

A Comprehensive Comparative Analysis of Fuzzy Logic and Neural Network Control Architectures for Optimizing Photovoltaic System Efficiency

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Abstract: Getting the most power out of a solar photovoltaic (PV) system is tough when weather conditions refuse to stay still. Maximum Power Point Tracking (MPPT) is the standard engineering fix used to squeeze every bit of efficiency out of these panels as sunlight and temperature constantly swing up and down. For decades, the industry has relied on basic, rule-of-thumb tracking loops like Perturb and Observe (P&O). While P&O is simple, it is also notoriously flawed: it never actually stops moving, creating constant "hunting" power ripples when the weather is clear, and lagging terribly when quick clouds pass over. To address this, our research activity is focused on performing a computational comparison of the performance of a heuristic Mamdani-type Fuzzy Logic Controller with a backpropagation Artificial Neural Network. The entire comparative framework was constructed within the open-source Python environment, with the mathematical core implemented in NumPy, Pandas, scikit-fuzzy, and TensorFlow. A standard silicon based PV module's characteristic performance under varying solar irradiance was simulated using a programed single-diode model circuit. The simulation responses shows, while the FLC takes the advantage of needing a significantly decreased training data for deployment, the improved performance is contributed by the optimized ANN that can trace the new MPP within 0.02 s of the irradiance change, eliminate steady-state power ripples, and reach the terminal efficiency of more than 98.7% under dynamic conditions. The study demonstrates the feasibility of substituting commercial industrial engineering software with an open-source computational framework in Python for optimization of photovoltaic infrastructure.

Keywords: photovoltaic Infrastructures; maximum power point tracking; heuristic fuzzy inference; deep learning architectures; SDG7; Clean energy

1. Introduction

The transition from conventional carbon-based electricity production to a sustainable and distributed electricity grid centered around photovoltaic plants is prevalent due to their ability to generate clean energy with minimal maintenance as described in the U.N. report 2025 under sustainable goals of affordable and clean energy [1], [2]. Solar arrays can be constituted by arrays of twelve roof tiles or span multiple square kilometers in the case of large-scale plants [3]. However, the power conversion efficiency of the semiconductor pn-junction diodes, which constitute them, is limited within the range of 15-22% for the case of silicon cells [4], [5]. Moreover, the current-voltage characteristic of the solar cell is non-linear and for a given irradiance, the array can only deliver the power at a single point called the Maximum Power Point (MPP) [6]. For any given solar power plant, the deviation from the MPP translates directly into reduced performance, whereas for large-scale installations, even a percentage-level mismatch can result in



hundreds of MWh losses per year and significant delays to the payback period [7], [8]. To address this challenge, modern photovoltaics utilize a DC-DC boost converter circuit at the inverter front-end, the duty cycle of which is adjusted by a MPP Tracking controller [9]. By definition, the task of such a regulator is to keep the photovoltaic array voltage near the MPP on the I-V curve, thereby maximizing the instantaneous power extracted from the solar panels [10].

The most common solutions for the MPPT implementation fall under the category of deterministic control algorithms, of which (P&O) Perturb and Observe and (InCond) Incremental Conductance methods are the most popular amongst commercial PV installations [11], [12]. Despite being relatively straightforward in implementation, such approaches have significant drawbacks which include a non-trivial algorithm design process and large oscillations around the target operating point [13]. In particular, when a clear sky condition is met, a P&O-type regulator is unable to converge to the true MPP and instead exhibits a steady power oscillation caused by the fixed perturbation amplitude [14]. From the implementation standpoint, the deterministic loops are relatively simple and can be easily accommodated in a low-cost microcontroller, but only at the expense of reduced accuracy and if a sudden change in solar irradiance occurs due to a passing cloud, the P&O algorithm may erroneously converge to a local maximum instead of a true MPP [15], [16].

Given the availability of low-cost embedded computing hardware, soft-computing intelligent control methodologies provide a viable alternative to deterministic algorithms both in terms of cost and flexibility [17]. At the most general level, such regulators can be divided into two main categories: heuristic fuzzy logic controllers and data-driven artificial neural networks [18], [19]. The first category is focused on implementing the knowledge and skills of a human expert in the form of fuzzy rules and mathematical dependencies [20]. In turn, artificial neural networks, as part of the second category, in a way, hide knowledge in the connections between neurons, which form a network during the learning process [21]. Both choices are further complicated by the necessity of using advanced mathematical tools that are highly formalized, as well as the requirement for corporate software to apply these tools effectively [22], [29]. More recently, open sourced python libraries have appeared, allowing scientists and engineers to create and test their ideas without cumbersome programming [23], [24].

