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Fuzzy T-S Observer Control for Maximum Power Point Tracking in PV Systems under Dynamic Weather Conditions

Fernando Diaz¹, Lucia Morales^{1*}, Diego Perez², Valeria Soto¹

Abstract

In this study, an observer-based fuzzy controller design approach is presented to enhance the efficiency and performance of a photovoltaic (PV) system. The targeted controller is developed by integrating linear matrix inequalities (LMIs). The system comprises a photovoltaic generator (PVG) linked to a boost converter, with a battery connected to the converter to store surplus energy for later utilization. A fuzzy controller incorporating a Takagi–Sugeno (T–S) fuzzy observer is proposed, ensuring predefined performance levels while achieving maximum power point tracking (MPPT) under varying weather conditions. To maintain maximum power operation, the system must follow an optimal trajectory. For this purpose, a dedicated reference fuzzy model is introduced to generate the desired trajectories. This technique enables accurate replication of the system dynamics across a wide operating range. Overall, the T–S fuzzy framework proposed in this paper aims to maximize energy recovery during battery charging under partially shaded conditions, thereby achieving higher system efficiency. The suggested approach is implemented and simulated in MATLAB/SIMULINK, with realistic reference trajectories applied while accounting for climatic variations. Simulation analysis, along with comparisons with two widely adopted methods, demonstrates that the proposed strategy successfully reduces tracking time and eliminates the oscillations typically observed around the maximum power point (MPP).

Keywords Photovoltaic system (PV), Observer-based fuzzy controller, Linear matrix inequalities (LMIs), Maximum power point tracking (MPPT)

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Introduction

The long-term sustainability and advancement of human society depend heavily on the availability of energy [1]. Growing attention has been directed toward various renewable energy sources and associated storage technologies [2]. Thanks to its abundant availability and minimal environmental impact, solar energy (particularly photovoltaic power systems [3]) has emerged as a highly favored option for sustainable development. It represents a practical solution for low-power applications in remote areas that are difficult or costly to connect to utility grids or that are supplied by small-scale generators. It is equally well-suited for diverse applications, such as solar-powered vehicles, water-pumping systems, and telecommunications infrastructure [4]. Nevertheless, electricity from photovoltaic systems tends to be more costly than grid-supplied power, which is derived from multiple conventional sources, primarily due to the necessary equipment [5].

It is important to recognize that a photovoltaic module exhibits multiple maximum power points, which vary with irradiance and temperature, due to the nonlinear relationship between voltage and current. Consequently, a control technique known

as maximum power point tracking (MPPT) has been developed to improve the efficiency of solar energy extraction. Variations in ambient temperature and solar irradiance significantly affect the power output of photovoltaic systems, leading to the development of numerous MPPT algorithms tailored to different applications. These trackers vary in cost, complexity, application range, sensor needs, convergence rate, and hardware compatibility. They can generally be grouped into three main classes: computational methods, artificial intelligence techniques, and hill-climbing approaches [6–8]. Among the most widely adopted and effective methods are perturbation and observation (P&O), incremental conductance (IC) [9], voltage scanning, the $0.8V_{oc}$ technique, and artificial neural network (ANN)-based strategies. While each method involves compromises among efficiency, tracking speed, and implementation complexity, they perform well in specific scenarios. As noted by Alabedin *et al.* [10], voltage scanning is a conventional technique that determines the maximum power point by evaluating voltage levels. It achieves moderate efficiency, typically around 85% [10], with correspondingly average settling time due to the relatively slow scanning procedure. Its primary strength lies in its simplicity, requiring no complex algorithms. The incremental conductance (IC) method adjusts the operating point based on changes in conductance, providing greater accuracy and faster adaptation to irradiance fluctuations, with efficiency reaching approximately 90% [11]. Its quick response to environmental changes results in short stabilization times, although it is somewhat more complex than voltage scanning, despite involving relatively simple computations.

In comparison, the P&O method tracks the MPP by applying small perturbations to the solar generator's voltage or current and comparing the resulting power to the previous value. This intuitive approach ties overall system efficiency to the balance between oscillation around the MPP and tracking speed [12]. Reducing the perturbation step size can lessen fluctuations but slow down the MPPT process. Furthermore, Dorofte *et al.* [13] report that the $0.8V_{oc}$ method, while straightforward to implement, suffers from long settling times and moderate efficiency of about 82% because it lacks dynamic adjustment to changing irradiance. In addition, several advanced control techniques have been explored to address these limitations, including enhanced incremental conductance [11], improved P&O [12], and adaptive P&O variants [14]. Such algorithms prove effective for MPP tracking under uniform irradiance conditions. However, a shared limitation across these conventional methods is the presence of steady-state oscillations and reduced efficiency near the MPP. Another critical challenge is their limited ability to locate the Global Maximum Power Point (GMPP) in photovoltaic arrays under partial shading conditions (PSC) [15], resulting in diminished system performance and lower energy yield.

On the other hand, MPPT control has advanced considerably through the adoption of advanced techniques such as artificial neural networks (ANNs). ANNs leverage both historical and real-time data to determine the reference point precisely. They achieve a high efficiency of 98.6% and respond rapidly to environmental changes, resulting in rapid stabilization. Nevertheless, this level of precision and responsiveness entails substantial complexity, due to the significant computational resources required and the neural network's prior training phase. Moreover, ANNs require sophisticated control mechanisms, further increasing implementation costs and overall complexity. In practical applications, photovoltaic panels are frequently connected in series. Consequently, when certain modules experience partial shading from objects such as clouds or buildings, the voltage and current of the entire string are reduced, resulting in a substantial decline in overall system performance [16, 17]. This issue is particularly relevant for solar arrays mounted on the roofs of electric vehicles or drones, where partial shading markedly diminishes total power output and thus reduces energy generation. Owing to the presence of bypass diodes, PV panels subjected to non-uniform irradiance under partial shading conditions (PSC) exhibit multiple peaks on the P–V characteristic curve [18]. Therefore, an effective MPPT technique capable of enabling PV arrays to operate at the global maximum power point (GMPP) under PSC is highly desirable.

Furthermore, in recent years, optimization researchers have drawn inspiration from the natural behaviors of various living organisms. For example, foraging and mating patterns in insects [19], flight and foraging behaviors in birds [20], and other animal characteristics [21] have given rise to numerous bio-inspired optimization algorithms. As a result, a range of such methods—including ant colony optimization [19], firefly algorithm, gray wolf optimization [21], and others—have been applied to enhance the efficiency of PV systems. Among these, particle swarm optimization (PSO) stands out as one of the most widely adopted MPPT techniques owing to its simplicity [22]. However, a common limitation in many PSO-based MPPT studies is their relatively slow convergence rate. More recently, hybrid approaches that integrate MPPT algorithms with neural network techniques have been introduced by Kumar *et al.* [23] and Eshak *et al.* [24] to mitigate this drawback.

Nonetheless, their practical applicability remains under debate. Indeed, as highlighted by Li *et al.* [22], the performance of these MPPT methods based on optimization algorithms is heavily influenced by tuning parameters and the initial particle distribution. In the referenced literature, efforts are made to increase the algorithm's randomness and exploration capabilities to avoid trapping at a local maximum power point (LMPP) and to improve tracking speed. Although some studies evaluate MPPT techniques under PSC within specific voltage ranges, works by Kermadi *et al.* [25], Celikel [26], Kermadi *et al.* [27], and Mansoor *et al.* [28] have also investigated global maximum power points across different voltage regions under complex partial shading patterns. These contributions share a common emphasis on sophisticated maximum power point search strategies that account for intricate partial shading variations, often employing optimized global tracking algorithms or bio-inspired optimization methods. Such approaches better address challenges arising from sudden changes in irradiance and voltage, delivering superior performance under dynamic environmental conditions. However, these techniques are primarily designed for stationary PV installations where shading patterns do not change abruptly or frequently. This contrasts sharply with applications such as electric vehicle roof-mounted systems, where an uneven distribution of solar irradiance is highly probable and evolves continuously as the vehicle moves, affecting the PV modules. In such dynamic scenarios, GMPP tracking must be both highly accurate and extremely rapid to maximize energy harvest.

To overcome the limitations outlined above, this paper introduces a comprehensive strategy to improve PV system efficiency. It relies on a fuzzy MPPT approach based on an observer that guarantees bounded estimation error. This observer is designed to rapidly and precisely identify the GMPP, even when information about the solar irradiance distribution across the modules is limited or when the PV system experiences fast-changing and continuously varying shading patterns. In recent times, a multi-model framework utilizing Takagi–Sugeno (T–S) models has been applied in the MPPT domain [29–31]. This framework decomposes the system dynamics into several operating regions, each represented by a low-order linear sub-model [32, 33]. Such modeling not only provides an accurate representation of system behavior across a broad operating range but also effectively balances model accuracy with computational complexity.

The present work builds upon and extends these prior results by proposing a complete observer-based T–S fuzzy MPPT controller strategy. This strategy enables optimal power extraction from PV panels under partial shading conditions. The PV system under investigation, illustrated in **Figure 1**, comprises two 38.25-W panels connected in series, an MPPT controller, a boost converter connected to the photovoltaic array, and a battery. This schematic depicts the configuration of the studied system, which an observer-based fuzzy controller regulates. The proposed methodology is assessed across four distinct operating scenarios: standard test conditions (STC), PSC1, PSC2, and PSC3. Its effectiveness and feasibility are evaluated by comparing it with the conventional P&O method [9] and an improved PSO-based approach under realistic simulation conditions. The suggested technique operates the system at the global MPP by accurately detecting it, guided by a reference fuzzy model that precisely determines the optimal operating voltage in accordance with the principles outlined by Allouche *et al.* [31] and Chaibi *et al.* [32].

In summary, this paper presents a method to enhance the stability and efficiency of a photovoltaic (PV) system using an observer-based fuzzy controller, underpinned by rigorous mathematical analysis based on Lyapunov functions and linear matrix inequalities (LMIs). The primary contributions of this work are as follows:

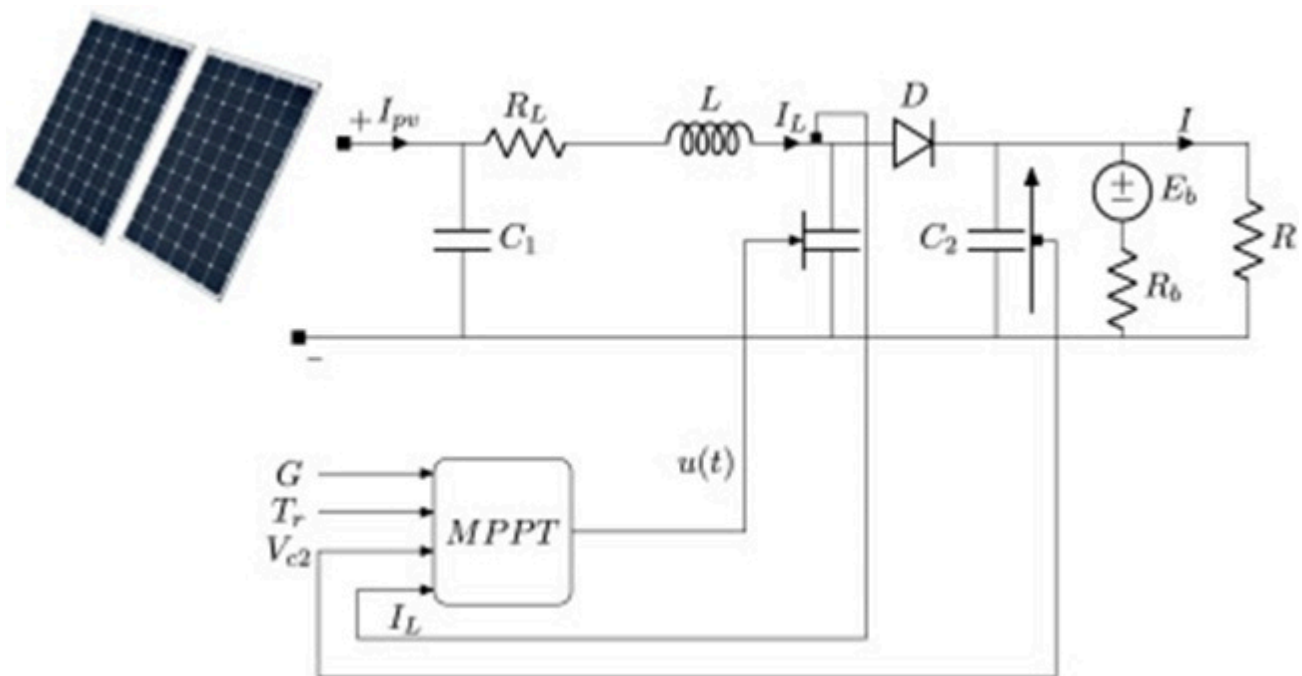


Figure 1. The photovoltaic system structure.

