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Markov chains estimation of the optimal periodicity for cleaning photovoltaic panels installed in the dehesa

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ABSTRACT

The European Dehesa has a very high potential for the production of clean energy due to the solar irradiation it receives. Its arid climate, however, means that airborne dust particles accumulate on the photovoltaic panels, with the resulting reduction in transmittance of the glass top-sheets. Cleaning the module surfaces involves an economic investment that, to be profitable, has to be offset by sufficient increased energy production. The objective of the present study was to determine the optimal periodicity for cleaning photovoltaic panels installed in the Dehesa, and thus subject to its specific climate. To this end, an experimental installation was set up, and three cleaning plans (monthly, quarterly, and semi-annually) were tested against equivalent not-cleaned controls. The results showed monthly cleaning to increase a year's worth of energy generation by 11.15%. From weekly inspections and continuous monitoring of the panels' output power, a Markov-chains based mathematical model of the degradation of energy production was developed. The conclusion drawn from it was that the cleaning frequency should be monthly from July to October (with the optimal frequency being every three weeks), but that from November to June cleaning is unprofitable since it provides no significant improvement in output. Modelling the degradation of energy output constitutes a powerful tool with which to increase the bankability of photovoltaic plants.

1. Introduction

The regions of southwestern Europe are occupied by open parkland ecosystems known as dehesas, and are preferred locations for photovoltaic power plants due to the solar radiation that they receive (5 kWh/m^2·day) [1]. Currently in Extremadura, a Spanish region bordering Portugal, the installed solar power using photovoltaic (PV) technology is 2568 MW [2] and great improvements are being made in the efficiency of electricity production in the regional energy mix compared with traditional generation. But, since this is a very dry area, deposition of airborne dust on the PV panels will be a problem of growing importance [3].

The dehesa is an open agro-sylvo-pastoral parkland ecosystem of holm or cork oak woodland (or sometimes other species) and herbaceous or scrub understorey. There has long been intense human activity in these systems, dedicated to livestock grazing and foraging, wild game, and the use of other forest products (firewood, charcoal, cork, mushrooms, etc.) [4]. At this time, large areas are being converted to PV solar power production [2]. The dehesa has a mediterranean climate, with hot, dry summers and mild winters [5].

The reliability and efficiency of PV installations depend on the environmental factors of their surroundings, including ambient temperature, wind, and rainfall. Likewise, air pollution and the build-up of dirt on the collection surface reduces the solar radiation reaching the PV cells. These factors also speed up the aging of the installation's equipment [6]. It has been proven that the performance of PV panels is significantly reduced when dirt accumulates on the top-sheet glass, with reductions in useable solar energy reaching up to 70% [7].

The output power of a PV module is proportional to the solar irradiance incident on the panel surface. Radiation varies substantially from day to day and from one geographic region to another. The efficiency of the modules is also affected by the temperature of the cells, the performance of flat-plate system devices,

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and adverse environmental conditions such as high levels of dust in the atmosphere, sandstorms, snow, hail, and high temperature and ultraviolet (UV) indices. These variables can induce a loss in efficiency of the PV effect that will contribute a specific factor of reduction and, in aggregate, may result in a drastic decline in the overall PV power output.

The efficiency of electrical energy production from solar PV technology is influenced by more factors [8]. The accumulation of dust and dirt on the glass cover reduces the amount of solar radiation that reaches the cells of the PV panels. To make the most of their production capacity, the panels have to be cleaned periodically. Dirt build-up not only prevents light from reaching the solar cells, but it also changes the thermal balance of the PV system and can cause the temperature to rise higher than normal since, as the dust particles accumulate, they retain heat [9].

This soiling can be divided into different classes, depending on the granulometry and composition of the deposited material. In addition, its effects will differ depending on its distribution on the capture surface. The cleaning options for its elimination range from manual techniques to automated activities using robotic devices, either with water or with other chemicals.

Losses due to dirt cause a reduction in the power of a PV generator due to the deposition of dust on the surface of the solar collectors [10]. Diffuse radiation is induced, reducing the spectral intensity when solar radiation attempts to penetrate through the dirt [11]. Losses due to dust and dirt depend not only on the aridity and wind at the installation site, but also on the frequency and intensity of rainfall. The typical annual values of these losses are between 2% and 5% in regions where a high degree of dirt is generated [12].

There are two types of shading cast by dirt — soft shading and hard shading. Soft shading occurs when some particles, such as dust on the glass of the PV panel or smog in the atmosphere, reduce the general intensity of the solar irradiation that is absorbed by the PV cells. Hard shading occurs when accumulated solids obstruct the sunlight in a clear and definable way. These two types of shading have different effects. A uniform covering of dirt leads to a decrease in the current and voltage delivered by the PV generator [13]. The presence of localized dirt (for example, bird droppings or leaves) leads to an increase in mismatch losses and in losses due to hotspot formation [14]. Both types of effect cause the shaded cell to act as an electrical resistance in a series circuit. Energy generated by the rest of the PV cells will then be dissipated as heat through that shaded cell. Strong shading affects the performance of the PV panel differently depending on the number of cells that are shaded and their distribution over the module. When some cells receive solar radiation, but others are shaded, there will be current flow.

There have been various studies carried out to analyse and quantify the impact of dirt on the performance of PV modules. To predict the performance of PV panels, it is necessary to know whether the rainfall is of sufficient intensity to clean them. When such rains do not occur, the need arises to decide how often the PV panels ought to be cleaned. While all previous studies agree on the need for periodic cleaning of PV modules to improve their performance, there is no consensus on how often this should be done. In financial analyses prior to the implementation of a PV solar installation, it is common in the sector to allow for a loss of performance attributable to the accumulation of dirt on the panels of between 2% and 6% of the total energy produced, even reaching 6.9% [15]. Considering that this type of installation has a useful life of approximately 25 years, the impact of these losses can be serious.

Table 1
Climatological parameters of the zone of the experiment.

Parameter	Maximum	Mean	Minimum
Temperature (°C)	40.7 (±1.8)	15.9 (±0.5)	9.1 (±0.6)
Relative humidity (%)	90.8 (±2.1)	68.5 (±3.1)	41.1 (±3.4)
Net radiation (MJ/m^2·día)	16.9 (±1.0)	8.2 (±0.8)	1.1 (±0.5)
Rainfall (l/m^2)		501.5 (±158.0)	

Using tap water for the cleaning is inadvisable since it contains lime and other minerals. Applying running water to the panels can produce incrustations that serve to hold the dirt in place [16]. While in some areas rainfall is sufficient to clean glass panes of PV panels [17,18], in other areas rain is not enough to remove all the impurities that can accumulate on the surface of PV panels over time [19]. Maintenance plans for these facilities must include actions that ensure the plate's collection surface is cleaned in order to improve the capture of solar energy [11]. Excessive cleaning will generate a major extra cost as it is necessary to use chemically treated water to avoid incrustations on the modules. Optimizing the consumption of water and the manpower allocated to cleaning operations by scheduling them only when necessary will contribute to the objective of minimizing operating expenses (OPEX) [20].

The extensive research on characterizing dust deposition and its impact on PV system performance recognizes the complexity of the phenomenon and the variety of the site-specific environmental and climatic conditions influencing it [21,22]. Adinoyi and Said [23] analysed the effect of dirt accumulation under outdoor environmental conditions on the electrical output of PV modules in Saudi Arabia. They monitored an installation's output over several months, and periodically characterized the dust deposited. They concluded that output could fall by up to 50% if cleaning is left for more than six months. Nonetheless, these studies were oriented at understanding the process of airborne dust particle deposition.

