RCTA
Revista Colombiana de Tecnologías de Avanzada
UNIPAMPLONA

Digital Object Identifier: 10.24054/rcta.v1i47.4291

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

MSc. Darwin Orlando Cardozo Sarmiento[1], PhD. Francisco Ernesto Moreno García [1], MSc. 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.*

Correspondencia: *darwinorlandocs@ufps.edu.co*

Received: *August 04, 2025.* ***Accepted:*** *December 20, 2025.* ***Published:*** *January 01, 2026.*

How to cite: *D. O. Cardozo Sarmiento, F. E. Moreno García, G. E. Sandoval Martínez, and F. A. Niño Pérez, "Experimental digital twin for MPPT-based load regulation and energy analytics in an isolated DC microgrid", RCTA, vol. 1, n.º. 47, pp. 90-98, Jan. 2026. Recovered from https://ojs.unipamplona.edu.co/index.php/rcta/article/view/4291*

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.

1. 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 power delivered by a solar panel exhibits variability due to irradiance and temperature conditions—factors that affect the Maximum Power Point (MPP) and the overall efficiency of the system [1]–[3].

Efficient utilization of the generated energy requires conversion and control strategies capable of maintaining the system operating at the MPP, compensating for environmental variations. For this purpose, Maximum Power Point Tracking (MPPT) technology represents a key solution to improve the performance of photovoltaic systems. This technology dynamically adjusts the operating parameters of the DC/DC converter so that the product of the panel's current and voltage remains at its maximum value 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 and fuzzy logic. Although advanced algorithms offer a faster response to irradiance fluctuations, their implementation often requires specialized hardware and higher computational demand. Therefore, the P&O algorithm remains a preferred option in educational and low-cost applications due to its robustness and operational simplicity [1]–[3].

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

This work presents the design and implementation of a charge regulation system with MPPT technology, complemented by environmental and electrical data analysis for the energy optimization of an isolated DC microgrid. The system integrates a Boost-type DC/DC converter, an MPPT P&O algorithm, and a controller programmed on an ESP32 platform, enabling efficient, low-cost architecture with digital monitoring capabilities. Through Matlab-Simulink simulation and experimental validation, the effects of environmental conditions on system efficiency are analyzed, demonstrating a strong correspondence between analytical and empirical results. Additionally, 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 validates the coherence between both environments and supports the design of future data-driven predictive control strategies [4]–[8].

The innovative contribution of this work lies in the combination of MPPT control with data analysis techniques for the energy characterization of the system, contributing to the advancement of the transition toward smart and sustainable power grids. This proposal is particularly relevant for academic environments and rural microgrids, where hardware simplicity and control precision determine the technological and economic feasibility of the implemented solutions.

2. METHODOLOGICAL DEVELOPMENT

The development of this work is structured into four methodological phases aimed at the design, implementation, and validation of a charge regulation system with MPPT technology, complemented by an analysis of environmental and electrical data.

2.1. Phase 1. Selection and Characterization of the Photovoltaic System

This phase involves gathering technical information and selecting the components that constitute the photovoltaic system. Various 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 most suitable photovoltaic module, six measurable criteria are defined, each directly influencing the performance of the charge regulation system [1]–[3]:

- Maximum Power Current (IMPP, A): Determines the panel's current delivery capacity under standard conditions (STC).
- Maximum Power Voltage (VMPP, V): Must be compatible with the Boost converter topology to avoid excessive voltage gain.
- Estimated Power at 700 W/m² (P700, W): Represents the panel's behavior under typical irradiance conditions at the implementation site (Cúcuta, Colombia).
- Maximum Efficiency (%): Reflects the photovoltaic conversion capability of the semiconductor material.
- Commercial Availability: A qualitative factor related to local access to spare parts and technical support.
- Number of Panels Required: A design with a single module is preferred to minimize connections and wiring losses.

Each criterion is weighted equally, assigning a uniform weight of 16.67%, thus giving the same degree of importance to electrical and availability variables.

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

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

Where:

Xnorm = normalized value,
Xi = value of the criterion for each panel,
Xmin= minimum value,
Xmax = maximum value.

Then, the Global Compatibility Index (GCI) is calculated as the weighted mean of the six criteria, shown in equation (2) [9].

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

where wi=0.1667 (represents the weight assigned to each criterion).

