Design of a Cleaning Program for a PV Plant Based on Analysis of Energy Losses

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***Abstract*—Solar photovoltaic (PV) energy has grown significantly over the past few years. However, despite the increase in installed capacity, this energy source still raises important concerns related to the variability of power production. The short-term effects such as cloud shadowing and supply interruptions, as well as long-term effects such as dust accumulation, seasonal variation, and ageing of PV modules, can cause variability of power production. Therefore, the analysis of all the variability sources in order to provide statistically consistent power production data is an important challenge. This study presents a methodology to analyze data from a PV plant in order to have an independent evaluation of the different effects of variability, identifying dust deposition, and proposing a cost-based optimal cleaning program for a PV plant installed in the northern region of Chile.**

***Index Terms*—Digital signal processing, environmental factors, photovoltaic (PV) systems.**

I. Introduction

ENVIRONMENTAL concerns and the increase of energy consumption have increased the acceptance of photovoltaic (PV) energy, as well as other renewable energy technologies, as an alternative way of maintaining and improving living standards [1]. In order to continue the fast growth rate and acceptance of solar energy, it is necessary to improve the reliability and predictability of this energy source, identifying short-term variability, with a period shorter than one day [2], and long-term variability, which can have a period of several days, months or even years [3]. It has been proven that short-term and long-term variabilities impact negatively the performance of the PV plant, but using information about these sources of variability, it is possible to improve the overall performance [4]–[6].

There are a number of environmental factors that can reduce the power production in PV systems. The soiling is one problem that can occur due to dust, sand, or snow. Among these factors, the dust accumulation on the panel surface is one of the most important [7]. The impact of the dust can be measured as a progressive reduction of the power over time due to the shadowing effect that it produces [8]. This effect changes depending on the type of dust [9], panel technologies, and environmental conditions such as wind and rain [10]. The same way, it depends on module mounting mechanisms, and the orientation affects the distribution of soiling on the surface of the PV panel [11]. Moreover, the analysis of energy lost due to soiling is dependent on the geographical location of the PV plant [12].

Within maintenance tasks of the PV plants, one of the less studied is the cleaning of the panel surface, which is usually not well scheduled [13]. Several methods to deal with the variability of power production of PV power plants have been proposed in the literature. The simplest approach is to define several performance factors, which depend on measurements and constructive data. These quality factors are applied over the data of the PV plant in order to obtain the range in which the produced power could vary [14]. This approach uses actual data of the PV plant, but it does not consider different sources of variability. On the other hand, it is possible to obtain an accurate prediction of the power variability based on the analysis of satellite observations [15], which takes into consideration the local geography and could also use weather forecasts to further adjust the results.

A statistical energy-based analysis has been proposed in order to supervise and monitor the PV plant [16]. However, the main drawback is that it only takes care of the long-term variations without using a model for the seasonal changes of production. Finally, an economical analysis has been performed in the literature, taking into account some parameters like the PV construction materials [17]. However, this method does not evaluate the effect of soiling in the power production, and it does not try to come up with an optimal cleaning schedule.

In this paper, a methodology to obtain statistically consistent information and its associated variability of a PV plant is proposed. The method is based on the correlation of measurements of power production data with an ideal model, and it attempts to obtain the decreasing slope of energy production due to soiling of the panels. The final goal is to assist cleaning programs for the studied plant, trying to maximize the power production and to minimize environmental impacts of cleaning. Moreover, it could allow quantification of payback time if the installation costs of PV plant are available.

II. Photovoltaic Plant Description and Variability Classification

The PV plant to be evaluated is located in the north region of Chile, near the city of Copiapó. The WGS84 geographical

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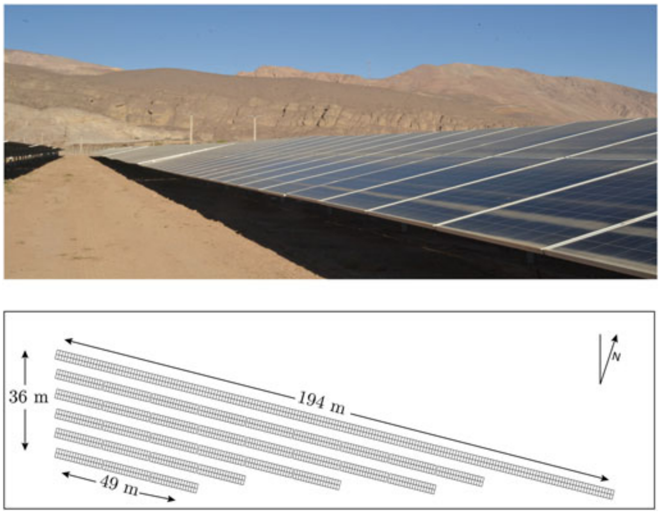

Fig. 1. Solar PV plant studied in this paper and the panel distribution.

