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RESEARCH ARTICLE

Advanced Signal Processing Techniques for Monitoring East/West Oriented Solar Photovoltaic Systems: A Case Study

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ABSTRACT Solar photovoltaic (PV) systems are increasingly recognized as crucial sustainable energy sources with diverse applications. Their implementation leverages rapid advancements in material engineering, communication systems, and computational intelligence tools. This paper focuses on selected mathematical methods for analyzing time series of power generated by PV systems, including numerical methods and algorithms for multichannel signal processing, digital filtering, and signal feature extraction. These methods monitor the characteristics of individual PV panels and identify their feature clusters. Specifically, it examines systems with east/west oriented photovoltaic panels, employing statistical methods and computational tools to analyze power signals, assess time and positioning data, evaluate symmetry coefficients, and apply machine learning tools to detect potential panel failures. Additionally, a general graphical user interface for data analysis is proposed. A detailed case study is presented, analyzing the distribution of selected features over time segments of a PV system comprising seven east-oriented and seven west-oriented panels, with data recorded over a selected set of days at a sampling rate of 15 minutes. The results reveal distinct and well-separated feature clusters for healthy PV panels. General conclusions underscore the effectiveness of signal processing tools in the statistical analysis of PV systems and the potential of feature clustering and symmetry estimation for evaluating disorders of system behaviour using communication technologies, data storage, and remote system monitoring.

INDEX TERMS Photovoltaic systems, renewable energy, computational intelligence, multichannel signal processing, signal features evaluation, fault detection.

I. INTRODUCTION

Due to the exponential growth of large-scale photovoltaic (PV) systems, automatic approaches for PV system analysis, optimization, and protection are becoming increasingly important. This progress includes advancements in both technological systems and artificial intelligence for controlling and monitoring their behavior [1], [2]. Globally, solar PV is projected to generate around 8.2% of total electricity in 2024, up from 6.7% in 2023. This increase is driven by the rapid expansion of solar installations worldwide [3], particularly in leading solar markets like China, the United States, and the European Union. The share of renewables in electricity generation is forecast to rise from 30% in 2023 to 37% in 2026, largely supported by the expansion of increasingly cost-effective solar systems.

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More than 61 countries worldwide support renewable energy (RE) systems research [4] to achieve 100% RE targets. The growing electricity demand of data centers [5], crucial for current information technology systems, highlights the need for improved energy efficiency to be entirely powered by renewable energy by 2032. These trends underscore the global push for renewable energy and technological advancements in solar power generation.

Photovoltaics, which involve the conversion of light into electricity, are based on the photovoltaic principle first demonstrated by French physicist Edmond Becquerel in 1839. The first solar cell, consisting of a layer of selenium covered with a thin film of gold, was created by Charles Fritts in 1884. In addition to the direct photovoltaic excitation of free electrons, an electric current can also arise through the Seebeck effect, first discovered in 1794 by Italian scientist Alessandro Volta and independently rediscovered by German physicist Thomas Johann Seebeck in 1821.

Photovoltaic systems have long been used in specialized applications such as stand-alone installations and space stations. Since the 1990s, grid-connected PV systems have become widely adopted as renewable energy sources, alongside wind, solar, geothermal, and hydropower. Modern home and large-scale photovoltaic systems employ solar modules, each comprising numerous solar cells that generate electrical power. Modeling these systems provides information about solar cell current/voltage curves [6] for a given radiation level, which is essential for configuring a solar system to operate near its optimal peak power point.

Physical PV configurations [7], [8] depend on many factors that aim to maximize system efficiency, minimize environmental degradation [9], [10], extend their lifetime [11], and consider architectural aspects of their implementation [12], [13]. The sensitivity of solar panels is mostly optimized for the 400-1100 nm wavelength range, allowing them to achieve high efficiency by focusing on the most abundant and energetically favorable parts of the solar irradiance spectrum [14] reaching the Earth. Studies in material engineering further optimize the transmission through panel materials [15], [16] and increase the ratio of electrical output to incident solar energy.