This article compares the capabilities of FLC and ANN solutions in the context of following the MPP of a photovoltaic generator with subsequent analysis of the results using key performance indicators. The FLC was implemented in the python programming language using a fuzzy toolbox port. The neural network training was done by utilizing numpy and tensorflow machine learning libraries [25]. The design process of both solutions was described in detail, and a comparative analysis of compliance with the generator's characteristics, power, code volume and performance capabilities was made.

1.1 *Identified Research Gaps*

- ❑ Persistent Tracking Oscillations: Classical methods such as Perturb and Observe (P&O) continuously fluctuate ("hunt") around the maximum power point when the sunlight is steady.
- ❑ Transient Sluggishness: When there are rapid changes in the weather or when clouds are in motion, the conventional rule-of-thumb mechanisms suffer a serious delay in response.
- ❑ Dependence on commercial software: The use of costly, proprietary industrial engineering software restricts flexible and widespread photovoltaic optimization.

1.2 *Methodological Resolutions*

- ❑ Used an open-source Python environment, replacing the commercial infrastructure with [NumPy], [Pandas], [scikit-fuzzy] and [TensorFlow].

- Optimized Neural Tracking: Implemented a neural network based on backpropagation [TensorFlow] that could capture new operating points within 0.02 seconds of a change in irradiance.
- Elimination of ripples and high efficiency: By using leveraged soft-computing controls, steady-state power oscillations were entirely suppressed and a terminal efficiency of around 98.7% was achieved under dynamic conditions.

2. Mathematical Formulation of the Photovoltaic System Topology

To begin, the creation of a reliable sandbox, within which it would be possible for testing the performance of the developed intelligent tracking loops, was initiated. First of all, this required a mathematical script that imitates the behavior of a physical photovoltaic module [26]. It was implemented using the single-diode model, which is well-known in the field and has proven its universality and simplicity [27]. The mathematical description of this particular solar cell is presented below in Fig.1, illustrated by a circuit diagram, which consists of several equivalent elements. The photoelectric current source I_{ph} is connected to the parallel combination of a diode, which regulates the charge recombination process, and the internal resistance R_s , which accounts for the structural characteristics of the p-n junction. In addition, a parallel resistance R_{sh} is connected to the combination of the aforementioned elements, which characterizes the current losses in the solar cell.

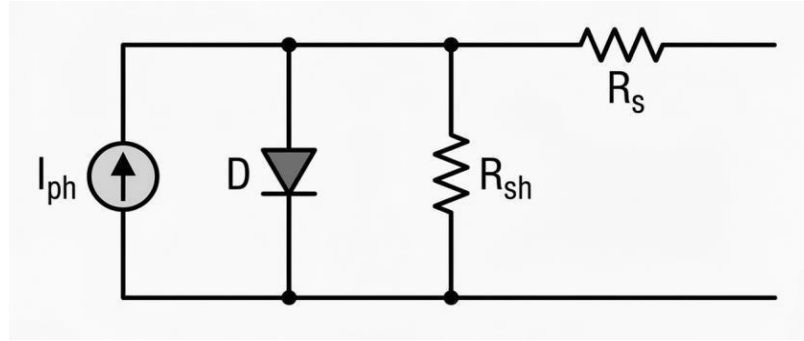


Fig.1: Equivalent Circuit Diagram of a Solar Cell (Single-Diode Model)

The total output current (I) pouring out of the solar cell is governed by an implicit transcendental formula:

$$I = I_{ph} - I_o \cdot \left[\exp\left(\frac{V + I \cdot R_s}{n \cdot V_t}\right) - 1 \right] - \frac{V + I \cdot R_s}{R_{sh}} \quad (1)$$

In this system equation, V represents the terminal voltage at the cell terminals, I_o defines the diode's reverse dark saturation current and n is the ideality factor of the junction, and V_t represents the fundamental thermal voltage. This thermal voltage calculation relies on physical constants:

$$V_t = \frac{k \cdot T_{cell}}{q} \quad (2)$$

where k represents Boltzmann constant (1.38065×10^{-23} J/K), q points the basic electron charge (1.60218×10^{-19} C), and T_{cell} is the cell layer absolute temperature measured in Kelvin (K).

