

Bridging Conventional and Intelligent MPPT Techniques: A Hybrid ANN-P&O Approach for Smart Photovoltaic Systems.

Abstract:

This study investigates maximum power point tracking (MPPT) for a 250.27 W photovoltaic module connected to a Buck converter. The proposed strategy combines an artificial neural network (ANN), which estimates the maximum-power-point voltage from irradiance and temperature, with a local perturb-and-observe (P&O) correction. The ANN rapidly repositions the voltage reference after an environmental change, while the hybrid P&O stage refines that reference using a small, bounded correction. Discrete simulations at 20 kHz are performed under a stepped irradiance profile of 1000, 600, 800, 400, and 1000 W/m² at 25 °C. The results are assessed using average PV power, P_{pv} ripple, and response time. Under this profile, conventional P&O exhibits up to 44 W of ripple and response times exceeding 100 ms during some transitions, whereas the ANN responds within a few microseconds, motivating the investigation of a hybrid refinement. In the nominal model, the hybrid controller nearly overlaps with the standalone ANN, as expected because the ANN was trained using the same PV model. The primary comparison should therefore be between conventional P&O and the hybrid controller; an out-of-model test is required to quantify the specific value of P&O refinement.

Keywords: photovoltaic systems; maximum power point tracking; artificial neural network; perturb and observe; hybrid control; buck converter.

1 Introduction

Maximum power point tracking is required because the current–voltage and power–voltage characteristics of a photovoltaic system vary with irradiance and cell temperature [1], [2]. Conventional techniques remain attractive because of their implementation simplicity [3], whereas data-driven controllers can directly infer an operating reference from measured environmental variables [4]. Comparisons of MPPT methods highlight a trade-off among speed, accuracy, and complexity [3], [5], which motivates hybrid strategies [9], [10]. Under the dynamic profile investigated here, conventional P&O requires more than 100 ms to settle after the 800→400 W/m² transition, with residual ripple close to 24 W; this observation is consistent with the perturbation-step/ripple trade-off described for P&O [6].

P&O is widely used in low-cost PV converters [3], [7]. Its main limitation is the persistent perturbation around the MPP, which produces steady-state power ripple and can delay tracking under rapidly changing irradiance [6], [7]. An ANN can estimate the MPP operating voltage from irradiance and temperature [4]. Its accuracy, however, depends on the representativeness of the training data and on the mismatch between the model used for learning and the system being controlled. Studies of hybrid strategies indicate the value of combining global search or intelligent estimation with local refinement, particularly under partial shading [8]–[10].

This work proposes an interpretable ANN–P&O hybrid architecture compatible with a voltage-control loop. Its contributions are: (i) an ANN trained using G and T to produce V_{mp} , I_{mp} , and P_{mp} , with V_{mp} used as the reference; (ii) P&O refinement applied to the voltage reference rather than direct mixing of duty cycles; (iii) a dynamic comparison with conventional P&O using the same converter and $G(t)$ profile; and (iv) an explicit analysis of the limitations arising from ANN training on the nominal PV model.

2 Photovoltaic System Modeling

2.1. Electrical Model of the Photovoltaic Module

✓ Single-Diode Electrical Model

To simulate the electrical behavior of a photovoltaic module under variable environmental conditions, a model relating the physical panel parameters to irradiance G and temperature T is required. The single-diode model is widely used for this purpose because it provides a useful compromise between accuracy and simplicity [1], [2].

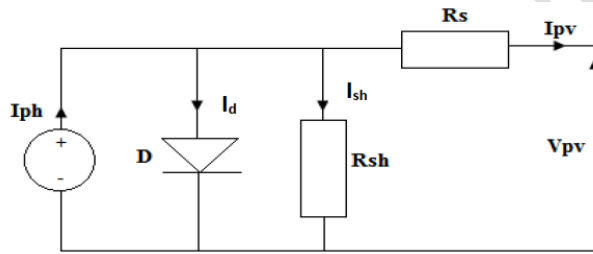


Figure 1: Equivalent circuit of a solar cell

✓ Characteristic Equation of a Photovoltaic Panel

The current–voltage (I – V) behavior of a PV generator is described by the following equation:

$$I = I_{ph} - I_s \left(\exp \left(\frac{q(V + R_s I)}{nkT} \right) - 1 \right) - \frac{V + R_s I}{R_{sh}} \quad (1)$$

I and V are the module output current (A) and terminal voltage (V), respectively; I_{ph} is the photocurrent, which depends on irradiance and temperature; I_s is the reverse diode saturation current; R_s and R_{sh} are the series and shunt resistances (Ω), respectively; q is the elementary charge (1.6×10^{-19} C), k is the Boltzmann constant (1.38×10^{-23} J/K), and n is the diode ideality factor (typically between 1 and 2).

