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Photovoltaic Cleaning Frequency Optimization Under Different Degradation Rate Patterns

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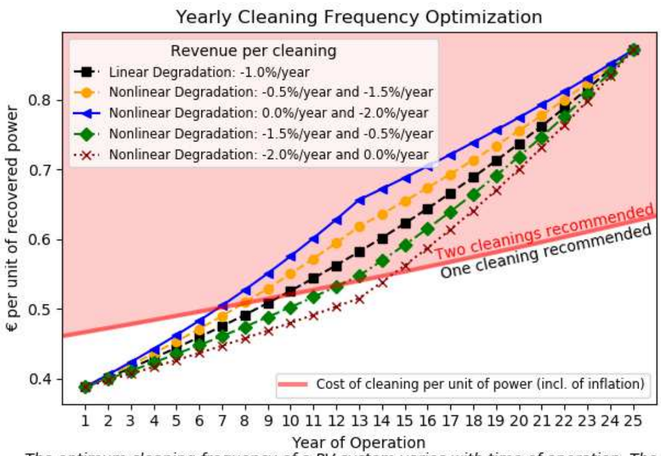
Abstract

Dust accumulation significantly affects the performance of photovoltaic modules and its impact can be mitigated by various cleaning methods. Optimizing the cleaning frequency is therefore 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 either compound or counterbalance the effect of degradation. The present study analyzes the impact of degradation, escalation in electricity price and inflation on cleaning frequency and proposes a methodology than can be applied to maximize the profits of soiling mitigation in any system worldwide. 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.

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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
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_{pretax} [€/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 revenue, as it makes it possible to maximize the efficiency and the revenues of photovoltaic (PV) 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 improving O&M costs and, hence, 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 on 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 (i.e., degradation rate) may not always be constant (i.e., linear) [4–6] due to a number of degradation modes that could 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 be generally 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 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.

2. Methodology

2.1. Soiling and degradation profiles

The energy performance and the soiling profiles considered in this study were extracted from a real PV installation, whereas the degradation rate patterns are theoretical and based on previous investigations [4,5,22].

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 [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 through Ref. [31], and the MERRA-2 site pressure.

The site is characterized by a seasonal soiling profile with long summer periods of no rain, exhibiting a peak power loss of 23% at the beginning of September. This is the result of a -0.28%/day soiling deposition rate occurring from mid-June to the end of the summer, a long period with no rainfall. A change in deposition rate occurred on June 22nd due to a dust-laden wind [23,32].

Although the modules were cleaned on August 5th, the effect of this action was removed in order to emulate a soiling profile as if no O&M action was performed. Similar to previously used models, the soiling extraction method used in this study is based on the assumption that the soiling rate does not change when cleaning is performed [15,33]. In order to be consistent with these assumptions, the soiling rate after the cleaning was considered equal to the one recorded before. Furthermore, soiling is assumed to accumulate on the PV surfaces immediately after a cleaning event [15,34,35], without any “grace period” (i.e. a fixed number of days following a cleaning event in which soiling does not deposit on the PV modules) [33].

According to this “no cleaning performed” assumption, 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 Southeastern US States and also 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 [36–38]. 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. 1. 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). For each frequency, the cleaning dates are identified solely based on the soiling profile, using the methodology described in Ref. [35]. These six 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 ones (i.e. those maximizing 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 were considered after each cleaning [18,23,35].