Solar photovoltaics are among the most prominent sustainable energy sources, representing an increasing percentage of renewable energy generation. Due to the rapidly growing number of PV systems, there is a need for improvements in monitoring technologies [17], [18], fault detection using spectral methods and thermal images [19] among others, integration with data transmission [20], and the development of fast communication systems [21], [22].

Many studies are devoted to the physical principles of photovoltaic systems, advancements in material engineering, and the rapid technological progress in energy acquisition, transmission, storage, and electrical power system architecture [23]. Selected studies focus on data processing and the optimization of PV system behavior. An important associated area is the monitoring of solar systems [24] and remote sensing to detect failures [25], [26] through infrared thermography [27], [28], [29], [30], [31], as well as general data processing methods [32], [33], [34], [35], and software tools for the analysis and modelling of PV systems [36].

Monitoring technologies play a crucial role in improving the performance and reliability of PV systems by tracking their operation and identifying potential failures. Basic monitoring systems focus on simple parameters like energy output, voltage, and current. Advanced real-time monitoring systems of large-scale PV installations measure a wide range of parameters including solar irradiance, module temperature [37], ambient temperature, shading, and wind speed. They can remotely detect system performance issues in real-time and suggest maintenance needs [38].

The orientation of photovoltaic panels [7], [39] plays a crucial role in their efficiency and energy output. In the northern hemisphere, south-facing PV panels are positioned to receive maximum sunlight throughout the day, especially around solar noon. Studies suggest that south-facing panels can capture up to 15% more energy than east/west-oriented panels under ideal conditions. While south-facing panels provide a higher total energy yield, east/west panels offer better alignment with energy consumption patterns and allow for more compact and potentially cost-effective installations.

Computational methods, artificial intelligence algorithms, and digital signal processing tools are pivotal in monitoring, optimizing, and addressing abnormal behavior in PV systems. Specific projects focus on signal processing for solar panel analysis, advanced algorithms for PV array monitoring, fault detection, and segmentation of solar PV systems [40], [41]. Mathematical methods include numerical and statistical methods, digital filtering tools, machine learning, and spectral analysis methods, which are especially useful for detecting and smoothing fluctuations in solar irradiance time series [42].

Special attention is paid to integration of artificial intelligence (AI) into photovoltaic systems [43], [44], [45], [46], [47] to improve their efficiency, reliability, to optimize system performance, and to detect faults [48]. Its application is

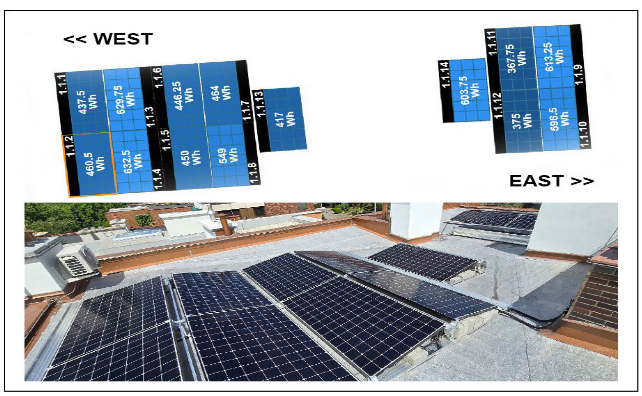

FIGURE 1. Positioning of photovoltaic panels on the flat roof with the east/west orientation and their description on the web model used for data acquisition from individual panels with the selected sampling period.