2.2. Influence of irradiance and temperature

• Photocurrent

The photocurrent I_{ph} varies almost linearly with solar irradiance G , which directly increases the short-circuit current and the maximum power of the PV module. The effect of temperature on I_{ph} remains limited and only weakly affects the operating point.

$$I_{ph} = [I_{sc_ref} + \alpha_{Isc}(T - T_{ref})] \cdot \frac{G}{G_{ref}} \quad (2)$$

I_{sc_ref} is the short-circuit current at the reference temperature T_{ref} ; α_{Isc} is the short-circuit-current temperature coefficient (A/K); G is the instantaneous irradiance (W/m^2) and G_{ref} is the reference irradiance ($1000 W/m^2$).

• Reverse saturation current I_s

The reverse saturation current I_s increases exponentially with temperature, causing a reduction in open-circuit voltage V_{oc} and a shift of the maximum power point toward lower voltages. Thus, temperature mainly affects the voltage component of the PV generator, whereas irradiance primarily affects the current component. The reverse saturation current is expressed as:

$$I_s = I_{s0} \left(\frac{T}{T_{ref}} \right)^3 \cdot \exp \left[\frac{qE_g}{nk} \left(\frac{1}{T_{ref}} - \frac{1}{T} \right) \right] \quad (3)$$

I_{s0} : saturation current at T_{ref}

E_g : material bandgap energy (Si: approximately 1.12 eV)

2.3. I–V and P–V characteristics

The performance of a photovoltaic module is mainly analyzed through its I–V and P–V characteristics. The I–V curve describes the relationship between panel current and voltage, whereas the P–V curve represents delivered power as a function of voltage. The power produced by the PV panel is given by:

$$P = V \times I$$

On the P–V curve, the maximum power point (MPP) is the maximum power that the panel can deliver for a given irradiance and temperature. This point is characterized by a voltage V_{MPP} and a current I_{MPP} .

The main objective of an MPPT algorithm is to force photovoltaic-system operation around this point in order to maximize the extracted energy.

3. DC–DC converter and power interface

3.1. Buck converter

The Buck converter is a step-down DC–DC converter that adapts the PV generator voltage to the load by controlling the duty cycle, as illustrated in Figure 2. It relies on high-frequency switching of an electronic switch together with an inductor and a capacitor to provide a regulated output voltage.

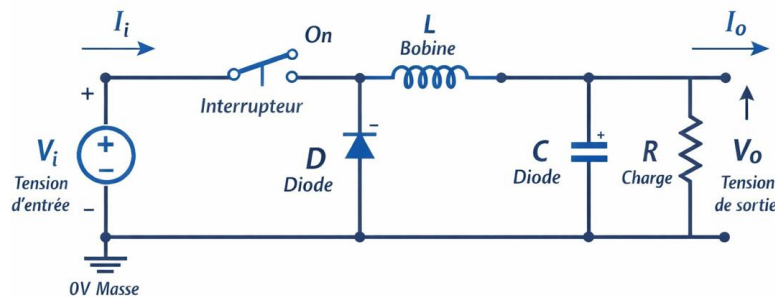


Figure 2. Schematic diagram of a Buck converter

3.2. Operating principle

The Buck converter operates through PWM switching of the electronic switch, alternating between conduction and blocking intervals to transfer and release energy to the load. In continuous-conduction mode, this operation is described by two sets of differential equations corresponding to the ON and OFF switch states, given by Eqs. (4) and (5), respectively.

3.3. Mathematical modeling

In continuous-conduction mode, the Buck converter is described by the inductor and capacitor equations. The electrical simulation includes an inductor, an input capacitor, an output capacitor, a diode, and a MOSFET switched at 20 kHz. The power-stage parameters are listed in Table 4.

When the switch is closed (ON):

$$\begin{cases} \frac{di_L(t)}{dt} = \frac{V_{in} - V_{out}}{L} \\ \frac{dV_{out}(t)}{dt} = \frac{i_L(t) - V_{out}(t)/R}{C} \end{cases} \quad t \in [0, \alpha T] \quad (4)$$

When the switch is open (OFF):

$$\begin{cases} \frac{di_L(t)}{dt} = \frac{-V_{out}}{L} \\ \frac{dV_{out}(t)}{dt} = \frac{i_L(t) - V_{out}(t)/R}{C} \end{cases} \quad t \in [\alpha T, T] \quad (5)$$

These equations are implemented in Simulink using logical subsystems (or Switch blocks) controlled by a PWM signal.

A Buck converter is a step-down DC–DC converter that produces an output voltage lower than the input voltage. Its conversion ratio depends directly on the switch ON time. This ratio is called the duty cycle, denoted D , and is defined as:

$$D = \frac{V_{out}}{V_{in}} \quad (6)$$

where V_{in} is the input voltage and V_{out} is the output voltage.

