Monitoring Analysis and Performance Assessment of 1.2 MWp High Concentration Photovoltaics

Suggestions for the development of real-time monitoring systems enabled by the VICINITY platform

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ABSTRACT: This thesis searches for the improvable aspects of 116 High Concentration Photovoltaic (HCPV) units own by Enercoutim – Alcoutim Solar Energy Association, by observing their monitoring data and quantifying their energy conversion losses throughout the year 2015. Following the data validation steps, flagging and exclusion actions prevented the propagation of measurements errors. The performance assessment considered each HCPV unit's tracking system, inverter and module as an individual sub-system. The analysis revealed general tracking inefficiencies. Three units were selected for a detailed analysis at module's level. Particularly negative results characterised the inverters' performance. Three consecutive months of downtime affected most of units' inverters likely due to a failure of the AC measurement equipment. To assess the module's level performance of selected units, the performance ratio (PR) was considered. The PR showed inconstant performance throughout the year. The study of the technology's behaviour under different atmospheric conditions is also accomplished. To minimise the influence of atmospheric conditions over the performance assessment, two PR corrections have been applied. To highlight possible shadowing and soiling effect, PR trends were compared considering the cumulative sum of differences between the corrected PR values and their expected values. The analysis showed partial shading effect caused by a tree over a specific unit; no soiling effect was possible to be assessed with the method used. Finally, the introduction of a machine learning based algorithm was suggested as a first step for the development of real-time continuous monitoring system considering the exploitation of the multi-user VICINITY platform.

1. INTRODUCTION

1.1. Enercoutim

Enercoutim – Alcoutim Solar Energy Association - is a non-profit organization working on the promotion of rural economic and social development of Portugal supporting projects related to renewable energy and sustainability [1]. One of Enercoutim's first project gave birth to the Alcoutim Solar Demonstration Platform (herein, the "solar platform"). The latter houses three different HCPV models for an overall installed capacity of 4MWp. Enercoutim and the solar platform have covered a central role in the development of this thesis for two main reasons: firstly, they provided the dataset over which the study is developed; secondly, Enercoutim and its solar Platform represent a stimulating framework through which develop innovative operation and maintenance (O&M) related business models. In fact, Enercoutim owns the solar assets installed in the Platform and manage their maintenance, while the HCPV units are operated by a second business body. The possibility to develop monitoring related services within a multi-user managed solar power plant inspired this study.

1.2. The VICINITY Project and Platform

The solar platform hosts one of the demo sites of H2020 Research & Innovation projects VICINITY [2]. VICINITY aims at building and demonstrate a new ecosystem of decentralised Internet of Things (IoT) infrastructures. The main expected outcome of this project is the provision of a software through which decentralised IoT devices and connections can communicate without the need of centralised databases and/or specific manufacturers' provided protocols. Once associated to the platform, users can benefit from the services provided by the decentralised IoT devices. Consequently, the platform offers the possibility to further develop added-value services through the indirect use of shared connected devices. The energy-related use-case developed by Enercoutim within VICINITY links the need of big-data management and the possibility of optimising the use of already installed IoT sensors. The use-case called "Smart-cleaning" intends to optimise resource deployment and cleaning schedule of the HCPV units considering several atmospheric parameters and available human resources with the implementation of the VICINITY platform. The access to reliable system's monitoring data is fundamental for a useful study of the HCPV plant performance and the improvements needed from the current monitoring system. This study will indicate the most relevant monitoring features and processes to be further developed within the IoT enabled VICINITY platform for the development of the Smart Cleaning use-case.

1.3. Operation and Maintenance for Solar Power Plant Trends: Big Data and O&M Split

Although the solar industry has historically seen operation and maintenance as a unique service provided by a single business body, reports now show that in the utility-scale solar industry a decoupling trend between O and M is taking place. In the US, research shows that a split between O&M service providers and the rapidly growing O&M

market value can benefit those market actors that strategically decide to specialise their services offer either on operation or maintenance [3]. It is in this context that this study demonstrates how a company like Enercoutim could benefit from the O&M split trend. Being the owner of the solar assets installed at the solar Platform and the subject providing maintenance to them, Enercoutim positions itself in an advantageous condition for the development of exclusively monitoring and maintenance related services. These services are intended to be sold to plants' operators which would benefit both from Enercoutim's experience and the interoperability provided by the VICINITY platform.

1.4. Research Focus

The thesis searches for the improvable aspects of the considered HCPV system by observing its monitoring data and quantifying its energy conversion losses. In addition, the technology's behaviour under different atmospheric conditions is analysed in order to identify the weather features influencing the solar energy conversion performance. Finally, considering the results of the monitoring analysis, suggestions for the development of a real-time monitoring system through the exploitation of the VICINITY platform are provided. The discussion aims at correlating the already in-place monitoring solutions with implementable ameliorations needed for the development of the "Smart-cleaning" use-case. The research focus of this master thesis can be summarized in two main points:

A) Analysis of the on-site direct monitoring measurements at three of the system's levels function: trackers, inverters and DC modules. The research analyses the energy yield losses and their possible causes while providing an understanding of the impact of atmospheric factors on the B. performance of the CPV units.

B) Discussion about the use of the VICINITY platform for monitoring practises in utility-scale solar plants, considering its advantages for the development of a continuous real-time monitoring system and the "Smart-cleaning" use-case.

