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Experimental digital twin for MPPT-based load regulation and energy analytics in an isolated DC microgrid

Gemelo digital experimental con control MPPT y analítica energética en microrredes DC aisladas

Darwin Orlando Cardozo Sarmiento[1]
Francisco Ernesto Moreno García[1]
Gloria Esmeralda Sandoval Martínez[2]
Fabio Alexander Niño Pérez[1]

[1] **Universidad Francisco de Paula Santander, Departamento de Electricidad y Electrónica, Cúcuta, Colombia.**

[2] **Universidad Autónoma de Bucaramanga – UNAB, Facultad de Ingeniería, Grupo de Investigación Recursos, Energía, Sostenibilidad - GIRES, Bucaramanga, Colombia.**

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Corresponding Author: Darwin Orlando Cardozo Sarmiento

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Abstract:

The development of data-driven control and monitoring strategies is a key factor in optimizing the energy performance of photovoltaic direct-current (DC) microgrids. This paper presents the implementation of an experimental digital twin for load regulation using Maximum Power Point Tracking (MPPT) technology, complemented by an energy analytics module to evaluate system efficiency and stability. The proposed methodology integrates a Matlab-Simulink simulation with a physical implementation on an ESP32 microcontroller, executing a Perturb and Observe (P&O) algorithm coupled to a Boost DC/DC converter. Electrical and environmental data are processed using data science tools (Python, Pandas, NumPy, Seaborn) to determine correlations among irradiance, temperature, voltage, and power. Experimental results demonstrate an overall efficiency of 91.6 % under real irradiance conditions and a 99.7 % correlation between simulation and physical measurement, validating the reliability of the digital twin. The hybrid approach combines electronic control, digital modeling, and statistical analysis, establishing a low-cost intelligent energy monitoring platform suitable for rural microgrids and educational environments.

Keywords: digital twin, MPPT, data science, DC microgrid, photovoltaic energy, ESP32.

Resumen:

El desarrollo de estrategias de control y supervisión basadas en datos constituye un factor clave en la optimización energética de microrredes fotovoltaicas de corriente continua (DC). Este trabajo presenta la implementación de un gemelo digital experimental para la regulación de carga mediante tecnología Maximum Power Point Tracking (MPPT), complementado con un módulo de analítica energética orientado a evaluar la eficiencia y la estabilidad del sistema. La metodología combina la simulación en Matlab-Simulink con la implementación física en un microcontrolador ESP32, ejecutando un algoritmo P&O acoplado a un convertidor DC/DC tipo Boost. Los datos eléctricos y ambientales se procesan mediante herramientas de ciencia de datos (Python, Pandas, NumPy y Seaborn) para determinar correlaciones entre irradiancia, temperatura, voltaje y potencia. Los resultados muestran una eficiencia global del 91.6 % bajo condiciones reales de irradiancia y una correspondencia del 99.7% entre simulación y medición física, confirmando la fiabilidad del gemelo digital. El enfoque híbrido propuesto integra control electrónico, modelado digital y análisis estadístico, configurando una plataforma inteligente de monitoreo energético de bajo costo aplicable en microrredes rurales y entornos educativos.

Palabras clave: gemelo digital, MPPT, ciencia de datos, microrred DC, energía fotovoltaica, ESP32.

INTRODUCTION

Photovoltaic generation is one of the main sustainable energy conversion technologies, driven by advances in semiconductor materials, reductions in production costs, and the growing need to replace fossil sources with clean alternatives. However, the energy delivered by a solar panel varies with irradiance and temperature conditions, factors that affect the maximum power point (MPP) and the system efficiency[1]-[3].

Using the generated energy efficiently requires conversion and control strategies capable of keeping the system operating at the MPP and compensating for environmental variations. Maximum Power Point Tracking (MPPT) technology offers a solution for improving the performance of photovoltaic systems. It consists of dynamically adjusting the operating parameters of the DC/DC converter so that the product of the panel current and voltage is maximum at all times[1]-[3].

Several algorithms have been proposed for MPPT, including Perturb and Observe (P&O), Incremental Conductance (IC), and others based on computational intelligence techniques such as artificial neural networks or fuzzy logic. However, although advanced algorithms offer a fast response to irradiance fluctuations, their implementation usually requires specialized hardware and a higher computational burden. Therefore, the algoritmo P&O remains a preferred option in educational and low-cost applications, thanks to its robustness and operational simplicity[1]-[3].

The integration of data science tools into energy control systems has made it possible to broaden the analysis from an electrical perspective to a statistical and descriptive approach. By collecting and processing data from irradiance, temperature, voltage, and current sensors, it is possible to characterize the dynamic behavior of the photovoltaic system, evaluate efficiency patterns, and determine the variables with the greatest influence on the generated power. This synergy between electronic control and data analysis strengthens decision-making for optimizing the operation of DC microgrids[1]-[3].