By definition, the duty cycle is the ratio of the ON time t_{on} to the switching period T and is bounded between 0 and 1. The output-current, inductance L , and capacitance C expressions are given in Eqs. (7) and (8), respectively.

$$I_{out} = \frac{P_{mp}}{V_{out}} \quad (7)$$

$$L = \frac{(V_{in} - V_{out}) \cdot D}{\Delta I_L \cdot f_s} \quad et \quad C = \frac{I_{mp} \cdot D}{\Delta v_0 \cdot f_{sw}} \quad (8)$$

4. Electrical parameters of the Jinko Solar PV 250W PV module

The electrical parameters used in the simulation are summarized in Table 1. They correspond to the Jinko Solar 250 W module selected in the PV Array block.

This table presents the electrical parameters actually used for the PV module and the single-diode model.

122 Table 1: Electrical parameters of the Jinko Solar 250 W module used in the PV model

Parameter	Values
Maximum power P_{max}	250.27 W
Open-circuit voltage V_{oc}	35.8 V
Short-circuit current I_{sc}	9.32 A
Voltage at maximum power point V_{mp}	29.0 V
Current at maximum power point I_{mp}	8.63 A
Light-generated current I_L	9.3424 A
Temperature coefficient of I_{sc}	0.041996 %/°C
Temperature coefficient of V_{oc}	-0.333 %/°C
Number of cells in series	60

123 **4.1. Overview of conventional MPPT algorithms**

124 MPPT modifies the apparent impedance seen by the PV generator to maintain operation near
 125 the MPP. Table 2 presents the common methods; P&O is selected as the conventional
 126 reference method because it is simple to implement but sensitive to the speed-ripple trade-off.
 127 The operating point is shifted by changing the converter duty cycle. In the Buck converter
 128 studied here, this action is produced indirectly by the V_{pv} control loop. Table 2 places P&O
 129 and the main alternatives in the MPPT literature.

130 Table 2: Comparison of the Main MPPT Methods

Algorithm	Principle	Advantages	Limitations
Perturb and Observe (P&O) [3], [6]	Perturbs the operating point and observes the power change by adjusting the duty cycle.	Simple, low cost	Oscillates around the MPP; sensitive to rapid variations.
Incremental Conductance (IncCond) [3], [5]	Compares instantaneous and incremental conductance to locate the MPP.	More accurate under rapid variations	More complex than P&O.
Fractional Open-Circuit Voltage [3], [5]	Estimates the MPP voltage from the open-circuit voltage.	Simple; few measurements	Lower accuracy; requires periodic open-circuit measurement.
Fractional Short-Circuit Current [3]	Estimates the MPP current from the short-circuit current.	Simple implementation	Power losses during short-circuit measurement.
Optimized methods (Fuzzy, Neural, PSO) [4], [9]	Use artificial intelligence or heuristic optimization.	Potentially high tracking performance	Higher computational burden and tuning effort.

131 In this study, the P&O algorithm was selected for its simplicity and effectiveness.

132 **4.2. Perturb and observe (P&O) method**

133 The conventional P&O algorithm measures $P_{pv} = V_{pv}I_{pv}$, calculates the power variation
 134 between two instants, and then increases or decreases the duty cycle according to the sign of
 135 that variation. The settings used here are $T_{s,P\&O} = 1$ ms, $\Delta D = 0.002$, and $D_0 = 0.82$.

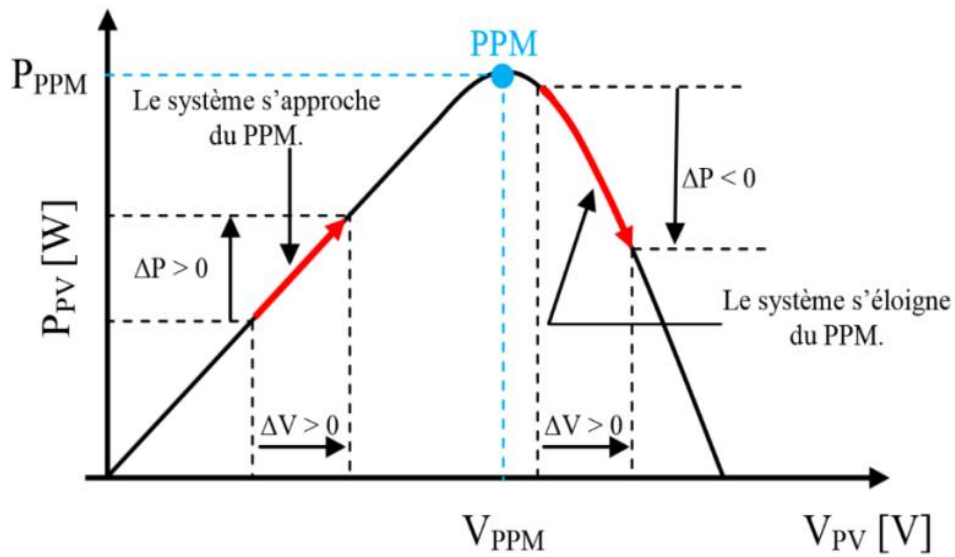


Figure 3. Maximum power point search using the P&O method [3], [6].