2. STATE OF THE ART

2.1. High Concentration Photovoltaic Technology

Concentration photovoltaics is considered as one of the most promising technology for large scale implementation of solar energy production [4]. These systems improve the effectiveness of traditional photovoltaic systems (PV) involving the use of reflective material, lenses, or mirrors to concentrate and focus incident solar radiation on special solar cells, namely multi-junction solar cells. Grid-connected HCPV systems are composed by HCPV modules collecting and concentrating direct normal irradiation (DNI) onto multi-junction (MJ) solar cells. The modules are connected in series and parallel, mounted on high-accuracy solar tracker and connected in turn to DC/AC inverters and other auxiliary equipment [5]. The solar concentrator is mainly formed by a single optical element called "primary optical element". Fresnel lenses are the most common primary optical element of refraction-based CPVs. Most recent HCPV technology designs propose the implementation of a secondary optical element which homogenises the luminous power on the solar cell surface improving the acceptance angle [7]. CPV designs can be classified by the concentration factor of its optics: low concentration PV (LCPV, <10suns), medium (10-100 suns), high (HCPV, <2000 suns) and ultrahigh (UHCPV, >2000 suns) [8].

2.2. Multi-Junction Solar Cells

CPVs' are characterised by complex and efficient solar cells: multi-junction solar cells. MJ solar cells stack specific materials belonging to group III and V of the period table with decreasing bandgaps from top to bottom, allowing photons to be absorbed in layers with a bandgap close to the photons' energy, thus resulting in a reduction of thermalization losses. In addition, being the absorption range of MJ solar cell wider than for single-junction ones, transmission losses are reduced [9]. Currently, MJ cells report efficiency values around 46%. Consequently, HCPV modules report efficiencies higher than traditional PV with values up to 36.7%, and they still present potential for further improvement [5].

2.3. Tracking Systems

CPV systems are required to strictly and permanently track the Sun's apparent daytime motion. Therefore, the vast majority of CPV system are equipped with an incorporated automatic sun-tracking structure allowing the concentrator optics to be positioned in alignment with the sun vector. In this way, the latter remains focused on the solar cells. Sun tracker structures function as moving base above which the solar modules are installed. the most common tracker, as well the one in use for all the HCPV units installed at the solar platform, is a single pole pedestal two-axis azimuth-elevation tracker. Modern tracking system controllers are only based on highly precise digital computation of analytic sun ephemeris equations [10]. Yet, tracking imprecisions happen and the sources of these issues can be multiple. For this reason, off-tracking tolerance is usually required. The tolerance of concentrators is commonly defined as "acceptance angle", being defined as the off-tracking angle at which power output drops below 90% [10].

2.4. Environmental Factors Affecting CPV Energy Conversion

As for traditional PV, also CPV systems are affected by environmental factors. Firstly, several components of CPV systems are affected by thermal effects: solar cell and modules in particular. An increase of temperature is usually translated into a decrease of the bandgap of each sub-cell within a MJ solar cell.

Simultaneously, each sub-cell is subjected to a variation of the amount of convertible light due to the change of irradiance distribution resulting by the effect of temperature over the refractive index of the primary optical element. The interaction between these two effects is important for the determination of the short-circuit current of the MJ cell. Although both active and passive cooling strategies are available for CPVs, only passive cooling methods have been tested to be cost-effective [11]. CPV's thermal behaviour can also be affected by wind speed and direction. Wind can have positive and negative effect on CPV systems: it can have an evident cooling effect on the cell producing positive electrical effects; at the same time, high wind speed could flutter the very sensitive tracking system and make it go out of its position causing losses in energy production. In addition, it is recognised that general dirt, coming from ambient air, pollution dust, rain, and other particles depositing on photovoltaic surfaces affect modules' electrical performance, thus reducing their energy conversion ability. CPV modules are found to be more cost-effective if cleaned more often than common PVs. Studies also highlight how soiling effect must be considered at the local level since losses produced by soiling are "site specific and difficult to generalise" [12].

2.5. Utility-Scale CPV Plant Monitoring Practises

Monitoring procedures, composed by sets of practical guidelines, methods and models systematically applied throughout plants' operation, are precious tools to understand technology's performance issues and to assure and enhance, plants' performance. Commercial solar power plants are today developing newer and more complete monitoring systems thanks to the use of advanced sensors providing direct measurements of parameters and indicators directly related to the plant performance. Yet, the development of good monitoring practises, especially for newer technology as HCPV, is continuously ongoing. The main objective of a CPV plant monitoring system is to record the overall operating parameters. While functioning as the tool to be used for the operation of the plant itself, it can also provide indirect measures of the plant's energy yield and useful information to assess the system performance and/or to identify possible system's flaws or malfunctions [13]. As for PV monitoring systems, CPV ones are also commonly based on Supervisory Control And Data Acquisition (SCADA) dedicated systems which gather all the data coming from the elements composing the power plant. The only additional feature to remark for CPV plants is the presence of data from the tracking system, fundamental for the optimum yield of the plant. Following the IEC 61724 standard "*Photovoltaic system performance monitoring – Guidelines for measurement, data exchange and analysis*" [14], a primary quality check of the input data is usually necessary to ensure the consistency of the measured data. For this purpose, ad-hoc data tests are necessary to exclude the presence of anomalies.

