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Energy Efficiency Optimization and Real-Time Monitoring of Photovoltaic Systems: Towards Intelligent Solar Power Management

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Abstract – This paper presents an integrated approach to optimizing the performance of photovoltaic (PV) systems by combining advanced monitoring techniques with hardware and software solutions. The study begins with a theoretical analysis of photovoltaic technologies, solar controllers (PWM (Pulse-Width Modulation), MPPT (Maximum Power Point Tracking)), and the environmental factors affecting efficiency. It then proposes a real-time monitoring system that collects data on temperature, humidity, and voltage across the panel and battery, enabling precise performance evaluation. Statistical methods are applied to analyze the collected data and identify optimal conditions. The system uses microcontrollers (ESP8266), sensors, and a virtual instrumentation dashboard for real-time visualization. The research demonstrates how continuous monitoring and data-driven analysis can improve energy efficiency, system reliability, and long-term cost reduction.

Keywords- photovoltaic systems; MPPT; monitoring system; energy efficiency; ESP8266; data analysis; renewable energy

I. INTRODUCTION

The energy transition and decarbonization targets are amplifying the pressure on operators and users of PV systems to extract maximum performance with minimal costs and high predictability. Although the instantaneous efficiency of a PV panel depends primarily on irradiation and temperature, the efficiency of a system depends in practice on several additional factors: impedance match to load, quality of power electronics (PWM/MPPT regulators), ohmic losses, thermal dissipation, battery condition, degradation over time and operating strategy. In the absence of fine-grained monitoring and informed control of data, these variables create a "performance gap" between potential and delivered power [1], [2].

Over the past decade, the convergence of IoT (Internet of Things)–edge computing–statistical analytics has paved the way for high-granularity, early diagnosis, and adaptive control [3]. Low-cost microcontrollers (ESP type), multi-parameter sensors and virtual instrumentation interfaces allow real-time collection of voltages, currents and environmental variables, and their processing (filtering, aggregation, explanatory models) supports better operational decisions: controller settings, battery charge management, partial shadow detection, anomaly identification and maintenance planning [4].

On the other hand, the literature reports a diversity of approaches for MPPT and for evaluating performance under dynamic conditions (variable irradiation, high temperatures, partial shading) [5]. Classical algorithms (P&O (Perturb and Observe), incremental conductance) coexist with rule-based methods, fuzzy logic, or heuristic optimization. However, the shift from algorithmic demonstrations to robust gains "in the field" is critically dependent on data quality and availability, hardware-software integration, and statistical validation of results in real-world operating scenarios [6].

This paper proposes an integrated approach that combines (i) a hardware platform for the acquisition and conditioning of electrical and environmental signals, (ii) a software chain for real-time collection, storage and visualization, and (iii) a statistical analysis aimed at quantifying the influence of key variables on performance and evaluating the impact of control decisions. The contributions aim at both the design of a cost-benefit monitoring system and a reproducible analysis methodology, linking measurements to performance indicators (energy produced, efficiency, operational stability). The main objective is to optimize the operation of a PV assembly connected to storage by: (a) instrumenting the system for complete observability (electrical & environmental), (b) benchmarking of control/MPPT strategies based on the collected data, and (c) demonstrating measurable improvements in efficiency and reliability. In addition, the paper aims to formulate operational recommendations (settings, thresholds, alerts) that can be transferred to practice.

The structure of the paper is as follows: Section 2 presents a review of the literature on PV technologies, PWM/MPPT regulators and monitoring and analysis techniques. Section 3 describes the proposed hardware architecture (sensors, microcontroller, conditioning, interconnection). Section 4 addresses the software component (data collection, processing, visualization and management). Section 5 details the statistical methodology (pre-processing, indicators, models and tests). Section 6 reports the experimental results, discussions and practical implications, and at the end the conclusions and future research directions are formulated.

II. LITERATURE REVIEW

A relevant example of practical implementation of a monitoring system for photovoltaic panels is presented in the paper [7], in which the authors propose a low-cost platform based on Arduino UNO and LabVIEW, intended for the acquisition of real-time data from a small PV system. The proposed system allows the continuous measurement of the voltage and current supplied by the solar panel, using the PmodISNS20 sensor and transmitting the data to a PC (Personal Computer) and via USB (Universal Serial Bus) connection. The interface developed in LabVIEW displays the measured values both numerically and graphically, by plotting the panel's operating point on the I-V and P-V characteristics. An important component of the work is the integration of an MS (Microsoft) Access database via ODBC (Open Database Connectivity), which allows storing historical data and viewing it remotely through a Windows Forms application. This integrated approach demonstrates the importance of constant monitoring of energy parameters to support optimization strategies such as MPPT and to facilitate predictive system maintenance.

The [8] paper focuses on optimizing solar energy conversion by using maximum power point tracking techniques, integrated into an IoT system based on the Arduino platform. The authors propose an efficient, low-cost system based on the ATmega328P microcontroller (Arduino UNO), capable of detecting and maintaining the optimal operating point of a photovoltaic panel under varying solar irradiation conditions. The algorithm used is an improved version of the classic P&O method, being characterized by an increased response speed and high accuracy in MPP (Maximum Power Point) point tracking. The proposed innovation consists of eliminating oscillations around the maximum power point, which reduces energy losses and contributes to increasing the efficiency of the system. In the study, the authors validate the performance of the solution through simulations in the Proteus environment and by building a functional hardware prototype. The experimental results indicate an efficiency of 99.21% under standard test conditions ($1000\ W/m^2$ at $25°C$), highlighting the robustness and practical applicability of the method. This paper is relevant for the field of optimizing the performance of photovoltaic panels because it illustrates a scalable, reliable and energy-efficient solution, applicable both in the industrial context and for domestic applications. The integration of a low-power architecture with MPPT functionality and IoT support provides valuable insights for expanding the monitoring and control capabilities of modern solar systems.

