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COMBINED NEURAL NETWORK-FUZZY CONTROL STRUCTURE ENHANCING MPP TRACKING FOR A PV-BASED BATTERY CHARGER

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Abstract. *An approach based on a Takagi Sugeno (T-S) fuzzy model is used to track the maximum power point (MPP) of a photovoltaic (PV) system. Specifically, an adaptive neuro-fuzzy inference system (ANFIS) is used to identify the optimized reference current. An H_∞ fuzzy controller is subsequently derived using a set of linear matrix inequalities (LMI). This innovative control scheme demonstrates outstanding performance under various environmental conditions, leveraging training data from a dynamic model of the photovoltaic (PV) module. Even amidst changing climatic conditions, the desired control exhibits commendable performance in terms of tracking accuracy, energy gain factor, and tracking speed. Simulation results illustrate that the proposed hybrid strategy generates cost-effective power while efficiently harnessing renewable energy sources without wasting available energy. When compared to certain existing methods, the suggested strategy outperforms established maximum power point tracking (MPPT) algorithms (e.g., P/O and ANN). Consequently, the proposed approach ensures the most feasible energy harvest for charging a lithium-ion battery under non-uniform environmental circumstances.*
Keywords: Takagi Sugeno (T-S) fuzzy systems, Maximum power point tracking (MPPT), Photovoltaic (PV) systems, Batteries, DC-DC boost converter, Adaptive neuro-fuzzy inference system (ANFIS)

1. **Introduction.** Worldwide consumption of electrical energy is constantly increasing, and demand is growing all the time [1]. Against this backdrop, solar power generated by photovoltaic cells is emerging as a promising renewable alternative to fossil fuels. It is a wise choice for a whole range of applications, including the supply of electricity in rural areas where demand is low and it is difficult to envisage a power grid or small generators. In addition, solar energy is used in a variety of fields, such as photovoltaic vehicles, orbital stations, pumping stations, street lighting, and telecommunications equipment. Despite the growing importance of solar power as a clean, sustainable, and abundant source of energy, photovoltaic (PV) technology faces several significant obstacles. One of the most important is solar panels' low energy conversion efficiency [2]. Energy conversion efficiency refers to the ability of solar panels to convert sunlight into useful energy [3]. In addition, the initial installation costs of solar systems remain considerable [4], while the complexity of the technology and the need for periodic adjustment contribute to the

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global cost of solar power generation [5]. In addition, the immediate impact of irradiation and temperature on the current and voltage generated by a photovoltaic system requires a control unit. This control unit is essential for monitoring the maximum power point (MPP) in different climatic environments to ensure maximum energy production using photovoltaic solar panels.

MPPT approaches can be categorized into three main groups: offline techniques relying on models of the PV module, online strategies independent of PV module modeling, and hybrid techniques combining the aforementioned approaches [6, 7]. Online methods such as P&O, Incremental Conductance (IC), and Hill Climbing are grounded in the concept of perturbing the PV system and analyzing its impact on the power output of the PV panels [8]. These methods are gaining popularity due to their ease of use and low cost. However, they come with significant drawbacks, including slow MPP tracking, oscillation around the MPP, and an inability to accurately track MPP under rapidly changing weather conditions [9]. These approaches have undergone various modifications. To address the issues associated with P&O, maximizing the perturbation step size or employing an adaptive one has been proposed to decrease steady-state error and expedite convergence [10]. Variable perturbation steps were introduced in [11]. In the case of IC and P&O, an adaptive perturbation step size was utilized in [12, 13], respectively. However, these approaches still depend on the original user-defined step constants and lack true adaptability. Based on [3], an accuracy of 94.3% to 97.6% can be attained with traditional MPPT techniques like P&O and INC. However, these techniques have certain limitations, such as oscillations in P&O and complicated calculations in INC. In addition, these techniques may not work properly in the event of abrupt weather changes.

On another note, the offline approaches include artificial intelligence-based (AI-based) techniques [14], including artificial neural networks (ANN), fuzzy logic (FL) and ANFIS, which have likewise been applied in this field; see [15, 16, 17]. The AI-based approaches can map extremely non-linear correlations between the system's inputs and outputs [16]. Complex systems may be modeled, predicted, and optimized using such approaches [2]. The maximum point algorithm based on neural networks needs significant representative input and output data. Moreover, training becomes time-consuming because of the abundance of input and output data [15, 18]. On the other hand, fuzzy logic-based MPP algorithms do not necessitate the creation of a mathematical model, but as most studies have noted [16, 19], the performance of fuzzy logic is determined by the rules defined in the fuzzy inference system, which can be viewed as the main disadvantage of putting these systems into practice. Moreover, AI-based techniques, are more resistant to environmental changes. AI-based solutions, such as ANN and LF, achieve 97% to 98.6% accuracy. Nevertheless, they require sophisticated empirical design (LF) or high processing power (ANN).