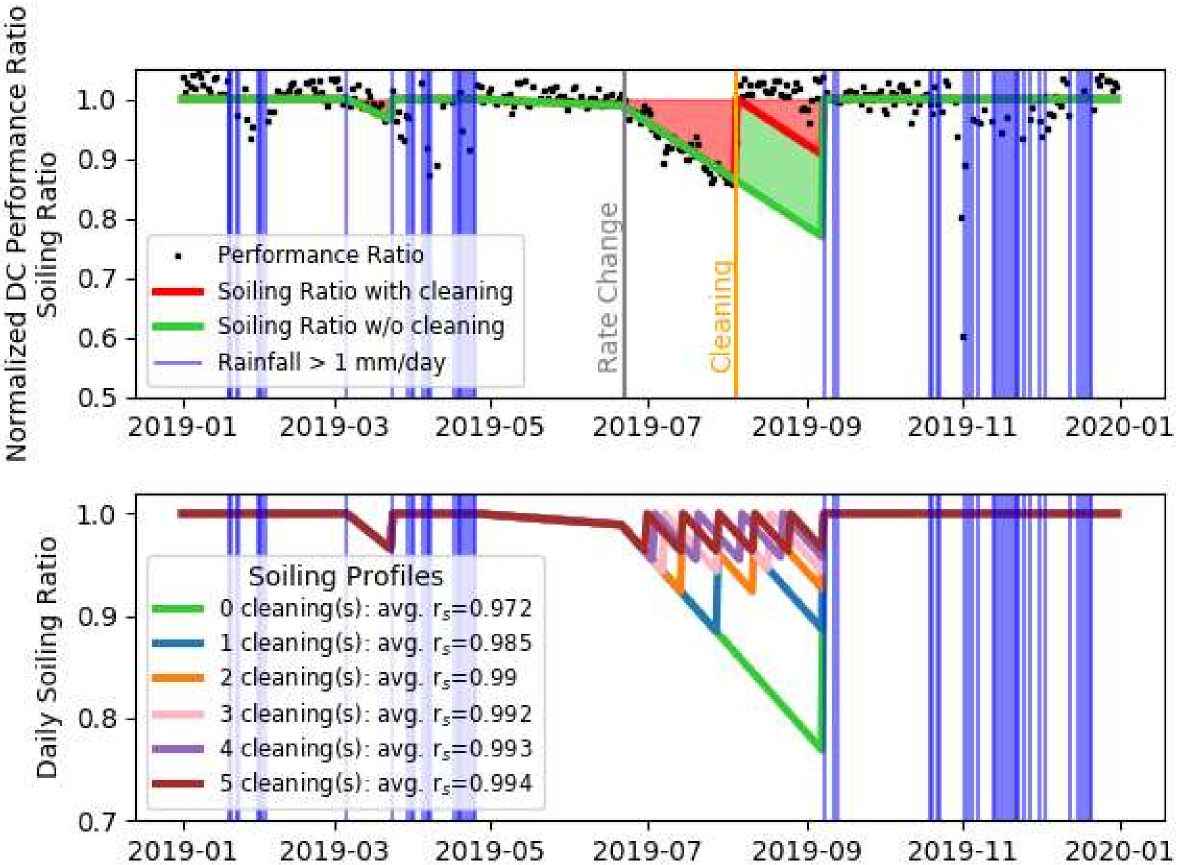

Fig. 1. Upper plot: DC performance ratio normalized to the median value (black dots), extracted soiling profile after the August 5th cleaning (red line) and modeled soiling profile without considering any cleaning (green line). Lower plot: Soiling profiles for optimized cleaning schedules with different frequencies ranging from 0 to 5 times per year.

With respect to system degradation, 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 on 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 normalized to cover a 25-year lifetime, these patterns could represent early life degradation modes such as light and elevated induced degradation (LeTID) [39], light induced degradation [40], and Staebler-Wronski [41] effects. Such types of degradation exhibit various time scales from a number of hours to years [4,5,22]. Furthermore, depending on the degradation-regeneration cycle of LeTID, Passivated Emitter and Rear Contact (i.e. PERC) PV modules could potentially exhibit minimal to even positive “degradation” rate in the field.

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.

