Methodology for Anomaly Detection and Alert Generation in Photovoltaic Systems

Roberto Alexandre Dias
Federal Institute of Santa Catarina (IFSC)
950, Av. Mauro Ramos
Florianópolis, SC, Brazil

Mário de Noronha Neto
Federal Institute of Santa Catarina (IFSC)
608, José Lino Kretzer Street, São José, SC, Brazil

Gregory Chagas da Costa Gomes
Federal Institute of Santa Catarina (IFSC)
950, Av. Mauro Ramos
Florianópolis, SC, Brazil

Fernando Benites
University of Applied Science Northwest Switzerland (FHNW)
AG, Switzerland

Stefan Gürtler
University of Applied Science Northwest Switzerland (FHNW)
AG, Switzerland

Siqueira de Moraes Neto
PV Operation
3339, Rodovia Dr. Antônio Luiz Moura Gonzaga,
Florianópolis SC, Brazil

Níkola Zaia de Figueiredo
PV Operation
3339, Rodovia Dr. Antônio Luiz Moura Gonzaga,
Florianópolis SC, Brazil

ABSTRACT
This article presents a methodology for identifying anomalies and generating alerts during the management of photovoltaic plants. The approach is mainly based on the analysis of AC power from inverters, eliminating the need for additional instrumentation. The methodology can be enhanced with solar irradiance data, enabling more precise anomaly detection and alert generation based on the Performance Ratio (PR) concept. The autoencoder technique was employed to detect anomalies in inverters using custom models based on equipment size, region, as well as specific times of day and year. Alert generation considers the quantity of detected anomalies and PR variation over a 30-day period. To validate the results, plants with previously recorded shading and 5k inverters in the regions of Santa Catarina and São Paulo (Brazil) were used. The obtained results demonstrated excellent performance in plant management, allowing for the analysis of anomaly recurrence and alert level variations over time.

General Terms
Anomaly Detection; Pattern Recognition; Photovoltaic Fault Detection; Machine Learning.

Keywords
Anomaly Detection; Machine Learning; Photovoltaic Systems; Autoencoder; Fault Detection.

1. INTRODUCTION
In recent years, photovoltaic (PV) technology has emerged as a key solution for renewable energy production, distinguished by its sustainability and ability to meet the growing demand for clean energy. However, the effectiveness of these systems is significantly impacted by non-ideal operational conditions such as shading, panel soiling, and component failures, which can reduce energy production and compromise system efficiency. Early and accurate detection of these anomalies is essential to maintain optimized operation and ensure the economic viability of solar energy investments.

The topic of fault classification and detection in photovoltaic (PV) systems is quite broad. The many of recent approaches address practical issues related to the analysis and processing of data available from plants commissioned by the project partner company. The managed plants vary in size, from residential to large corporate installations. Not all plants are instrumented, with only certain electrical parameters available from inverters, and in some cases, irradiance data provided by pyranometers. In some units, this information was obtained from satellite monitoring services, however this information is not always recorded at the required time.

In this context, the present article aims to develop a robust methodology that integrates advanced machine learning techniques with solar irradiation data analysis to generate accurate alerts and detect anomalies in photovoltaic systems. By using an autoencoder to model inverter behavior and incorporating solar irradiation data, an innovative approach is proposed that not only identifies anomalies with high precision but also provides a scalable and adaptable tool for continuous monitoring of solar plants of different sizes, regions, and specific times of day and year.

2. Literature Review
Recent studies in the field of PV system monitoring and diagnostics have applied advanced machine learning techniques, such as autoencoders, to efficiently identify faults and anomalies. For instance, Barraz et al. emphasize in [1] the importance of retraining pre-trained models to optimize anomaly detection in PV systems. Similarly, Miraftabzadeh et al. validate in [2] the effectiveness of autoencoders in monitoring photovoltaic plants without requiring additional equipment data. Additionally, the integration of these systems with cloud-based and container-based architectures, as explored by Doukha et al. in [3], provides a scalable and efficient infrastructure for deploying deep learning applications, facilitating the implementation and management of distributed PV systems.