These drawbacks were addressed through the implementation of an adaptive neuro-fuzzy inference system (ANFIS)-based MPPT control [20]. ANFIS, an artificial intelligence technique that combines fuzzy logic with neural networks, offers advantages from both methods. It is user-friendly and does not necessitate an extensive amount of input-output data. The performance achievable with this approach has seen significant improvement since its introduction [21]. In [22], the authors use cell temperature and current to form the ANFIS MPPT controller, with the optimum voltage at maximum power as the output. While in [23], temperature and radiation are employed to form the ANFIS MPPT controller. Revathy et al. [24] used ANFIS for MPPT in various weather conditions. However, practical issues, including its constrained dynamic range, are associated with the real-world application of ANFIS. Furthermore, the gathered data is specific to a certain geographic area, and the data collection period should be sufficiently lengthy to enhance

ANFIS performance. In [17], an ANFIS-based controller and a particle swarm optimizer (PSO) were introduced as a training unit to ensure the MPPT of a pair of two PV modules linked to an interleaved soft-switching DC boost. Although PSO training of the ANFIS controller facilitates the detection of the global MPP under various circumstances, it complicates system implementation and results in a slower dynamic response.

We draw the reader's attention to the fact that Takagi-Sugeno (T-S) models are becoming more and more popular because they can effectively accommodate a wide variety of nonlinear systems, as suggested in this study [25]. Using this formalization, several significant findings have already been proposed [26]. Appropriate LMI criteria are established in [27] to guarantee overall stability. However, T-S fuzzy systems are currently used in very small numbers in the context of MPPT, despite the wide variety of MPPT methodologies. Authors in [28, 29] propose an MPPT T-S fuzzy controller that can operate in a range of weather conditions on a photovoltaic system that has battery storage.

The method presented in this paper, which is based on the T-S fuzzy model and an improved ANFIS structure, outperforms these approaches. Our approach, which incorporates adaptive learning of the ANFIS, dynamically adjusts the fuzzy rules in response to weather variables, unlike P&O and INC. As a result, it offers greater stability than ANNs without requiring a large amount of training data. Moreover, higher robustness to uncertainties is guaranteed by the use of linear matrix inequalities (LMI) in the construction of the H_∞ controller, which is rarely taken into account in conventional MPPT approaches.

Taking all of these improvements into consideration, the current work uses Simulink for modeling and tracking the MPP of a system consisting of a solar generator and a DC-DC boost while allowing for a range of environmental changes. The primary goal of this work is to construct an improved ANFIS structure employing the T-S fuzzy model approach. During training, the ANFIS determines the ideal MPP current I_{pvopt} according to the radiation factors on the photovoltaic panels. From this, the T-S fuzzy reference model is developed to offer an ideal trajectory that should be followed to ensure maximum power operation, depending on the estimated MPP current. It is at this point that a set of LMIs must be solved in order to get the T-S fuzzy controller gains. The proposed fuzzy robust control offers high-efficiency MPP tracking while attenuating perturbation effects using an H_∞ performance controller. Less training data than the standard control structure is required for the novel control structure based on combining the ANFIS reference generation and the T-S fuzzy controller. The suggested structure is supposed to offer improved accuracy, a quicker reaction, better tracking, and operational efficiency.

2. A Photovoltaic System Model.

2.1. Single versus double-diode models.

Before introducing in detail the photovoltaic system considered in this paper, let us recall some facts about diodes models. Double-diode and single-diode models are the two basic categories under which PV models may be categorized [30, 31]. The double-diode model has an excellent precision [31]; however, its complexity induces a slow computing speed. As a result, the model with one diode is often employed in power electronics simulation research. It provides, indeed, a good balance between accuracy and simplicity. Furthermore, the data sheet's information is the only source from which it is parameterized.

2.2. Photovoltaic panel.

The photovoltaic panel considered in this paper, is made up of solar cells that are linked either in series or parallel. To generate the appropriate voltage, current, and power, panels are also linked in series and parallel. As seen in Figure 1, a single-diode model is used to represent a PV cell in order to establish the mathematical

Table 1. Nomenclature

IC	Incremental inductance
GM	Global maxima
GMPP	Global maximum power point
LM	Local maxima
LMPP	Local maximum power point
MPP	Maximum power point
MPPT	Maximum power point tracking
P&O	Perturb and observe
PSCs	Partial shading conditions
PSO	Particle swarm optimization
ANFIS	Adaptive neuro-fuzzy inference system
PV	Photovoltaic
SOC	State of charge
STC	Standard test conditions

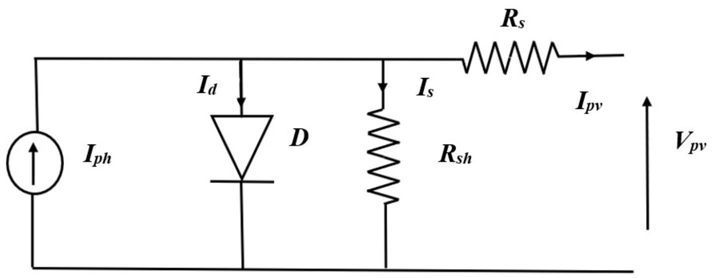

Figure 1. Photovoltaic cell equivalent circuit model

model of a PV generator [32]. The PV panel, which consists of a number of series cells N_s, is represented mathematically by the equations shown below.