This work presents the design and implementation of a load regulation system with MPPT technology, complemented by an analysis of environmental and electrical data for the energy optimization of an isolated DC microgrid. The system integrates a Boost-type DC/DC converter, a P&O MPPT algorithm, and a controller programmed on an ESP32 platform, which enables an efficient, low-cost architecture with digital monitoring capability. Through simulation in Matlab-Simulink and experimental validation, the effects of environmental conditions on system efficiency are analyzed, showing the correspondence between analytical and empirical results. In addition, the system is conceived under the Experimental Digital Twin approach, in which the virtual model developed in Matlab-Simulink replicates the dynamic behavior of the implemented physical system. This interaction between simulation and reality makes it possible to validate the coherence between both environments and provides the basis for designing future data-based predictive control strategies[4]-[8].

The innovative contribution of this research lies in combining MPPT control with data analysis techniques for the energy characterization of the system, contributing to strengthening the transition toward smart and sustainable electrical grids. This proposal is especially relevant for academic environments and rural microgrids, where hardware simplicity and control precision determine the technological and economic viability of the implemented solutions.

METHODOLOGY

The research is structured in four methodological phases aimed at the design, implementation and validation of a load regulation system with MPPT technology, complemented by an analysis of environmental and electrical data.

Phase 1. Selection and characterization of the photovoltaic system

This phase comprises the collection of technical information and the selection of the components that make up the photovoltaic system. Different commercial modules are analyzed considering nominal power, voltage at the maximum power point (VMPP), current (IMPP), efficiency under standard test conditions (STC) and market availability.

To determine the appropriate photovoltaic module, six measurable criteria that directly influence the performance of the load regulation system are established[1]-[3]:

- Maximum power current (IMPP, A): determines the current delivery capacity of the panel under standard test conditions (STC).
- Maximum power voltage (VMPP, V): must be compatible with the Boost converter topology to avoid excessive voltage gains.
- Estimated power at 700 W/m² (P700, W): represents the behavior of the panel under irradiance conditions typical of the implementation environment (Cúcuta, Colombia).
- Maximum efficiency (%): reflects the photovoltaic conversion capacity of the semiconductor material.
- Commercial availability: qualitative factor associated with local access to spare parts and technical support.
- Number of panels required: a single-module design is preferred to minimize connections and wiring losses.

Each criterion is weighted with a uniform weight of 16.67 %, granting the same degree of importance to the electrical and

availability variables.

To compare values measured in different units (amperes, volts, watts and percentages), a min–max normalization process is applied, expressed in (1)[9].

$$X_{norm} = \frac{X_i - X_{min}}{X_{max} - X_{min}} \times 100 \quad (1)$$

X_{norm} (normalized value)

X_i (represents the criterion value for each panel)

X_{min} (minimum value)

X_{max} (maximum value)

Then the global compatibility index (GCI) is calculated as the weighted average of the six criteria, shown in (2)[9].

$$ICG = \sum_{i=1}^{6} w_i \cdot X_{norm,i} \quad (2)$$

$w_i = 0.1667$ (weight assigned to each criterion)

After the multicriteria analysis applied to six panels (see Fig. 1), the Yingli Solar YL245P-29b module (245 W) was selected, with 94.86 % compatibility with the electrical requirements of the design.

Solar Panel	IMPP (A)	VMPP (V)	P700 (W)	Efficiency	Compatibility
Yingli Solar	8.11	30.2	173.3	15.0	**94.9%**
Trina Solar	7.98	30.7	168.1	15.0	**77.8%**
Jinko Solar	7.89	29.8	166.0	14.0	**77.7%**
JA Solar 340	9.79	34.7	250.5	20.2	**83.3%**
JA Solar 245	9.16	38.8	245.3	19.3	**66.3%**
Restar Solar	10.47	20.1	145.2	19.2	**43.0%**

Optimal Moderate Critical

Fig. 1. *Panel Compatibility.*
Source: Own work.

Phase 2. Comparison and selection of the MPPT algorithm

Once the photovoltaic module has been defined, two classic maximum power point tracking algorithms are compared:

Perturb and Observe (P&O): iteratively adjusts the panel voltage by observing the power response. If it increases, the perturbation continues in the same direction; if it decreases, the direction is reversed. It is robust, easy to program, and requires low processing (see Fig. 2)[10]-[17].

Incremental Conductance (IC): it evaluates the equality between the incremental conductance (ΔI/ΔV) and the instantaneous conductance (I/V) (see Fig. 3). Its accuracy is higher under varying irradiance conditions, but its computational cost increases[10]-[17].