3. METHODOLOGY

For this study, 116 CPV units of the Magpower model MagSun CMP132-TRK95 accounting for 1.102 MWp of the total solar Platform installed capacity have been considered. With the term "unit", it is meant to encompass 1 two-axis tracking system, 1 inverter and 72 concentrating modules. The modules are arranged in 3 arrays connected in series (24 modules per array). The punctual concentrating element, individually positioned over each MJ solar cell, is a Polymethylmethacrylate Fresnel Lens having a geometric concentration factor of 800 suns. Each unit has a nominal power of 9.504 kW. Figure 1 proposed the schematic drawing of the units' model.

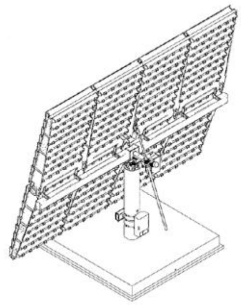

Figure 1: MagPower MagSun CMP132 - TRK95 unit

3.1. Datasets

Two sets of direct measurements data were provided by Enercoutim to accomplish the analysis planned: energy data referring to the solar energy production of the 116 units considered, and a set of meteorological data directly measured on-site. The former encompasses measurements of energy and electric parameters provided with a time interval of 6 minutes for each of the 116 units. The atmospheric dataset records direct measurements every 15 minutes of the following atmospheric features: air temperature [°C] (Tair), relative humidity [%], direct normal irradiation [Wh/m2] (DNI), average wind speed [m/s] (Ws), wind direction [°] (Wdir), precipitation [mm], atmospheric pressure [hPa]. Both datasets provide information from January 1st to December 31st, 2015. It is important to remark that 2015 has been the first year of operation of the units considered. Since the different time granularity of the datasets measurements (6 and 15 minutes) represents an obstacle to the direct calculation of the system's performance indicators, the synchronization of the datasets represents the first step of the monitoring analysis. The synchronization avoids information distortion and data noise and allows to proceed with the quality check of the overall measurements available. The application of the synchronization algorithm re-organises the two datasets at the same time granularity of 15 minutes. The choice to adapt the granularity of the energy dataset from 6 min to 15 min, is mainly due to the lower error introduced by bundling data over a larger period of time.

3.2. Tracking System Performance Analysis

In order to compare the measured angles of the tracking systems with the actual sun's angles, the sun's azimuth and elevation angles are computed for each timestamp at which energy measurements were accomplished (tracking angles were provided in the energy dataset). The computation is based on the SANDIA National Laboratory Collaborative Toolbox for MATLAB PV_LIB version 1.32 [15]. To understand the efficiency of the tracking system, the angle of incidence θ is calculated as (1):

$$\theta = arccos(cos\,\beta c \cdot cos\,\theta z + sin\,\beta c \cdot sin\,\theta z \cdot cos(\gamma s - \gamma c)) \tag{1}$$

βc is the slope angle which, for dual-tracking systems coincides with the elevation angle of the tracker; γc is the surface azimuth (horizontal tracking angle), while γs is the solar apparent azimuth angle and θz is the zenith tracking angle. Comparing the tracker's angle of acceptance (θacc) with the computed angle of incidence, the concept of "tracker availability" is defined. Whenever a measurement reports $\theta \leq \theta acc$, the tracker is considered available, and whenever $\theta \leq \theta acc$ is not satisfied the tracker is considered unavailable.

3.3. Inverters Performance Analysis

The solar platform benefits of a tracker-inverter configuration: each unit is equipped with a power inverter which receives the DC outputs of the unit's arrays and converts it in a unique AC output, then injected in the grid. The inverter's efficiency is thus computed as the ratio between the AC power output and the DC power input on a daily base.

3.4. Module Level Performance Analysis

The DC module level performance analysis only focuses over the best performing units at tracking level. A useful method to assess modules' performance is to evaluate the performance ratio (PR) at DC level. This specific application of the PR indicator measures how effectively the units' modules convert sunlight into DC energy with respect to the nameplate rating and the standard conditions. The calculation of the PR at module level allows to isolate the DC performances from the rest of the units' system. The PR at module level is defined as $y_A = PR \cdot y_r$, where y_A is the actual module DC yield and y_r is the module reference DC yield [13]. For this study, equation (2) is considered:

$$\mathrm{PR}\,[\%] = \frac{\frac{P}{DNI \cdot \eta_{tr} \cdot \eta_{opt}}}{\frac{Pstc}{DNIstc}} \cdot 100 \tag{2}$$