With regard to studies aimed at establishing an optimal cleaning periodicity based on a set of imposed constraints, Stridh [24] made a break-even point analysis of cleaning off dirt (and even snow) for three PV plants in Europe. The analysis involved a computerized virtual simulation of the plants' output, quantifying the energy to be recovered in order to make the investment in cleaning actions economically viable. The conclusion was that cleaning off the dust is profitable in central and southern European climates, but in Nordic climates removing snow is not. Hammoud et al. [25] studied how successive cleaning of panels affected the electricity generation of a PV plant in times of sparse rainfall. They estimated a 32.27% increase in production over other non-cleaned panels, but they did not determine any optimal periodicity that took cleaning costs into account. Al-Addous et al. [26] evaluated the economic viability of fortnightly vs monthly cleaning scenarios. They estimated the production of three PV systems of different powers based on a data collection of a soiling loss index. They concluded with the periodicity that would be optimal in accordance with the governing tariff of PV projects. Chiteka et al. [27] found that dirt does not build up uniformly as days go by, but depends on day-to-day differences in weather conditions. They observed that dirt build-up was high from July to November, and lower in May and June. Cleaning every 15 days was found to be necessary to minimize losses due both to frequent cleaning and to absence of cleaning the PV panels. Conceiçao et al. [28] developed a particular model of effective radiation that includes a simulation of losses due to dirt. To this end, they crossed data on the deposition of dirt on surfaces at multiple inclination angles and historical solar radiation data. They recommended periodic cleaning from April to September to achieve a desired efficiency range. Nonetheless, they did not specify any time interval between cleaning operations or the cost effectiveness of carrying them out. Jiang et al. [20] developed a theoretical method to determine the cleaning frequency as a function of particle size, density, and deposition rate. They found a 20.7 day

Table 2
Characteristics of the photovoltaic panels employed in the experiment.

Electrical characteristics	
Model no.	JAP60S01-270/SC
Peak power (P_{max})	270 W
Peak efficiency	16.51%
Power per unit area at Standard Test Condition (STC)	165.1 W/m^2
Open circuit voltage (V_{oc})	38.17 V
Max. power voltage (V_{mp})	31.13 V
Short circuit current (I_{sc})	9.18 A
Max. power current (I_{mp})	8.67 A
Nominal voltage	24 V
Power tolerances	0%/+2%
Series Fuse Rating	20 A
Maximum System Voltage	1,000 V
Nominal Cell Operating Temperature (air at 20 °C, wind 1 m/s and irradiance 800 W/m^2)	45±2 °C
Temperature coefficients at STC (Irradiance 1,000 W/m^2 and cell temperature 25 °C)	
Temperature coefficient of I_{sc} (α_I_{sc})	+0.058%/°C
Temperature coefficient of V_{oc} (β_V_{oc})	−0.330%/°C
Temperature coefficient of P_{max} (γ_P_{max})	−0.410%/°C
Mechanical characteristics	
Length/Width/Depth	1,650 mm/991 mm/35 mm
Weight	18.2 kg
Cell characteristics	
Cell type	Polycrystalline Silicon
Cell dimensions	156.75 mm × 156.75 mm
Number of cells	60 (6 × 10)

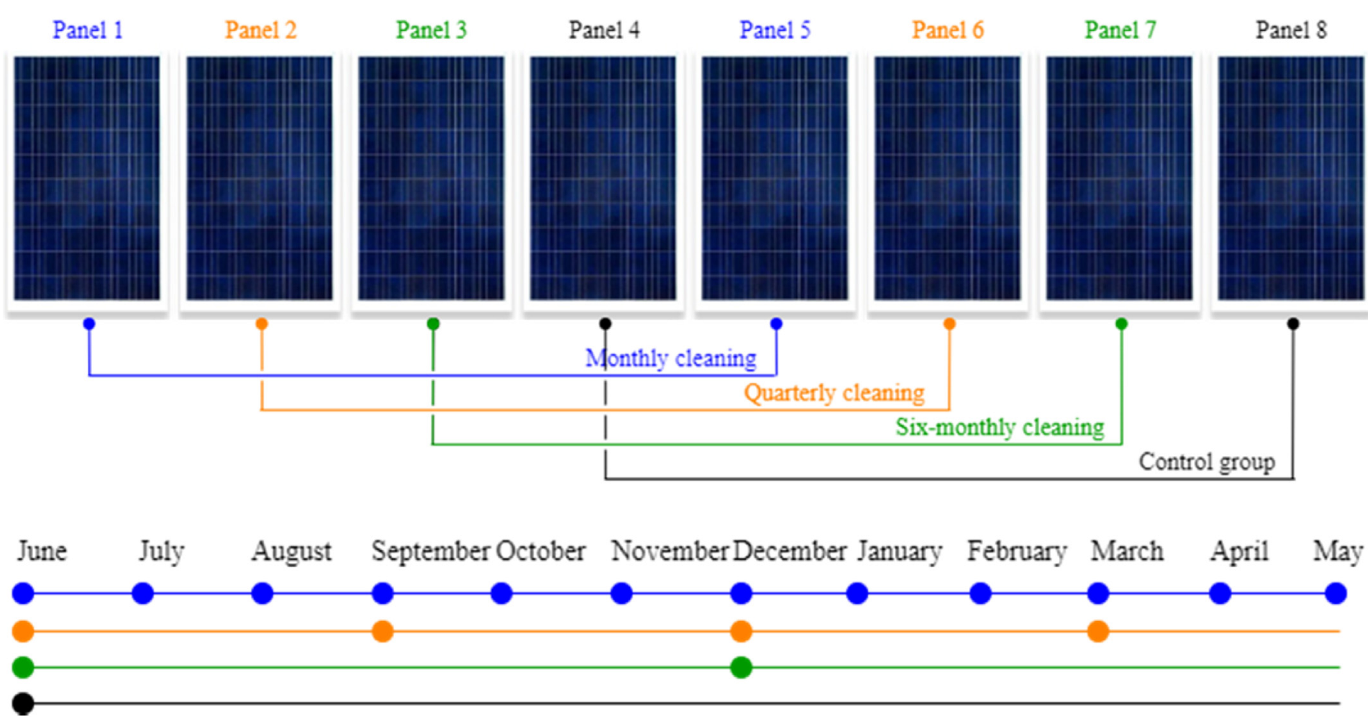

Fig. 1. Experimental set-up and cleaning periodicity.

periodicity to be optimal for cleaning PV panels with an inclination of 0° in a desert climate. Their work, however, recommends this method in the absence of rain, whereas the present study takes rainfall into account.

Optimizing the cleaning procedure involves finding a trade-off between the cost of cleaning and the loss in revenue from energy sales due to not cleaning. Frequent cleaning will increase OPEX, while overly long intervals between cleaning operations will result in power losses. The cleaning schedule cannot be detrimental to the LCOE (levelized costs of electricity) as a metric which indicates the unit cost of energy production [29].

Since most studies in the literature address the problem through empirical methods, other approaches such as stochastic methods have not been widely explored. This paper aims to fill this gap in knowledge. Consequently, the objective of the present work was to infer the periodicity of execution of cleaning actions that maximizes the profitability of electricity production in PV installations in the Dehesa by means of Markov chains. In this way, PV plant managers will have a suitable tool available for making maintenance decisions.

