Centralized Control Topology for PV Farms
Shading Detection and GMPP Searching
Restarting Condition

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ABSTRACT
The power output of the solar panels follows a power-voltage (P-V) characteristic containing only one Global Maximum Point (GMP) in the normal conditions. However, under Partial Shading Conditions (PSC), the unbalanced irradiance in the panels creates Local Maximum Points (LMP) in the P-V curve. Standard control techniques for Maximum Power Point Tracking (MPPT) cannot properly locate the GMP, stagnating in LMPs and generating losses in the energy harvesting. Specific techniques to locate the GMP are presented in the literature. However, the condition to restart the GMP is not widely discussed. The main challenges of global search algorithms are related to the restarting conditions. Avoiding unnecessary searching and providing an assertive GMP restarting condition is crucial for PV systems operation. In every GMP search, the solar inverters oscillate the power exchanged with the grid, causing frequency and voltage variations depending on the size of the PV plant. This paper proposes a novel technique that uses a centralized controller to identify the shaded inverters, creating flags that locally start the GMP searching. The solution minimizes the number of times the search is performed by providing an assertive GMP restarting condition, saving energy, and avoiding unnecessary output power oscillation. The proposed control technique was evaluated using the data of a real 150-kW solar farm containing five inverters with two MPPT trackers each.

INDEX TERMS
Solar power generation, partial shading, maximum power point trackers, global searching, central controller, SCADA.

I. INTRODUCTION
A. MOTIVATION AND INCITEMENT
Several benefits of Renewable Energy Sources (RESs), such as zero CO2 emission, sustainability, increasing resilience, etc., make these resources a motivating option for replacing fossil fuels. Among those resources, solar energy has the most potential to be considered a trustworthy choice for electric power systems [1]–[3]. However, some aspects like the implementation cost, weather dependency, storage, intermittency, shading effect, and the ample space required cause limitations in solar energy’s rapid and wide utilization.

PV farms consist of numerous solar panels with series-parallel connections based on the required power.
The incident irradiance and operating temperature are two effective factors in photovoltaic power production.

The Partial Shading Conditions are caused by clouds, high buildings, and peripheral structures around the farm. PSCs affect the Maximum Power Point (MPP) of Solar PV systems. During the PSCs, some panels receive different values of irradiance, which affects the Maximum Power Point Tracker (MPPT) performance [4]–[7]. All panels have the same MPP in the P–V (power–voltage) characteristic curve in ideal conditions. However, the shaded curve might contain one or more Local MPPs (LMPPs) and just one Global MPP (GMPP) during the PSCs. Finding the GMPP point is a goal that can significantly increase the amount of power extracted from panels and arrays under shading conditions.

B. LITERATURE REVIEW

Several well-known traditional methods such as Perturb and Observe (P&O), Short-Circuit Current (SCC), Incremental Conductance (IC), Open-Circuit Voltage (OCV), and Hill Climb (HC) have already been used in the uniform irradiance conditions. These techniques present a simple structure enabling easy implementation of PV systems. Nevertheless, the mentioned techniques cannot properly track the GMPP in the shading conditions and frequently get stuck in the LMPP, which reduces the potential of electrical power generation [2]–[8]. Soft computing-based approaches are one category of algorithms being used to find the GMPP during PSCs. Numerous approaches such as Cauchy and Gaussian Sine Cosine Optimization (CGSCO), Fuzzy Logic, Normal Harmonic Search (NHS), and Artificial Neural Networks (NNs) are in this category [9]–[14]. Another class of GMPP detection is based on evolutionary algorithms such as Particle Swarm Optimization (PSO), Gray Wolf Optimizer (GWO), Firefly Algorithm (FA), Intelligent Monkey King Evolution Algorithm (IMKE), and Genetic Algorithm (GA), have shown good performance to this end [10], [15]–[19].

In [20]–[22], authors presented interesting and novel approaches for re-initializing the searching algorithms. These algorithms use a Fuzzy Logic Controller (FLC) associated with power change or time variation to provide the requirements to trigger the restart of the PSO and GWO. These studies have proved that improving the re-initialization of the searching algorithms increases the power production of the solar system. These algorithms focus on a single-inverter operation, relying on local irradiance and power measurements. However, they did not consider some information that can be extracted from the system, such as the zone location of the PSC. Using the zone monitoring measurements from inverters or conjunction boxes is possible to identify those locations in the solar farm.

Besides the partial shading, other underperformance faults such as dirt (generalized and irregular), snow, plants, hot spots, and module degradation are other issues that can similarly affect the power generation. Traditionally, the Supervisory Control and Data Acquisition (SCADA) system is used in PV power plants to monitor the signals and detect faults in the system. These signals can be used to maintain the system with the proper data management algorithm [23]. Researchers have also used the SCADA system and centralized controller to evaluate underperformance, including shading conditions. An automatic fault diagnosis in PV systems with distributed MPPT has been presented in [24]. However, the research focused on the fault detection and performance of the PV system without addressing the integration of GMP search algorithms.

C. RESEARCH GAP

The main focus of these algorithms is to find the global maximum point faster and with a lower number of interactions. However, they do not cover or describe in detail the restart method, which might lead to unnecessary searches and power losses. The restarting condition is the situation that triggers a new search for the GMPP. This research divided the current literature on GMPP searching algorithms into four categories based on their restart trigger conditions: power change, irradiance variation, time-based, and not defined.

Power change as a trigger can differentiate between the shading effect and intrinsic power changes during the morning and evening. In [25], the authors mentioned that the algorithm performs a new search based on power variation, but it lacks details about how the trigger condition is detected. Resetting based on the irradiance variation is another approach that has not been clearly described in [26] and relies on numerous sensors for measuring the irradiance. For big solar farms, the number of sensors is limited and might not detect the PSCs in some zones or arrays. Thus, irradiance-based restart conditions might fail to detect local PSCs properly.