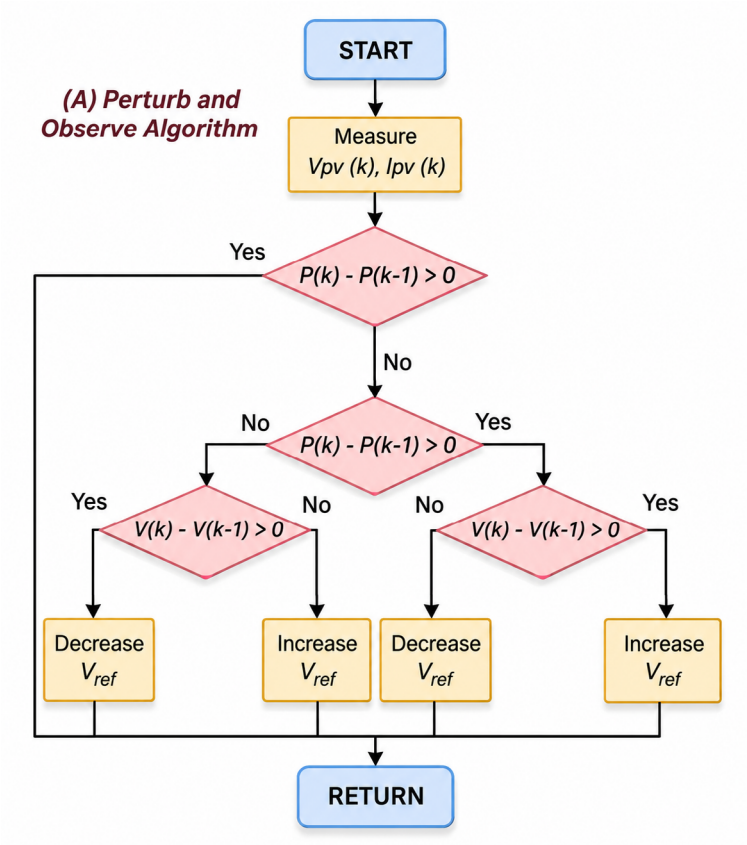


Fig. 2. *Basic P&O algorithm.*
Source: Adapted from [6].

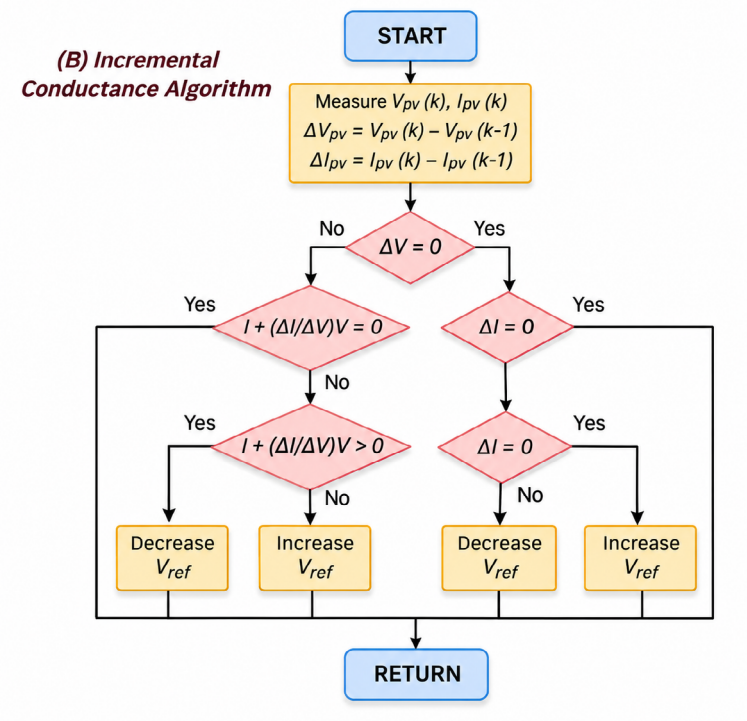


Fig. 3. *Incremental conductance algorithm.*
Source: Adapted from [6].

Phase 3. Implementation of the control system in the DC microgrid

This phase covers the physical integration of the proposed system. The DC/DC Boost converter is designed to operate with an input voltage of 30 V and an output of 70 V.

The control is implemented by means of a digital PID, tuned to minimize the steady-state error and improve the transient response to rapid irradiance variations.

An ESP32 microcontroller executes the MPPT algorithm and acquires data from voltage and current sensors through INA219 modules, processing the measurements every 100 ms. The values are displayed on an LCD screen integrated into the didactic module and are stored locally in CSV format for subsequent analysis.

The system is connected to an isolated DC microgrid composed of an RL resistive load and a subsequent inverter stage. The tests are carried out under an average irradiance of 700 W/m², representative of the study area.

To quantitatively validate the correspondence between the virtual model and the physical system, evaluation metrics are incorporated that allow determining the fidelity of the Experimental Digital Twin. The power data obtained in Matlab-Simulink are compared with the real measurements recorded in the ESP32 microcontroller under equivalent irradiance and temperature conditions. Error and correlation indicators widely used in the digital twin validation literature are applied, defined from (3) to (6)[4]-[8].

