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Photovoltaic Cleaning Frequency Optimization Under Different Degradation Rate Patterns

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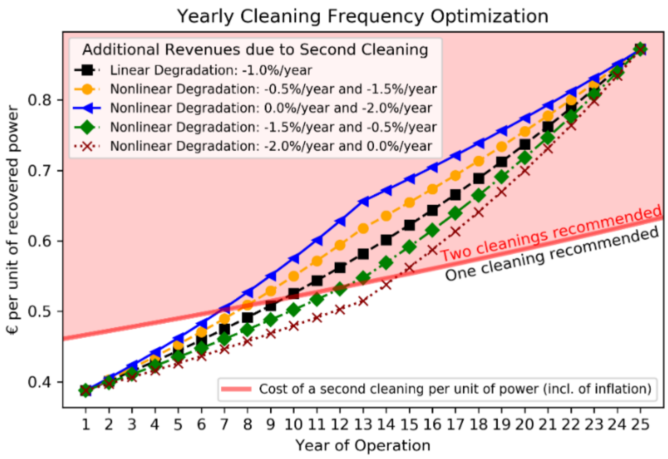
Abstract

Dust accumulation significantly affects the performance of photovoltaic modules and its impact can be mitigated by various cleaning methods. Optimizing the cleaning frequency is essential to minimize the soiling losses and, at the same time, the costs. However, the effectiveness of cleaning lowers with time because of the reduced energy yield due to degradation. Additionally, economic factors such as the escalation in electricity price and inflation can compound or counterbalance the effect of degradation on the soiling mitigation profits. The present study analyzes the impact of degradation, escalation in electricity price and inflation on the revenues and costs of cleanings and proposes a methodology to maximize the profits of soiling mitigation of any system. The energy performance and soiling losses of a 1 MW system installed in southern Spain were analyzed and integrated with theoretical linear and nonlinear degradation rate patterns. The Levelized Cost of Energy and Net Present Value were used as criteria to identify the optimum cleaning strategies. The results showed that the two metrics convey distinct cleaning recommendations, as they are influenced by different factors. For the given site, despite the degradation effects, the optimum cleaning frequency is found to increase with time of operation.

Keywords: *Soiling; Cleaning Frequency; Optimization; Photovoltaics; Degradation Rate; Economics.*

Graphical Abstract



The optimum cleaning frequency of a PV system varies with time of operation. The profitability of cleaning is affected by the PV degradation rate pattern and the variability of electricity price and cleaning costs. This work analyzes the separation line that defines the most cost effective cleaning frequency at each year of operation.

Highlights

- The optimum cleaning schedule varies depending on time of operation and health state
- Different cleaning schedules can be recommended based on the LCOE and NPV
- PV degradation does not affect the LCOE based cleaning decision algorithm
- Inflation influences the profitability of cleaning schedule over time
- Nonlinear degradation affects the cleaning frequency and its profitability

Nomenclature

C [€/kW]	Installation Costs
CC_s [€/kW]	Initial Surface Cleaning Cost
CC_w [€/kW]	Specific Cost of Cleaning
d [%]	Discount Rate
D_n [€/kW/year]	Annual tax depreciation
E [kWh/kW/day]	Daily Energy Yield
E_s [kWh/kW/year]	Soiling ratio–corrected energy yield
i	Day of the year
LCOE [€/kWh]	Levelized Cost of Electricity
n	Year of operation
N [Years]	PV system lifetime
$n_{c,n}$	Number of yearly cleanings in year *n*
N_d [year]	Depreciation period
NPV [€/kW]	Net present value
OM_n [€/kW/year]	Yearly Operating and Maintenance Costs
p [€/kWh]	Initial price of electricity, taxes included
P_{DC} [kW]	DC capacity of the PV system
$p_{pre\text{-}tax}$ [€/kWh]	Initial price of electricity before taxes
P_{type} [kW]	Installed capacity of the PV modules of a specific type
PV[$I(N)$] [€/kW]	Present value of the inflows
PV[$O(N)$] [€/kW]	Present value of the outflows
R_D [%/year]	Degradation Rate
f_D [%]	Degradation Factor
r_{om} [%/year]	Annual escalation rate of the O&M costs
r_p [%/year]	Annual escalation rate of the electricity price
r_s	Daily Soiling Ratio
T [%]	Income Tax
VAT [%]	Value-added tax
η_{type} [%]	Efficiency of the PV modules of a specific type

1. Introduction

Active monitoring of photovoltaic (PV) performance is critical for ensuring the highest energy yield and profit, as it makes it possible to maximize the efficiency and the revenues of photovoltaic power plants through improved operation and maintenance (O&M) strategies. The ability to accurately predict the projected energy yield of such systems by also identifying trend-based performance losses allows condition-based maintenance strategies, which are important for minimizing O&M costs and, hence, improving the financial payback of a PV project.

Sources of performance loss can be either reversible (i.e., lost energy can be recovered by maintenance) or irreversible (i.e., lost energy is unable to be recovered unless the component is completely replaced) [1]. Examples of reversible performance loss include dust deposition (i.e. soiling), snow, vegetation, fuse failures etc. whereas irreversible performance loss may occur due to several degradation mechanisms such as discoloration, delamination, hot spots, cracks etc. In order to account for the performance loss in PV power prediction models, a degradation rate value is usually considered, which is either taken as an assumption or extracted from a statistical model [2,3]. Such models, however, have no knowledge of whether the loss is due to reversible or irreversible effects. Furthermore, routine maintenance due to reversible performance loss, such as cleaning frequency of PV modules, is commonly executed at a fixed rate per year during the project's lifetime.

Field data demonstrated that irreversible performance loss rates may not always be constant (i.e., linear) [4–6] due to a number of degradation modes that can occur during the initial and wear-out phases of a PV system's lifetime. Even when the same lifetime performance loss is assumed under different linear and nonlinear degradation rate patterns, the economic impact will vary [4,5]. Therefore, due to the different paths of performance loss that could be observed, it is important to optimize the maintenance strategies on a condition-based manner because the energy recovery and corresponding financial gains will depend on the system's health-state, inflation etc. In order to achieve this, algorithms must be developed to respond quickly and intelligently to different operational issues.

Soiling is one of the most common reversible performance losses experienced by PV modules, as it can generally be removed by natural or artificial cleaning. Rainfall is the most frequent natural cleaning process [7,8]. Artificial cleanings are performed by O&M operators or robots, and their cost depends on a number of factors, which vary depending on the geographical location; even within the same country [9]. If not mitigated, soiling can cause significant economic losses [10,11]. Furthermore, the impact of soiling is likely to be more severe in future; this is due to the combination of increased deployment of PV modules in regions characterized by high insolation and soiling and the improved PV module efficiencies [9]. As such, soiling mitigation strategies must be optimized in order to maximize the energy output of the system, while minimizing the cleaning expenses.

