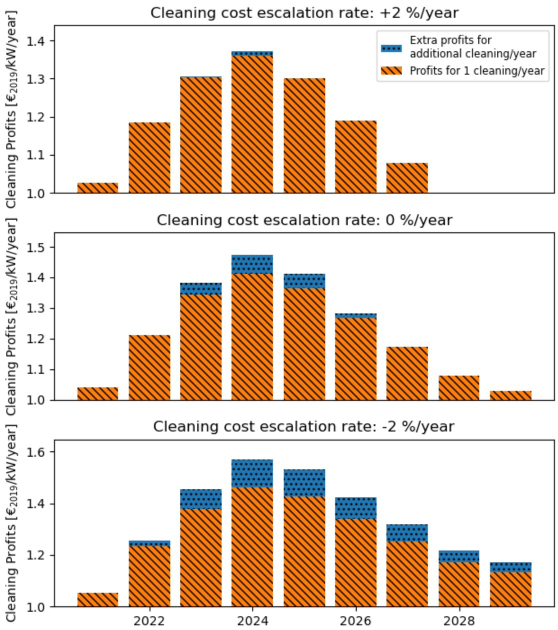


Fig. 11. Expected evolution of the economic impact of the performance losses at Site B for a linear -1%/year performance loss rate. The calculation is based on electricity prices in €$_{2019}$/MWh.

These two case studies show how the future higher electricity prices could incentivize loss mitigation and maintenance in general, thanks to the higher "reward" obtained per kWh of recovered electricity. Higher electricity prices in future are expected to provide a double benefit for PV: (i) increased profits directly made by selling the same energy for a higher return, (ii) additional incomes due to maintenance actions that would have not been as profitable at lower electricity prices. This PV loss mitigation can be pursued in two ways:

- Incentivizing improved durability and reliability of components, by prioritizing quality over cost and incorporating loss-preventing solutions proactively, e.g., anti-soiling coatings.
- Incentivizing monitoring and O&M to respond quickly and intelligently to operational issues such as soiling, failures, etc.

However, while the O&M action strategy can be optimized on a regular schedule, preventive actions require a better and longer-term advanced estimation of the future energy and economic trends.

In conclusion, while higher electricity prices will benefit PV owners and operators, these will also affect consumers, forced to pay more for the same amount of energy. However, as mentioned, the higher electricity prices will improve the overall efficiency of the PV plants, as higher quality components and rigorous O&M will be incentivized. One can expect that this will have indirect benefits also for the population. Indeed, the higher efficiencies will increase the PV market shares and may attract more investments on this technology, with positive consequences for the population, environment, and climate.

3.4. Price variability: typical assumptions and extreme fluctuations

As mentioned in the Introduction, most of the previous PV-related works have not considered the variability of electricity prices. Linearly escalating or fixed prices make it possible to simplify the analysis. In this section, these assumptions are compared against the commercial forecasts, to evaluate the different estimations they would provide over the 2020-2030 period. In addition, the effect of the short-term price variability on the PV revenues and O&M strategies is also discussed.

The results in Table 1 show the linear price escalation rates that would return the minimum absolute deviation from each modelled price scenario over the 2020-2030 period. The magnitude of the deviation is reported in the parentheses and is calculated for each scenario and for each country. As it can be seen, the fixed price assumption (i.e., no variation over time) is the one returning the minimum error only for Scenario B, the one depicting the lowest prices. In all the other cases, higher rates should be considered. Rates between 5 and 6%/year are recommended for the Iberian countries in Scenarios A and C. These are close to the 4.5%/year rate employed in a cleaning optimization work conducted in Spain [24]. The rates are consistently higher for Italy, because of the greater prices expected in this country towards the end of the decade (Fig. 7).

Table 1. Optimal linear price escalation rates (%/year) and, in parentheses, the magnitude of the deviations (€$_{2019}$/MWh) for different scenarios over the 2020-2030 period. Linear rates between -10%/year and +15%/year have been considered. The scenarios are shown in Fig. 4.

