Edge AI for Solar: Embedded Deployment of Neural Network MPPT on Low-Cost Microcontrollers

Salvador Yabar
Engineering Department – Electricity and Electronics Section
Pontificia Universidad Católica del Perú
Lima, Peru
syabar@pucp.edu.pe

Carlos Paragua-Macuri
Engineering Department – Electricity and Electronics Section
Pontificia Universidad Católica del Perú
Lima, Peru
carlos.paragua@pucp.edu.pe
https://orcid.org/0009-0005-1695-0857

***Abstract*—Renewable energy, particularly solar photovoltaics, presents a growing, sustainable alternative to meet the rising global energy demand. In order to achieve higher efficiency, intelligent Maximum Power Point Tracking algorithms must be implemented. Extensive research has been done on Neural Network-based solutions; however, their deployment on low-cost hardware is yet to be explored. This paper presents a methodology for implementing and validating such algorithms in low-cost microcontrollers, achieving an average tracking efficiency of 99.2% in Hardware-in-the-Loop testing under varying environmental conditions by interfacing the ESP32 MCU with a Simulink simulation. The ported model has low memory usage and fast inference time (200 μs), ensuring its feasibility for real-time applications.**

***Index Terms*—MPPT, Neural Networks, Edge AI, Low-cost microcontroller, PV systems**

I. Introduction

As global energy demand increases, the need for sustainable and affordable solutions becomes urgent. Renewable energy sources have experienced exponential growth in the last decade, with solar photovoltaic (PV) expansion occurring at the fastest pace [1]. However, renewable sources, and solar energy in particular, are heavily dependent on environmental variables. In order to achieve energy security, these systems must seek optimal performance for a given set of conditions. PV cells have characteristic I-V and P-V curves, inherent to the non-linear behavior of the p-n junction. These curves shift with changes in environmental variables, largely due to variations in temperature and irradiance. The operating point of the PV module changes with the curves, potentially achieving states of lower power than expected. Maximum Power Point Tracking (MPPT) algorithms aim to force the operating point of a PV module or array to converge to the Maximum Power Point (MPP), thereby ensuring the optimal performance of the PV system. Recent research has highlighted Neural Networks (NN) [2]–[4] and soft computing techniques [5] as promising approaches for these algorithms. The carbon footprint of PV systems has been a subject of significant concern and rigorous assessment in recent literature [6]–[9]. To mitigate this, new solutions must maximize energy extraction over the system's operational lifetime, thereby reducing the energy payback time (EPBT) [10]. Consequently, the deployment of low-cost MPPT algorithms is a critical strategy to ensure the cost-effective and energy-efficient expansion of solar usage. This paper is structured as follows: First, an overview of MPPT algorithms is presented in Section II. Section III presents the proposed system, algorithm, and microcontroller setup. Section IV outlines the process to deploy the pre-trained Neural Network into a compatible format for microcontrollers. Section V presents the results of embedded deployment and Controller Hardware-in-the-loop (HIL) testing. Section VI provides a discussion of the obtained results. Finally, Section VII summarizes the presented work and findings.

II. Overview of MPPT Control Strategies

A. Classic Algorithms

Perturb and Observe (P&O) is an MPPT algorithm based on adjusting the operating voltage by applying a small perturbation and observing the change in power. If the perturbation results in an increment of power, the algorithm follows the same sign of perturbation, and vice versa. The sign of the change in power denotes whether the operating point is to the left or right of the MPP; the duty cycle is updated accordingly with a fixed step.

Incremental Conductance (INC) has a similar behavior, modifying duty cycle step-wise, but determines the direction by computing the instantaneous (I/V) and incremental conductance (dI/dV). At the MPP, the derivative of power with respect to voltage is zero, which leads to the condition shown in (1),

$$\frac{dP}{dV} = 0 \implies I + V \times \frac{dI}{dV} = 0 \implies \frac{dI}{dV} = -\frac{I}{V} \qquad (1)$$

Both algorithms are simple to implement on any controller. Their main limitations are long settling times and poor robustness over fast variations of environmental conditions [11]. The settling time depends on step size; small steps result in low oscillations but slow convergence, while large steps converge quickly but oscillate around the MPP.