In 2010, Mani and Pillai listed some recommendations for soiling mitigation strategies based on the climatic zone and the characteristics of the region where PV systems are located [12]. These are useful guidelines, but the mitigation strategy should always be refined depending on the specific conditions of each site [13,14]. Several cleaning optimization methods have been proposed in literature to maximize the profits [15–18]. These are useful methods to determine the optimum cleaning schedule at given conditions, but they do not consider that the "value" of recovered energy (i.e., difference in revenue before and after cleaning) changes with time, mainly due to the system's health state and, in particular, degradation. Indeed, as discussed by Urrejola et al. [19], PV degradation lowers the energy yield with time. This translates directly into a lower cash inflow and makes cleaning less effective with the time of operation, considering that the impact of some economic parameters also changes. In particular, the rise of the cleaning costs caused by inflation can compound the impact of degradation, because cleaning would become more expensive with time.

In addition, it should be considered that, in some countries, the electricity price is subject to a daily market-based competition [20]. This means that the price of electricity sold by the PV system producer to the grid may vary over time, depending on supply and demand. In these markets, an escalation in the price of electricity can, at least partially, counterbalance the effects of degradation and rise in cleaning costs, increasing revenues, and therefore incentivize the cleanings. Taking these factors into account, along with the influence of discount rate, one could expect that the optimum cleaning schedule that maximizes the revenues and minimizes the costs would vary with the year of operation.

In order to verify this hypothesis, a sensitivity analysis was performed to investigate the impact of different PV degradation rate patterns on the profitability of cleaning schedules taking into account the variability of economic parameters and soiling profiles extracted from a 1 MW PV plant in Spain. A similar analysis was conducted on a PV system in Chile [19] taking into account fixed values for electricity price and cleaning costs whereas the degradation rate was based on a fixed performance loss value extracted from a 2-year period. A model to optimize the optimal cleaning schedule also based on linear degradation and fixed electricity price and cleaning costs was recently presented by Alvarez et al. [21]. In the present work, these economic parameters are realistically modeled to vary annually, and the effects of their variation is thoroughly discussed. For the first time, different degradation rate patterns are considered enabling the cleaning schedule optimization over time using the levelized cost of electricity (LCOE) and net present value (NPV) metrics as criteria.

The paper is structured as follows. The methodologies to analyze the PV performance data, to extract the soiling profile and to calculate the effects of different cleaning scenarios and degradation rate patterns are described in 2.1. The economic parameters and equations are detailed in 2.2, whereas the cleaning optimization process is described in 2.3. The results' section is split into two subsections: in 3.1, the cleaning frequency is optimized for every year of the PV plant operation considering different linear degradation rate values and various inflation and electricity price scenarios whereas, in 3.2, nonlinear degradation rate patterns are introduced and their effects on the profitability of different cleaning frequencies are discussed.

2. Methodology

2.1. PV performance

The energy performance and soiling profiles considered in this study were extracted from a real PV installation, whereas the degradation rate patterns were theoretical and based on previous investigations [4,5,22]. The methodology used to process the performance timeseries is described in 2.1.1. Subsequently, the methodologies employed, and the assumptions made to calculate the soiling loss profile and the optimal cleaning schedule are discussed in 2.1.2. Finally, the degradation profiles modelled in this work are reported in 2.1.3.

2.1.1. PV data analysis

1-year of hourly data from a 1 MW system installed in the province of Granada, in Southern Spain, were considered. The system consists of mono-crystalline modules facing South and mounted at a tilt angle of 30°. The installed DC capacity is 961 kW and no inverter clipping was observed. The energy yield and soiling profiles were extracted using the same methodology employed by Micheli *et al*. [23], considering the weather data downloaded from MERRA-2 [24]. The following PV corrections, available in the *pvlib-python* library [25], were employed to analyze the performance of the site:

- The ASHRAE transmission model for the angular correction of incident light [26,27],
- Sandia PV Array Performance Model for the spectral and temperature corrections [28]. All coefficients were sourced from the Sandia PV Module Database.

The absolute and relative air mass [29,30] were defined from the apparent zenith, calculated with the solar position algorithm [31], and the MERRA-2 site air pressure.

2.1.2. Soiling extraction

Soiling is commonly quantified through two metrics: the soiling ratio and the soiling rate. The soiling ratio expresses the ratio of the output of the soiled PV system to the output of the PV system without soiling [32]. It has a value of 1 in clean conditions and decreases as soiling accumulates. The soiling losses can be expressed as (*1 - soiling ratio*). On the other hand, the soiling rate quantifies the rate at which soiling deposits on the PV modules and is calculated as the daily derate in soiling ratio (i.e. slope of the soiling ratio profile), expressed in %/day and reported in negative values [33]. A soiling rate of 0%/day occurs when there is no soiling being deposited, and its value decreases as the soiling deposition rate increases.

The daily soiling ratio values were extracted from the aforementioned performance data, considering only the hours near noon on high-irradiance days [32]. To ensure relatively clear-sky conditions, only data conditions when plane-of-array irradiance was > 700 W/m^2 was used. This threshold is higher than that used previously [34,35], but it minimizes the noise in the soiling ratio estimation.

The soiling ratio profile is shown in Figure 1a. The investigated site is characterized by seasonal soiling, with a long summer period of no rain exhibiting a peak power loss of 23% at the beginning of September. This results in a soiling rate of -0.28%/day occurring from mid-June to the end of the summer. A change in soiling rate occurred on June 22nd due to a dust-laden wind [23,36].

The aim of this work was to analyze the optimum number of cleanings (i.e. cleaning frequency) that would maximize the profits from soiling mitigation. To do that, it was necessary to understand the extent of the soiling losses if no mitigation actions had been in place (worst-case scenario of no cleaning) and therefore to extract the natural soiling profile of the site. For this reason, the effect of the artificial cleaning event performed by the O&M team on August 5th was removed. As such, the positive shift in the soiling ratio profile on August 5th was eliminated by propagating the same soiling rate (i.e., -0.28%/day) until the following rain event in September (see green line in Fig. 1a for natural soiling profile). Similarly, artificial cleanings are modelled in a way to produce a sudden positive shift in the soiling ratio profile, restoring its value to 1, but without a change in soiling rate (i.e., soiling rate before cleaning is equal to soiling rate after cleaning). This decision is already employed in other cleaning optimization studies [15,37] and is based on the assumption that cleaning washes off deposited dust from the modules and does not have any effect on the external atmospheric conditions that cause soiling deposition (such as suspended particle concentration, wind speed, relative humidity [38,39]). Consensus has not yet been reached within the community regarding “grace periods” (i.e., a fixed number of days following a cleaning event in which soiling does not deposit on the PV modules) [15,33,40]. Therefore, soiling was assumed to accumulate on the PV surfaces immediately after a cleaning event, without any “grace period” [37].

In a “no cleaning performed” assumption (green line in Fig. 1a), it is estimated that the AC energy yield of the system would have been 1691 kWh/kW, with an average soiling loss of 2.8%. This represents the worst-case scenario, in which no mitigation is put in place to address soiling. The soiling profile in this site can be considered as representative for southern Europe and a number of Southwestern US States, including California, due to the combination of low and infrequent precipitation and elevated levels of suspended dust, which are commonly observed during the summer months. Similar yearly losses, in the order of 3 to 4% were reported for a number of studies worldwide [41–43]. Therefore, the results extracted from this study could be associated with installations exposed under similar climatic locations elsewhere.