Therefore, the research focused on identifying references that address anomaly detection with limited input data, particularly the generated AC power which was consistently available from the inverters.

In this regard, [4] examines analytical data methods for fault detection and classification in grid-connected PV systems. It emphasizes the importance of reliable monitoring of PV installations to ensure their long-term reliability and performance. The study discusses techniques based on electrical signature, numerical methods (machine learning), and statistical analysis for fault diagnosis, highlighting recent advancements and the applicability of these approaches in detecting and classifying faults based on acquired performance data. The article presents fault classification and various methods for data acquisition and analysis. In many situations presented, module-level sensing is impractical, especially in electrical signature methods. Therefore, the use of machine learning techniques was highlighted as a more suitable alternative.

In [5], an innovative methodology is presented for monitoring partially shaded photovoltaic systems. Using a time-series data analysis approach, the methodology aims to distinguish energy losses caused by shading from other system malfunctions. This is achieved by comparing the performance data of a partially shaded PV system with an unshaded reference system, using algorithms that automatically detect shading-induced energy losses and differentiate them from other losses. This study is particularly relevant for PV systems with module-level power electronics, common in residential and commercial installations. The article discusses significant impacts of partial shading on photovoltaic plants and presents a clustering methodology and outlier identification for anomaly detection.

Article [6] addresses the development and validation of a practical approach for fault detection in photovoltaic systems with online implementation. Using field measurements from a Canadian PV system, the methodology demonstrated a high fault detection rate, successfully handling anomalies present in real-life measurements. The method relies on comparing energy production measurements, generated AC power, and predictions from a model using solar irradiance and PV panel temperature measurements. The study shows that models based on hourly averages are more accurate than those using 10-minute measurements, and models for different irradiance intervals result in a fault detection rate exceeding 90%. The research significantly contributes to preventive maintenance and optimized performance of PV systems, emphasizing the importance of online implementation of fault detection techniques for effective monitoring and timely corrective action.

In [7], an innovative methodology for anomaly detection in photovoltaic power predictions for Virtual Power Plants (VPPs) is presented, using convolutional autoencoders and Principal Component Analysis (PCA). The research highlights how this approach can significantly improve prediction accuracy by identifying and filtering anomalous data, with experiments demonstrating up to a 23% reduction in prediction error. This method represents a significant advancement in integrating renewable energies into the power system, ensuring more reliable and efficient predictions for VPP operation.