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|P_{sim,i} - P_{exp,i}| \quad (3)$$

$$MAPE = \frac{100}{n}\sum_{i=1}^{n}\left|\frac{P_{sim,i} - P_{exp,i}}{P_{exp,i}}\right| \quad (4)$$

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(P_{sim,i} - P_{exp,i})^2}{\sum_{i=1}^{n}(P_{exp,i} - \bar{P}_{exp})^2} \quad (5)$$

$$NSE = 1 - \frac{\sum_{i=1}^{n}(P_{sim,i} - P_{exp,i})^2}{\sum_{i=1}^{n}(P_{exp,i} - \bar{P}_{exp})^2} \quad (6)$$

P_{sim} (simulated power)

P_{exp} (experimental power)

Phase 4. Data analysis and energy correlation

To experimentally validate the performance of the MPPT system, data science techniques are used to analyze the energy efficiency through the Google Colab platform with the Python programming language[17]-[23].

Acquisition and debugging: The power records were collected through two experimental configurations (with MPPT and without MPPT), totaling 40 comparable samples for each case. The data were structured in CSV formats for systematic processing.

Statistical processing: The data were processed with Python (using Pandas, NumPy and SciPy) to calculate measures of central tendency (mean, median), dispersion (standard deviation, range) and relative efficiency metrics. Column names were normalized and temporal filtering was applied to ensure comparability[17]-[23].

Descriptive visualization: Using Matplotlib and Seaborn, the following were generated:

- Comparative time-series plots of power
- Histograms and box plots for distribution
- Trend analysis with Gaussian smoothing
- Visualizations of aggregated metrics

Quantitative validation: The results were exported in CSV format for technical documentation, including descriptive statistics and analytical summaries that made it possible to quantify the advantage of the MPPT system.

RESULTS AND DISCUSSION

The validation of the system was carried out in two stages: simulation in Matlab-Simulink and experimental verification on the implemented DC microgrid. The results obtained allow analyzing the behavior of the charge controller, the accuracy of

the MPPT algorithm, and the consistency between the theoretical model and the physical assembly.

Performance of the MPPT algorithms

The MPPT algorithms were simulated in Matlab-Simulink, considering fluctuating irradiance profiles between 400 and 1000W/m² and a temperature of 25–45°C.

Fig. 4 presents the simulated comparison of the power delivered as a function of irradiance for the P&O and IC algorithms, together with the power. Both methods maintain tracking close to the maximum power point throughout the 200–1000W/m² range. Both curves converge toward the maximum power point without appreciable oscillations, confirming the stability of the system under variable irradiance. Mean efficiencies of 98.34% (P&O) and 99.15% (IC) were obtained. The accumulated energy difference in favor of IC is 0.82%, a margin that is offset by the lower computational cost and simplicity of implementation of P&O.

Finally, P&O was selected as the final algorithm due to its simplicity and lower memory consumption, to be implemented in the microcontroller.

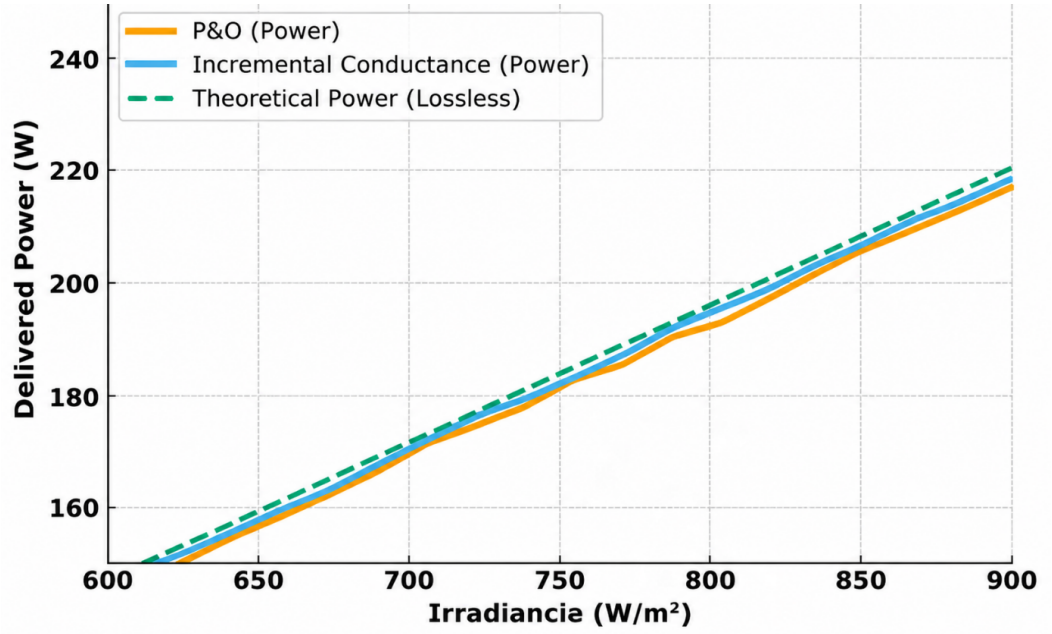


Fig. 4. *Power vs Irradiance.*
Source: Own work.