Ideally, if soiling was completely removed (i.e. soiling loss of 0%), the yield would have been 1748 kWh/kW. It should be noted that the energy yield variation is larger than the average soiling loss because the highest dust deposition occurs in summer. This yield represents the best-case scenario and is used as a baseline to quantify the benefits of different cleaning frequencies. Six potential cleaning schedules were considered in this study and their effects on the soiling profile are shown in Fig. 1b. The considered schedules include cleaning frequencies ranging from 0 to 5 times per year, which are assumed to be performed on the dates that maximize the soiling ratio (i.e. minimize the energy losses). Similar to the procedure described by Micheli *et al.* [40], for each frequency, a soiling profile is modelled for each possible combination of cleaning dates . The dates that return the highest average soiling ratio (i.e. the minimum annual losses) are the optimal cleaning dates for each given cleaning frequency scenario. These six optimized soiling profiles are analyzed in the rest of the paper, introducing the economic metrics and parameters described in Section 2.2, in order to identify the most cost competitive cleaning frequency (i.e. the one that maximizes the difference between revenues and cleaning costs). For the purposes of this study, the soiling profile was assumed to repeat every year of operation and no change in soiling rate was considered after each cleaning [18,36].

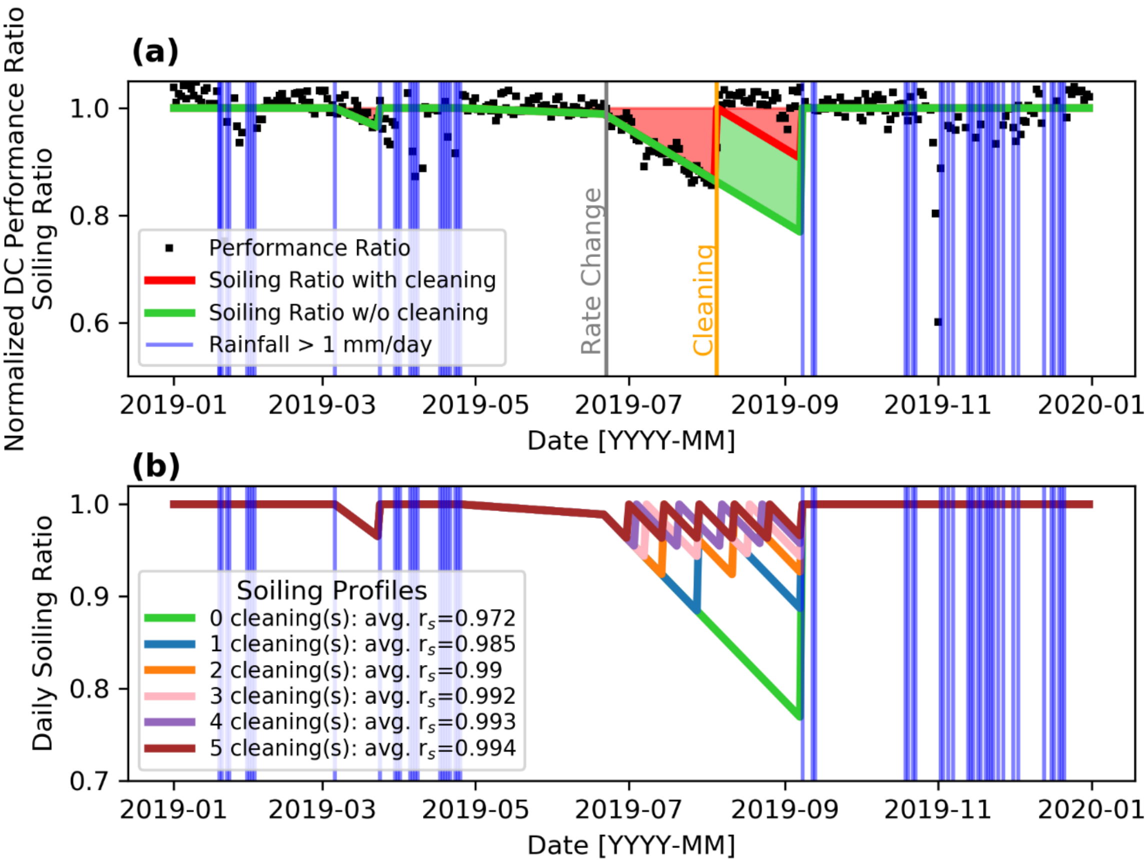


Fig. 1. (a) Soiling and performance profiles of a 1 MW power plant located in Granada, Spain. The black dots represent the DC performance ratio normalized to the median value and the red line shows the extracted soiling profile including the August 5th cleaning event (marked with a yellow vertical line); the modeled soiling profile without considering any cleaning is also displayed with green color. The blue vertical lines are the rainfall events whereas the change in soiling deposition rate is marked with a grey vertical line. (b) Soiling profiles for optimized cleaning schedules with different frequencies ranging from 0 to 5 times per year. The average daily soiling ratios are also shown for each scenario.

2.1.3. Performance degradation profiles

The aforementioned energy yield did not include the effect of degradation, which was modelled from synthetic data. Five different performance loss patterns were considered as illustrated in Fig. 2. These include:

A. Linear degradation of -1.0%/year,
B. Nonlinear: -0.5%/year initially followed by -1.5%/year,
C. Nonlinear: 0%/year initially followed by -2.0%/year,
D. Nonlinear: -1.5%/year initially followed by -0.5%/year,
E. Nonlinear: -2.0%/year initially followed by 0%/year.

All nonlinear degradation patterns assume that the rate changes in year 13 (out of 25 years of operation). Similar to [4,5,22], the theoretical linear and nonlinear patterns were selected in a way to reflect the same power loss at the end of the system's lifetime (i.e., 24% loss of power in year 25). Although the patterns are normalized to cover a 25-year lifetime, they could represent early life degradation modes such as light and elevated temperature induced degradation (LeTID) [44] observed in Passivated Emitter and Rear Contact (i.e. PERC) PV modules, light induced degradation [45] in crystalline silicon PV modules, and Staebler-Wronski [46] effects in amorphous silicon. Such types of degradation occur at various time scales from a number of hours to years [4,5,22]. Furthermore, depending on the degradation-regeneration cycle of LeTID, PERC modules could potentially exhibit minimal to even positive “degradation” rate in the field [47].

For the purposes of this work, the various strings and inverters of the PV system are assumed to degrade and soil at the same rate. Further studies will be conducted in future, as new data become available, on the non-uniformity of soiling and degradation within a given site.

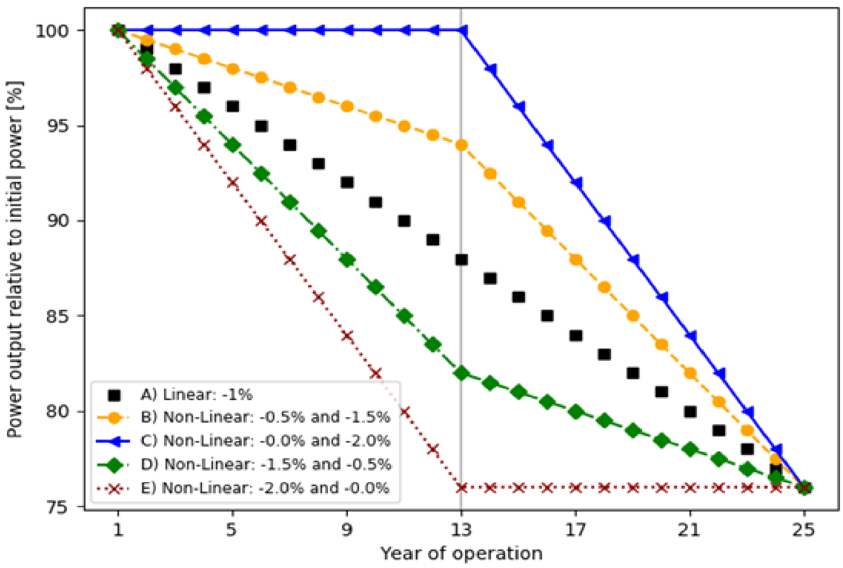


Fig. 2. Theoretical degradation rate profiles considered in this study.

