Design of a Smart Metering Device with Edge Computing for Monitoring Silicon Photovoltaic Panels

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Abstract—**Optimizing power generation with photovoltaic panels seeks to achieve the best performance and efficiency, both of single panels and grids comprising several of them. The outcomes depend on ambient conditions, such as irradiance or temperature, but also on external causes (e.g., soiling) that may lead to critical power losses. This paper proposes a smart metering device containing sensors to monitor these panels continuously by collecting I-V curves, a Maximum Power Point Tracker (MPPT) to maintain the optimal operation, as well as security elements to prevent external accesses and protect the generated data. The objective is to create a predictive maintenance system with artificial intelligence algorithms on the edge. Developing those algorithms requires a characterization of the selected panels to get optimal results, detecting failures and troubles swiftly, both of the panel and the smart device. Moreover, periodically or in case of noteworthy events, the device reports the information to a cloud platform by using LoRa 2.4GHz communication protocol. The device must ensure the proper operation of panels, allowing to take sustainable corrective measures by preventing an unnecessary waste of resources (electricity or water, among others). The aim is to avoid irreparable failures that imply high costs and reach high efficiency of the monitoring system and the energy generation process.**

Keywords— PV panels, predictive maintenance, IoT, edge computing

I. INTRODUCTION

Smart grid technologies are nowadays envisaged as an ultimate solution for the intelligent provision of the electrical power flow through an enhanced integration of components at different stages: power generation, transmission, distribution, securitization, or energy consumption. These technologies are aimed to develop novel bidirectional electricity delivery systems capable of both providing controllable and reliable power flow measurements and supporting the extended integration of renewable resources and local storage capacities [1]. They are also expected to overcome the limitations of current power infrastructures by reducing the power consumption in peak demand periods, and by optimizing the energy demand distribution, as directed by European regulations [2]. Up to now, smart metering tools have been used to acquire the consumption of electric energy in defined intervals, and record the information for monitoring and billing through bidirectional communication channels [3] [4]. However, the creation of innovative metering systems is crucial for developing energy management algorithms and enabling robust, intelligent, and secured infrastructures.

This work proposes the integration of several metering solutions for the optimal utilization and exploitation of energy generated by photovoltaic (PV) panels installed at any location. The new integrated system monitors every panel of a grid individually, gathers data and computes Predictive Maintenance (PM) algorithms to achieve the optimal operation of the grid. To this end, Internet of Things (IoT) sensors and components are employed to measure parameters with a relevant impact over the performance of PV panels (e.g., irradiation level or device temperatures) [5], in addition to store and communicate data, compute results, provide information about the individual panels and the grid, and help to detect emergency conditions or operating faults.

The smart metering device uses a Maximum Power Point Tracker (MPPT) to maintain the panel in its optimal working point but allowing the collection of I-V curves without disconnecting that tracker. It also includes two innovative components: on the one hand, a security module to implement encryption protocols (RSA, SHA, etc.) for guaranteeing the safety of collected data, the results of the edge computing and the communication with the cloud, seeking to protect the infrastructure against external attacks that can compromise the energy generation process [6]. On the other hand, a new transceiver to provide communication by LoRa modulation in the 2.4 GHz band, aiming to transmit data wirelessly to the cloud platform for further processing and visualization [7].

Among the current PV technologies, the proposed solution uses silicon (Si) PV modules to build the grid, that have been widely employed over the years [8]. These panels have been characterized under different conditions using a climatic chamber to finely control conditions, such as the irradiance or the temperature. Results serve as inputs for developing Artificial Intelligent (AI) algorithms and generate predictive models about the future state of the grid. Likewise, these data also allow determining the energy generation profiles through I-V curves and approaches based on tracking the maximum power point [9].