Another mentioned method in recent studies is the time-based resetting approach [27]. In this strategy, the search occurs with fixed intervals in inverters/arrays/panels with and without shading. The downside of this approach is related to the energy lost in each unnecessary search interaction run in panels without shading.

Some other researchers have only presented the search algorithm without mentioning the resetting detection, which was not the focus of the paper [8], [28]–[31]. This lack of details regarding the reset conditions can affect the practical implementation of these GMP searching techniques in real systems. For example, in small PV systems like residential applications, the power losses associated with the restart condition are not noticeable. However, in large-scale PV plants, the restart search condition can affect the solar farm power output and the losses associated with unnecessary GMP searching performed.

D. CONTRIBUTION AND PAPER ORGANIZATION

This paper proposes a novel concept to detect shaded and underperforming panels in large-scale solar systems, creating flags to identify the specific arrays/zones that need to restart the global searching mechanism. The novel solution addresses the challenges related to the restart condition.
of GMPP, searching techniques that use system-level information, and the lack of research on this topic.

The proposed approach considers a central controller topology to efficiently flag shaded and underperforming arrays based on measurements from all inverters in the PV farm. The computation technique uses a series of power normalization, filtering, and statistical analysis to create the shading flags. These flags can be integrated into the solar inverters as a control variable, defining when the GMPP tracking should be restarted. Additionally, the flags can be used as a performance indicator that comparatively evaluates the inverters’ power output. In this work, the GMPP technique chosen for the analysis is the OD-PSO presented in [32], an approach based on the Overall Distribution (OD) and PSO algorithm.

The main contributions of this research are summarized as follows:

- Provide an evaluation of the challenges associated with the current techniques used in the restart conditions for the GMPPT when using measurements of a single inverter.
- Provide a novel algorithm based on statistical analysis to detect shading conditions in solar panels and create shading flags to be integrated with the GMPPT techniques.
- Demonstrate the performance of the presented controller in locating the shading condition with the data from a 150-kW PV facility.
- Improve the efficiency of the solar farm by reducing the number of inverters that run the searching algorithms by the presented controller for the restart condition.

The remaining sections of this paper are organized as follows. Section II provides a detailed overview of solar power generation. Section III describes some well-established global search algorithms. Section IV clarifies the challenges associated with the global search algorithms. In Section V, the proposed control scheme for shading detection and restarting conditions is explained in detail. Section VI describes the data collection for the analysis. Section VII presents and discusses the simulation results. Finally, Section VIII provides the conclusion of the present study.

II. SOLAR POWER GENERATION
Researchers have proposed several methods to better use the available solar power generation by finding the GMPP over the operation time and improving conventional searching approaches. Even though it adds more complexity to the algorithm, most techniques require characteristic parameters of the PV panels, such as SCC, OCV, and others. In the sequence, the PV panel and inverter equations and models are presented. Beyond that, the operation impact due to shading and partial shading over the plant is explained.

A. PV EQUATIONS AND MODEL
Photovoltaic cells are compounded by a relation of semiconductors which brings nonlinear characteristics to the device.

Simplified models of solar cells have been developed to overcome these nonlinearities, making their modeling and electrical studies feasible. Figure 1 shows a simplified single-diode model of the PV cell.

\[
I_D = I_s \left( e^{-\frac{V_{cell} + I_{cell}R_s}{nqVT}} - 1 \right)
\]

This characteristic is obtained from the Shockley diode equation. The Shockley diode equation makes a connection between the current of a p-n junction diode, \(I_D\), and the cell output voltage, \(V_{cell}\), as shown in Eq. II-B [33].

\[
I_{cell} = I_{ph} - I_s \left( e^{-\frac{V_{cell} + I_{cell}R_s}{nqVT}} - 1 \right) - \frac{V_{cell} + I_{cell}R_s}{R_p}
\]

The cell’s power losses are mainly caused by the current circulation through different parts of the device and modeled by the series resistance, \(R_s\). The effects of leakage currents of the p-n junction are modeled by a shunt resistance, \(R_p\).

B. DC-DC AND DC-AC CONVERTERS
Different control techniques have been implemented to investigate the current power system’s scenario requirements regarding both functionalities and performance. Grid-tied inverters have widely been used to interface RES into low-voltage electrical distribution systems, particularly the integration of PV power generation systems to residential customers. Most traditional PV inverter topologies have a DC-DC converter connected to a DC-AC inverter [34]. Figure 2 depicts the schematic representation of a simple three-phase PV converter, compounded by a DC-DC boost converter and a DC-AC full-bridge inverter.

The first stage, “DC-DC Boost Converter” is responsible for regulating the voltage from the PV array side to achieve the desired power output. The boost converter’s voltage transfer function is given by Eq. II-C [35]:

\[
\frac{V_{DC}}{V_{PV}} = \frac{1}{(1-\delta)}
\]
where, $V_{PV}$ is the voltage at the source side, $V_{DC}$ is the voltage at the DC-link, and $\delta$ is the duty cycle of $S_7$ [36].

The second stage, “DC-AC Inverter” can be modeled as a resistive load as demonstrated in [37]. However, this approach neglects several aspect intrinsics in the DC-AC converter behavior. The present study considers the entire DC-DC and DC-AC converter stages, prioritizing the model’s fidelity.

Based on the DC link, a DC-AC converter stage is responsible for inverting the direct current. The full-bridge three-phase inverter is structured by six switches modulating the current based on the system’s frequency and voltage level.

### C. SHADING AND PARTIAL SHADING

The irradiance received on unshaded panels in normal conditions is the same over the plant strings. At the same time, the irradiance during the partial shading is not the same over the system. For example, buildings, trees, or physical structures around the power plant, irradiance oscillation, passing clouds, and sun angle changes during the day can shade different cells of the system.