2.2. Economic metrics and parameters

The cleaning schedule optimization against different degradation scenarios was assessed using the LCOE and NPV as criteria. Depending on the metric, the optimization was realized by selecting the cleaning frequency that either minimized the LCOE or maximized the NPV (see 2.3). The values of the economic metrics were calculated for each of the soiling profiles (Fig. 1b) and degradation rate scenarios (Fig. 2), taking into account the cost of the corresponding cleaning and the revenues granted by the corresponding energy yield. The methodologies used to calculate each of the economic metrics are independently discussed in the following subsections: 2.2.1 (LCOE) and 2.2.2 (NPV).

2.2.1. Levelized Cost of Electricity

The LCOE quantifies the unitary cost of each kWh of electricity generated, considering its entire lifecycle and is defined as [48]:

$$LCOE = \frac{C + \sum_{n=1}^{N} \frac{(OM_n + n_{c,n} \cdot CC_w) \cdot (1-T) \cdot (1+r_{om})^n}{(1+d)^n} - \sum_{n=1}^{N_d} \frac{D_n}{(1+d)^n} \cdot T}{\sum_{n=1}^{N} E_s(n_{c,n}) \cdot f_D(n)/(1+d)^n} \qquad (1)$$

where C are the installation costs, OM_n the yearly O&M costs, $n_{c,n}$ the number of yearly cleanings (i.e. cleaning frequency on the year *n*), CC_w the initial Specific Cost of Cleaning (in €/W), T the income tax, r_{om} the annual escalation rate of O&M costs, d the discount rate, E_s the soiling ratio–corrected energy yield, $f_D(n)$ a factor taking into account the effect of degradation, D_n is the annual tax depreciation for the PV power plant. The values of the parameters used in (1) are reported in Table 1. In this analysis, the annual escalation rate of the O&M costs was set to be equal to the inflation rate. Tax depreciation allows recovering part of the investment cost through reduced taxes and has been assumed to be linear and constant over a given period of time (N_d) [49]. It is acknowledged that the method used to model tax depreciation (e.g. straight line or declining balance) can affect the analysis.

The soiling ratio–corrected energy yield, E_s, used in (1), is calculated as:

$$E_s(n_{c,n}) = \sum_{i=1}^{365} r_{s,nc}(i) \cdot E(i) \qquad (2)$$

with $r_{s,nc}$ being the soiling ratio for a $n_{c,n}$ number of yearly cleanings as shown in Fig. 1b and E is the daily energy yield profile in no soiling conditions. E_s has a value of 1748 kWh/kW/year in conditions of no soiling and lowers to a minimum of 1691 kWh/kW/year when soiling and no cleaning are considered. In this work, the degradation rate is assumed to affect the annual soiling ratio – corrected energy yield, rather than the daily performance profiles and for this reason is present in (1) through the factor f_D and not in (2). Assuming linear degradation R_D, the factor f_D can be calculated as:

$$f_D(n) = (1 + R_D)^n \qquad (3)$$

On the other hand, if degradation rate is indeed nonlinear, the equations can be rewritten to take into account the two different rates, R_{D1} and R_{D2} (as shown in Fig. 2):

$$f_D(n) = (1 + R_{D1})^{n_1} \cdot (1 + R_{D2})^{n_2} \qquad (4)$$

where n_1 and n_2 are the number of years in which R_{D1} and R_{D2} occurred, respectively, and follow these rules: $n_1+n_2=n$, $n_2=0$ if $n < N/2$, $n_1=N/2$ if $n \geq N/2$.

The term CC_w used in (1) is referred to as "initial" because the cleaning cost varies with time according to the escalation rate of the O&M costs (r_{om}). In particular, it can be derived from the Surface Cleaning Cost (CC_s) following the methodology detailed in [9,23]:

$$CC_W\left[\frac{€}{kW}\right] = \sum_{type} \frac{\frac{CC_s}{\eta_{type} \cdot 1\frac{kW}{m^2}} \cdot P_{type}}{P_{DC}} \qquad (5)$$

where P_{DC} is the DC capacity (961 kW), and η_{type} and P_{type} is the nameplate efficiency and power of the installed PV modules.

2.2.2. Net Present Value

The second metric used in this work to estimate the economics of various cleaning frequencies is the Net Present Value (NPV). The NPV compares revenues and costs over the lifetime of the projects. An investment is considered profitable when NPV > 0. In this work, the following equation has been adopted:

$$NPV = -C + PV[I(N)] - PV[O(N)] \tag{6}$$

where the present value of inflows PV[I(N)] and outflows PV[O(N)] over a project's lifetime are defined as:

$$PV[I(N)] = \sum_{n=1}^{N} \frac{p \cdot E_s(n_{c,n}) \cdot (1-T) \cdot f_D(n) \cdot \left(1+r_p\right)^n}{(1+d)^n} + \sum_{n=1}^{n_d} \frac{D_n}{(1+d)^n} \cdot T \tag{7}$$

$$PV[O(N)] = \sum_{n=1}^{N} \frac{\left(OM_n + n_{c,n} \cdot CC_w\right) \cdot (1-T) \cdot (1+r_{om})^n}{(1+d)^n} \tag{8}$$

where p is the price of electricity and r_p the average annual rate of increase in the price. The price of electricity is calculated as:

$$p = p_{pre-tax} \cdot (1 + VAT) \tag{9}$$

where $p_{pre\text{-}tax}$ is the initial price of electricity before taxes, and VAT is the value-added tax (21%). The average yearly pre-tax price of electricity is affected by several factors and can vary with time and location depending on the available supply and demand. Similar to the cleaning cost, p is considered as an *initial* electricity price, because its value varies with the year of operation.

The majority of existing PV plants in Spain, where this investigation is conducted, sell their energy directly to the electricity market. This direct sale of produced electricity has become extremely popular - and profitable - for the past three years due to the combination of consistently high electricity prices and falling costs of PV installations. Spanish banks have long experience in financing photovoltaic projects and have been financing only those installations that sell their electricity on the market [50]. For these reasons, a varying electricity price has been taken into account as a primary scenario. In particular, the value of r_p was set equal to the average annual increase in electricity price in Spain for the last 10 years [51,52]. Despite that, power purchase agreements (PPAs) are a common practice in many countries and PPAs are effective in some new PV projects in Europe [53]. This scenario, represented by an r_p of 0%/year, is also discussed in the paper.

Table 1. Economic parameters used in this study and sourced from the literature for utility-scale PV systems in Spain. The asterisk marks that the value has been converted from U.S. dollars, considering a 0.92 $/€ conversion factor.