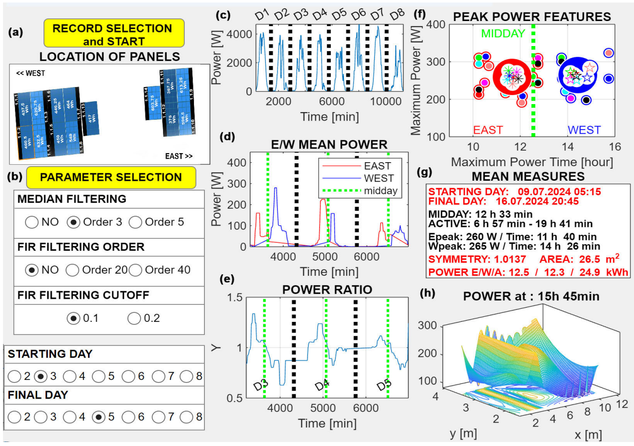

FIGURE 2. Graphical user interface that allows processing of power data from individual east/west oriented panels with selected parameters allowing selection of filtering methods and days for detail processing presenting (a) an area for data import and location of panels, (b) an area for parameters selection, (c) the total power of selected string, (d) the mean power from east and west oriented panels, (e) normalized power ratio of east/west oriented panels, (f) the peak power features, (g) the numerical results, and (h) the 3D power distribution at a selected time.

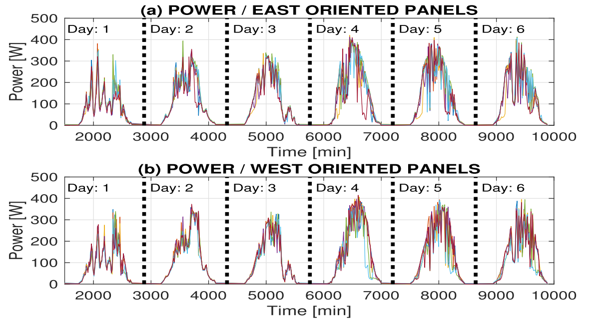

FIGURE 3. Power generated by individual panels with (a) the east and (b) the west orientation during selected 6 days.

mostly in maximizing the potential of east/west-oriented solar installations, data processing, and model management in different conditions [49]. Computational intelligence techniques help optimize power generation by addressing challenges such as fluctuating solar irradiance and system orientation. Specific research is devoted to AI application in advanced remote supervision and control [50].

This paper reflects the focus on advanced computational tools, signal processing, and a specific case study, as well as the practical applications and implications of the research of the east/west oriented system presented in Fig. 1. It contributes to the mathematical analysis of signals recorded from individual panels and their systems installed in specific locations. The goal of the paper is in the use of computational intelligence and digital signal processing methods for (i) remote monitoring of signals acquired from panels with different orientations for detection of possible defects and for system optimization, (ii) determination of time and location factors from different power patterns acquired from the set of panels, (iii) classification of power data using pattern vectors acquired during different time periods, and (iv) studies of specific areas of AI implementation in PV systems research and education.

The rest of the paper is organized as follows. Section II discusses data acquisition, describes the proposed methodology, and summarizes signal processing methods. Section III presents selected results of multichannel power signal analysis associated with the specific case study and describes the proposed general graphical user interface. Section IV contains the discussion. Section V presents the conclusions and remarks on possible future research.

II. METHODS

The dataset comprises data captured through an Internet connection to photovoltaic solar systems. The proposed methodology utilizes both system monitoring via smartphone technology and data processing in the computational environment of Matlab 2024a (MathWorks, Natick, MA). The evaluation algorithm in the suggested graphical user interface is presented in Fig. 2. The data processing steps include the following:

(a) Downloading power data from individual east/west oriented panels recorded by the PV system, stored in the form of a CSV table containing timestamps and the power output of individual panels.
(b) Selecting processing parameters, including the definition of digital filtering and the selection of the data subset.
(c) Filtering the total power of the selected string.
(d) Estimating the mean power from the east and west oriented panels to identify power peaks for both sets of panels.
(e) Evaluating the normalized power ratio of east/west oriented panels to detect midday.
(f) Computing peak power features of individual panels and their mean values to identify potential defects in individual panels.
(g) Evaluating numerical results.
(h) Visualizing the 3D power distribution at a selected time.

A. DATA ACQUISITION

Figure 1 presents a selected configuration of photovoltaic panels on a flat roof with east/west orientation, along with their description in the web model used for data acquisition from individual panels with the selected sampling period. Figure 3 shows the power generated by individual panels with east and west orientation over a selected time period.