Despite its advantages, P&O has notable limitations, including permanent oscillations around the MPP at steady state and poor performance under rapid irradiance variations.

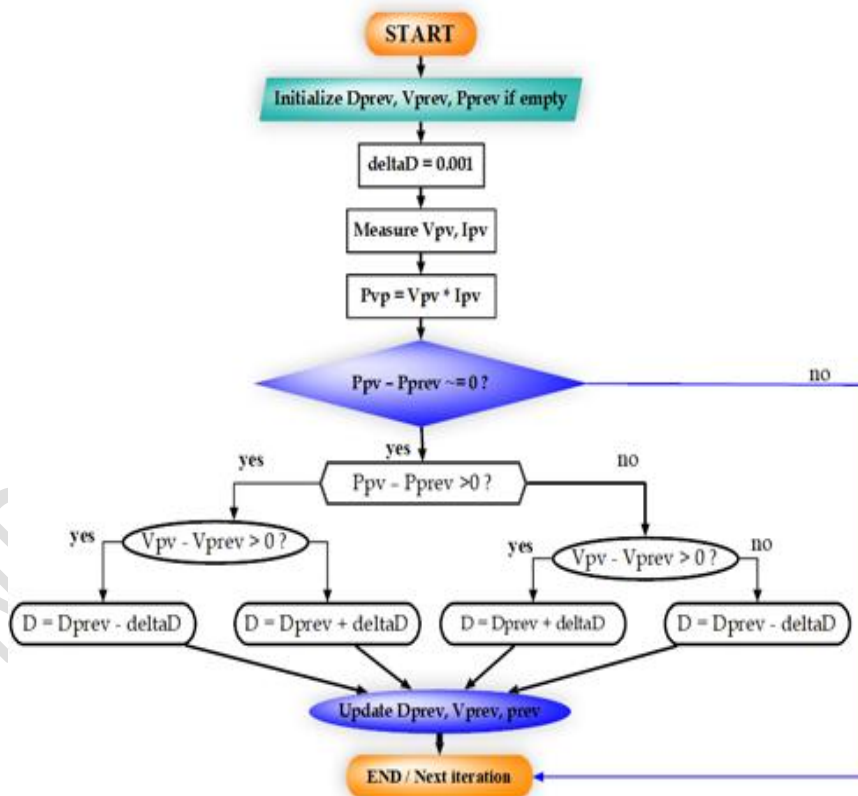


Figure 4. Flowchart of the P&O algorithm for a PV system

4.3. Hybrid ANN–P&O MPPT

An artificial neural network (ANN) is used as a static MPP estimator. It does not replace the converter; it provides a reference input to the control loop. Its quality depends on the operating range covered by the training data.

In this study, the ANN receives irradiance G (W/m^2) and temperature T ($^{\circ}\text{C}$). It produces V_{mp} , I_{mp} , and P_{mp} ; only V_{mp} is used as the V_{ANN} reference. The MLP network has two hidden layers with 32 and 16 neurons and three outputs, and it was trained using data from the nominal PV model.

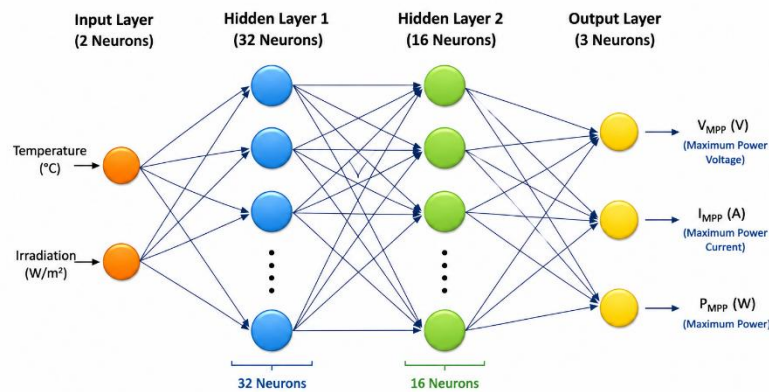


Figure 5. ANN architecture diagram

5. Hybrid ANN- P&O

5.1. Overall system architecture

The architecture proposed in Figure 6 combines a photovoltaic generator, a Buck DC–DC converter, an equivalent resistive load, and a hybrid ANN–P&O MPPT controller.