In (2), P is the DC energy converted in a defined period of time and DNI is the direct normal irradiance cumulated over the same interval of time; $Pstc$ is the nominal power of the unit, equal to 9.504 kW, and $DNIstc$ is the standard DNI at operation condition, equal to 900 W/m^2; η_{tr} and η_{opt} are respectively the tracking efficiency and the optical efficiency of the module. The latter is considered constant and arbitrary at 85% [7], [11]. In order to exclude the influence of the most impacting meteorological condition over the performance assessment, two corrections are applied to the PR values computed. The corrections consider the influence of DNI, air temperature ($Tair$) and wind speed (Ws) over the cell temperature ($Tcell$) and thus, over the energy yield at module level. Since no direct measurements of the cell temperature are available in the raw datasets, a heat transfer mode is chosen to estimate the cell temperatures. The heat transfer model used in this study derives from the SANDIA National Laboratories paper "Photovoltaic Array Performance Model" [16]. Although studied and presented for PV systems, the heat model presented in [16] is explicitly suggested to be used for CPV modules considering suitable coefficients and irradiance components. Equation (3) describes the thermal model:

$$Tcell = DNI \cdot \{e^{(a+b \cdot Ws)}\} + Tair + \frac{DNI \cdot Eff_{tr} \cdot Eff_{opt}}{DNIstc} \cdot \Delta Tcnd \tag{3}$$

Coefficients *a* and *b* are empirically determined constants representing the variation of the module temperature in relation to sunlight and to the effect of the wind speed respectively. Their values for this specific study are estimated to be a = -3.2 and b = -0.09. The selection of *a* and *b* is based on the consultation of the SANDIA National Laboratories' software SAM, after having input the CPV characteristics of the units under analysis. The term $\Delta Tcnd$ represents the temperature difference between the cell and the root of the heat sink on the back of the module. $\Delta Tcnd$ is set equal to 58°C as for the results concerning the model under analysis and the similar one used in reference [17]. In order to correct the values of the PR, the cell temperature needs to be compared with a reference temperature. This study considers and compares the corrections using as corrective temperatures the standard reference temperature (Tstc = 20 °C), and an estimated location-related reference temperature (Tcell-typ) [13], [18]. The corrected PR is the result of the ratio between the actual DC energy converted and the expected DC energy converted considering the difference between the cell temperature and the reference temperature. The corrected PR is expected to provide higher and more constant values than the non-corrected ones. The corrected PR values are then used to assess units' performance. Analysing and comparing corrected PR values throughout the year, considering time intervals of 15 minutes and 24 hours, allows to identify modules' performance variations and the related variation sources. To analytically examine increasing or decreasing corrected PR trends, the cumulative sum of the differences found between the corrected PR results and the PR values deriving from a linear regression is considered. This method, hereafter called as “cumulative sum of differences method”, represents the mathematical tool allowing the identification of the system’s behaviour change trends.

4. RESULTS AND DISCUSSION

4.1. Data Quality Verification

The raw data quality verification of the primary datasets highlighted three main issues: a) timestamp issues related to unsynchronised datasets required the application of a synchronization algorithm. b) timestamps in the atmospheric dataset were found corresponding to timestamps in the energy dataset reporting high energy values. The fact that each of the selected units reported a different percentage of this issue over the common total number of measurements sustains the hypothesis of singularities at each specific sensor level. Because of the high relevance of both energy and DNI values in the computation of PR, the timestamps showing this kind on un-related DNI-energy measurements were flagged and excluded from the performance assessment. c) Missing data were recorded in the atmospheric dataset. To avoid data misinterpretation, the timestamps corresponding to void measurements were flagged in both datasets and excluded from the analysis. Being the missing data only the 1.1% of the overall number of measurements, the issue is acknowledged from the author but considered as non-critical.

4.2. Tracking System Performance Assessment

The majority of the trackers resulted having a daily average availability above 90%, while the worst tracking units resulted to have a daily average tracking availability around 50%. Units A, B and C are chosen for the module level analysis because of their superior tracking systems’ performance, recording an average daily availability of 98.22%, 93.79% and 93.58% respectively. Among the three selected units, several days are found having common critical tracking issues: October 4th, 10th and 17th; November 1st, December 14th and 28th. All these days present a daily tracking availability lower than 50%. It was discovered that each of these days was a cloudy day. It is thus reasonable to think that the units might have been kept not operating during these days due to unfavourable weather conditions. Cleaning procedures are also contemplated as possible explanation although no cleaning schedule have been available to confirm this hypothesis.

4.3. Inverters Performance Assessment

The analysis of the units’ inverters has been particularly challenging from a data-quality stand point. To avoid the repetition of critical measurements issues, a revision of the inverters’ measurements equipment calibration is suggested. Figure 2 presents the daily average inverter efficiency of the 116 units analysed. The very low daily average efficiency of the inverters was found to be due to a 3-months failure period of the inverters’ AC-side measurement equipment between March and May. The higher values of average daily efficiency spiking in Figure 2 are units Y and Z correct inverters’ operation during the other units’ downtime period.

