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A new trade-off approach to photovoltaic power smoothing

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ABSTRACT

Renewable energy sources, such as grid-connected photovoltaic systems, present a challenge due to the intermittent nature of solar irradiance. In this research, the authors have suggested an approach for irradiance profile smoothing based on different sample sizes of measurements. The analysis has been performed using experimental measurements based on the irradiance and temperature of the series smart pyranometers (SMP3) pyranometer manufactured by Kipp & Zonen. The power smoothing uses a variable window size to compensate for a flat and intermittent profile. The moving standard deviation has been used to evaluate the window size in different ranges. The evaluation focuses on days with higher irradiance variability and the results for the suggested approach show better performance than the smoothing process with a large or small window. The suggested approach reaches an autocorrelation index of 0.988, which is more than 6% with respect to the constant window size. Furthermore, the analysis shows that more than 50% of the data have variability in the moving standard deviation within a range of 1% and 25%, as with this approach a flexible window size helps the smoothing process. An estimation of photovoltaic power between constant and variable window size has been evaluated and a difference of less than 1.5% has been obtained.

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1. INTRODUCTION

The photovoltaic system (PVS) is a technology integrated into the electrical system with several years of contribution to the energy matrix in different countries. For example, several countries in Latin America have photovoltaic and wind power plants to take advantage of natural resources such as irradiance and wind. During the last decade, an increase from 1% to 13% in renewable energy generation has been achieved thanks to its modularity and flexibility [1]. However, this technology, like other renewable energy sources, could have a negative impact on the grid, especially at high penetration levels. Intermittent and injected power could lead to grid frequency and voltage instability, power quality problems, and an increased risk of blackouts; the increase of renewable technologies with the incorporation of power electronics decreases the inertia of the electrical system so that the frequency and consequently the voltage are more sensitive to change in the event of a disturbance. For this reason, external devices such as batteries are widely used to minimize the power fluctuation of renewable energy sources [1]–[4]. Other approaches to control power system stability with renewable energy injection have also been suggested. Frequency variability could be improved by robust grid control in the case of grid-integrated PVS [5]–[8]. Power fluctuation is directly related to weather conditions, including irradiance variability, ambient temperature, cloud movement, wind speed, and other weather conditions. Conventional generation cannot easily track the variability of PVS plants, and the consequences could affect the grid such as an over limit in control error in interconnected areas, violation of dispatch generation, and other issues related to operating costs [9]–[12]. Another consequence related to irradiance and temperature variations is the performance of maximum power point tracking algorithms for PVS, so a smoothing profile is a convenient alternative to reduce this problem, i.e., an irradiance profile with less variability allows better optimization of the energy production of the PVS [13].

One possible solution for power fluctuations is ramp control and power smoothing (flattening of the radiation profile). The smoothing process increases the overall system cost, requires extensive evaluation of historical data, and part of the prediction approach has a certain accuracy rate [9]. Some studies approach power smoothing based on the combination of geographic dispersion, considering clusters of PVS and the distance between them., The use of storage batteries and backup capacitors are probably the most convenient technologies to reduce power fluctuation as well as peak generation time management and system functionality during outages [14], [15]. Some studies take advantage of the intermittency of PVS power as in general, it could improve the overall voltage profile, and reduce losses, but the daily voltage and daily production are affected by the variability of the generation source [16].

The correct processing of irradiance measurements allows discriminating values with high variation and low variation, through a process of separation of measurements, and averaging of measurements between successive values to reduce variability peaks. Low-pass filtering and moving averages are tools used to smooth the power generated in PVS. These approaches use a smoothing power with a large window and produce a time delay, both of which affect the sizing of the storage system [17], [18]. This sizing can be critical as it is related to the overall cost. A new adaptive control based on moving average with adjustable filter window size has been suggested. It has the advantage of a trade-off between power smoothing and computational efficiency [19]. The moving average is not the unique solution, the width of the window and the focus of the filter can improve the final signal. Two moving average filters in a series with the same windows, exponential smoothing, and other derivatives are part of the filter-based approach, but the applications are different [17], [20]. There are other methods to smooth the PVS power, the pumped variable speed with high response to absorb or generate the extra power in the control scheme [21], and also the electric spring to reduce the ramp rate in conjunction with the battery system [22].