B. Neural Network-based MPPT

The application of Deep Learning techniques to solar energy encompasses a wide variety of areas. Applications range from degradation classification through computer vision [12], to fault mitigation and PV modeling [13]. Particularly, they have been applied to MPPT algorithms, exclusively or in combination with soft computing techniques and classic algorithms [11]. Intelligent MPPT methods such as NN are complex control systems, with higher implementation costs [14]. In [15], a very simple NN architecture of one hidden layer and two neurons is implemented in a PIC microcontroller. With the current advancements of Deep Learning, new NN-based solutions have tens [16] to thousands of neurons [3]. A popular option is the use of Raspberry PI or similar devices [4], although their price and power consumption are not negligible.

III. System Architecture

A. Proposed Control Strategy

MPPT algorithms drive the operating point of a PV Array to the corresponding MPP by modifying the Duty Cycle of a DC/DC converter. The proposed system integrates environmental sensors (a pyranometer and temperature sensor), electrical characteristics of the panel from its datasheet, and voltage and current measurements at the PV array output to compute the corresponding Duty Cycle for a given set of environmental conditions. A simplified connection diagram is shown in Fig. 1.

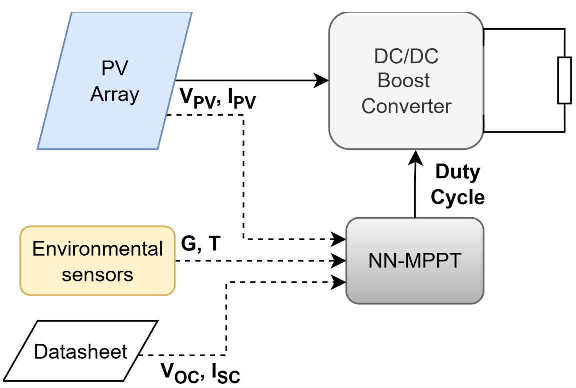

Fig. 1. Diagram of the proposed NN-based control strategy

B. Proposed Neural Network

The Neural Network used in this paper was pre-trained using a real-world dataset [17], [18]. The specifics regarding training and optimization are described in a separate ongoing work. The network (Fig. 2) consists of 4 inputs and 1 output. The inputs are: 1) Irradiance at Plane of Array (G) [W/m^2], 2) Module Temperature (T) [$°C$], 3) Open Circuit Voltage (V_{OC}) [V], and 4) Short Circuit Current (I_{SC}) [A]. G and T are measured continuously, while V_{OC} and I_{SC} are constants characterizing the PV module. The single output is the Reference Voltage (V_{ref}), corresponding to the MPP voltage for the given conditions.

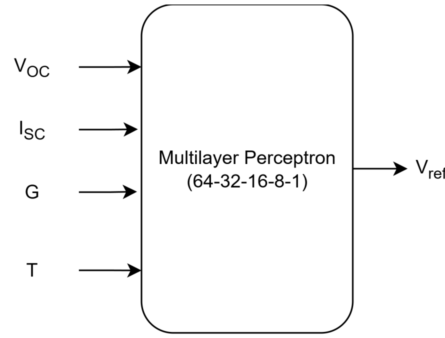

Fig. 2. Diagram of proposed Neural Network

C. Proposed Algorithm

The proposed MPPT algorithm is shown in Fig. 3. First, measurements of Irradiance and Module Temperature are taken. Then, measured values are compared to previous ones to check for a significant change. To reduce computational cost, inference is triggered by significant changes in G or T. V_{ref} is then updated by running the Neural Network inference. The operating current of the PV array is then measured to compute the desired Duty Cycle using (2).

$$D = 1 - \sqrt{\frac{R_{mp}}{R_o}} \tag{2}$$

where R_{mp} is the equivalent resistance at MPP defined by (3) while R_o represents to the load resistance.

$$R_{mp} = \frac{V_{mpp}}{I_{mpp}} \simeq \frac{V_{ref}}{I_{PV}} \tag{3}$$

Equation (2) can be derived from the Boost Converter transfer function:

$$\frac{V_o}{V_i} = \frac{1}{1-D} \tag{4}$$

D. ESP32 Microcontroller

The Espressif ESP32 is a widely available and popular microcontroller for IoT applications. Its specifications [19], [20] are shown in Table I.