System validation in simulation

The photovoltaic system model is built in Matlab-Simulink (see Fig. 5), including the solar panel, the Boost converter and the MPPT controller. This model is used for the prior validation of the PID control and of the Boost converter.

Fig. 6 shows the power obtained in simulation with and without the P&O-type MPPT algorithm. The panel power stabilizes at around 173.3W, whereas without MPPT the useful power remains around 100–120W over the same time interval.

This represents an approximate 44% increase in the available power thanks to the action of the MPPT algorithm. In addition, the system reaches stabilization in less than 0.6 seconds, which shows fast convergence toward the maximum power point. The small difference between the actual power (173.33W) and the power estimated by the algorithm (172.94W) reflects the precision of the implemented control, with a relative error below 0.23%.

Likewise, the integrated digital PID controller is observed to regulate the output voltage of the Boost converter at around 70V ±2%, guaranteeing the stability of the system during irradiance variations. The power reaches its steady state in approximately 0.6 s, giving a fast recovery without significant overshoots. This demonstrates the adequate tuning of the proportional, integral and derivative gains, and evidences the efficiency of the control implemented together with the MPPT algorithm.

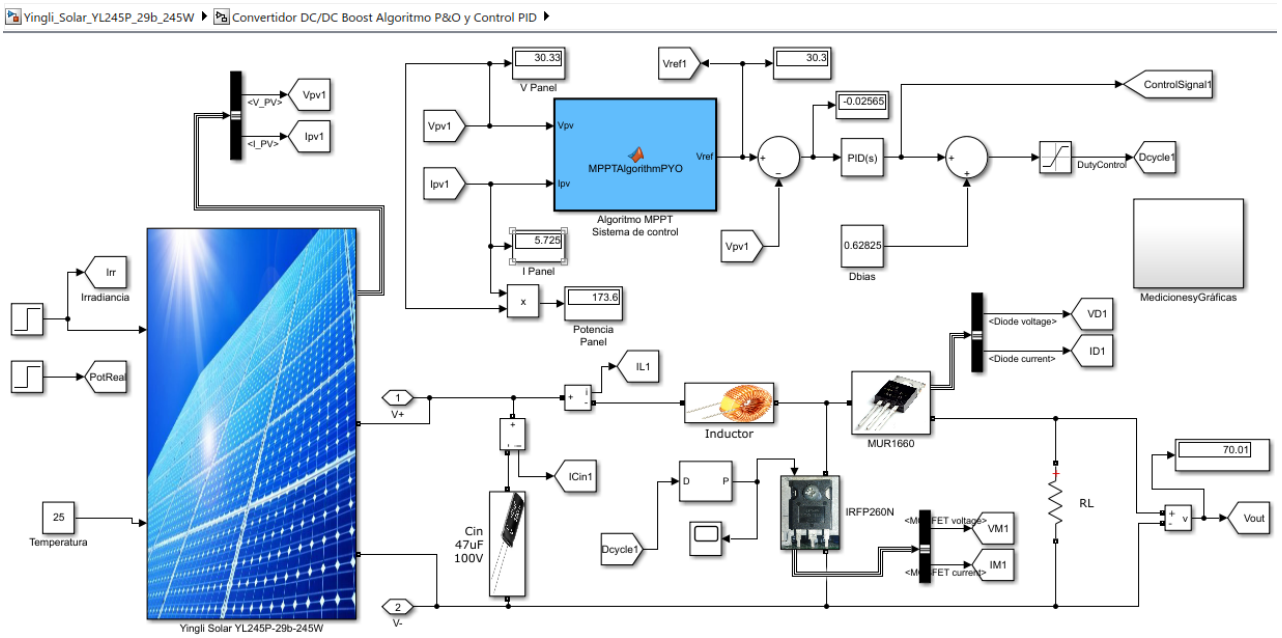


Fig. 5. *Photovoltaic system coupled in Matlab-Simulink.*
Source: Own work.