The paper [9] proposes the development and testing of an embedded system for monitoring the performance of photovoltaic panels, using the Arduino UNO R4 microcontroller and a series of specialized sensors for measuring voltage and current. The objective of the research is to obtain a real-time measurement system, with high accuracy and a minimum error rate, capable of operating in variable environmental conditions. The hardware system uses the ZMPT101B AC sensor, the ACS712 current sensor for AC (Alternating Current) and DC (Direct Current), as well as a DC sensor to monitor the direct output of the solar panel. The Arduino R4 processes the analog signals coming from these sensors and displays the data in real time, the experimental tests being carried out with tasks represented by a mini-fan and a speaker. The results obtained showed a remarkable accuracy of the system, with errors below 0.1%: 0.069% for the ZMPT101B, 0.094% for the DC sensor and 0% for the current measured with the ACS712. These performances highlight the viability of the Arduino UNO R4 platform for deploying intelligent and autonomous energy monitoring systems, while the paper also suggests expanding capabilities by integrating IoT modules (such as ESP32-S3) for cloud transmissions and advanced data analytics.

[10] presents a hardware and software platform designed for experimenting with battery charging in photovoltaic systems, using an Arduino Mega microcontroller. The platform includes a DC-DC converter controlled by PWM signal, sensors for measuring voltage, current and temperature at the PV panel and battery level, as well as an interface for displaying and storing data in Excel files. The system allows the battery charge to be controlled based on a three-step strategy (OFF, Bulk and Floating), protecting the battery against overcharging or over-discharging. Among the development prospects are the integration of an MPPT algorithm, WiFi connectivity, remote monitoring and the replacement of the Arduino board with the Raspberry Pi. The study highlights the importance of a reliable BMS (Battery Management System) for optimizing battery life and performance in hybrid photovoltaic applications.

The paper [11] proposes an integrated system for monitoring and controlling the energy produced by photovoltaic panels, using a combination of Arduino hardware and the LabVIEW software platform. The system is composed of two GUI (Graphical User Interfaces: a server-type one, installed locally next to the solar panels for direct monitoring and control, and a client-type one, accessible remotely via a web browser. The implemented hardware includes the Arduino Mega 2560, current and voltage sensors (such as ACS712), relays and a $50W$ polycrystalline solar panel. The interfaces allow real-time display of current, voltage and power values, as well as control of the operation of the PV system (including emergency shutdown or switching of power supplies). The communication between the client interface and the server system is carried out through web services configured in LabVIEW, thus allowing efficient and extensible monitoring. This solution demonstrates the feasibility of a low-cost solar monitoring system with high potential for applicability in remote areas or distributed renewable energy systems.

Paper [12] proposes an intelligent cooling system for solar panels, based on ambient temperature, to increase their efficiency and reduce the negative effects of overheating. The authors use an Arduino UNO microcontroller and LM35 temperature sensor to automatically control a system of DC-powered fans mounted on the back of the panel. The system is integrated with the Arduino IoT Cloud platform, allowing remote monitoring and control, as well as manual shutdown or activation depending on weather conditions. The main components include: the Arduino microcontroller, temperature sensors, DC fans and passive cooling panels (wood wool cooling panels). The system automatically starts at temperatures above $25°C$ and increases the fan speed in proportion to the temperature, reaching a maximum speed of $50°C$. If the temperature exceeds this threshold, the system emits an alarm signal through the buzzer and notifies the user via IoT. According to testing, the use of this active/passive cooling system can lead to an increase in the power generated of more than 32%, a decrease in panel temperature of more than $7.2°C$ and an increased efficiency of energy conversion. The cost of implementing the system is low (approx. 1500 INR (Indian Rupee) for $50W$), compared to the benefits obtained. The paper highlights the potential of simple, affordable, and integrated IoT technologies to optimize photovoltaic performance in residential or industrial applications.

The authors of the paper [13] propose the development and implementation of an EMS (Energy Management System) for a hybrid renewable energy system, using the Arduino Mega 2560 and Matlab Simulink. This system combines photovoltaic panels, batteries, a fuel cell and an electrolyze, with the aim of efficiently managing electricity production and consumption and extending the life of the batteries. The EMS intelligently controls the connection of different energy sources and consumers, depending on the current load, the state of charge of the battery and the energy available from the photovoltaic panels. The work identifies four modes of operation depending on the ratio between energy produced and consumption, as well as the battery charge level, consequently activating various consumers or sources (battery charging, feeding the load from the battery or fuel cell, using excess for electrolysis). Matlab-Simulink simulations demonstrate the correct operation of the system, and the hardware implementation on the Arduino experimentally confirms the behavior of the EMS by automatically switching the four digital outputs. The proposed system offers an efficient and low-cost solution for optimizing energy consumption in a hybrid renewable energy scenario, also having the potential to expand by adding sensors for hydrogen pressure or integrating other sources.

III. PV MONITORING SYSTEM HARDWARE ARCHITECTURE

This section describes the physical architecture of the system, the logic of the interconnection of the modules and the role of each component in the measurement-drive chain. The goal is to achieve a robust platform for data acquisition, telemetry transmission and local command, with a focus on electrical reliability and ease of maintenance.

The electrical diagram presented in Figure 1, illustrates how to integrate the main blocks: the Arduino Mega 2560-based control unit, the Wi-Fi ESP8266 communication module for telemetry, the I^2C (Inter-Integrated Circuit) LCD (Liquid Crystal Display) display for local feedback, as well as the sensor and drive subsystems. Power distribution is achieved via two DC–DC converters (an XL6009 boost for voltage raising where needed and a buck for stabilizing voltages), while a monostable relay provides control of power loads (e.g. pump or auxiliary circuits). A piezo buzzer provides audible signaling for events and alarms, and green terminal blocks facilitate tidy wiring and quick service.

Sensorially, the assembly includes a DHT11 for ambient temperature and humidity, an irradiance/illuminance sensor (dedicated optical module), sensors for current and voltage on critically monitored branches, as well as at least one temperature sensor mounted on or in the vicinity of the battery. This minimum package allows estimating conversion yield, panel operating points and losses on the route. The digital signals for controlling the LED (Light-Emitting Diode) panel and relay are routed from the Arduino, and serial/I^2C communication provides interface with the LCD and measurement modules. Connection organization aims to separate power paths from acquisition paths to limit unwanted inductive and electrical couplings.