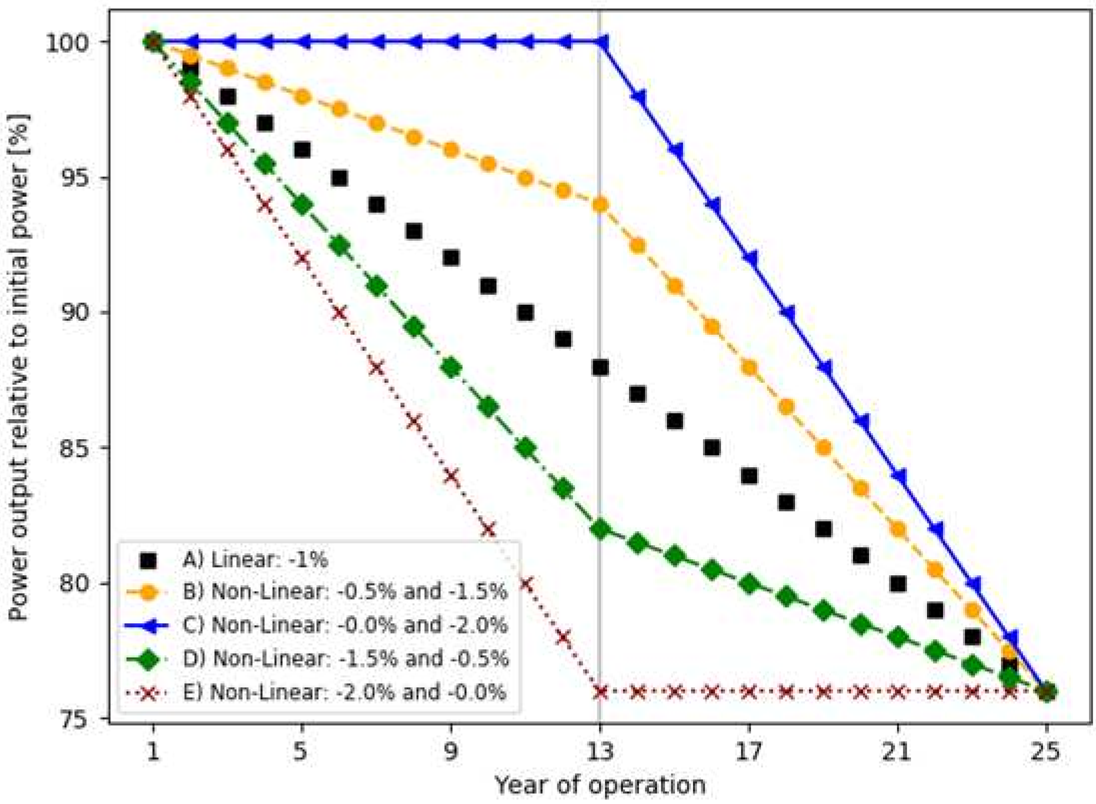

Fig. 2. Theoretical degradation rate profiles considered in this study.

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. The values of the economic metrics were calculated for each of the soiling profiles (Fig. 1) 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 LCOE quantifies the unitary cost of each kWh of electricity generated, considering its entire lifecycle and is defined as [42]:

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

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), 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 term CC_w 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 this analysis, the annual escalation rate of the O&M costs was set to be equal to the inflation rate, whose average, maximum, and minimum values in the last 10 years were 1.23%, 3.20% (in 2011) and -0.50% (in 2015), respectively [43]. Tax depreciation allows recovering part of the investment cost through reduced taxes. In this work, the depreciation for tax purposes is assumed linear and constant over a given period of time (N_d) with a maximum linear coefficient of 5% and a depreciation period of 20 years (D_n=C/N_d) [44]. It is acknowledged that the method used to model tax depreciation (e.g. straight line or declining balance) can affect the analysis. Assuming linear degradation R_D, the factor f_D can be calculated as:

$$f_D(n) = (1 + R_D)^n \tag{2}$$

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

$$f_D(n) = (1 + R_{D1})^{n_1} \cdot (1 + R_{D2})^{n_2} \tag{3}$$

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 value of each parameter used in equation (1) is defined in Table 1. The soiling ratio–corrected energy yield is calculated as:

$$E_s = \sum_{i=1}^{365} r_s(i) \cdot E(i) \tag{4}$$

with r_s being the soiling ratio as shown in the lower plot of Fig. 1 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. The degradation rate is assumed to affect the soiling ratio – corrected energy yield, rather than the daily performance profiles.