Parameter	**Symbol**	**Value**	**Units**	**References**
Years of operation	N	25	years	
O&M costs, cleaning excluded	OM_n	15	€/kW/year	[48]*
Installation Costs	C	700	€/kW	[54]
Initial Surface Cleaning Cost	CC_s	0.09	€/m^2/cleaning	[9]
Specific Cost of Cleaning	CC_w	0.62	€/kW/cleaning	calculated from (5)

Discount Rate	d	6.4	%/year	[48]
Annual escalation rate of the operation and maintenance cost	r_{om}	1.23	%/year	[55]
Income Tax	T	25	%	[48]
Depreciation period	N_d	20	years	[49]
Average annual rate of increase in the electricity price	r_p	4.48	%/year	[51,52]
Value added tax	VAT	21	%	[49]
Initial pre-tax price of electricity	$p_{pre\text{-}tax}$	0.04778	€/kWh	[51,52]

2.3. Yearly Cleaning Frequency Optimization

The cleaning frequencies that minimize the LCOE and maximize the NPV were calculated in this work for each year of the system's lifetime. Compared to previous studies [19,21], where fixed numbers of cleanings throughout the lifetime of the system were assumed, in this case, the optimum cleaning frequency was varied with time due to performance degradation, electricity price, and O&M costs. The cleaning frequency that minimized the LCOE in each *n*-year of operation was found using the following formulation:

$$min\left(\frac{(OM_n + n_{c,n} \cdot CC_w) \cdot (1-T) \cdot (1-r_{om})^n}{E_s(n_{c,n}) \cdot f_D(n)}\right) \tag{10}$$

with $0 \le n_{c,n} \le 5$ and the values described in Table 1. Similarly, the cleaning frequency that maximized the NPV in each *n*-year of operation was found using the following formulation:

$$\max\left(\frac{p \cdot E_S(n_{c,n}) \cdot (1-T) \cdot f_D(n) \cdot (1+r_p)^n}{(1+d)^n} - \frac{(OM_n + n_{c,n} \cdot CC_w) \cdot (1-T) \cdot (1+r_{om})^n}{(1+d)^n}\right) \tag{11}$$

The cleaning frequencies returning the minimum LCOE and maximum NPV were found by comparing the results of each potential cleaning scenario for every year of operation. Therefore, for each of the 25 years of operation, six values were calculated and compared to solve (10) and six additional values were calculated and compared to solve (11). It should be highlighted that the cleaning frequency ($n_{c,n}$) does not affect the degradation rate (quantified in f_D, see (3) and (4)), but it can only modify the soiling profiles used to calculate E_s (see (2)). Furthermore, performance degradation affects the profitability of each cleaning, because it reduces the amount of energy that each cleaning can recover. Therefore, one can expect lower profits after each cleaning as the PV system degrades. However, while the energy recovery lowers with time, other parameters in (10) and (11) can influence the economic effect of degradation on the cleaning frequency; these are being investigated in Section 3.

3. Results and Discussion

3.1. Yearly Schedule Optimization

In this section, the cleaning frequency that minimizes the LCOE and maximizes the NPV for each year of the system's lifetime is discussed assuming a linear degradation scenario. Compared to the previous studies [19,21,23], where fixed numbers of cleanings throughout the system lifetime were assumed, in this case, the optimum cleaning frequency is allowed to vary with time due to performance degradation, electricity price, and O&M costs. The results of this analysis for the two economic metrics considered in this study are shown in Fig. 3. As expected, the optimum cleaning frequency indeed changes with time. Under the given conditions, both metrics are found to favor more frequent cleanings towards the end of the life of the system.

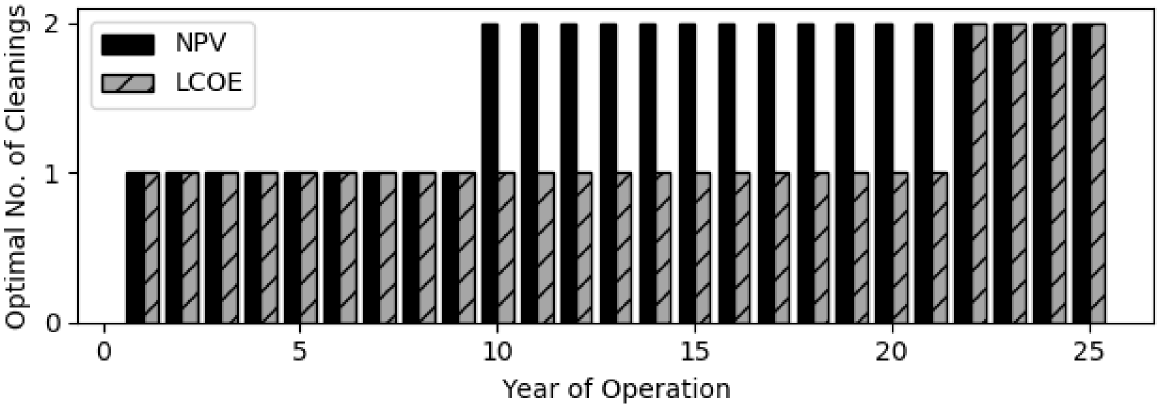


Fig. 3. Optimum cleaning frequency as a function of LCOE and NPV, in presence of a linear degradation rate of -1%/year (Scenario A).

To maximize NPV, it is recommended to switch to two cleanings/year in year 10, while to minimize LCOE, the switch is recommended in year 22. The different results are due to the different structures of the metrics. If (1) is solved for the cleaning cost, it is found that, in order to minimize the LCOE, the switch from a schedule of $n_{c,n}$ cleanings/year to $n_{c,n}$+1 cleanings/year occurs in year n in which the following criterion is met:

$$(1+r_{om})^n \cdot CC_W\left[\frac{€}{kW}\right] < \frac{\left(\frac{E_s(n_{c,n}+1)}{E_s(n_{c,n})}-1\right)\cdot\left((1+d)^n\cdot\frac{C}{N}+OM_{t,n}\cdot(1+r_{om})^n\cdot(1-T)-D_n\cdot T\cdot[n\leq Nd]\right)}{(1-T)} \quad (12)$$

where $E_s(n_{c,n}+1)$ and $E_s(n_{c,n})$ are the corresponding energy yields for $n_{c,n}$+1 and $n_{c,n}$ cleanings/year. First, the equation shows that the LCOE-based cleaning decision is independent of the degradation rate. This is due to the fact that the degradation has the same effect on the energy yields of the two cleaning approaches. This finding should not lead to the misunderstanding that the degradation has no impact on the LCOE. Simply, if the LCOE is used as an economic metric, the yearly cleaning schedule would not change because of the degradation pattern. Second, for the effect of discounting, the cost of cleanings in the calculation of the LCOE becomes less significant year-after-year compared to the installation cost, which is the only non-discounted parameter in (1). This becomes even more important if the annual tax depreciation is only valid for a number of years N_d<N. For this reason, cleanings toward the end of the PV system life have a lower economic impact on the LCOE and might contribute to reducing its overall value.