The periodic data gathering, and the subsequent application of AI algorithms seek detecting phenomena that can affect negatively to individual panels or the whole grid, and thus the proper energy generation. Some examples are soiling, which can be remarkable hinging on the location of the deployment; ageing that PV panels endure with the passage of time; or obstacles that avoid the irradiation fall upon the panels thoroughly [10] [11]. It is also indispensable that these algorithms can distinguish other natural and non-controllable phenomena, such as shading due to the presence of clouds [12]. The final objective is to take corrective actions when required to improve both the lifetime and the efficiency of panels, as well as targeting the energy demands of the specific locations where the grids are located.

Extensive research is available about PM systems for solar plants or individual PV panels [13] [14]. This maintenance method prevails over other solutions, either outdated, as visual inspection, or innovative but expensive, such as the usage of drones [15]. This solution reduces costs and increases the efficiency and the possibility to detect faults and errors in advance, avoiding more costly actions. Furthermore, the PM process also aims that these systems become sustainable, adopting one or several Sustainable Development Goals (SDG) to, not only improving the performance of the energy generation, but reducing the consumption of resources (e.g., water to clean) to the minimum extent.

The smart device includes edge computing for providing a swift and effective method to detect failures in a PV installation without needing a cloud platform for analyzing and display data for visualization. In this manner, the device becomes stand-alone, avoiding communication troubles and allowing to take corrective actions quickly to solve failures or damages to the infrastructure that may end in future malfunctioning. The algorithms use real data from panels to evaluate the state of the grid, both present and future, after a previous treatment to remove corrupted or fail data. Thus, it is essential to characterize the panels for identifying the most relevant parameters to examine their behavior, as well as applying the proper algorithms so that results are sound and corrective actions lead to optimize the installation.

II. CHARACTERIZATION OF PV PANELS

Troubles affecting energy generation or power losses in a PV grid depend on the installed panels. They can be hardware-related (e.g., electrical connectivity or cable breakings), or come from external causes, such as soiling, shading or ageing. It is then required to characterize the selected PV modules (CL-SM30M Cellevia Power) for adapting the PM system to the specific requirements of the grid, using the results to identify the main parameters for evaluating phenomena affecting the panels and developing the planned AI algorithms. The process is conducted using a climatic chamber for maintaining controlled conditions of irradiance and temperature, and an I-V checker (EKO MP-11) to collect I-V curves (see Fig. 1).

Figure 1. Solar panel in the climatic chamber for characterization

The characterization consists of two phases:

- Tests in climatic chamber to collect I-V curves in controlled environmental conditions of irradiance and temperature. The chamber allows the configuration as follows:
    - Temperature of the climatic chamber: 0, 10, and 25 ºC
    - Lamp power (irradiance level): 250, 450, 800, and 1.000 W/m^2 .
- Soiling tests in climatic chamber to collect I-V curves under changeable soiling settings, and fixed ambient conditions (10 ºC and 1.000 W/m^2). The conditions are as follows:
    - Types of soil: standardized and soil from the vicinity of the installation in Leitat facilities.
    - Soiling methods: spraying and painting using a dispersion of soil in water.

The study of resulting I-V curves requires focusing on the characteristic PV parameters and select those which define behavior trends more reliably. Some examples are the maximum power point (P_{max}), the short-circuit current (I_{SC}), the open-circuit voltage (V_{OC}), the irradiance level, the temperatures (both ambient or panel), the efficiency of the panel (η) or the Fill Factor (FF).

A. *Results of the Characterization*

1) *Tests in Climatic Chamber*

Fig. 2 shows three I-V curves with similar irradiance levels (around 1.000 W/m^2), and different temperatures. The graphs show similar device temperatures as regards the chamber conditions since the lamp heats up the PV panel when working. In the three graphs, P_{max}, I_{SC}, and V_{OC} keep similar values.

A similar behavior appears when comparing curves with lower and fixed irradiance values (250 or 450 W/m^2), and the same three temperatures (0, 10 and 25 ºC). A decrease of panel temperature appears when reducing the chamber temperature, but there are not significant variations, and the three characteristic parameters remain approximately equal.