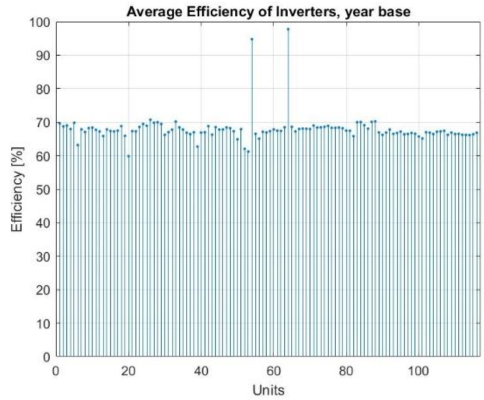

Figure 2: Daily Average Efficiency of Units' Inverters

4.4. Modules Performance Assessment

The analysis at module level is conducted on the selected units A, B and C utilising the synchronised measurements with temporal granularity of 15 minutes. A filter is applied over the DNI values in order to consider only values above 400 W/m^2 (100 Wh/m^2) and maintain robust data quality. The calculation of the PR shows a high variability of the performances of the selected units throughout the year. For what concerns the effect of atmospheric features over PR values, the strict relation between air temperature and PR is evident in Figure 3, where the reduction of the PR values corresponds to increased air temperatures. However, it was not possible to understand the reasons behind specific units’ reaction to similar air temperatures mainly because atmospheric temperature is only one of the parameters affecting modules’ performance. On the contrary, the relations between PR values and wind speeds are not straightforward as shown by Figure 4. The results of the $Tcell$ estimation found maximum $Tcell$ values of 116 °C, slightly higher than the maximum suggested operating temperature of 110°C [19]. This fact can be become problematic in case of prolonged overheating. Figure 5 proposes the relations found between the estimated $Tcell$ and the PR values. Since the estimation of the $Tcell$ already considers the effect of DNI, $Tair$ and Ws, Figure 6 can be considered as comprehensive of the relations presented by Figure 3 and Figure 4. The behaviour of the PR in relation to $Tcell$ is a consequence of the impact that the atmospheric features have over the electric parameters of the cell, particularly voltage and current. Figure 6 shows the unusual behaviour of the array 1 of unit A. The double line was found likely being the results of a maintenance action which fixed a lower than normal voltage response of the array in July. The double line results due to the behaviour of the array before July, and after July. In these two periods all the air temperature shown were experienced and the array responded in both expected and failure-like ways.

The typical operating cell temperatures resulted to be 65.38°C, 65.35°C and 65.36°C respectively for unit A, B and C. The results values' differences between corrected and uncorrected PRs shown by Figure 8, were expected. Figure 7 presents the comparison of corrected and uncorrected PRs values on a daily base for unit A. Almost identical results were found for both unit B and C. In fact, the robustness of the PR correction is given by the difference between the temperature used as correction term and the estimated cell temperature: for any $Tcell$ higher than 20°C, the difference between $Tstc$ and $Tcell$ is greater than the difference between the Tcell-typ and $Tcell$, and so it is the correction applied to the corresponding PR. An additional consideration must be made in regards of the Tstc-corrected PR values. In fact, although no uncorrected PR values above the unit were found, the correction using $Tstc$ enhances the PR values above 100%. These high values are a consequence of the mathematical operations imposed by the correction. The calculation of the monthly average performance allowed for the comparison with the literature references. Studies showed that monthly average PRs at module level for similar HCPV are expected to have values between 90% and 95%. In the same range of values should also fall the global yearly average PR [20]. Although the variability of the performance throughout the year could have negatively affected these results, the yearly average corrected PRs result to be 84.84%, 87.69% and 90.05% respectively for unit A, B and C, while the yearly average uncorrected PR accounts at 82.11%, 84.58% and 86.79% for unit A, B and C. Considering these values, it is presumed that unit C and is the most affected by weather-related module's effects.

With the use of the PR assessment presented, shadowing and soiling analysis were also completed considering the cumulative sum of differences methods. Due to its statistically non-representative quantity of PR values below 100%, the Tstc-corrected PR data series is not taken into consideration for the following shadowing and soiling analysis.