- Stability of the photovoltaic system is rigorously proven through Lyapunov-based analysis, ensuring robust performance despite weather-induced disturbances. This proof relies on feasibility conditions expressed as a set of linear matrix inequalities (LMIs).
- By estimating unmeasurable state variables, the observer drives the tracking error—defined as $(t) = (t) - \hat{x}(t)$ —asymptotically to zero, regardless of environmental changes. Optimal operation requires the system to follow a precisely defined reference path generated by a dedicated Takagi–Sugeno (T–S) reference model.
- The fuzzy tracking control problem is solved via a clear, optimization-driven procedure built entirely around LMI techniques.
- An observer-based Takagi–Sugeno fuzzy controller enables swift and accurate reaching of the maximum power point (MPPT) under highly variable meteorological conditions, while simultaneously supporting effective battery recharging during partial shading episodes.
- When benchmarked against classical techniques such as P&O and PSO, the presented solution exhibits markedly improved robustness together with superior energy harvesting capability—most notably through the virtual elimination of power oscillations in the vicinity of the MPP.

PV Cell Modeling and Partial Shading Condition

Basic characteristics of a PV cell

The photovoltaic cell constitutes the elementary component of any PV generator: it converts incident light (photons) directly into electrical power. In its idealized form, a solar cell is represented by a photocurrent source placed in parallel with a diode. Real-world effects such as internal ohmic losses and leakage paths are accounted for by adding a series resistance and a shunt resistance [34]. **Figure 2** depicts a commonly accepted equivalent circuit for a practical PV cell. Several cells are wired in series to form a photovoltaic module; multiple modules are then combined—either in series,

parallel, or both—to produce a complete PV generator that delivers the target voltage and current levels. In the associated power circuit, L stands for the inductance, D is the power diode, I_d indicates the current through the diode, $C1$ and $C2$ represent the input-side and output-side capacitors, R is the load resistance, and $u(t)$ denotes the duty ratio controlling the DC–DC boost converter.

Application of Kirchhoff's current law yields the following expression for the output current delivered by a solar PV cell:

$$I_{pv} = I_{ph} - I_{sh} - I_d = I_{ph} - I_0 \left[\exp \left(\frac{I_{pv} R_s + V_{pv}}{n K T} \right) - 1 \right] - \left(\frac{V_{pv} + R_s I_{pv}}{R_{sh}} \right) \quad (1)$$

Where:

$$K_T = \frac{KT}{q} \quad (2)$$

$$I_{ph} = (K_n (T - T_r) + I_{scr}) \left(\frac{G}{1000} \right)$$

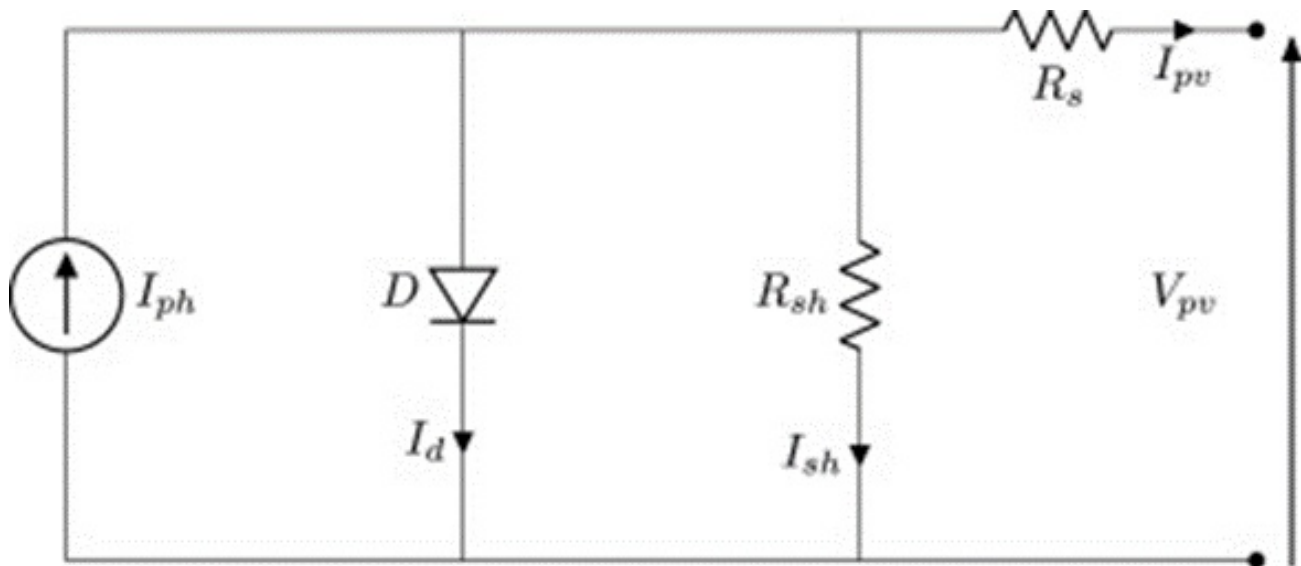


Figure 2. Equivalent circuit model of a PV cell.

I_{pv} and V_{pv} are the terminal current and voltage of the PV panel, respectively. I_{ph} symbolizes the light-generated (photocurrent) component. I_0 is the reverse-saturation current of the diode. I_{scr} and K_n represent the short-circuit current at reference conditions and its temperature coefficient, respectively. The elementary charge is $q = 1.6 \times 10^{-19}$ C and the Boltzmann constant is $K = 1.3805 \times 10^{-23}$ J/K. Throughout the text, G will indicate solar irradiance (in W/m²), and T_r will denote the reference cell temperature (in °C). Finally, R_s is the series resistance, and R_{sh} is the shunt (parallel) resistance of the cell.

The equations given below characterize the PV module analyzed in this work. The module comprises N_p strings connected in parallel, and each string consists of N_s cells connected in series.

$$I_{pv} = I_{ph} N_p - I_0 N_p \left[\exp \left(\frac{R_s I_{pv} + V_{pv}}{n K T} \right) - 1 \right] - N_p \left(\frac{V_{pv} + R_s I_{pv}}{N_s R_{sh}} \right) \quad (3)$$

Impact of partial shading on a PV array

To achieve higher power ratings, multiple solar panels are commonly configured in series-parallel combinations. Under uniform irradiance conditions—where every cell receives the same amount of solar radiation—the power-voltage (P–V) characteristic exhibits a single maximum power point (MPP). However, real-world factors such as passing clouds, building shadows, or other obstructions frequently cause substantial spatial variations in irradiance. These differences lead to a mismatch in current flow through series-connected cells, resulting in hot-spot formation and overall mismatch losses [35]. Consequently, shaded modules deliver significantly reduced current, severely limiting the efficiency and output of the affected parts of the array. Non-uniform illumination produces a multi-peak pattern in the P–V curve, as illustrated in Figure 3. Although multiple local maxima (LM) appear, only one global maximum (GM) exists. Reliably locating and tracking this global peak among several local ones demands advanced MPPT algorithms.

The current-voltage (I–V) characteristics under different irradiance levels during partial shading conditions (PSC) are presented in Figure 3a. The corresponding power-voltage (P–V) curves for the same scenarios are shown in Figure 3b. Four distinct operating cases are examined in this study: standard test conditions (STC) and three partial shading patterns labeled PSC1, PSC2, and PSC3. STC assumes a uniform irradiance of 1000 W/m² at 25 °C, whereas the PSC cases incorporate non-uniform illumination and the activation of bypass diodes. Table 1 summarizes the nominal local maximum power points (LMPP) and the global maximum power point (GMPP) values extracted from the P–V curves for each investigated PSC scenario.

Table 1. Investigated shading patterns.

Cases	Shade design	LMPP (W)	GMPP (W)
STC	[1000, 1000]	76.42	76.42
PSC1	[400, 800]	29.62	34.07
PSC2	[600, 900]	32.9	50.37
PSC3	[800, 1000]	36.29	65.44

Remark 1

Implementing numerous sensors to monitor temperature, irradiance, current, and voltage can increase the complexity of the control algorithm and elevate overall system cost, as depicted in Figure 1. Nevertheless, this multi-sensor configuration enhances the precision of MPPT tracking. Several related studies [29, 31, 32, 36, 37] have similarly incorporated multiple sensor measurements—albeit arranged differently—to enable better real-time adaptation. To ensure a fair and direct performance evaluation, the present work includes a comparative simulation of the proposed method and the approach described by El Hammoui et al. [29], thereby providing a comprehensive assessment of both energy yield and implementation cost. While additional sensors increase total costs, the resulting gains in energy conversion efficiency and system reliability often justify the added investment, especially under unpredictable meteorological conditions. Furthermore, although the works of Allouche et al. [31] and Allouche et al. [36] demonstrate practical validation of T–S fuzzy control applied to MPPT, those works do not concurrently address partial shading conditions (PSC) and the battery's state of charge (SOC). In contrast, this paper examines the influence of MPPT strategies on battery SOC during PSC episodes. It analyzes how external variables—such as temperature and irradiance—affect battery behavior in realistic operating environments.

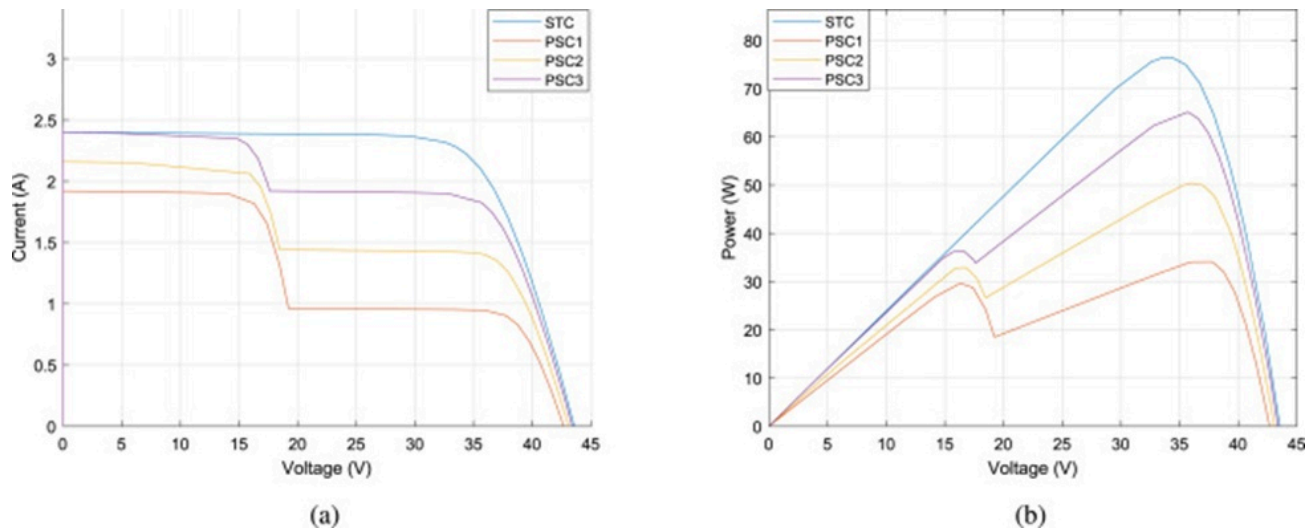


Figure 3. I–V and P–V curves under various PSC scenarios.

Boost converter (DC–DC)

A boost converter regulates the voltage delivered from the PV array to the load by varying its duty cycle (d), thereby enabling operation at the MPP. Positioned between the PV panel and the battery, the boost converter forms a key element of the studied PV system, whose overall architecture is illustrated in [Figure 1](#). The dynamic behavior of the complete boost converter circuit—connected to the battery load—can be described by two sets of linear differential equations, depending on whether the switch is in the ON or OFF state. For simplicity, when the battery reaches full charge, the MPPT control law is applied without additional battery-charging constraints. The state-space equations for the DC–DC boost converter in the “ON” state are given as follows [30]:

$$\begin{cases} \frac{dV_{pv}(t)}{dt} = \frac{1}{C_1} (I_{pv}(t) - I_L(t)) \\ \frac{dI_L(t)}{dt} = \frac{V_{pv}(t)}{L} - \frac{R_L I_L(t)}{L} \\ \frac{dV_{c2}(t)}{dt} = -\frac{V_{c2}(t)}{RC_2} \end{cases} \quad (4)$$

During the OFF period, the following equalities hold :

$$\begin{cases} \frac{dV_{pv}(t)}{dt} = -\frac{1}{C_1} (I_L(t) - I_{pv}(t)) \\ \frac{dI_L(t)}{dt} = \frac{1}{L} V_{pv}(t) - \frac{R_L I_L(t)}{L} - \frac{V_{c2}(t)}{L} \\ \frac{dV_{c2}(t)}{dt} = \frac{I_L(t)}{C_2} - \frac{V_{c2}(t)}{RC_2} \end{cases} \quad (5)$$

Where V_{pv} is the input voltage from the PV array, I_L denotes the inductor current, and V_{c2} represents the output capacitor voltage (across the battery).