On the other hand, Fig. 3 shows three I-V curves with decreasing irradiance levels and constant temperature (25 ºC), even though the irradiance slightly changes depending on the lamp power, which may affect the collected curves. In this case, P_{max}, I_{SC}, and V_{OC} considerably reduce, following the decreasing of the irradiance level. Moreover, the trials with decreasing irradiances and other fixed temperatures (10 and 0 ºC) always show the same behavior, evidencing the influence of the irradiance on the collected I-V curves.

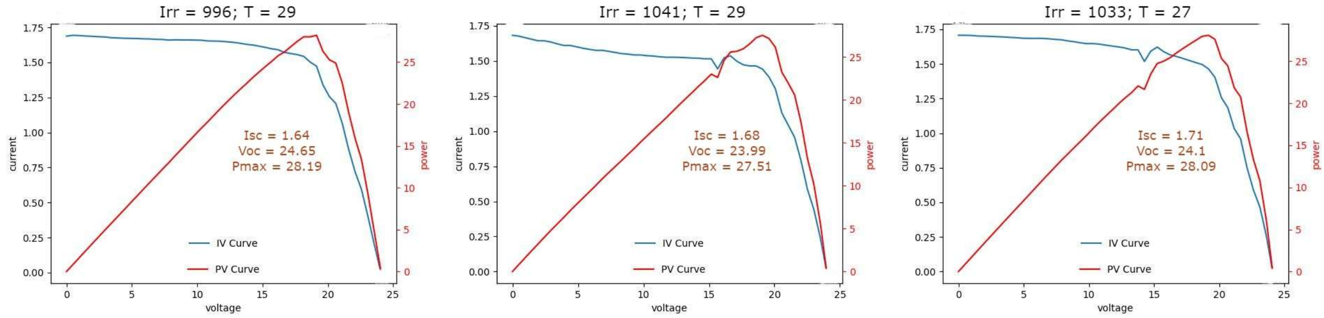

Figure 2. I-V / P-V curves with fixed irradiance level (1000 W/m^2) and different chamber temperatures (25ºC on the left, 10ºC in the middle, and 0ºC in the right). The behavior is always similar (V_{oc}, I_{sc}, and P_{max}) because the chamber heats due to the influence of the lamp.

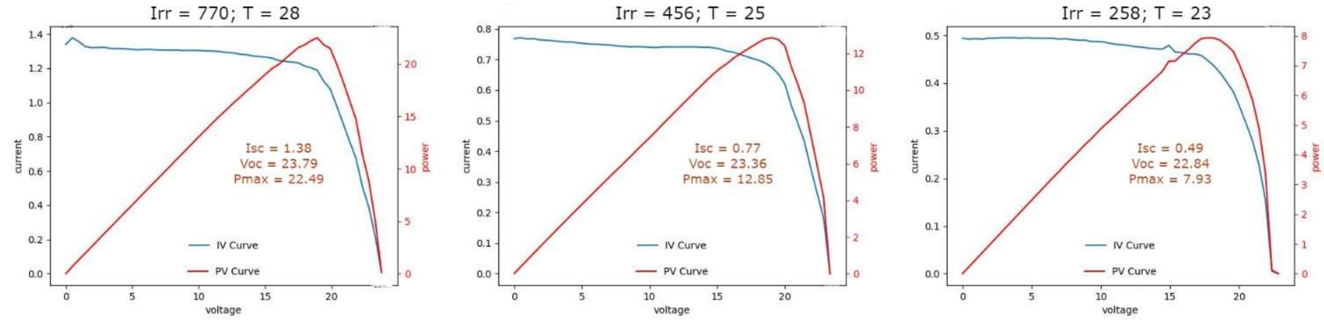

Figure 3. I-V / P-V curves with fixed temperature (25 ºC) and decreasing irradiances in W/m^2 (800 in the left, 450 in the middle and 250 in the right). The relevant parameters of the curves decrease gradually when the irradiance level drops, proving the relevancy of this parameter to get the maximum performance of PV panels.

2) Soiling Tests in Climatic Chamber

These trials intend to figure out whether the soiling may cause a reduction of the performance when the radiation cannot fully hit the PV panel by studying how the I-V curves change in those cases.