The initial Specific Cost of Cleaning can be derived from the Surface Cleaning Cost (CC_s) following the methodology detailed in [9,23]:

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

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. Assuming a surface cost of cleaning of 0.09 €/m^2, the specific cost of cleaning is 0.62 €/kW.

The Net Present Value (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:

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

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

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:

$$p = p_{pretax} \cdot (1 + VAT) \tag{9}$$

where p_{pretax} is the initial price of electricity before taxes, and VAT is the value-added tax (21%). The average yearly pretax 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. Furthermore, *p* was set equal to the average 2019 electricity price in Spain (i.e., 0.04778 €/kWh) [45].

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 [46]. 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 to 4.48%/year, which is the average yearly increase in electricity price in Spain for the last 10 years [45,47].

Despite that, power purchase agreements (PPAs) are a common practice in many countries and PPAs are effective in some new PV projects in Europe [48]. 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	[42]*
Installation Costs	C	700	€/kW	[49]
Initial Surface Cleaning Cost	CC_s	0.09	€/m2/cleaning	[9]
Discount Rate	d	6.4	%/year	[42]
Annual escalation rate of the operation and maintenance cost	r_{om}	1.23	%/year	[43]
Income Tax	T	25	%	[42]
Depreciation period	N_d	20	years	[44]
Average annual rate of increase in the price	r_p	4.48	%/year	[45,47]
Value added tax	VAT	21	%	[44]
Initial pretax price of electricity	p_{pretax}	0.04778	€/kWh	[45,47]

3. Results and Discussion

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3.1. Yearly Schedule Optimization

The cleaning frequency that minimizes the LCOE and maximizes the NPV for each year of the system's lifetime is calculated. Compared to the previous studies [19,21,23], where fixed numbers of cleanings throughout the lifetime of the system were assumed, in this case, the optimum cleaning frequency can vary with time due to degradation, electricity price, and O&M costs. The results of this analysis for the two 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.

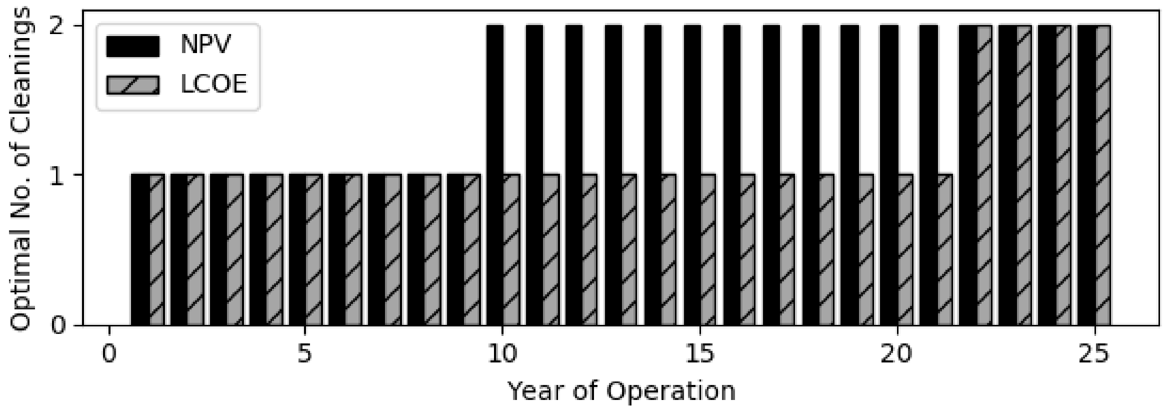

Fig. 3. Optimum cleaning frequency as a function of LCOE and NPV, in presence of a linear degradation rate of -1%/year (Scenario A).