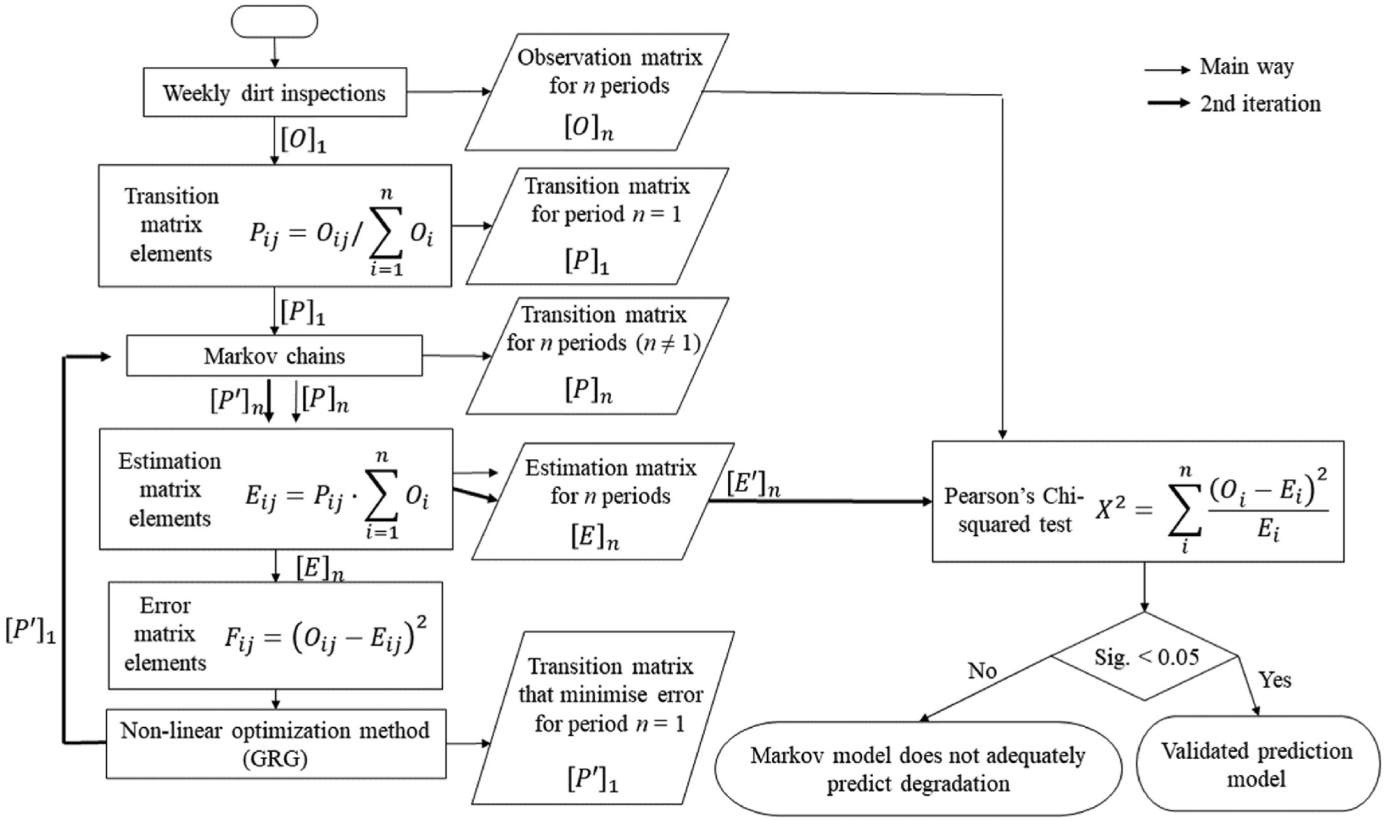

Fig. 2. Flowchart of the Markov chain method.

Table 3
Soiling conditions of the photovoltaic panels.

Level	State	Description	Illustration
1	Adequate	The photovoltaic panel surface is dirt-free	
2	Inadequate	The photovoltaic panel surface has dirt which affects its output	
3	Unacceptable	Output is sharply reduced by the large amount of dirt on the photovoltaic panel	

2. Material and methods

2.1. Design of the experiment and data gathering

An *ad-hoc* experimental station was installed in Extremadura (a region in southwestern Spain bordering Portugal) to measure the electricity production from June 2018 to May 2020 based on different PV panel cleaning periodicities.

The climatological parameters of the zone obtained from the last 20 years' data (2000–2020) are presented in Table 1 [30].

The experimental setup consisted of eight 270 Wp PV panels mounted on a fixed structure with a 18° tilt so as to ensure building integration. The inclination of the PV panel will influence the predisposition to accumulate dirt. This arrangement is becoming a trend and will be representative in rooftop installations although the trend in industrial plants is towards one- and two-axis tracking systems. Their technical characteristics are listed in Table 2.

The panels were paired to form four study groups in order to minimize the measurement error. To avoid inter-annual climatological dependence, data from the same month were averaged for the two years of study. Three cleaning plans were tested – monthly, quarterly, and semi-annually – with one pair used as a control group (without cleaning during the course of each year). The maintenance actions throughout the project are illustrated in Fig. 1.

The electricity production (output current and voltage) and backside temperature of the cells of four pairs of PV panels were monitored at 1-min intervals over two years (June 2018–May 2020). An individual 3.6-Ω load resistor (requesting power at full load) and a weather station (temperature and relative humidity of the environment, wind speed and direction, and rain) were installed. Each PV panel was equipped with its own electronic instrumentation.

2.2. Analysis of the influence of cleaning

A randomized one-factor design with four levels of the cleaning factor was chosen for the experiment. A fixed-effects model was generated to estimate the effects of the treatment. In particular, the influence of surface dirt on daily energy production was evaluated, determining whether there was a significant difference in energy production between at least two cleaning treatments. From the results of this analysis, which will be presented in Sec. 3.2, an observation matrix was determined in accordance with the Markov chains, as will be explained in the following subsection. This matrix corresponds to the state of soiling of the PV panels during the period from July to October.

Since 30 monthly data were available, the Shapiro-Wilk test was applied to check whether the daily energy production samples were normally distributed. The result was that the null hypothesis could not be accepted, so that a non-parametric Kruskal-Wallis test [31] was applied to determine whether at least two of the monthly energy production means of the four treatments under study differed significantly.

2.3. The Markov chains method

The accumulation of dirt on the glass cover of a PV panel complies with the criterion of a Markov process since its future state will depend only on its present state, not on its past history [32]. The condition of the PV panels' surface over time could thus be evaluated by means of Markov chains as shown in Fig. 2. The thick arrows in this figure represent the path of the second iteration – an internal process of the method, with which nonlinear optimization is carried out.

From weekly visual inspections, three possible states of soiling of the PV panels were defined. These states represented how much dirt and dust was found on the glass covers for a certain time (see Table 3).

State 3 must be avoided by undertaking maintenance tasks. These consisted of cleaning the glass cover with a medium-density (20 kg/m^3) polyurethane foam brush and distilled water to remove the deposited dirt.

The periodicity of the cleaning tasks was established from the results of the transition matrix that minimized the optimization error. For this calculation, the observation matrix was first obtained for the n periods analysed, with its elements O_{ij} being the number of PV panels that were found in each of the observation states j originating from state i after one week.

The probabilities that a PV panel evolves from a state i to state j in a week formed the transition matrix P_{ij} as defined in Equation (1):

$$P_{ij} = \frac{O_{ij}}{\sum_{i=1}^{3} O_i} \tag{1}$$

where O_{ij} are the elements of the observation matrix, O_i the elements of row i of the observation matrix, and P_{ij} the elements of the transition matrix.