All trials maintain the same irradiance and temperature values: 1.000 W/m^2 and 10 ºC, respectively, whereas the soiling conditions change. Figs. 4 and 5 shows I-V curves to compare between the clean panel (left images) and soiled panels (middle and right images) with different soils by spraying and painting. In the spraying case, the values of P_{max}, I_{SC}, and V_{OC} reduce in the soiled panels, either with standardized or Leitat's soil. The same behavior appears when the soil is applied by painting, although the reduction is less pronounced in that case.

III. Smart Metering Device

A. Hardware System

The smart metering device (see Fig. 6) employs an STM32L4 microcontroller to manage several sensors, monitor the state and the operation of PV panels, and compute AI algorithms on the edge.

- Pyranometer [EKO ML-02-10P] to get the solar irradiance reaching the panel. It is placed over the panel edge to obtain the value accurately.
- Ambient temperature sensor [Telaire – T9602]. It is placed in the outer part of the box containing the metering system.
- Panel temperature sensor (Pt-1000). It is attached to the posterior face of the PV panel to avoid blocking the solar irradiance.

The device also includes a subsystem to obtain I-V curves since it is the main method to know the performance of PV panels [9]. Commonly, monitoring systems include an MPPT to maintain the PV panel in its optimal working point, but the collection of I-V curves requires disconnecting the tracker for using an external equipment. In this case, there is no need to disconnect the panel, which avoids stopping the operation and save time and costs for evaluating the panel status. Moreover, this subsystem collects more points than the EKO MP-11 to generate the I-V curves, providing more thorough information about the panel status, and obtaining the point of maximum power with higher efficiency and accuracy to enhance the performance of the PM algorithms.

The device includes a security element with several functionalities (Optiga Trust M – Infineon). On the one hand, collected data about the PV panel status and the results of the edge computing are encrypted by using RSA protocols, and they are only decrypted when data reach the cloud. The required RSA keys are, in turn, encrypted by employing a random number generator, setting a double encryption layer. Furthermore, the system uses the SHA protocol to create digital certificates, forcing the software platform to authenticate for enabling the communication and the reception of data coming from the metering device. The three security protocols enable a secure way since the device collects data from the PV panel to reception by the cloud platform.

The communication between the device and the cloud is conducted by using LoRa 2.4 GHz. This protocol is a variant of the original LoRa protocol, and it uses different frequencies to transmit messages. The main advantage is the absence of limitations regarding the length of messages that caused the original protocol was not an option for this application (the I-V curves can contain up to 1500 current and voltage values). Although 2.4 GHz frequency is also used by other protocols (e.g., Wi-Fi), the immunity is ensured [7]. Likewise, the protocol also ensures that the communication distance is

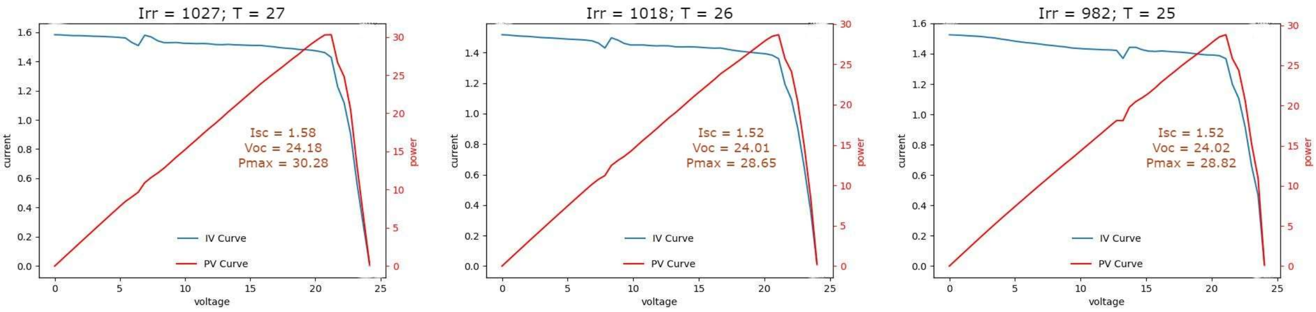

Figure 4. I-V / P-V curves for different kinds of standardized soiling: clean (left), soiled by spraying (middle) and soiled by painting (right). Minor differences appear in both curves for soiled panels, being mainly noticeable in the I_{SC} value and the maximum power.