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 equation (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:

$$CC_W\left[\frac{€}{kW}\right] < \frac{\left(\frac{E_{n_{c,n}+1}}{E_{n_{c,n}}}-1\right)\cdot\left((1+d)^n\cdot\frac{C}{N}+OM_{t,n}\cdot(1+r_{om})^n\cdot(1-T)-D_n\cdot T\cdot[n\leq Nd]\right)}{(1+r_{om})^n\cdot(1-T)} \quad (10)$$

where $E_{n_{c,n}+1}$ and $E_{n_{c,n}}$ 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 equation (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:

$$CC_W\left[\frac{€}{kW}\right] < \frac{p \cdot (E_{n_{c,n}+1} - E_{n_{c,n}}) \cdot (1+R_D)^n \cdot (1+r_p)^n}{(1+r_{om})^n} \quad (11)$$

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 in Fig. 4, the switch in cleaning frequency occurs when the value of recovered energy meets the specific cost of cleaning. According to equation (11), two cleanings/year are more profitable when the value of the recovered energy ≥ CC_W, otherwise one cleaning should be preferred. It should be noted that, under some conditions, no switch occurred, while in other cases, more than one switch might be recommended.

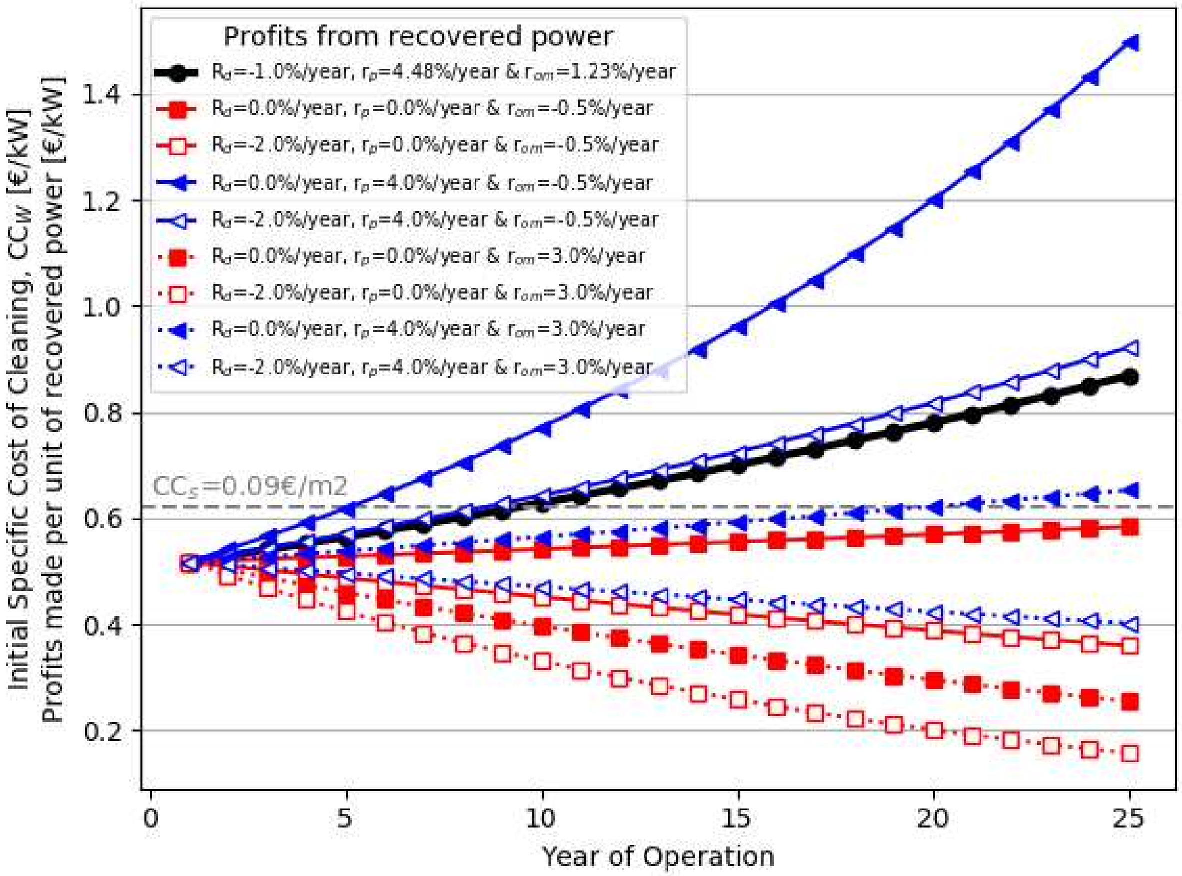

Fig. 4. Sensitivity analysis of profits made from recovered energy for different values of linear degradation rate, escalation of electricity price and variation in O&M costs. The r_p = 0%/year (i.e. no changes in electricity price) condition is representative for sites with a fixed PPA in place.