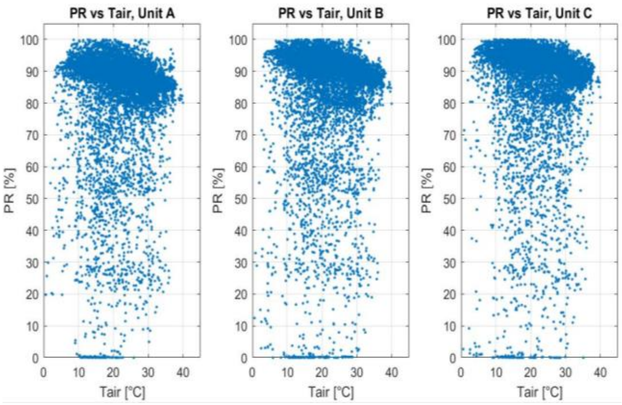

Figure 3: Air Temperature vs PR, Selected Units

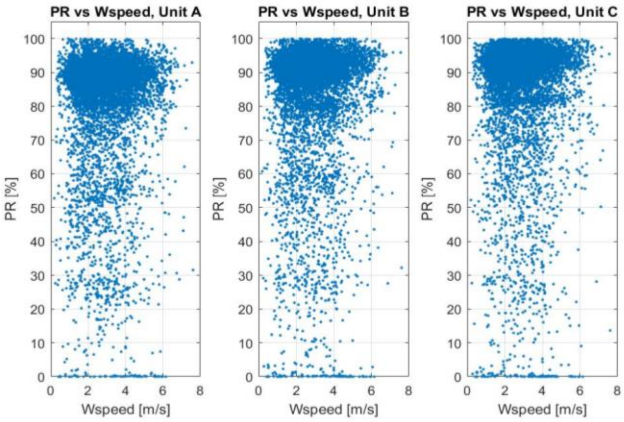

Figure 4: Wind Speed vs PR, Selected units

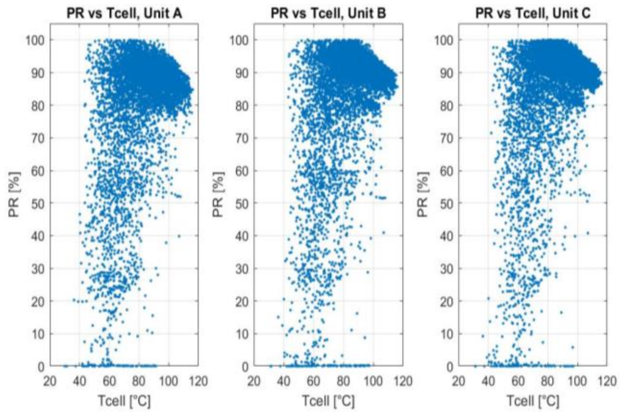

Figure 5: Cell Temperature vs PR, Selected Units

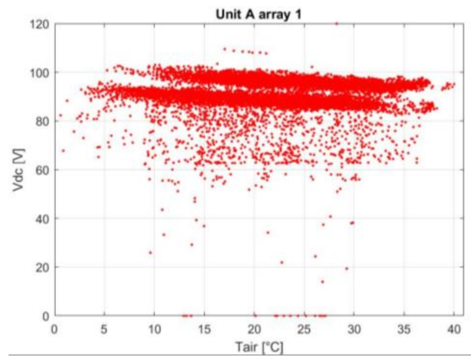

Figure 6: Air Temperature vs Voltage (Unusual Behaviour) - Array 1, Unit A

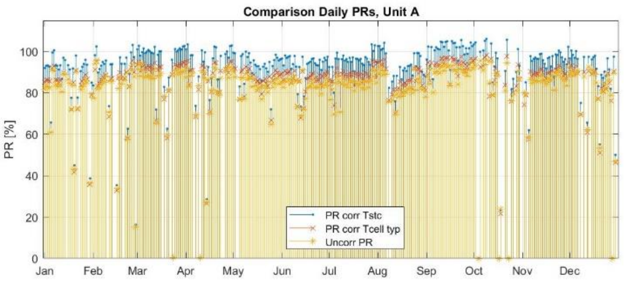

Figure 7: Uncorrected and corrected daily PRs, Unit A

4.5. Shadowing Analysis

The application of the cumulative sum of difference method is used to identify possible shadowing effect with the only use of empirical evaluations. The shadowing analysis focuses over the hypothesis of partial shading effect, at sunset hours of winter months, due to the presence of a tree in the proximity of unit W. To compare the performance of unit W to the other ones, all the monitoring analysis steps have been repeated over unit W's data too. The analysis outcomes show similar operational behaviour of unit W with respect to units A, B and C, thus allowing their performance comparison. The shadowing analysis compares the performance of unit W to the performance of units A, B and C with the application of the cumulative sum of differences method. The time-period chosen to apply the method is a single day of operation and the data points considered are the Tcell-typ corrected PR values of the mentioned units. Figure 8 shows the decrease of the Tcell-typ corrected PR of unit W happening earlier than the other units every day (January 1st-2nd) with respect to the other units. The same phenomenon is found happening until the month of March, not happening during the summer, and happening again since November. Figure 9 presents the differences generally found between summer and winter months. From these results, it is possible to state that the analysis outcomes provide explicit proves for the theory of cyclical partial shading over unit W caused by the close-by tree and the applicability of the cumulative sum of differences method for shadowing empirical-based data analysis.