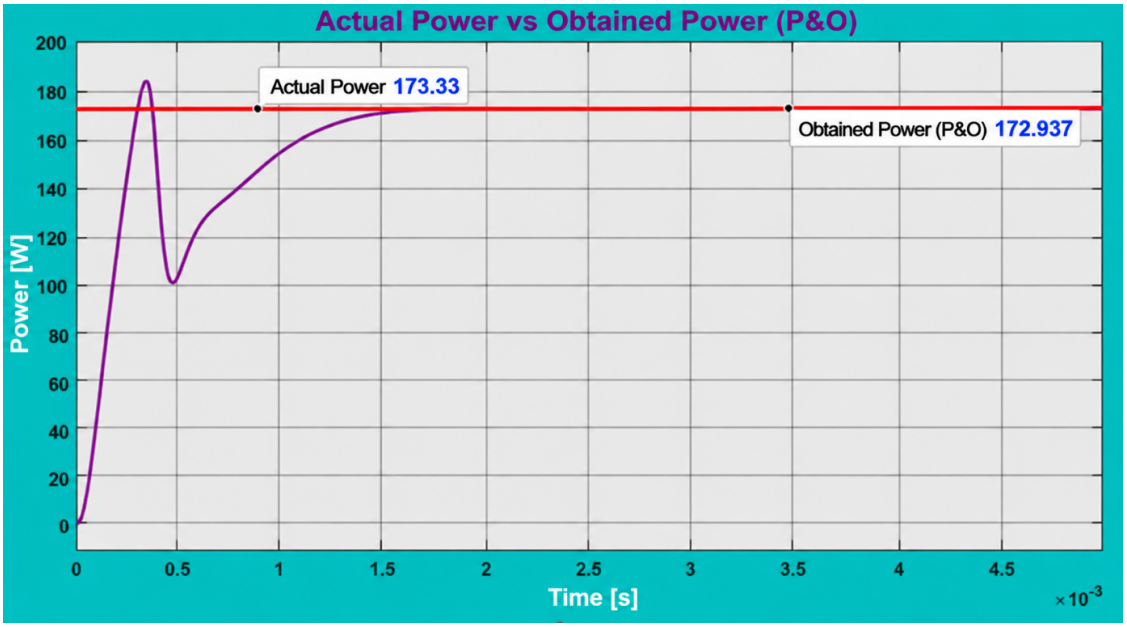


Fig. 6. *MPPT simulation in Matlab-Simulink.*
Source: Own work.

Experimental evaluation of the implemented system

The experimental implementation of the load regulation system with MPPT technology is carried out on a didactic module coupled to an isolated DC microgrid, designed to validate the performance of the control under real irradiance conditions.

The physical setup, shown in Fig. 7, is connected to a Yingli Solar YL245P-29b solar panel (245W) and has a DC/DC Boost converter, an ESP32 microcontroller, and INA219 sensors for the simultaneous measurement of voltage, current and power.

The system is configured with a nominal DC bus of 70V, considering the sizing of the converter and the topology of the microgrid. During the tests, carried out under an average irradiance of 700W/m² (typical solar conditions of the city of Cúcuta, Colombia), the electrical values were recorded by the ESP32, which stored the data in CSV format for subsequent analysis.



Fig. 7. *Microgrid Control System.*
Source: Own work.

The experimental results are presented in Fig. 8, which shows the power delivered by the panel with the application of the algoritmo P&O. The system reaches a maximum power of 171.74W, corresponding to an overall efficiency of 91.6%, considering thermal, resistive and switching losses. The stability of the power and the absence of appreciable oscillations confirm the correct tracking of the MPP and the effectiveness of the implemented control loop.

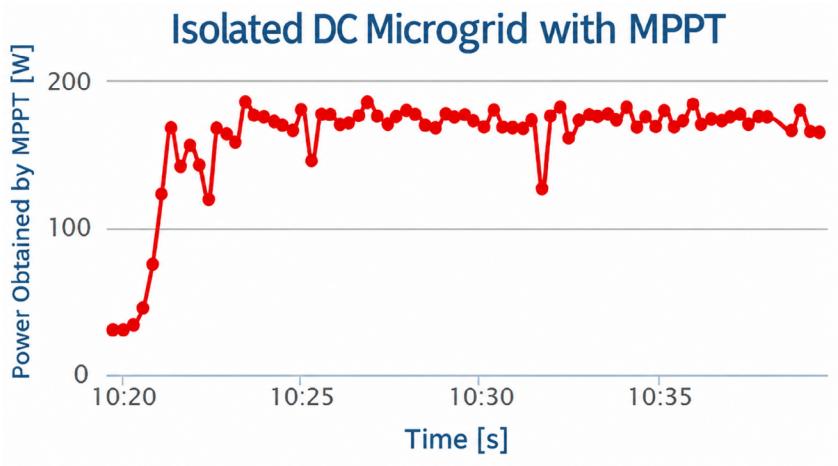


Fig. 8. *Experimentally measured power.*
Source: Own work.