Detailed descriptions of observations can be found on IEEE DataPort (Solar PV Data Analysis, 10.21227/n891-rw53, [51]) for further investigation. This repository contains a selected dataset of power generation by the PV system, comprising seven east-oriented and seven west-oriented panels, with data recorded over a period of several days at a sampling interval of 15 minutes. Additionally, a graphical abstract of the paper is available in the repository.

B. SIGNAL PROCESSING

The database of records was organized into a matrix with timestamps in the first column and records of generated power in the subsequent columns, each associated with individual panels through their titles. The sampling period T_s was constant, set to $T_s = 15$ minutes, in the ideal case, making resampling unnecessary. This data was used for (i) evaluating midday by analyzing the time evolution of the power ratio between east and west-oriented panels, (ii) estimating sunrise and sunset times, (iii) potentially estimating the PV system's longitude and latitude, and (iv) evaluating selected panel features to detect possible panel failures. Additional analysis included interpolating energy production over the PV system area for potential comparison with infrared images to further investigate panel failures.

Time series N values long of energy data defined simultaneous vectors $\{s_p(n)\}_{n=1}^{N}$ for each panel $p = 1, 2, \cdots, P$ out of their set of P units and for each time instant $t = n \times T_s$ for $n = 1, 2, \cdots, N$. These vectors formed columns of the data matrix $A = [s_1, s_2, \cdots, s_P]$.

Signal preprocessing included digital filtering of the given data as the first step. Due to the nature of the data values, median filtering of a selected order was applied to each column of the matrix A to reduce isolated peaks in the data. This step was necessary because fluctuations in data from photovoltaic panel optimizers can occur due to variable sunlight intensity, temperature variations, grid instability, the presence of harmonics, or the algorithms used by the optimizers to maximize power. Digital filtering was then performed using a low-pass finite impulse response (FIR) filter of the selected order M and its cutoff frequency f_c was the optional next step of data preprocessing. For each panel $p = 1, 2, \cdots, P$, the new sequence:

$$S_p(n) = \sum_{m=1}^{M} b(m)\, s_p(n-m) \tag{1}$$

was evaluated for values $n = 1, 2, \cdots, N$ and coefficients $\{b(m)\}_{m=1}^{M}$ associated with the selected cutoff frequency f_c. Power generated by individual panels was then evaluated by the simple rectangular integration rule.

The least squares method was then used to estimate key features associated with the PV location. A linear approximation of the signal, defined as the ratio of power generated by east- and west-oriented panels, was employed to estimate midday, with this value being close to one. A cubic approximation of the power generated by these two panel categories helped identify morning and afternoon power peaks for these two categories of panels, detecting their individual and mean characteristics crucial for identifying potential panel failures. These signals were also used to monitor the initial and final times of power generation during selected days.

Additional information was derived from the specification of panel locations within the selected coordinate system. Two-dimensional spline interpolation of power generated by individual panels across the entire PV system area enabled the visualization of power generated from east- and west-oriented panels at chosen time instants. These results provide a basis for further potential correlation of power data with infrared images of individual panels to detect possible panel failures.

Fundamental statistical methods were used to evaluate selected features for both individual panels and the global analysis of the entire PV system. Features associated with east- and west-oriented panels were then used to define their clusters and for further analysis.

Evaluating the symmetry coefficient of an east- and west-oriented photovoltaic system involves comparing the performance or output characteristics of the PV arrays oriented in these two directions. The calculation of this coefficient includes:

- Gathering of data on the power output generated by both the east and west-oriented PV arrays. This data should be collected over the same time periods to ensure comparability.
- Selecting a time frame, which can include daily, weekly, monthly, or yearly data, depending on the required level of detail.
- Normalizing the power output data to account for differences in the number of panels or the installed capacity between the east and west arrays, if they are not identical in size. This can be done by dividing the power output by the total installed capacity of each array.
- Calculatinng the symmetry coefficient (SC), defined as the ratio of the total power produced by the east-oriented array (P_{east}) to power produced by the west-oriented array (P_{west}):

$$SC = \frac{P_{east}}{P_{west}} \tag{2}$$

Additional statistical analysis can further explore symmetry coefficient changes with seasons, related to the variation of the sun's angle and daylight hours.