Three principles were followed for the hardware integration: modularity (each function is encapsulated in an easy-to-replace module), electrical compatibility (logic levels and voltage ranges according to specifications) and resilience (filtering, decoupling and short paths for sensitive signals). Dedicated connectors for sensors, ground separation for power and signal, as well as neat mounting on the rail or prototype board contribute to the stability of measurements over time and the reduction of noise-induced errors.

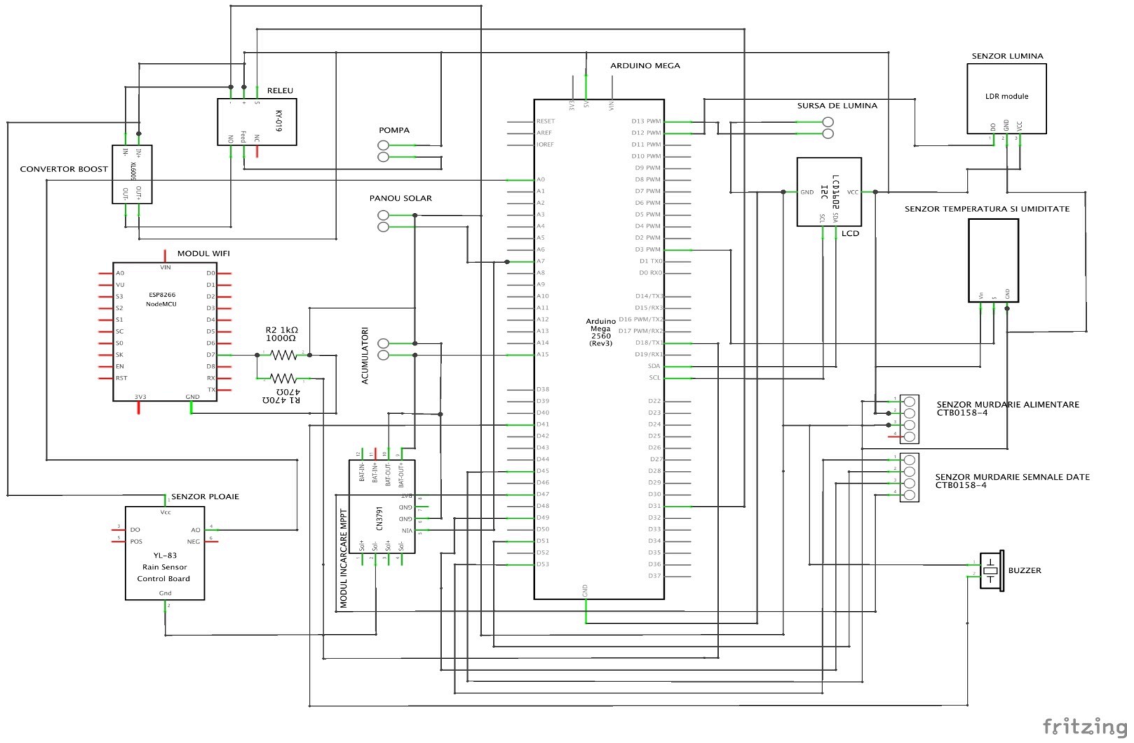


Figure 1. Electrical diagram of the photovoltaic monitoring system

IV. SYSTEM SOFTWARE DESIGN

Within the photovoltaic panel optimization system, the software component ensures the functional integration between the sensors, actuators and the monitoring platform, orchestrating data acquisition, control logic and publication of telemetry to the web interface. The implementation is divided into two levels: the firmware run on the Arduino Mega (acquisition + local control) and the web server running on the ESP8266 (viewing, querying and data exchange), with an authentication stage performed on a local server (Flask).

A. *Software Design of the PV Optimization and Monitoring System*

Within the photovoltaic panel optimization system, the software component ensures the functional integration between the sensors, actuators and the monitoring platform, orchestrating data acquisition, control logic and publication of telemetry to the web interface. The implementation is divided into two levels: the firmware run on the Arduino Mega (acquisition + local control) and the web server running on the ESP8266 (viewing, querying and data exchange), with an authentication stage performed on a local server (Flask).

The development of the firmware was done in the Arduino IDE, which allows writing, compilation and fast loading on the Arduino Mega board, also offering a serial monitor for testing. The rich support of libraries (LCD I2C, DHT11, TCS230, relay, etc.) has reduced the integration time [14], [15].

The firmware architecture on the Arduino Mega covers the following functions:

- **Sensor acquisition**: temperature/humidity (DHT11), luminance (LDR (Light Dependent Resistor)), rain, TCS230 optical sensor for panel dirt detection; The values are processed/filtered and prepared for display/transmission.
- **Local display**: A 20×4 LCD synthetically presents key parameters (temperature, humidity, dirt level, light status, panel-battery information string), using dedicated update routines.
- **Actuator control**: KY-019 relay control (flush pump) and acoustic signaling (buzzer), based on status rules and detected conditions.
- **Communication with the web interface**: data exchange with ESP8266 via UART (Universal Asynchronous Receiver-Transmitter); for logical compatibility, a resistive splitter was used on the TX line of the Arduino to the ESP RX.

B. *Web Server Software Design*

The web server running on the ESP8266 provides a browser-accessible interface for real-time data display and basic interactions. The application serves an HTML (HyperText Markup Language) / CSS (Cascading Style Sheets) / JS (JavaScript) page and exposes HTTP (Hypertext Transfer Protocol) (GET) endpoints used by JavaScript scripts to periodically request updated values (AJAX (Asynchronous JavaScript and XML) / fetch). The interface includes distinct zones for temperature, humidity, and luminance, with specific labels and units [16], [17].

Exposed endpoints: ***/readTemperature***, ***/readHumidity***, ***/readGas***, ***/readLx*** – each handler reads the related sensor, formats the value, and responds to text/plain; on the front-end, JavaScript functions send requests at regular intervals and update elements on the page.