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

Panel Solar	IMPP (A)	VMPP (V)	P700 (W)	Eficiencia	Compatibilidad
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%**

Óptimo Moderado Crítico

Fig. 1. *Panel Compatibility.*
Fuente: *Authors.*

2.2. Phase 2. Comparison and Selection of the MPPT Algorithm

Once the photovoltaic module was defined, two classical Maximum Power Point Tracking (MPPT) algorithms were compared:

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

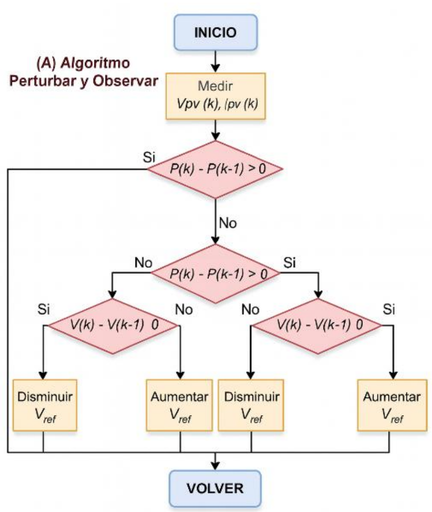

***Fig. 2**. Basic P&O algorithm.*
***Fuente:** Adapted from [6].*

Incremental Conductance (IC): Evaluates the equality between incremental conductance (ΔI/ΔV) and instantaneous conductance (I/V) (see Fig. 3). It offers higher accuracy under variable irradiance conditions, but at the expense of increased computational cost [10]–[17].

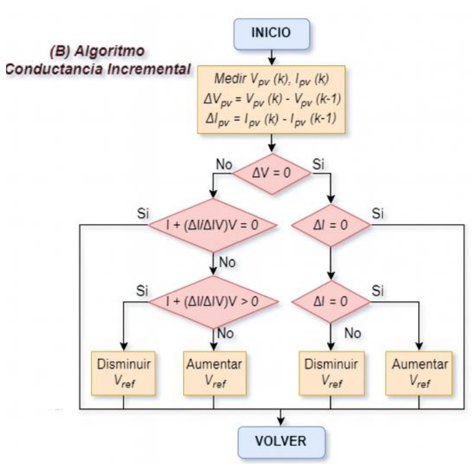

***Fig. 3**. Incremental Conductance algorithm.*
***Fuente:** Adapted from [6].*

2.3. Phase 3. Implementation of the Control System in the DC Microgrid

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

The control is implemented through a digital PID controller, tuned to minimize steady-state error and improve transient response under rapid irradiance variations.

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

The system is connected to an isolated DC microgrid composed of a resistive load (RL) and a subsequent inverter stage. The tests are performed 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 to determine the fidelity of the Experimental Digital Twin. Power data obtained from Matlab-Simulink simulations are compared with the real measurements recorded by the ESP32 microcontroller under equivalent irradiance and temperature conditions. Error and correlation indicators widely used in the digital twin validation literature are applied, as defined in equations (3)–(6) [4]–[8].

$$MAE = \frac{1}{n}\sum_{i=1}^{n}\left|P_{sim,i} - P_{exp,i}\right| \tag{3}$$

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

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

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

Where: *P*sim = simulated power,
*P*exp = experimental power.

2.4. Phase 4. Data Analysis and Energy Correlation

To experimentally validate the performance of the MPPT system, data science techniques were employed to analyze energy efficiency using the Google Colab platform and the Python programming language [17]–[23].

Data acquisition and cleaning: Power measurements were collected under two experimental configurations—with MPPT and without MPPT—totaling 40 comparable samples for each case. The data were structured in CSV format for systematic processing.

Statistical processing: The data were processed in Python (using Pandas, NumPy, and SciPy) to compute measures of central tendency (mean, median), dispersion (standard deviation, range), and relative efficiency metrics. Column name normalization and temporal filtering were applied to ensure data comparability [17]–[23].

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

- Comparative time-series power plots
- Histograms and box plots for distribution analysis
- Trend analysis with Gaussian smoothing
- Aggregated metric visualizations

Quantitative validation: The results were exported in CSV format for technical documentation, including descriptive statistics and analytical summaries that quantified the performance advantage of the MPPT-based system.

3. 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 for an analysis of the behavior of the charge regulator, the accuracy of the MPPT algorithm, and the consistency between the theoretical model and the physical setup.