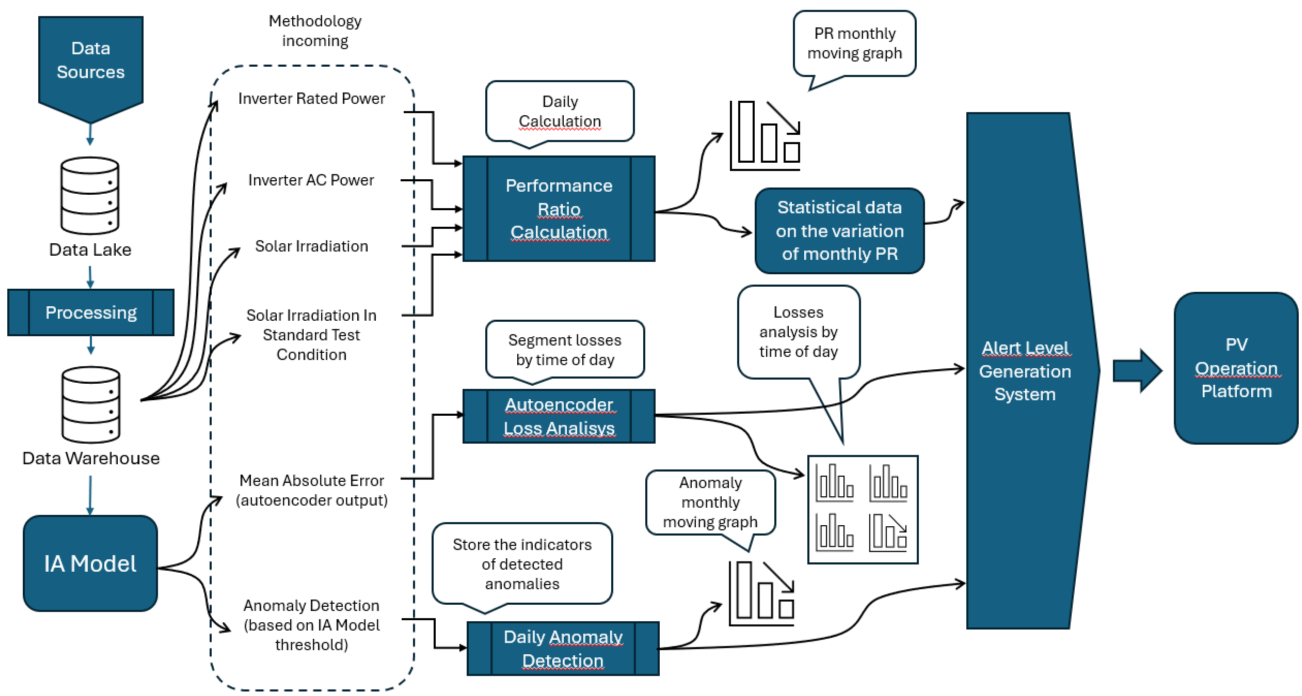

Figure 1: Block Diagram of the Developed Methodology

Article [8] introduces a new procedure for automatic supervision and fault detection in photovoltaic systems (PV) based on power loss analysis. This automatic supervision system was developed in the Matlab&Simulink environment and includes parameter extraction techniques to calculate key parameters of the PV system from monitored data under real working conditions, considering environmental irradiance and PV panel temperature evolution. The automatic supervision method analyzes power losses in the DC part of the PV generator, defining two new power loss indicators: thermal capture losses (Lct) and various capture losses (Lcm). Processing these indicators allows the supervision system to generate a fault signal as an indicator of fault detection in the PV system operation. The article details the modeling process of a photovoltaic array output using the equivalent electrical circuit model. This model enables precise simulation of the PV system behavior under real conditions, comparing monitored data with simulation results to calculate energy losses. Capture losses mainly occur on the DC side of the PV conversion chain and are attributed to operating temperature, PV efficiency, solar irradiance dependency, shading, and losses when sunlight hits at a high angle. Despite the relevance of this work, given the variety of plant architectures commissioned by the company, the mathematical modeling approach of the plants proved impractical for the project at hand.

The analysis of references pointed towards the development of a methodology for fault detection and alert management in photovoltaic plants that could be applied to systems with low sensing levels and with the information available from all plants commissioned by the company, especially the profile of generated AC power, irradiance provided by pyranometers, or estimated by satellite monitoring services. Given the unavailability of historical fault labeling in the company's databases, a recurrence-based alert management methodology was proposed in this work. An advantage presented by the developed methodology is the possibility of achieving reliable alerts using only the AC power provided by the inverters. To filter out the stochastic effects of clouds on generation, the point-by-point moving average strategy was used over a period of 28 days. Besides, the methodology delivers to the user an alert level just after another 30 days of results using an ensemble of several models applied over the data, a sufficient response time over failure, reported by the PV Operation company.

3. METHODOLOGY FOR ANOMALY ALERT MANAGEMENT IN PHOTOVOLTAIC SYSTEMS

The methodology developed in this project is primarily based on collecting AC power data from inverters, eliminating the need for additional instrumentation for anomaly detection. To achieve this, we used autoencoders to model the normal behavior of inverters and identify deviations that indicate anomalies. The integration of solar irradiance data allows for refined detection and alert generation, using the Performance Ratio (PR) as a key performance indicator. When using PR, alert levels are defined based on variations in this parameter and the presence of anomalies within a specific period, facilitating quick and precise intervention. Figure 1 illustrates a general block diagram for this methodology. In this figure, we can observe sets of important blocks in this process, ranging from data processing and storage structure to an alert generation system. The main steps of this methodology will be described next.