Once the transition matrix for the period $n = 1$ had been obtained, the Markov chains were applied to determine the transition matrix in the $n \neq 1$ periods analysed This is done by applying the power n to the transition matrix for the first period. Subsequently, an estimation matrix was calculated whose elements E_{ij} represent the number of solar panels found in each of the degradation states, as given by Equation (2):

$$E_{ij} = P_{ij} \cdot \sum_{i=1}^{3} O_i \tag{2}$$

where P_{ij} are the elements of the transition matrix, O_i the elements of row i of the observation matrix, and E_{ij} the elements of the estimation matrix.

Next, the elements of an error matrix F_{ij} were calculated as the square of the difference between the elements of the observation matrix and the elements of the Markov chain estimation matrix for the n periods analysed.

Finally, the error that was produced in the elements comprising the error matrix for the n periods analysed was added. The result was the transition matrix of the first period that minimizes the total error between what is observed and the Markov estimation after

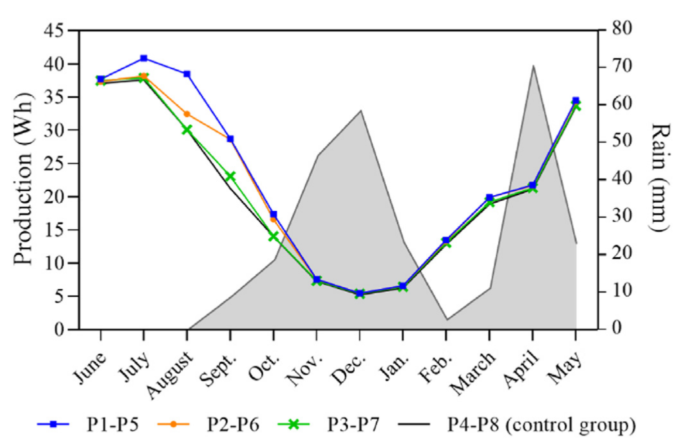

Fig. 3. Monthly energy production of each pair of PV panels and monthly rainfall.

Table 4
Increase in output relative to the control group.

Month	P1–P5		P2–P6		P3–P7	
June	*	1.74%	*	−0.73%	*	1.17%
July	*	8.59%		1.52%		0.75%
August	*	27.89%		7.86%		0.02%
September	*	35.25%	*	34.84%		8.80%
October	*	24.16%		18.51%		0.33%
November	*	3.82%		3.19%		0.58%
December	*	3.94%	*	4.19%	*	3.00%
January	*	5.42%		4.55%		2.88%
February	*	5.17%		3.97%		2.08%
March	*	5.50%	*	5.49%		1.67%
April	*	3.00%		2.65%		0.73%
May	*	3.07%		2.51%		0.63%

applying the nonlinear Generalized Reduced Gradient method [33].

To validate the model, Pearson's χ^2 test was used to establish whether the discrepancy between what was observed and what was predicted had a significance level of less than 0.01. Equation (3) is the expression for Pearson's χ^2.

$$\chi^2 = \sum_{i}^{n} \frac{(O_i - E_i)^2}{E_i} \tag{3}$$

Subsequently, Equation (4) was applied to determine the probability that a PV panel is in each of the states defined (adequate, inadequate, and unacceptable) for a period n knowing the panel's initial state and its maintenance:

$$E_n = E_{n-1} \cdot [M] \cdot [P]_n \tag{4}$$

where E_n corresponds to the vector of states in period n, E_{n-1} is the vector of states in the preceding period, $[M]$ is the maintenance matrix, and $[P]_n$ is the transition matrix in period n.

The condition of a PV panel after cleaning will always be in State 1, regardless of its preceding state. Thus the maintenance matrix is:

$$[M] = \begin{bmatrix} 1 & 0 & 0 \\ 1 & 0 & 0 \\ 1 & 0 & 0 \end{bmatrix}$$

Finally, the reliability R of the PV panels was calculated over time, i.e., the probability that the PV panel will be in State 1 and State 2 after a certain time, in accordance with Equation (5).

$$R = E_n \cdot F \tag{5}$$

where R is the reliability of the PV panel, and F is the condition constraint vector (null for the state of unacceptable condition, and unity for the other two states).

A value of 60% was set for the characteristic life as the lowest threshold of acceptable reliability below which cleaning tasks must be undertaken. A lower value indicates that the collection surface is covered by an amount of dirt that significantly reduces production (State 3).

2.4. Cost-benefit analysis of cleaning programs

The assumption of a proportional relationship between the energy generated by a PV panel and that by a PV plant is a suitable approximation due to the modularity of such installations. Therefore, the present work's results for unitary samples can be scaled up to systems of greater power. A cost-benefit analysis was made for each cleaning program considering a 100 kWp plant.

The increase in electricity production $\Delta P_{e_{m,i}}$ for the month m of each treatment i due to cleaning was calculated by applying Equation (6).

$$\Delta P_{e_{m,i}} = SF \cdot (E_{m,i} - E_{m,c}) \tag{6}$$

where SF is the scalability factor (370.37 kWp/kWp), representing the ratio between the power of the 100 kWp PV plant and that of the experiment's setup (270 Wp), $E_{m,i}$ is the energy produced during the month under cleaning protocol i, and $E_{m,c}$ is the energy of month m produced by the control group.

This monthly increase in energy production $\Delta P_{e_{m,i}}$ means an increase in revenue from the operation of the plant. Current prices for the output energy of a PV plant are between 3 c€/kWh and 5 c€/kWh depending on access to economies of scale.

Also, the cleaning cost C_c of 1 kWp installed is found to be 2.71 €/kWp after applying Equation (7)

$$C_c = C_{mp} + C_w + D_m \tag{7}$$

where C_{mp} represents manpower costs (2.59 €/kWp), C_w are water costs (0.04 €/kWp) and D_m are depreciation of machinery (0.08 €/kWp).

3. Results

3.1. Electric power production

The monthly rainfall and mean accumulated energy production of the pairs of modules for each treatment of the experiment are shown in Fig. 3. One observes that, in general, in the month following one of no or little (<8.8 mm) rain, there is an increased difference in production. This is the case of the months of June, July, August, and September. It was also found that, although it rained in September (after three summer months of accumulating dust) and February, it was not intense enough (8.8 mm and 2.6 mm, respectively) to properly clean the glass. Consequently, there were differences in energy production in the months of October and March.

Table 4 lists the percentage increments in the average output power of each cleaning treatment's PV panel group relative to the control group. The asterisks (*) mark that a maintenance action had been carried out at the beginning of that month. The greatest increment is reached in September for both the monthly and the quarterly cleaning protocols. This does not mean that these two cleaning programs achieved the same results. Rather, the explanation is that their cleaning actions coincided in that month.

Disaggregating the monthly data on energy production and rainfall to the daily level (Fig. 4), one can better visualize the effect of rainfall. During the time of no rainfall (June–August), the difference in production between treatments was accentuated. From September onwards, it rained every month. Nonetheless, the rainfall did not always manage to restore the state of cleanliness that maintenance did. Prolonged exposure to rain, however, did achieve such restoration, as was the case at the end of October and throughout November, December, and January. Equality of production was maintained during February when, even though there was less rain, the glass was already clean. In the remaining months (March–May), differences in production were detected even though rain fell. This was due to the accumulation of airborne dirt during the dry days of those months, which then became compacted after being wetted by rain and then drying out in the sun.