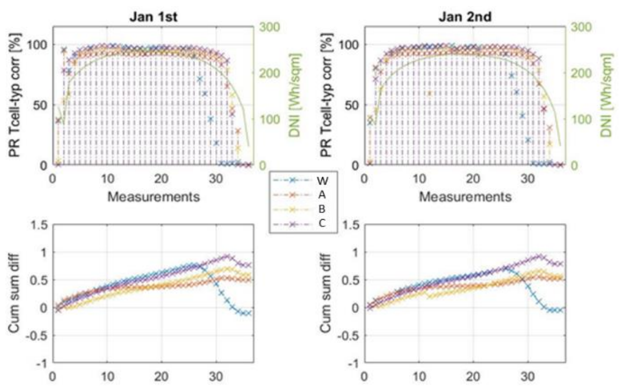

Figure 8: Shadowing analysis, January 1st - 2nd

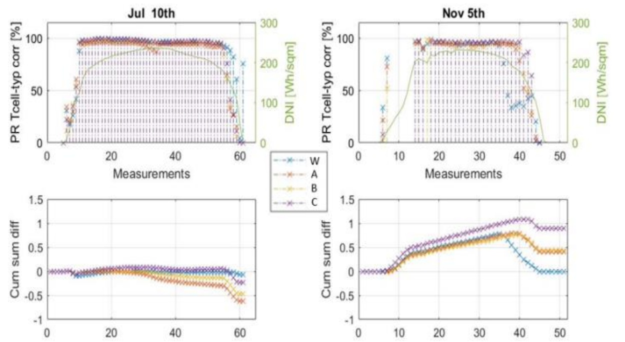

Figure 9: Shadowing analysis, July 10th and November 5th

4.6. Soiling Analysis

Since soiling effect causes performance decrease [12], [21], [22], the cumulative sum of differences method is used to identify possible soiling effect without the use of direct measurement from soiling sensors. The aim of the cumulative sum of difference method application is to identify decreasing performance trends and verify their correlations with the presence of prevailing southern winds and precipitation events. Southern winds have been associated to soiling effect because of the evidence found in the literature of the higher concentration of dust and particulate transported to the south of Portugal from winds blowing from North Africa [23]. The association of performance trends to rainfalls also derives from the literature findings [12]. December resulted to be the only month in which southern winds prevail over the other directions and it is thus chosen to be the month over which compare units' performance trends for soiling effect research. Figure 10 shows the soiling analysis findings and it is articulated over three levels: the first graph presents the daily wind directions distribution and the cumulative sum of differences results for the month of December (Linear regression computed only over the month of December); the second graph shows the amount of daily precipitations; the third graph displays the daily values of the Tcell-typ corrected PR and daily wind direction distributions. The days in which the PR values are not shown in this third graphs are consequence of flagged data. Considering third graph of Figure 10, the corrected PR values of the days from December 15th to December 20th seem to decrease in correspondence of continuous and prevailing presence of southern winds. The same decrease it's slightly visible also for the days between December 25th and December 28th. For both cases though, the cumulative sum of difference (first graph of the same figure) does not show any major trend decrease. Therefore, either considering the variations of the corrected PR over the single period of December or the variations of the corrected PR considering the average behaviour over the whole year, no critical trend changes are found. Considering the remarkable precipitations of December 20th, the following days' PR values increase at values slightly higher than those of December 19th and keep being mostly

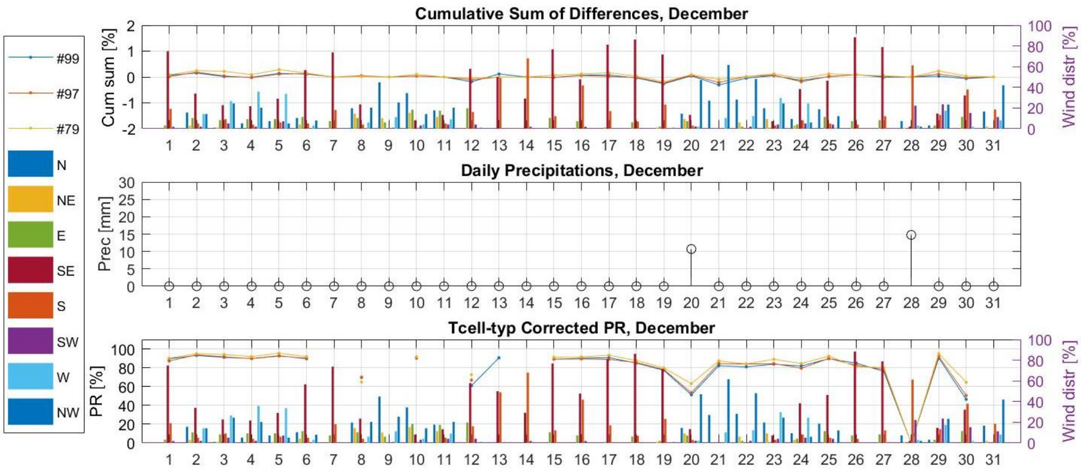

Figure 10: Soiling Analysis, Selected Units, December

constant until the 24th. For the same period, the cumulative sum of difference decreases slightly of about 0.25%, though suggesting no major variation from the average behaviour. The same considerations can be made for the PR decrease shown for the days of December 26th and 27th, and their related cumulative sum of differences. If the prevalence of southern winds was the main cause of the PR decrease, the related cumulative sum of differences would have shown a major negative trend change. Therefore, given the results of the soiling analysis, it is not possible to state that the prevalence of southern winds blowing over the solar platform in 2015 is associated with soiling effect for the units analysed.

4.7. Suggested Improvements

This section describes the possible enhancements for monitoring practises through the exploitation of VICINITY's platform. In fact, the monitoring issues highlighted from this paper can be turned into business opportunities thanks to the characteristics of the VICINITY platform. The interoperability offered by the latter could help solving missing data and incorrect measurements issues without the need to reinstall a new dedicated SCADA system. Exploiting the ability of the VICINITY platform to receive data from different sources, the already installed sensors could send direct measurements to the VICINITY platform. Once the direct measurements are received, a data inspection algorithm should be programmed to confirm the validity of the measurements exploiting machine learning techniques. If a data is recognised as an isolated incorrect measurement, statistical methods can be implemented to overwrite a new alike measurement based on series of historical data [24]. In case of prolonged and continuous series of flagged timestamps, the algorithm should alert the VICINITY platform users for sensors' misconduct or failures. Meanwhile, incoming data considered acceptable are treated by the algorithm to calculate the performance indicators chosen for monitoring purposes. It must be specified that synchronised timestamps from the different sensors would provide a superior data quality. All the information elaborated by the algorithm are stored in the VICINITY cloud for statistical and double-check purposes. Moreover, storing the information in a multi-user cloud is foreseen to help developing preventing maintenance actions by the provision of an organised and easily accessible archive of past operation and maintenance high quality information.