Login: access to the dashboard is protected by a login page made locally in Flask; After validation, the user is redirected to the ESP8266 server address (real-time interface).

The code for the backend (Flask) and the login page (HTML/CSS) is included in the appendices of the chapter, along with screenshots of the login page (Figure 2) and dashboard (Figure 3).

Data persistence and scale-out: Metrics published by ESP8266 can be saved in an Excel file for offline analysis and feed into a statistical analysis/AI (Artificial Intelligence) module (adaptive optimization, predictive maintenance) in perspective. This separation between authentication, collection, and analytics provides security, modularity, and energy efficiency.

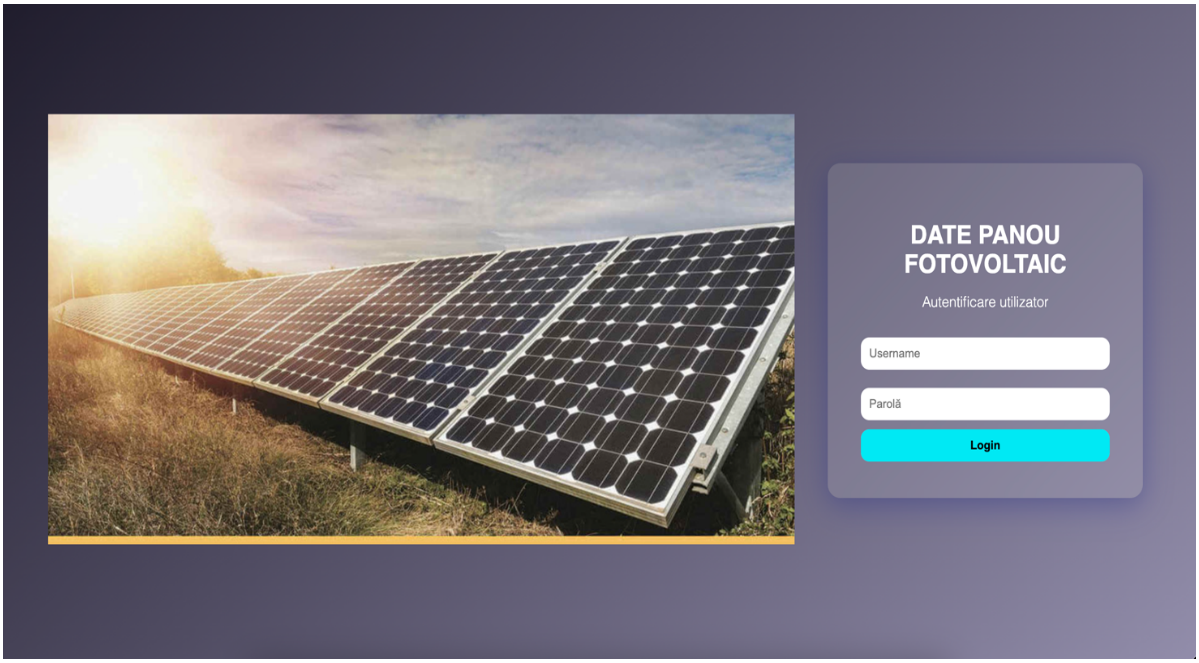
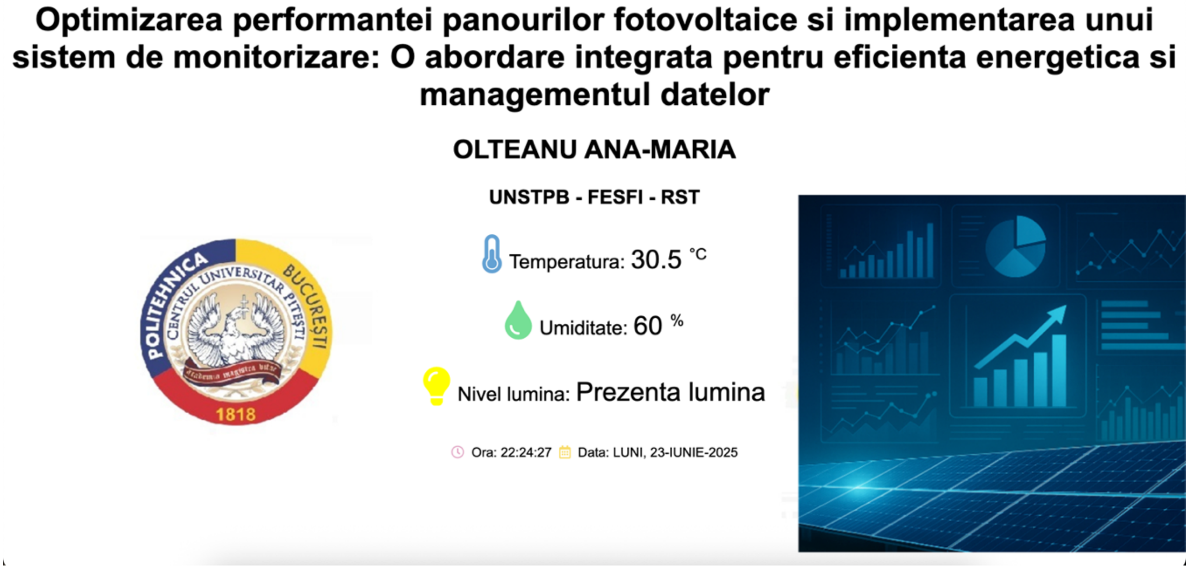


Figure 2. Login Page (Flask) – local access validation



Optimizarea performantei panourilor fotovoltaice si implementarea unui sistem de monitorizare: O abordare integrata pentru eficienta energetica si managementul datelor

OLTEANU ANA-MARIA

UNSTPB - FESFI - RST

Temperatura: 30.5 °C

Umiditate: 60 %

Nivel lumina: Prezenta lumina

Ora: 22:24:27 Data: LUNI, 23-IUNIE-2025

Figure 3. ESP8266 dashboard with AJAX parameter update

V. Statistical Analysis and Data Management

In this chapter, the statistical processing of the data collected by the photovoltaic system is carried out and their management flow is described (collection → storage → analysis → visualization → decision). The dataset includes daily measurements (12:00 p.m.) over ~50 days: panel voltage/current, battery voltage/current, power, temperature, and humidity. A representative sample is shown in TABLE I, and the time series aggregated in Figure 4. The data is saved in Excel/CSV format for further analysis in environments such as Python/MATLAB/Power BI and for later integration with anomaly detection algorithms and predictive maintenance.