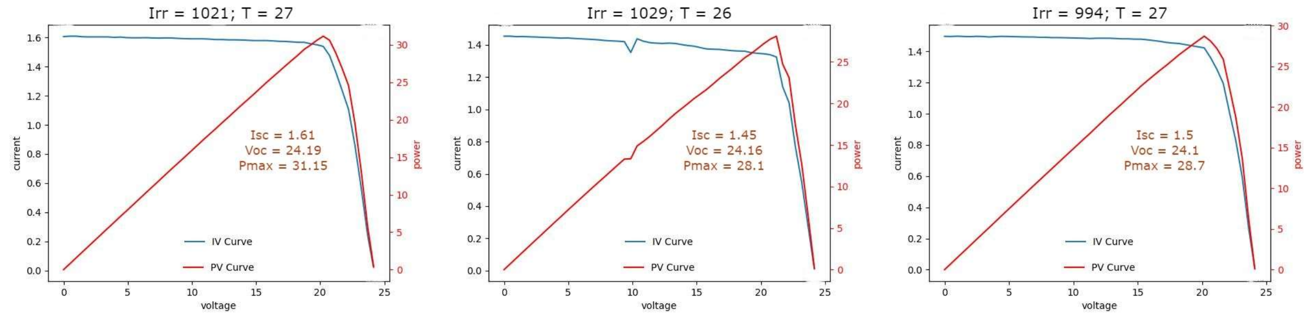

Figure 5. I-V / P-V curves for different kinds of LEITAT soil: clean panel (left), soiled by spraying (middle), and soiled by painting (right). In this case, the differences are more noticeable in both soiled curves, appearing a drop of the I_{SC} value and a considerable decrease of the maximum power.

enough for the deployment since it can reach until 450 meters in urban environments [7].

B. *Edge Computing*

The local processing module runs on the edge with four objectives: 1) identify and remove outliers; 2) compare panel and ambient temperatures; 3) evaluate I-V curves; and 4) generate a log of events.

The device computes the identification of outliers when it collects data every five minutes (default interval) from all sensors: temperatures (panel and ambient), irradiance, current, and voltage. The process consists of filtering data to ensure good data quality, besides detecting trends for identifying potential failures or malfunctions in the PV panel.

The second functionality compares both measured temperatures (panel and ambient). If the difference is above 20 ºC, the device raises a warning event, whereas if the difference is above 30 ºC, it raises an alarm to the log. Those high differences may appear when read values are technically acceptable, but not concordant between them. The result could indicate an overall failure of the device or a particular failure in a temperature sensor.

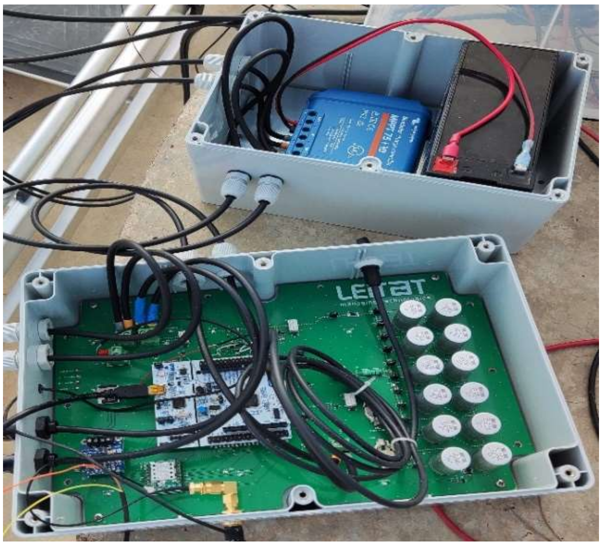

Figure 6. Smart metering device

The main objective is to analyze I-V curves to detect the occurrence of phenomena that can reduce the performance or the efficiency of a PV panel or the whole grid. This technique is widely used, and it does not need visual inspection, so the process must run on each device to monitor the status of each PV module individually.