On the other hand, when NPV is considered, switching from an $n_{c,n}$ to an $n_{c,n}$+1 cleaning schedule occurs when the cost of cleaning becomes lower than the profits made per unit of power recovered:

$$(1+r_{om})^n \cdot CC_W\left[\frac{€}{kW}\right] < p\cdot\left(E_s(n_{c,n}+1)-E_s(n_{c,n})\right)\cdot(1+R_D)^n\cdot\left(1+r_p\right)^n \quad (13)$$

As shown in the equation, the discount rate and the income taxes do not affect the cleaning decision when NPV is used as the criterion. Also, the installation, fixed O&M costs and depreciation mechanism do not impact the cleaning decision, because they would not be affected by the different energy yields and would have the same impact under any cleaning scenarios.

The optimum yearly cleaning frequency varies depending on the input parameters. The sensitivity analysis taking into account the escalation rate of O&M costs and electricity prices for different degradation rates (and patterns) is shown in Fig. 4. As can be seen, the switch in cleaning frequency occurs when the value of recovered energy meets the cost of cleaning. According to (13), two cleanings/year are more profitable when the value of the recovered energy ≥ $CC_w \cdot (1 + r_{om})^n$, otherwise one cleaning should be preferred. It should be noted that, under some conditions (e.g. r_p = 0.0 %/year), no switch occurs, while in other cases, more than one switch might be recommended.

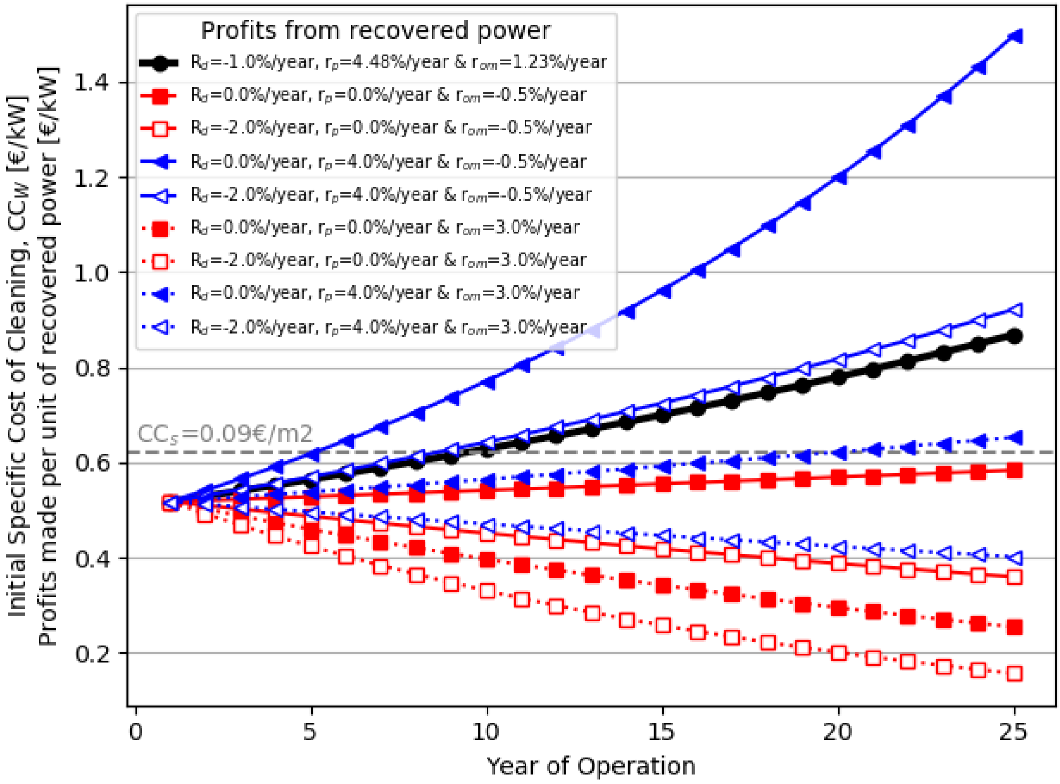


Fig. 4. Sensitivity analysis of NPV taking into account changes in electricity price and O&M costs and in recovered energy under different values of degradation rate. An additional cleaning is recommended when the profits are higher than the initial cost of cleanings (grey dashed line). The r_p = 0%/year (i.e. no changes in electricity price) condition is representative for sites with a fixed PPA in place. In this graph, the NPV values are calculated by moving the term $(1+r_{om})^n$ from the left-hand side to the denominator of the right-hand side of (13).

As can be seen in Fig. 4, the slope of the curve increases while (i) the degradation rate decreases, (ii) the escalation rate of the O&M costs decreases or (iii) the escalation rate of the electricity price increases. The initial price of electricity would not affect the slope but would only change the intercept. It is important to highlight, that the slopes can be either positive or negative. A positive slope occurs when cleanings become more profitable with time, as long as:

$$|R_d| < 1 - \frac{1 + r_{om}}{1 + r_p} \tag{14}$$

These findings confirm that, even if the amount of energy recovered by cleaning decreases because of degradation, the inflation and the variation in the cleaning costs can make it possible to profitably increase cleaning frequency over time.

For the PV site investigated in this work, a cleaning schedule with a variable number of cleanings/year leads to an increment in NPV < 0.1% compared to the case in which the modules are always cleaned twice a year. The benefits of this approach should be evaluated on a case-by-case basis, since the magnitude of this variation changes depending on the severity of degradation rate and values of discount rate.

Overall, the LCOE and NPV evaluate differently the costs and benefits of the various cleaning schedules, because the parameters that influence the decision of whether to clean or not are different (see (12) and (13)). It is interesting to note that the cleaning schedule that maximizes the profits is not necessarily the one minimizing the cost of electricity and vice versa. At the given soiling conditions, an LCOE-optimized cleaning schedule would cause a loss in profits of 0.1% compared to an NPV-optimized cleaning. This loss becomes more substantial as soiling increases; e.g. if the soiling rates were multiplied by a factor of 1.5x and 3x, the difference in profits would become 0.4% and 0.7% respectively. In addition, this difference would become more significant for locations with higher electricity prices. Indeed, higher electricity prices would incentivize more frequent cleanings, while the LCOE recommendation would not change, since LCOE is not sensitive to electricity price.

3.2. Impact of Non-Linear vs. Linear Degradation Rates

The influence of linear degradation rate on the profitability of soiling mitigation was discussed in 3.1. However, nonlinear degradation rates can have a strong impact on the LCOE and, hence, on the profitability of a PV project [4,5]. The most profitable cleaning schedule changes depending on the degradation rate because, given the same soiling ratio, the amount of recovered energy per cleaning lowers. In this section, the analysis is repeated by taking into account the nonlinear degradation rate scenarios exhibited in Fig. 2. Initially, a fixed number of cleanings/year are considered for the lifetime of the system, whereas, in the second part of the section, the cleaning frequency is optimized every year.

Fig. 5 illustrates the impact of the different degradation rate patterns on the LCOE and NPV as a function of cleaning frequency. The two optimum cleaning strategies include the one with the lowest cost of electricity for all the degradation rate scenarios and the one returning the highest profits (i.e. maximum NPV).

Transitioning from a no-cleaning to a single annual cleaning approach leads to a decrease of 0.7% in LCOE; independently of the degradation rate pattern. When NPV is used as a criterion, the twice a year-cleaning scenario is the most profitable cleaning schedule for all the degradation scenarios but the scenario E, which favors a one-cleaning approach. The differences between the one-cleaning and two-cleaning approaches are limited in all the degradation scenarios. Overall, the optimum cleaning frequency leads to profit raises of up to 2.7% in the case of NPV, when compared to the no-cleaning approach (i.e. no soiling mitigation in place).