3.1 Data Processing

Data preprocessing was a crucial process for preparing and performing the developed methodology. Initially, raw data was collected from various sources and stored in a Data Lake, which served as a centralized repository comprising data from inverters, plants, weather stations, and external climate data sources. Subsequently, this data underwent a processing phase, which included cleaning, synchronization, and merging of inverter generation data with irradiance information. This process ensured the quality and integrity of the data for subsequent analyses and training of the machine learning algorithm used, in this case, the autoencoder technique.

The goal of anomaly detection in PV systems can be achieved through different approaches, but the premise of not using external measurements beyond the inverter limited the possibilities in this context. Therefore, it was decided to initiate the first prototype of an anomaly detection algorithm using a shallow neural network architecture known as an autoencoder. This architecture was chosen due to its recognized effectiveness in the literature for anomaly detection [9], with previous applications including shading detection in PV systems. The autoencoder was selected after studies and preliminary tests showed its good performance with the available historical data.

Defining anomaly detection thresholds was an important step to minimize false positives and negatives, making the methodology robust and adaptable. With the use of AutoML techniques, the system was scalable by training autoencoder models adapted to various classes of plants, considering specific regions and generation capacities, without the need for extensive manual parameter tuning and deep expertise in machine learning techniques.

3.2 The Use of Autoencoder

The objective of detecting anomalies in PV systems can be achieved through different approaches, but the premise of not using external measurements or even labeled data ended up reducing the possibilities to be used in the context of this case.

In [9], the use of autoencoders for anomaly detection was proposed. The fundamental concept is that the neural network generates an output which is a reconstruction of the input signal. Due to the information bottleneck, the network cannot store the entire signal but only a condensed representation of it. As a result, the network effectively stores and reproduces common patterns in the training data. However, patterns that are not familiar to the network will be reconstructed with significant errors. Each such uncommon pattern can be a potential anomaly.

Based on this concept, the initial prototype of the anomaly detection algorithm was developed using a shallow autoencoder neural network. This architecture was selected due to its proven effectiveness in anomaly detection, as documented in the literature, particularly for detecting shading in PV systems. Additionally, shallow networks offer the advantage of being easily interpretable.

The architecture of neural networks in the form of autoencoders allows unsupervised learning of the network, something that was a premise, since the database provided did not have quality labels and there was not enough time and resources to label it. However, unsupervised training of an autoencoder network relies heavily on the quality and quantity of data delivered to it. Another but very simplified perspective to describe the model is that an autoencoder network can be viewed as a copier, so it will shape itself to be able to copy the input data into its output with less error as possible. In this case, when it comes to anomaly detection using this technique, there are at least two approaches to train the autoencoder: deliver examples of regular or anomalous PV systems to the network. In the first case, the network will be trained to copy regular generation profiles and therefore will have difficulty copying anomalous generation profiles. In this way, by comparing the input and output data from the network, it is possible to classify the input data as regular or anomalous. In the second case, the exact opposite occurs, the network has difficulty copying regular data. It brings us to the different power generation profiles due the geographic distribution of PV plants and different inverter rated power that couldn’t be used together to train a model.

The segmentation of inverters by installed power and region was the strategy adopted and allowed the creation of more accurate models, considering specific characteristics.

3.3 Information Processing

As mentioned earlier in this section, the methodology was developed to operate only with AC power data from inverters, which is sufficient for training the autoencoder algorithms used in anomaly detection. However, this methodology can be enhanced if solar irradiance data is available. Therefore, in this subsection, we will present information processing pipeline considering that all the data specified in the methodology is available, which includes:

- Inverter Rated Power: Represents the total energy generation capacity of the installed solar panels, serving as a reference parameter for expected performance.