TABLE I
ESP32 Specifications

Specification	Value
Operating Voltage	3.3 V
Clock Frequency	240 MHz
Flash Memory	4 MB
SRAM	520 KB
Number of GPIO Pins	30
Integrated Peripherals	Wi-Fi and Bluetooth BLE
Price (USD)	\$8.94

This specific microcontroller is listed in the supported platforms for TensorFlow Lite Micro. which enables deployment of Neural Networks for embedded applications.

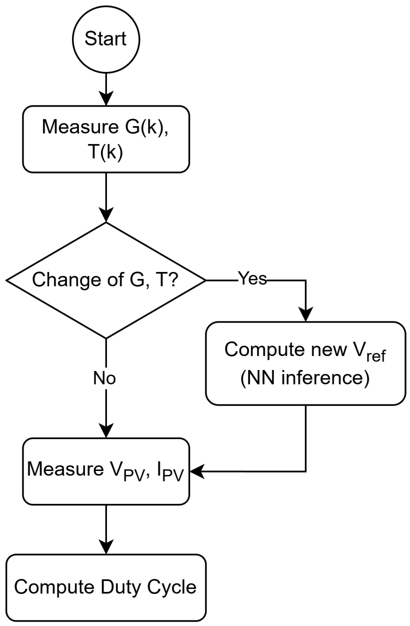

Fig. 3. Flow Diagram of Proposed Algorithm

E. Hardware-in-the-Loop Setup

Hardware-in-the-Loop (HIL) testing was performed to validate the proposed system. The HIL setup consists of a Simulink model of a PV module and a DC-DC Boost converter, which communicates with the ESP32 microcontroller via UART protocol. The electrical system in Simulink is shown in Fig. 4. The ESP32 reads the environmental conditions (G and T) and PV Operating Point from the simulated model, and sends back the computed Duty Cycle to shift the operating point towards the MPP. Simulink's Pulse Width Modulation (PWM) Generator block handles the generation of the PWM signal based on the received Duty Cycle. Zero Order Hold (ZOH) is used to send data at fixed intervals (10 ms) to the ESP32. (Fig. 5)

The flow of data during HIL testing is depicted in the diagram in Fig. 6, where processing of data is performed inside the ESP32 microcontroller.

The UART interface utilizes a custom protocol with fixed packet sizes. The 18-byte packet sent from Simulink consists of a start byte, four 32-bit floating-point values (G, T, V_{PV}, I_{PV}), and an end byte. The response from the ESP32 is an 8-byte packet containing a start byte, the computed Duty Cycle (4 bytes), and an end byte.

IV. Neural Network Deployment

A. Exporting to Tensorflow Lite

The pre-trained Neural Network was developed using TensorFlow Keras. In order to deploy it on the ESP32, it must be converted to TensorFlow Lite format. The process is described in the TensorFlow documentation [21]. The model was converted using the function `tf.lite.TFLiteConverter.from_keras_model`, which generates a `.tflite` file with reduced size that can be deployed to the target microcontroller.

A size reduction of 79% was achieved without any discernible loss of accuracy. No further quantization was performed, since the `.tflite` model size was already small enough to fit into the ESP32's memory. Table II shows a comparison of the MAE, RMSE, and R^2 metrics for the Keras and TFLite models.

TABLE II
PERFORMANCE COMPARISON OF CONVERTED MODEL

Model	Size (KB)	MAE (V)	RMSE (V)	R^2
Keras	70.83	0.232189	0.328457	0.999052
TFLite	14.57	0.232190	0.328457	0.999052

B. ESP32 Inference

After performance validation, the TFLite model was converted to a C array using the command `xxd -i converted_model.tflite > model_data.cc` [22]. This C array was then included in a library for the ESP32 project.

The `Arduino_TensorFlowLite_ESP32` library [23] was utilized to instantiate the TensorFlow Lite interpreter and execute inference operations, facilitating the loading of the model from the generated C array.

V. Results

A. MCU Performance

To evaluate the performance of the deployed model on the ESP32, inference was run on the test set, consisting of 36220 samples across 10 different PV modules with varying environmental conditions. The results are summarized in Table III.