3.1. MPPT Algorithm Performance

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

Fig. 4 presents the simulated comparison of the power delivered as a function of irradiance for the P&O and IC algorithms, along with the corresponding power curves. It can be observed that both methods maintain close tracking of the Maximum Power Point (MPP) throughout the entire irradiance range of 200–1000 W/m². Both curves converge toward the MPP without noticeable oscillations, confirming system stability under variable irradiance conditions.

The average efficiencies obtained were 98.34% for P&O and 99.15% for IC. The accumulated energy difference in favor of IC was 0.82%, a margin that is offset by the lower computational cost and implementation simplicity of the P&O algorithm.

Consequently, the P&O algorithm was selected as the final implementation due to its simplicity and lower memory usage, making it suitable for deployment on the microcontroller.

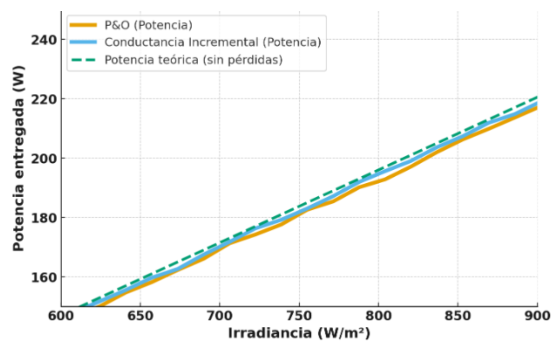

Fig. 4. *Power vs. Irradiance.*
Fuente: *Authors.*

3.2. MPPT Algorithm Performance

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

Fig. 6 shows the simulated power output with and without the P&O-type MPPT algorithm. It can be observed that the panel power stabilizes around 173.3 W, whereas without MPPT, the useful power remains between 100–120 W over the same time interval. This represents an approximate 44% increase in available power due to the action of the MPPT algorithm. Additionally, the system reaches stabilization in less than 0.6 seconds, demonstrating rapid convergence toward the Maximum Power Point (MPP). The small difference between the actual power (173.33 W) and the estimated power from the algorithm (172.94 W) evidences the precision of the implemented control, with a relative error below 0.23%.

RCTA
Revista Colombiana de Tecnologías de Avanzada
UNIPAMPLONA

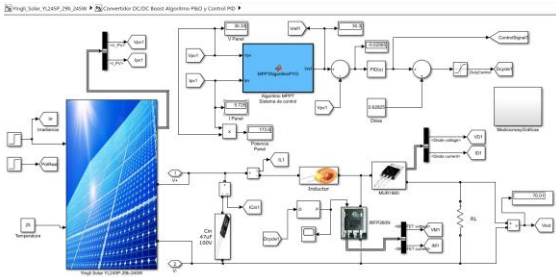

Fig. 5. *Photovoltaic system coupled in Matlab-Simulink.*
Fuente: *Authors.*

It is also observed that the digital PID controller integrated into the system regulates the Boost converter's output voltage around 70V ±2%, ensuring system stability during irradiance variations. The power reaches its steady-state regime in approximately 0.6 seconds, achieving a rapid recovery without significant overshoot. This demonstrates proper tuning of the proportional, integral, and derivative gains, and highlights the efficiency of the implemented control in conjunction with the MPPT algorithm.

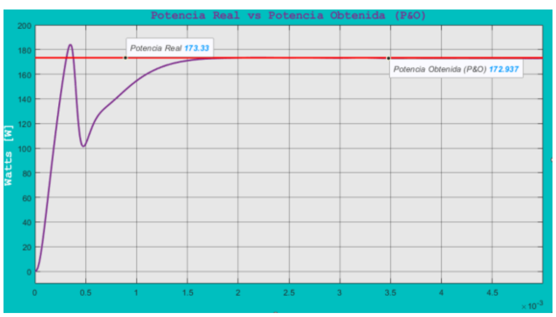

Fig. 6. *MPPT simulation in Matlab-Simulink.*
Fuente: *Authors.*

3.3. Experimental Evaluation of the Implemented System

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

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

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

Fig. 7. *Microgrid Control System.*
Fuente: *Authors.*

The experimental results are presented in Fig. 8, showing the power delivered by the panel under the P&O algorithm. 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 output and the absence of noticeable oscillations confirm proper MPP tracking and the effectiveness of the implemented control loop.