When the “ON” switch is turned on, the state space equations are given as follows:

$$\dot{x}(t) = \mathcal{A}_1 x(t) + \mathcal{F}d(t) \quad (6)$$

When the switch is in the “OFF” state, the corresponding state-space equations become:

$$\dot{x}(t) = \mathcal{A}_2 x(t) + \mathcal{F}d(t) \quad (7)$$

Where:

$$\begin{aligned} \mathcal{A}_1 &= \begin{bmatrix} 0 & -\frac{1}{C_1} & 0 \\ \frac{1}{L} & -\frac{R_L}{L} & 0 \\ 0 & 0 & -\frac{1}{RC_2} \end{bmatrix}, \mathcal{F} = \begin{bmatrix} \frac{1}{C_1} \\ 0 \\ 0 \end{bmatrix}, \mathcal{A}_2 = \begin{bmatrix} 0 & -\frac{1}{C_1} & 0 \\ \frac{1}{L} & -\frac{R_L}{L} & -\frac{1}{L} \\ 0 & \frac{1}{C_2} & -\frac{1}{RC_2} \end{bmatrix}, d(t) \\ &= I_{pv}(t), \quad x(t) = \begin{bmatrix} V_{pv}(t) \\ I_L(t) \\ V_{C2}(t) \end{bmatrix}. \end{aligned}$$

Consequently, the overall dynamic model of the photovoltaic system can be expressed in the compact form:

$$\dot{x}(t) = (\mathcal{A}_1 x(t) + \mathcal{F}d(t))u(t) + (\mathcal{A}_2 x(t) + \mathcal{F}d(t))(1 - u(t)) \quad (8)$$

Or equivalently:

$$\dot{x}(t) = \mathcal{A}_2 x(t) + (\mathcal{A}_1 - \mathcal{A}_2)x(t)u(t) + \mathcal{F}d(t) \quad (9)$$

With:

$$\dot{x}(t) = \mathcal{A}_2 x(t) + \mathcal{B}(x(t)u(t)) + \mathcal{F}d(t) \quad (10)$$

Where the control input $(u) \in [0,1]$ is the duty cycle that governs the power switch.

The input matrix B is defined as:

$$\mathcal{B}(x(t)) = \begin{bmatrix} 0 \\ \frac{V_{C2}(t)}{L} \\ -\frac{I_L(t)}{C_2} \end{bmatrix}.$$

Materials and Methods

T–S fuzzy observer-based control structure

The nonlinear dynamics of the system under study can be effectively represented using Takagi–Sugeno (T–S) fuzzy models, which are recognized as universal approximators of nonlinear functions [32]. Unlike Mamdani-type fuzzy systems that rely primarily on linguistic rules [38], the consequent parameters of a T–S fuzzy controller are tunable, allowing the generation of a virtually continuous range of control gains. This flexibility enables the controller to extract the maximum available power from the solar array with minimal oscillations, even when solar irradiance or ambient temperature varies significantly.

T–S fuzzy modeling of the DC boost converter

The nonlinear dynamics of the PV system, as given in Eq. 10, are approximated using a Takagi–Sugeno (T–S) fuzzy model following the procedure described by Allouche et al. [31]. Let the premise variable be defined as $(i) = (i) > 0$, where $l = 1, 2$, and $\varphi(i)$ is confined within the interval $[\varphi_{min}, \varphi_{max}]$. Applying the identical fuzzy modeling technique presented by Allouche et al. [31], the subsequent equations provide an accurate representation of the nonlinear function (i) .

$$\begin{cases} \varphi_1(i) = V_{c2}(i) \\ \varphi_2(i) = I_L(i) \end{cases} \quad (11)$$

The degree of activation for each rule is captured by the weighting functions $\eta_{l,(\varphi(i))}$ and $\eta_{l,max(\varphi(i))}$, for $l = 1, 2$.

$$\begin{aligned} \eta_{1,min}(\varphi(i)) &= \frac{\varphi_1(i) - \varphi_{1,min}}{\varphi_{1,max} - \varphi_{1,min}}, & \eta_{1,max}(\varphi(i)) &= 1 - \eta_{1,min}(\varphi(i)) \\ \eta_{2,min}(\varphi(i)) &= \frac{\varphi_2(i) - \varphi_{2,min}}{\varphi_{2,max} - \varphi_{2,min}}, & \eta_{2,max}(\varphi(i)) &= 1 - \eta_{2,min}(\varphi(i)) \end{aligned}$$

The general expression for the membership functions h_n is derived as follows:

$$\begin{aligned} h_1(\varphi(i)) &= \eta_{1,min}(\varphi(i)) \eta_{2,min}(\varphi(i)), & h_2(\varphi(i)) &= \eta_{1,min}(\varphi(i)) \eta_{2,max}(\varphi(i)) \\ h_3(\varphi(i)) &= \eta_{1,max}(\varphi(i)) \eta_{2,min}(\varphi(i)), & h_4(\varphi(i)) &= \eta_{1,max}(\varphi(i)) \eta_{2,max}(\varphi(i)) \end{aligned}$$

where $\eta_{l,(\varphi(i))} = \eta_{l,max(\varphi(i))}$ for $\varphi(i) = \varphi_{max}$ and $\eta_{l,(\varphi(i))} = \eta_{l,min(\varphi(i))}$ for $\varphi(i) = \varphi_{min}$. $\eta_{l,(\varphi(i))}$ denote the maximum and minimum bounds of the variable, and $h(\varphi(i)) \geq 0$, for $n = 1, 2, \dots, r$ and $\sum_{n=1}^r h_n(\varphi(i)) = 1$ for all t .

$$\mathcal{B}_1 = \begin{bmatrix} 0 \\ \frac{V_{c2min}(t)}{L} \\ -\frac{I_{Lmin}(t)}{C_2} \end{bmatrix}, \quad \mathcal{B}_2 = \begin{bmatrix} 0 \\ \frac{V_{c2min}(t)}{L} \\ -\frac{I_{Lmax}(t)}{C_2} \end{bmatrix}, \quad \mathcal{B}_3 = \begin{bmatrix} 0 \\ \frac{V_{c2max}(t)}{L} \\ -\frac{I_{Lmin}(t)}{C_2} \end{bmatrix}, \quad \mathcal{B}_4 = \begin{bmatrix} 0 \\ \frac{V_{c2max}(t)}{L} \\ -\frac{I_{Lmax}(t)}{C_2} \end{bmatrix}$$

Using these membership functions, the T–S fuzzy model of the system can be formulated in the following standard form:

$$\begin{aligned} \dot{x}(t) &= \sum_{n=1}^4 h_n(\varphi(i)) [\mathcal{A}_2 x(t) + \mathcal{B}_n(t) u(t) + \mathcal{F}d(t)] \\ y(t) &= \sum_{n=1}^4 h_n(\varphi(i)) \mathcal{C}_n x(t) + \nu(t) \end{aligned} \quad (12)$$

The next result, a standard inequality frequently used in stability analysis, serves as a prerequisite for the main result presented in Theorem 1.

Lemma 1 ([39]). Given matrices X , Q , U , and $\mathcal{M}$ of compatible dimensions and a scalar ξ , the matrix inequality:

$$T + \mathcal{M}^T Q^T + Q \mathcal{M} < 0 \quad (13)$$

Holds if and only if the following condition is satisfied:

$$\begin{bmatrix} T & * \\ \xi Q^T + U \mathcal{M} & -\xi (U + U^T) \end{bmatrix} < 0$$

Remark 2

Several studies have thoroughly investigated the maximum power extraction from PV systems—both under uniform and partial shading conditions—using Mamdani-type fuzzy logic controllers [38, 40]. A primary limitation of these approaches lies in the intricate implementation of the fuzzy logic controller, which demands substantial computational resources and memory allocation. Consequently, the MPPT control strategies derived from such methods leave room for further enhancement. It has been established that certain nonlinearities inherent to the system can be effectively and accurately modeled through Takagi–Sugeno fuzzy representations based on IF-THEN rules [29, 31].

Leveraging T–S fuzzy models, the nonlinear dynamics typically encountered in MPPT control frameworks can be simplified and significantly improved [32]. The primary objective of the T–S reference model introduced in this work is to define the optimal reference trajectory for the system to track to operate at the MPP. Thanks to its superior characteristics, the T–S fuzzy controller proposed here achieves rapid convergence of the PV power toward the MPP. This fast-tracking behavior leads to a noticeable improvement in the battery's state of charge (SOC) and ensures more consistent energy production from the PV array. Furthermore, by incorporating an L2 performance criterion, the design effectively mitigates the adverse effects caused by abrupt changes in weather conditions.

MPPT reference model

The purpose of the MPP reference model is to generate a suitable reference signal that guides the tracking process. This reference model is deliberately constructed so that the variable (r) represents the desired trajectory that the system state (r) should follow to attain optimal performance. In this framework, I_{pvopt} corresponds to the ideal operating current, while u_{opt} acts as the associated control input. The dynamics of the MPP reference model are expressed as:

$$\dot{\chi}_r(t) = \mathcal{A}_r \chi_r(t) + r(t) \quad (14)$$

With:

$$\mathcal{A}_r = \begin{bmatrix} 0 & -\frac{1}{C_1} & 0 \\ \frac{1}{L} & -\frac{R_L}{L} & -\frac{1}{L}(1-u_{opt}) \\ 0 & \frac{1}{C_2}(1-u_{opt}) & -\frac{1}{RC_2} \end{bmatrix}, \quad r(t) = \begin{bmatrix} \frac{I_{pvopt}}{C_1} \\ 0 \\ 0 \end{bmatrix}, \quad u_{opt} = \sqrt{\frac{V_{pvopt}}{RI_{pvopt}}}$$

To represent the nonlinear reference equation (14), two fuzzy rules are defined using the premise variable $\varphi_r = 1 - u_{opt}$:

Rule 1: IF $\varphi_r(t)$ is N_{min} THEN $\dot{\chi}_r(t) = \mathcal{A}_{r1}\chi_r(t) + r(t)$

Rule 2: IF $\varphi_r(t)$ is N_{max} THEN $\dot{\chi}_r(t) = \mathcal{A}_{r2}\chi_r(t) + r(t)$

The corresponding membership functions and normalized weighting functions are computed according to the following expressions:

$$h_1(\varphi_r(t)) = N_{min}(\varphi_r(t)) = \frac{\varphi_r(t) - \varphi_{r,min}}{\varphi_{r,max} - \varphi_{r,min}}, \quad h_2(\varphi_r(t)) = N_{max}(\varphi_r(t)) = 1 - h_1(\varphi_r(t))$$

The state-space matrices of the reference model are specified as:

$$\mathcal{A}_{r1} = \begin{bmatrix} 0 & -\frac{1}{C_1} & 0 \\ \frac{1}{L} & -\frac{R_L}{L} & -\frac{1}{L}\varphi_{r,min} \\ 0 & \frac{1}{C_2}\varphi_{r,min} & -\frac{1}{RC_2} \end{bmatrix}, \quad \mathcal{A}_{r2} = \begin{bmatrix} 0 & -\frac{1}{C_1} & 0 \\ \frac{1}{L} & -\frac{R_L}{L} & -\frac{1}{L}\varphi_{r,max} \\ 0 & \frac{1}{C_2}\varphi_{r,max} & -\frac{1}{RC_2} \end{bmatrix},$$

And the complete T–S fuzzy reference model is given by:

$$\dot{\chi}_r(t) = \sum_{l=1}^2 h_l(\varphi_r(t)) [\mathcal{A}_{rl}\chi_r(t) + r(t)] \quad (15)$$

T–S fuzzy observer-based controller design

In practical applications, not all system states can be directly measured, making the design of a state observer essential for accurate estimation. This section introduces a Takagi–Sugeno (T–S) fuzzy Luenberger-type observer with the following proposed structure:

$$\begin{cases} \dot{\hat{x}}(t) = \sum_{n=1}^r h_n(\varphi(t)) (\mathcal{A}_2 \hat{x}(t) + \mathcal{B}_n u(t) + L_n (y(t) - \hat{y}(t))) \\ \hat{y}(t) = \mathcal{C} \hat{x}(t) \end{cases} \quad (16)$$

Where L_n represents the observer gain matrix to be determined, $\hat{x}(t)$ denotes the estimated state vector, and $\hat{y}(t)$ is the estimated output. The primary objective is to guarantee that, irrespective of variations in weather conditions, the state estimation error $e(t) = x(t) - \hat{x}(t)$ asymptotically converges to zero.