As can be seen, 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:

$$|R_d| < 1 - \frac{1 + r_{om}}{1 + r_p} \tag{12}$$

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 (Eqs 10 and 11). 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. Nonlinear Degradation Rate

Nonlinear degradation rate affects the cost of energy and hence, 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. 6 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 scenarios. Overall, the optimum cleaning frequency lead to profit raises up to 2.7%, when compared to the no-cleaning approach.

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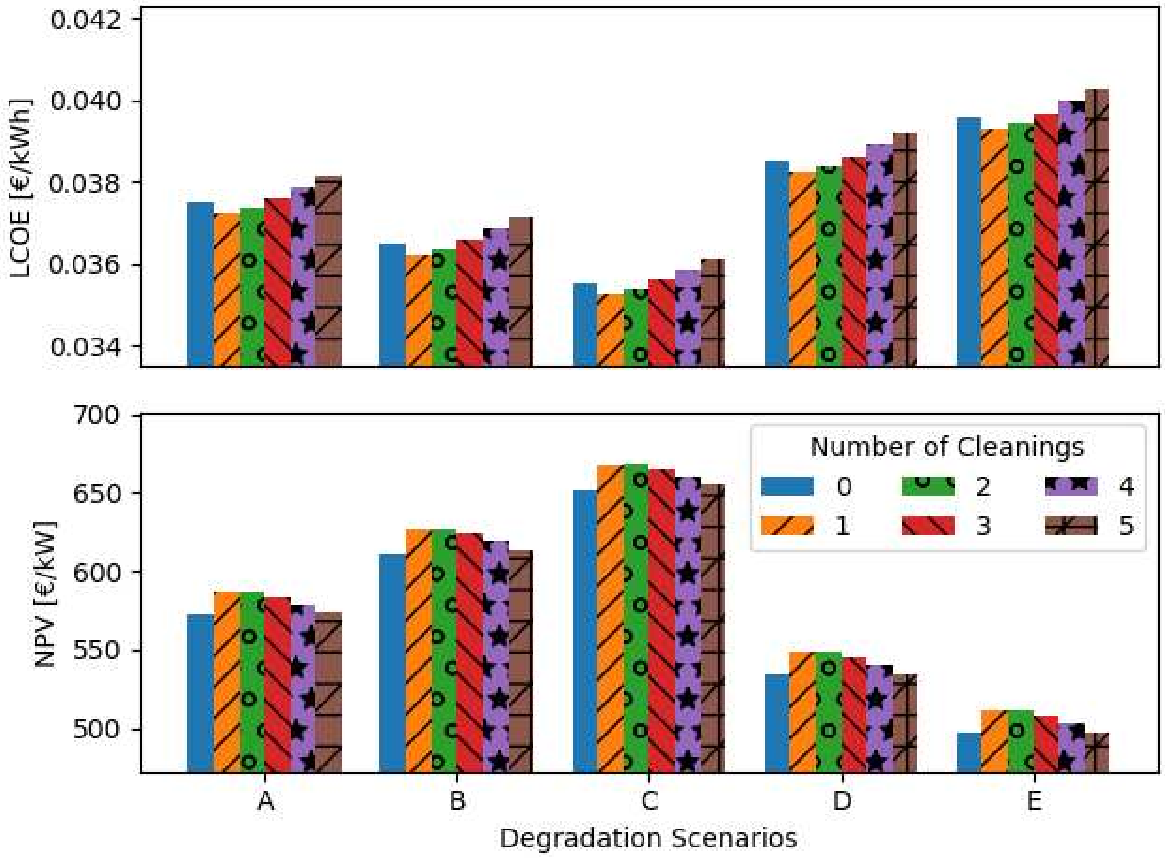

Fig. 5. LCOE and NPV depending on the cleaning frequency for various degradation rate scenarios. The optimum cleaning schedule is the one that minimizes the LCOE and/or maximizes the NPV.