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

with

$$V_T = \frac{KT}{q}$$
$$I_{ph} = [F_i(T - T_r) + I_{scr}] \left(\frac{G}{1000} \right) \tag{2}$$

In these equations, we introduce a number of variables:

- I_{ph} represents the photocurrent of the solar panel, which mostly relies on cell temperature and radiation,
- I_0 represents the saturation current of a diode which is also modified by temperature,
- F_i designates the short circuit temperature coefficient,
- I_{scr} the short circuit current at a reference condition,
- T_r the reference temperature,
- G (W/m^2) the solar irradiance,
- q is the electronic charge,
- K indicates the Boltzmann constant,
- N_p is the number of parallel strings,
- N_s the number of series panels,

- R_{sh} is the parallel resistance,
- R_s is the series resistance,
- I_{pv}, V_{pv}, and T indicate respectively the output current, output voltage and cell temperature of the photovoltaic array.

The following equation can then be used to represent the PV mathematical model.

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

Matlab/Simulink© is used to generate and simulate a photovoltaic module to show the impact of altering climatic variables (G and T) on the MPP. Figure 2 shows the photovoltaic system considered in this paper. It comprises of a photovoltaic panel linked to a battery charge, DC-DC boost and MPPT that assumes optimal energy transfer efficiency.

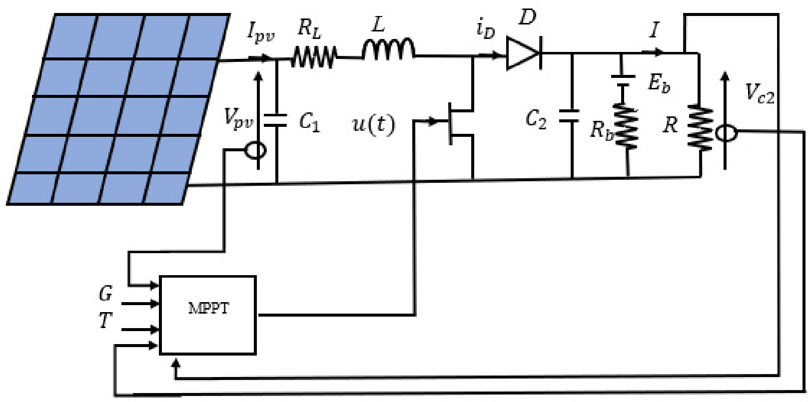

FIGURE 2. The overall construction of the photovoltaic system, including the storage battery

Figure 3 displays the current-voltage and power-voltage relations for various solar irradiances and various cell temperatures, respectively. As can be observed, solar radiation and cell temperature have a considerable effect on the fluctuation in maximum PV panel output. MPPT systems are therefore essential to continue achieving the maximum possible output from photovoltaic panels or arrays. The model of the suggested DC-DC converter and the MPPT controller configuration are described in next sections.

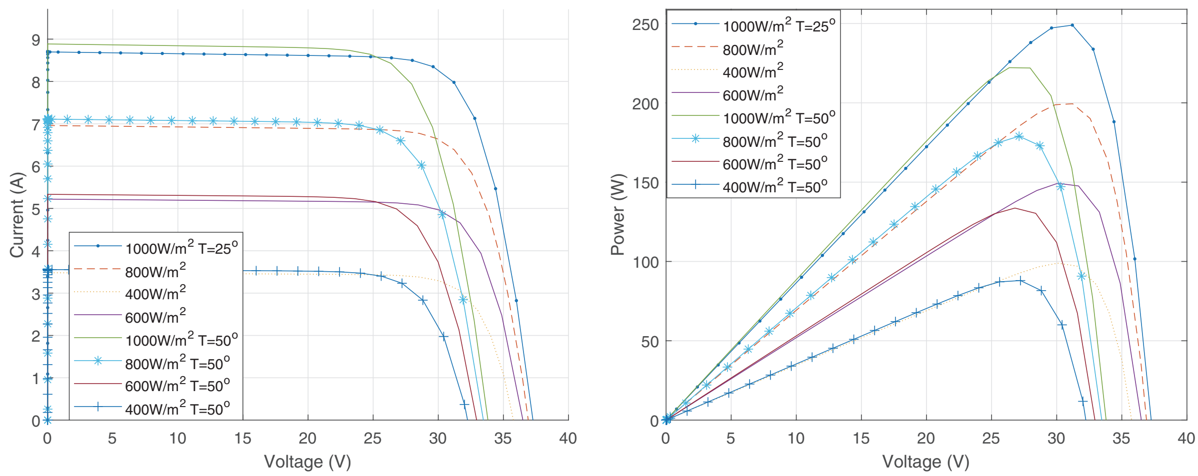

FIGURE 3. A photovoltaic generator's power-voltage and current-voltage relationships for various sun irradiances and cell temperatures

2.3. **DC-DC boost.** The DC-DC boost is situated between the load and the solar panel. The DC-DC boost converter is used because of its extensive use and great reliability in contrast to other, more complicated configuration. The MPP tracker regulates the DC-DC converter's duty cycle to provide the load with as much power as feasible. An earlier article [33] provides a detailed description of the boost converter's numerical model. Depending on whether the switch is turned ON or OFF, two sets of linear differential equations describe the dynamic model of the DC-DC boost converter. When the battery is completely charged, an MPPT control setup is used to justify the search. The differential equation of a DC-DC boost converter [34]: may be expressed as follows while it is in the "ON" state:

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

During the OFF period, we have the following equalities:

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

where V_{pv} is the input voltage. The inductive current is indicated by I_L, and the output voltage is represented by V_{c2}.