The P-V curve has a single peak whenever all PV strings receive uniform insolation. Changing the received irradiance to the PV cells makes the P-V curve no longer has a unique peak, but multiple peaks appear on the P-V curve. However, even with several peaks, just one peak with the highest output power is called the GMPP. Other maximum points with lower output power are LMPPs.

The shaded strings receive less or no irradiance. These strings try to keep the amount of current the same as shaded strings, which causes a reverse-biased voltage. Figure 3 illustrates a comparison between the operation curve of an unshaded and shaded PV cell, where $P_1$ is the operating point of an unshaded cell and $P_2$ is the operating point of a shaded cell in the reverse bias region [13].

It is possible to observe that the shaded cells’ operating point is reverse-biased, interrupting the direct current flow. Figure 4.a shows the practical operation of a PV string with all cells in direct bias. In contrast, Fig. 4.b shows how one cell in a reverse-biased state can impact the string’s operation.

The forward voltage drop of the diode is indicated by $V_D$. Shading causes a current mismatch within PV strings. Bypass diodes are utilized to limit the power losses caused by shading, enabling bypass strings with reverse bias. The bypass diode starts conducting by satisfying the condition

$$V_4 - \sum_{i=1}^{n} V_i \geq V_D, \quad i \neq 4$$

in Eq. III [38]

Figure 5.a shows the uniform irradiance condition in which all three bypass diodes are not conducting. During the shading conditions, the current flows through the bypass diode $D_2$, shown in Fig. 5.b.
With a shaded operation, the PV panel no longer has one peak on its P-V curve but several small peaks. As soon as the panel is shaded and one bypass diode starts to conduct, the P-V curve presents several local peaks beyond the global one.

A system with three solar panels connected in series and under different irradiance scenarios is presented in [32], and it is shown in Fig. 6 to demonstrate the effect of the partial shading condition. The applied irradiances for the three cases are given in Table 1. In Case I, two different irradiance values are applied to the solar panels, 1000 W/m² on panel 1 and 500 W/m² on panels 2 and 3. In Case II, the PV panels obtain three different irradiance values: 1000 W/m² for panel 1, 600 W/m² for panel 2, and 300 W/m² for panel 3. In Case III, the solar irradiance values are identical (1000 W/m²) for all solar panels with no shading. Cases I and II simulate the shading/partial shading conditions in the solar panels. The bypass diodes in Fig. 6 might conduct current in the cases where the irradiances are different. These different irradiances lead to different MPPs on the P–V curve. Figure 7 shows the LMPPs and GMPPs in each case. Case I has one LMPP and one GMPP, and Case II has two LMPPs and one GMPP, while Case III has only one GMPP. This image shows that the partial shading with different irradiances in the inverters connected in series creates a more complex P-V curve. This complexity is a challenge to the searching mechanisms.

### TABLE 1. Cases’ conditions.

| Condition | Irradiance [W/m²] |
|-----------|-------------------|
|           | Panel 1 | Panel 2 | Panel 3 |
| Case I    | 1000    | 500     | 500     |
| Case II   | 1000    | 600     | 300     |
| Case III  | 1000    | 1000    | 1000    |

#### III. MPPT AND GLOBAL SEARCHING ALGORITHMS

Under shading or partial shading, the MPPT algorithm performs a search for the MPP. However, by using simple algorithms, the achieved MPP can be either LMPP or GMPP. Several methods to improve conventional approaches have been presented to ensure finding the GMPP instead of LMPP. First, in [31], [39], an algorithm based on an integrated circuit with the capability of tracking GMPP and the LMPPs was considered. In [5], the presented method used the OCV to predict the GMPP; then, this point is given to the P&O approach to follow the GMPP. This combination provides good dynamic performance, but the complicated shading does not show enough capability. The most common and well-established algorithms for MPPT and global searching are presented in detail in the following.

#### A. CONVENTIONAL P&O MPPT

The conventional P&O has a simple structure, and it is easy to implement its conventional method for tracking the MPPT, which has been extensively used for PV applications. Figure 8 indicates the flowchart of the P&O algorithm, which has a continuous process to converge to the MPP. Based on the structure of the P&O technique, the measured power and
voltage in $k$ and $k-1$ sample times are compared. By having those differences, the time to reach the MPP can be predicted. A small variation of voltage can change the power of the solar panel. If $\Delta P > 0$, the voltage will be tracked the same as before. If $\Delta P < 0$, the MPP is far away, and the power will be decreased to the MPP [40], [41].

### B. OD P&O

Some algorithms based on artificial intelligence for GMPP detection extract the output power as accurately as possible during the shading conditions. However, they are sensitive to the initial condition. Several optimization methods have been applied to reach these values. An algorithm based on the Overall Distribution Maximum Power Point Tracker (OD-MPPT) has been presented by [32] and considered one of the most precise methods for obtaining the initial particles for applying to the PSO algorithm. The OD algorithm is a good complement for the PSO algorithm to extract power from the PV systems as much as possible. Figure 9 shows the topology of the OD-PSO algorithm and highlights the restarting condition issue discussed, clarified, and solved by the present study.

Finding an initial region around GMPP is a big challenge that the OD-MPPT has addressed. This algorithm was proposed in 2012 by [42], [43] and applied to hydrothermal power systems to optimize the short-term dispatch. This algorithm finds the area in the GMPP vicinity. The mathematical formulation of the OD algorithm is as follows.