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 Eq. 8 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 the lower plot in Fig. 6, 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 (numerator of Eq. (11)), 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.

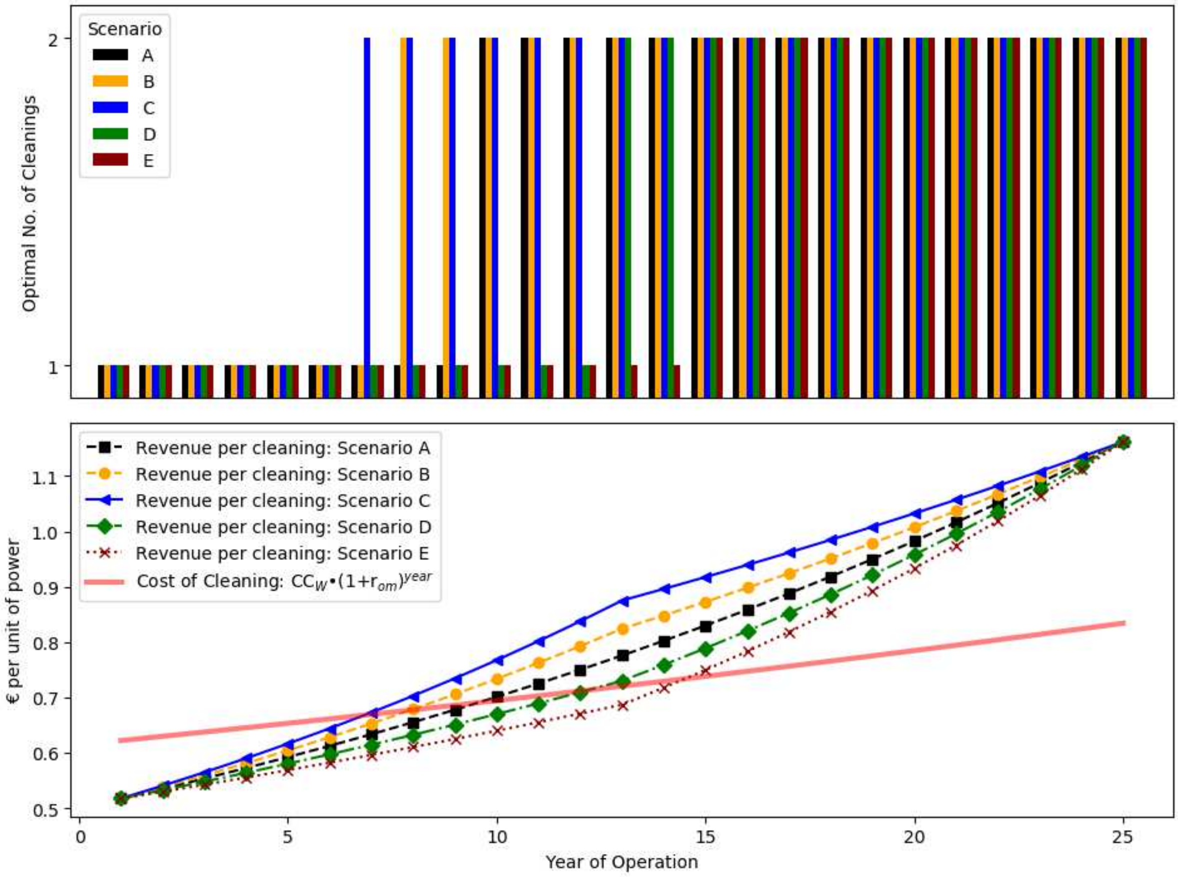

Fig. 6. Upper plot: Numbers of annual cleanings that maximize NPV in different degradation scenarios. Lower plot: the yearly cost of cleaning per unit of power and the trends of revenues per cleaning depending on the degradation rate scenario. An additional cleaning is profitable when the revenue per 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 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, left plot of Fig. 8). 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. 8 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.