TABLE I
PV PLANT PARAMETERS

Variable	Parameter	Value
P_{pv}	PV module peak power	240 [W]
V_{mpp}	Voltage at maximum power point	29.9 [V]
I_{mpp}	Current at maximum power point	8.03 [A]
P_n	Nominal installed power	310 [KW]
G_{stc}	Solar irradiance at STC	1000 [W/m^2]
T_{stc}	Temperature at STC	25 [°C]

coordinates of the site are (lat: -27.7347, lon: -70.1911). The location is a narrow valley surrounded by steep mountains as shown in Fig. 1, which reduces the direct irradiation during the sunrise and sunset. The PV modules have been installed facing north with a slope of 30°, without a tracking system. The data were recorded using a three-phase power quality and energy analyzer (Fluke 430 Series II). The accuracy of the instrument is $\pm 1\%$. The data were recorded within an interval of 1 min, and the digital signal processing was made using MATLAB software.

The modules are distributed in six strings of panels, each one with its own MPPT system provided by a dc–dc converter connected between each string and the main dc link. The plant is connected to the medium-voltage grid through a main inverter fed by the dc-link and a step-up transformer. The PV plant parameters are listed in Table I. The nominal values are used as base values for the results shown in the following sections.

One of the problems for the installation of PV plants in this geographical region is the proximity to mining facilities. Therefore, the dust accumulation represents an important problem in the modules as shown in Fig. 2. This dust accumulation directly affects the power production reducing the extracted power, and taking into account the environmental concerns, the analysis is important because there is a restricted amount of water available for the cleaning process.

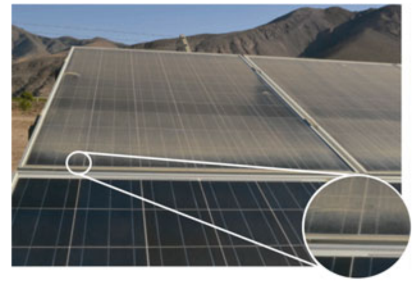

Fig. 2. Solar PV plant studied in this paper; the soiling view is amplified.

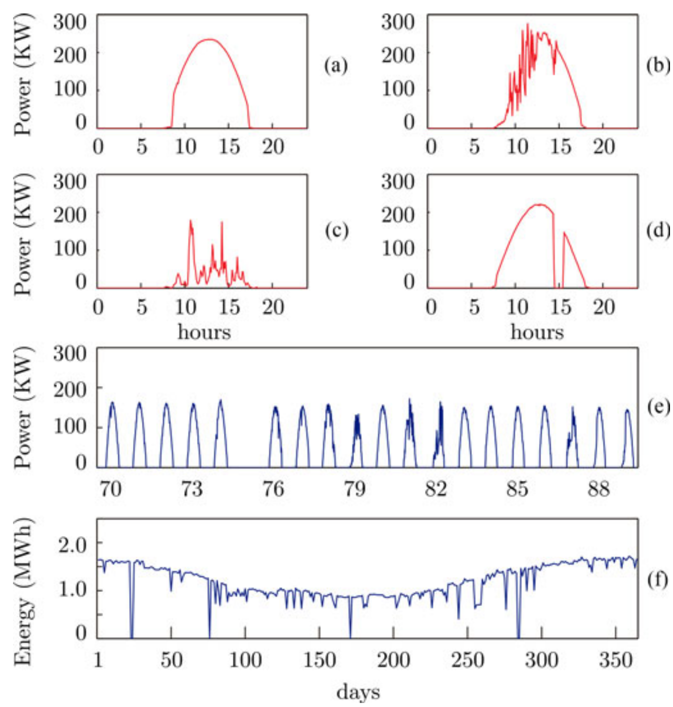

Fig. 3. Variability presented in a PV system. (a) Clear sky day production. (b) Light cloud effect. (c) Strong cloud effect. (d) Communication failure. (e) Major fault in the PV plant. (f) Seasonal variation.

A. *Classification of Variability Types in Photovoltaic Power Production*

The different types of variability of PV power production can be classified either by source, depending if they are produced by environmental conditions, or by duration, if the duration could last a few hours or even several months.