The performance ratio (PR) can then be estimated from the daily mean power output P_{actual} [kWh/day] of the PV system by relation:

$$PR = \frac{P_{actual}}{P_{theoretical}} \tag{3}$$

where the theoretical power output $P_{theoretical}$ [kWh/day] with its seasonal variations can be calculated from the average solar irradiance G_{avg} [kWh/m^2/day], the area of the PV system A [m^2], and module efficiency η as

$$TP = G_{avg} \times A \times \eta \times PR \tag{4}$$

The east/west oriented PV system are very efficient with this metric usually higher than 0.8 [39], [52]. In these systems, the calculation must account for different solar angles throughout the day, which leads to variations of solar irradiance. East/west systems tend to produce more power in the morning and afternoon compared to south-facing arrays that peak at midday. Machine learning models are applied to predict the most efficient configuration for east/west arrays. These algorithms can process large datasets, including weather patterns and shading effects, to find the optimal design parameters.

Fundamental statistical methods were used to evaluate selected features for both individual panels and the global analysis of the entire PV system. Additional statistical analysis can further be employed to analyze the symmetry coefficient, comparing the distributions of the outputs from the two arrays by calculating the mean and standard deviation of the output ratios over multiple time periods.

III. RESULTS

During the signal preprocessing stage, median filtering of the third order was applied followed by FIR low-pass filtering of order $M = 20$ with the normalized cutoff frequency $f_c = 0.1$ to remove fast signal fluctuations. Detailed numerical results of the power generated by the east- and west-oriented panels over six consecutive days are presented in Table 1. The normalized symmetry coefficient in the last column should be close to one for a healthy system. If a panel fails, this equilibrium changes, indicating the need for a more detailed system analysis.

Figure 4 presents an analysis of the power generated by east/west oriented PV panels. The mean power generated by these panels is shown in Fig. 4(a). The difference and the ratio of power generated by the east- and west-oriented panels are presented in Figs. 4(b) and 4(c), respectively. These signals were used to estimate midday and the active power generation period each day. These values can then be used to estimate the observation date and the latitude/longitude of the PV system, as described in some papers. The datasets used for this analysis are stored in IEEE DataPort, as mentioned above.

TABLE 1. Power generated by the east/west oriented PV panels, the total value of power produced during 6 subsequent days, and the symmetry coefficient.

Day	*Power [kWh]*			*Symmetry Value*
	East	*West*	All	
1	10.9	10.9	21.8	1.000
2	14.5	14.9	29.4	0.974
3	15.1	13.9	28.9	1.087
4	18.1	18.4	36.4	0.983
5	17.8	17.6	35.4	1.016
6	15.7	15.3	30.9	1.026
SUM	92.0	90.9	182.9	1.013

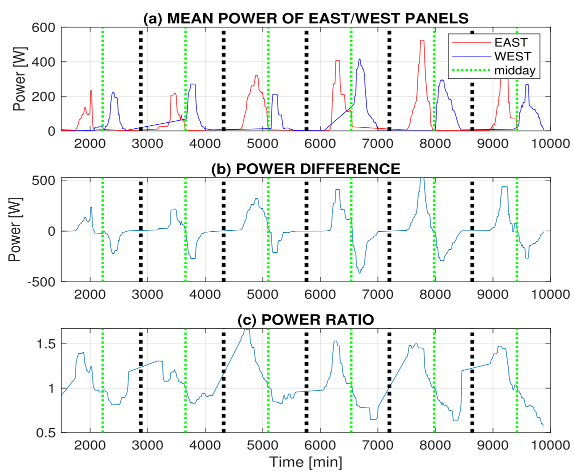

FIGURE 4. Analysis of the power generated by PV panels presenting (a) the mean power generated by east and west oriented panels after the application of median filtering, (b) power difference, and (c) power ratio during selected 6 days.