There are two basic approaches to analyze the curves:

1. Comparison between a reference clean PV panel and the monitored panel. If the difference in power exceeds a threshold, the panels must be cleaned or substituted. This approach is not optimal since workers must go to the installation to perform inspection tasks, not allowing remote monitoring.
2. Comparison between expected and measured power according to experimental equations. This approach only works if the conditions are similar to the standard ones (1.000 W/m^2 of irradiance and 25 ºC of device temperature). Furthermore, it would only work at the middle of the day when the sun hits the panel perpendicularly, and the temperatures are not extreme.

Considering the drawbacks of the previous options, the optimal solution is to employ AI algorithms trained with characterization data to determine if the installed panels are operating properly by analyzing the collected I-V curves. Data from characterization must be previously studied to find the most relevant parameters that help to detect if panels are enduring soiling, any operating problems, or whichever

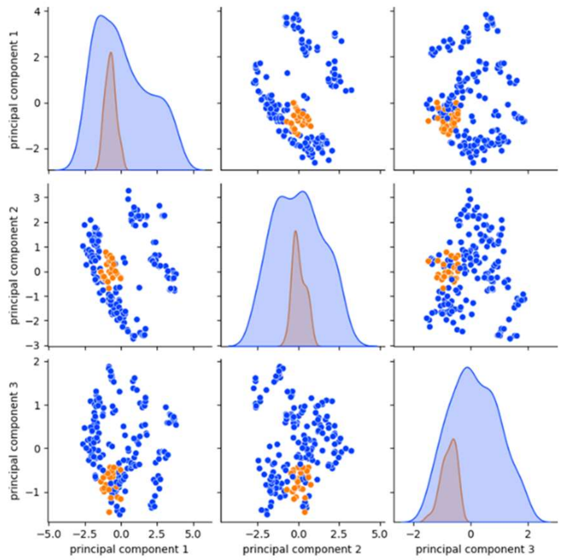

Figure 7. Pair plot of the three identified principal components: irradiance (PC1), I_{SC} (PC2), and V_{OC} (PC3). The orange points represent values from soiled panels and the blue ones represent values from clean ones.

phenomena that can affect negatively to its performance. A Principal Component Analysis (PCA) allows to discern between the main identified parameters (see Section II) and obtain trends to differentiate and separate between the I-V curves from soiled and clean PV panels. Fig. 7 shows the results of the PCA and three principal components: irradiance level (PC1), I_{SC} (PC2), and V_{OC} (PC3). Orange clusters represent those parameters of soiled panels, whereas blue clusters correspond to the clean panels.

After identifying the components, the next step is to develop a classifier for running on the edge and inferring whether the PV panel has soiling affecting its performance and efficiency. The PCA only runs as the previous action to enhance the development of the AI model, reducing the computational load and optimizing the operation of the smart metering device. Ten Machine Learning (ML) models for classifying were trained using Scikit-learn (www.scikit-learn.org) with three combinations of features: 1) I_{SC} and V_{OC}; 2) I_{SC} and irradiance level; 3) P_{max} and V_{OC}.

Fig. 8 shows the contours of six models, although the most reliable result emerges when applying the Support-Vector Machines (SVM) algorithm using a Radial Basis Function (RBF) kernel. In this case, the algorithm separates results of soiled and clean panels employing the two features with the highest discrimination power: I_{SC} and V_{OC} (first row in Fig. 8). Moreover, an 60/40 train-test split shows a 100% classifying accuracy, even that does not imply optimal performance on site. A 5-Fold Cross Validation was also performed to obtain more robust metrics because the dataset is unbalanced.