Fig. 3 shows different types of variability, which were obtained from the recorded power in the PV plant in the year 2014. Fig. 3(a) shows the clear sky day production during one time frame of 24 h. It is possible to notice, at sunset and sunrise, the shadowing effect caused by the surrounding mountains. Fig. 3(b) and (c) shows the power produced in cloudy days, which could vary depending on the amount and thickness of clouds and duration of the shading. Fig. 3(d) shows a failure in the communication link between the sensor and the data logger, causing a lack of information. This variability is not related to

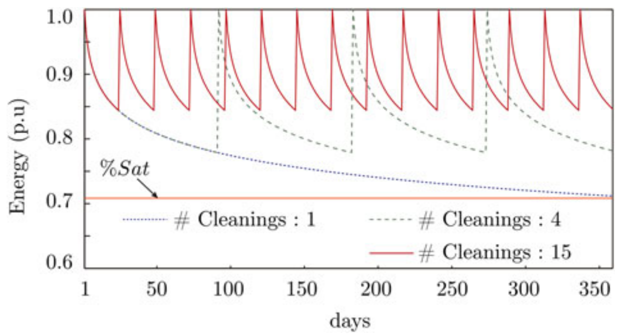

Fig. 4. Effect in the produced energy depending on different number of cleanings in one year.

production; however, it affects the analysis. The three previous conditions can be classified as short-term variations.

In Fig. 3(e), a gap in day 75 is shown, which was caused by an interruption in communication. Finally, Fig. 3(f) shows the energy generated in the whole year, where the seasonal variability can be clearly identified. These two last types of variation are considered as long-term variations.

III. Soiling Effects and Cleaning Program in Photovoltaic Plants

One of the most important factors that can be controlled during the life of a PV plant is the energy losses due to soiling. It affects the power production and the reliability of the system [7] and is mainly caused by dust accumulation on the surface of the panels.

Due to the high investment cost of a PV plant installation, it is necessary to consider an accurate prediction of the plant efficiency and the maintenance costs, in order to schedule an efficient cleaning program and to quantify the payback time. At some locations, cleaning can be quite expensive due to poor water availability and high air pollution; hence, cleaning program must be reduced due to environmental regulations [18].

In order to show the effect of the cleaning in PV panels, it is assumed that each cleaning process attempts to remove all dust, but with time progression, dust tends to stain the glass and be more and more difficult to be removed. Since the plant is new, the assumption is considered valid for the proposed analysis. Therefore, the performance of the plant after the cleaning is the same as without soiling effect, making it possible to compare the energy production, while the number of cleaning cycles increases.

Fig. 4 shows a schematic effect of different cleaning schedules of the PV panels. As shown in the figure, when the PV panels are not cleaned, the energy production is considerably reduced along the year, but as the number of cleanings increases, the yearly produced energy also grows.

It is possible to notice that the reduction is limited by a coefficient of saturation ($\%Sat$), which directly depends on the type of dust. The coefficient shown in the figure is an empirically value obtained at the installed PV plant. Its value will change, depending on the atmospheric conditions in the location of the PV plant, but it does not reach zero with dust accumulation. The complete snow accumulation is the only one that can seize the power production completely, when the snow cover is thick enough to block the sunlight [19].

Using the information about the economical cost associated with energy losses and the cost of the cleaning process, it is possible to program a cleaning schedule, optimizing overall operating costs.

IV. Analysis of the Photovoltaic Power Data

In this section, the proposed methodology to analyze and process the data from the studied PV plant is described. The methodology is based on the comparison between the real data, recorded at a PV plant, and an ideal model of produced power [20]. The schematic diagram of the proposed methodology is shown in Fig. 5. It could be summarized in the following way.

1) Record the power data at a PV plant.
2) Obtain an ideal model of the produced power in the geographic location where the PV plant is installed.
3) Divide the real data and the ideal data into daily frames as can be seen in Fig. 5(a). Each daily frame will be used in the following algorithms until they are finally combined to represent the whole year.
4) Filter out the empty frames caused by long-term system failures using the algorithm shown in Fig. 5(b). This step is necessary to allow calculation of meaningful daily energy values.
5) Filter out the frames affected by stationary atmospheric conditions using the algorithm shown in Fig. 5(c). This step is necessary to allow the calculation of the mean value of the power of either cloudy or total rainy daily frames.
6) Filter out the frames affected by short-term system failures and temporary atmospheric conditions using the algorithm shown in Fig. 5(d). It is necessary to calculate the standard deviation of the power of each daily frame to filter out those with extra variation due to clouds.
7) Fill the missing data and reconstruct the PV power data.
8) Filter the seasonal variability and extract the effect of dust using an adaptive filter. In Fig. 5(e), it is possible to notice that the input signals of the real and ideal energy are implemented in the algorithm, and therefore, the daily power amounts need to be integrated.
9) Obtain the functions of the decrease of energy caused by the dust accumulation, as shown in Fig. 5(f).
10) Evaluate the economical losses due to the dust accumulation and compare them to the cleaning costs in order to obtain the optimal cleaning program, as shown in Fig. 5(g).