A. Arithmetic Mean

The arithmetic mean evaluates the central trend of each monitored parameter and serves as a benchmark for detecting daily deviations. For a set of n values $\{\bar{x}\}$, the average is calculated with (1) [18]:

$$\bar{x} = \frac{1}{n}\sum_{i=1}^{n} x_i \tag{1}$$

Where:

- $\bar{x}$: average value.
- x_i : the individual value of the analyzed parameter (voltage, current).
- n: total number of observations.

The graph presented in Figure 5 highlights the average values recorded for each parameter monitored in the photovoltaic system, over the entire analysis period.

TABLE I. Sample From the Acquired Dataset

Date	Voltage Panel (V)	Voltage Battery (V)	Current Panel (A)	Current Battery (A)	Power Panel (W)	Power Battery (W)	Temperature (°C)	Humidity (%)
2025-03-01 12:00:00	4,01	3,69	0,39	0,26	1,56	0,96	33	63,7
2025-03-02 12:00:00	4,16	3,83	0,61	0,57	2,54	2,18	20,3	46,9
2025-03-03 12:00:00	3,8	3,67	0,59	0,33	2,24	1,21	33,3	42,2
2025-03-04 12:00:00	4,13	3,82	0,67	0,54	2,77	2,06	31,9	35,1
2025-03-05 12:00:00	4,06	3,76	0,53	0,46	2,15	1,73	16,2	34,2
2025-03-06 12:00:00	3,96	3,62	0,69	0,41	2,73	1,48	27	59,7
2025-03-07 12:00:00	4,1	3,77	0,32	0,4	1,31	1,51	29,1	52,1
2025-03-08 12:00:00	3,87	3,84	0,58	0,43	2,24	1,65	18,6	34,1
2025-03-09 12:00:00	3,9	3,79	0,45	0,43	1,76	1,63	19,3	51,4

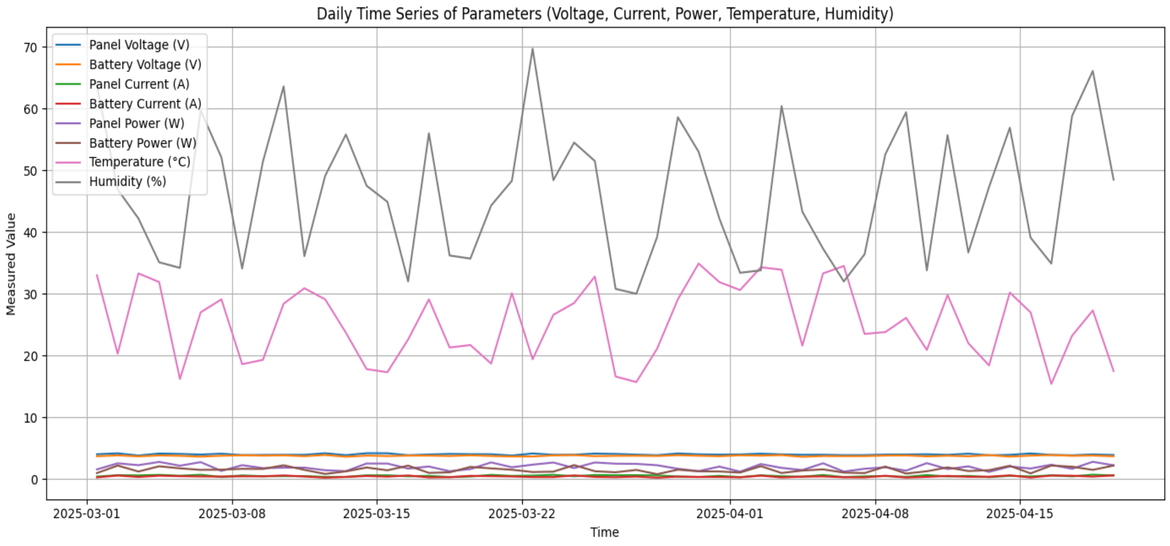


Figure 4. Graphical representation of the daily variation of the measured parameters

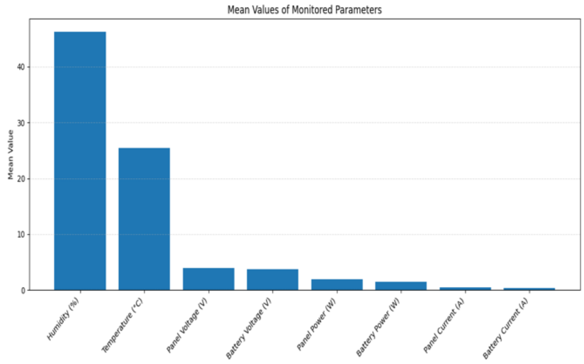


Figure 5. Arithmetic mean of the parameters monitored within the photovoltaic system

It is observed that the highest values belong to the environmental parameters (temperature and humidity), while the electrical values (voltage, current, power) of the panel and battery are moderate, reflecting a balanced operation of the system under various conditions.

B. Median

The median is robust at extreme values and describes the "typical value" of the system under normal conditions. For ascending ordered values $\{x_{(i)}\}$, (2) [19]:

$$Med(x) = \begin{cases} x_{\frac{n+1}{2}}, if\ n\ is\ odd \\ \dfrac{x_{\frac{n}{2}} + x_{\frac{n}{2}+1}}{2}, if\ n\ is\ even \end{cases} \quad (2)$$

Meaning of the terms:

- $Med(x)$: Median.
- x_i : the individual value of the measured parameter (voltage, current).
- n : total number of observations (days measured).