This paper addresses the problem of irradiance variability in photovoltaic power generation to analyze the variable window size (WS) applied to high and low irradiance intermittency profiles. The suggested variable WS smoothing approach is compared with a constant WS of large and small widths. The autocorrelation coefficient, moving standard deviation, and PVS power are the metrics used for the power smoothing analysis in this research. Section 2 describes the procedures used to verify the data quality, section 3 establishes the power smoothing approach with the application of the filtering process, and section 4 includes the unit diode model for the PVS used for power evaluation. Finally, section 5 describes the suggested approach using the variable WS for the PVS power smoothing process.

2. ANALYSIS OF THE IRRADIANCE MEASUREMENT

2.1. The data collected

This study analyzes the power smoothing approach based on experimental data. Irradiance and temperature are the main data collected by specialized instruments. The SMP3 Kipp & Zonen pyranometer was installed in the province of Huancayo to measure irradiance, and a temperature sensor was installed next to it. The city of Huancayo, like other cities in the highlands, has unique climatic conditions during the first 4 months of the year. These months experience rain, sun, and clouds throughout the day, resulting in a very intermittent irradiance profile on some days. The analysis of the smoothing process is more challenging at this time of year. The data analyzed is from 6:30 to 18:00 with a one-minute interval for March and April 2023.

2.2. The data quality procedure

The design, modeling, monitoring, and predictive analysis of PVS require accurate data. This means the data collected must be subject to quality control procedures and several institutions have contributed to the data cleaning knowledge, such as the International Electrotechnical Commission (IEC) through its published consensus standards [23]. The IEC 71724:2016 standard provides a high-resolution (15-minute) approach to filtering the data and for irradiance, a range between -6 and 1500 $W.m^{-2}$ is suggested. The 2017 version of the same standard recommends measurements with a threshold of 20 $W.m^{-2}$ for in-plane irradiance [24]. The literature review identifies a group of approaches to irradiance data quality that assume the availability of diffuse horizontal irradiance, global horizontal irradiance (GHI), and direct normal irradiance. To recommend their widespread use and application, the baseline surface radiation network approach has been applied in this study. Consequently, the physically possible and extremely rare limits used for the measurement of GHI refer to values based on geographical conditions (latitude and longitude, among others) and the values should be in appropriate ranges [23], [25]–[28]. The upper bound of the GHI, based on physically possible limits (PPL), is shown in (1), with -4 as the lower bound. Extremely rare limit (ERL) bounds for GHI are based on (2) with a lower bound of -2 [23], [26], [29].

$$PPL = 1.5G_{0n}(\cos\theta)^{1.2} + 100 \tag{1}$$

$$ERL = 1.2G_{0n}(\cos\theta)^{1.2} + 50 \tag{2}$$

The PPL and ERL depend on G_{0n} and θ, they refer to the irradiance in the horizontal plane at the top of the atmosphere and the zenith angle respectively according to (3) and (4). Where d_n is the cardinal day of the year and ϕ, δ and ω are the latitude, solar declination and hour angle respectively. The collected data provided for a measurement process has a certain bias to the exact value, but the use of a high-precision instrument such as the SMP3 reduces this problem. Another relative problem could be high peak irradiance and negative values or repetitive data, so a basic data quality filter was applied to ensure data quality.

$$G_{0n} = 1367[1 + 0.033\cos(\frac{360d_n}{365})] \tag{3}$$

$$\cos\theta = \cos\phi\cos\delta\cos\omega + \sin\phi\sin\delta \tag{4}$$

2.3. The classification data

To analyze the measurements based on a variability criterion, indexes have been used to classify the irradiance measurements based on the measurements made during a specific day. The research focuses on the assessment of irradiance variability, considering cases with high variability to evaluate the behavior of the WS. The classification of irradiance profiles is based on the daily clarity index (DCI) and the daily variability index (DVI) [30]. In this work, the cases with high irradiance variability were selected for analysis considering the values of DVI and DCI. Conveniently, a daily irradiance profile with high DVI was chosen, as the high variability implies a more complex situation for power smoothing.