A. *Ideal Model of Irradiance Based on Geographic Information*

In order to obtain a more accurate ideal solar irradiance model, that is consistent with the data of the studied PV plant, a global digital elevation model (GDEM) [21] was used as the input

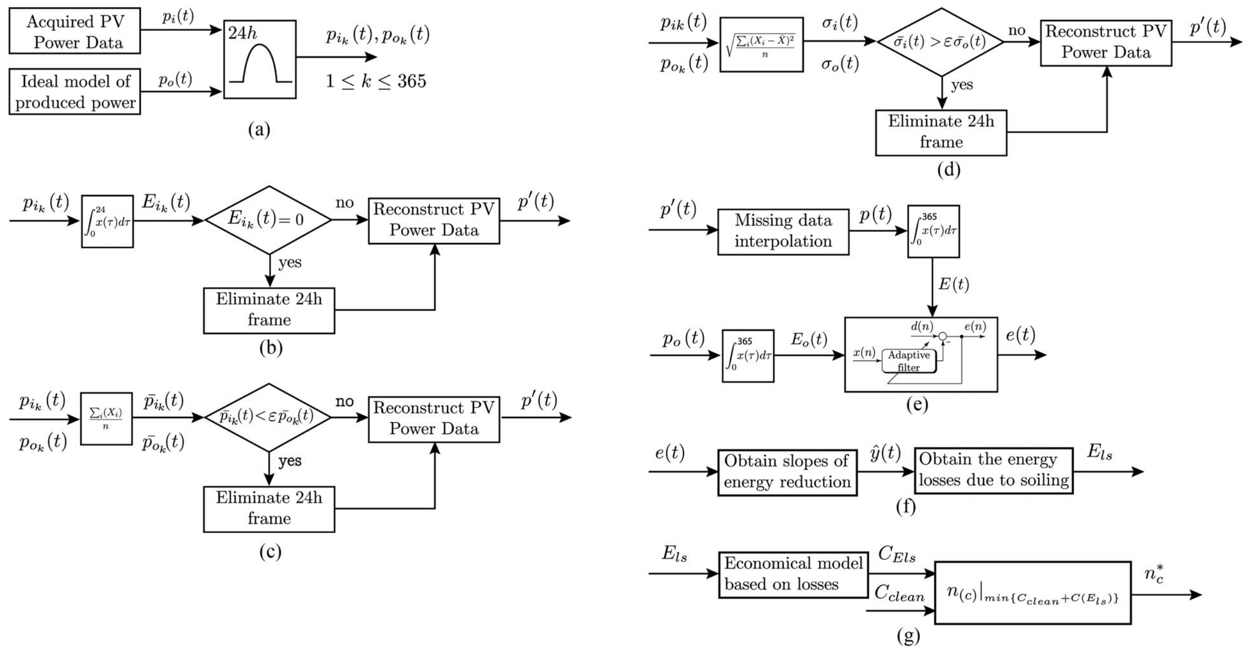

Fig. 5. Flowchart of the filtering stages. (a) Data separation in frames of 24 h. (b) Filtering of long-term failures. (c) Filtering of stationary atmospheric conditions. (d) Filtering of temporary atmospheric conditions and short-term failures. (e) Filtering of seasonal variability. (f) Obtaining energy losses due to soiling. (g) Obtaining optimal cleaning program.

raster in calculating the solar irradiance. Estimation was done with a software based on Point Solar Radiation tool in ArcGIS v10.2 (ESRI, Redlands, CA) Spatial Analyst Extension. ASTER GDEM 2 tile S28W071 (size $1^\circ \times 1^\circ$) covers the power plant Subsole area including all surrounding mountains. It has an estimated vertical accuracy root-mean-square deviation of 8.68 m [22] and 1 arc-second spatial resolution (pixel size is less than 30 m $\times$ 30 m on the ground). Solar Power Plant Subsole center location with (lat: -27.7347, lon: -70.1911) was used as the solar irradiance estimation point. Original DEM was converted to metric coordinates (*WGS_1984_UTM_Zone_19S*) and 10 m $\times$ 10 m resolution by interpolating the elevation values of the original decimal degree file.

In Fig. 6, the results of the ideal model are shown. Fig. 6(a) shows the ideal daily solar irradiance curves for the whole year. The effect of the surrounding mountains is shown mainly at the time of sunrise, where a small amount of power is lost. Fig. 6(b) shows the resulting viewshed for a specific day of the year. It characterizes whether the sun at certain sky direction is visible, as shown inside the circle, or obstructed, as shown in black. The dashed line shows the trajectory of the sun in that specific day.