The position of the particle $i$ is defined with $d_i^{j+1}$ in the iteration $j + 1$, and $\alpha$ is the contracting coefficient. $R^j$ is the Cauchy (C) radius in the $j$th iteration, the number of Cauchy Distribution (CD) is defined as $C_i^{j+1}$. The value of the scale parameter is $\lambda$, which is a random number.

\[
\begin{align*}
R^{j+1} & = \alpha \cdot R^j \\
d_i^{j+1} & = mppt_{gb}^j + R^{j+1} \cdot C_i^{j+1} \\
C_i^{j+1} & = -\lambda \cdot \tan (\pi \cdot r_i) \\
i & = 1, 2, \ldots N, \quad \text{Cauchy} \in [-2, 2], \quad \alpha \in (0, 1)
\end{align*}
\] (5)

Based on Eq. (5), the confident region around GMPP can set particles $d_i^{j+1}$. The OD algorithm will be finalized when the area is smaller than $\varepsilon$. $R^j$ represents the $C$ radius in the OD algorithm, and it is between 0 and 1. It defines the
distribution region of the particles at the jth iteration. Updating $R^j$, $C$ and $mppt_{gb}^j$ by the position of particles. The best-extracted position of the particle is presented by $mppt_{gb}^j$ in the OD algorithm with $j$ iterations. The fitness situation value that defines the highest one between these particles is the best position. For example, the fitness function of the power production is shown below by Eq. (6).

$$P(d_i^{j+1}) = V \cdot I$$

The voltage and current of the PV are denoted by $V$ and $I$. Initializing the duty cycles for the DC/DC converter is the first step of the OD-MPPT algorithm. These duty cycles are indices as $d_i^j (i = 1, 2, \ldots, N)$. Equation (7) calculates the power corresponding to each duty cycle. The highest value of fitness value will be saved as a set of $t^k_best$, $t_{gb}$. The description of $mppt_{gb}$ will be satisfied by Eq. (7).

$$P(mppt_{gb}^j) \geq P(t_{gb}^k), \quad (k = 1, 2, \ldots, j)$$

The process of updating for reaching the GMPP and updating the duty cycles $d_i^j (i = 1, 2, \ldots, N)$ is done by Eq. (5). Following $C$ can create new duty cycles near $mppt_{gb}^j$ in a threshold of $R$ (between 0 and 1). The iteration will end when $R$ is less than $\epsilon$. $C$ is categorized as a continuous probability distribution for continuous data, and it is utilized to bring up-to-date particles. Equation (8) expresses the C function.

$$F(C) = \frac{1}{\pi} \left( \tan^{-1} \left( \frac{C-x_0}{\lambda} \right) - \frac{\pi}{2} \right)$$

where the position parameter and the scale parameter have been defined as $\lambda$ and $x_0$, respectively. The density function for $C$ is represented by Eq. III-C.

$$F(C; x_0, \lambda) = \frac{1}{\pi \cdot \lambda \cdot \left[ 1 + \left( \frac{C-x_0}{\lambda} \right)^2 \right]^2}$$

Based on $C$, the probability of $mppt_{gb}$ concentration is adjusted by changing $\lambda$. More details of the method can be found in [32]. By considering the step-by-step procedure of the OD-MPPT algorithm, the small area for reaching GMPP will be achieved quickly without any need to have the OCV and SCC of the PV panels.

C. OD PSO MPPT ALGORITHM

The PSO algorithm was proposed in 1995 and utilized for optimization purposes [43], [44]. The mathematical logic of the PSO-MPPT is based on Eq. (10).

$$\begin{align*}
  v_{i}^{k+1} &= \omega \cdot v_{i}^{k} + c_1 \cdot r_2 \cdot (P_{bi} - x_{i}^{k}) \\
            &+ c_2 \cdot r_3 \cdot (G_{gb} - x_{i}^{k}) \\
  x_{i}^{k+1} &= x_{i}^{k} + v_{i}^{k+1}
\end{align*}$$

In this equation, $c_1$ and $c_2$ are the cognitive coefficient and social coefficient, $r_2$ and $r_3$ are random values within $[0, 1]$, $k$ is the iteration number, and $\omega$ is the inertia weight. $v_{i}^{k}$ and $x_{i}^{k}$ represent the offset vector and position vector of the particle $i$ at the $k$th iteration, respectively. Therefore, $v_{i}^{k}$ and $x_{i}^{k}$ are updated by the best $P_{bi}$ position and the best $G_{gb}$ position particle of the particle swarm. $v_{i}^{k}$ pushes $x_{i}^{k}$ to move closer to the GMPP. This is an inherent feature of the PSO algorithm to converge to the GMPP when $P_{bi} = G_{gb}$. The PSO-MPPT speed of tracking is low. The OD-MPPT algorithm accelerates the PSO by finding the best initial particles to find $G_{gb}$ rapidly and precisely. The OD-PSO algorithm is fast and accurate wherever the OD-MPPT algorithm initializes the particle for the PSO algorithm by finding the initial particles around the GMPP region. The tracking process is defined by Eq. IV, where $P_{n}$ is the nth output of the PV arrays and $\epsilon$ is the threshold value.

$$\frac{|P_{n+1} - P_{n}|}{P_{n}} \geq \epsilon$$

IV. CHALLENGES ON GLOBAL SEARCH ALGORITHMS

Even though the OD-PSO-MPPT and P&O are powerful and good techniques to ensure the maximization of PV power generation, they are not supposed to define when the analysis process should restart. This lack of details regarding the reset condition directly affects the practical implementation and efficient utilization of the GMPP searching techniques in real systems. Every restarting process to find a new GMPP causes power losses. If the PV system operates in an LMPP, it is reasonable to start a new search. However, if the system is already in the GMPP, a new global search will only waste power that could be injected into the electrical system tied to the PV plant. The main challenges of global search algorithms are related to the restarting conditions and the power losses and oscillations caused by unnecessary restarting.

A. RESTART CONDITION

Numerous researches have been done on GMPP. Those that considered the restarting conditions suggested some restarting methods, which can be categorized as triggered by power change, irradiance change, or time-based. Besides, most GMPP studies do not approach the restarting conditions, avoiding explaining this search challenge. Therefore, each of the currently proposed restarting methods and its issues is discussed in the sequence.

1) POWER CHANGE

Power change is a common technique for finding the GMPP. The power from the past and the present step are compared. If this power difference is greater than a threshold, a flag is sent to the algorithm to reset the GMPP search. This resetting approach is misled during the morning and afternoon due to changing of power generation at these periods.