3. THE ANALYSIS FOR POWER SMOOTHING

Smoothing the variability of power generation ensures a more stable and reliable supply for renewable energy systems. Power smoothing strategies are divided into moving average and ramp control. Moving average has a simple implementation and low processing cost [31]. Power smoothing approaches based on battery power systems for wind and solar energy are an effective tool to reduce the fluctuating power, the main disadvantage is the cost [32]. The power smoothing is defined based on the windows and the measurement group analysis on the windows. For this approach, the moving average and the low pass filter produce a common application, but the first has better results. The power smoothing result complies with WS regulation [17], [33]. First, taking into account the moving average of the signal, (5) presents a filter to analyze an average value defined in a time window [19].

$$\mu = \frac{\sum_{\tau=1}^{W} P(t-\tau)}{W} \tag{5}$$

where W is the window size and τ is the measure for the filtering process. The process of evaluating the moving average can be performed with an index. In [32], the index based on the maximum, minimum, and nominal values in a given time interval is used. This index cannot analyze the variability of the moving average. The index in expression 6 is used to analyze the short-term variability and represents the derivation of the moving standard deviation according to [19].

$$\sigma = \sqrt{\frac{\sum_{\tau=1}^{W}[P(t-\tau)-\mu]^2}{W-1}} \tag{6}$$

4. THE PHOTOVOLTAIC SYSTEM MODELLING

The photovoltaic system has been analyzed in the scientific literature considering different modeling techniques [34]–[36]. In this research, a trade-off between model complexity and computational effort was considered, and then the unit diode model based on four parameters was chosen. The total PVS current injected into the load or into the grid is defined in (7) [34], [35].

$$I_{pv} = I_{ph} - I_0[exp(\frac{V_{pv}}{V_t.A_n} - 1)] \tag{7}$$

Where I_{ph} is the photocurrent, I_0 is the diode saturation current, and R_s is the series resistance. In (6) solved according to the technical parameters of the PVS shown in Table 1. This PVS panel is MAXPOWER CS6U-325, manufactured by Canadian Solar. The power smoothing analysis also includes the estimation of the power output during the day. This process is completed based on the operating condition of the maximum power point of the system and the current estimation using the single diode model.

Table 1. Datasheet MAXPOWER CS6U-325 solar module

Parameter	Maximum power	Operating voltage	Operating current	Open circuit voltage	Short circuit current
Value	325 W	37 V	8.78 A	45.5 V	9.34 A

5. THE PROPOSED POWER SMOOTHING APPROACH

In this investigation, the power smoothing is based on a flexible approach with high and low irradiance levels. The objective is to change the WS depending on the base conditions of the moving standard deviation and to use different thresholds to select the WS. The following steps explain the procedure for the suggested approach:

a Collect irradiance and temperature readings for a 1-minute interval, using a pyranometer and temperature sensor through a data logger for data download to a computer.

b Based on section 2, assessment of quality and erroneous data which assesses data outside the physical boundaries, making it possible to rule out radiation measurements that do not meet the requirements established by IEC.

c The previous evaluation of different WS values has been performed through an analysis based on the correlation coefficient of the estimated PVS power values. This allows an appropriate choice to be made based on the correlation coefficient and the WS increment. For the evaluation of the autocorrelation of the moving standard deviation with a different WS based on section 3, the goal is to estimate the minimum WS with a high autocorrelation coefficient. This WS will be the same for the entire evaluation of the moving standard deviation.

d Analyze the trend of the moving standard deviation and check the variability of the rate of change considering successive values. The moving average filter is re-evaluated based on the rate of change of the moving standard deviation, this rate is called the moving index (MI). The following MI intervals and associated WS are used to perform the signal filtering.

  - MI greater than 50% was assigned where WS=2.
  - MI between 25% and 50% was assigned where WS=4.
  - MI between 10% and 25% was assigned where WS=6.
  - MI between 1% and 10% was assigned where WS=8.
  - MI less than 1% was assigned where WS=10.

  High variability is associated with low WS, and low variability is associated with high WS. This criterion captures high variability by considering the behavior of successive measurements. Lower variability is analyzed with a high WS and less computational effort is put into the processing.

e The experimental data after the smoothing process allows for estimating the photovoltaic power successively at each time interval. The measured data and the new irradiance profile with a smoothing approach applied with a different WS are used to estimate the photovoltaic power. A final comparison was performed to evaluate the difference in PVS production. The comparison is made between radiation profiles with and without the smoothing process.