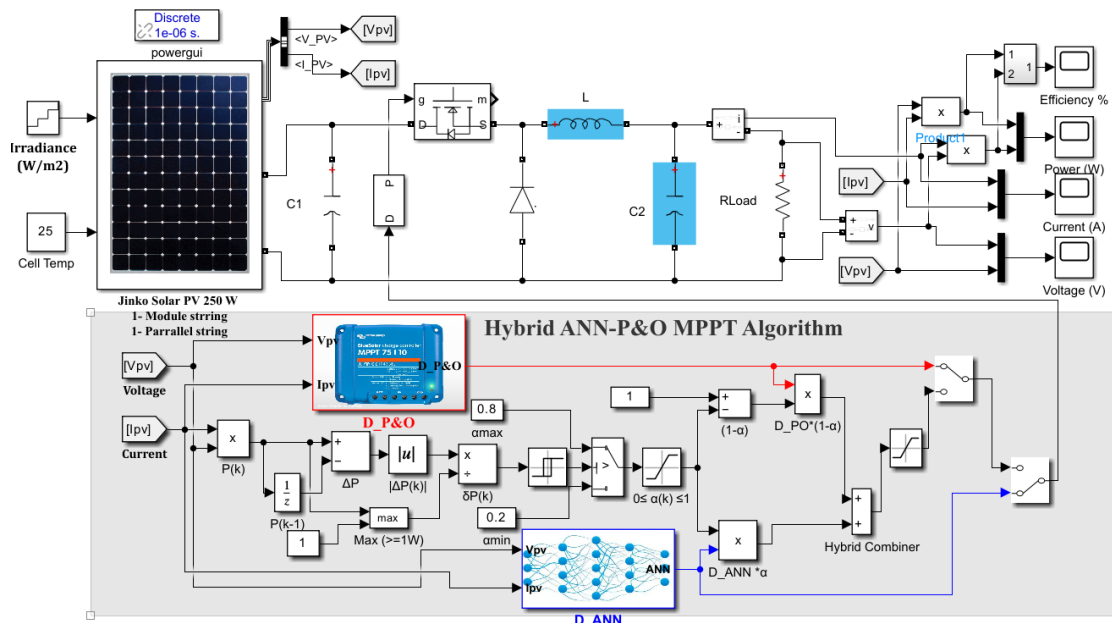


Figure 6: Photovoltaic system with hybrid ANN–P&O MPPT control

The photovoltaic generator is modeled using a single-diode model whose behavior depends on solar irradiance G and cell temperature T . The panel electrical variables, namely PV voltage V_{pv} and PV current I_{pv} , are measured to calculate the instantaneous power. The hybrid controller receives G , T , V_{pv} , and I_{pv} . The ANN estimates the optimal voltage V_{ANN} , close to the voltage corresponding to the maximum power point. This estimate enables rapid repositioning of the operating point after a change in irradiance or temperature. A local P&O correction is then applied around the ANN reference. The final reference is defined as $V_{ref} = V_{ANN} + \Delta V_{PO}$, where ΔV_{PO} is a small voltage correction. The correction is bounded to avoid excessive excursions around the operating point estimated by the ANN. The voltage reference V_{ref} is compared with the measured voltage V_{pv} . The resulting error is processed by a PID controller, which generates the PWM duty cycle. This signal drives the Buck-converter MOSFET and adjusts the apparent impedance seen by the PV panel. Thus, the ANN provides rapid repositioning toward the MPP region, while P&O performs fine adjustment around that region. This structure can reduce the search time observed with conventional P&O while retaining a local correction capability when the ANN estimate is inaccurate due to variations in operating conditions or model mismatch.

5.2. Hybrid controller principle

Hybrid operation has two complementary phases. After a detected change in G or T , V_{ref} is immediately reset to V_{ANN} for 10 ms. P&O then refines V_{ref} every 5 ms with a 0.01 V step. The correction is bounded to ± 1.5 V around V_{ANN} , and V_{ref} is limited to 20–34 V. The ANN provides a fast global MPP estimate, whereas the hybrid P&O performs only a local search. Under nominal conditions, the hybrid and standalone ANN are expected to be very close. The expected benefit of hybrid P&O is mainly correction of ANN estimation errors. P&O performs local refinement around this point to reduce steady-state oscillations. This combination addresses the individual limitations of each method:

- slow tracking and oscillations for P&O;
- dependence on training quality and training-domain validity for the ANN [4], [9].