- Inverter AC Power: Data on the energy effectively converted by the inverters.

- Solar Irradiance: Information on the amount of irradiation received at the location, essential for evaluating expected versus actual performance.

- Mean Absolute Error (MAE) value of the autoencoder: A measure of how well the autoencoder model can reconstruct the input data, indicating the presence of anomalies when the error is significantly high.

- Anomaly Detections by the autoencoder: Specific identifications of abnormal behaviors in the data, suggesting potential issues like shading.

With these inputs, the methodology proceeds with calculating the Performance Ratio (PR), an indicator of the actual performance of photovoltaic systems relative to their maximum potential. A residual analysis based on the autoencoder MAE is conducted to identify when and where shading or other anomalies are occurring, providing valuable insights into the timing and location of problems. The number of anomalies is stored daily, along with their recurrence.

3.4 Alert Generation

The alert generation system is powered by the processed information to determine the quantity of anomalies, their recurrence, and the variation of the Performance Ratio (PR) over a 30-day interval. This system is structured into 10 alert levels, ranging from level 0 (indicating expected operation) to level 9 (indicating the worst level of inverter operation). Classification into one of these levels is done by comparing the current PR with the PR from the previous 30 days. The percentage variation of PR, along with the quantity and recurrence of anomalies detected by the autoencoder during the period, is used to determine the specific alert level.

Additionally, the system can provide indicators of future failures by analyzing level changes over the 30 days. The use of a 30-day analysis period was a key point to achieve accuracy in the results, while also being a practical timeframe for diagnosing inverter performance.

This integrated approach enables early and accurate anomaly detection, facilitating quick and informed interventions to maintain or enhance the performance of photovoltaic systems. Moreover, the use of the autoencoder and solar irradiance data analysis significantly enhances detection accuracy, reducing the risk of false positives and enabling more effective management of maintenance and operation of photovoltaic systems.

4. RESULTS AND ANALYSIS

To validate the methodology, we used a database consisting of 34 5k inverters and 61 5k inverters in the state of São Paulo and Santa Catarina, respectively. To showcase the main results and analyses of this deployment, we will divide this section into three subsections. The first subsection will demonstrate the performance of the autoencoder technique in detecting anomalies in photovoltaic systems. The second subsection will showcase the results of the methodology in a real production environment without using the PR. The third subsection will highlight the impact of utilizing the PR on enhancing the methodology.

4.1 Performance Evaluation of Autoencoder Technique in Detecting Anomalies in Photovoltaic Systems

We evaluate the performance of an autoencoder in detecting anomalies in photovoltaic systems by using AC power data from four inverters, where three operated under normal conditions and one exhibited lower-than-expected performance. The analysis was conducted within a time window from 7:30 AM to 5:00 PM, considering 80 weeks of energy generation data for model training and 20 weeks for testing under normal conditions, as well as 26 weeks for testing with modules under shading conditions. In this analysis, one regular inverter was used for model training, while the others were used for testing. All inverters had the same rated power and were in the same region.

However, even with this segmentation, feeding autoencoder networks from daily data on AC power generated did not result in models capable of identifying regular generation patterns. The fact is that even generation data considered regular presents high randomness, mainly due to the high incidence of clouds in the region that was being used in these first tests. Furthermore, the approach using more data to bring more satisfactory results to the model had to be discarded due to limited available data and time to acquire more data.

To address the issue of noise generated by stochastic cloud cover, preprocessing was applied to the data using moving averages. We experimented with window sizes of 7, 14, and 28 days to enhance the accuracy of the autoencoder-generated model. This strategy allowed for a detailed analysis of the autoencoder's behavior under different moving average configurations.

The result of this data pre-processing is shown in Figure 2 and Figure 3. The points represent the daily generation, and the red lines display the averages. Figure 2 shows a regular generation curve, while Figure 3 illustrates the effect of a morning shadow affecting power generation.