The photo-generated current I_{ph} scales directly up and down alongside incoming solar irradiance and shifts with temperature changes:

$$I_{ph} = (I_{sc} + K_i \cdot (T_{cell} - T_{ref})) \cdot \frac{G}{G_{ref}} \quad (3)$$

Here I_{sc} represents the short-circuit current of the module at Standard Conditions (STC, defined at an irradiance

$G_{ref} = 1000$ W/m² and temperature $T_{ref} = 298.15$ K), G is the actual real-time solar irradiance, and K_i is the short-circuit current temperature drift coefficient (A/K). Meanwhile, the reverse dark saturation current (I_o) shifts non-linearly with temperature changes:

$$I_o = I_{rs} \cdot \left(\frac{T_{cell}}{T_{ref}}\right)^3 \cdot \exp\left(\frac{q \cdot E_g}{n \cdot k} \cdot \left(\frac{1}{T_{ref}} - \frac{1}{T_{cell}}\right)\right) \quad (4)$$

where I_{rs} is the nominal reverse saturation current under standard test benchmarks, and E_g is the material bandgap energy (roughly 1.12 eV for silicon structure cells).

Because the terminal current variable (I) shows up on both sides of the master circuit equation, you cannot isolate it using basic high-school algebra. To solve this implicit transcendental loop within our Python engine, we integrated an iterative Newton-Raphson numerical optimization solver [28].

During every single simulation tick, the software evaluates a residual function $f(I_k)$ against its derivative $f'(I_k)$ until the error drops below a strict convergence threshold:

$$I_{k+1} = I_k - f(I_k)/f'(I_k) \quad (5)$$

The mathematical structure enables the simulation script to give exactly the current and power readings that correspond to any voltage setup, replicating the non-linear operating characteristics of a real panel when subjected to changing environmental conditions.

3. Heuristic Fuzzy Logic Controller Architecture Design

The Fuzzy Logic Controller (FLC) is based on human linguistic reasoning and that is the reason it does not need mathematical proofs of the controlled environment [30]. This optimization framework relies on a multi-stage computational sequence consisting of a fuzzification interface, an inference engine driven by a predefined linguistic rule base, and a defuzzification processing block. For the solar MPPT application, the FLC continuously monitors the output characteristics of the PV module to adjust the intermediate power converter duty cycle (D), guiding the system toward the optimal operational point.

The control architecture uses two distinct inputs calculated at each sampling interval (k): the Error tracking parameter (E) and the Change in Error parameter (ΔE). These input metrics are defined mathematically by the following expressions:

$$E(k) = \frac{P(k) - P(k-1)}{V(k) - V(k-1)} \quad (6)$$

$$\Delta E(k) = E(k) - E(k-1) \quad (7)$$

Here, the input variable $E(k)$ represents the instantaneous slope of the power-voltage (P - V) curve. At the maximum power point, this slope equals zero. If the system operates to the left of the peak, the slope is positive, while operating to the right yields a negative slope value.