6. RESULTS AND DISCUSSION

6.1. Data quality and classification of irradiance measurements

The first step in the investigation is to analyze the data to be used in the moving average process. Based on section 2, data quality was performed on every minute measurement. Data outside the physically possible limits and extremely rare upper limits were corrected based on the maximum allowed values. After applying the data quality process, the classification criteria defined in section 2 for all days in March and April were evaluated. Table 2 shows the classification of the irradiance profiles and only the profiles with the highest DVI were considered for analysis in this research. This allowed the analysis of the group of measurements with the greatest variability, and consequently, those with the greatest successive fluctuations, to obtain the response of the suggested criterion under unfavorable conditions

Table 2 shows the DVI and DCI indices for the group of measurements studied. The data were filtered based on both indices and high irradiance profiles for March and April. For March, 10 cases with high variability irradiance profiles were considered. For April, 13 cases were analyzed. Between 30% and 40% of the data have a high variability profile and the minimum value of the DVI with high profile type is 10 [30]. According to Table 2, for the month of March, 70% of the evaluated data have a DVI index higher than 10. In the case of April, approximately 85% of the data have a DVI index greater than 10. Thus, the data tested in this research could make the challenge of power smoothing analysis and the approach to flatten the irradiance profile more difficult. Figure 1 shows a typical profile for the analyzed measurements. These profiles are the days with a high DVI index for each month.

Table 2. Experimental measurements with high-rate radiation profiles

Case	Day	DCI Index	DVI Index	Day	DCI Index	DVI Index
1	2023-03-01	0.4	12.9	2023-04-01	0.4	14.7
2	2023-03-03	0.5	12.8	2023-04-02	0.5	12.8
3	2023-03-04	0.5	12.8	2023-04-03	0.6	14.3
4	2023-03-07	0.5	10.3	2023-04-08	0.5	12.5
5	2023-03-19	0.6	10.2	2023-04-09	0.5	12.9
6	2023-03-25	0.4	11.4	2023-04-10	0.6	18.6
7	2023-03-26	0.6	11.1	2023-04-18	0.7	11.4
8	2023-03-27	0.6	10.8	2023-04-20	0.5	10.4
9	2023-03-30	0.6	17.4	2023-04-21	0.7	10.1
10	2023-03-31	0.6	16.8	2023-04-25	0.7	20.1
11	-	-	-	2023-04-28	0.5	11
12	-	-	-	2023-04-29	0.7	19.5
13	-	-	-	2023-04-30	0.7	17

Figure 1 shows profiles with high irradiance intermittency. Both cases are referred to as the highest DVI cases for March and April. For the March case in Figure 1(a), the data between 10:00 to 12:00 and 13:00 to 16:00 show dense behavior with high intermittency. A similar profile in April is shown in Figure 1(b) where between 11:00 and 14:00 the irradiance has a high variability. In general, the irradiance has values higher than 1000 $W.m^{-2}$ in both cases. This phenomenon is typical due to the cloud enhancement related to the reflection and refraction process.

6.2. Analysis of the windows size for smoothing process

Based on the theory explained in section 4 and the equations presented in sections 2 and 3, the window size is a key parameter for the moving average approach. A small window is more suitable for high variability and less suitable for low variability. However, the process of finding an appropriate window size is based on the autocorrelation function for different window sizes. The aim is to find a unique window size to evaluate the moving standard deviation. Figure 2 shows the analysis to estimate the appropriate window size based on the autocorrelation coefficient of the moving standard deviation. The highest DVI cases in each month were evaluated to ensure the operability of the proposal in cases with high and low variability of radiation