TABLE III
PERFORMANCE OF MODEL RUNNING ON ESP32

Parameter	Value
Inference Time (μs)	200.89 ± 4.5
MAE (V)	0.232189
RMSE (V)	0.328457
R^2	0.999052
RAM (KB)	56.93
Flash (KB)	335.49

As shown in Table III, the inference time is approximately 201 μs, which is suitable for real-time MPPT applications. The accuracy metrics (MAE, RMSE, and R^2) remain consistent with those obtained during model validation (Table II), indicating that the deployment process did not compromise model performance. Additionally, the memory usage remains within acceptable limits for the ESP32 microcontroller, with only 17.4% of RAM and 25.6% of Flash memory utilized.

B. HIL Performance

To evaluate the performance of the deployed MPPT algorithm, HIL testing was performed under varying environmental conditions. These tests guarantee the system's robustness and

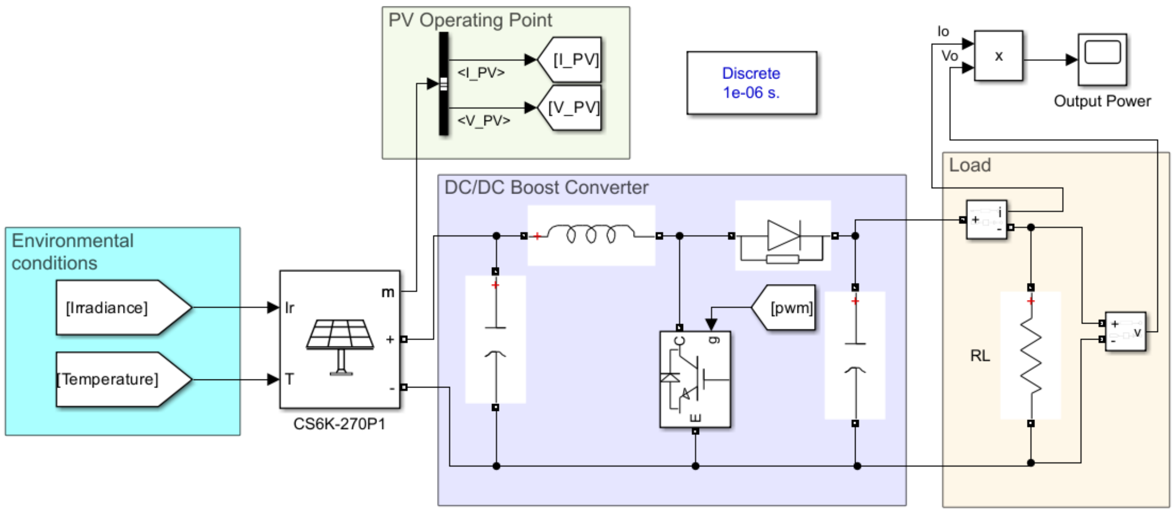

Fig. 4. PV module and DC-DC Boost converter in Simulink environment

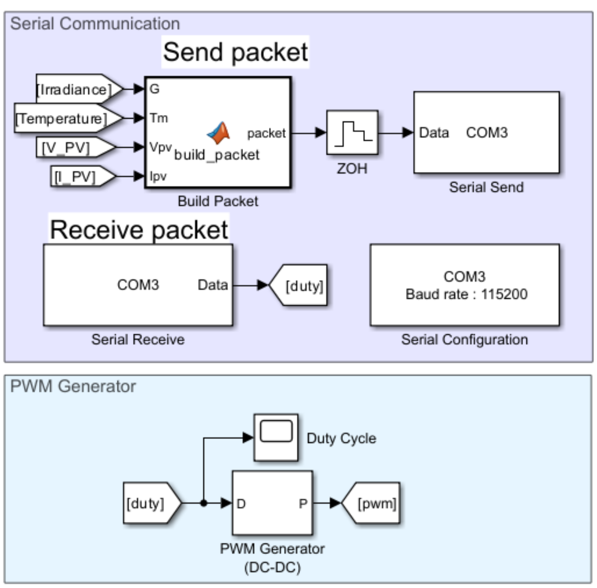

Fig. 5. Serial Communication with ESP32 and PWM generator

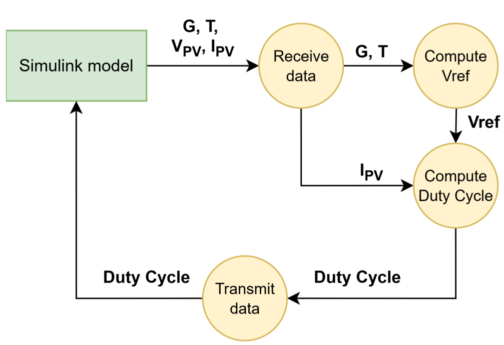

Fig. 6. HIL Data Flow Diagram

reliability, specifically under unstable conditions, such as solar-energy vehicles [24]. The power curves obtained at the PV module output and their respective environmental conditions are shown in Fig. 7. The power at the converter output (P_{out}) and at the PV module (P_{in}) were recorded and are shown in Table IV. Tracking Efficiency (TE) was computed using (5).