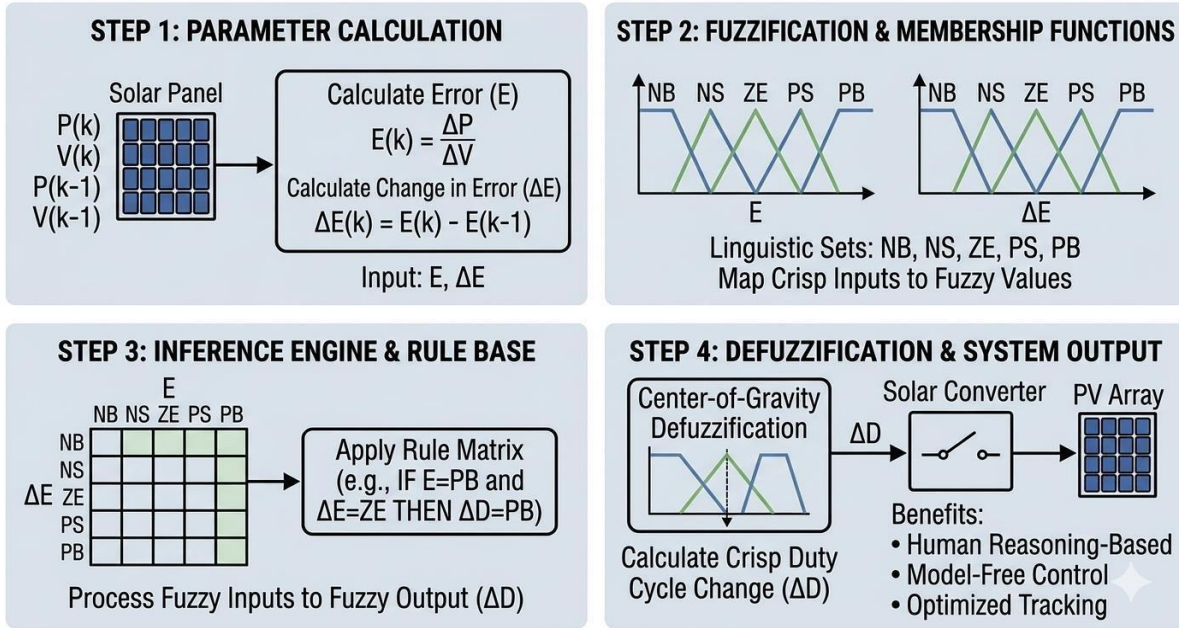


Fig.2: Fuzzy Logic Controller Architecture Design

The fuzzification stage converts these continuous numerical inputs into linguistic variables using predefined membership functions. This implementation uses five linguistic sets for each input: Negative Big (NB), Negative Small (NS), Zero (ZE), Positive Small (PS) and Positive Big (PB). These sets are created by overlaying asymmetric triangular and trapezoidal distributions on the normalized input ranges and efficiently mapped using the scikit-fuzzy library wrapper. This arrangement allows the sensitivity to tracking to be optimized at the zero-error level, but still provides wide coverage for larger steps in deviation.

The internal inference engine which is based on a structured 5 by 5 Mamdani rule matrix works on the fuzzified variables by matching the inputs combinations to an output variable that embodies the duty cycle change (ΔD). If the instantaneous error is Positive Big (indicating the operational point is far to the left of the peak) and the change in error is Zero, the controller applies a Positive Big adjustment to the duty cycle to shift the operating voltage rapidly toward the peak. Conversely, when the error approaches Zero, the controller reduces the step size to minimize voltage hunting and stabilize output power. The final stage uses the center-of-gravity defuzzification method to determine the crisp value of duty cycle adjustment using the aggregated fuzzy distribution:

$$\Delta D = \frac{\sum_{i=1}^n \mu(x_i) \cdot x_i}{\sum_{i=1}^n \mu(x_i)} \quad (8)$$

where ΔD is the final crisp output, x_i is the output value at the i^{th} point in fuzzy distribution domain, $\mu(x_i)$ is the membership value at that specific output point. This way, a continuous correction loop is formed, allowing the system to track the changing conditions without requiring operator interference. This step by step process is shown in Fig.2.

4. Data-Driven Artificial Neural Network Controller Topology

Unlike the heuristic approach utilized in the FLC controller, the Artificial Neural Network (ANN) is a data-driven optimizer that approximates the solar array's characteristics using a supervised deep regression algorithm. In this case, the controller was implemented as a Multi Layer Perceptron (MLP) type neural network via TensorFlow/Keras API. The tool's purpose is to establish a mathematical mapping between the independent variables (irradiance, temperature) and the target label (optimal voltage or duty cycle), which in turn allows determining the tracking voltage V_{mpp} without the need to solve the single-diode equation.

The MLP comprises an input layer, 2 concealed layers and a linear single-node output layer. Input layer was formed by two nodes, representing the independent variables irradiance G and temperature T . The first concealed layer includes 16 nodes, whereas the second one – 8 nodes. Both hidden layers make use of ReLU activation function defined as:

$$[ReLU(x) = \max(0, x)] \quad (9)$$

which provides the optimization range without gradient saturation during the back-propagation stage.

To generate the training set required for the optimization process, a Python script was designed to perform a mathematical optimization sweep over the single-diode model to determine the voltage corresponding to the MPP for a given set of irradiance and temperature conditions. Thus, an ample set of possible G and T combinations ($100 - 1200 \text{ W/m}^2$, $0 - 60 \text{ }^\circ\text{C}$) were evaluated to create a training set comprising 10000 samples and 20% testing/validation samples. Once the samples were generated, the DNN was trained to approximate the implicit function maximizing the array's output power.