The graph in Figure 6 highlights the median values of each monitored parameter in the PV system, providing a robust picture of central trends that are not influenced by extreme values or anomalies.

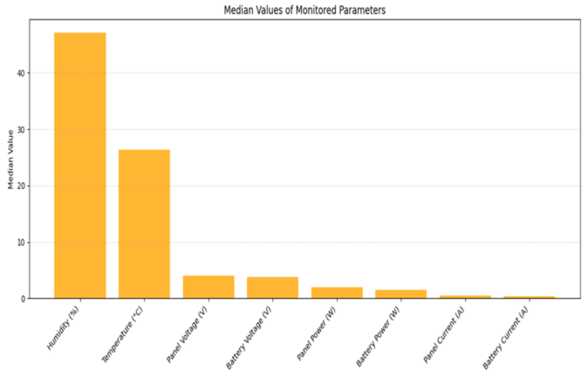


Figure 6. Median of the parameters monitored within the photovoltaic system

C. Standard Deviation

The standard deviation σ quantifies the variability from the mean (3) [20]:

$$\sigma = \sqrt{\frac{1}{n} \cdot \sum_{i=1}^{n} (x_i - \bar{x})^2} \quad (3)$$

If you are working with a sample (not the entire dataset), divide by $n-1$ is used, thus obtaining the standard deviation of the sample. Meaning of the terms:

- σ: standard deviation.
- x_i: individual value.
- $\bar{x}$: the arithmetic mean of the data set.
- n: Total number of values.

Figure 7 shows the standard deviation of the values recorded for each parameter analyzed, highlighting their degree of variability over the monitored period.

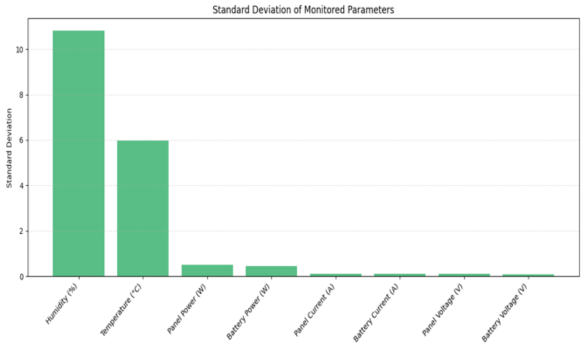


Figure 7. Standard deviation of the monitored parameters within the photovoltaic system

D. Variance

The variance is the square of the standard deviation and measures the dispersion of values (4) [21]:

$$\sigma = \frac{1}{n} \cdot \sum_{i=1}^{n} (x_i - \bar{x})^2 \quad (4)$$

In the case of a sample, the formula becomes like the one presented in relation (5) [21]:

$$s^2 = \frac{1}{n-1} \cdot \sum_{i=1}^{n} (x_i - \bar{x})^2 \quad (5)$$

Meaning of the terms:

- σ^2: dataset variance.
- s^2: sample variance.
- x_i: individual value.
- $\bar{x}$: arithmetic mean.
- n: number of observations.

Figure 8 illustrates the variance values for each monitored parameter, providing insight into the data dispersion to the arithmetic mean, which is essential in assessing the stability of the PV system's performance.

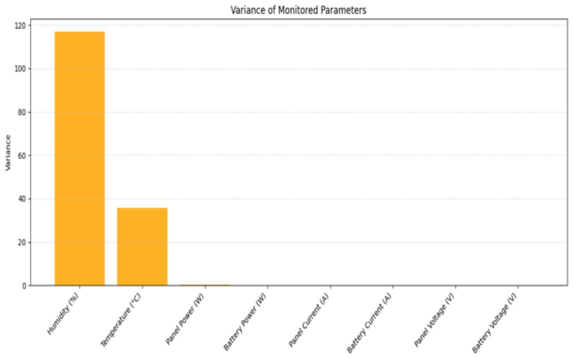


Figure 8. Variance of the monitored parameters within the photovoltaic system

E. Pearson Correlation

Pearson correlation is a statistical indicator that measures the strength and direction of the linear relationship between two quantitative variables. In the performance analysis of photovoltaic panels, this method is essential to determine whether there is a significant relationship between parameters such as temperature and power generated, humidity and efficiency, or current and voltage on the panel. The result is a correlation coefficient r with values between -1 and 1 [22]:

- $r = 1$: perfectly positive correlation (values grow together).
- $r = -1$: perfectly negative correlation (one increases, the other decreases).
- $r = 0$: No linear correlation.

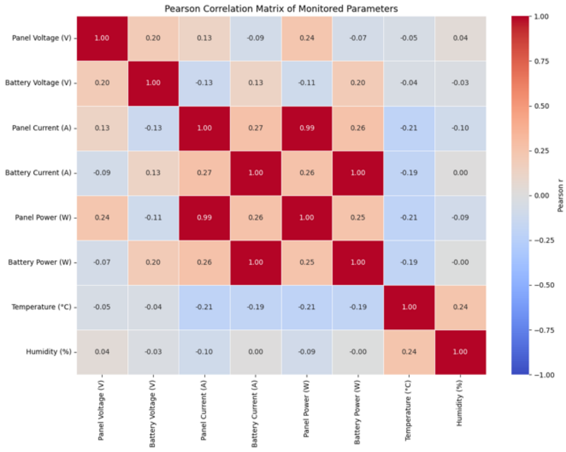
It is a valuable tool to identify what factors influence the performance of the system, thus facilitating its optimization. For two sets of data $X = \{x_1, x_2, \dots, x_n\}$ and $Y = \{y_1, y_2, \dots, y_n\}$, thus results the relation (6) [22]:

$$\mathrm{R} = \frac{\sum_{i=1}^{n}(x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum_{i=1}^{n}(x_i - \bar{x})^2 \cdot \sum_{i=1}^{n}(y_i - \bar{y})^2}} \tag{6}$$

Meaning of the terms:

- r: Pearson correlation coefficient.
- x_i, y_i: the individual values of the analyzed variables.
- $\bar{x}, \bar{y}$: arithmetic means of variables X and Y.
- n: total number of observations.