Fig. 5 shows the monthly mean energy production for each cleaning treatment and the corresponding standard deviation. The variability in production differs little between treatments and is much greater in the months of greater production. The smallest ranges of variation corresponded to November, December, and

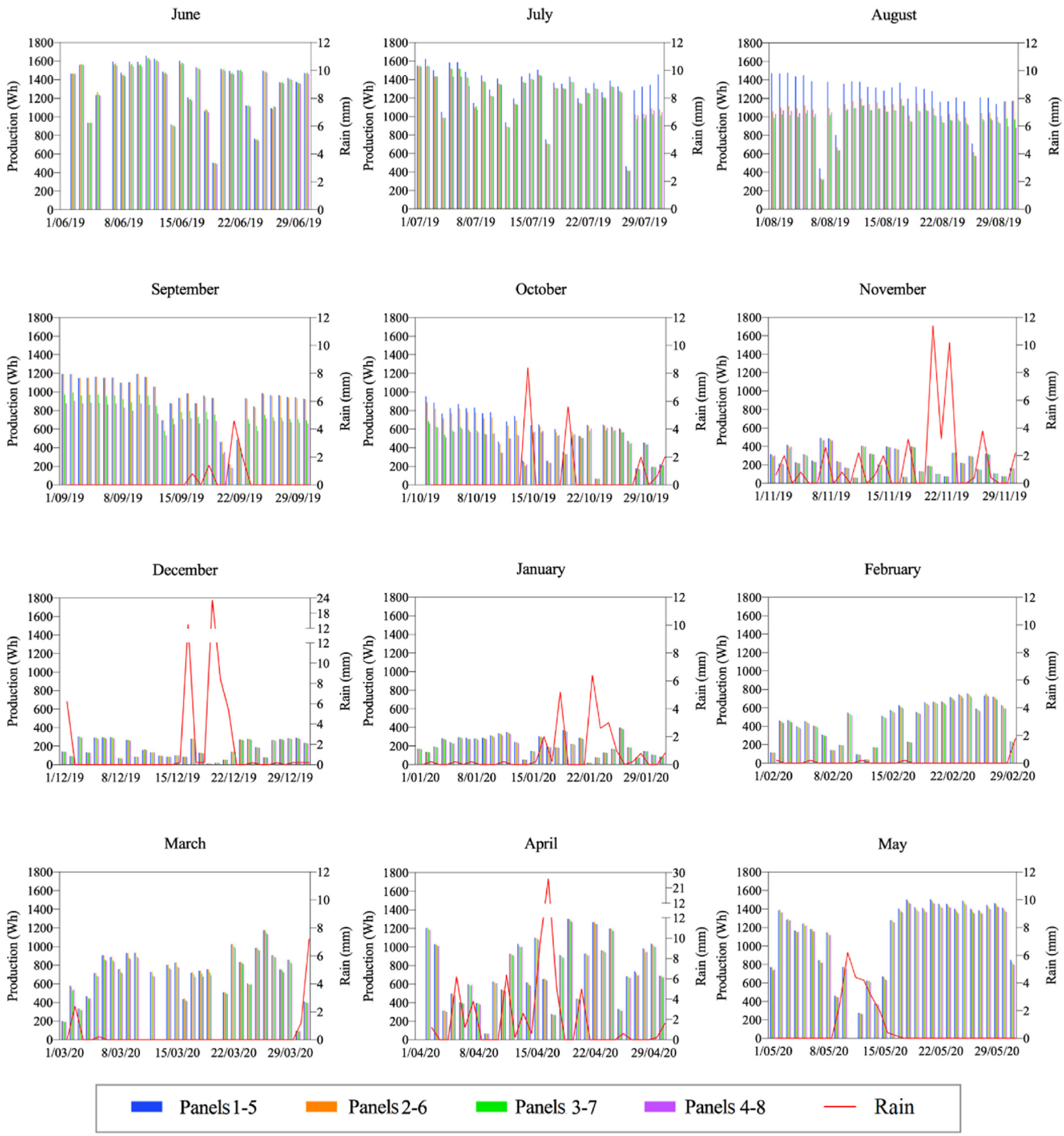

Fig. 4. Daily energy production by pairs of photovoltaic panels and accumulated rainfall.

January, with values between 92.9 Wh and 127.54 Wh. The widest ranges of deviation corresponded to April and May – 327.15 Wh and 376.34 Wh, respectively. The range of deviation for the rest of the months was of the order of 200–300 Wh.

Fig. 6 shows the data of the energy accumulated during the experiment. Table 5 lists the accumulated values of parameters of interest for each cleaning program. The surplus of electricity production is relative to the control group as basis.

The monthly cleaning program managed to produce 11.15% more energy than the control group. The quarterly cleaning schedule added 6.89% of energy, while the semi-annual schedule added only 1.62% to the production. For a PV panel with 270 Wp power, this translates into increases in energy production of 27.32 kWh/year, 16.88 kWh/year, and 3.96 kWh/year, respectively.

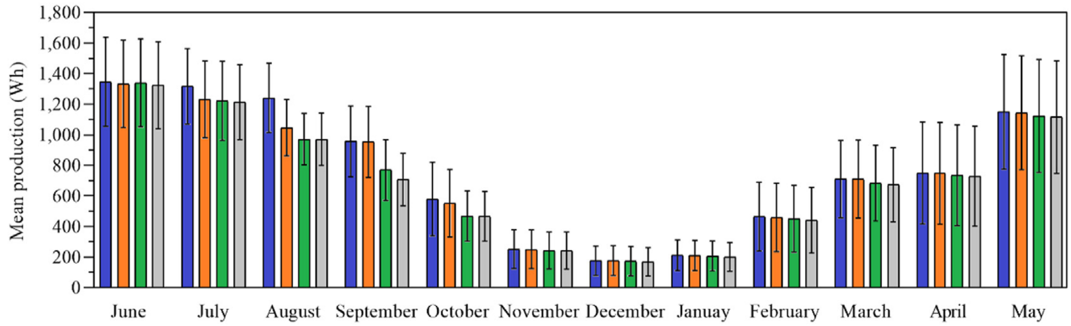

Fig. 5. Monthly average energy production and deviation.

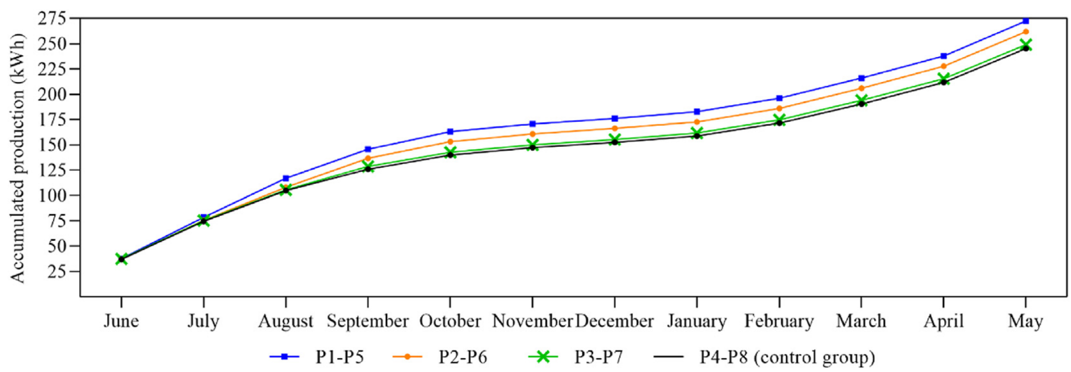

Fig. 6. Energy accumulated during the experiment for each cleaning protocol group.

Table 5
Energy values accumulated throughout the experiment.