2) IRRADIATION CHANGE

Irradiance is the fundamental of power generation in PV systems. Finding the GMPP based on solar irradiance is an effective way to iterate the algorithm. The approach is similar to the power change. As soon as the difference between
two irradiances measurements is greater than a threshold, the GMP search is restarted. Nevertheless, measuring irradiance is cost-consuming. The met tower is a common device used for measuring irradiance in PV plants. This tower only covers a determined region where it is installed and assumes the measured irradiance is uniform in the remaining areas. Figure 10 illustrates how irradiance measurement becomes an imprecise variable once the PV plant gets larger. By requiring a large amount of met towers, the GMP restart condition based on irradiation change becomes a solution not economically feasible.

3) TIME-DELAY
The time-delay resetting algorithm is another approach that restarts the global search at every specific time window. The algorithm will be reset without considering any electrical or weather parameters. If the inverter operates far from the GMPP, the global search will efficiently find a new GMPP. However, if the system is already operating in the GMPP, the system would unreasonably lose a substantial amount of power in each iteration.

4) NOT MENTIONED
The resetting algorithm is not discussed in most of the research related to the OD-PSO algorithm. The authors focused on running the method instead of showing how the technique detects the shading.

B. POWER LOSS AND OSCILLATION
Global search algorithms vary the voltage and current to localize the GMPP. This variation provides deviations and oscillations on the PV plant power generation. If the oscillations occur on high power inverters, the power deviation can cause instability and power quality issues in the tied grid. An OD-PSO global search algorithm has been simulated in MATLAB/Simulink for a 300-W PV system. The power oscillation and losses results are demonstrated in Fig. 11. The global search starts in 3 seconds, and the red shaded area is the amount of power lost over the search process.

C. SOLUTION NECESSITY
Even though the GMP searching techniques are efficient enough to find the GMPP under shading and partial shading conditions, there is still a research gap on how to define the right moment to restart the search by considering a feasible technical-economical solution. Power change restarting conditions can be easily misled on morning and end afternoon periods. Irradiation change restart condition requires a large investment on met towers to make this an effective solution. Time-based GMP search restarting condition does not identify shaded or partial shaded conditions and initiate several unnecessary searches. Considering the research gaps stated above, the present study proposes an effective methodology for GMP restarting conditions. By using electrical measurements available in plant’s inverters, the method utilizes a statistical approach to identify arrays under shaded conditions, efficiently triggering the GMP search only on the shaded arrays at the right time. The proposed solution can be easily integrated into the PV plant’s central controller, which usually already has all electrical measurements for monitoring and control.

V. PROPOSED TOPOLOGY FOR GMPP SEARCHING RESTART CONDITION
The MPPT restart condition is not efficient based on time, irradiance, or power changes, leading to losing a high level
of potential generation capability every time this process happens unnecessarily. The problem to be investigated is illustrated in Fig. 12. The present paper proposes a new control topology capable of individually identifying which MPPT arrays are underperforming and allowing the global search to execute only in these specific arrays. The algorithm is based on a central controller capable of collecting the PV farm measurements and analyzing the shaded arrays. In the following, the central controller topology and its algorithm are explained.

A. CENTRAL CONTROLLER TOPOLOGY

Integrating a central controller in the PV shading algorithm enables the centralization and comparison of the generation of different PV arrays. For example, a PV farm contains several inverters, and these inverters can have one or more arrays. Each array can have one dedicated MPPT, and the central controller is responsible for collecting the power generation level of each array. A shading detection algorithm is executed inside the controller, providing a command vector for all PV farm arrays. This command is responsible for triggering and restarting the shaded arrays’ MPPT search. Based on this approach, the communication between the central controller and the inverters is made every couple of seconds over the entire day of operation. However, the MPPT is only restarted whenever it receives a trigger signal which means that the central controller has detected a shading on this array. Figure 13 shows the complete central controller topology.

B. SHADING DETECTION ALGORITHM

Inside the central controller, the shading detection algorithm is responsible for computing the measurements from each inverter and distinguishing which arrays are shaded. The proposed topology considers a data analysis where it is possible to outlier the arrays in the underperformance. For each main controller computation time step, a three-step analysis based on the Median Absolute Deviation (MAD) is performed. The MAD considers a dataset where the average distance between each data value and the median of the entire dataset is computed. This is a robust statistical analysis for outliers detection, which describes the variation in a dataset.

The standard deviation considers the square distances from the mean so that large deviations are weighted more. In contrast, the deviations of a small number of outliers are irrelevant in the MAD analysis. For this reason, outliers can influence more in the standard deviation than in the MAD [45].

1) DATA FILTERING

For each control sample, i, the shading detection algorithm’s first step is to filter the N measurements from each array of each inverter. This filtering is based on the MAD, while by considering a window of W past measurements, the outlier measurements are mapped and replaced by the median value of this window. Being \( P_i^m \) the power measurement of array \( n \) at sample \( i \), the median for each array is given by Eq. (12).

\[
m_i^n = \text{median} \left( P_i^m, P_{i-1}^m, \ldots, P_{i-W}^m \right) \quad \forall n = 1, 2, \ldots, N
\]  

By definition, the MAD is the median of the absolute differences of each value in the dataset and their median. Equation (13) provides the MAD of each array \( n \) at sample \( i \), considering a window of \( W \) past samples.

\[
\text{MAD}_i^n = \text{median} \left( |P_i^m - m_i^n|, |P_{i-1}^m - m_i^n|, \ldots, |P_{i-W}^m - m_i^n| \right) \quad \forall n = 1, 2, \ldots, N
\]  

The standard deviation of each data, \( \sigma_i^n \), can be obtained by the multiplication of its MAD and the factor \( k \) as given by Eq. (14). This constant factor is obtained from a relation with the Gaussian error function, \( \text{erf} \), as presented by Eq. (15).