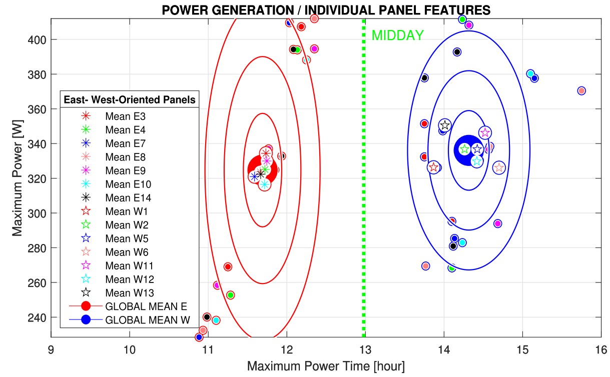

FIGURE 5. Analysis of the PV system features defined by the maximum power value and its associated time for each east- and west-oriented panel presenting (i) distribution of these features for individual panels for the period of selected days with the *c* multiples of standard deviations for c = 1.0, 1.2, · · · , 1.5, (ii) mean power values over individual panels (with asterisks and pentagrams for east- and west-oriented panels), and (iii) global mean values for the two categories of panels.

The behavior of the PV system can be analyzed in more detail through signal features estimated from data that specify power generation by individual panels. Figure 5 presents an analysis of the PV system features defined by the maximum power value and its associated time for each east- and west-oriented panel, showing the distribution of these features for individual panels over the selected number of days. Detailed distribution of these features is associated with individual panels for the period of selected days with the c multiples ($c = 1.0, 1.2, \cdots, 1.5$) of standard deviations S_1, S_2 of features standing for maximum power time $f_1(i)$ and their values $f_2(i)$ for individual east- and west-oriented panels for $i = 1, 2, \cdots, N$ related to their mean values where

$$S_k = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(f_k(i) - mean(f_k))^2} \tag{5}$$

for $k = 1, 2$. The mean power values over individual panels (specified by asterisks and pentagrams for east- and west-oriented panels) should form compact clusters for the healthy system. The specific markers show global mean values for east- and west-oriented panels.

The position of the PV panel set shown in Fig. 1 was specified in the selected coordinate system, enabling visualization of the time evolution of power generated by individual units. Figure 6 presents the results of 3D interpolation of the generated power, depicted in mesh and contour plots at the selected time. This allows tracking the

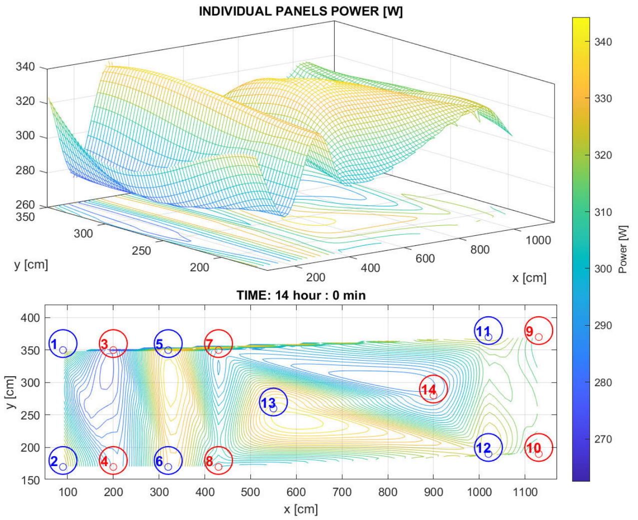

FIGURE 6. Positioning of 7 east-oriented (numbered in red) and 7 west-oriented photovoltaic panels (numbered in blue) in the selected coordinate system and the 3D interpolation of the generated power at the selected time instant.

peaks of power generated by the east- and west-oriented panels.