When the "ON" switch is turned on, the state space equations are as given below:

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

For the "OFF" period, the state space equation is given by the next expression.

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

where

$$\mathcal{A}_1 = \begin{bmatrix} 0 & -\dfrac{1}{C_1} & 0 \\ \dfrac{1}{L} & -\dfrac{R_L}{L} & 0 \\ 0 & 0 & -\dfrac{1}{RC_2} \end{bmatrix}, \quad \mathcal{A}_2 = \begin{bmatrix} 0 & -\dfrac{1}{C_1} & 0 \\ \dfrac{1}{L} & -\dfrac{R_L}{L} & -\dfrac{1}{L} \\ 0 & \dfrac{1}{C_2} & -\dfrac{1}{RC_2} \end{bmatrix}$$

$$\mathcal{F} = \begin{bmatrix} \dfrac{1}{C_1} \\ 0 \\ 0 \end{bmatrix}, \quad \xi(t) = \begin{bmatrix} V_{pv}(t) \\ I_L(t) \\ V_{C2}(t) \end{bmatrix}, \quad d(t) = I_{pv}(t)$$

Therefore, the photovoltaic system's dynamic may be rewritten as below:

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

or as well

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

also,

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

where $u(t) \in [0, 1]$ refers to the duty cycle used to regulate the power switch. Here, the matrix $\mathcal{B}$ is defined by $\mathcal{B}(\xi(t)) = \begin{bmatrix} 0 \\ \frac{V_{c2}(t)}{L} \\ -\frac{I_L(t)}{C_2} \end{bmatrix}$.

Radiation and the ambient temperature have an impact on the maximum PV power P_m. The available P_m of the PV module increases with increasing irradiation and decreasing ambient temperature. It is obvious that radiation affects PV output P_{pv} more than ambient temperature.

3. **Neural Network-Fuzzy Control Structure Enhancing MPP Tracking for a PV.** This section introduces the new ANFI T-S fuzzy hybrid-based MPPT method for photovoltaic systems. The suggested work combines the approach of an ANFIS with a T-S fuzzy model for optimal usage. Here, the ANFIS estimates the ideal MPP current I_{pvopt} of the control signal for the offline approach based on temperature and irradiance levels. The optimal signal for the online method is predicted using T-S fuzzy control. The proposed method is detailed next.

3.1. **ANFIS-based MPP current estimate.** ANFIS is a kind of artificial neural network that employs the Takagi-Sugeno fuzzy inference technique. By combining the two ideas, it could be able to bring together the advantages of fuzzy logic and neural networks into a single, coherent framework. Its inference mechanism correlates to its fuzzy IF-THEN rules, which have the potential to learn to approximate nonlinear functions. It is utilized by intelligent and situation-sensitive energy management systems. It consists of a rule basis, a database, an interface for fuzzification and defuzzification, and a decision-making unit.

The ANFIS algorithm is used to determine the optimum MPP current I_{pvopt} for maximal power transmission at various irradiance and temperature levels. A fuzzy inference system is constructed by initializing the membership function parameters using the ANFIS function (Genfis1) in Matlab toolbox©. The ANFIS function learns the ANFIS model using data from G, T, by adjusting the parameters of the neural network. To collect all the data required to train the ANFIS model, the ambient temperature is subdivided into 4 intervals ranging from 15°C to 30°C in 5°C steps, and the radiation range is subdivided into several intervals (13 intervals), ranging from 400 W/m^2 to 1000 W/m^2, in 50 W/m^2 steps. The ideal current calculated to correspond to the MPP current I_{pvopt} is calculated for each set of this operating data and recorded. In the end, 52 training data sets were generated. Table 2 contains a sample of the ideal current I_{pvopt} values at $T = 15 : 5 : 30$°C and $G = 800 : 50 : 1000$ W/m^2. Due to the dominant influence of radiation on P_{pv} over ambient temperature, the number of membership functions (MFs) for each input (T and G) is set at three and seven, respectively, to build the first fuzzy inference system (FIS). Thus, 21 fuzzy rules are produced. There are two types of output MFs and eight types of input MFs available in the ANFIS editor. In this investigation, MFs of both the linear and triangular types are used. The MPP search module receives the results of the analysis of irradiance and temperature and sends them along with the best MPP current I_{pvopt}. The reference model uses this as an input control to produce the necessary state $\xi_r(t)$.

Table 2. An example of training data: I_{pvopt} at $T = 15 : 5 : 30$°C and $G = 500 : 50 : 1000$ W/m^2

	$T = 15$°C	$T = 20$°C	$T = 25$°C	$T = 30$°C
G	I_{pvopt}	I_{pvopt}	I_{pvopt}	I_{pvopt}
500	3.982	4.009	4.051	4.078
550	4.784	4.397	4.408	4.447
600	4.784	4.851	4.914	4.810
650	5.310	5.203	5.297	5.334
700	5.701	5.595	5.649	5.755
750	6.054	6.001	6.041	6.152
800	6.461	6.400	6.453	6.543
850	6.863	6.833	6.720	6.831
900	7.174	7.091	7.304	7.260
950	7.617	7.676	7.625	7.703
1000	8.061	8.046	8.091	8.064

3.2. **T-S fuzzy controller design.** Takagi-Sugeno models, which are thought of as universal approximators of nonlinear systems, may be able to adequately describe the dynamic behavior of the considered system [29]. One important component of the TS fuzzy controller is the fuzzy rule. In contrast to Mamdani's conclusions, it is made changeable via its settings, allowing the controller to produce unlimited gain changes. This allows the solar array to produce its maximum power with the fewest possible oscillations, despite changes in sunlight or temperature.