	P1–P5 (monthly)	P2–P6 (quarterly)	P3–P7 (six-monthly)	P4–P8 (control)
Energy (Wh)	272 366.51	261 930.00	249 008.04	245 049.59
Difference (Wh)	27 316.92	16 880.41	3958.45	–
(%)	11.15%	6.89%	1.62%	–
Average energy (Wh/month)	763.20	734.89	699.08	687.95
Mena standard deviation (Wh/month)	436.92	410.09	402.65	399.97

3.2. Influence of cleaning

Fig. 7 shows the monthly energy production averaged by pairs. In June, the distribution of the production is very similar for all four treatments due to the prior simultaneous start-up and exposure to the same external conditions. Then, from July to October, there is an evident difference between at least the monthly cleaning strategy and some other treatment. From November to May, the difference between groups in energy generation is not significant.

Table 6 lists the values of the Shapiro-Wilk normality test statistic and the corresponding significance. The significance is < 0.05 for all cases except P1–P5 (monthly) and P2–P6 (quarterly) in the month of October, so that the null hypothesis of normality must be rejected. Consequently, the daily energy production readings are not normally distributed.

Table 7 lists the results of the Kruskal-Wallis H test for each month under study, with three degrees of freedom. For July, the p-value is greater than 0.05, so that the hypothesis is accepted that there is no significant difference between the means of at least two samples for this first month of study. For August, September, and October, however, there do exist significant differences between cleaning protocols.

Despite no statistically significant difference between the treatments being detected for July, there is an evident difference in the distribution of the production data. This can be seen in the different sizes of the boxes in Fig. 7.

3.3. The Markov model of degradation

The transition matrix $[P]$ that minimizes the difference between what is observed and what is predicted by the Markov model is the following:

$$[P] = \begin{bmatrix} 0.451 & 0.386 & 0.163 \\ 0 & 0.706 & 0.294 \\ 0 & 0 & 1 \end{bmatrix}$$

One observes that $[P]$ reflects a gradual degradation, i.e., the probability that the PV panel passes to State 3 from being initially in State 2 is greater than the probability of its transition from State 1. This confirms the initial assumption of the suitability of applying Markov chains. The value of element P_{23} means that a PV panel has a 29.4% probability that, being in State 2, it will be found in an unacceptable state after one week. The transition diagram is shown in Fig. 8.

The chi-squared test yields a value of $\chi^2 = 2.67$, which is less than the 19.24 corresponding to a significance level of 0.01 and 36°

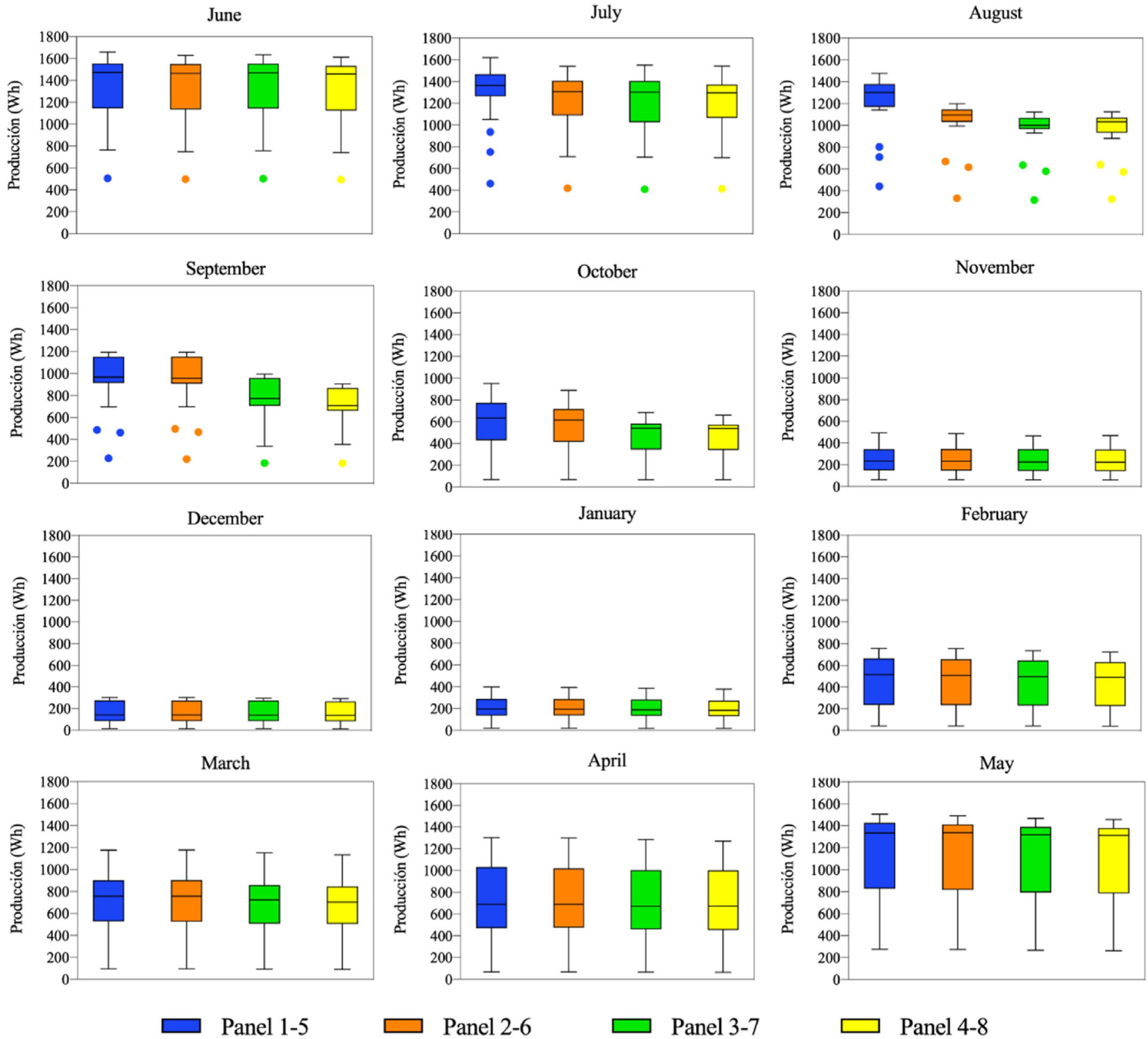

Fig. 7. Monthly electricity production averaged by pairs.

Table 6
Results of the Shapiro-Wilk test.

Group	P1–P5		P2–P6		P3–P7		P4–P8	
Month	Statistic	Sig.	Statistic	Sig.	Statistic	Sig.	Statistic	Sig.
July	0.838	$3\cdot10^{-4}$	0.899	$7\cdot10^{-3}$	0.909	0.01	0.894	0.005
August	0.780	$2\cdot10^{-5}$	0.652	$2\cdot10^{-7}$	0.656	$3\cdot10^{-7}$	0.711	$2\cdot10^{-6}$
September	0.820	$2\cdot10^{-4}$	0.828	$2\cdot10^{-4}$	0.865	0.01	0.861	0.01
October	0.942	0.106	0.931	0.053	0.838	$3\cdot10^{-4}$	0.835	$3\cdot10^{-4}$

of freedom. This therefore validates, at a 99% confidence level, the Markov model a predictor of the state of surface soiling of the PV panels over time.

Assuming that the maintenance is only performed once in a one-week period, the probabilities according to the Markov model that the PV panels will be found in States 1, 2, and 3 of degradation are given in Table 8.

One observes that, as the weeks pass, the probability that the condition of the PV panel is adequate (State 1) falls sharply. The unacceptable condition (State 3) grows over time, reaching a value of approximately 64.5% probability after one month. The probability of an inappropriate condition (State 2) increases up to the

Table 7
Results of Kruskal-Wallis test.