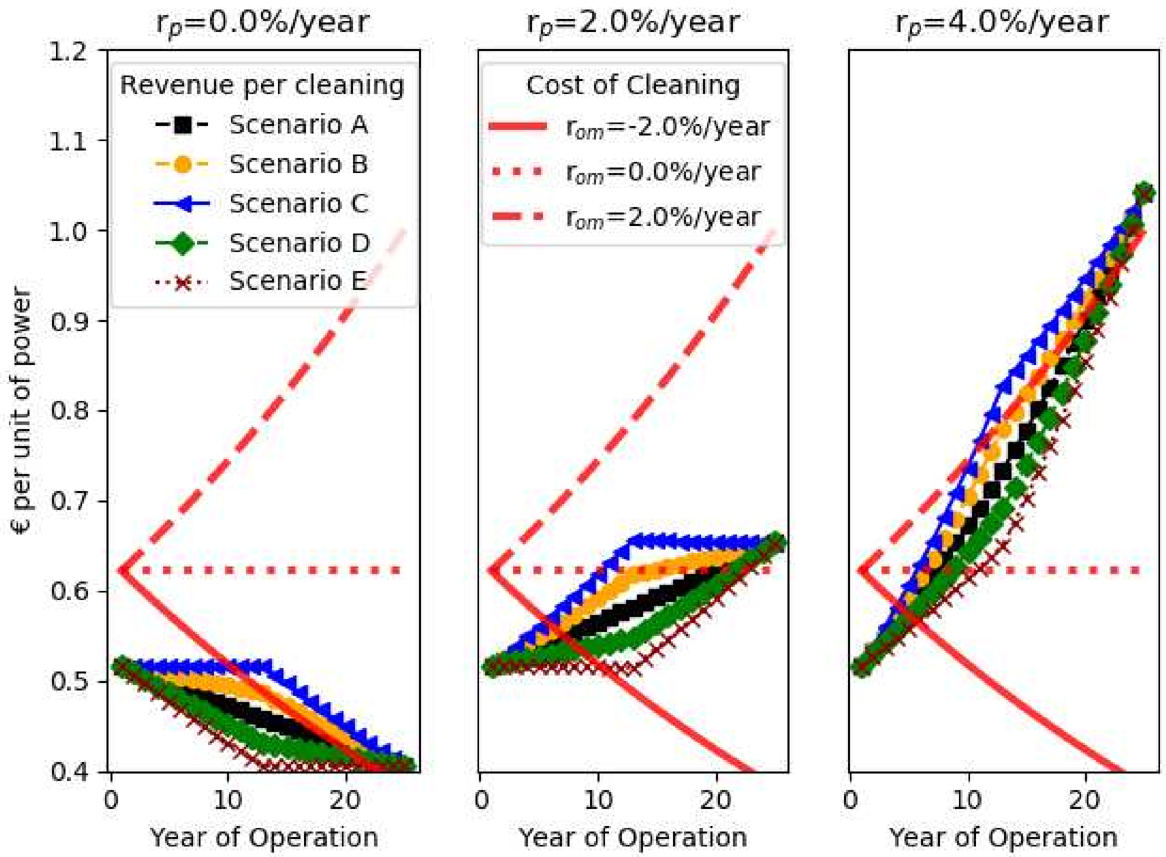

Fig. 7. The yearly cost of cleaning and the yearly values of recovered energy for variable rates of electricity prices and cost of cleanings. The left plot (rp = 0.0%/year) is representative for sites with a fixed PPA in place.

4. Conclusions

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

First, it is found that the degradation rate does not affect the cleaning frequency that minimizes the LCOE. 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-based approach and LCOE-based approaches showed limited differences, which are expected to increase with the severity of 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 to also 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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