5.3. Switching Strategy

The transition between phases is triggered by $|G - G_{prev}| > 20 \text{ W/m}^2$ or $|T - T_{prev}| > 0.5 \text{ }^\circ\text{C}$. At each change, the P&O memory states are reset and the ANN temporarily takes control; P&O refinement starts only after the repositioning interval. Switching therefore does not rely on an unbounded power perturbation. It relies on changes in G and T available in the model, which makes the control logic reproducible.

$$\left| \frac{\Delta P}{P} \right| > \varepsilon$$

The system is considered to be in a transient regime when a significant change in irradiance or temperature is detected, and the ANN is activated to rapidly reposition the operating point. Once the system approaches the MPP region, the P&O method takes over to refine the tracking and reduce oscillations. The system is close to the MPP, and the P&O method takes over to refine tracking and reduce oscillations.

The threshold ε is selected empirically to ensure a speed–stability compromise; this tuning trade-off is commonly discussed for fixed-step and adaptive-step P&O methods [6], [7].

6. Simulation and results

Monthly climate data from Ziguinchor are used for Buck-converter pre-sizing. They do not replace the dynamic profile used to compare the MPPT methods. Table 3 presents the monthly operating points used to estimate the L and C constraints. P_{max} , V_{mp} , and I_{mp} are calculated for each (G,T) pair in Table 3 using the PV model. They are used to select standardized component values with sufficient margin for the most demanding operating conditions. Table 3 summarizes the monthly climate data and the Buck pre-sizing values.

Table 3: Climate Data and Buck Converter Pre-Sizing

Month	Irradiance G (W/m ²)	Temperature (°C)	Pmax (W)	VMP (V)	IMP (A)	Lmin (μH)	Cmin (μF)
January	756.28	28.6	186.7	28.88	6.513	130.3	40.5
February	803.05	30	197.5	28.68	6.873	119	42.9
March	880.38	31.5	215.4	28.39	7.58	103.4	46.7
April	859.88	32.4	209.7	28.28	7.42	103.9	45.5
May	701.14	32.74	170.3	28.38	6.00	130.5	37
June	591.62	31.28	143.6	28.45	5.05	156.9	31.2
July	517.54	29.02	125.9	28.65	4.42	185.6	27.3
August	497.01	28.18	120.8	28.68	4.21	194.5	26.2
September	613.89	29.09	150.4	28.74	5.25	157.9	32.6
October	664.30	29.79	162.8	28.61	5.69	142.5	35.3
November	799.22	30.93	195.8	28.58	6.85	117.9	42.5
December	745.87	29.87	183.3	28.68	6.39	128.2	39.8

Pre-sizing yields a maximum L_{min} value close to 195 μH and a maximum C_{min} value close to 47 μF. The selected values are $L = 220$ μH, $C_1 = 220$ μF, and $C_2 = 470$ μF. C_1 decouples the PV generator, whereas C_2 limits output ripple.

The Buck converter supplies an equivalent 2.3 Ω resistive load at approximately 24 V. This choice validates MPPT operation and conversion losses; it does not model the electrochemical dynamics of a 24 V battery. Table 4 summarizes the final Buck-converter parameters used in the simulation.

Table 4: Buck Power Converter Specifications

Parameters	Value
Inductance L	220 μH
Input capacitor C1	220 μF
Output capacitor C2	470 μF
Switching frequency fs	20 kHz
Load resistance RL	2.3 Ω
Nominal output voltage	24 V
Discrete electrical time step	1 μs

6.1. Effect of temperature and irradiance on the maximum power of the PV panel

Figure 7 illustrates the dependence of P_{max} on irradiance and temperature in the monthly data. This figure is a pre-sizing analysis rather than the dynamic MPPT comparison scenario.