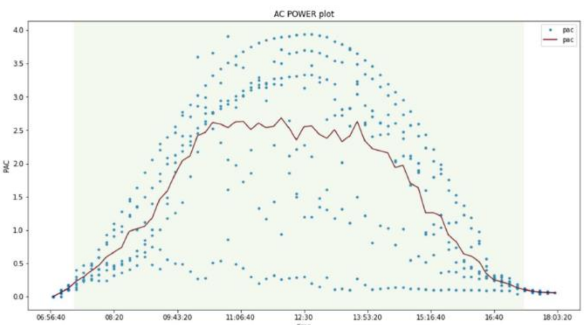

Figure 2: Moving average effect over a regular generation curve.

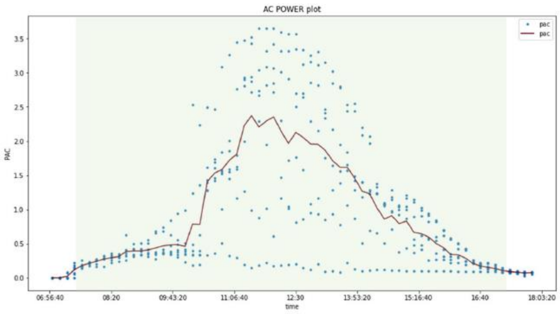

Figure 3: Moving average effect over an anomalous generation curve.

The autoencoder architecture was defined using an AutoML process, which was restricted to finding an acceptable configuration of layers and neurons within predefined limits of the same architecture. Among the configurations tested, the architecture chosen for testing had 18,458 trainable parameters. It is important to note that we did not use AutoML to define different neural network architectures, as we opted to employ a data-centric approach and apply MLOPS concepts, rather than focusing on model-centric techniques and fine-tuning parameters.

The results of these tests indicated a significant variation in the effectiveness of the autoencoder based on the number of days considered for the moving average. Sensitivity, specificity, precision, and accuracy of the model were calculated, demonstrating the autoencoder's capability to identify anomalies in photovoltaic systems. The comparative analysis of the results, considering different moving average configurations, can be observed in Table 1.

Table 1: Autoencoder performance metrics in time windows of 1, 2 and 4 weeks

Days	Sensibility	Specificity	Precision	Accuracy
7	1.00	0.88	0.69	0.91
14	1.00	0.98	0.92	0.98
28	1.00	1.00	1.00	1.00

According to Table 1, the 28-day window yielded excellent results, achieving 100% in all evaluated metrics. Considering that, in practical terms, evaluating an inverter's performance over a one-month period is acceptable, choosing a 28-day moving average becomes the most attractive option to include in our methodology.

4.2 Analysis of Methodology Results in a Production Environment

To test our infrastructure and methodology, we opted for a segmentation strategy for ML models guided by three main justifications, reflecting the complexity and diversity of photovoltaic systems. Firstly, the significant climatic distinction between Brazil's regions suggests the need for specific models by federative unit or regions, aiming to capture the regional nuances that affect solar energy generation. Additionally, the variation in behavior between inverters of different sizes and the importance of identifying anomalies at specific times of the day motivated the creation of models also differentiated by inverter size and periods of the day.

Table 2: Models for the São Paulo (SP) and Santa Catarina (SC) region

Model	Region	Number of Inverters Used to Train [abs/%]	Training Time [s]
2Y-SP-5-D	SP	7 (21%)	34,1
2Y-SP-5-M	SP	7 (21%)	30,9
2Y-SP-5-T	SP	7 (21%)	31,7
2Y-SC-5-D	SC	13 (22%)	34,4
2Y-SC-5-M	SC	13 (22%)	30,9
2Y-SC-5-T	SC	13 (22%)	31,4

The evaluations of our methodology were carried out without the use of PR, to show that in situations of restricted meteorological data, accurate results can also be obtained. Three models were used in two regions for plants with 5kW installed power. Table 2 presents the model data. Every model was generated and tested on a personal computer with the following configuration: Ubuntu 22.04.4 LTS Operating System, Processor AMD Ryzen 5 4600g and 16GB RAM Memory (no GPU was used).