	Rate returning minimum absolute error in 10-year average price [%/year] (error [€$_{2019}$/MWh])		
Country	Spain	Portugal	Italy
Scenario A	5 (0.99)	5 (0.77)	7 (0.42)
Scenario B	0 (0.14)	0 (0.32)	1 (0.89)
Scenario C	5 (1.09)	6 (0.97)	8 (0.55)
Scenario D	8 (0.33)	8 (0.58)	13 (0.56)

However, one should also take into account that the energy produced by the system will decrease with time due to system degradation. As shown in Fig. 11, the central years of the decade are those in which the soiling profits for Site B are the maximum, because of the limited accumulated degradation, and the high prices. However, this cannot be reproduced if linear escalation rates are considered. Indeed, if a constant rate is considered in place of a baseline forecast trend, which predicts higher initial rates and lower rates afterwards, cleaning optimization might not return the optimal recommendations. For example, assuming a 5%/year escalation rate in cleaning optimization of Site B would lead to an underestimation of the losses in between 15 and 20% compared to the baseline price scenario. This means that also cleaning profits and recoverable energy will be underestimated. Indeed, lower economic loss will be expected initially, leading to a lower cleaning frequency recommendation, at least in the first years of the decade. The estimation would be closer to that provided by the baseline forecast if a linear escalation rate in between 8% and 9%/year was considered. Therefore, while a linear trend can be a reasonable assumption, one should always consider the different uncertainties they introduce depending on the aims of the analysis.

As discussed in 2.2, even when non-linear forecasts are employed, the electricity prices can be subject to major, sudden variations other than the aforementioned long-term and seasonal trends. These are typically more difficult to predict, especially at long-term, and might last for short periods. However, they can still have a significant impact on the profitability of PV performance and of loss mitigation. For example, the lockdown measures imposed in the first half of 2020 led to substantial drops in electricity consumption [67], followed by a subsequent fall in electricity prices. In Spain, the average electricity prices reached values 34% lower than the previous 5-year averages, with significant losses in terms of electricity market turnover [64]. The revenues per point of PV performance index over the investigated region fell to values in between 1.3 and 2.1 €/MW/day/%$_{PI}$ in that period. To translate this into actionable maintenance, it would mean that no more than 1 cleaning per year would be profitable at site B.

After the initial drops and since the second half of 2021, the actual electricity prices in the investigated countries have experienced an unprecedented growth. This has been due to the raise in price of natural gas and the ongoing energy crisis [68]. This electricity price raise has led to PV performance revenues higher than 12 €/MW/day/%$_{PI}$ in the southernmost regions of the investigated countries. Fig. 12 shows the difference in revenues in between 2022 and 2020. Under these extremely high prices, O&M becomes extremely profitable and reversible issues such as soiling must be addressed more carefully. For example, cleaning soiling in Site B three or four times a year becomes 30% more profitable than cleaning once per year and 4 to 5% more profitable than cleaning twice per year. Thanks to the higher cleaning frequency, the energy yield also increases compared to a two-cleaning scenario.