3.2.1. *T-S fuzzy design for the DC boost converter.* The dynamic model of the PV system in Equation (10) has been approximately shown by the fuzzy T-S fuzzy as in [35]. Consider a T-S fuzzy system characterized by the specified equation below [28].

Rule^i: IF $\varphi_1(t)$ is M_1^i and, ..., and $\varphi_k(t)$ is M_k^i, THEN

$$\dot{\xi}(t) = \mathcal{A}_2\xi(t) + \mathcal{B}_i(t)u(t) + \mathcal{F}d(t) \tag{11}$$

where $i = 1, 2, 3, 4$, is the number of IF-THEN rules, M_j^i, $j = 1, 2, \ldots, k$ are fuzzy sets, and $\varphi_j(t)$ indicates the premise variables. $\mathcal{A}_2$, $\mathcal{B}_i$, and $\mathcal{F}$ are matrices of adequate size.

The global dynamics of T-S fuzzy system (11) may be deduced by employing a center-average defuzzifier, product inference, and singleton fuzzifier.

$$\dot{\xi}(t) = \sum_{n=1}^{4} h_n(\varphi(t))[\mathcal{A}_2\xi(t) + \mathcal{B}_n(t)u(t) + \mathcal{F}d(t)] \tag{12}$$

where

$$\mathcal{B}_1 = \begin{bmatrix} 0 \\ \dfrac{V_{c2\min}(t)}{L} \\ -\dfrac{I_{L\min}(t)}{C_2} \end{bmatrix}, \quad \mathcal{B}_2 = \begin{bmatrix} 0 \\ \dfrac{V_{c2\min}(t)}{L} \\ -\dfrac{I_{L\max}(t)}{C_2} \end{bmatrix}, \quad \mathcal{B}_3 = \begin{bmatrix} 0 \\ \dfrac{V_{c2\max}(t)}{L} \\ -\dfrac{I_{L\min}(t)}{C_2} \end{bmatrix}, \quad \mathcal{B}_4 = \begin{bmatrix} 0 \\ \dfrac{V_{c2\max\xi(t)}}{L} \\ -\dfrac{I_{L\max}(t)}{C_2} \end{bmatrix}$$

and

$$h_i(\varphi(t)) = \frac{\rho_i(\varphi(t))}{\sum_{i=1}^{r}\rho_i(\varphi(t))}, \quad \rho_i(\varphi(t)) = \prod_{j=1}^{l} M_j^i(\varphi_j(t)) \tag{13}$$

and $M_j^i(\varphi_j(t))$ is the membership value of $\varphi_j(t)$ in M_j^i. It is seen from Equation (13) that $\forall i \in \{1,2,3,4\}$, $h_i(\varphi(t))$ possesses the following characteristics:

$$h_i(\varphi(t)) \geq 0, \quad \sum_{i=1}^{r} h_i(\varphi(t)) = 1 \tag{14}$$

The proof of T-S fuzzy modeling is not presented in this work because of the word count limitation; interested readers may view [28].

3.2.2. *MPPT reference model.* To provide an acceptable reference condition for monitoring, the MPP reference model was created. The reference model is created specifically such that $\xi_r(t)$ indicates the required trajectory that $\xi(t)$ follows for what maximum performance. In this case, I_{pvopt} is the ideal current value, and serves as the control input. The expression of the MPP reference model is as follows:

$$\dot{\xi}_r(t) = \mathcal{A}_r\xi_r(t) + \varsigma(t) \tag{15}$$

with

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

The two rules below can be used to describe the reference equation (15), which is likewise non-linear using the premise variables $\varphi_r = 1 - u_{opt}$:

Rule^i: IF $\varphi_{r1}(t)$ is ϑ_1^i, and $\varphi_{rl}(t)$ is ϑ_l^i THEN

$$\dot{\xi}_r(t) = \mathcal{A}_{ri}\xi_r(t) + \varsigma(t)$$

The overall model of reference T-S fuzzy system (15) is

$$\dot{\xi}_r(t) = \sum_{l=1}^{2} h_l(\varphi_r(t))[\mathcal{A}_{rl}\xi_r(t) + \varsigma(t)] \tag{16}$$

The definition of the matrices of the reference model is

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

3.2.3. *LMI based fuzzy controllers.* The tracking error term is added to the control rule, which is the primary distinction from a standard parallel distributed compensation controller:

$$e(t) = \xi(t) - \xi_r(t)$$

In the following, the goal is to develop a state robust fuzzy MPPT control that can force the photovoltaic array to function extremely near its maximum power trajectory, independently of the parameter fluctuations and environmental circumstances related to climate change. Accordingly, the tracking issue is transformed into a fuzzy state feedback based controller, and the suggested control rule is provided by

$$u(t) = \sum_{j=1}^{4} h_j(\varphi(t))F_j(\xi(t) - \xi_r(t)) = \sum_{j=1}^{4} h_j(\varphi(t))F_je(t) \tag{17}$$

where F_j are feedback matrix gains to be computed.