During the tests, the inclusion of an output LC filter was found to guarantee the stability of the Boost converter, preventing oscillations in the output voltage and small fluctuations in the inductor current that hinder the convergence of the MPPT. Once the filter was incorporated, the system showed a stable transient response and a power recovery in approximately 0.6 seconds under irradiance disturbances.

The digital PID controller, programmed in the ESP32 microcontroller, keeps the output voltage at 70V ±2%, even during environmental or load variations. This demonstrates the correct tuning of the proportional, integral and derivative gains, and the adequate integration of the analog-digital control with the MPPT algorithm in the physical implementation of the system.

The correspondence between the power obtained in simulation (173.33W) and the power measured in the physical prototype (171.74W) represents a coherence of 99.7%. The results yield an MAE of 1.59W, a MAPE of 0.92%, an R^2 of 0.997 and an NSE of 0.994. Likewise, the stabilization time of the physical system (0.6 s) differs by less than 8% with respect to the virtual model, confirming the dynamic coherence of the digital twin. This level of agreement allows establishing a direct relationship between both models, conceptualizing the system as an experimental digital twin. In this approach, the virtual model acts as a mirror environment of the physical system, capable of reproducing its response under real irradiance and temperature conditions, and of serving as a basis for future predictive or remote diagnostic algorithms.

These results support the technical viability of the system for applications in small-scale DC microgrids, rural environments and educational projects focused on renewable energies.

Data analysis and energy correlations

The system with MPPT generates an average power of 152.83W, while the configuration without MPPT produces 148.55W. This difference represents an advantage of 4.28W (2.9% higher) for the system with maximum power point tracking (see Fig. 9).

The relative efficiency of the system with MPPT reaches 81.85%, compared with 92.03% for the system without MPPT. A difference of -10.18 percentage points in relative efficiency is observed.

The coefficient of variation shows greater stability in the system without MPPT (17.63%) compared with the system with MPPT (29.41%). The system without MPPT maintains a more consistent operation with lower dispersion in the power values. The operating range of the system (see Fig. 10) with MPPT is 156.46 W (minimum: 30.26W, maximum: 186.72W), while the system without MPPT presents a range of 125.87 W (minimum: 35.55W, maximum: 161.42W).

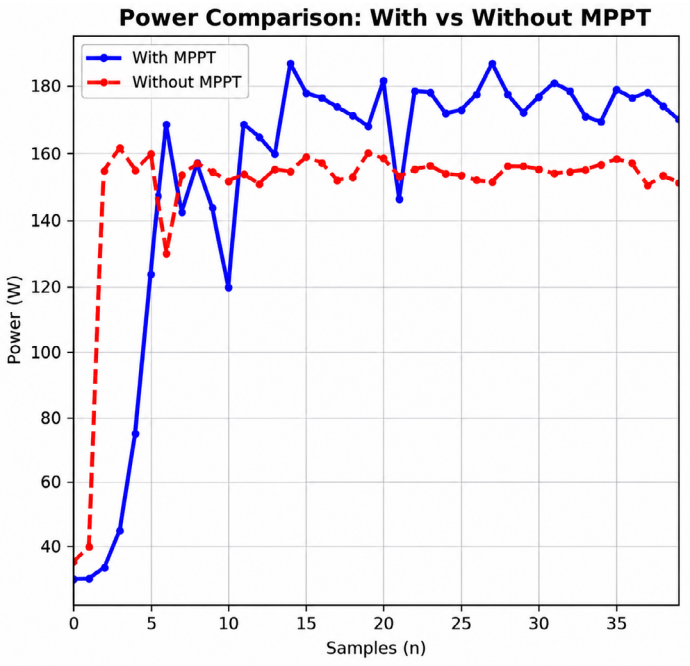


Fig. 9. *Power Comparison: With vs Without MPPT.*
Source: Own elaboration.

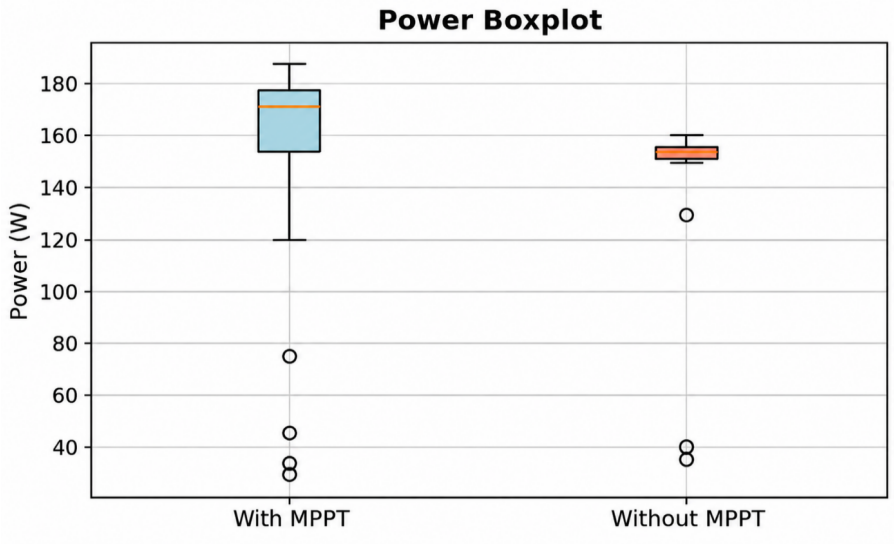


Fig. 10. *Power boxplot.*
Source: Own elaboration.