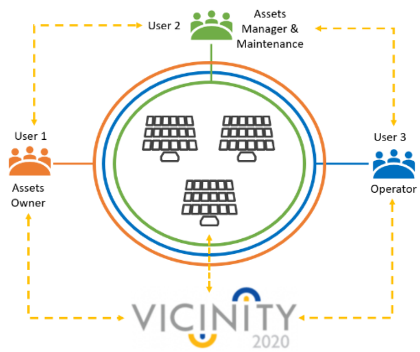

Figure 11: "Smart-cleaning" Operational Framework

The implementation of the above described machine learning-based algorithm for data validation is considered fundamental for the development of continuous real-time monitoring services and thus to the successful exploitation of the "smart-cleaning" use-case. The latter aims at the creation of added-value services linked to soiling analysis and cleaning procedures through real-time performance assessment. Figure 11 presents the O&M framework within which the "smart-cleaning" use case is foreseen to operate. User 1 owns the solar system installed in the solar plant and licenses user 2 to manage his assets and to operate maintenance actions, while user 3 operates the plant. Being all these users connected to the VICINITY platform and its cloud, they have real-time access to the information produced and stored by the algorithm. All the users are thus enabled to access the continuous real-time monitoring system. Therefore, the signals sent by the algorithm informing of possible soiling issues are received by all the users at the same time. If soiling occurs, the plant operator (user 3) would request planification of cleaning procedures from the maintenance (user 2) who is already aware of the soiling occurrence and planning its resources to operate efficiently the cleaning. The asset owner (user 1) could monitor and receive direct feedback in regards of its assets' condition.

The quicker response to occurrences linked to performance losses would avoid communication issues and delays in maintenance actions. The added-value introduced by services such as "smart-cleaning" is the adaptability of the VICINITY platform to already functioning solar plants in which assets ownership, operation and maintenance are not under a unique business body. The development of new business models on the base of the transparency and interoperability of the VICINITY platform could be taken as an opportunity by Enercoutim by proposing added-value services to other already functioning solar plants in need of better data management and real-time monitoring for enhanced plant's performance.

5. CONCLUSIONS

This paper completed a monitoring analysis and performance assessment of 116 units of Enercoutim solar platform during the year 2015. The preliminary steps of the monitoring analysis found several issues related to the quality of the primary data recorded by the solar platform sensors. Missing data, uncorrelated data values between DNI and DC energy and unsynchronised timestamps are the three main data quality issues encountered: the synchronization of the atmospheric and energy datasets was necessary to continue with the study.

The performance assessment was accomplished at three levels: tracking systems, inverters and modules. Among the 116 units, three units were selected for a more detailed performance assessment because of their average superior tracking performance. The inverters level analysis found unexpected negative results. The average daily efficiency of the inverters resulted to be lower than 70% against a nominal inverter efficiency of 98%. The cause of the very low average daily efficiency of the 116 inverters analysed was found in a three-month downtime of the inverters' AC-side measurement equipment. The module level analysis considered the performance ratio as the main indicator of the performance of units A, B and C. To consider the influence of weather features such as DNI, air temperature and wind speed, two different weather-related corrections were applied to the PR values and their results compared. To complete the correction, the cell temperature of the units' selected was estimated for each of the measurements available. The weather-related correction did not normalise as much as expected the PR values throughout the year: this fact is supposed to be linked to the lower sensitivity of MJ cell to higher air temperature than traditional PV. Throughout 2015, the comparison of the units' performance highlighted constant performance trends during summer months and, variable and scattered performance during winter months. Considering the typical operating cell temperature corrected PR, two additional analysis have been presented: partial shading and soiling analysis. Both these analyses exploited the application of the cumulative sum of differences method to identify module's performance trends hypothesized as correlated to shadowing and soiling effects. The shadowing analysis found substantial evidence of partial shading caused by a tree over unit W during sunset's hour in winter month. On the contrary, soiling effects couldn't be identified in correlations of consecutive days recording prevalent southern winds. In both cases, the use of the cumulative sum of differences as a method to assess performance losses utilising only empiric data showed its relevance for the application proposed. The monitoring analysis served as fundamental step to draw important considerations for the implementation of real-time continuous monitoring procedures. Suggestions regarding the use of machine learning for data quality verification were advanced on the base of the architecture of the VICINITY platform. Finally, the benefits deriving from the suggestions proposed are explained considering their application within the "smart-cleaning" use-case.

5.1. Limitations and future work

Although missing data in monitoring is a common occurrence, the data quality and their asynchronous timestamps are recognised as possible bias for the final outcomes of the analysis completed. The lack of direct measurements of cell temperatures and effective irradiance also introduced a level of uncertainties in the performance assessment. Nevertheless, the results provided by the thermal model used in the analysis aligned with the literature's values. Additional studies should apply the cumulative sum of differences method to further validate the evidence presented in this paper for both shadowing and soiling effects. Testing the soiling analysis proposed in this paper in locations heavily affected by soiling issues could also provide a validation of the technique applied. Considering the soon-to-happen implementation of the VICINITY platform, tests over the functionalities of the solutions proposed in regards of the "smart-cleaning" use-case will be fundamental to understand the weight of the data quality improvements and their impact on real-time monitoring practises. In a second moment, the results achieved should be analysed to seize possible business opportunity related to the development and sale of additional value-added services.

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