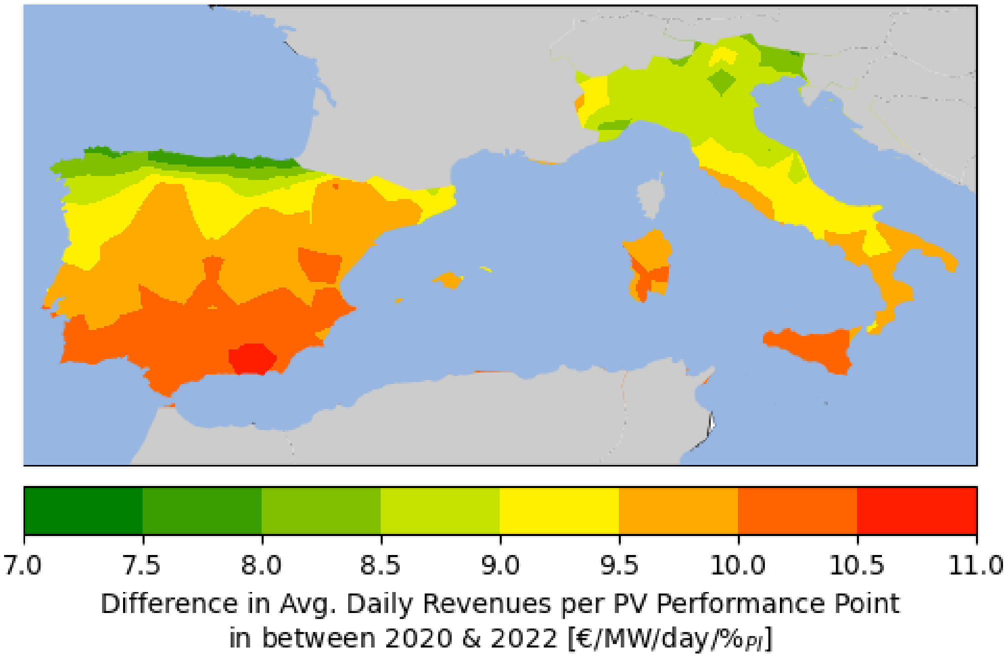


Fig. 12. Difference in average revenues per point of PV performance index in Portugal, Spain, and Italy between 2020 and 2022. The average prices in the whole 2020 and in the first 5 months of 2022 are considered.

Overall, it is found that using forecasts over linear price trends could benefit the planning of maintenance strategies. However, the recent events highlight that even these forecasts could be subject to uncertainty. These are difficult to predict but should be taken into account to correct the yearly O&M strategies.

4. Conclusions

When electricity is sold in a spot market, the profitability of PV varies spatially and temporally. Indeed, the same amount of electricity can be sold at significantly different prices in different seasons and in different years, even if generated by the same system. The present work investigates the distribution and the variability of the PV revenues in Spain, Portugal, and Italy.

These three countries are among those with the highest-PV potential in Europe and share similarly structured electricity markets.

The analysis, based on multi-year historical daily price trends and commercial forecasts, showed that the interannual variation in electricity price is the dominant factor in year-to-year variations of PV profits. The monthly variation in the economic value of PV is found to be predominantly influenced by the irradiation seasonality. The analysis shows also that the economic loss caused by linear performance loss rates does not necessarily increase linearly and may vary significantly with time.

Most current forecasts predict that electricity prices are likely to lead to an increased profitability of PV in 2030 compared to the 2010s by factors of up to 60%. It is shown that these expected trends might not be fully reproduced if linear escalation rates are assumed. It is also found that the uncertainty due to constant or linear price assumptions varies depending on the goals of the analysis.

Higher electricity prices incentivize increasing the PV conversion efficiency, both proactively and reactively. For example, array cleaning and/or the deployment of higher quality and more degradation-resistant modules combined with monitoring and O&M strategies that enable quick and intelligent responses to operational issues become more likely. As such, the higher electricity prices are expected to generate a double economic benefit for suppliers, due to (i) the higher revenues per kWh and (ii) the additional loss mitigation efforts that they will incentivize. However, the funds available for these loss mitigation activities will be strictly dependent on the solar resource available at each location. This is the result of the different revenues achievable because of the diverse climates, irradiance, and weather conditions. In general, there will be more money available in the southernmost sites for quality improvements and/or additional O&M, because of the higher yields and, therefore, higher potential revenues. However, the analysis also shows that unexpected and sudden fluctuation in prices, due to unforeseen events or policies, can alter the forecasts and significantly affect the expected revenues.

The present analysis shows that the expected higher electricity price will benefit PV owners and operators in two ways: increasing the profits per kWh and the energy produced thanks to incentivized O&M and/or higher quality components. The improved loss mitigation expected in higher electricity price scenarios will also have a positive impact as photovoltaic modules will be operating at higher yields. These increased PV efficiencies could at least partially counteract the effects of higher electricity prices for the consumers.

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Author contributions

Conceptualization, L.M.; Methodology, L.M., and M.T.; Data Curation: L.M., and D.L.T.; Software, L.M.; Investigation, L.M.; Validation, L.M., M.T., J.S.S., and D.L.T.; Visualization, L.M.; Writing – Original Draft, L.M. and M.T.; Writing – Review & Editing, M.T., D.L.T., G.N., J.S.S., E.F.F., and F.A.

Declaration of interests

The authors declare no competing interests.

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