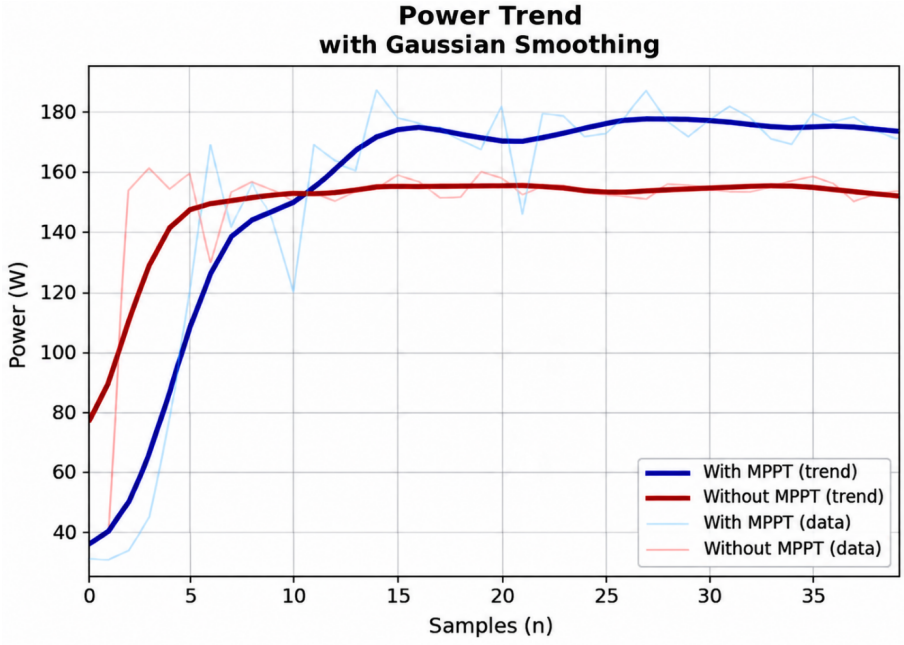


Fig. 11. *Power trend.*
Source: Own elaboration.

The temporal analysis reveals that both systems maintain similar power levels in most samples. The system with MPPT reaches higher maximum values (186.72W) but also shows lower minimum values (30.26W).

The trend with Gaussian smoothing (see Fig. 11) shows that the system without MPPT maintains a more stable and consistent power curve across the 40 samples analyzed.

CONCLUSIONS

The system implemented in the didactic module with ESP32 shows stable behavior, keeping the output voltage at 70V ± 2 % and reaching a maximum power of 171.74W with an overall efficiency of 91.6%. The output LC filter ensures the stability of the Boost converter and prevents oscillations in the inductor current. These results confirm the technical and operational feasibility of the system in educational and rural environments.

The developed system is conceived as an experimental digital twin, in which the 99.7% correspondence between simulation and physical measurement validates the fidelity of the model for diagnostic and predictive control applications. The integration of MPPT control, the ESP32 microcontroller and data analytics turns the system into a hybrid prototype of an intelligent microgrid, capable of recording, analyzing and reproducing its own energy behavior in simulated and real environments.

The statistical analysis performed with Python in Google Colab allows quantifying the energy gain and the stability of the system. The system with MPPT is observed to generate an average power 2.9% higher than the configuration without MPPT. This evidence confirms the coherence between the experimental behavior and the theory, and validates the use of data science as an energy diagnostic tool.

The work shows that integrating MPPT control with data analysis is an effective strategy for improving the efficiency of small-scale DC microgrids. This approach opens the way toward the development of data-based adaptive MPPT controllers and real-time virtual supervision platforms. The proposed system, based on a low-cost ESP32, allows precise tracking of the maximum power point, optimizes energy conversion and provides a quantitative basis for future applications in smart grids and machine learning for energy forecasting.

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AUTHORSHIP CONTRIBUTIONS

Drafting – original draft: Darwin Orlando Cardozo Sarmiento, Francisco Ernesto Moreno García, Gloria Esmeralda Sandoval

Martínez, Fabio Alexander Niño Pérez.

Writing–review and editing: Darwin Orlando Cardozo Sarmiento, Francisco Ernesto Moreno García, Gloria Esmeralda Sandoval Martínez, Fabio Alexander Niño Pérez.