Subtracting the observer dynamics from the plant model given in Eqs. 12 and 16 yields the error dynamics:

$$\dot{e}(t) = \sum_{n=1}^4 h_n(\varphi(t)) [(\mathcal{A}_2 - L_n \mathcal{C}_m) e(t) + \mathcal{F} d(t) - L_n \nu(t)]. \quad (17)$$

The subsequent objective is to develop a robust fuzzy MPPT control law capable of driving the photovoltaic array to operate as closely as possible along its optimal maximum-power trajectory. This performance must remain robust against parameter uncertainties and environmental disturbances arising from changing climatic conditions. To achieve this, the tracking problem is recast as a fuzzy state-feedback control problem, and the proposed control law takes the following form:

$$u(t) = \sum_{m=1}^4 h_m(\varphi(t)) K_m (\hat{x}(t) - \chi_r(t)) \quad (18)$$

Where K_m is the feedback gain matrix to be synthesized. Substituting the control law (18) into the fuzzy plant model (12) results in the closed-loop augmented system described by:

$$\dot{\zeta}(t) = \sum_{n=1}^4 \sum_{m=1}^4 \sum_{l=1}^2 h_n(\varphi(t)) h_m(\varphi(t)) h_l(\varphi_r(t)) [\bar{A}_{nml} \zeta(t) + \bar{E}_n \bar{d}(t)] \quad (19)$$

Where:

$$\begin{aligned} \zeta(t) &= \begin{bmatrix} e(t) \\ x(t) \\ \chi_r(t) \end{bmatrix}, \quad \bar{d}(t) = \begin{bmatrix} \nu(t) \\ d(t) \\ r(t) \end{bmatrix}, \quad \bar{E}_n(t) = \begin{bmatrix} -L_n & E & 0 \\ 0 & E & 0 \\ 0 & 0 & I \end{bmatrix}, \quad \bar{A}_{nml} \\ &= \begin{bmatrix} \mathcal{A}_2 - L_n \mathcal{C}_m & 0 & 0 \\ -\mathcal{B}_n K_m & \mathcal{A}_2 + \mathcal{B}_n K_m & -\mathcal{B}_n K_m \\ 0 & 0 & \mathcal{A}_{rl} \end{bmatrix}, \end{aligned}$$

The term $r(t)$ represents the weather-dependent external input, while $d(t)$ captures the perturbation arising from variations in the input voltage, incorporating the terms I_{pvopt} and I_{pv} .

To attenuate the influence of these disturbances on the estimation and tracking performance, a $\mathbb{H}_2$ -gain performance criterion is introduced as follows, to minimize the transfer from $\bar{d}(t)$ to the regulated output ζ :

$$\int_0^\infty \zeta^T(t) \bar{\mathcal{Q}} \zeta(t) dt \leq \gamma^2 \int_0^\infty \bar{d}^T(t) \bar{d}(t) dt, \quad \bar{\mathcal{Q}} = \begin{bmatrix} \mathcal{Q} & 0 & 0 \\ 0 & I & 0 \\ 0 & 0 & I \end{bmatrix} \quad (20)$$

The structure of the weighting matrix is chosen such that attenuation is focused specifically on the tracking error (ζ).

At this stage, sufficient conditions can be established to ensure the existence of a T–S fuzzy controller of the form (18) that enables the PV system to track its maximum power trajectory with high accuracy. These conditions are formulated as linear matrix inequalities (LMIs) and are presented in the following theorem.

Theorem 1. Suppose there exist positive scalars $\alpha > 0$, $\xi > 0$ and matrices $P_{11} > 0$, P_{33} , U , N_n (with $n = 1, 2, \dots, 4$) such that the following linear matrix inequalities (LMIs) hold:

$$\Pi_{nml} < 0, \quad l = 1, 2 \quad (21)$$

$$\Pi_{nml} + \Pi_{mnl} < 0, \quad l = 1, 2, \quad n = 1, \dots, r-1, \quad m = n+1, \dots, r \quad (22)$$

Where:

$$\Pi_{nml} = \begin{bmatrix} \Gamma_{nml} & \Theta_{nm} \\ * & -\xi(U + U^T) \end{bmatrix} \quad (23)$$

$$\Gamma_{nml} = \begin{bmatrix} \Gamma_{11nm} & \Gamma_{12nm} & 0 & -\lambda_{11}R_n & P_{11}E & 0 \\ * & \Gamma_{22nm} & \Gamma_{23nm} & 0 & P_{22}E & 0 \\ * & * & \Gamma_{33l} & 0 & 0 & P_{33} \\ * & * & * & -\rho^2 I & 0 & 0 \\ * & * & * & * & -\rho^2 I & 0 \\ * & * & * & * & * & -\rho^2 I \end{bmatrix} \quad (24)$$

$$\Theta_{nm}^T = [-N_m \quad \xi(P_{22}\mathcal{B}_n - \lambda_{22}\mathcal{B}_n U)^T + N_m \quad -N_m \quad 0 \quad 0 \quad 0] \quad (25)$$

$$\begin{aligned} \Gamma_{11nm} &= \text{sym}\{P_{11}\mathcal{A}_2 - \lambda_{11}R_n C_m\} + \mathcal{Q} \\ \Gamma_{12nm} &= -\lambda_{22}N_m^T \mathcal{B}_n^T \\ \Gamma_{22nm} &= \text{sym}\{P_{22}\mathcal{A}_2 + \lambda_{22}\mathcal{B}_n N_m\} + I \\ \Gamma_{23nm} &= -\lambda_{22}\mathcal{B}_n N_m \\ \Gamma_{33l} &= \text{sym}\{P_{33}\mathcal{A}_{rl}\} + I \end{aligned} \quad (26)$$

Then the closed-loop system (19) is asymptotically stable and satisfies the $\mathbb{L}_2$ performance criterion (20) with guaranteed attenuation level γ . Moreover, the feedback controller gains K_m can be recovered from the relation.

$$K_m = U^{-1} N_m, m = 1, 2, \dots, r.$$

Proof. Assume that the LMIs (21)–(22) are feasible. This immediately implies that $\xi U - \xi U^T < 0$, which ensures that the matrix U is nonsingular. The LMI conditions (21)–(22) can then be equivalently rewritten in the following manner:

$$\begin{aligned} & \sum_{l=1}^2 h_l \left[\sum_{n=1}^4 h_n^2 \Psi_{nml} + \sum_{n=1}^3 \sum_{m=i+1}^4 h_n h_m [\Psi_{nml} + \Psi_{mnl}] \right] \\ & = \sum_{l=1}^2 \sum_{n=1}^4 \sum_{m=1}^4 h_l h_n h_m \Psi_{nml} < 0 \end{aligned} \quad (27)$$

This congruence holds if and only if

$$\Pi_{nml} = \begin{bmatrix} \Gamma_{nml} & \Theta_{nm} \\ * & -\xi(U + U^T) \end{bmatrix} < 0 \quad (28)$$

Where the matrices Γ_{nml} and Θ_{nml} are given by expressions (24) and (25), respectively, invoking Lemma 1 yields the equivalent condition.

$$\Gamma_{nml} + \text{sym} \left\{ \begin{bmatrix} 0 \\ P_{22} \mathcal{B}_n - \lambda_{22} \mathcal{B}_n U \\ 0 \\ 0 \\ 0 \\ 0 \end{bmatrix} \times U^{-1} \begin{bmatrix} -N_m & N_m & -N_m & 0 & 0 & 0 \end{bmatrix} \right\} < 0 \quad (29)$$

From relation Eq. 29, it follows that.

$$\Gamma_{nml} + \begin{bmatrix} 0 & \bar{T}_{12nm} & 0 & 0 & 0 & 0 \\ * & \bar{T}_{22nm} & \bar{T}_{23nm} & 0 & 0 & 0 \\ * & * & 0 & 0 & 0 & 0 \\ * & * & * & 0 & 0 & 0 \\ * & * & * & * & 0 & 0 \\ * & * & * & * & * & 0 \end{bmatrix} < 0 \quad (30)$$

With:

$$\begin{aligned} \bar{T}_{12nm} &= -N_m^T U^{-T} (P_{22} \mathcal{B}_n - \lambda_{22} \mathcal{B}_n U)^T \\ \bar{T}_{22nm} &= \text{sym} \{ (P_{22} \mathcal{B}_n - \lambda_{22} \mathcal{B}_n U) U^{-1} N_m \} \\ \bar{T}_{23nm} &= (P_{22} \mathcal{B}_n - \lambda_{22} \mathcal{B}_n U) U^{-1} N_m \end{aligned}$$

Substituting the definition of Γ_{nml} from Eq. 24 into Eq. 30 and performing the change of variables $N_m = UK_m$, $P_{22}n = \lambda_{22}nU$, $P_{11}Ln = \lambda_{11}RnU$ leads to:

$$\begin{bmatrix} \Phi_{11nm} & \Phi_{12nm} & 0 & -P_{11}L_n & P_{11}E & 0 \\ * & \Phi_{22nm} & \Phi_{23nm} & 0 & P_{22}E & 0 \\ * & * & \Phi_{33l} & 0 & 0 & P_{33} \\ * & * & * & -\rho^2 I & 0 & 0 \\ * & * & * & * & -\rho^2 I & 0 \\ * & * & * & * & * & -\rho^2 I \end{bmatrix} < 0 \quad (31)$$

$$\begin{aligned} \Phi_{11nm} &= \text{sym} \{P_{11} (\mathcal{A}_2 - L_n C_m)\} + \mathcal{Q} \\ \Phi_{12nm} &= -K_m^T \mathcal{B}_n^T P_{22} \\ \Phi_{22nm} &= \text{sym} \{P_{22} (\mathcal{A}_2 + \mathcal{B}_n K_m)\} + I \\ \Phi_{23nm} &= -P_{22} \mathcal{B}_n K_m \\ \Phi_{33l} &= \text{sym} \{P_{33} \mathcal{A}_{rl}\} + I \end{aligned} \quad (32)$$

Observe that:

$$\bar{P} = \begin{bmatrix} P_{11} & 0 & 0 \\ 0 & P_{22} & 0 \\ 0 & 0 & P_{33} \end{bmatrix},$$

Which transforms the preceding inequality into:

$$\begin{bmatrix} \text{sym} \{\bar{P} \bar{A}_{nml}\} + \bar{\mathcal{Q}} & \bar{P} \bar{E}_n \\ * & -\rho^2 I \end{bmatrix} < 0 \quad (33)$$

Now consider the quadratic Lyapunov function candidate.

$$V(\zeta(t)) = \zeta^T(t) \bar{P} \zeta(t) \quad (34)$$

Its time derivative along the trajectories of the closed-loop system is given by:

$$\begin{aligned} \dot{V}(\zeta(t)) &= \sum_{l=1}^2 \sum_{n=1}^4 \sum_{m=1}^4 h_l h_n h_m \left\{ \left[\zeta^T(t) \bar{A}_{nml}^T + \bar{d}^T(t) \bar{E}_n^T \right] \bar{P} \zeta(t) + \zeta^T(t) \bar{P} [\bar{A}_{nml} \zeta(t) + \bar{E}_n \bar{d}(t)] \zeta(t) \right\} \end{aligned} \quad (35)$$

Taking into account condition Eq. 35, whenever inequality Eq. 33 is satisfied, one readily obtains:

$$\dot{V}(\zeta(t)) + \zeta^T(t) \bar{\mathcal{Q}}\zeta(t) - \rho^2 \bar{d}^T(t) \bar{d}(t) < 0 \quad (36)$$

Integrating both sides of inequality Eq. 36 from 0 to ∞ gives:

$$\begin{aligned} \int_0^\infty \dot{V}(\zeta(t)) dt + \int_0^\infty \left(\zeta^T(t) \bar{\mathcal{Q}}\zeta(t) - \rho^2 \bar{d}^T(t) \bar{d}(t) \right) dt &= V(\zeta(\infty)) - V(\zeta(0)) \\ + \int_0^\infty \left(\zeta^T(t) \bar{\mathcal{Q}}\zeta(t) - \rho^2 \bar{d}^T(t) \bar{d}(t) \right) dt &< 0 \end{aligned}$$

Under the assumption of zero initial conditions, this establishes that the $\mathbb{L}_2$ -gain performance criterion (20) is fulfilled. This completes the proof.

Our approach leverages linear matrix inequalities (LMIs)—a mathematical tool frequently overlooked in conventional MPPT strategies—to deliver a formally rigorous solution. This added layer of mathematical robustness is essential to sustain peak performance amid fluctuating environmental conditions. By relying on these LMIs, the designed H_∞ controller achieves rapid and precise convergence toward the maximum power point even when weather parameters vary, while simultaneously strengthening the system's resilience to uncertainties. More specifically, the method provides a strict mathematical guarantee of fast and accurate tracking of the maximum power point under dynamic climatic conditions, grounded in the Lyapunov function Eq. 34 and the LMI constraints (21)–(22). An optimal operating trajectory is generated with the aid of a reference model (15) built around the ideal current I_{pvopt} . This framework, structured around IF-THEN fuzzy rules, enables regulation of PV voltage and current to maintain operation at the maximum power point. Ultimately, the T–S fuzzy controller (18) adjusts the DC–DC converter's voltage and current to optimize performance across a wide range of environmental conditions.