The algorithm has been validated with real I-V curves collected from May'22 to July'22 in the outdoor installation consistent of three panels at LEITAT facilities. Results reveal a probability around 0.96 that panels are clean and working optimally, coinciding with visual inspections. Nonetheless, more data in different conditions should be collected for attaining stronger results.

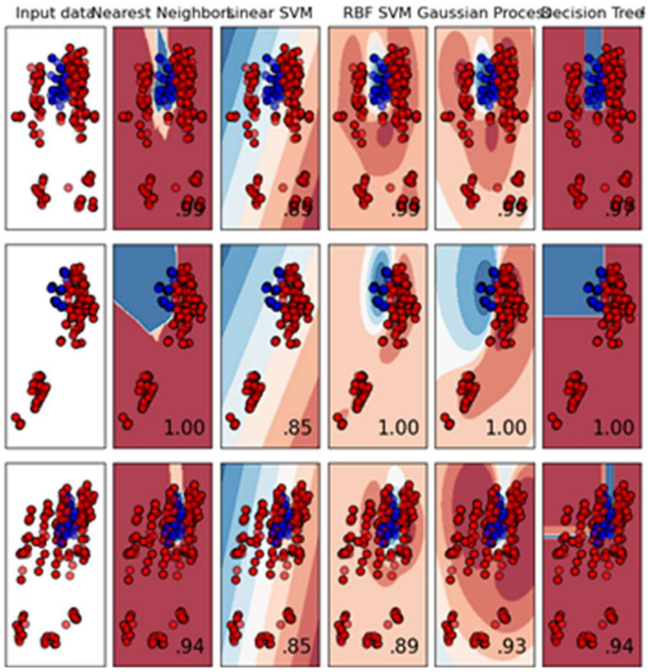

Figure 8. Comparative of six ML models for the three combinations: 1st row) I_{SC} vs V_{OC}; 2nd row) I_{SC} vs irradiance; 3rd row) P_{max} vs V_{OC}. The RBF SVM model provides the most promising results with all combinations, being able to classify properly the curves from soiled and cleaned panels.

IV. Discussion

The smart metering device allows monitoring each PV panel separately and autonomously, applying AI algorithms on the edge to determine failures or malfunctions due to internal or external causes. The results of that processing serve to take corrective actions for improving the efficiency and the overall performance of PV panels.

The AI algorithms analyze the collected I-V curves from a PV panel in real time to determine its current status. Developing and training these algorithms for attaining optimal outcomes requires characterizing the panels in real outdoor conditions simulated with the climatic chamber. In this manner, they are able to identify the most relevant parameters related to the performance and the efficiency, besides phenomena affecting the panels' operation.

Tests in the climatic chamber indicated that the irradiance level is the main ambient factor affecting the panels, whereas the device temperature has minor influence. Despite configuring the chamber's temperature at low values (0 or 10 ºC), the power lamp heats the panel, increasing the temperature to always reach values higher than 20 ºC. Even so, Fig. 2 show similar behaviors (P_{max}, I_{SC}, and V_{OC} values) when the irradiance was 1000 W/m^2 and the temperature changes, prevailing the influence of the irradiance over the temperature.

Therefore, it is essential to evaluate the performance of PV panels when the irradiance levels are around 800 – 1000 W/m^2, because the sun reaching perpendicularly the panel in outdoor conditions has a similar effect to the lamp. Those values maximize power generation, and the resulting I-V curves provide more accurate information to develop the AI algorithms. In this manner, the soiling tests were performed with the standard irradiance value (1000 W/m^2), and the final algorithms must also apply with similar values to get optimal results for the PM process. Otherwise, lower irradiance levels could imply unexpected behaviors, leading to take unnecessary or wrong corrective actions.

Soiling tests always indicated a reduction in the efficiency and performance of PV panels if they are not completely clean, regardless of the soil (standardized or Leitat) and the different application methods (spraying and painting). I-V curves of soiled modules show a drop in P_{max}, as well as values of I_{SC} and V_{OC}. Nevertheless, the losses are slightly more pronounced when the soil is thicker (Leitat's). Moreover, the sprayed panels generate less power than the painted ones, but the differences are not significant enough to claim that the performance differs.