Fig. 6(c) shows the seasonal variation of the solar irradiance for the whole year.

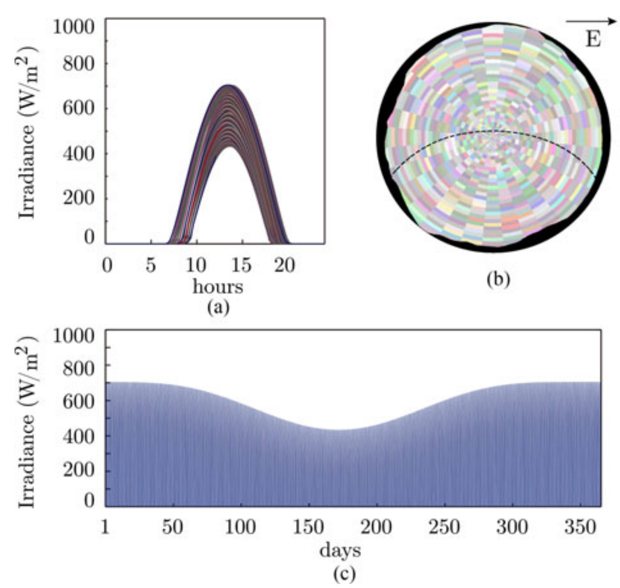

Fig. 6. Ideal model of solar irradiance based on geographic information system. (a) Daily irradiance during the year. (b) Resultant viewshed of the evaluated area. (c) Seasonal variation of irradiance during the year.

B. Irradiance/Temperature-Based Ideal Model

This model is based on information obtained directly from the standard test condition (STC) PV module data and data of irradiance and temperature. The following equation expresses the obtained power [23]:

$$p_o = \frac{G}{1000[\mathrm{W/m^2}]} \cdot P_{\mathrm{STC}} \cdot (1 - \beta_p(T_c - T_{\mathrm{STC}})) \tag{1}$$

where p_o is the power output, G is the solar irradiance, P_{STC} is the nominal power of PV module at standard condition, β_p is the solar cell power temperature coefficient, and T_{STC} is the temperature of solar cell at standard condition. T_c is the solar cell temperature, which is calculated using the normal operating cell temperature, the relation between the measured irradiance G and hemispherical solar irradiance defined as a constant [24], being expressed in the following equation:

$$T_c = T_a + (T_{\mathrm{NOCT}} - 20\,^\circ\mathrm{C}) \cdot \frac{G}{800[\mathrm{W/m^2}]} \tag{2}$$

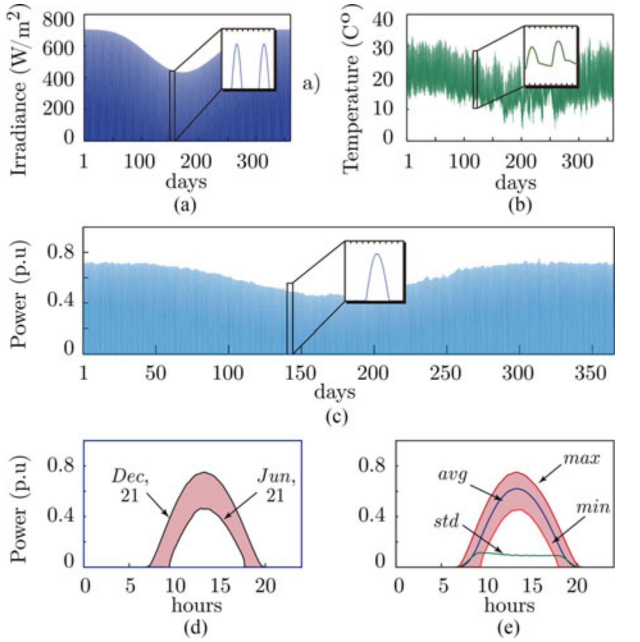

Fig. 7. Ideal power production model. (a) Solar irradiance data. (b) Temperature information. (c) Ideal power production. (d) Summer and winter ideal power. (e) Maximum, minimum, average, and standard deviation of the power.