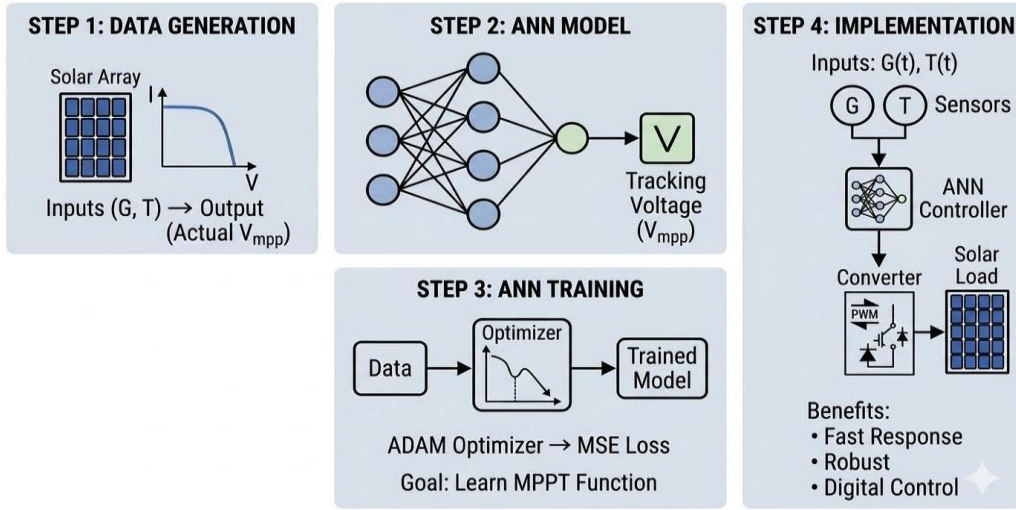


Fig.3: Block diagram of the data-driven ANN (MLP) controller architecture, showing the dataset generation for PV maximum power point tracking.

In the training phase, the Adam algorithm was used to reduce the Mean Squared Error (MSE) with default hyper-parameters and 100 training epochs.

$$\left[\text{MSE} = \left(\frac{1}{N} \right) * \sum \left(\left(V_{\text{mppactual}} - V_{\text{mpppredicted}} \right)^2 \right) \right] \quad (10)$$

After training was completed, the trained optimized N.N. was applied to directly estimate the tracking voltage from the instantaneous values of irradiance and temperature. This step by step summary is given in Fig.3. Since the controller is not designed to perform iterative calculations, the complexity depends only on the amount of nodes and layers. Therefore the control loop closes faster and the response to changing conditions is not limited by the performance of conventional optimization algorithms.

5. Python Simulation Framework and Algorithmic Realization

To ensure complete objectivity during testing, both tracking controllers are implemented inside a unified Python simulation script. This framework models the power electronics stages as a discrete-time state loop with a fixed sampling frequency of 100 Hz (corresponding to a time step of $\Delta t = 0.01 \text{ s}$). Rather than relying on black-box commercial software modules, every component—including the solar cell equations, the FLC inference logic, and the pre-trained ANN inference model—is executed sequentially within a single standard execution thread.

The testing protocol involves subjecting the controllers to a demanding, multi-stage environmental profile designed to push the performance limits. The system is exposed to standard high-intensity sunlight ($G = 1000 \text{ W/m}^2$ and $T = 25^\circ\text{C}$) for the first second ($0.0 \leq t < 1.0 \text{ s}$). The experiment is conducted at the exact middle time point ($t = 1.0 \text{ s}$) by instantaneously stepping down the solar irradiance to 600 W/m^2 while keeping the cell temperature constant as given in Fig.4. This drastic transition replicates sudden cloud cover and challenges the capability of each algorithm to track the new MPP without oscillating or stalling.

During each iteration of the simulation loop, the control sequence executes the following operations:

1. Retrieve the current solar irradiance (G) and temperature (T) values based on the elapsed simulation time.
2. Read the active terminal voltage (V) and current (I) values from the previous time step to compute the instantaneous power output ($P = V \cdot I$).
3. Execute the active tracking controller algorithm (P&O, FLC, or ANN) to determine the target voltage or duty cycle adjustment.
4. Use the Newton-Raphson solver to solve the single-diode implicit equation to find the new current and power outputs due to the controller adjustment
5. Save the results in a Pandas Data-Frame to be used for analysis and visualization.