\[
\sigma_i^n = k \times \text{MAD}_i^n \quad \forall n = 1, 2, \ldots, N \tag{14}
\]

\[
k = \frac{1}{\sqrt{2\text{erf}^{-1}(\frac{1}{2})}} \approx 1.4826 \tag{15}
\]

Each measurement is filtered by a limit of three sigmas. If the absolute difference between the power measurement and its median is higher than three sigmas, the measurement is considered an outlier, and its median replaces it; otherwise, the measurement is maintained. The filtered measurements, \( Pf_i^n \), is given by Eq. (16).

\[
Pf_i^n = \begin{cases} 
P_i^m, & |P_i^m - m_i^n| \leq 3.\sigma_i^n \\
m_i^n, & |P_i^m - m_i^n| > 3.\sigma_i^n 
\end{cases} \quad \forall a = 1, 2, 3 \ldots N \tag{16}
\]

Once the outliers’ measurements are mapped, a moving average is used to smooth the analyzed data. The moving average also considers a window of \( W \) past measurements. The new treated dataset of measurements, \( Pma_i^n \), is obtained by Eq. V-B2.

\[
Pma_i^n = \frac{1}{W} \sum_{j=1}^{W} Pf_{i-j}^n \quad \forall n = 1, 2, 3 \ldots N \tag{17}
\]
2) MEASUREMENTS NORMALIZATION

Once each array’s new measurement is filtered based on its previous \( W \) samples, its installed capacity normalizes each measurement. Each array in the PV plant can have a different configuration and installed generation capacity. Accordingly, it is important to first normalize the current generation of each array based on its maximum capability. The installed capacity of each array, \( P_{nom}^n \), can be defined by Eq. (19).

\[
P_{nom}^n = NS^n \cdot NP^n \cdot P_{pan}^n, \quad \forall n = 1, 2, 3 \ldots N
\]  

where \( NS^n \) is the quantity of strings in the array \( n \), \( NP^n \) is the quantity of panels in the array \( n \), and \( P_{pan}^n \) is the nominal power of each panel at array \( n \). By having the nominal capacity, \( P_{nom}^n \), it is possible to normalize the filtered measurements, \( P_{na}^n \), by Eq. (20).

\[
P_{norm}^n = \frac{P_{na}^n}{P_{nom}^n} \quad \forall n = 1, 2, 3 \ldots N
\]  

Once the arrays’ measurements are normalized, they can be compared at the same base. With this comparison, it is possible to quantify the performance of each array based on the rest of the PV plant’s arrays generation. The normalized performance of each array \( n \) at sample \( i \), \( P_{npf}^n \), is given by Eq. (20).

\[
P_{npf}^n = \frac{P_{norm}^n}{\max(P_{norm}^1, P_{norm}^2, \ldots, P_{norm}^N)} \quad \forall n = 1, 2, 3 \ldots N
\]  

The normalized performance results in understanding how distinct the arrays’ performance is at the same PV plant. A new MAD analysis is performed in the arrays’ normalized performance, \( P_{npf}^n \). The median, \( mnpf_i \), and the MAD, \( MAD_{npf} \), are given by Eq. (21) and (22), respectively. The standard deviation, \( \sigma_{npf} \), of this set of data at sample \( i \) is given by Eq. V-B3.

\[
mnpf_i = \text{median} \left( P_{npf}^1, P_{npf}^2, \ldots, P_{npf}^N \right)
\]  

\[
MAD_{npf} = \text{median} \left( \left| P_{npf}^1 - mnpf_i \right|, \ldots, \left| P_{npf}^N - mnpf_i \right| \right)
\]  

\[
\sigma_{npf} = k \times MAD_{npf}
\]  

3) TRIGGERING GENERATION

The MAD result provides a value capable of representing how the dataset is varied around its median value. The standard deviation of this dataset can be utilized as a threshold. However, it is also necessary to integrate another threshold before the final limit to account for some conditions where most of the panels are shaded. The present study considers a limit trigger, \( Lim_i \), the maximum value between a constant of 0.9 and the difference between the median normalized performance and three sigmas as given by Eq. (24). In this study, the distribution of the power provided by the panels around the mean is assumed as normal distribution and three sigmas corresponding to 99.87% of the population:

\[
Lim_i = \max \left( 0.9, mnpf_i - 3 \cdot \sigma_{npf} \right)
\]  

Any normalized array performance below the limit, \( Lim_i \), is considered an outlier and, therefore, an array in underperformance. Accordingly, the triggering flag for each inverter, \( Flag_i^n \), can be given by Eq. (25).

\[
Flag_i^n = \begin{cases} 
0, & P_{npf}^n \geq Lim_i \\
1, & P_{npf}^n < Lim_i 
\end{cases}
\]  

Keeping in mind the irradiance unevenness during morning and evening periods, the triggering command is restricted to be sent only for the arrays with normalized generation higher or equal than 0.5 p.u. Thus, the final trigger command, \( F^n \), is given by Eq. VI.

\[
F^n = \begin{cases} 
Flag_i^n, & \max(P_{norm}^n) \geq 0.05 \\
0, & \max(P_{norm}^n) < 0.05 
\end{cases}
\]  

Over the day, the central controller keeps computing these three steps for each sampling. Once one array is considered in underperformance, the central controller sends the final trigger command to the inverter, restarting the MPPT global search. The present central controller solution also allows monitoring and maintenance analysis on PV plants. For example, if a specific array is considered underperforming for consecutive hours, it is possible to assume that this array is not only shaded but also potentially damaged or covered. Whenever this happens, the central controller triggers a maintenance flag, notifying the operator which array is potentially damaged and when it was initially detected.

VI. DATA COLLECTION

The Global Laboratory for Energy Asset Management and Manufacturing (GLEAMM) combines the research and commercialization expertise of Texas Tech University. Located in Lubbock, Texas, USA. the GLEAMM’s primary goal is to provide a real-scale testbed for innovative studies in different areas related to microgrids such as grid modernization, energy management, power quality, control, and operation.