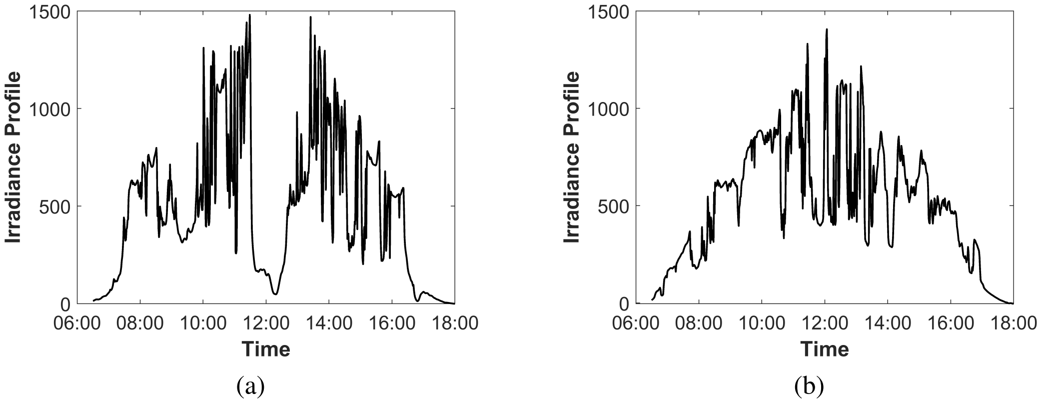


Figure 1. High DVI index radiation profile (a) March 30 and (b) April 25

Figure 2 shows the autocorrelation function for the higher DVI cases. Figure 2(a) shows the results for March, where a window size equal to 7 has an autocorrelation index of 0.95, then when increasing the window size the value of the coefficient approaches 1. The situation is similar for Figure 2(b) in the month of April; with the window size equal to 5 the coefficient has a value higher than 0.9. Considering a situation with an autocorrelation coefficient close to 1, a window size equal to 11 has been considered for power smoothing analysis in the suggested approach. Based on Table 2, cases with low irradiance variability were tested to understand the advantages or disadvantages of the window size. The aim is to analyze the variation of the moving average in the periods where the irradiance has a lower variability. Figure 3 shows the variability of the moving average deviation with different window sizes for the low DVI cases.

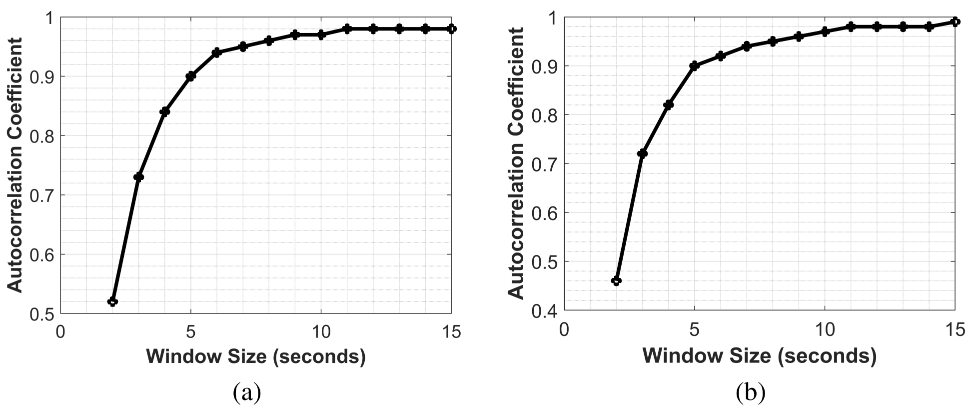
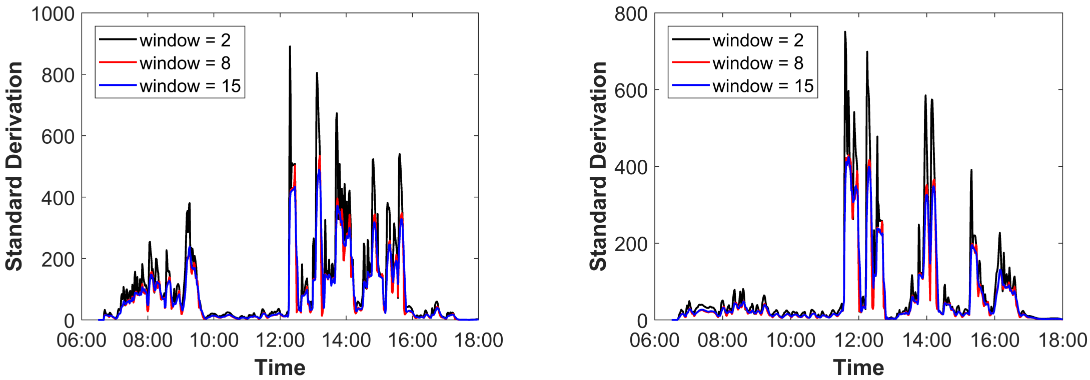


Figure 2. The autocorrelation coefficient estimation for windows size (a) March 30 and (b) April 25

Figure 3(a) shows a constant standard deviation during the first minutes of the day until 7:00, between 10:00 and 12:00, and from 16:00 to 18:00. Although the size of the windows is different, at the time of variable irradiance their size is equal to 2 and presents more standard deviation. Figure 3(b) shows a constant value of the standard deviation until 11:00, at some periods during the day, and in the last hours of the day. For these periods, the window sizes could be 2 or 15, so it is irrelevant to use small window sizes because the standard deviation in this range does not depend on the window size. A low computational cost is used for non-small window sizes. According to Figure 3(a) and Figure 3(b), as the window size increases, the smoothing process can reduce the maximum values and variability, thus reducing the standard deviation. It should be noted that there are certain periods of time where the standard deviation is the same despite the increase or decrease in the size of the windows used. So the windows could be constant in some periods and small or large in others, depending on the variability of the irradiance.