$$TE = \frac{P_{in}}{P_{ref}} \times 100\% \tag{5}$$

where P_{ref} is the reference power at MPP obtained from the corresponding P-V curve of each environmental condition.

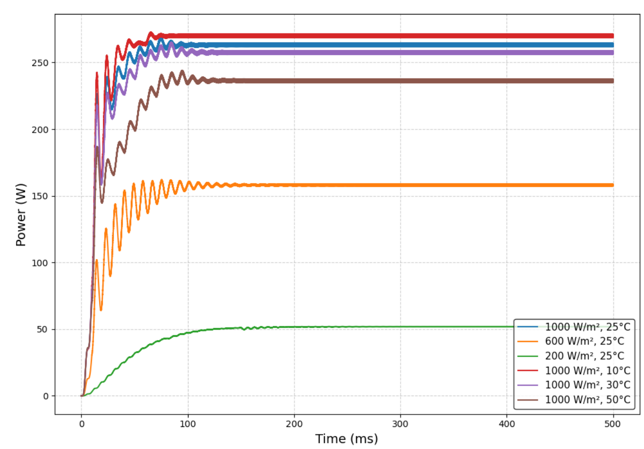

Fig. 7. Power curves obtained from HIL under varying environmental conditions

To validate the dynamic performance of the controller, a stress-test profile combining step changes and linear ramps was applied to the system. The irradiance profile $G(t)$ transitions through abrupt steps (200, 400, 800 W/m^2) to evaluate transient response, followed by continuous linear ramps between 200 W/m^2 and 1000 W/m^2 to test tracking stability.

TABLE IV
ACHIEVED POWER AND TRACKING EFFICIENCY UNDER DIFFERENT CONDITIONS

Condition	P_{out} (W)	P_{in} (W)	TE (%)
1000 W/m^2, 10°C	269.815	275.537	96.942
1000 W/m^2, 25°C	263.047	268.629	99.985
1000 W/m^2, 30°C	257.452	262.937	99.805
1000 W/m^2, 50°C	236.323	241.440	99.608
200 W/m^2, 25°C	51.858	53.337	99.770
600 W/m^2, 25°C	158.059	161.949	99.367

Fig. 8 illustrates the system's power output in response to these variations.

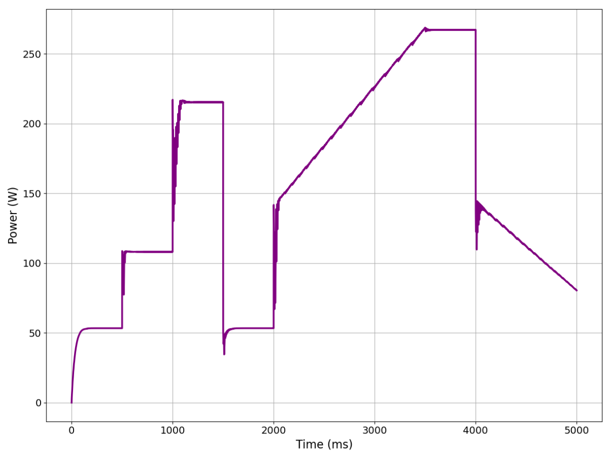

Fig. 8. Dynamic response of PV Power under step and ramp changes in irradiance

A fast settling time was observed during step changes, with no significant overshoot. Furthermore, the controller successfully updated the duty cycle during the ramp phases, allowing the system to maintain the MPP with minimal steady-state error.