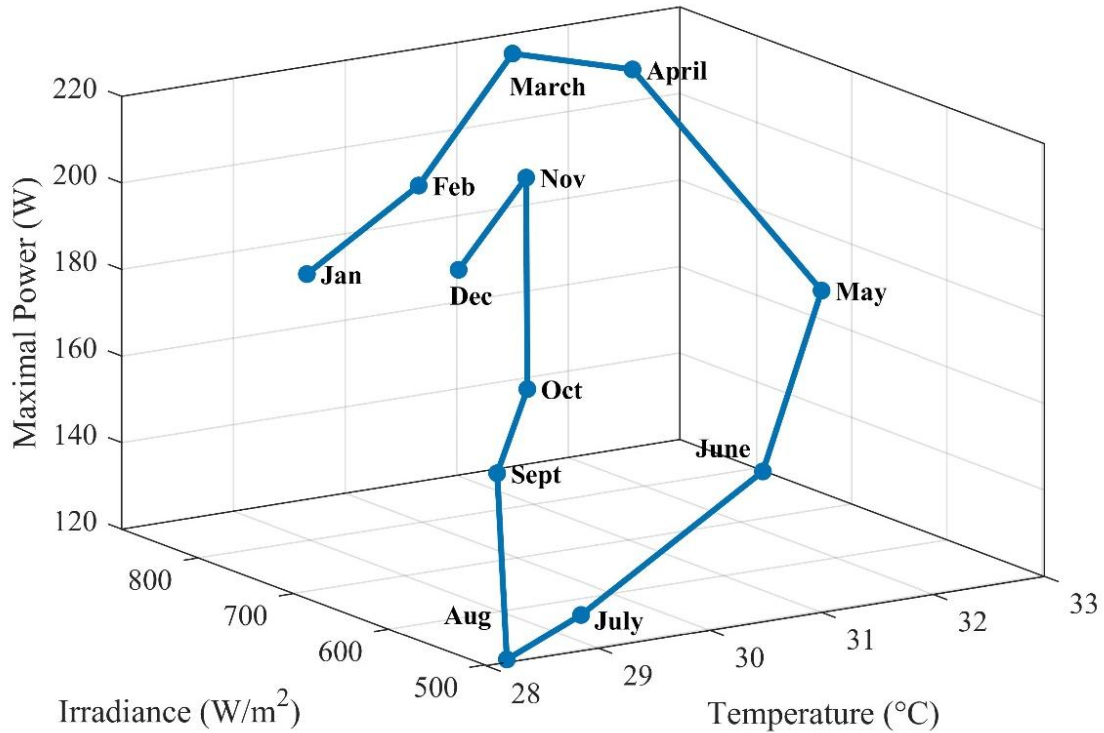


Figure 7: Maximum power as a function of temperature and irradiance

Table 3 confirms that irradiance is the dominant factor affecting maximum power over the range studied. Temperature mainly modifies the MPP voltage and makes a secondary contribution to P_{max} variation.

The highest monthly value in this series occurs in March: $G = 880.38 \text{ W/m}^2$, $T = 31.5 \text{ }^\circ\text{C}$, and $P_{max} = 215.4 \text{ W}$. April is close, with $P_{max} = 209.7 \text{ W}$.

The thermal effect must not be confused with the irradiance effect: at equal irradiance, increasing T generally reduces V_{oc} and shifts V_{mp} ; in the monthly data, G and T vary simultaneously.

From May to August, the decrease in mean irradiance explains most of the decrease in P_{max} . For example, the minimum of the series occurs in August with $G = 497.01 \text{ W/m}^2$ and $P_{max} = 120.8 \text{ W}$.

These climate data are useful for assessing seasonal potential and sizing the converter. The transient performance of the MPPT methods is evaluated separately using the $G(t)$ profile defined below.

6.2. Comparison of MPPT

The dynamic comparison uses a total duration of 0.5 s and the following profile at $T = 25 \text{ }^\circ\text{C}$: 1000 W/m^2 (0 - 0.1 s), 600 W/m^2 (0.1 - 0.2 s), 800 W/m^2 (0.2 - 0.3 s), 400 W/m^2 (0.3 - 0.4 s), and 1000 W/m^2 (0.4 - 0.5 s). At 20 kHz, the simulation contains 10,000 PWM periods; each plateau contains 2,000 PWM periods and 100 conventional P&O updates.