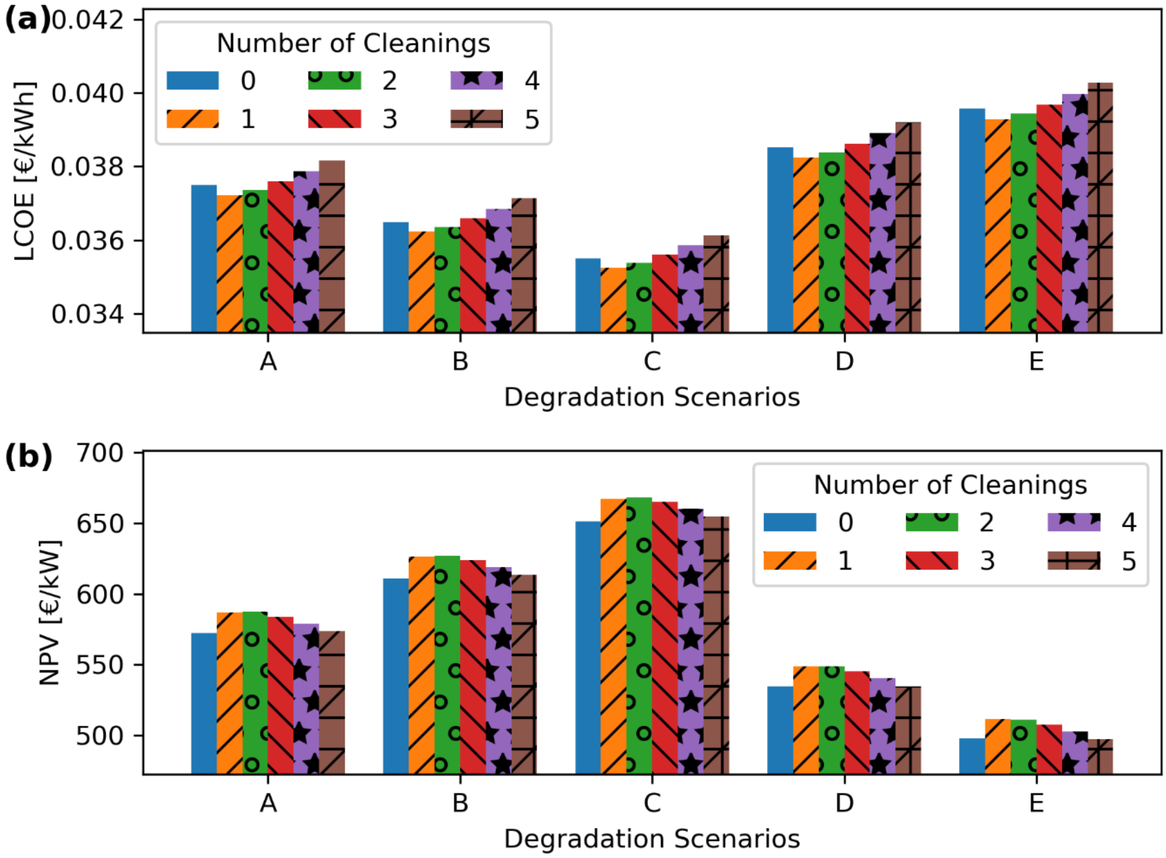


Fig. 5. a) LCOE and b) NPV values depending on the cleaning frequency for various degradation rate scenarios. The optimum cleaning schedule is the one that minimizes the LCOE and/or maximizes the NPV.

As shown in the previous section, the number of annual cleanings can be optimized every year. In this analysis, the LCOE metric is neglected since (12) and Fig. 5 demonstrated that an LCOE-based cleaning decision is not affected by the degradation rate value and/or pattern.

The cleaning frequencies were calculated and exhibited in Fig. 6 for the various degradation scenarios in order to optimize the NPV. As expected, systems with the best performances (i.e. lower initial degradation rates) require more frequent cleaning for longer periods, because cleaning tends to be more profitable. These results are explained by Fig. 6b, where the evolution of the cleaning cost, obtained as $CC_w \cdot (1 + r_{om})^n$, is compared to the revenue obtained by moving from a one-cleaning to a two-cleaning scenario (right-hand side of (13)), which is affected by the degradation rate and by the annual increase in electricity price. Overall, higher degradation rates lower the slopes of revenue per cleaning. The switch in cleaning frequency occurs when the cost of cleaning line intercepts the revenue per cleaning. The high initial degradation modelled in Scenario E keeps the revenue per cleaning lower than the cost of cleaning for longer time, justifying a one-cleaning approach until year 14 of operation. On the other hand, conditions for a profitable additional cleaning are reached faster in scenario C, because of the initial lack of degradation.