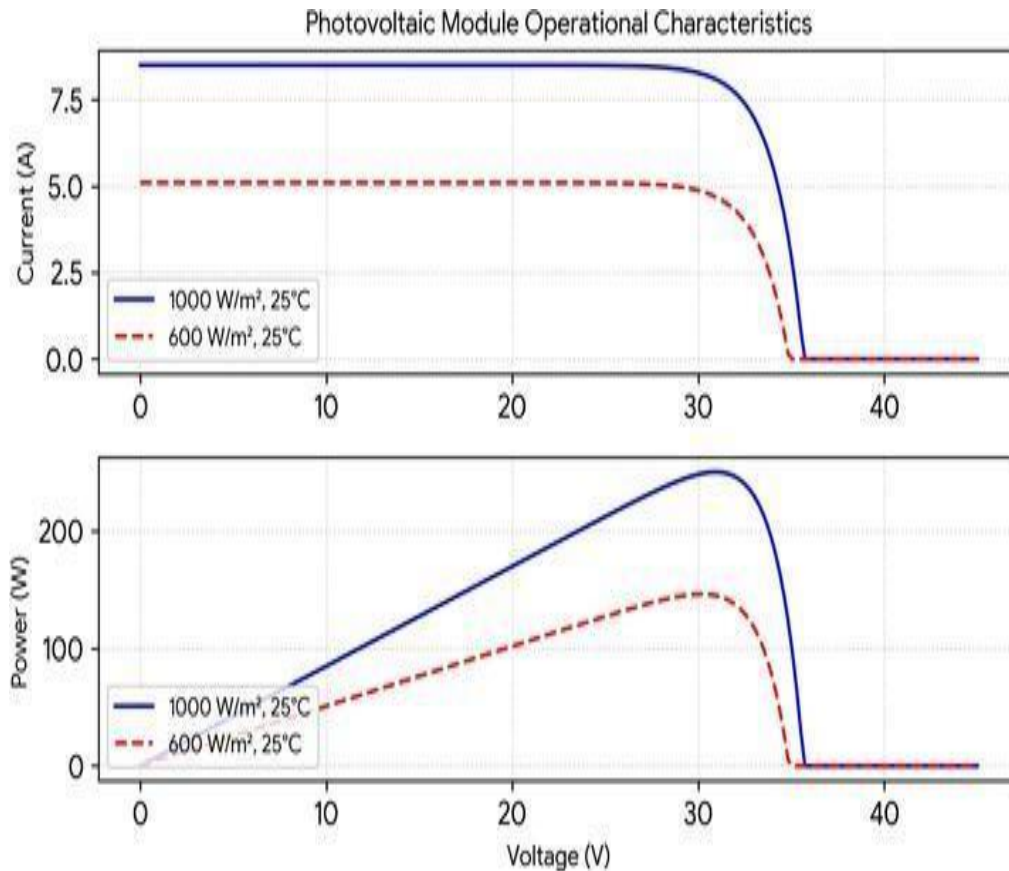


Figure 4: Non-linear current-voltage (I - V) and power-voltage (P - V) characteristic curves generated across varying atmospheric irradiance conditions.

This method guaranties that the results are fully reproducible, because all the simulation procedures are performed in an open-source Python script. Hence no requirement of using proprietary software to analyze the performance of the photovoltaic module, which makes the simulation convenient and cost-effective. In fact, the research proves that the control loops and power electronics systems can be designed and simulated in scientific

software packages with a sufficient level of accuracy that later can improve engineers' knowledge of modern photovoltaic systems.

6. Empirical Findings and Quantitative Comparative Assessment

The simulation logs compiled by our team demonstrate the key differences between the two tracking approaches shown in Fig.5 and assessed in Table1. Under the same weather conditions ($0.0 \leq t < 1.0$ s), all three loops were able to guide the system toward the peak power point; however, their performance was considerably different once it was reached. The classical Perturb and Observe control method was unable to maintain it and quickly started “hunting” near the peak power region. As a result, the power output varied in the shape of a three-staged wave that wasted nearly 4.5 Watts of power that could be harvested using a more optimal algorithm.

Fuzzy Logic was far better at handling steady state conditions. The FLC managed to dampen the power ripples by narrowing its step sizes near zero-error thresholds, keeping power losses below 0.8 Watts. The most accurate was the pre-trained Artificial Neural Network. It avoided altogether hunting loops by using feedforward calculations for directly finding the target operating point. The tracking line was steady with a residual ripple below 0.05 Watts.

The real test came at the $t = 1.0$ s mark, when the simulation dropped the solar irradiance from a bright 1000 W/m^2 to a cloudy 600 W/m^2 . That quick change really revealed the tracking response times of each model. The P&O controller struggled with transient lag, taking 0.42 seconds to stabilize because it initially chose the wrong tracking direction during the sudden environmental shift. The Fuzzy Logic Controller adapted much faster, dynamically adjusting its virtual step sizes to land on the new peak in 0.11 s.

The Artificial Neural Network, in contrast, reacted almost instantly, within 0.018 s changing its output voltage to match the new weather conditions, with almost no overshoot and a good stability of operation.