Figure 9 highlights the matrix of Pearson correlation coefficients between the monitored parameters of the photovoltaic system. There is a very strong correlation between the current of the panel and the power generated by it (0.99), while the rest of the variables show weak or almost non-existent correlations, which indicates a low interdependence between environmental conditions and energy performance.



	Panel Voltage (V)	Battery Voltage (V)	Panel Current (A)	Battery Current (A)	Panel Power (W)	Battery Power (W)	Temperature (°C)	Humidity (%)
Panel Voltage (V)	1.00	0.20	0.13	-0.09	0.24	-0.07	-0.05	0.04
Battery Voltage (V)	0.20	1.00	-0.13	0.13	-0.11	0.20	-0.04	-0.03
Panel Current (A)	0.13	-0.13	1.00	0.27	0.99	0.26	-0.21	-0.10
Battery Current (A)	-0.09	0.13	0.27	1.00	0.26	1.00	-0.19	0.00
Panel Power (W)	0.24	-0.11	0.99	0.26	1.00	0.25	-0.21	-0.09
Battery Power (W)	-0.07	0.20	0.26	1.00	0.25	1.00	-0.19	-0.00
Temperature (°C)	-0.05	-0.04	-0.21	-0.19	-0.21	-0.19	1.00	0.24
Humidity (%)	0.04	-0.03	-0.10	0.00	-0.09	-0.00	0.24	1.00

Figure 9. Pearson correlation coefficients matrix between electrical parameters and environmental conditions in the photovoltaic system

F. Linear Regression

Linear regression is a mathematical model used to describe the relationship between a dependent variable (e.g., the power generated by the panel) and an independent variable (such as the current of the panel). This relationship is modeled as a straight line that best estimates the trend of data points. In the context of photovoltaic systems, simple linear regression can be used, for example, to estimate how the power of the panel varies as a function of current, as shown in the relationship (7) [23]:

$$y = a + b \cdot x \tag{7}$$

Where:

- y: predicted value (dependent variable – Panel Power).
- x: known value (independent variable – Panel Current).
- a: intercept (the value of y when $x = 0$).
- b: the slope of the regression line (the change in y for each unit of growth in x).

The coefficient b is calculated as in relation (8) [23]:

$$\mathrm{b} = \frac{\sum_{i=1}^{n}(x_i - \bar{x})(y_i - \bar{y})}{\sum_{i=1}^{n}(x_i - \bar{x})^2} \tag{8}$$

And $a = \bar{y} - b\bar{x}$. Meaning of the terms:

- $\bar{x}$: the mean of the values in the independent variable.
- $\bar{y}$: the average of the values in the dependent variable.
- b: slope of the regression line.
- a: interception.

Figure 10 illustrates the linear regression applied between the current of the photovoltaic panel and the power generated by it. A strong positive correlation is observed, and the regression model manages to capture the general trend of the data, thus confirming the direct dependence between these two variables in the functioning of the system.

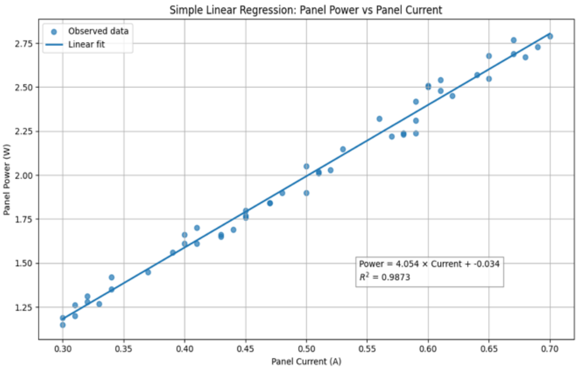


Figure 10. Linear regression between panel current (A) and generated power (W), highlighting the direct proportionality relationship

To respect the validity range of the approximately linear relationship between delivered power and current, the $P - I$ regression was restricted to the range $[0, 0.9 \cdot I_{mpp}]$. In this domain the voltage at the terminals remains almost constant (around V_{mpp}), so that the slope of the fit overlaps with V_{mpp}, and the coefficient of determination indicates a very good fit. The points in the vicinity of the knee of the characteristic $I - V$ were excluded, because they do not comply with the linearity hypothesis.

According to the panel datasheet [24], the maximum-power-point current is $I_{mpp} = 1A$; therefore, the linear regression in Figure 10 was restricted to the quasi-linear interval (9), which contains the $0.7A$ operating point and excludes the knee/open-circuit region, consistent with standard PV $I - V$ / $P - V$ behavior.

$$I \in [0, 0.9 \cdot I_{mpp}] = [0, 0.9 \cdot 1A] = [0, 0.9A] \quad (9)$$

The application of statistical algorithms in the analysis of data from the photovoltaic system allows a deep and objective understanding of its energy behavior. Through descriptive methods, such as arithmetic mean, median, standard deviation and variance, fundamental information is obtained about the distribution of the recorded values, indicating the average levels, dispersion or stability of parameters such as voltage, current or temperature. Pearson's correlation analysis brings added value in understanding the direct relationships between variables, highlighting the influence of environmental factors on panel performance. At the same time, linear regression techniques offer predictive tools capable of estimating future energy values based on the monitored parameters.

VI. RESULTS

The experimental stand integrated all the designed modules: the acquisition and control board (Arduino Mega), voltage/current and environmental sensors, the Wi-Fi module for telemetry, the local interface (LCD, buzzer, relay) and the battery/load bank allowing synchronous data logging and transmission to the monitoring application. The testing followed the accuracy of the measurement (comparison with benchmark instruments), the robustness of the communication (24-hour logging, reconnections, packet loss) and the energy behavior in variable irradiation scenarios. The physical configuration of the bench and the main connections are illustrated in Figure 11.