The distinguishing feature of this work is the explicit incorporation of linear matrix inequalities (LMIs), a feature rarely considered in traditional maximum power point tracking (MPPT) algorithms such as Perturb and Observe (P&O) or Particle Swarm Optimization (PSO). This inclusion enables the formulation of a mathematically rigorous control solution that ensures swift, accurate convergence to the MPP while markedly improving robustness against environmental uncertainties. Through the Lyapunov function, the proposed H_∞ controller is proven to deliver optimal stability and performance regardless of weather variations. The technique constructs highly effective reference trajectories using an ideal model parameterized by I_{pvopt} . Precise state estimation provided by the observer ensures that the tracking error (t) = (t) – $\hat{x}(t)$ converges asymptotically to zero irrespective of climatic changes. This advancement not only enhances overall energy capture but also virtually eliminates the persistent oscillations around the peak power point—a well-known drawback of earlier techniques. In summary, the comprehensive T–S fuzzy methodology introduced here is specifically aimed at maximizing energy harvest for efficient battery recharging under partial shading conditions, thereby elevating the overall system efficiency.

Simulation Results

Simulation settings

The performance of the proposed T–S fuzzy controller was evaluated using a 76.5-W photovoltaic system composed of two 38.25-W panels connected in series and interfaced to a storage element via a boost converter. Key characteristics of the PV system under standard test conditions (STC) are listed in Table 2. This particular setup is especially suitable for rooftop mounting on electric vehicles. The energy storage is a lead–acid battery whose state of charge (SOC) is dynamically regulated and monitored by the T–S fuzzy controller, yielding a realistic SOC evolution profile. Partial shading effects were emulated in MATLAB by applying the diverse irradiance levels specified in Table 1, which generate multi-

peak P–V characteristics. Each peak corresponds to a distinct operating voltage and power level, with the total number of peaks depending on how many string sections are affected by shading.

The power tracking behavior of different MPPT techniques under partial shading conditions (PSC) is illustrated in **Figures 4–8**. The corresponding SOC profiles for the photovoltaic storage system appear in **Figures 9–13**. Battery current (I_b) and voltage (V_b) waveforms are also presented, where negative I_b indicates charging and positive I_b indicates discharging.

The simulation parameters for the proposed boost converter are as follows: $L = 21$ mH, $C1 = 425$ μ F, $RL = 10^{-3}$ Ω , $R = 80$ Ω , $C2 = 416$ μ F. Application of the conditions stated in Theorem 1 yields a minimal $\|z\|_2$ disturbance attenuation level of $\gamma_{min} = 0.1688$, together with the computed controller and observer gain matrices:

$$\begin{aligned} K_1 &= [-0.1214 \quad -0.2779 \quad 0.9497], \quad K_2 = [-0.0644 \quad -0.0744 \quad 0.6013], \\ K_3 &= [-0.0995 \quad -0.4171 \quad 0.7856], \quad K_4 = [-0.0627 \quad -0.1787 \quad 0.5982], \\ L_1 &= \begin{bmatrix} 5.4263 \\ 0.0409 \\ 0.0298 \end{bmatrix} \times 10^3, \quad L_2 = \begin{bmatrix} 5.4179 \\ 0.0409 \\ 0.0333 \end{bmatrix} \times 10^3, \quad L_3 = \begin{bmatrix} 5.4332 \\ 0.0409 \\ 0.0291 \end{bmatrix} \times 10^3, \quad L_4 \\ &= \begin{bmatrix} 5.4226 \\ 0.0409 \\ 0.0326 \end{bmatrix} \times 10^3. \end{aligned}$$

The roof-mounted PV array of an electric vehicle is subject to highly variable shading patterns. Moreover, as the vehicle moves, its orientation and position relative to surrounding objects (buildings, trees, etc.) continuously change, thereby altering the irradiance distribution across the panels. To account for these realistic dynamics, four representative irradiance combinations were simulated for the PV system. In each scenario, a uniform temperature was assumed across all panels.

Table 2. Simulation parameters for the solar panel and battery.

Parameter	Symbol/Notation	Value
Open-circuit voltage	V_{oc}	21.8 V
Maximum power output	P_{max}	38.25 W
Voltage at maximum power	V_{mpp}	17 V
Current at maximum power	I_{mpp}	2.25 A
Short-circuit current	I_{sc}	2.4 A
Nominal battery capacity	C	200 Ah
Battery internal resistance at reference condition	RB (at 0.64×12)	7.68 m Ω
Nominal battery voltage (at reference condition)	EB (at 5×12)	60 V

Results analysis

The configuration of the photovoltaic system along with the boost converter is illustrated in **Figure 4**. **Table 1** lists the global maximum power point (GMPP) and local maximum power point (LMPP) values extracted from the P–V

characteristics under different irradiance levels. In **Figure 6**, the PV panel output power is plotted during the PSC1 scenario. Over the 3-second interval of PSC1, the conventional Perturb and Observe (P&O) method reaches an output power of 29.62 W after 0.69 s. However, it fails to locate the true GMPP and instead stabilizes at an LMPP, accompanied by noticeable steady-state oscillations around this suboptimal point. Consequently, P&O proves inadequate for accurate MPP tracking under partial shading conditions (PSC), as it tends to lock onto local rather than global maxima.

Under identical irradiance conditions during PSC1, the Particle Swarm Optimization (PSO) algorithm is applied for the same 3-second duration, achieving an output power of 32.88 W in 2.55 s. Compared with P&O, PSO delivers superior power extraction and overall performance. Nevertheless, its convergence remains slower than several other reported techniques. The extended settling time stems from the computational overhead of sampling and optimization iterations, which also introduce persistent oscillations near the GMPP. Reducing the sampling interval or adopting an alternative strategy would be necessary to suppress these oscillations while further improving power capture.

In contrast, the robust T–S fuzzy control strategy proposed in this work features a significantly shorter sampling period. Moreover, the integrated T–S fuzzy observer effectively suppresses oscillations once the GMPP is reached. During PSC1, the T–S algorithm successfully tracks the GMPP to 34.05 W in only 0.12 s, demonstrating precise, rapid global maximum power point tracking.

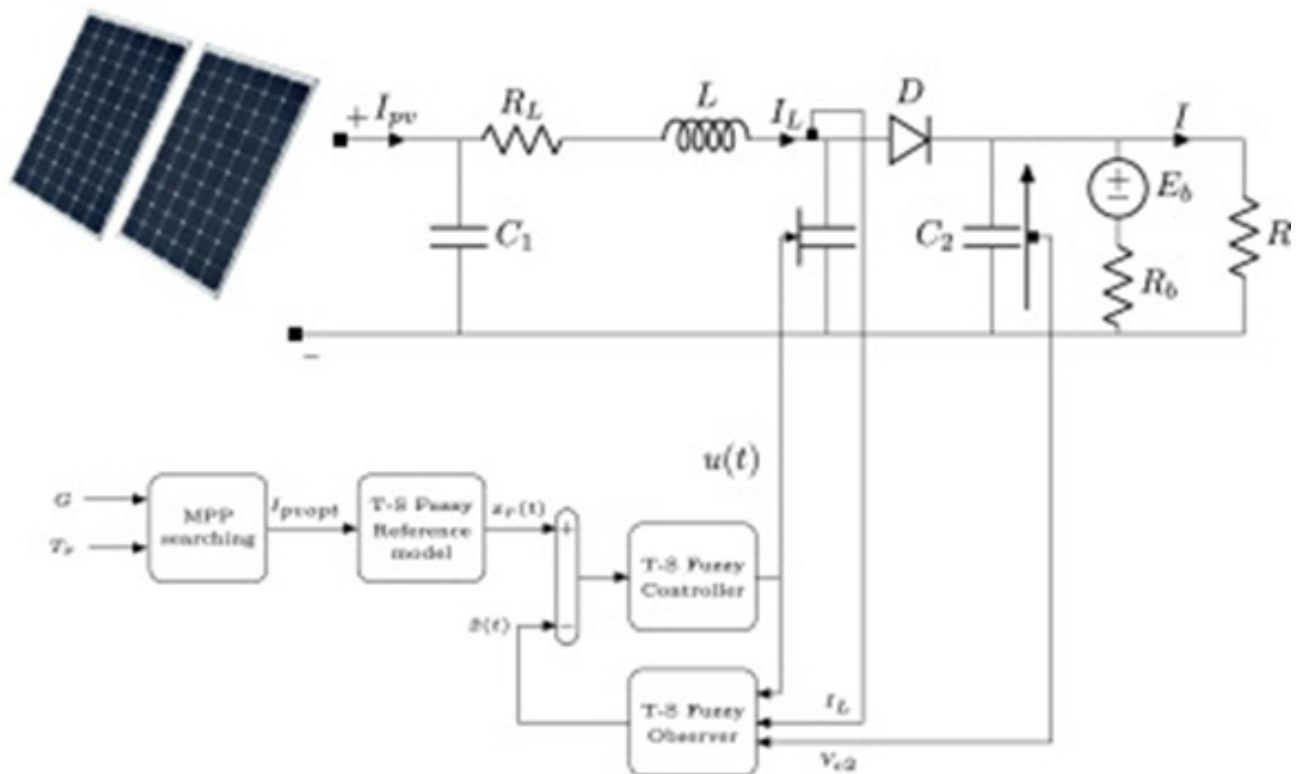


Figure 4. Architecture of the fuzzy MPPT system.

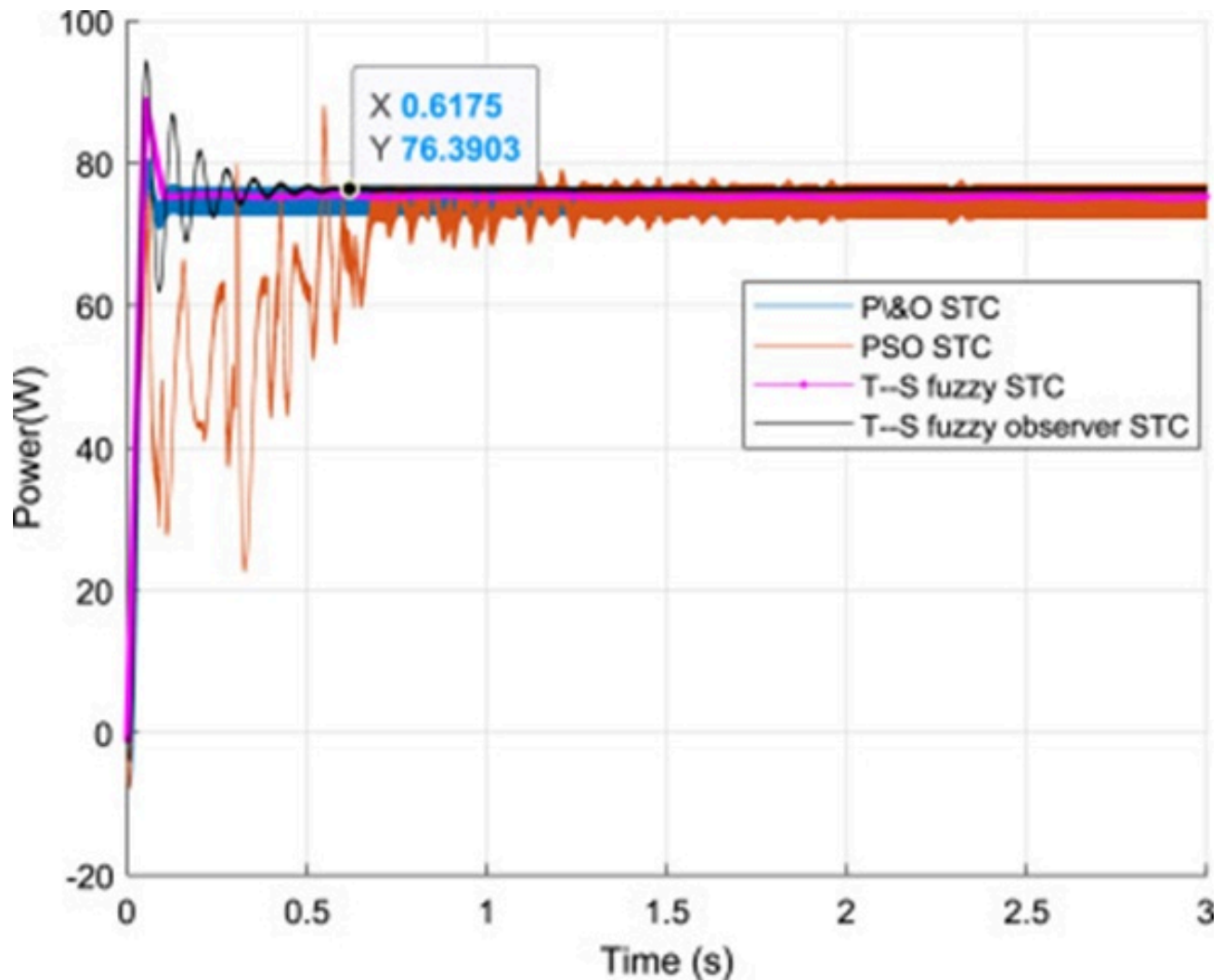


Figure 5. Closed-loop power output under standard test conditions (STC).