VI. Discussion

A. Feasibility of NN-MPPT on low-cost MCUs

The results demonstrate that deploying the Neural Network model on an ESP32 Microcontroller did not result in any significant loss in accuracy. The model's memory usage and inference time are both low. These are significant constraints in embedded systems applications, successfully overcome by the proposed algorithm.
The system was tested using HIL under different conditions of irradiance and temperature, obtaining favorable results, with high Tracking Efficiency. The lower efficiency observed at 10 °C is due to the training set containing fewer samples at low temperatures. The difference between P_{in} and P_{out} is attributed to switching and conduction losses in the converter stage. The results suggest great adaptability to different sets of environmental conditions. This is an important factor to consider for real-world deployment of the proposed system.
Considering the performance of the MPPT algorithm, with practically no drawbacks from deployment on a low-cost microcontroller, it is deemed a feasible and recommended platform, given its low cost and energy consumption, especially compared to systems using more powerful and resourceful alternatives like NVIDIA Jetson and Raspberry Pi.

B. Limitations

The proposed system's performance depends heavily on the quality and diversity of the training data, which may limit its generalization to unseen conditions or PV modules with characteristics that differ from those in the training set. To overcome this, future research should expand on the dataset with other PV modules and geographic locations.
The current implementation does not account for changes in load conditions. A constant value is assumed for R_o in (2), which may not reflect real-world scenarios.
The Simulink model used for HIL testing is an ideal representation of a PV module and does not reflect the real environmental factors that may affect the system's performance, such as ambient temperature and wind speed.
While the reliance on external sensors (pyranometers and temperature probes) is often cited as a drawback compared to sensorless algorithms, these instruments are standard in commercial-scale PV plants for performance monitoring. Therefore, the proposed system leverages existing infrastructure without incurring additional hardware costs in such scenarios.

Effective Tracking depends on the Neural Network's ability to accurately predict V_{ref}, which is fixed for a given set of environmental conditions. A significant error in prediction may lead to operating further from the MPP.

C. Future steps

The proposed algorithm can be improved by incorporating adaptive mechanisms to adjust the Duty Cycle after the initial inference by the Neural Network. Combination with classic MPPT algorithms, such as P&O or INC, could improve tracking efficiency.

Testing with real hardware must be performed to validate the system's performance under real-world conditions. Sensor noise, measurement inaccuracies, and sensing delays should be taken into account for a physical implementation of the system.

VII. Conclusion

This paper presented the pipeline for the deployment and evaluation of a Neural Network-based MPPT algorithm.
Model conversion from the pre-trained Keras model to the microcontroller-compatible TensorFlow Lite was performed successfully, without any discernible loss in accuracy. The converted model uses low memory resources and has fast inference time, making it suitable for deployment.
HIL tests under varying environmental conditions were carried out to evaluate the integration of the ESP32 with the PV

module and DC-DC control loop. High tracking efficiency was achieved, with quick settling times and low ripple.
Low-cost microcontrollers are therefore feasible and recommended as a platform for deployment of Neural Network-based MPPT algorithms, providing a more cost-effective and efficient alternative.

Acknowledgment

The authors would like to thank the MatER group at Pontificia Universidad Católica del Perú for providing the dataset used in this study.

References

[1] International Energy Agency, "Renewables 2024," International Energy Agency, Tech. Rep., 2024. [Online]. Available: https://iea.blob.core.windows.net/assets/17033b62-07a5-4144-8dd0-651cdb6caa24/Renewables2024.pdf

[2] L. Hichem, O. Amar, and M. Leila, "Optimized ANN-fuzzy MPPT controller for a stand-alone PV system under fast-changing atmospheric conditions," *Bulletin of Electrical Engineering and Informatics*, vol. 12, no. 4, pp. 1960–1981, Aug. 2023. [Online]. Available: https://beei.org/index.php/EEI/article/view/5099

[3] S. A. Hamad, M. A. Ghalib, A. Munshi, M. Alotaibi, and M. A. Ebied, "Evaluating machine learning models comprehensively for predicting maximum power from photovoltaic systems," *Scientific Reports*, vol. 15, no. 1, p. 10750, Mar. 2025. [Online]. Available: https://www.nature.com/articles/s41598-025-91044-6