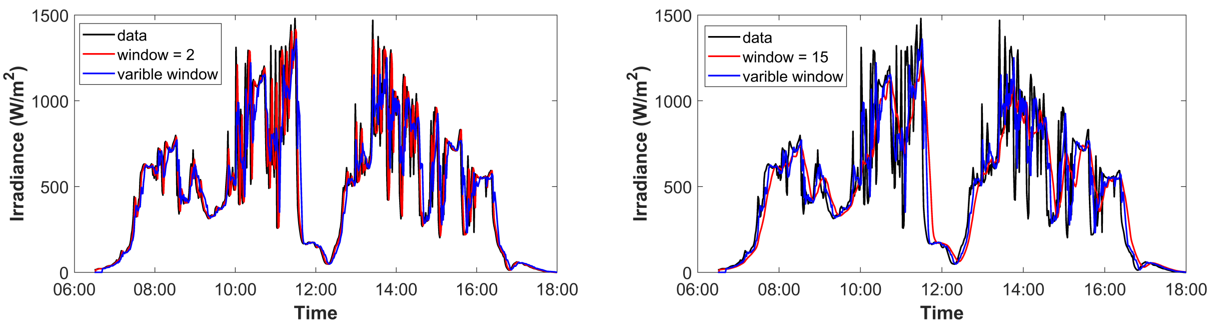
(a) (b)

Figure 3. Standard deviation for different windows size (a) March 19 and (b) April 21

6.3. The suggested power smoothing algorithm

The size of the windows is the key factor in the power smoothing analysis, taking into account the experimental measurement of irradiance. The first steps validate the quality of the experimental data and determine the WS based on the correlation coefficient. The WS is considered variable based on the intervals given in section 5 and is related to the rate of change of the standard deviation. Figure 4 shows the situation on March 30, the day with the highest variability between March and April.

Figure 4(a) shows the comparison with the lowest WS and the suggested variable WS condition. It can be seen that in the periods with lower variability, both WS have a close irradiance value. In the time interval between 11:30 and 13:00, the variable WS is close to the original irradiance profile with the experimental data. In the time interval with high variability, the variable WS has changed according to the variation of the data. Figure 4(b) shows a smoothing trend for WS=15, but the results with the variable WS show a variable irradiance profile in correlation with the experimental data, in contrast to WS=15. A more detailed analysis could be made using the number of measurements in a given interval and the standard deviation with different window sizes. Figure 5 shows a heat map for analysis of measurements for March 30 and April 25.



(a) (b)

Figure 4. Comparison of the irradiance profile for March 30 (a) the case with a 2-second and variable window and (b) the case with a 15-second and variable window

The heat map allows the determination of the WS intervals where the greatest range of variability of radiation measurements has been reported. According to Figure 5(a), a WS equal to 8 covers 34% of the measurements and is part of the lowest variability rate. More than 50% of the measurements are in the range of variability between 1% and 25% and this group is part of dense measurements in some intervals. The rate change case with more than 50% variability has a window size of 2. This approach captures high variability with a low WS and low variability with a high WS. The results for March 25 are shown in Figure 5(b). The high variability rate is captured in the interval from 1% to 25% and 70% of the dense data is in this interval. The higher standard deviation variability means that the data has changed by more than 50% and less than 12% represents this extreme condition. In general, the irradiance profile could be analyzed with a WS of between 6 and 8, only 30% of the data would need to be evaluated with a small WS such as 4 or 2. For the extreme cases with a WS equal to 2 or 15, each option was analyzed taking into account the correlation coefficient. This coefficient varies according to the time lag (time interval until the next measurement); 1-minute and 5-minute lags were tested. Table 3 shows the results for all the days analyzed. The cases with the highest variability could be considered the most challenging for power smoothing.