Additionally, **Figures 7 and 8** display the output power trajectories for all three algorithms across the tested scenarios. The superiority of the T–S fuzzy method over the benchmark approaches is clearly evident. **Table 3** confirms that the fuzzy-based algorithm consistently outperforms both PSO and P&O in terms of tracking efficiency, energy payback time across varying irradiance levels, accuracy, and response speed.

Conventional MPPT methods, such as P&O and PSO, have significant limitations, particularly under partial shading, where they struggle to identify the MPP accurately. This results in inconsistent power yield and diminished overall energy efficiency. To counteract the adverse effects of PSC, the present study employs a T–S fuzzy observer-based controller. The incorporation of linear matrix inequalities (LMIs) within this framework ensures swift convergence to the MPP, even during abrupt irradiance transitions. The proposed technique stands out for its robustness and ability to deliver stable energy output under diverse conditions. Simulation results show that the T–S fuzzy approach markedly improves energy efficiency, virtually eliminates oscillations around the MPP (reducing power losses), and achieves faster settling times and higher extraction efficiency than P&O and PSO. Ultimately, the suggested MPPT strategy reliably identifies and tracks the global maximum power point using a dedicated fuzzy reference model.

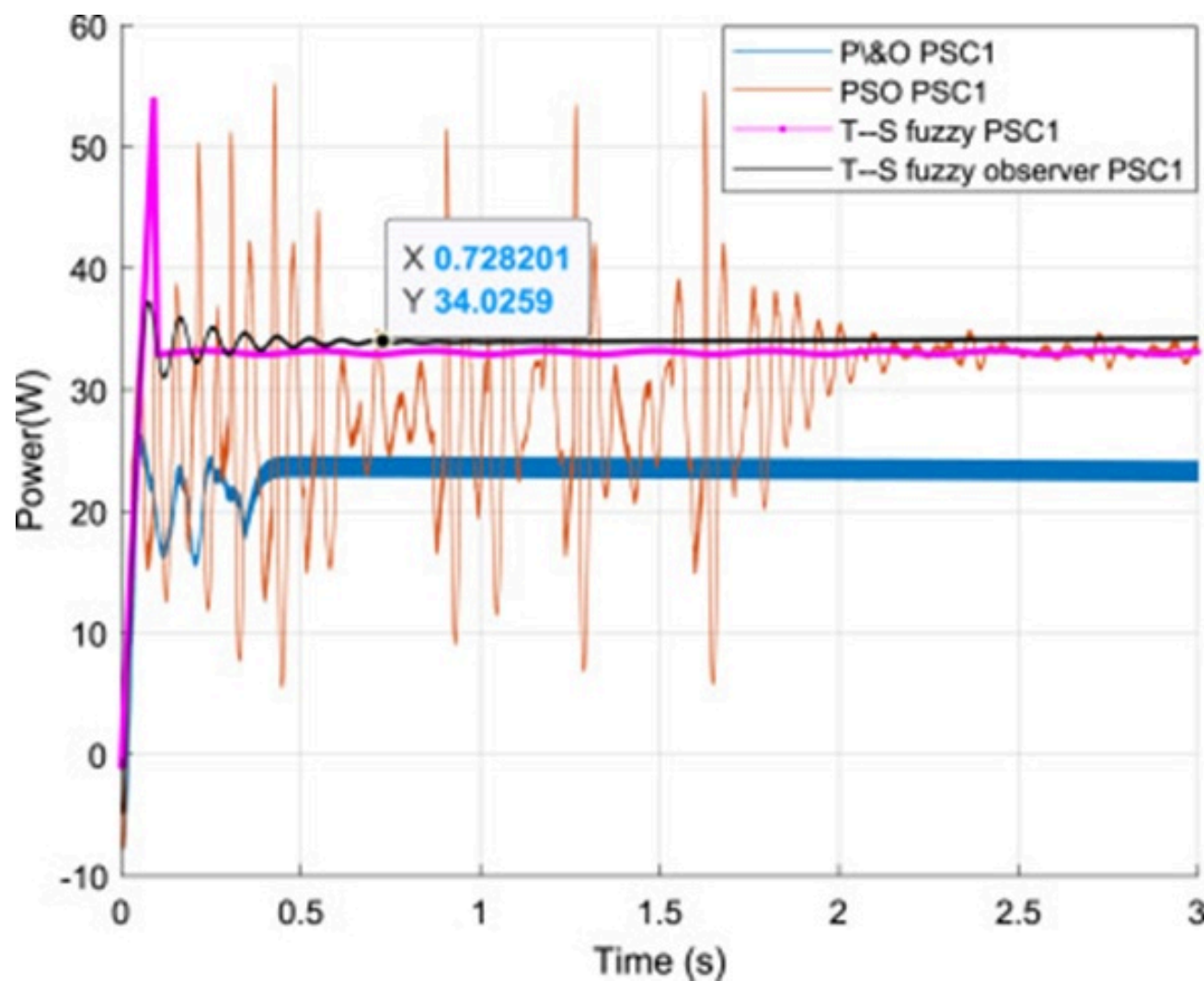


Figure 6. Closed-loop power output under PSC1.

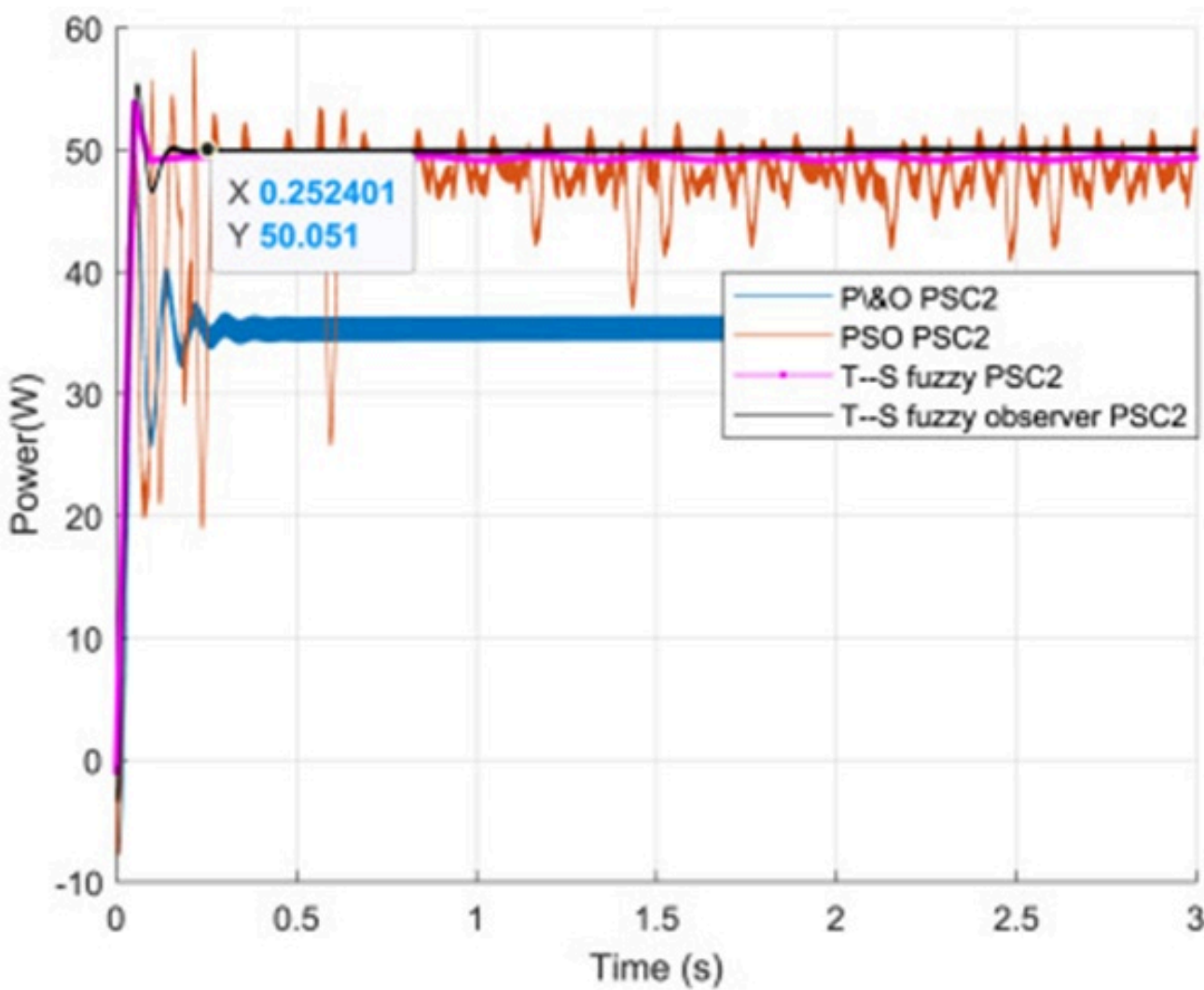


Figure 7. Closed-loop power output under PSC2.

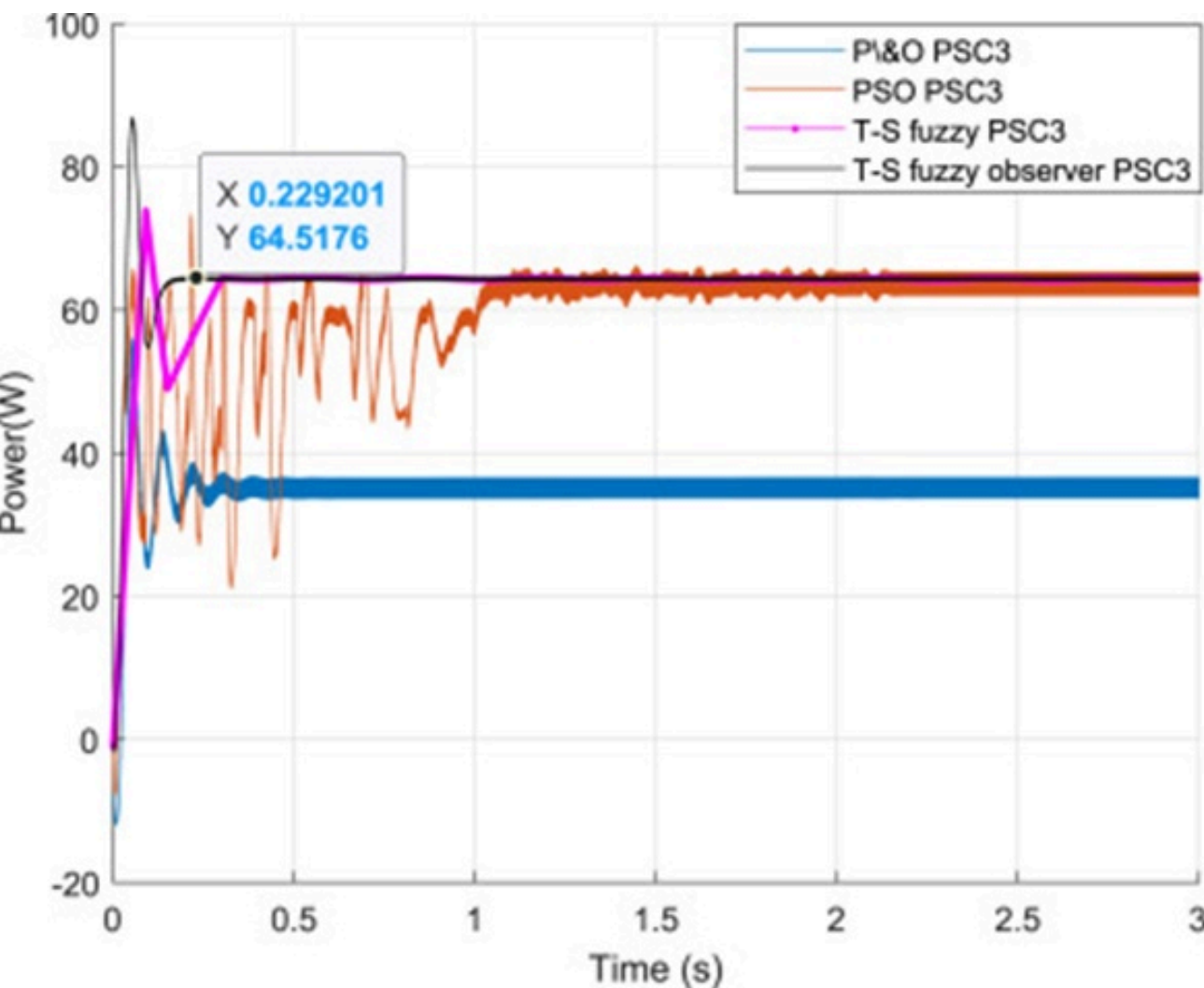


Figure 8. Closed-loop power output under PSC3.