The characterization reinforces the necessity of a PM process so that PV panels achieve its optimal operation. Power generation always drops due to soiling and, hence, the smart device should inform when a cleaning is necessary. It is required to set a threshold as of which the loss is not acceptable and corrective actions must be taken, which depends on the model of PV panel and the installation where they are integrated.

The AI algorithms must employ, as inputs, both the previous results and the collected I-V curves in real time from installed panels. Results of applying ML models demonstrated that the RBF SVM algorithm was the best option to identify the presence of soiling. According to Fig. 8, this algorithm is the only one which keeps the soiled I-V curves in a perfectly delimited area in the three rows (the blue points corresponding to soiled panels perfectly fit to the blue area in the background). The optimal solution corresponds to the classifier with two parameters of the curve: I_{SC} and V_{OC}. This result coincides with the results both of the characterization, which show drops of those parameters when PV panels had any soil, and the PCA that identified them as two principal components.

The third identified parameter in the PCA was the irradiance level and, although it has lower classifying power, it is also feasible to use in the SVM classifying algorithm (see the delimited area in the second row of Fig. 8). Furthermore, the importance of this parameter also coincides with the characterization results, which indicated a strong influence of the irradiance in the performance of PV panels (see Fig. 3).

However, it is necessary to widen the capabilities of the computing process in future versions. For instance, considering cases that the classifying algorithm may associate to soiling even if they are caused by other phenomena, such as shading due to the presence of clouds. In those cases, it is vital attending to the variations of the irradiance level and the common values throughout the day. The algorithms must detect the trends properly to determine the presence of clouds and avoid that I-V curves are classified as soiling wrongly.

The algorithm has another drawback related to the irradiance level since all trials with soiled panels considered values above 700 W/m^2. Hence, the edge computing only works optimally during the highest irradiation moments of the day regardless of the temperature. Predictions at other day times should be carefully considered by now, although next versions of the algorithm will be trained with more data from soiled panels at different irradiances so that the PM system can provide results at every possible condition.

The preliminary installation only consists of three PV panels, but it is possible to install these smart devices in grids containing more panels or in PV plants, but only with silicon panels. In all cases, it would be necessary to include a device for each panel, which could increase the costs significantly. Nonetheless, there are no limitations regarding the extent of the installation providing that the distance between the furthest panels and the LoRa receiver complies with the defined ranges [7]. Likewise, the losses of power generation will be minimal since the device requires very low current consumption for its operation.

Finally, a secondary objective of the PM system is to be able to take corrective actions in line with SDGs. Cleaning panels after a visual inspection, or if they are clearly dirty, may generate an excessive water consumption and more polluting emissions. A properly designed PM system may optimize the transfers to the installation and only suggest corrective actions when they are strictly necessary. In this manner, it will be possible to avoid losses of performance, achieving an optimal power generation of each PV panel with the maximum sustainability.

V. Conclusions

This work proposes the design and development of a smart metering system for monitoring PV panels, collecting I-V curves and maintain the panel in its optimal operation point using an MPPT tracker. The device includes edge computing for performing the PM process to detect failures due to internal or external causes, such as soiling, as well as components to securitize and send the obtained data. The predictive algorithms are based on the characterization of selected panels, and they classify the collected I-V curves of deployed panels in real time to determine its current status.

The characterization and the subsequent analysis prove that I-V curves and some of their parameters (P_{max}, V_{OC}, and I_{SC}) are the most reliable method to check and predict the status of panels. Using those results, the AI algorithms have been developed so that the device performs the maintenance and inform about the necessity of taking corrective actions to clean a panel or fix troubles in the device. These algorithms have been tested with real data obtaining promising outcomes.

As future work, the characterization will be extended to improve the AI algorithms, attaining more information about soiling, with more irradiance values, and about the degradation and ageing of panels. Thus, the predictive system will consider a wide range of failures, seeking to achieve the utmost efficiency in PV panels operation.

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