[4] B. Mandal and P. S. Bhowmik, "A Deep Neural Network-Based Highly Simplified Intelligent Approach for Maximum Power Point Tracking of Dye-Sensitized Solar Panel System," *IEEE Journal of Emerging and Selected Topics in Industrial Electronics*, vol. 6, no. 1, pp. 196–203, Jan. 2025. [Online]. Available: https://ieeexplore.ieee.org/document/10598336/

[5] D. Fernandez and C. Paragua-Macuri, "A Control Algorithm Based on Fuzzy Logic Control for PV Systems in a Non Stable Environment," in *SoutheastCon 2025*. Concord, NC, USA: IEEE, Mar. 2025, pp. 13–18. [Online]. Available: https://ieeexplore.ieee.org/document/10971588/

[6] S. H. C. Perez, M. E. Y. Cortez, C. A. Paragua-Macuri, D. A. S. Talledo, and M. P. Morales, "Dispersion analysis of the energy consumption and carbon footprint of photovoltaic energy use through design of experiments (DOE)," in *2024 IEEE XXXI International Conference on Electronics, Electrical Engineering and Computing (INTERCON)*. Lima, Peru: IEEE, Nov. 2024, pp. 1–8. [Online]. Available: https://ieeexplore.ieee.org/document/10833500/

[7] M. E. A. Y. Cortez, C. A. Paragua-Macuri, L. S. M. Pérez, D. A. S. Talledo, and M. P. Morales, "Contribution of the Recycling Stage to the Carbon Footprint in the Life Cycle of Photovoltaic Energy Use," in *2024 IEEE International Humanitarian Technologies Conference (IHTC)*. Bari, Italy: IEEE, Nov. 2024, pp. 1–5. [Online]. Available: https://ieeexplore.ieee.org/document/10855080/

[8] D. A. S. Talledo, C. A. P. Macuri, M. P. Morales, and M. G. P. Macuri, "Study, analysis qualitative-quantitative and carbon footprint impact from photovoltaic energy use," in *2022 IEEE XXIX International Conference on Electronics, Electrical Engineering and Computing (INTERCON)*. Lima, Peru: IEEE, Aug. 2022, pp. 1–4. [Online]. Available: https://ieeexplore.ieee.org/document/9870097/

[9] L. S. Morales Pérez, C. A. Paragua-Macuri, D. A. Sánchez Talledo, M. E. Yovera Cortez, and M. P. Morales, "Development of an Integrated Web Tool for Assessing the Energy Consumption and Carbon Footprint of the Photovoltaic Cycle: A New Perspective," in *2024 IEEE XXXI International Conference on Electronics, Electrical Engineering and Computing (INTERCON)*. Lima, Peru: IEEE, Nov. 2024, pp. 1–8. [Online]. Available: https://ieeexplore.ieee.org/document/10833455/

[10] M. E. A. Yovera Cortez, C. A. Paragua-Macuri, and M. Paragua Morales, "Study, qualitative-quantitative analysis, and sizing of the environmental impact of the photovoltaic panel recycling process," *EPJ Photovoltaics*, vol. 15, p. 37, 2024. [Online]. Available: https://www.epj-pv.org/10.1051/epjpv/2024035

[11] Ratnakar Babu Bollipo, Suresh Mikkili and Praveen Kumar Bonthagorla, "Hybrid, optimization, intelligent and classical PV MPPT techniques: Review," *CSEE Journal of Power and Energy Systems*, 2020. [Online]. Available: https://ieeexplore.ieee.org/stamp/stamp.jsp?tp=&arnumber=9171659

[12] J. A. P. López, C. A. Paragua-Macuri, D. A. M. Aucaruri, J. R. A. Abanto, and J. A. Töfflinger, "Classification of solar panel technology and photovoltaic cell status applying machine learning to electroluminescence images," in *2024 IEEE 22nd Mediterranean Electrotechnical Conference (MELECON)*. Porto, Portugal: IEEE, Jun. 2024, pp. 121–126. [Online]. Available: https://ieeexplore.ieee.org/document/10608551/

[13] A. Olabi, M. A. Abdelkareem, C. Semeraro, M. A. Radi, H. Rezk, O. Muhaisen, O. A. Al-Isawi, and E. T. Sayed, "Artificial neural networks applications in partially shaded PV systems," *Thermal Science and Engineering Progress*, vol. 37, p. 101612, Jan. 2023. [Online]. Available: https://linkinghub.elsevier.com/retrieve/pii/S2451904922004188