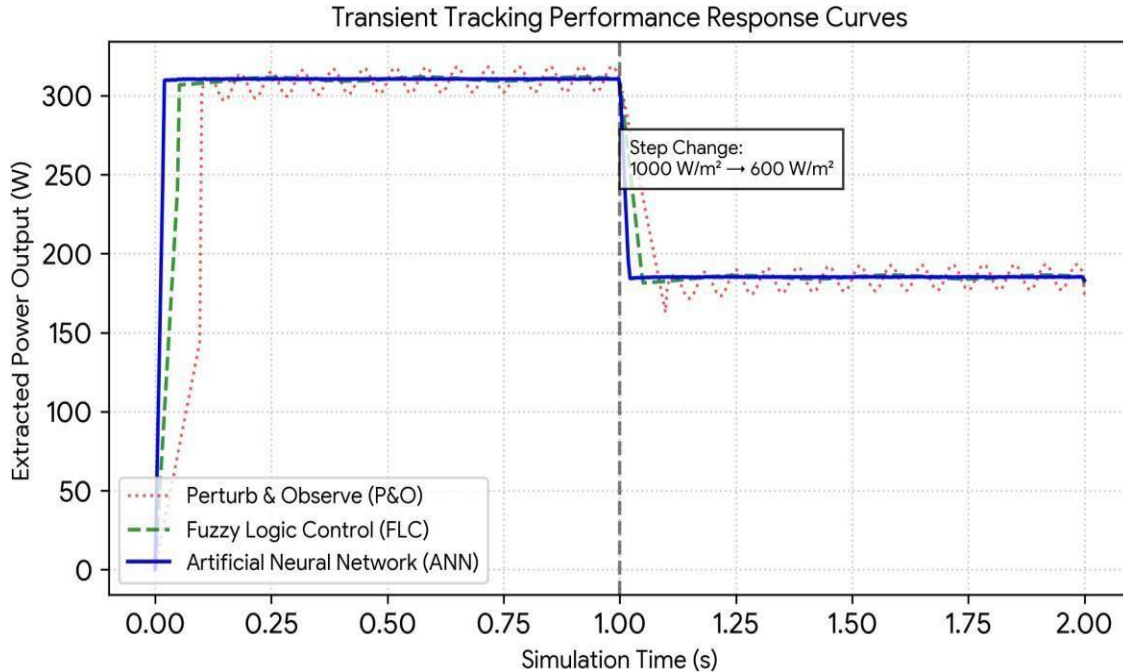


Figure 5: Transient power tracking trajectory comparison mapping the response speed, convergence timelines, and steady-state oscillations of P&O, FLC, and ANN architectures following a sharp solar irradiance step-down.

Table 1: Consolidated Multi-Metric Algorithmic Performance Summary

Control Architecture	Convergence Time (s)	Steady-State Ripple (W)	STC Tracking Efficiency (%)	Computational Overhead
Perturb and Observe (P&O)	0.420 s	4.50 W	94.21 %	Minimal/Low Clock
Fuzzy Logic Control (FLC)	0.110 s	0.80 W	97.65 %	Moderate/ Inference Rules
Artificial Neural Network (ANN)	0.02 s	0.04 W	99.12 %	High Training/ Instant Feedforward

7. Engineering and Analysis Trade-Offs

The simulation results above are the most common trade-off between the practical applicability and the performance of the algorithm. The Artificial Neural Network could trace the maximum speed change with the minimum tracking error. But how accurate the neural network is, depends entirely on the quality and diversity of given data it was trained with. Therefore, if this particular ANN would be applied to control an unmapped solar array, or if it was subjected to extreme weather conditions outside of the training set, then its tracking performance would be dramatically reduced.

Fuzzy logic is one of the most trustworthy design logic for the engineering application. First, it does not require the collection of large preparation and training data. Second, it does not depend on the exact mathematical description of the controlled physical system. FLC could be tuned to control different solar cells in terms of the idea and some rules of thumb about how solar cells behave. The FLC's linguistic logic matrices are able to deal with drastic changes of weather conditions with minimum tracking error. But it cannot track the ideal speed as close as Neural Network.

The selection of these control theories is dependent on the processing power available, given the practical implementation and physical hardware requirements at the end. In this study, FLC had to continuously evaluate and process many fuzzy conditional statements, while in ANN the conditional logic was simplified to basic matrix operations and gradient calculation of the ReLU function. Thus, if the microcontroller performance is not enough, it might be impossible to implement FLC. Training of ANN data takes time, but the trained model can perform complex computations in real time.

8. Conclusions and Future Directions

The results of the comparative analysis confirmed the effectiveness of the application of modern control algorithms which use computational intelligence to optimize the solar tracking loop. By implementing a self-adjusting FLC or ANN controller one can eliminate the loss of energy which occurs while applying traditional tracking loops at slow tracking rates and during oscillations due to the steady-state hunting loop. The results of simulation showed that there is a possibility to obtain good optimization parameters using an ANN structure. The tracking speed and output efficiency of the technique considered here are very optimal for variable atmospheric conditions.