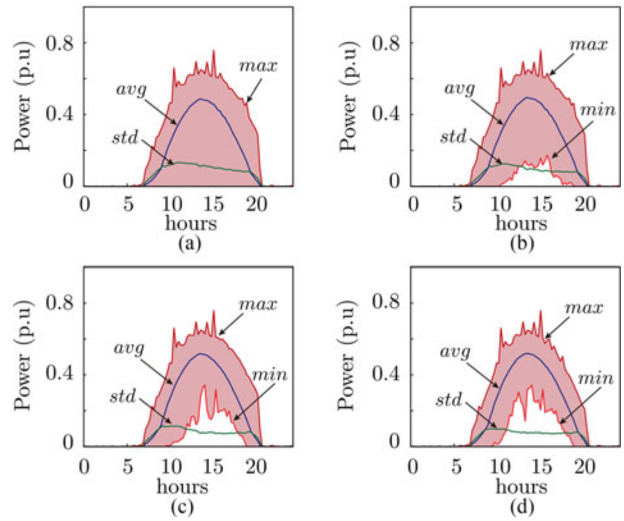

Fig. 8. Progressive filtering of PV data. (a) Original data. (b) Without effect of long-term failures. (c) Without effect of stationary atmospheric conditions. (d) Without effect of temporary atmospheric conditions and short-term failures.

where T_a is the ambient temperature, and T_{NOCT} is the normal operation cell temperature.

The irradiance and temperature data are shown in Fig. 7(a) and (b), respectively. Fig. 7(c) shows the ideal power waveform, and it is possible to notice the resemblance with the irradiance waveform, and the examples of daily generated power at summer and winter solstices are shown in Fig. 7(d). Fig. 7(e) shows the maximum, minimum, average, and standard deviation of filtered recorded data.

C. Analysis of Production Loss due to Long-Term Failures

The filtering process starts separating the data of produced power in frames of 24 h as shown in Fig. 5(a). Fig. 8(a) shows these data, and the minimum, maximum, average, and standard deviation are identified. The first step of filtering is the removing of long-term failures, which produce zero output power information for one or several days as shown in Fig. 3(e). To remove the long-term failure information, the power in each frame of 24 h is integrated, and if the resulting energy is zero, the complete frame is eliminated. The implemented algorithm is shown in Fig. 5(b). Fig. 8(b) shows the result of this filtering process, where the increase of the average value can be seen. It can be noted that the standard deviation is reduced but not at the ideal power level. However, as the minimum value is not zero, it is possible to see that the frames that have no information were properly eliminated.

D. Analysis of Production Loss due to Stationary Atmospheric Conditions

The stationary atmospheric conditions refer to a condition which lasts the whole day, generating a very small amount of power. It could be either a completely cloudy day or a total rainy day. In order to eliminate this variation from the data, the frames with an average value lower than an empirically chosen threshold (ε) from the ideal power production are removed from the analysis. Fig. 8(c) shows the result of this filtering process. There, it can be seen that the average value is increased, the ratio between the average and the maximum value is similar to the ideal waveform, and the standard deviation is reduced but not yet at the ideal power level.

E. Analysis of Temporary Atmospheric Conditions and Short-Term Failures

The temporary atmospheric conditions refer to situations when a group of clouds passes over the PV plant. The short-term failures, as shown in Fig. 3(d), also reduce the generated power in a short period of time.

It is not possible to filter these conditions using the average value of the frame because the effect can be comparable with the effects of seasonal variations or soiling of the panels. Instead, noticing that the standard deviation of both conditions is high, it is possible to eliminate this variability calculating the standard deviation of each frame and comparing the result with a given limit based on the ideal standard deviation. If the frame has a higher standard deviation than the limit, the entire frame is removed.

The result of this filtering process is shown in Fig. 8(d), where it is possible to notice that its statistical descriptors are similar to the ideal power waveform shown in Fig. 7(e), in terms of the ratio between average and maximum values, as well as the standard deviation.

F. Missing Data Interpolation

After the previous processing stage, the filtered data have statistically consistent information that correspond to the ideal

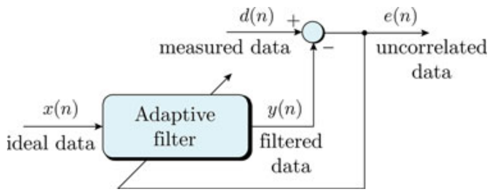

Fig. 9. Adaptive filter implemented to extract the seasonal variability.

theoretical models in terms of 24 h frames. However, there are a number of missing frames along the year that have been filtered out. The filtered days due to long-term failures correspond to 1.09% of the data, the filtered days due to stationary-atmospheric conditions correspond to 1.92% of the data, the filtered days due to temporary-atmospheric conditions correspond to 3.01% of the data. The total filtered data correspond to 6.02% of the data. There are many strategies in order to fill the missing data, such as, leave in blank the missing information after filter process and draw a linear fit between missing days [25], the replacement with historical data, or with average values [26].

To obtain a suitable model for long-term effects analysis, frames corresponding to the sinusoidal ideal power production are inserted in order to fill the gaps of power along the year. The amplitude of each one of these frames must be consistent with the normalized amplitude of the ideal model in the corresponding period of the year.