[14] M. Kumar, K. P. Panda, J. C. Rosas-Caro, A. Valderrabano-Gonzalez, and G. Panda, "Comprehensive Review of Conventional and Emerging Maximum Power Point Tracking Algorithms for Uniformly and Partially Shaded Solar Photovoltaic Systems," *IEEE Access*, vol. 11, pp. 31 778–31 812, 2023. [Online]. Available: https://ieeexplore.ieee.org/document/10083133/

[15] P. Petchjatuporn, W. Ngamkham, N. Khaehintung, P. Sirisuk, W. Kiranon, and A. Kunakorn, "A Solar-powered Battery Charger with Neural Network Maximum Power Point Tracking Implemented on a Low-Cost PIC-microcontroller," in *TENCON 2005 - 2005 IEEE Region 10 Conference*. Melbourne, Australia: IEEE, Nov. 2005, pp. 1–4. [Online]. Available: http://ieeexplore.ieee.org/document/4084958/

[16] R. B. Roy, M. Rokonuzzaman, N. Amin, M. K. Mishu, S. Alahakoon, S. Rahman, N. Mithulananthan, K. S. Rahman, M. Shakeri, and J. Pasupuleti, "A Comparative Performance Analysis of ANN Algorithms for MPPT Energy Harvesting in Solar PV System," *IEEE Access*, vol. 9, pp. 102 137–102 152, 2021. [Online]. Available: https://ieeexplore.ieee.org/document/9481908/

[17] L. A. Conde Mendoza, A. Carhuavilca, R. Perich, J. Montes-Romero, J. Angulo, A. Guerra, E. Muñoz, and J. De La Casa, "Performance Evaluation and Characterization of Different Photovoltaic Technologies Under the Coastal, Desertic Climate Conditions of Lima, Peru," in *Proceedings of the ISES Solar World Congress 2019*. Santiago, Chile: International Solar Energy Society, 2019, pp. 1–11. [Online]. Available: http://proceedings.ises.org/citation?doi=swc.2019.16.01

[18] L. A. Conde Mendoza, J. Montes Romero, A. M. Carhuavilca Vela, R. A. Perich Ibañez, J. A. Guerra Torres, M. A. Sevillano Bendezú, B. X. Calsi Silva, J. R. Angulo Abanto, J. De La Casa Higueras, and J. A. Palomino Töfflinger, "Puesta en marcha de un laboratorio para la caracterización de tecnologías fotovoltaicas a sol real bajo las condiciones climáticas de Lima: Colaboración con el XXIII Simposio Peruano de Energía Solar," *TECNIA*, vol. 30, no. 1, pp. 80–89, May 2020. [Online]. Available: http://REVISTAS.UNI.EDU.PE/index.php/tecnia/article/view/835

[19] Mouser Electronics, "ESP32-DevKitC-32E," 2025. [Online]. Available: https://www.mouser.pe/ProductDetail/Espressif-Systems/ESP32-DevKitC-32E?qs=GedFDFLaBXFpgD0kAZWDrQ%3D%3D

[20] Random Nerd Tutorials, "Getting Started with the ESP32 Development Board," May 2024. [Online]. Available: https://randomnerdtutorials.com/getting-started-with-esp32

[21] Google AI, "Convert TensorFlow models," Aug. 2024. [Online]. Available: https://ai.google.dev/edge/litert/models/convert_tf

[22] ——, "LiteRT overview," May 2025. [Online]. Available: https://ai.google.dev/edge/litert/microcontrollers/overview

[23] Masayuki Tanaka, "Arduino_tensorflowlite_esp32," May 2022. [Online]. Available: https://github.com/tanakamasayuki/Arduino_TensorFlowLite_ESP32/tree/master

[24] W. R. Ccoñas, D. F. Baca, and C. A. Paragua-Macuri, "Design of an MPPT Algorithm Based on Neural Networks and Fuzzy Logic for Different Photovoltaic Panel Technologies," in *2025 IEEE XXXII International Conference on Electronics, Electrical Engineering and Computing (INTERCON)*. Arequipa, Peru: IEEE, Aug. 2025, pp. 1–7. [Online]. Available: https://ieeexplore.ieee.org/document/11244660/