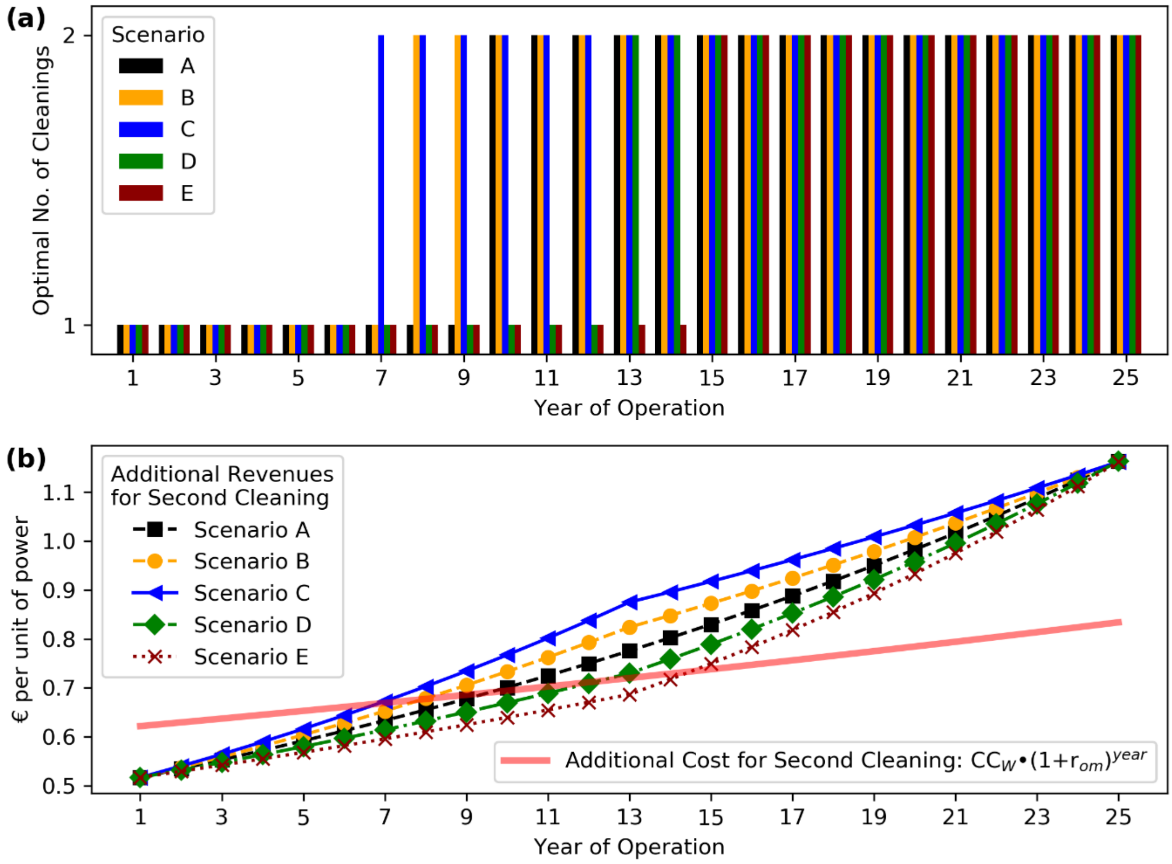


Fig. 6. a) Cleaning frequencies that maximize NPV for different degradation scenarios and b) annual cost of cleaning per unit of power and the trends of revenues per cleaning depending on the degradation rate scenario. An additional cleaning is profitable when the revenue per cleaning is higher than the cost of cleaning.

The slopes of revenue per cleaning lines are positive as long as the degradation rate is lower than the annual increase in electricity price, which is always true in the investigated case because of the high electricity price escalation rate (4.48%/year). Each subplot in Fig. 7 shows the additional revenues and costs of a second cleaning compared to a single cleaning scenario for the investigated site, and demonstrates how the trends would change for a different value of r_p. The red lines represent the cleaning cost escalation rate, ranging from +2%/year (dashed line) to -2%/year (continuous line). The latter scenario was considered because, given the expected increasing impact of soiling in future [9], the development and wide-scale deployment of novel cleaning technologies could actually lower the soiling mitigation costs.

The revenue per cleaning lines are flat when $r_p = R_D$. As expected, the slopes become negative when degradation rate becomes greater than the escalation rate in electricity price. This is the case for PV sites under a power purchase agreement with a fixed price (i.e. $r_p = 0$%/year, Fig. 7a). In these conditions, the profits made by cleaning the modules lowers with time. A once/year cleaning scenario would be recommended, unless the cost of cleaning lowered by 2.0%/year. In this case, Scenario C would be the fastest in switching to a twice/year cleaning approach.

The theoretical examples demonstrated in Fig. 7 return either a fixed number of cleaning frequency or a switch from one to two annual cleanings. In reality, a switch from twice a year cleaning frequency to once a year might occur when the increase in cleaning cost is higher than the combined effect of degradation rate and electricity price inflation.

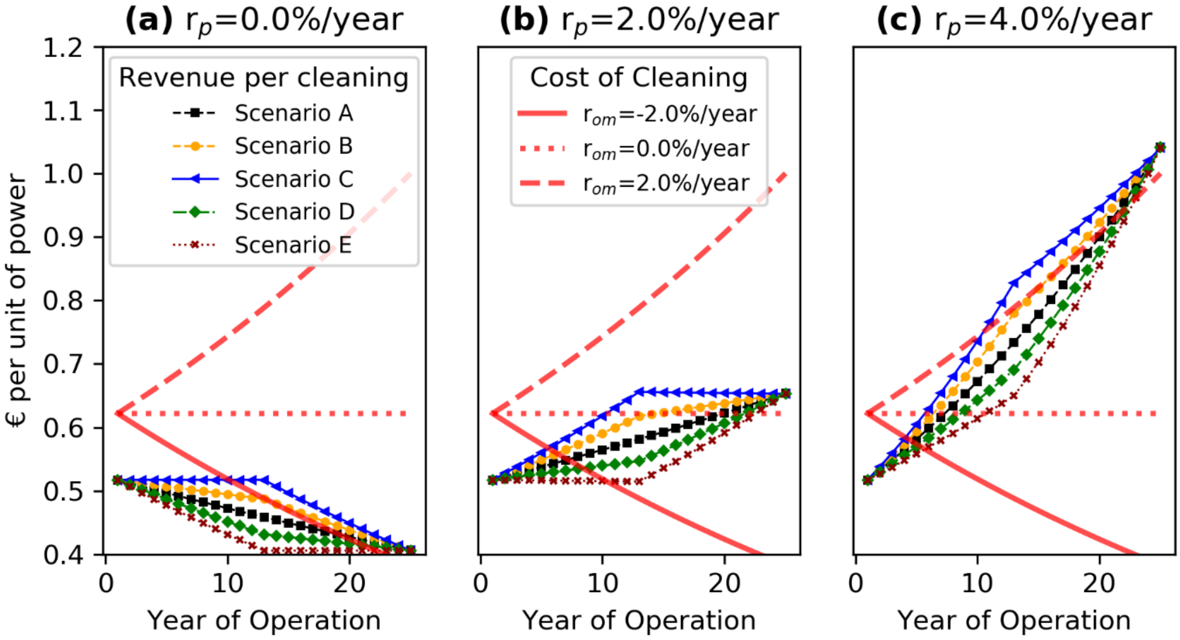


Fig. 7. Additional revenue per cleaning due to recovered energy (lines with markers) and additional cost of a second cleaning (red lines) for different degradation and inflation (r_{om}) scenarios. Each plot takes into account a different escalation rate of electricity price, r_p. Plot (a) is representative for sites with a fixed PPA in place (r_p = 0.0%/year).

4. Conclusions

This study investigated the impact of degradation rate patterns on soiling mitigation strategies taking into account various economic metrics and parameters. In order to reduce the LCOE or increase the NPV, the cleaning frequency can vary annually, since the cost of cleaning and value of recovered energy may also change with time.

First, it is found that the degradation rate or pattern does not affect the cleaning frequency decision, when optimized based on the LCOE. While different degradation scenarios do have an impact on the absolute LCOE values, the cleaning strategy that minimizes the LCOE is independent of degradation. On the other hand, the cleaning optimization algorithm based on the NPV neglects the discount rate, income taxes and depreciation. This leads to different results for the two approaches and means that a cleaning schedule that maximizes the profits could affect the cost of electricity and vice versa. Because of the relatively low soiling rates at the investigated site, the NPV- and LCOE-based approaches showed limited differences, which are expected to rise with an increase in soiling and electricity prices. In addition, nonlinear degradation rate patterns can have an effect on the results of the NPV optimization algorithm, because they can influence the annual revenue rates.

The investigated site is characterized by a significant seasonal soiling profile, with a maximum power drop higher than 20% in summer, but an average energy loss lower than 3%. The results of the analysis can be considered valid for climatic conditions similar to the Mediterranean region. Despite that, the methodology presented in this work can be used to analyze soiling losses, identify the most advantageous cleaning schedule and calculate the profitability of PV systems in any location. The results of the sensitivity analysis are presented to show the variation of the trends depending on the value of the input parameters: degradation, inflation rate, electricity price and cleaning cost. For this reason, the benefits of a yearly optimized schedule should be considered on a case-by-case basis. More investigations should be conducted in future to characterize the correlation between the cleaning strategies and degradation rate for a larger number of sites that exhibit different soiling profiles. Future work will also include the impact of non-uniform soiling and degradation rates that may occur across different inverters and strings within the same site.

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