The following formulas may be used to compute the error dynamics of systems (12), (16), and (17).

$$\dot{e}(t) = \sum_{i=1}^{4}\sum_{j=1}^{4}\sum_{k=1}^{2} h_i(\varphi(t))h_j(\varphi(t))h_k(z_r(t))[(\mathcal{A}_2 + \mathcal{B}_iF_j)e(t) + (\mathcal{A}_2 - \mathcal{A}_{rk})\xi_r(t) + \mathcal{F}d(t) - \varsigma(t)] \tag{18}$$

The closed-loop system is obtained by adopting an enhanced state-space form and substituting the control rule (17) in the fuzzy model (12):

$$\dot{\bar{x}}(t) = \sum_{i=1}^{4}\sum_{j=1}^{4}\sum_{k=1}^{2} h_i(\varphi(t))h_j(\varphi(t))h_k(\varphi_r(t))\left[\bar{A}_{ijk}\bar{x}(t) + \bar{E}\bar{d}(t)\right] \tag{19}$$

where

$$\bar{x}(t) = \begin{bmatrix} e(t) \\ \xi_r(t) \end{bmatrix}, \quad \bar{d}(t) = \begin{bmatrix} d(t) \\ \varsigma(t) \end{bmatrix}, \quad \bar{E} = \begin{bmatrix} \mathcal{F} & -I \\ 0 & I \end{bmatrix}, \quad \bar{A}_{ijk} = \begin{bmatrix} \mathcal{A}_2 + \mathcal{B}_iF_j & \mathcal{A}_2 - \mathcal{A}_{rk} \\ 0 & \mathcal{A}_{rk} \end{bmatrix}$$

The external input, which depends on the weather, is represented by $\varsigma(t)$, and the perturbation induced by the change in the input voltage, which includes the variables I_{pvopt} and I_{pv}, is represented by $\bar{d}(t)$. The suitable performance of H_∞ can then be defined as below to quickly minimize the effects of perturbations on such a closed-loop system:

$$\int_0^\infty \bar{x}^T(t)\bar{\phi}\bar{x}(t)dt \leq \gamma^2 \int_0^\infty \bar{d}^T(t)\bar{d}(t)dt \tag{20}$$

where $\bar{\phi} = \begin{bmatrix} \phi_1 & 0 \\ 0 & 0 \end{bmatrix}$.

The present research applies the H_∞ tracking technique to offering a certain amount of attenuation against external disturbance influence and enabling the photovoltaic system to track its peak power output trajectory in the event of fluctuating irradiance and temperature levels.

The following are the sufficient criteria for the availability of a fuzzy controller T-S (17) that will cause the solar array to run extremely near the highest possible power trajectory: The advantage of this method is that it lowers the tracking error to the highest possible power even in situations where weather conditions change quickly. We deduced the following theorem from the considerations above.

Theorem 3.1. [28] *The closed loop system* (19) *is asymptotically stable given positive scalars* α *and* δ*, and if there exist any matrices* $P_1 > 0$, $P_2 > 0$, P_3, U, N_i, $i = 1, 2, 3, 4$, *the* H_∞ *performance* (20) *with the attenuation level* γ *is satisfied, for the optimization problem as follows:*

$$\Psi_{iik} < 0, \quad k = 1, 2 \tag{21}$$

$$\Psi_{ijk} + \Psi_{jik} < 0, \quad k = 1, 2 \tag{22}$$

where

$$\Psi_{ijk} = \begin{bmatrix} \Psi_{ijk}^{11} & \Psi_{ijk}^{12} & P_1\mathcal{F} & P_2 - P_1 & \Psi_{ijk}^{15} \\ * & \Psi_{ijk}^{22} & P_2\mathcal{F} & P_3 - P_2 & \Psi_{ijk}^{25} \\ * & * & -\gamma^2 I & 0 & 0 \\ * & * & * & -\gamma^2 I & 0 \\ * & * & * & * & -\delta U - \delta U^T \end{bmatrix} \tag{23}$$

$$
\begin{aligned}
\Psi_{ijk}^{11} &= sym\{P_1\mathcal{A}_2 + \mathcal{B}_i N_j\} + \phi_1 + \alpha P_1 \\
\Psi_{ijk}^{12} &= P_1(\mathcal{A}_2 - \mathcal{A}_{rk}) + P_2\mathcal{A}_{rk} + \left(\mathcal{A}_2^T P_2 + \lambda N_j^T \mathcal{B}_i^T\right) + \alpha P_2 \\
\Psi_{ijk}^{15} &= \delta(P_1\mathcal{B}_i - \mathcal{B}_i U) + N_j^T \\
\Psi_{ijk}^{22} &= sym\{P_2(\mathcal{A}_2 - \mathcal{A}_{rk}) + P_3\mathcal{A}_{rk}\} + \alpha P_3 \\
\Psi_{ijk}^{25} &= \delta(P_2\mathcal{B}_i - \lambda\mathcal{B}_i U)
\end{aligned} \tag{24}
$$

Additionally, the matrices for the controller gains are provided by $F_j = U^{-1}N_j$.