Figures 9 and 11 present the battery voltage (V_b) and current (I_b) profiles during several partial shading cases. The irradiance variation patterns for the two-series-connected PV panels are shown in **Figure 10**. It is worth noting that the battery state of charge (SOC) varies substantially with irradiance intensity. The SOC evolution closely reflects the MPPT algorithm's effectiveness in handling PSC. The proposed method consistently selects the appropriate GMPP under partial shading, thereby maximizing the energy delivered to the battery for charging (**Table 4**).

Table 3. Performance comparison of various MPPT algorithms under partial shading conditions.

Test condition	MPPT algorithm	Theoretical maximum power (W)	Obtained power (W)	MPPT efficiency (%)	Tracks global maximum?	Tracking time (s)
STC	P&O	76.42	76.09	99.56	YES	0.2
STC	PSO	76.32	76.32	99.86	YES	1.24
STC	T–S fuzzy observer	76.41	76.41	99.99	YES	0.62
PSC1	P&O	34.07	24.44	71.73	NO	0.50

PSC1	PSO	32.88	32.88	96.50	YES	2.55
PSC1	T–S fuzzy observer	33.99	33.99	99.76	YES	0.73
PSC2	P&O	50.37	35.64	70.74	NO	0.45
PSC2	PSO	49.70	49.70	98.66	YES	3.0
PSC2	T–S fuzzy observer	50.02	50.02	99.30	YES	0.25
PSC3	P&O	65.44	36.12	55.19	NO	0.52
PSC3	PSO	64.98	64.98	99.28	YES	2.21
PSC3	T–S fuzzy observer	64.50	64.50	98.55	YES	0.22

A second set of simulations investigates the influence of ambient temperature on battery SOC during PSC. Temperature data recorded by the Moroccan National Institute of Meteorology on June 7, 2022 [41] were utilized to validate the approach. **Figure 12** depicts the temperature profile in the Fez region, Morocco, measured between 12:00 p.m. and 00:00 a.m. under predominantly clear-sky conditions. The resulting SOC profiles across different PSC scenarios and temperature levels are illustrated in **Figure 13**. It is apparent that elevated temperatures slow the rate of SOC increase, leading to prolonged charging periods.

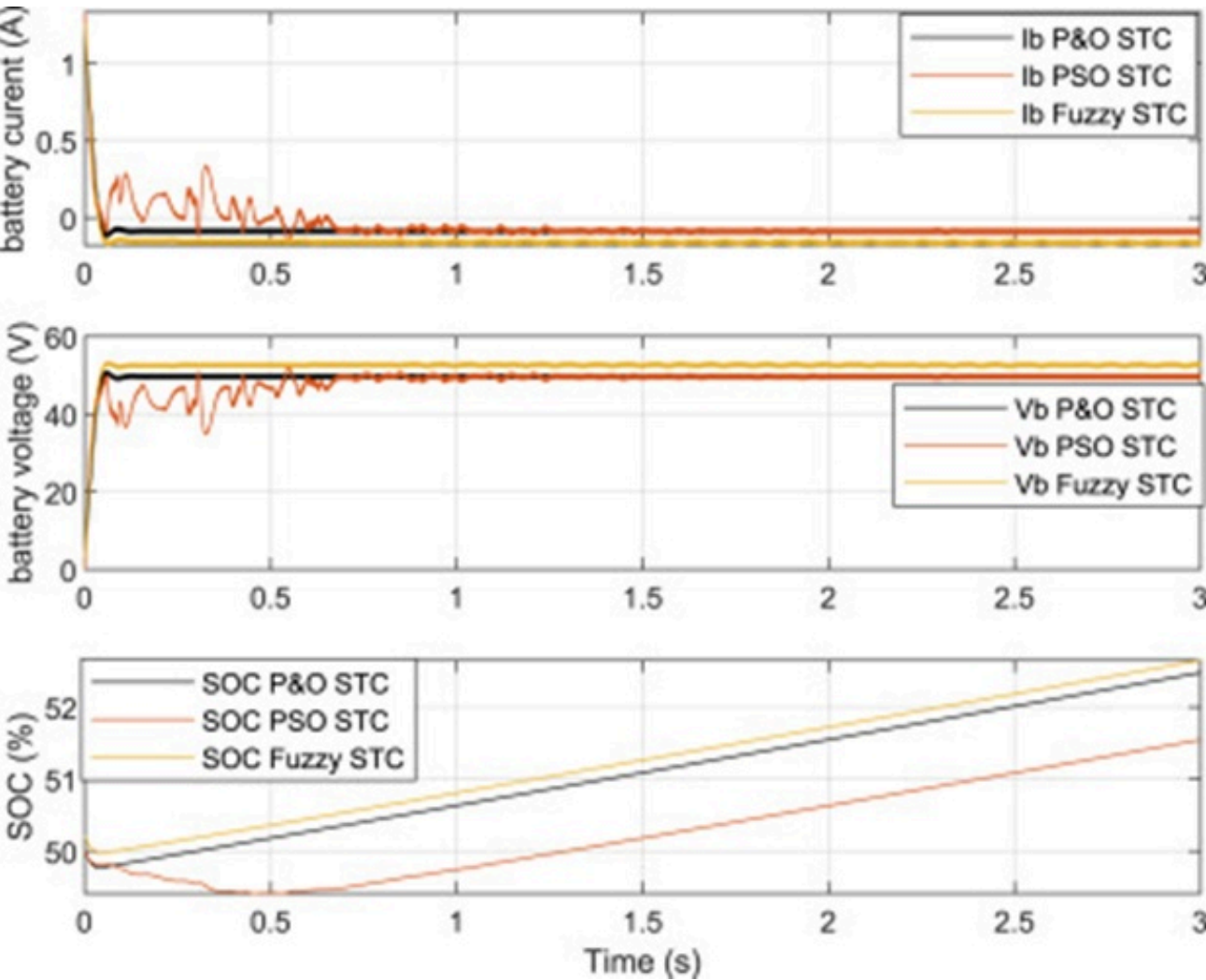


Figure 9. Battery charging curves under STC.

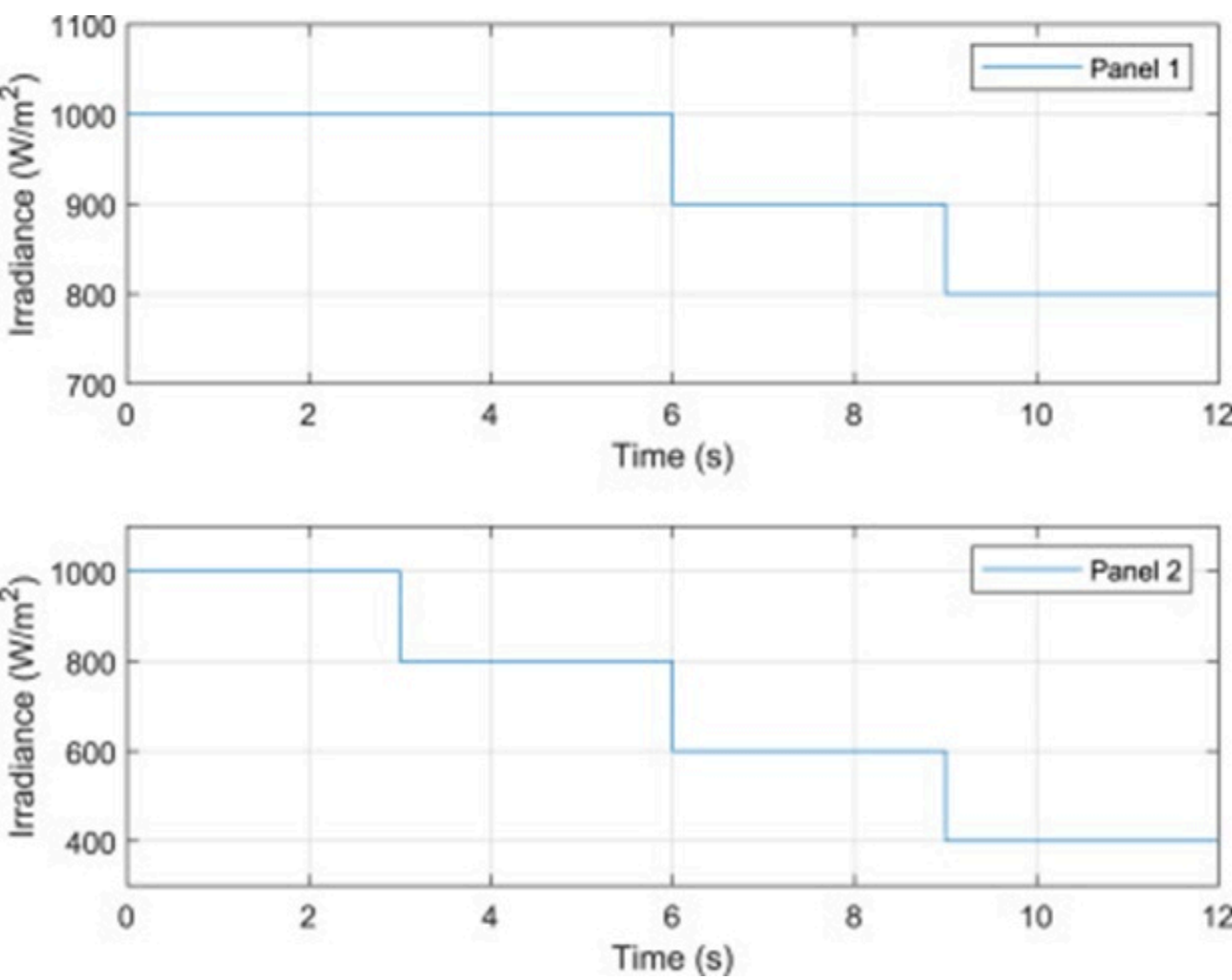


Figure 10. Stepwise irradiance variation profile for PSC cases.

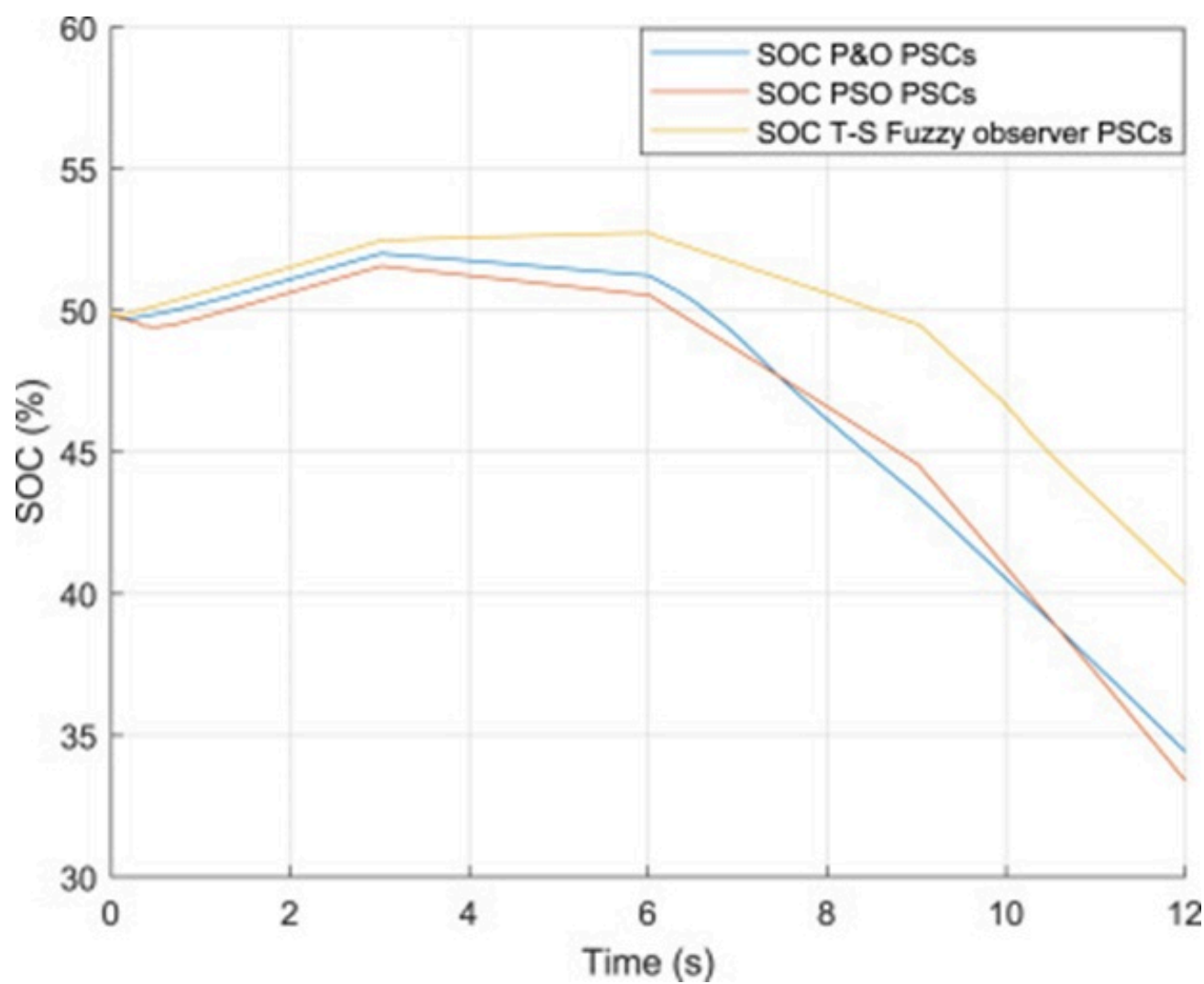


Figure 11. Battery charging curves under various PSC scenarios.