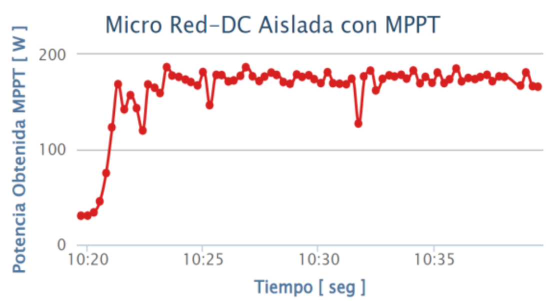

Fig. 8. *Experimental measured power.*
Fuente: *Authors.*

During testing, it was identified that including an LC output filter ensures the stability of the Boost converter, preventing oscillations in the output voltage and small inductor-current fluctuations that hinder MPPT convergence. Once the filter was incorporated, the system exhibited a stable transient response and power recovery within approximately 0.6 s after irradiance perturbations.

The digital PID controller, programmed in the ESP32 microcontroller, maintained the output voltage at 70 V ± 2%, even under environmental or load variations. This demonstrates proper tuning of the proportional, integral, and derivative gains, as well as the effective integration of analog-digital control with the MPPT algorithm in the physical implementation.

The correspondence between the simulated power (173.33W) and the measured power in the physical prototype (171.74W) represents a 99.7% agreement. The results yielded a MAE of 1.59 W, 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 (0.6s) differs by less than 8% from the virtual model, confirming the dynamic coherence of the digital twin.

This level of correspondence establishes 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 serving as a foundation for future predictive or remote-diagnostic algorithms.

These results demonstrate the technical feasibility of the system for small-scale DC microgrid applications, rural environments, and educational projects focused on renewable energy technologies.

3.4. Data Analysis and Energy Correlations

The system with MPPT generated an average power of 152.83W, while the configuration without MPPT produced 148.55W. This difference represents an advantage of 4.28W (2.9% higher) for the system operating with Maximum Power Point Tracking (MPPT) (see Fig. 9).

The relative efficiency of the system with MPPT reached 81.85%, compared to 92.03% for the system without MPPT. A difference of –10.18 percentage points in relative efficiency was observed.

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

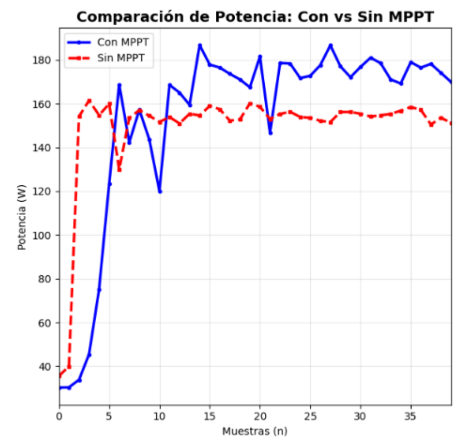

Fig. 9. *Power Comparison: With vs. Without MPPT.*
Fuente: *Authors.*

The temporal analysis reveals that both systems maintained similar power levels across most samples. The MPPT-based system reached higher maximum values (186.72W) but also exhibited lower minimum values (30.26W).

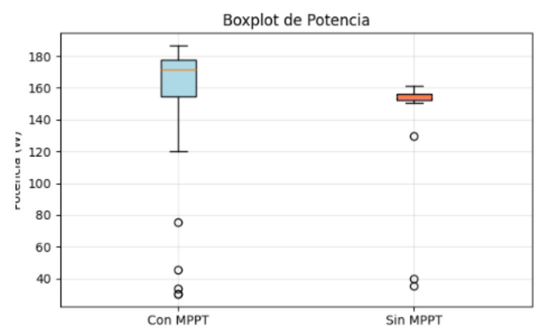

Fig. 10. *Power boxplot.*
Fuente: *Authors.*

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

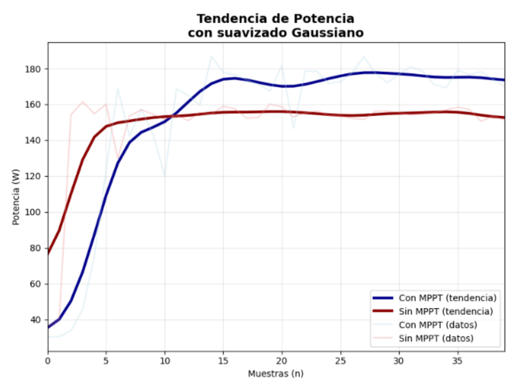

Fig. 11. *Power trend.*
Fuente: *Authors.*

4. CONCLUSIONS

The system implemented in the didactic module with an ESP32 microcontroller exhibits stable performance, maintaining the output voltage at 70 V ± 2% and reaching a maximum power of 171.74 W with an overall efficiency of 91.6%. The inclusion of an LC output 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, where the 99.7% correspondence between simulation and physical measurement validates the model's fidelity for diagnostic and predictive control applications. The integration of MPPT control, the ESP32 microcontroller, and data analytics transforms the system into a hybrid intelligent microgrid prototype, capable of recording, analyzing, and reproducing its own energy behavior in both simulated and real environments.