Month	Statistic	Sig.
July	5.530	0.137
August	54.132	0.000
September	38.289	0.000
October	12.228	0.007

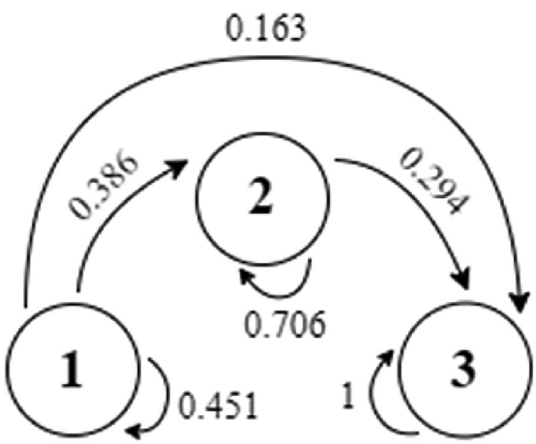

Fig. 8. Transition diagram according to the Markov model of the PV panels' soiling degradation.

Table 8
Probability of the PV panels being in the different states of degradation over time.

Week	Probability (%)			Reliability (%)
	State 1	State 2	State 3	
1	45.12	38.60	16.28	83.72
2	20.36	44.68	34.96	65.04
3	9.18	39.42	51.40	48.60
4	4.14	31.39	64.47	35.53

second week. From then on, the probability that it is in the unacceptable condition (State 3) is greater than that of it being in the first two states.

In accordance with Table 8, three weeks should be the periodicity of cleaning maintenance to ensure that the reliability of the PV panels is always above the reference characteristic life threshold (60%). This maintenance frequency is only necessary for the months of July to October.

3.4. Economic analysis

The relationship between the increase in revenue due to greater energy production and the cost of cleaning affects the decision on the periodicity of cleaning. In Appendix A, the monthly increase in electrical energy production is given for each maintenance schedule with respect to the control group. Fig. 9 shows the gain in revenue due to the increase in production from cleaning the PV panels for three different electricity sale prices.

The annual increase in revenue from the sale of surplus energy due to the cleaning program for three electricity sale prices has to be compared with the cost of cleaning. Taking into account that C_c is 2.71 €/kWp, the monthly cleaning program of a 100 kWp plant will be economically viable for all three energy sale prices proposed. In ascending order of sale price, the increases in revenue will be € 303.52, € 404.70, and € 505.87 €. For quarterly cleaning, the break-even point is 4.35 c€/kWh, so that it is unprofitable for the medium and low levels of energy prices for which the revenue from electricity sales would be € 187.56 and € 250.08, respectively. Semi-annual cleaning is unprofitable in all three cases, obtaining € 43.98, € 58.64 and € 73.30 for the sale of that electricity.

4. Discussion

It was found that regular cleaning not only improves energy production but will also minimize the risk of a hotspot effect occurring. It also avoids that any localized dirt might shade some of the series-connected PV cells which would then present a resistance obstructing the PV effect. If adequate preventive or corrective measures are not taken, these operating anomalies will end up accelerating the PV panel's deterioration [34].

To avoid deterioration of a PV panel's electronic circuits, an

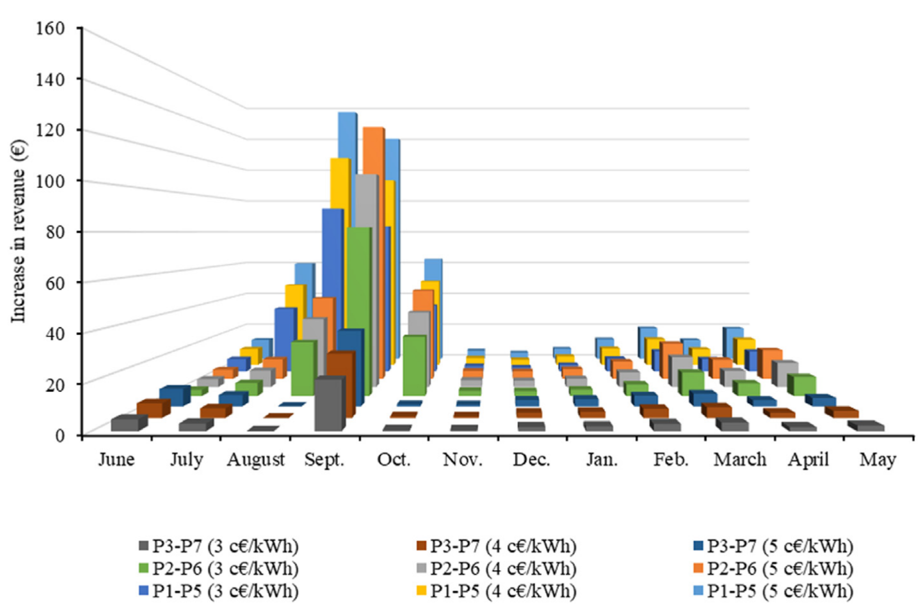

Fig. 9. Increase in revenue due to cleaning.

appropriate preventive measure is to install a bypass diode in parallel with each set of cells in series [35]. This, however, will increase the plant's investment costs [36]. A predictive system that, by balancing the parameters considered in this present work, determines when to undertake cleaning is a very useful tool. There is a trade-off between the cleaning costs and the decrease in energy production as a function of the deposited dirt, but it is also necessary to take into account the expectation of restorative rain. One cannot set a minimum rainfall level above which it will effectively perform proper cleaning. The results suggest that the intensity of rain, the amount of dirt accumulated, the time that it has been left deposited, and the inclination of the PV panel, among other factors, condition the cleaning capacity of rain. In addition, due to the use of small inclinations, building integration, which is increasingly being implemented, aggravates the problem of the build-up of dirt as well as of sludge when the dirt mixes with rainwater [37].

It was also found that cleaning every three weeks during the dry months ensures that the PV panels' reliability does not fall below 60%. This result is similar to that obtained by Jiang et al. [20], (although for a different latitude and longitude) who calculated the optimal periodicity in a desert climate to be every 20.7 days (i.e., every three weeks). In other research studies, the optimal periodicity was estimated to be a cleaning schedule of every 15 days [27]. The slight difference in those results is because the experiments were contextualized in quite different environments. Nonetheless, they are of the same order of magnitude, indicative of the consistency of the values (Table 9).

Trusting that the rain has restorative power to clean the surface of the PV panel is an alternative strategy that has been addressed in the literature [38]. Applying a preventive coating avoids the deposition of particles and facilitates their removal by rainwater [39]. In southwestern Spain however, rain is not abundant [40]. The use of surfactant products can increase production, but it also raises the cost of the materials needed for cleaning [41]. Installing cleaning devices can enhance the effectiveness of maintenance, but at the cost of substantially increased investment and hence a longer payback period for the installation.

Brushing the dust off the glass will improve its transmittance relative to the non-brushed state. But the cleaning efficiency of nylon brushes is less than that of cleaning with water and cloths of delicate fabrics. The surface of samples of glass showed some changes after being brushed with different mechanisms and materials [42], but it was shown that there was no permanent effect on the glass's optical characteristics after the simulated equivalent of 20 years of cleaning.

Since utility-scale solar plants cover large areas, different zones of the solar field will become soiled differently [43]. It was found that the Markov model is capable of modelling this behaviour and of planning maintenance tasks [44] by dividing the installation into sectors according to the evolution of the deposition of dirt.