G. Analysis of Seasonal Variability

After the previous filtering process, only the long-term variability features are preserved. In order to separate the data correlated with seasonal variability, an adaptive digital filter is implemented as shown in Fig. 9.

The output of the filter *y(n)* is subtracted from the PV plant energy data *d(n)*, obtaining the error signal *e(n)*. The adaptive coefficients change in order to converge the error signal to zero. Once the filtering process is done, the error signal represents the uncorrelated data; hence, it will contain the nonperiodic features of the energy production.

This filter could be implemented to cancel noise in a signal [27]. However, it is also possible to use the filter in order to determine the error when the ideal reference is known.

The results of filtering process are shown in Fig. 10. In Fig. 10(a), the yearly energy obtained from the PV plant after the interpolation method is shown. In Fig. 10(b), the normalized ideal energy is shown. Finally, in Fig. 10(c) and (d), the noncorrelated signals are shown.

H. Analysis of Nonperiodic Long-Term Characteristics

The results of the previous adaptive filtering process are shown in Fig. 10(c) and (d). It will give the amount of energy that is not correlated with seasonal variability $e(n)$. Therefore, it will have information about the energy losses produced by long-term disturbances such as dust accumulation and ageing of PV modules. Assuming that the energy losses produced by degradation of the PV panels at beginning of year is not significant

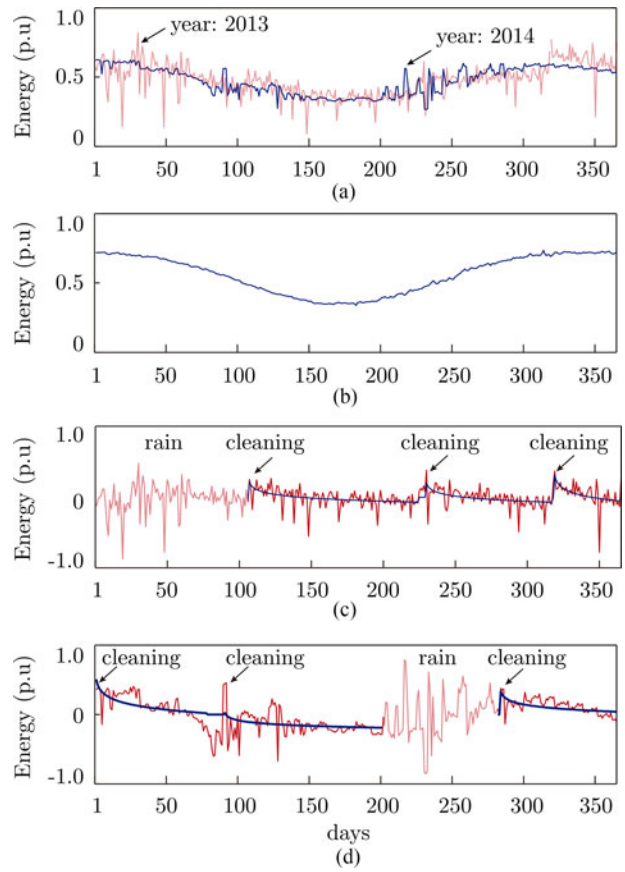

Fig. 10. Adaptive filtering of PV data. (a) Real energy. (b) Ideal energy. (c) Noncorrelated signals in the year 2013. (d) Noncorrelated signals in the year 2014.

[28], [29], the effect will not be considered in the proposed analysis. Therefore, the resulting energy will have only information related to dust accumulation and other long-term atmospheric conditions like wind and rain effects.

Using the cleaning cycles made in the year, it is possible to quantify the energy reduction, which show a decreasing amount of energy from a maximum value.

According to Fig. 10, in 2013, there were more periodical cleanings due to the rain which occurred mainly at the beginning of the year, as can be seen in Fig. 10(c). Moreover, in this year, other studies were made in this PV plant, and it was necessary to clean the panels on days 105, 230, and 325, which are highlighted in the continuous line.

In 2014, as can be seen in Fig. 10(d), there were some cleanings during the year and some rainy days especially in winter. However, there were three important cleanings at the beginning of the year, on days 91 and 284.

The information about dust accumulation obtained by implementing this method and by studying power losses can be used to design an optimal cleaning schedule.

V. Design of the Proposed Cleaning Program

The results of the previous process give information about the decreasing trend of the energy due to the dust accumulation. It is possible to determine a trend curve that fits the values in order to obtain a function in time domain that represents the decay of power produced in the year. This function has the form:

$$y(t) = a \cdot \ln(t) + b \quad 1 \leq t \leq 365, \quad t\epsilon\mathbb{N}. \tag{3}$$

With each decreasing curve, the different equations are calculated; the value t varies, depending on the number of days that last on decrease the energy. By using linear regression models, it is possible to find the coefficients a and b, in order to obtain the decreasing energy curve.