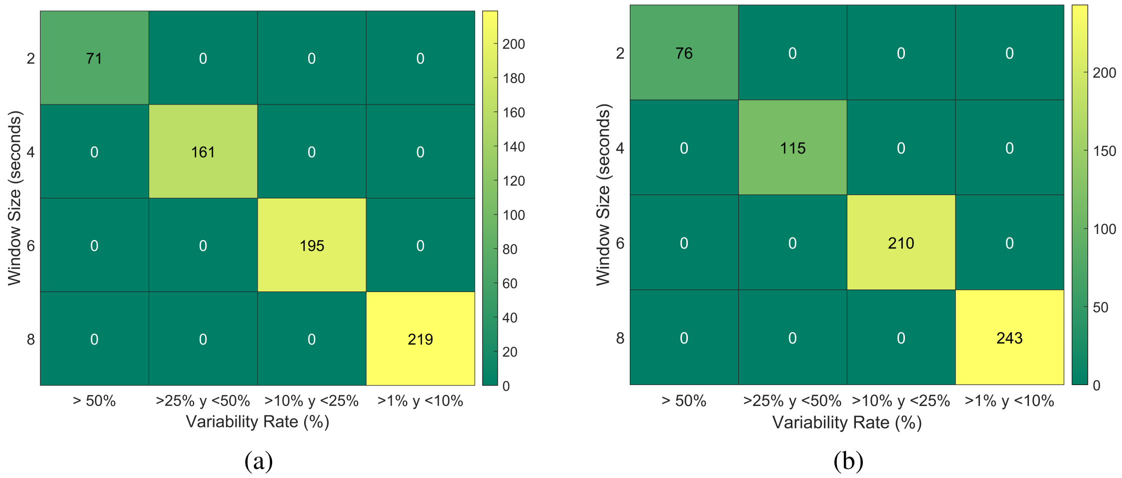


Figure 5. Heat map to analyze data in different time windows (a) March 30 and (b) March 25

The results in Table 3 show that a high correlation coefficient was obtained in March, especially in the case of a time lag equal to 1, with a value of 0.988. In the case of a lag equal to 5, a better value was obtained, of 0.888. Another aspect concerning the WS is the decrease in the correlation coefficient as the WS decreases. A smoothing process with a small WS implies a low correlation coefficient, which is the typical tendency in a dense measurement situation. Considering that a delay equal to one minute represents a good choice for the analysis of the measurement prediction, the variable WS is a good choice for power smoothing. For all the cases evaluated in March, the variable WS is the best option. In the worst case, 0.981 was obtained against 0.919 and 0.973 for a WS equal to 2 and 15 respectively. The suggested solution increases the value of the correlation coefficient by more than 6%. In the case of March 30, the case with the highest variability of the month, the WS equal to 15 could represent a good option with a coefficient of 0.981, but it could be improved by using a small WS in periods with high variability. Thus, a variable WS reaches 0.984, improving the coefficient and the trade-off between low and high computational effort. The analysis is also extended to April, the month with the highest variability and challenge for the smoothing process. The best result could be analyzed in the case of the highest variability. A correlation coefficient of 0.937 was obtained with a WS equal to 2, which is a good result, but when using a WS equal to 15 a coefficient of 0.984 was obtained. The smoothing analysis and the balance between small and large windows were achieved with the suggestion presented in this paper, and then a coefficient of 0.988 was obtained.

After analyzing the WS with the different options, the PVS power is analyzed as a function of irradiance. The aim is to determine if there is any power variation between the original data and the smoothed irradiance profiles. The data measured at one-minute intervals is taken as the base data for the analysis. Table 4 shows the results for the PVS power in all cases analyzed for March and April with the different WS.

Table 3. Correlation coefficients for each day analyzed for March and April

Case	Date	Variable window size		Window size=2		Window size=15	
		Lag=1	Lag=5	Lag=1	Lag=5	Lag=1	Lag=5
1	2023-03-01	0.983	0.87	0.920	0.607	0.977	0.781
2	2023-03-03	0.985	0.872	0.925	0.658	0.982	0.826
3	2023-03-04	0.985	0.872	0.925	0.658	0.982	0.826
4	2023-03-07	0.988	0.888	0.93	0.629	0.982	0.809
5	2023-03-19	0.984	0.833	0.932	0.596	0.979	0.742
6	2023-03-25	0.987	0.877	0.931	0.655	0.984	0.817
7	2023-03-26	0.981	0.829	0.919	0.515	0.973	0.718
8	2023-03-27	0.986	0.876	0.935	0.591	0.980	0.786
9	2023-03-30	0.984	0.841	0.927	0.634	0.981	0.78
10	2023-03-31	0.984	0.815	0.927	0.574	0.978	0.73
11	2023-04-01	0.986	0.883	0.927	0.728	0.984	0.847
12	2023-04-02	0.982	0.832	0.923	0.574	0.976	0.751
13	2023-04-03	0.988	0.865	0.932	0.677	0.984	0.809
14	2023-04-08	0.982	0.809	0.92	0.545	0.975	0.703
15	2023-04-09	0.986	0.869	0.93	0.591	0.981	0.783
16	2023-04-10	0.985	0.884	0.919	0.649	0.982	0.818
17	2023-04-18	0.985	0.839	0.934	0.619	0.982	0.789
18	2023-04-20	0.98	0.799	0.939	0.536	0.977	0.693
19	2023-04-21	0.987	0.856	0.943	0.596	0.982	0.762
20	2023-04-25	0.988	0.885	0.937	0.655	0.984	0.813
21	2023-04-28	0.985	0.845	0.939	0.654	0.982	0.783
22	2023-04-29	0.987	0.857	0.939	0.631	0.981	0.784
23	2023-04-30	0.983	0.788	0.949	0.541	0.980	0.689