Carrying out a specific economic analysis is a limitation to the extrapolation of the present results. Nonetheless, the Markov degradation model is easily up-datable and adaptable to the characteristics of any solar installation to establish the cost-effectiveness of maintenance tasks. Consequently, the forecasting model that we have developed is applicable to PV plants that differ in location, technology, arrangement of collector elements, etc.

This study is of interest for PV plant operation and maintenance (O&M) managers since it will allow them to increase energy production by reducing OPEX, which in turn will lead to a more competitive LCOE. Future work should be aimed at comparing the effectiveness of cleaning with distilled water or with a product that is a mix of anionic and cationic surfactants.

5. Conclusions

The cleaning plans that were tested increased electricity production by from 1.62% (semi-annual plan) to 11.15% (monthly plan) relative to the control group after one year of experimentation. For the months from July to October in particular, the increased production ranged from 2.14% (semi-annual plan) to 21.85% (monthly plan).

In September, the monthly cleaning led to an increase of 35.25% due to the accumulation of dust on the control group and the lack of summer rain. Nonetheless, the rainy season that followed (November–February) reduced the production increases to an average of 4.59% for the monthly plan, 3.98% for the quarterly plan, and 2.13% for the semi-annual plan.

It was also found that rain does not always have any restorative power. Specific conditions of rainfall intensity and duration must come together to produce the desired positive effect on the state of soiling of the glass. In such a situation, rain can be as effective as manual cleaning.

The Markov model that was developed allows one to infer the optimal periodicity of preventive maintenance of the PV panels. The model of the evolution of the PV panels' degradation was obtained from weekly visual inspections and continuous monitoring of electricity output over a year. It was concluded that, to optimize electricity production, from July to October cleaning should be monthly. Nonetheless, during the rest of the year, i.e., the seasons with the greatest probability of rain (November–February) and with occasional rains (March–June), there is no significant improvement in production.

This new knowledge was applied to a 100 kWp plant to quantify what the improvements would be on an industrial scale. A cost-effectiveness analysis showed monthly cleaning to be profitable and semi-annual cleaning to be economically inviable. A threshold for profitability of the quarterly cleaning plan was estimated based on the unit cost of energy production.

CRediT authorship contribution statement

Gonzalo Sánchez-Barroso: Investigation, Data curation, Writing – original draft, preparation. **Jaime González-Domínguez:** Investigation, Software, Visualization, Writing – original draft, preparation. **Justo García-Sanz-Calcedo:** Investigation, Conceptualization, Methodology, Supervision. **Joaquín García Sanz:** Investigation, Validation.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A

Table 9
Increased revenue from increased electricity production for each cleaning programme

Month	E_1 (P1-P5)	E_a (P4-P8)	E_1-E_a	Scaled to 100 kWp plant	5 c€/kWh	4 c€/kWh	3 c€/kWh
June	37,706.47	37,063.06	643.41	238,300.00	11.91 €	9.53 €	7.15 €
July	40,838.25	37,606.41	3,231.84	1,196,977.78	59.85 €	47.88 €	35.91 €
Aug.	38,476.51	30,086.37	8,390.14	3,107,459.26	155.37 €	124.30 €	93.22 €
Sept.	28,713.56	21,230.58	7,482.98	2,771,474.07	138.57 €	110.86 €	83.14 €
Oct.	17,386.13	14,003.46	3,382.67	1,252,840.74	62.64 €	50.11 €	37.59 €
Nov.	7,551.37	7,273.62	277.75	102,870.37	5.14 €	4.11 €	3.09 €
Dec.	5,441.81	5,235.56	206.25	76,388.89	3.82 €	3.06 €	2.29 €
Jan.	6,583.98	6,245.40	338.58	125,400.00	6.27 €	5.02 €	3.76 €
Feb.	13,466.35	12,804.85	661.50	245,000.00	12.25 €	9.80 €	7.35 €
Mar.	19,901.63	18,863.78	1,037.85	384,388.89	19.22 €	15.38 €	11.53 €
Apr.	21,783.54	21,148.78	634.76	235,096.30	11.75 €	9.40 €	7.05 €
May	34,516.91	33,487.72	1,029.19	381,181.48	19.06 €	15.25 €	11.44 €
Total	*272,366.51*	*245,049.59*	*27,316.92*	*10,117,377.78*	*505.87 €*	*404.70 €*	*303.52 €*
Month	E_2 (P2-P6)	E_a (P4-P8)	E_2-E_a	Scaled to 100 kWplant	5 c€/kWh	4 c€/kWh	3 c€/kWh
June	37,333.42	37,063.06	270.36	100,133.33	5.01 €	4.01 €	3.00 €
July	38,179.21	37,606.41	572.80	212,148.15	10.61 €	8.49 €	6.36 €
Aug.	32,450.96	30,086.37	2,364.59	875,774.07	43.79 €	35.03 €	26.27 €
Sept.	28,627.18	21,230.58	7,396.60	2,739,481.48	136.97 €	109.58 €	82.18 €
Oct.	16,595.71	14,003.46	2,592.25	960,092.59	48.00 €	38.40 €	28.80 €
Nov.	7,505.85	7,273.62	232.23	86,011.11	4.30 €	3.44 €	2.58 €
Dec.	5,455.04	5,235.56	219.48	81,288.89	4.06 €	3.25 €	2.44 €
Jan.	6,529.86	6,245.40	284.46	105,355.56	5.27 €	4.21 €	3.16 €
Feb.	13,313.66	12,804.85	508.81	188,448.15	9.42 €	7.54 €	5.65 €
Mar.	19,900.17	18,863.78	1,036.39	383,848.15	19.19 €	15.35 €	11.52 €
Apr.	21,709.28	21,148.78	560.50	207,592.59	10.38 €	8.30 €	6.23 €
May	34,329.66	33,487.72	841.94	311,829.63	15.59 €	12.47 €	9.35 €
Total	*261,930.00*	*245,049.59*	*16,880.41*	*6,252,003.70*	*312.60 €*	*250.08 €*	*187.56 €*
Month	E_3 (P3-P7)	E_a (P4-P8)	E_2-E_a	Scaled to 100 kWp plant	5 c€/kWh	4 c€/kWh	3 c€/kWh
June	37,496.17	37,063.06	433.11	160,411.11	8.02 €	6.42 €	4.81 €
July	37,888.78	37,606.41	282.37	104,581.48	5.23 €	4.18 €	3.14 €
Aug.	30,091.98	30,086.37	5.61	2,077.78	0.10 €	0.08 €	0.06 €
Sept.	23,098.82	21,230.58	1,868.24	691,940.74	34.60 €	27.68 €	20.76 €
Oct.	14,049.58	14,003.46	46.12	17,081.48	0.85 €	0.68 €	0.51 €
Nov.	7,315.60	7,273.62	41.98	15,548.15	0.78 €	0.62 €	0.47 €
Dec.	5,392.41	5,235.56	156.85	58,092.59	2.90 €	2.32 €	1.74 €
Jan.	6,425.30	6,245.40	179.90	66,629.63	3.33 €	2.67 €	2.00 €
Feb.	13,071.25	12,804.85	266.40	98,666.67	4.93 €	3.95 €	2.96 €
Mar.	19,178.03	18,863.78	314.25	116,388.89	5.82 €	4.66 €	3.49 €
Apr.	21,302.14	21,148.78	153.36	56,800.00	2.84 €	2.27 €	1.70 €
May	33,697.98	33,487.72	210.26	77,874.07	3.89 €	3.11 €	2.34 €
Total	*249,008.04*	*245,049.59*	*3,958.45*	*1,466,092.59*	*73.30 €*	*58.64 €*	*43.98 €*

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