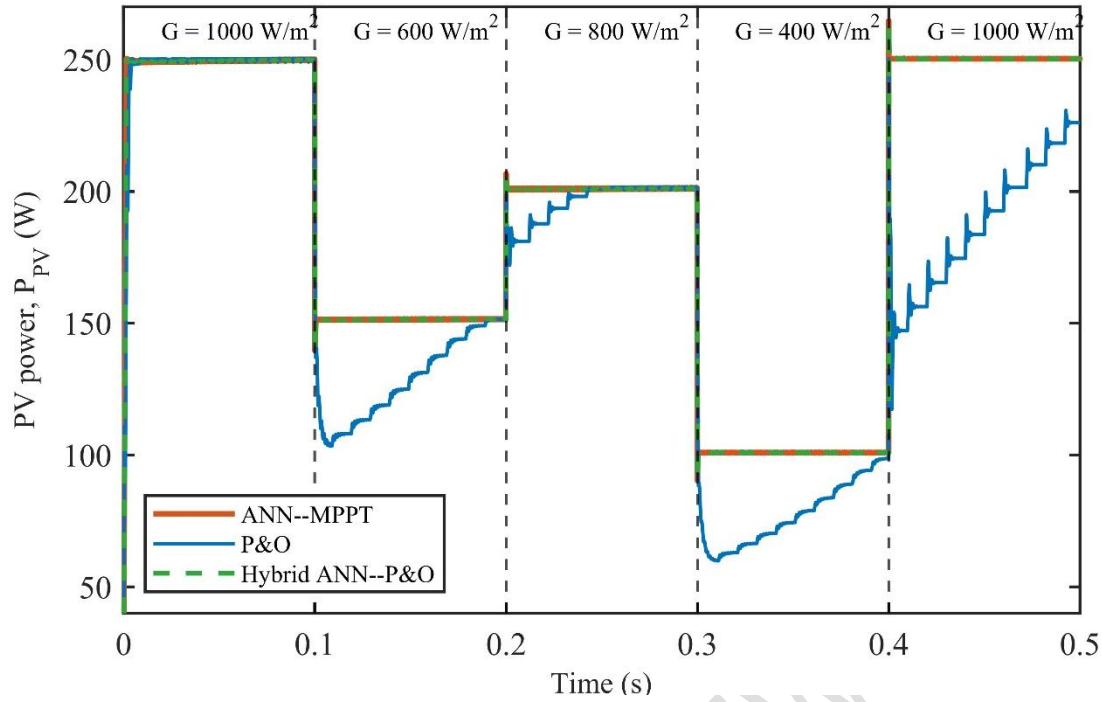


Figure 8: Dynamic performance comparison of MPPT algorithms

Table 5 compares the indicators extracted for standalone ANN and conventional P&O under the same dynamic profile.

Table 5 presents the available results for standalone ANN, conventional P&O, and the hybrid ANN-P&O controller. The ANN reaches the reference within the resolution of the discrete model, and its filtered ripple ranges from 0.061 to 0.665 W over the steady-state windows. Conventional P&O exhibits substantially larger oscillations after some transitions and does not settle before the end of the final two windows. Efficiency values slightly above 100% result from discretization and the finite analysis window; they do not represent physical efficiency above 100%. This behavioral difference follows from the nature of the two methods: the ANN directly evaluates a trained function, yielding microsecond-scale response times, whereas P&O converges through successive $\Delta D = 0.002$ steps every millisecond, structurally linking its speed to the pair $(\Delta D, T_{s,P\&O})$. Although standalone ANN is already effective under nominal conditions, the specific benefit of P&O refinement is expected when the ANN estimate deviates from the real model, which the robustness test described in the conclusion is intended to quantify.

Literature-based interpretation: the degradation observed with conventional P&O after irradiance changes is qualitatively consistent with the analyses of Femia et al. [6], which link the perturbation step to oscillations and convergence time, and with the experimental comparisons of Hohm and Ropp [7]. The results should not be compared numerically on a one-to-one basis with those studies because the PV module, converter, switching frequency, sampling interval, and response-time indicators differ. The relevant correlation is therefore a trend-level consistency: P&O exhibits a speed-ripple trade-off, whereas an ANN estimate can rapidly reposition the reference but must be validated outside its training domain [4], [9].

266 Table 5: Dynamic Indicators for Standalone ANN and Conventional P&O

Transition (W/m ²)	ANN mean Ppv (W)	ANN ripple (W)	ANN response	P&O mean Ppv (W)	P&O ripple (W)	P&O response	Hybrid mean Ppv (W)	Hybrid ripple (W)	Hybrid response
1000→600	151.49	0.414	$\leq 3 \mu s^*$	141.73	22.17	82.80 ms	151,48	0,631	$\leq 2 \mu s$
600→800	201.06	0.665	$\leq 2 \mu s^*$	201.29	0.800	32.57 ms	201,09	0,850	$\leq 2 \mu s$
800→400	100.95	0.061	$\leq 1 \mu s^*$	86.58	23.94	> 100 ms	100,92	0,182	$\leq 1 \mu s$
400→1000	250.25	0.225	$\leq 2 \mu s^*$	206.72	44.23	> 100 ms	250,25	0,308	$\leq 2 \mu s$

267 7. Conclusion

268 This article presented the modeling of a 250.27 W PV module, a Buck converter, and three
 269 MPPT strategies: conventional P&O, ANN, and hybrid ANN–P&O. The hybrid controller is
 270 formulated around a voltage reference, making it consistent with the Vref–PID–PWM loop
 271 and avoiding direct mixing of duty cycles.

272 Nominal simulations show that conventional P&O is slower and more oscillatory than ANN.
 273 The hybrid controller nearly overlaps with ANN in the nominal model because the ANN was
 274 trained on that same model. This observation validates that the hybrid control does not
 275 degrade nominal operation, but it does not demonstrate that it systematically outperforms
 276 standalone ANN. The study therefore establishes the methodological framework for the
 277 hybrid approach; its specific added value remains to be demonstrated by the defined
 278 robustness test, in which the simulated PV model is altered ($R_s = 0.352 \Omega$, i.e., +20%, and
 279 $R_{sh} = 97.41 \Omega$, i.e., –20%) without retraining the ANN, while keeping the same G(t) profile,
 280 converter, and P&O parameters. This test will enable comparison of standalone ANN, P&O,
 281 and hybrid control when the ANN estimate is imperfect and will determine whether the P&O
 282 refinement provides a specific benefit.

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