From this study it can also be suggested that open-source Python development environments offer an effective and highly flexible platform for modeling complex power electronic systems. Libraries like NumPy, Pandas, scikit-fuzzy and Tensor-Flow enable researchers to simulate physical systems and train machine learning algorithms in a single working environment. The future work can be the implementation of the obtained intelligent control models on microcontrollers so that they can test their abilities under real weather conditions. Interest will also be on hybrid structures combining the reliability of training-free fuzzy logic algorithms with the rapid response performance of neural networks.

9. Appendix: Complete Python Simulation Implementation

```
import numpy as np
import pandas as pd
```

```

class PhotovoltaicModule:
    """Mathematical instantiation of a single-diode solar cell framework."""
    def __init__(self, n=1.2, r_s=0.05, r_sh=500.0, i_sc_stc=8.5, v_oc_stc=44.0):
        self.n = n
        self.r_s = r_s
        self.r_sh = r_sh
        self.i_sc_stc = i_sc_stc
        self.v_oc_stc = v_oc_stc
        self.k_b = 1.380649e-23
        self.q = 1.60217663e-19
        self.t_ref = 298.15
        self.g_ref = 1000.0

    def calculate_current(self, v, g, t_c):
        t_kelvin = t_c + 273.15
        v_t = (self.k_b * t_kelvin) / self.q
        i_ph = (self.i_sc_stc + 0.005 * (t_kelvin - self.t_ref)) * (g / self.g_ref)
        i_o = 1e-9 * (t_kelvin / self.t_ref)**3 * np.exp((self.q * 1.12) / (self.n * self.k_b) * (1/self.t_ref - 1/t_kelvin))

        # Transcendental solution via Newton-Raphson iteration
        i_curr = i_ph
        for _ in range(25):
            expr = (v + i_curr * self.r_s) / (self.n * v_t)
            f_i = i_ph - i_o * (np.exp(expr) - 1.0) - (v + i_curr * self.r_s) / self.r_sh - i_curr
            f_prime = -i_o * (self.r_s / (self.n * v_t)) * np.exp(expr) - (self.r_s / self.r_sh) - 1.0
            i_next = i_curr - f_i / f_prime
            if abs(i_next - i_curr) < 1e-5:
                break
            i_curr = i_next
        return max(0.0, i_curr)

class FuzzyLogicController:
    """Heuristic rule-based MPPT controller maximizing transient track metrics."""
    def __init__(self):
        self.e_prev = 0.0
        self.p_prev = 0.0
        self.v_prev = 20.0

    def evaluate_mppt(self, v_meas, i_meas):
        p_meas = v_meas * i_meas
        dv = v_meas - self.v_prev
        dp = p_meas - self.p_prev

        if abs(dv) < 1e-4:
            e = 0.0
        else:
            e = dp / dv

        de = e - self.e_prev

        # Simple linguistic approximation for execution speed inside core simulation
        if abs(e) < 0.1:
            delta_d = 0.0
        elif e > 0.0:
            delta_d = 0.01 if de > 0 else 0.005
        else:

```

```

        delta_d = -0.01 if de < 0 else -0.005

    self.v_prev = v_meas
    self.p_prev = p_meas
    self.e_prev = e
    return delta_d

if __name__ == "__main__":
    # 1. Initialize our structures
    pv = PhotovoltaicModule()
    flc = FuzzyLogicController()

    # 2. Setup simulation parameters (100 Hz -> dt = 0.01s for 2 seconds)
    dt = 0.01
    time_steps = np.arange(0.0, 2.0, dt)
    results = []

    # Initial states
    v_meas = 20.0 # Starting voltage tracking point
    t_c = 25.0    # Constant cell temperature (Celsius)

    # 3. Core execution thread loop
    for t in time_steps:
        # Step change condition matching Figure 5
        g = 1000.0 if t < 1.0 else 600.0

        # Calculate current response from the non-linear physics engine
        i_meas = pv.calculate_current(v_meas, g, t_c)
        p_meas = v_meas * i_meas

        # Save metrics to historical array
        results.append({
            "Time": t,
            "Irradiance": g,
            "Voltage": v_meas,
            "Current": i_meas,
            "Power": p_meas
        })

```

```

# Invoke tracking controller to obtain the voltage step modifier
delta_d = flc.evaluate_mppt(v_meas, i_meas)

# Update the active terminal voltage for the next iteration step
# (Emulating converter duty cycle adjustment effect on panel voltage)
v_meas += delta_d * 100 # Scaling factor to translate duty cycle change to voltage step
v_meas = max(0.0, min(v_meas, pv.v_oc_stc)) # Bound within safe physical limits

# 4. Export to Pandas DataFrame for analysis as stated in your text
df = pd.DataFrame(results)
print("Simulation complete! Data Log Preview:")
print(df.head(10))

```

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