The suggested technique for tracking the maximum power point (MPP) combines an ANFIS structure with a Takagi-Sugeno (T-S) fuzzy model. It is essential to follow these procedures to the letter for effective implementation of this strategy.

Using training data based on solar radiation (G) and panel temperature (T) in Table 2, ANFIS is first offered. After that, it uses these environmental inputs to calculate the optimum current (3) in real time at the point of greatest power. To minimize mean square error during simulations, ANFIS settings, including membership functions and the number of fuzzy rules, have been chosen. To build an operational trajectory, an optimum reference model is constructed (15), (16) based on I_{pvopt}. This paradigm is made up of fuzzy rules, (IF-THEN), each of which gives a matching control action and handles a certain range of input values. The system will run at maximum power under a variety of scenarios thanks to the model's optimal settings for V_{pv} and I_L. Simulations are used to define T-S model parameters, such as partition functions and linear sub-model approximation coefficients, and to reveal non-linear variations in system behavior. The $u(t)$ control signal (17) is then produced by the T-S fuzzy controller, controlling the DC-DC converter to modify the PV voltage and current and maintain the maximum power point. The controller is designed to be resistant to modeling uncertainties and environmental fluctuations using LMI (21)-(22). The whole system design is shown in Figure 4, where I_{pvopt} is estimated by the ANFIS using temperature T and solar radiation G data collection and the T-S fuzzy reference model receives this current and uses it to create a perfect trajectory for the T-S controller to follow.

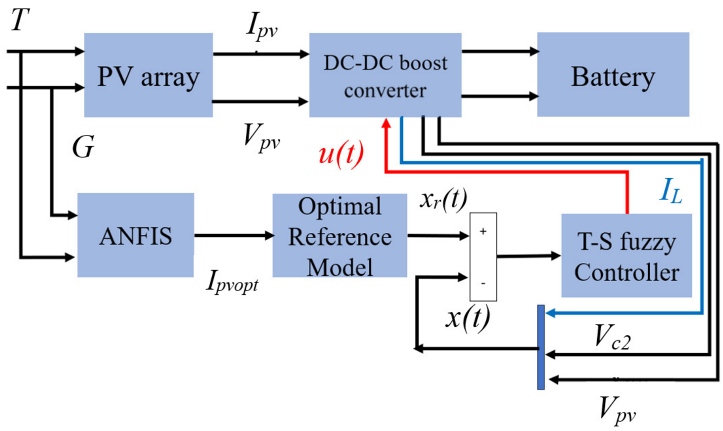

FIGURE 4. An overview of the photovoltaic generator coupled to the battery using the suggested method

4. **Simulation Results.** The system considered as a whole is given by the diagram in Figure 4. It is tested with the help of Matlab software under various environmental conditions to assess its performance. The specifications of the PV250 W module, which forms part of the tracking system studied are summarized in Table 3, and the characteristics

TABLE 3. PV250 W module and lead acid battery specifications

Parameters	Value
P_{pvopt}	250 W
I_{pvopt}	8.15 A
V_{pvopt}	30.7 V
I_{sc}	8.66 A
V_{oc}	37.3 V
C	6.5 Ah
R_{Bat}	35 Ω
E_{Bat}	6 × 12 V (72 V)

TABLE 4. Boost specifications

Parameters	Value
L	3 mH
C_1	100 μF
R	40 Ω
C_2	100 μF

of the boost are compiled in Table 4. An AC lead-acid battery serves as the storage mechanism. The primary battery characteristics are shown in Table 3. In detail, Figure 4 shows the photovoltaic generator, the DC-DC boost linked to a battery, and the suggested MPPT algorithm. The ANFIS block alters the duty cycle variable for the fuzzy controller at each step under the inputs. The MPPT fuzzy variable step generates the duty cycle necessary for optimizing photovoltaic voltage. Solar irradiance G and temperature T are the environmental factors used for modeling. Two simulated cases are investigated to show the value of the suggested strategy for enhancing MPPT efficiency and raising DC output. Both simulation case studies address gradual and ramped changes in G and T.

We determine the lowest possible level of disturbance attenuation H_∞ $\gamma_{\min} = 0.35$, as well as the following control gains, by resolving the LMI requirements of Theorem 3.1

$$F_1 = [0.0012 \quad -0.0462 \quad -0.1088]$$
$$F_2 = [-0.0000 \ \ 0.0611 \quad -0.0034]$$
$$F_3 = [0.0002 \ \ 0.0008 \quad -0.0229]$$
$$F_4 = [0.0002 \ \ 0.0106 \quad -0.0506]$$

In order to evaluate the ANFIS approach in conjunction with T-S fuzzy control, proposed variations of G and T are illustrated in Figure 5. Through modeling the PV array linked to the battery, it is determined if it is feasible to use such an ANFIS-based algorithm to enhance the T-S fuzzy MPPT approach.