Currently, the GLEAMM structure consists of a 150-kW solar plant, 569-kVA diesel generator, two resistive dynamic load banks of 500 kW each, one inductive dynamic load bank of 187.5 kVAR, and the building critical and non-critical loads. The critical loads rely on an outback inverter and battery that operates as a UPS in the case of lack of energy [46], [47]. Figure 14 shows the microgrid structure and its primary devices. Three wind turbines are already in the process of being connected to the facility, each with 300 kVA nominal power. Through an Automatic Transfer Switch (ATS), the microgrid can be connected either to the grid or the diesel generator, depending on its operation mode. The transition between these scenarios can be planned or unplanned. The usual scenario is when the microgrid is connected to the utility grid, and the diesel generator is off. The second operation
C. A. Negri et al.: Centralized Control Topology for PV Farms Shading Detection and GMPP Searching Restarting Condition

FIGURE 13. Central controller topology for shading detection.

mode is when the microgrid is disconnected from the utility grid, and the diesel generator becomes the system’s primary source in the island mode. To connect all these devices in the main microgrid bus, the MCC, the facility has several circuit breakers, fuses, and command panels that ensure the system’s protection and safety.

The microgrid operation and control are made through an SEL-3530 Real-Time Automation Controller (RTAC) with bi-directional communication with all the microgrid elements and Human-Machine-Interface (HMI), allowing the operator to visualize the system’s measurements and send commands back to each device. Furthermore, measurements in different devices and nodes allow the microgrid’s observability, data acquisition, and supervision. Finally, all these measurements are sent to a DELL R620 database, where the complete information is recorded for the post-event analysis. Beyond establishing communication with all elements of the microgrid, the RTAC also contains several internal control algorithms. In one of them, the power outputs of the five solar inverters are controlled to match the microgrid load. This operation mode allows the reduction of the energy consumed from the grid or generator.

The 150-kW solar plant is compounded by a total of 468 photovoltaic panels that are unsymmetrically assigned to ten sets of MPP trackers on five three-phase inverters. These are panels from SolarWorld Company, Sunmodule SW 320 XL mono model. Table 2 shows the detailed panels’ parameters.

The panels are arranged in a certain way to reach the 150 kW of nominal generation capacity using the five inverters. Each inverter is compounded by two MPP tracker controllers, receiving a different array of panels in each tracker controller input. Therefore, the plant is structured in ten arrays of panels. The inverters are from SMA Company, Sunny Tripower 30000TL-US type, rated 30 kW each. Table 3 shows the main parameters of the SMA inverters.
TABLE 3. Sunny tripower 30000TL-US inverter parameters.

| Side          | Parameter                           | Symbol | Symbol |
|---------------|-------------------------------------|--------|--------|
| DC            | Max. array Power                    | 45     | kW     |
|               | Rated MPPT voltage range            | 500-800| V      |
|               | Max. operating input current per    | 35     | A      |
|               | MPPT tracker                         |        |        |
|               | Max. short circuit current per       | 53     | A      |
|               | MPPT tracker                         |        |        |
| AC            | Nominal power                        | 30     | kW     |
|               | Max. Apparent power                  | 30     | kVA    |
|               | Max. output current                  | 36.2   | A      |

With the bi-directional communication between the RTAC and the five SMA inverters, it is possible to read the measurements of each device, as well as command back the inverters. The device’s user guide provides a complete point list. Still, the current and voltage levels for each DC tracker input and AC power output are the most pertinent values to be collected from each inverter to perform the present study.

Once the RTAC reads these measurements through a Modbus polling every two seconds, they are sent to the DELL R620 to be stored in the microgrid’s database. Figure 15 shows the detailed solar plant’s array structure and parameters, as well as the device’s communication through the facility’s Virtual Local Area Network (VLAN).

VII. SIMULATION AND RESULTS

A. METHODOLOGY ANALYSIS ON GLEAMM MICROGRID

Real PV power generation profiles have been collected from the GLEAMM microgrid and its five inverters to test and validate the proposed algorithm and its restarting condition. By considering the same day of analysis, Feb. 07\textsuperscript{th} of 2021, Fig. 16 depicts the total standard deviation of the normalized power generation for each array, followed by Fig. 17, which shows the standard deviation profile.

The central controller topology considers parallel measurement for each MPPT on every control’s computational time step. First, based on the installed capacity of each array, the DC power output measurements are received and filtered by Eq. (12)-V-B2. Next, the MPPT profiles are normalized based on their installed capacity with the filtered power generation, following Eq. (18) and (19). Next, the relation between the normalized power generation and current maximum capacity is obtained by Eq. (20)-V-B3. Finally, the outlier MPPTs are mapped and triggered by the flag generator, Eq. (24)-VI, indicating the underperforming inverters and requiring a new global search. Figures 18, 19, 20, 21, and 22 show the control steps analysis for the GLEAMM’s five inverters based on the profile of Feb. 07\textsuperscript{th} of 2021.

It is possible to observe each array’s response and generation characteristic during the operation day. The shading problem can be caused by different factors, such as weather reasons and physical structures around the plant.

The GLEAMM facility has a communication tower located southwest of the PV plant. This tower has approximately 80 meters in height, and it is responsible for some of the facility’s shadings. The SunCalc online shading simulator was utilized to better understand the tower’s impact on the PV plant. SunCalc is a web platform capable of showing the movement of the sun and sunlight phase for a certain day at a
certain place, and it provides a perspective of the shading of a physical structure.

Considering Feb. 07th of 2021, the simulator can explain the tower’s impact on the PV generation, and algorithm triggers over the studied day. Figures 23, 24, and 25 show the shading simulation for the GLEAMM location, considering the tower’s impact for three different periods at 1:34 PM, 3:15 PM, and 6:28 PM, respectively.