Table 4. Comparative performance of different MPPT algorithms versus the proposed T–S fuzzy observer-based MPPT.

MPPT algorithm	Complexity of implementation	Convergence speed	Tracking efficiency	Adaptability to changing conditions
P&O [42]	Easy	Varies	Very low	Medium (oscillations around the MPP)
Recursive P&O [43]	High	Moderate	High	Good (better stability compared to P&O)
INC [44]	Easy	Fast	Low	Medium (oscillations around the MPP)
0.8V [13]	Easy	Slow	Moderate	Weak (does not adapt dynamically)
ANN [45]	High	Fast	Medium	Excellent (reacts quickly)
Fuzzy logic [46]	High	Fast	Medium	Excellent (reacts quickly)

PSO [47]	Medium	Moderate	Medium	Excellent (reacts quickly)
T–S fuzzy observer	Medium	Very Fast	Very high	Excellent (reacts quickly)

The findings indicate that higher ambient temperatures substantially affect the dynamics of battery charging and discharging. As the temperature rises, the internal battery resistance increases, delaying charging and lowering overall efficiency. These results underscore the critical role of thermal management in PV-battery system design, particularly in regions prone to wide temperature swings. By contrast, the proposed T–S fuzzy observer-based method provides a clear advantage: it maintains optimal MPP tracking. It mitigates the detrimental influence of temperature variations on battery SOC more effectively than traditional techniques. Consequently, the approach ensures stable and high-efficiency energy delivery even when temperature conditions fluctuate.

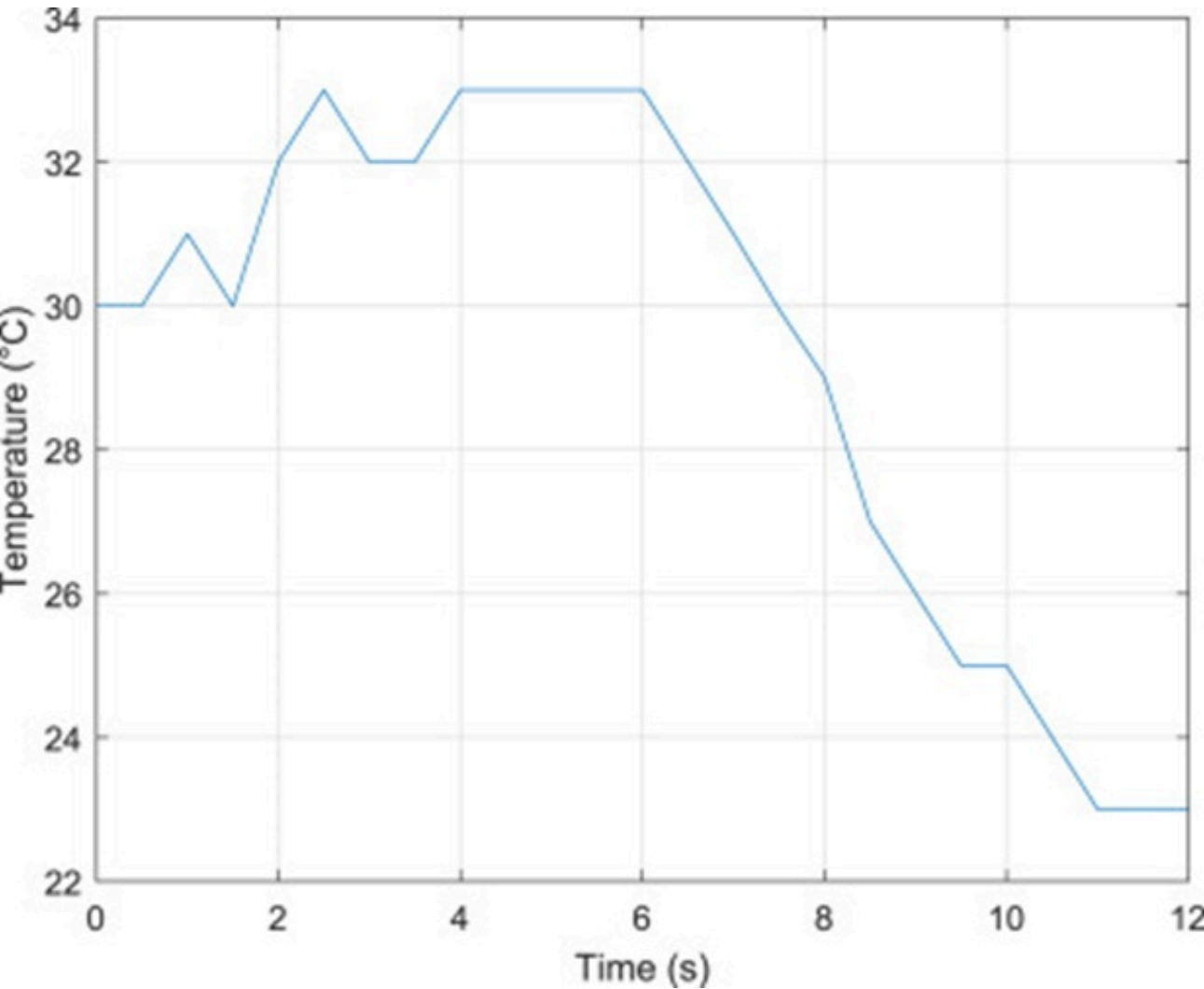


Figure 12. Temperature profile recorded in Fez, Morocco.

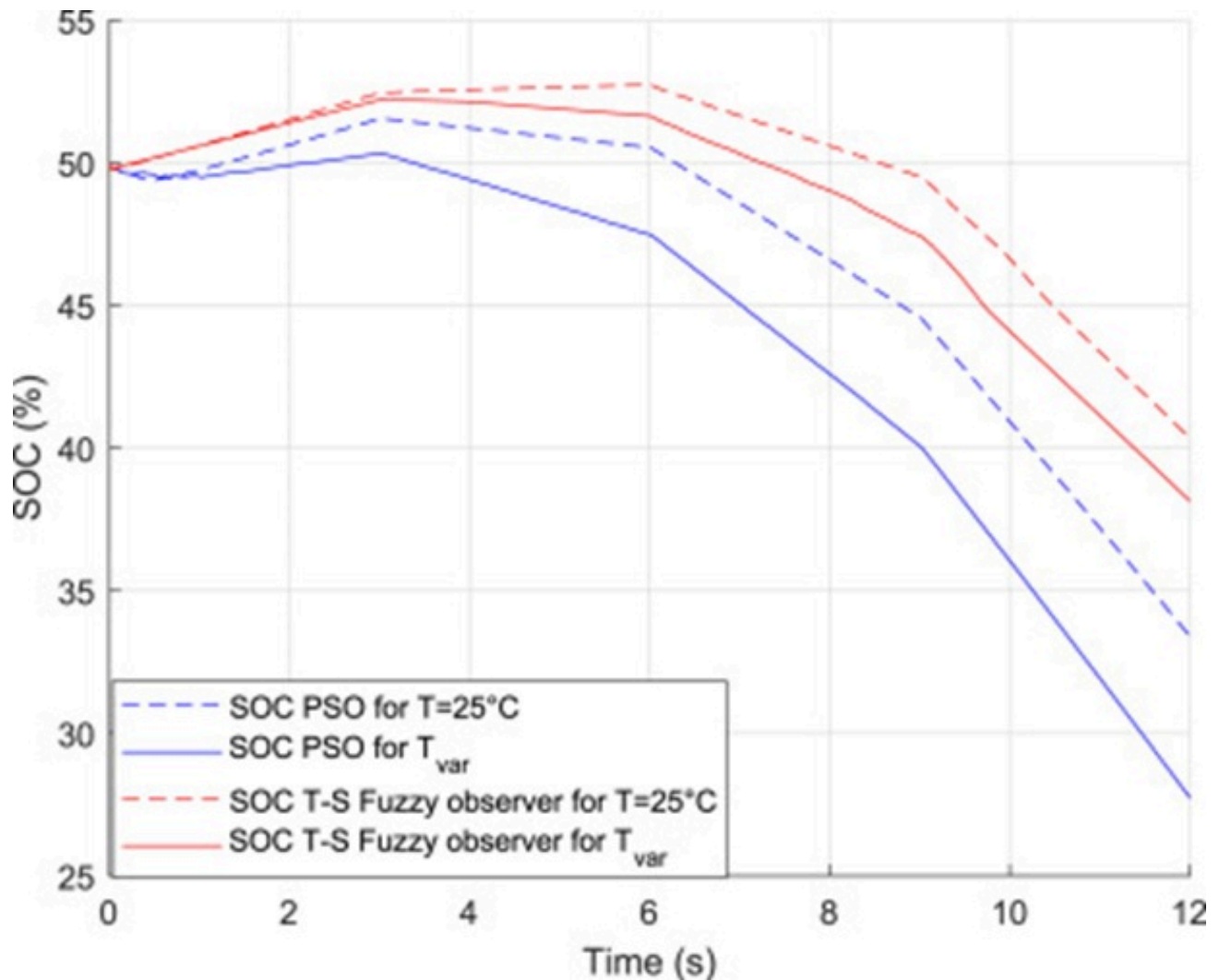


Figure 13. Impact of temperature on battery behavior during partial shading conditions.

Conclusion

This paper introduces an advanced $\mathcal{H}_2$ observer-based fuzzy controller specifically designed to track the global maximum power point (GMPP) in photovoltaic battery systems subjected to partial shading conditions (PSC). The observer and controller gains are computed in a single step by solving a set of linear matrix inequalities (LMIs), thereby ensuring the closed-loop robustness of the overall system.

The proposed fuzzy observer-based control strategy eliminates the need for direct PV current and voltage measurements as inputs. Instead, it relies on a fuzzy reference model that computes the optimal PV current I_{pvopt} and employs this reference, along with other available measured signals, to drive MPPT via a dynamic observer-based controller. Furthermore, the $\mathcal{H}_2$ performance constraint incorporated into the T–S fuzzy MPPT framework effectively suppresses the influence of external disturbances on the closed-loop behavior. By reformulating the tracking performance objective, this constraint minimizes the MPPT controller's sensitivity to environmental perturbations, such as rapid changes in climatic conditions.

The developed method achieves efficiencies of 98.55% to 99.98%, confirming its ability to maximize energy harvest across varying operating environments. It also exhibits exceptionally fast convergence, with settling times ranging from

0.22 s to 0.62 s—substantially outperforming traditional algorithms such as P&O and PSO. Validation was performed through simulations covering four representative partial shading scenarios. Even under highly dynamic conditions, the control scheme reduces tracking error to negligible levels while virtually eliminating power oscillations in all tested cases, in clear contrast to widely used conventional techniques.

Comprehensive analysis of the simulation results demonstrates that the proposed fuzzy controller surpasses optimization-based alternatives in the following key aspects:

- tracking accuracy,
- robustness against disturbances,
- convergence speed,
- computational tractability (thanks to a straightforward LMI-based optimization),
- and superior flexibility in handling data uncertainties compared with most existing approaches.

These advantages extend beyond transient performance to deliver substantial long-term gains, most notably a marked improvement in battery state of charge (SOC), thereby enhancing daily energy storage capacity. Overall, the presented technique represents a significant advancement in photovoltaic system control, promoting more efficient and sustainable exploitation of solar energy resources. While the current simulations focus on GMPP tracking under PSC within a specific voltage range, future investigations will address the more challenging problem of locating global maxima across multiple voltage regions under complex partial shading patterns.

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Conflict of interest

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