The results for each region are presented in confusion matrices in the Figure 6. The methodology developed works with the ensemble technique, thus, the results of all models available for each group (region/power) generate only one combined result, following a vote that classifies as true (or anomalous) days that present two or more positive results among the results of the three available models.

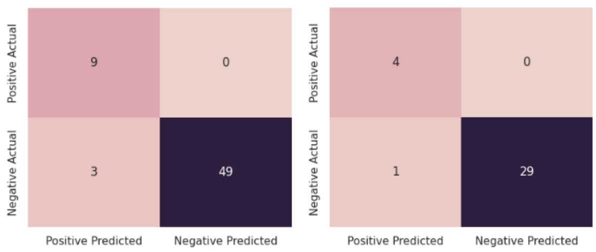

Figure 6: 2 Years Training SC (left) an SP (right) Models Ensemble Confusion Matrix

When evaluating the performance of models that use data from two years of generation for their training, it was decided to test the capacity of models with data from just one year of generation. Table 3 presents the results of the evaluation metrics for these results. The accuracy and precision of models drops drastically when training data is reduced to one year.

However, the recall was not computed in any of the cases, as the team did not assess whether the inverters classified as regular by the models are regular.

Table 3: Performance metrics of 1 year- vs. 2 year-models

Model	Accuracy	Precision
2Y-SC-5 Ensemble	0.95	0.75
2Y-SP-5 Ensemble	0.97	0.80
1Y-SC-5 Ensemble	0.52	0.23
1Y-SP-5 Ensemble	0.32	0.15

Figures 7, 8 and 9 show examples of average generation curves per 30-day period where the system identified shadows. These examples present different situations and different shading intensities. Figure 7 shows morning shading.

Figure 7: Inverter 2026

In Figures 8 and 9, corresponding to inverters "1626" and "1627," a notable drop in generation at noon was observed, an atypical pattern for photovoltaic systems. Such behavior suggests consistent shading at noon, which was later confirmed with the information of a nearby building construction, a factor that caused the shading.

Figure 8: Inverter 1626

Figure 9: Inverter 1627

This analysis reinforces the effectiveness, versatility, flexibility, and robustness of the developed system, highlighting its ability to accurately detect anomalies and adapt to different operational conditions and configurations.

5. CONCLUSIONS

This study presents a methodology for detecting anomalies and generating alerts in photovoltaic systems, employing an approach using only the moving average of AC power available in the inverters as input of a light autoencoder network or combining AC power with solar irradiation data to increase the confidence level of the alert. The use of autoencoders allowed precise modeling of inverter behavior, facilitating the identification of deviations that indicate operational anomalies.

The implementation of the methodology in an infrastructure based on Docker containers proved to be a scalable and energy-and time-efficient solution, enabling rapid deployment and adaptation of the system to different configurations of photovoltaic plants. The results obtained, validated in plants with regular inverters and shading, demonstrated the effectiveness of the methodology in managing the operation of photovoltaic systems, thus ensuring the optimization of energy generation and the economic viability of investments.

Detailed analysis of the performance of the autoencoder technique, especially with the application of moving averages over different time windows, reinforced the importance of an adaptive and data-centric approach to anomaly detection. The tests carried out without using the Performance Ratio (PR) emphasized the potential of the methodology to significantly improve the accuracy of anomaly detections and the generation of relevant alerts, mainly with the use of the ensemble technique. This technique has great potential especially for identifying specific faults. Currently, we only differentiate shadows at different times of the day, but with more models for specific defects it will be possible to increase the level of certainty regarding their detection, as failures in photovoltaic panels normally affect more than one characteristic of the power generation.

In conclusion, the developed methodology represents a reliable, efficient and scalable option to be applied in the monitoring and maintenance of photovoltaic systems in a non-intrusive manner, offering a low-cost solution that uses only data already available from the inverters.

6. ACKNOWLEDGMENTS

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