The proposed graphical user interface, shown in Fig. 2, facilitates processing power data from individual east- and west-oriented panels recorded by the solar system with the given sampling period. his environment allows remote selection and import of any PV system segment, data preprocessing with chosen parameters by selected digital filtering methods, their processing, and analysis including classification of signal features. Results display the total power of a selected string, the mean power from east- and west-oriented panels, and the normalized power ratio of east-to west-oriented panels. Additional windows present peak power features (values and associated time) of individual panels, numerical results, and the 3D power distribution at a selected time, based on the panel localization within the selected coordinate system.

Numerical results presented by the graphical user interface in Fig. 2 provide fundamental information related to the selected database of power records over the chosen time period. Information about the selected PV system includes the mean daily power generated during the chosen period and the area of solar panels, which can be used to evaluate the performance ratio according to Eq. (3) for the mean solar irradiance in that period.

IV. DISCUSSION

The widespread availability of photovoltaic systems, combined with rapid advancements in material engineering, artificial intelligence, and communication technologies, is driving the rapid development of solar systems. This progress is enabling the application of innovative computational and machine learning methods.

This paper focuses on the study of east/west architecture in solar systems and the use of computational methods for analyzing signals acquired from individual panels. It demonstrates the potential of these methods for system analysis and anomaly detection in power supply.

The results indicate that the east/west orientation of panels is beneficial not only for efficiently distributing power generation throughout the day but also for conducting additional system analysis and fault detection. The symmetry coefficient can monitor the health of the entire system through a simple evaluation of acquired signals. Further analysis can then be based on more sophisticated computational tools and artificial intelligence methods to predict power generation, optimize design parameters, and assess overall system efficiency.

The presented case study analyzed 14 panels, with half oriented east and the other half west. The mean symmetry coefficient evaluated from observations over six days was 1.013, with a standard deviation of 0.041 and well-separated clusters of selected panel features. The mean difference between peak power supply from east- and west-oriented panels was 2 hours and 30 minutes.

The reliability of the proposed computational system is closely related to the quality of data available from the remote database system, the sampling period, and time synchronization of signals from individual panels. Higher sampling rates (typically with $T_s = 1$s) are recommended for advanced fault detection [20] and real-time performance optimization, especially for individual panels. In the given case, the sampling period $T_s = 15$min was selected as a recommended standard monitoring setup providing a balance between capturing performance variations and minimizing data storage/processing demands. Recording was reliable with time-synchronized signals. In case of not so sophisticated systems, the time interpolation of missing values and resampling can cause additional processing errors.

V. CONCLUSION

The global use of solar energy is projected to rise significantly in the coming years, becoming a primary energy source that supports economic growth. This progress must be driven by high-quality research from both academic institutions and industrial sectors. Recent studies focus on advancements in material engineering, the integration of artificial intelligence, improvements in energy storage systems, and the development of new technologies, including concentrated solar power systems. These efforts aim to enhance the efficiency, reliability, and sustainability of solar energy solutions to meet future energy demands effectively.

This paper addresses the analysis of east/west photovoltaic systems using data from individual panels and the application of computational methods for their processing. The proposed algorithm evaluates the symmetry coefficient and the distribution of selected signal features.

The results indicate that this method could be beneficial for distinguishing between the behavior of east- and west-oriented panels, optimizing system performance, and detecting possible failures. Future work should focus on more sophisticated methods and the application of infrared cameras for a more detailed analysis of potential panel failures.

Further research should be devoted to developing algorithms and software tools for improving the performance of the associated hub inverter, its integration into the grid, and the construction of battery systems. The entire interdisciplinary field of solar energy utilization requires a deep understanding of electrical engineering, material science, communication technologies, and artificial intelligence, with a wide range of applications.

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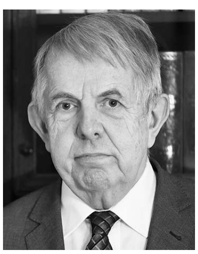

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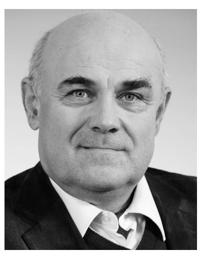

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