It is possible to observe that the tower significantly impacts the PV plant shade and, consequently, its power generation. The tower provides a clockwise shade in the plant over the winter afternoons impacting all panels and arrays.

On Feb. 07th of 2021, at 1:34 PM, the shade starts to impact the MPPT 2 of inverters 4 and 5. The shade moves, and MPPT 1 of inverters 4 and 5 are impacted as a result. At 3:15 PM, the shade starts to impact the MPPT 2 of inverters 1, 2, and 3.

Again, as a result, MPPT 1 of inverters 1, 2, and 3 are affected. Finally, around 6:28 PM, the shade has completely passed over the plant. Table 4 and Fig. 26 show the GLEAMM facility shading trigger and the top-view picture obtained from Google Earth.

It is interesting to highlight that the central controller algorithm results, shown in Fig. 18, 19, 20, 21, and 22, match with the tower’s shade simulation presented by Fig. 23, 24, 25, and 26, and also Table 4. The central controller was able to find the outlier arrays and trigger the global search algorithm.
in the moment they were shaded, maintaining the arrays that were not shaded on their current GMPP.

B. RESULTS AND DEPLOYMENT DISCUSSION

The evaluation of the proposed restarting condition technique considered two different analyses, one for performance and another one for validation. The first analysis considered real measured data from the GLEAMM microgrid. All the ten arrays power profiles for a specific day were submitted to the proposed restarting condition approach. The simulation results had shown that the algorithm was able to distinguish arrays that were underperforming during the day as
Even though the flags were triggered in the exact periods of shading/partial shading conditions, a secondary analysis was proposed to validate the flagging creation. The SunCalc platform was utilized for the validation analysis. By selecting the same day of the power profile analysis, and the coordination of the GLEAMM PV plant, the SunCal provided the visual impact of shading over the PV plant. Several snapshots were obtained for the analysis day where the shading over the plant and which arrays it is impacting can be seen.

By comparing both analysis results, the proposed method performance matched with the shading profile. The statistical method was able to identify arrays under shading conditions and create flags to signalize them. The flag creation can not only trigger the new GMPP searching but also work as an array parameter. As soon as the method is utilized over several days, each array will have a flagging profile. This profile can present the array’s characteristic of shading. If the array is flagged in several days during a specific period, it can imply a physical structure around the facility that is causing the shading. Also, if the array is flagged for a long period of time, it can also imply that the array is covered, damaged, or even dirty. These profiles can be of great use for maintenance planning and execution. Some of the biggest advantages of this method are:

- Efficiency and assertiveness on shading/partial shading detection.
- Only utilizes electrical measurements, avoiding the requirement of irradiance values.
- Simple mathematical analysis capable of being performed by commercial software.
Flag profile creation for maintenance planning and execution.

Most of the solar PV inverters are mounted with communication capabilities. The device makes available several electrical measurements and internal control points available for reading, besides other control points for external command. Medium- and large-size PV plants usually have central controllers able to centralize all these inverters’ measurements for data acquisition, monitoring, and control. The proposed method is a mathematical approach that utilizes basic and statistical functions which can be deployed in any commercial central controller. By already having all the required electrical measurements in the central controller, the restarting condition approach implementation on real PV plants becomes a feasible solution without additional financial investments.

**VIII. CONCLUSION**

Global searching is an essential tool in the process of PV systems generation. This technique can find the GMPP of PV arrays under different shading and partial shading conditions. Even though the global search technique is well-developed and known, most of the studies that approach global searching do not mention restarting conditions. The ones that approached this issue proposed to trigger the new GMPP search based on power variation, irradiance variation, or fixed time step. These conditions disregard the fundamental shading statement, where shading is not uniform over PV power plants. Thus, the traditional resetting conditions presented by the current literature perform several unnecessary global searching. However, every search process introduces power oscillation and losses to the system, leading to voltage and frequency variations.

The present research proposed a novel restarting condition based on an outlier statistical analysis. The PV plant electrical measurements are centralized in the plant’s central controller, where the algorithm is computed over the operation day. Based on a comparative statistical analysis, the algorithm triggers outlier arrays, which are under shading or partial shading conditions. The trigger is responsible for restarting the GMPP, searching only on those arrays in underperformance, maintaining the reaming arrays on their current GMPP.

The proposed restarting condition approach was validated using real measurement data from the GLEAMM microgrid. The daily generation profiles from 10 arrays of 5 inverters were submitted to the proposed restarting condition algorithm. The results have shown an efficient performance of the resting condition based on outliers statistical analysis. The algorithm’s response was also validated through an online shading calculator. Both results matched, flagging the shaded arrays over the operation day. Furthermore, with the capability to identify the exact arrays shaded over the operation time, the control strategy can also identify arrays in underperformance, which can be damaged or covered.

The main contributions of this research are:

- Evaluation and discussion on the current techniques used for restart conditions of GMPPPT.
- Explanation of the necessity of a more efficient and assertive GMPP search restarting condition.
- Propose a novel algorithm based on statistical analysis to detect shading arrays and create flags to restart their GMPP search.
- Provide an efficient and asserting restarting condition solution that can be easily deployed on real PV plants.
- Evaluate the proposed algorithm performance in locating the shading condition with real data from a 150-kW PV plant.

Most medium- and large-scale solar power plants are mounted with central controllers for data acquisition, monitoring, and automation. The integration of such a statistical approach on these controllers can efficiently improve the performance of PV plant generation without compromising its processing capability or requiring additional investments.

The future directions of this research consider the deployment of the proposed algorithm in a real PV facility and closing the control loop. The central controller with the inverters measurement will host the proposed restarting condition algorithm, and the created flags will be sent back to the inverters. High-level signals will trigger the inverter’s MPPT for a new global search as the low-level signals will maintain the arrays on their current GMPP. Besides that, there is still a wide field for study in how analysis the created flag profiles. The shading flags profile has crucial information for the PV plant operation that, if correctly analyzed, can identify damaged arrays and decide the need for maintenance.

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