Table 4. Power PVS estimation

Case	Date	The total power production every minute during the day (kW)			
		Variable Window Size	Window Size=2	Window Size=15	Measured Data
1	2023-03-01	98.67	97.37	97.45	97.32
2	2023-03-03	102.41	102.06	102.22	101.99
3	2023-03-04	102.14	101.80	101.93	101.74
4	2023-03-07	124.3	124.37	124.59	124.29
5	2023-03-19	132.51	133.09	133.24	133.04
6	2023-03-25	85.97	85.93	85.926	85.92
7	2023-03-26	114.59	114.25	114.29	114.23
8	2023-03-27	119.47	119.71	119.76	119.69
9	2023-03-30	109.02	108.71	108.79	108.67
10	2023-03-31	105.97	105.21	105.26	105.19
11	2023-04-01	100.13	99.53	99.67	99.46
12	2023-04-02	104.66	104.89	104.96	104.88
13	2023-04-03	121.06	121.69	121.80	121.65
14	2023-04-08	104.62	103.76	103.78	103.75
15	2023-04-09	106.56	105.46	105.51	105.44
16	2023-04-10	105.13	105.75	105.85	105.71
17	2023-04-18	130.72	130.54	130.62	130.50
18	2023-04-20	80.58	80.16	80.11	80.18
19	2023-04-21	122.74	123.15	123.13	123.15
20	2023-04-25	112.37	112.29	112.37	112.27
21	2023-04-28	76.77	75.73	75.81	75.69
22	2023-04-29	120.11	121.5	121.47	121.49
23	2023-04-30	100.57	100.80	100.86	100.77

The PVS power was evaluated to determine the difference when PVS production uses the smoothed irradiance profile compared to a high variability profile. According to Table 4, there is a small difference between the results with the original measured data and the variable WS. In the worst case, March 1 and April 28 are likely to have a lower DCI, but there is no more than a 1.4% variation. The cases with the least variation are March 7, March 25, and April 25; in all cases, there is no more than a 0.1% variation. The April 25 case is the day with a DVI greater than 20, although the results with a variable WS and real data are practically the same. Therefore, the use of a smoothing profile that combines the analysis of dense data and flattened data is a good tool for estimating power PVS. The March 30 case has a variation of 0.3%, which proves that the variable WS is a good option. In general, without considering the extreme values of March 1 and April 28, the difference between the power estimated with real data and with the smoothed profile with a variable WS has an average value of 0.1%. Moreover, considering the results analyzed in Table 3, the WS variable presents a good performance for autocorrelation and power estimation, so a compromise between a small and large WS could be a good option as an analysis tool in PVS operation.

7. CONCLUSION

The analysis of the smoothing process was carried out and suggests a new approach to reduce irradiance intermittency, taking into account the original variability of the irradiance data. Based on the analysis of highly variable irradiance measurements in the city of Huancayo, data quality control and classification based on the DVI and DCI indicators were performed to select as a study the profiles with the highest daily variability index. The window sizes based on the standard deviation intervals were evaluated. After performing the autocorrelation analysis, a coefficient of 0.98 was obtained for the suggested procedure, compared to a value of 0.95 for the case of window sizes equal to 2 or 15. Finally, the evaluated PVS power production shows a difference of less than 1.5% compared to the power production estimated with the original data. In the most favorable situations, a difference of less than 0.1% was obtained. The proposed methodology for the analysis of PV power profiles allows to reduce the intermittency of PV generation, preserving the total energy value during the day. This tool is suitable for power smoothing and PVS generation analysis.

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