The statistical analysis performed in Python (Google Colab) enables quantification of the system's energy gain and stability. It was observed that the system with MPPT generated an average power 2.9% higher than the configuration without MPPT. These findings confirm the consistency between experimental behavior and theoretical expectations, validating the use of data science as an energy diagnostic tool.

This study demonstrates that integrating MPPT control with data analysis constitutes an effective strategy to improve the efficiency of small-scale DC microgrids. This approach paves the way for the development of data-driven adaptive MPPT controllers and real-time virtual monitoring platforms. The proposed system—based on a low-cost ESP32—enables accurate tracking of the Maximum Power Point, optimizes energy conversion, and provides a quantitative foundation for future applications in smart grids and machine-learning-based energy forecasting.

REFERENCES

[1] A. Ali, et al., "Investigation of MPPT Techniques Under Uniform and Non-Uniform Solar Irradiation Condition–A Retrospection," IEEE Access, vol. 8, pp. 127368–127392, 2020, doi: 10.1109/ACCESS.2020.3007710.

[2] L. Shang, H. Guo, and W. Zhu, "An Improved MPPT Control Strategy Based on Incremental Conductance Algorithm," Protection and Control of Modern Power Systems, vol. 5, no. 2, pp. 1–8, Apr. 2020, doi: 10.1186/s41601-020-00161-z.

[3] L. Liu, C. Huang, J. Mu, J. Cheng, and Z. Zhu, "A P&O MPPT With a Novel Analog Power-Detector for WSNs Applications," IEEE Trans. Circuits Syst. II: Express Briefs, vol. 67, no. 10, pp. 1680–1684, Oct. 2020, doi: 10.1109/TCSII.2019.2940212.

[4] C. Bae, E. Choi, and S. Lee, "Technologies, Applications, and Challenges of Digital Twin Across Industries: A Systematic Review of the State-of-the-Art Literature," IEEE Access, vol. 13, pp. 152843–152869, 2025, doi: 10.1109/ACCESS.2025.3601615.

[5] Y. Lee, M.-S. Baek, and K. Yoon, "Digital Entity Management Methodology for Digital Twin Implementation: Concept, Definition, and Examples," IEEE Trans. Broadcasting, vol. 71, no. 1, pp. 19–29, Mar. 2025, doi: 10.1109/TBC.2024.3517138.

[6] MathWorks, "The MathWorks / MATLAB – Simulink: MPPT Algorithm," 2022. [Online]. Available: https://la.mathworks.com/solutions/electrification/mppt-algorithm.html

[7] W. Wang, M. Liu, and J. Li, "Research and Realization of Virtual-Real Control of Robot System for Off-Heap Detector Assisted Installation Based on Digital Twin," IEEE Journal of Radio Frequency Identification, vol. 6, pp. 810–814, 2022, doi: 10.1109/JRFID.2022.3209715.

[8] Y. Zhou, et al., "Digital Twins Visualization of Large Electromechanical Equipment," IEEE Journal of Radio Frequency Identification, vol. 6, pp. 993–997, 2022, doi: 10.1109/JRFID.2022.3217123.

[9] A. Boumaiza, A. Sanfilippo, and N. Mohandes, "Modeling multi-criteria decision analysis in residential PV adoption," Energy Strategy Reviews, vol. 39, art. 100789, Jan. 2022, doi: 10.1016/j.esr.2021.100789.

[10] B. Zhang, M. Zhang, T. Dong, M. Lu, and H. Li, "Design of Digital Twin System for DC Contactor Condition Monitoring," IEEE Trans. Industry Applications, vol. 59, no. 4, pp. 3904–3909, Jul.–Aug. 2023, doi: 10.1109/TIA.2023.3256978.

[11] M. R. Javed, A. Waleed, U. S. Virk, and S. Z. ul Hassan, "Comparison of the Adaptive Neural-Fuzzy Interface System (ANFIS) Based Solar Maximum Power Point Tracking (MPPT) with

Other Solar MPPT Methods," in Proc. IEEE 23rd Int. Multitopic Conf. (INMIC), Bahawalpur, Pakistan, 2020, pp. 1–5, doi: 10.1109/INMIC50486.2020.9318178.