The results are shown in Fig. 10(c) and (d) as continuous lines. Due to the fact that obtained curves have a small deviation between them, caused by random measurement errors. Moreover, the model curves can be represented by a probability density function, and they depend on an aleatory variable. Hence, it is possible to define a function based on probabilistic analysis related to choosing global trend for whole 2013 and 2014. Therefore, to determine the trend function, it is necessary to obtain the first moment for a random variable, where X is an aleatory variable, $Y = h(X)$, and the probabilistic density function $p_X(x)$ is defined; therefore

$$E(Y) = \sum_{j=1}^{\infty} h(x_j) p_X(x_j). \tag{4}$$

However, a good approximation of the first moment in discrete time domain is the mean value [27]. Moreover, if random soiling events occurred during the years and they followed a normal distribution, then the utilization of averages values is justified

$$\bar{y}(t) = \bar{a} \cdot \ln(t) + \bar{b}. \tag{5}$$

With this trend function, the following step is the determination of the optimal cleaning program.

The first goal is to define the energy losses function E_{ls}. It could be done by subtracting the decreasing energy function $\bar{y}(t)$, related to terms of the cleaning cycles n_c instead of days t, from the nominal energy produced over the entire year without dust accumulation

$$E_{ls} = E_n - \bar{y}(n_c) \quad 1 \leq n_c \leq 365 \quad n_c = \frac{365}{t}. \tag{6}$$

In the economical analysis, it is necessary to compare energy losses with the costs of the PV plant cleaning. Assuming that the costs of cleaning increase linearly with the number of cleaning cycles, a function C_{clean} can be defined, and the function of economical costs based on energy losses is represented as $C(E_{ls})$. The optimal cleaning schedule is defined as n_c^*, and the ideal cleaning cycle is obtained looking for the n_c value that minimizes the sum of both economic costs

$$n_c^* = n_c|_{\min\{C_{\text{clean}} + C(E_{ls})\}}. \tag{7}$$

In order to validate the methodology at this PV plant, the following economical costs are given: The energy cost per KWh

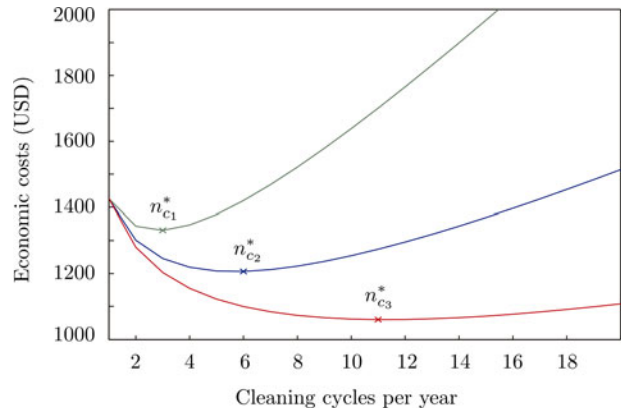

Fig. 11. Optimal cleaning program based on costs of maintenance and the cost of energy loss.

is 0.20 USD, and the cleaning costs per plant of 1.0 KW of installed energy are 15, 10, and 7.5 USD, depending on the technology of cleaning process. The method that only uses water for the cleaning process costs 7.5 USD, and it is higher than the other one because this is an arid location.

In Fig. 11, three cleaning functions are shown; these functions represent the sum of both economic costs. The most expensive cleaning program is represented by n_{c_1} and the cheaper is represented by n_{c_3}. The optimal cleaning program will depend on economical losses due to energy reduction and the costs of the PV plant cleaning. Therefore, depending on each economical costs, the optimal $n_{(c)}^*$ values are 3, 6, and 11, respectively. The result shows that when the cleaning process is more expensive, the optimal number of cleaning cycles decreases. Moreover, by using the obtained results and with information about installation costs of the PV plant, it could allow quantification of payback time.

VI. Conclusion

An optimal cleaning program methodology, based on the cost associated with energy losses and cleaning process, has been developed in this study. The program uses information recorded at a plant located in Chile, the collected power depends directly on the dust accumulation over the surface of the panels at this location. A methodology to obtain statistically consistent information from generated PV power data, based on the correlation of the obtained data from the real PV plant, and the ideal PV power obtained from a model based on geographical data, has been used to develop a model of the cumulative losses. Results show that the PV plant behavior can be accurately modeled implementing the proposed approach, and by using the functions of the decrease of energy, it is possible to schedule an optimal cleaning program.

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