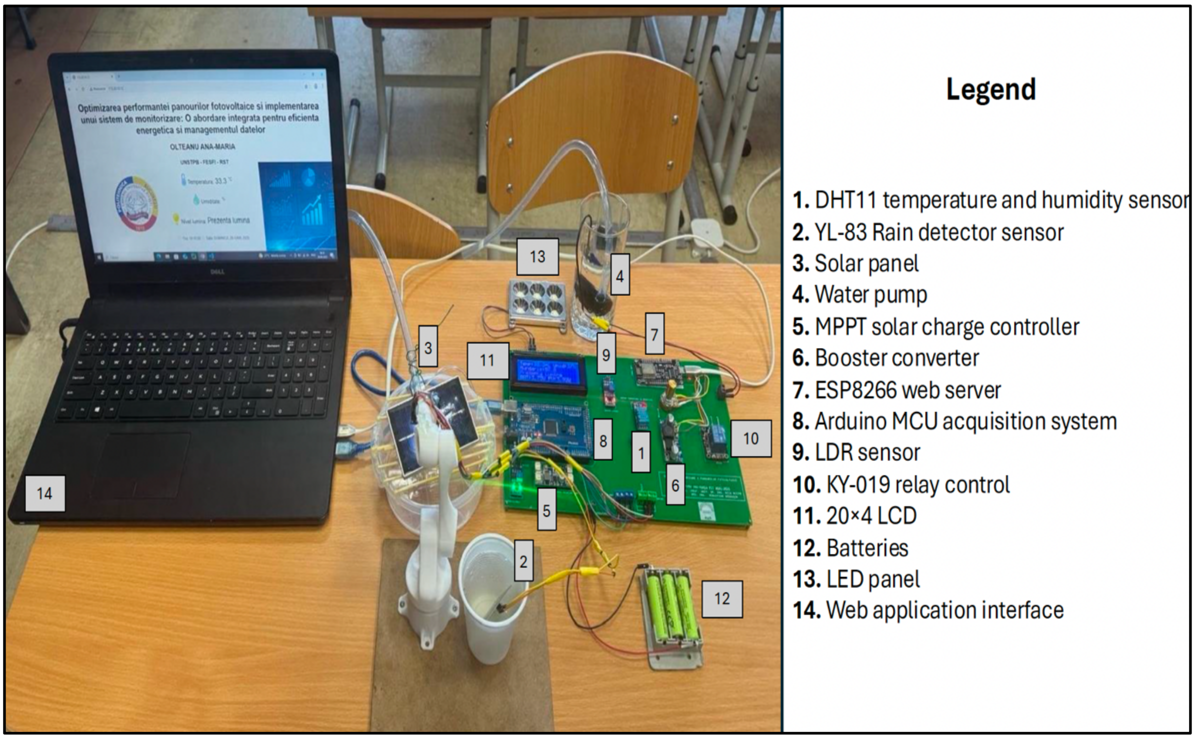


Figure 11. Experimental stand for PV monitoring system validation

Statistical analyses confirmed the physical coherence of the series: panel current and power showed high Pearson correlations, and simple linear regression (Panel Power vs Panel Current) showed an almost proportional relationship on the intervals with stable irradiation. Deviations increase during periods of rapid light variability, underscoring the usefulness of dynamic power point tracking algorithms. Extended logins indicated operational stability, with proper recovery after short network outages.

CONCLUSION

The paper proposed and demonstrated an integrated approach to optimizing the performance of photovoltaic panels, combining robust hardware components with a software chain oriented towards monitoring, statistical analysis and reproducible data interpretation. The physical architecture of the system, based on sensors for voltage, current and environment, the conditioning and acquisition interface, respectively the PWM/MPPT type control, ensured the reliable collection of the relevant operational variables. This material base was complemented by a software suite that standardized the ingestion of spreadsheets, standardized the names of the indicators and generated temporal and comparative visualizations, necessary for rapid performance diagnosis.

From the perspective of data analysis, graphical representations of daily variance provided a clear picture of the dynamics of the system according to environmental conditions, and descriptive indicators (mean, median, standard deviation and variance) captured both the central level of operation and the dispersion of key parameters. The Pearson correlation coefficient matrix highlighted significant relationships between the electrical variables of the panel, confirming the robustness of the expected physical dependencies. In the same direction, simple linear regression showed a strongly positive relationship between the panel's current and the power delivered, suggesting that an important part of the power variation can be explained by the current variation, according to the principled electrical modeling of a photovoltaic generator.

Hardware-software integration facilitated not only observability, but also the ability to intervene informedly. The proposed monitoring flow allows the identification of deviations from the expected behavior, their correlation with environmental factors and the prioritization of maintenance actions. From this perspective, the main contribution of the work is to translate the principles of energy optimization into a practical, modular and extensible framework, easy to adapt to various photovoltaic configurations and levels of complexity.

The limitations of the research derive mainly from the time horizon of the observations and from the specificity of the analyzed site. The relatively short duration of the time series and the dependence on a single installation context can induce biases related to seasonality, microclimate or construction particularities. In addition, sensor calibration, thermal drift, and possible sampling lags can affect correlation estimates and regression slopes. At the control level, the comparison between PWM and MPPT strategies was treated at the conceptual level; A side-by-side experimental evaluation, under the same irradiation and temperature conditions, would strengthen the conclusions on the actual energy gain.

Future work directions aim to extend the monitoring duration and include more sites to capture seasonal and geographical variability. From an algorithmic point of view, the integration of an adaptive MPPT, assisted by machine learning at the edge (edge), could improve the tracking of the maximum power point in dynamic conditions (partial shadows, fast clouds). In addition, the development of an early anomaly detection module (e.g. identification of soiling or hotspot degradation) would reduce unplanned losses. On the software front, migrating to a real-time web dashboard, API (Application Programming Interface) for continuous ingestion, and containerized versions for reproducibility would facilitate technology transfer and scaling.

Overall, the results show that a well-designed combination of instrumentation and statistical analysis provides a coherent operational picture of PV performance and creates solid prerequisites for optimization. The paper pragmatically contributes to understanding the relationships between electrical and environmental variables, provides a transparent workflow for monitoring and analysis, and paves the way for algorithmic and software improvements that can turn data into more efficient energy decisions.

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