[12] S. Xu, R. Shao, B. Cao, and L. Chang, "Single-Phase Grid-Connected PV System With Golden Section Search-Based MPPT Algorithm," Chinese Journal of Electrical Engineering, vol. 7, no. 4, pp. 25–36, Dec. 2021, doi: 10.23919/CJEE.2021.000035.

[13] O. Abdel-Rahim and H. Wang, "A New High Gain DC-DC Converter With Model-Predictive-Control Based MPPT Technique for Photovoltaic Systems," CPSS Trans. Power Electron. Appl., vol. 5, no. 2, pp. 191–200, Jun. 2020, doi: 10.24295/CPSSTPEA.2020.00016.

[14] S. Uprety and H. Lee, "A 0.65-mW-to-1-W Photovoltaic Energy Harvester With Irradiance-Aware Auto-Configurable Hybrid MPPT Achieving >95% MPPT Efficiency and 2.9-ms FOCV Transient Time," IEEE J. Solid-State Circuits, vol. 56, no. 6, pp. 1827–1836, Jun. 2021, doi: 10.1109/JSSC.2020.3042753.

[15] J. Maeng, J. Jeong, I. Park, M. Shim, and C. Kim, "A Time-Based Direct MPPT Technique for Low-Power Photovoltaic Energy Harvesting," IEEE Trans. Industrial Electronics, vol. 71, no. 5, pp. 5375–5380, May 2024, doi: 10.1109/TIE.2023.3288183.

[16] X. Yue and S. Du, "A Single-Stage Bias-Flip Regulating Rectifier With Fully Digital Duty-Cycle-Based MPPT for Piezoelectric Energy Harvesting," IEEE J. Solid-State Circuits, vol. 60, no. 3, pp. 850–860, Mar. 2025, doi: 10.1109/JSSC.2024.3495232.

[17] D. O. Cardozo Sarmiento and M. Pardo, "A Model for an Interconnected Photovoltaic System Using an Off-Grid Inverter as a Reference Node in Island Mode," IEEE Latin America Transactions, vol. 17, no. 6, pp. 1029–1038, Jun. 2019, doi: 10.1109/TLA.2019.1234567.

[18] D. O. Cardozo, M. Pardo, and C. R. Algarín, "Fuzzy Logic Controller for Maximum Power Point Tracking Based on Voltage Error Measurement in Isolated Photovoltaic Systems," in Proc. IEEE ANDESCON, Santiago de Cali, Colombia, 2018, pp. 1–6, doi: 10.1109/ANDESCON.2018.1234567.

[19] D. O. Cardozo, B. Medina, C. Quintero, and M. Pardo, "Enhancing Solar Radiation Prediction for Computational-Constrained Environments Using Hybrid Artificial Neural Networks," IEEE Access, vol. 12, pp. 112233–112240, 2024, doi: 10.1109/ACCESS.2024.1234567.

[20] D. García-Carrillo, E. A. Anaya-Vejar, et al., "Ciencia, Tecnología, Ingeniería y Matemática (STEM) como Método de Enseñanza en Ingeniería," Respuestas, vol. 25, no. 1, pp. 50–65, 2020.

[21] H. O. Luna-Pereira, W. R. Avendaño, and G. Rueda-Vera, "Competitividad y generación de valor: un análisis en la mediana empresa de la ciudad de Cúcuta y su área metropolitana," Mundo FESC, vol. 11, no. 21, pp. 45–54, 2021, doi: 10.24054/mundofesc.v11i21.890.

[22] E. R. Reyes-Moreno, "ChatGPT en la educación: un enfoque bibliométrico de la integración de sistemas de chatbots en los procesos educativos," AiBi Revista de Investigación, Administración e Ingeniería, vol. 13, no. 3, pp. 55–68, 2023, doi: 10.5377/aibi.v13i3.3245.

[23] B. A. Villamizar-Medina, A. J. Soto-Vergel, B. Medina-Delgado, et al., "Neural Network Quantification for Solar Radiation Prediction: An Approach for Low Power Devices," AiBi Revista de Investigación, Administración e Ingeniería, vol. 13, no. 1, pp. 11–19, 2025, doi: 10.5377/aibi.v13i1.1234.