The suggested MPPT method is contrasted with two approaches to demonstrate its efficacy. The first is the traditional P&O approach, while the second is the ANN method. Two perspectives are taken into account while comparing these strategies. The first factor is continuous power production, which is important for determining how efficient a PV system is. Tracking speed is the second. The comparison between the suggested approach and some MPPT strategies is presented in Figure 6. The DC output power of the photovoltaic generator is improved both statically and dynamically when the ANFIS approach based on T-S fuzzy is used. The increased power output during times of constant G and T serves as a visual cue to the improvement in static performance. Rapid tracking of

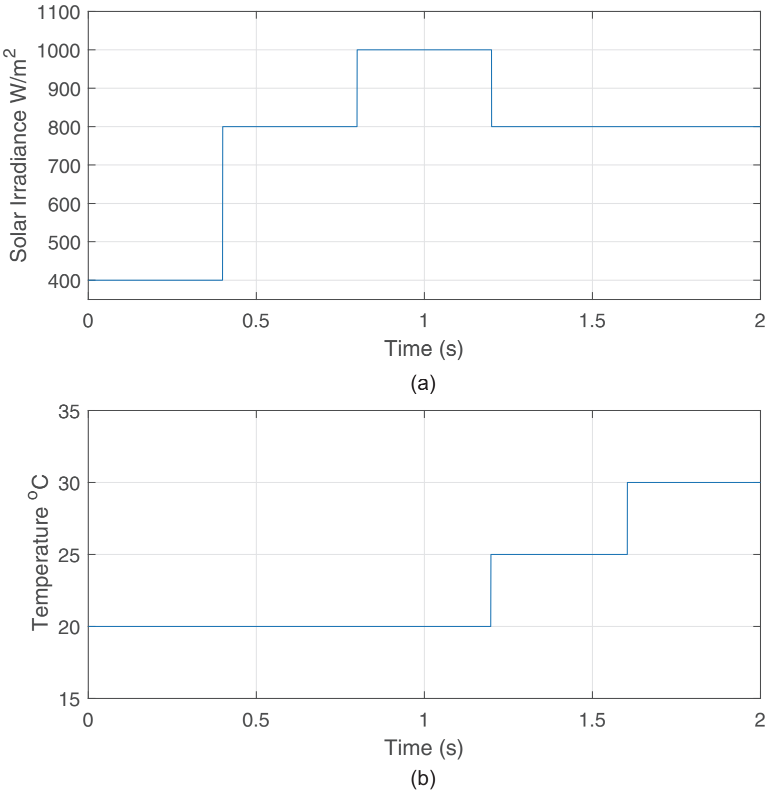

FIGURE 5. Variable weather circumstances include (a) a profile of solar irradiance and (b) a profile of temperature

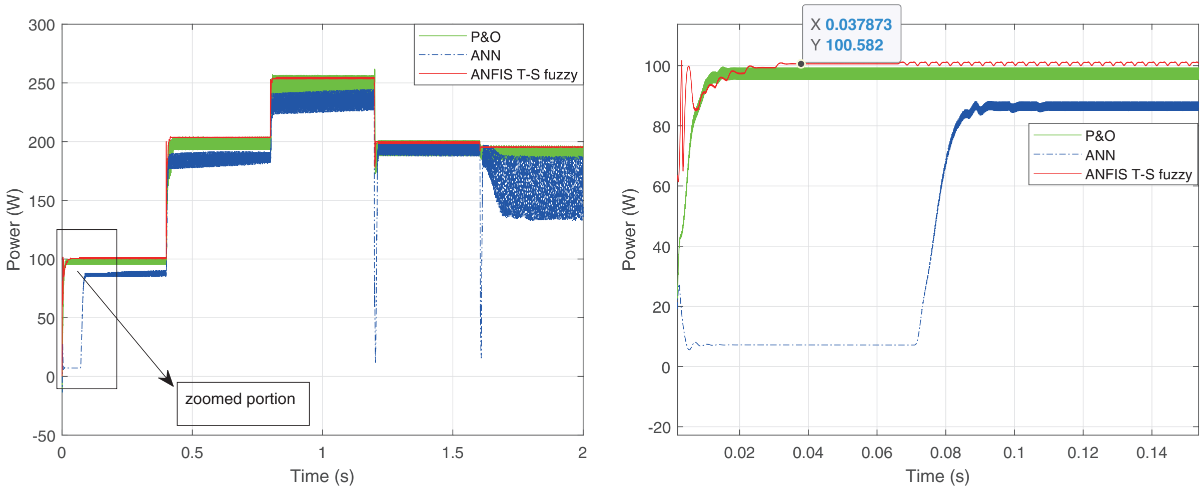

FIGURE 6. Comparison of DC output power for MPPT applying the P&O approach, the ANN approach and the ANFIS-based T-S fuzzy approach

changes in G or T reports dynamic performance improvement. The suggested hybrid approach, as can be observed, reaches maximum power more quickly than the others. Due to the impact of the first stage, the tracking speed to achieve MPP was reduced to 0.034 s, compared to 0.095 s for the ANN. Although P&O's tracking speed 0.019 s is lower than the 0.034 s measured by the proposed approach, it still exhibits serious oscillations. Furthermore, as already mentioned, the T-S fuzzy controller provides a quick dynamic reaction without oscillation. In addition, the proposed hybrid approach solves the steady-state error problem associated with the ANFIS approach, because of the extremely small size of the perturbation step used in the fine-tuning step. The small oscillation almost completely eliminates power loss while also protecting the technology from minute variations in radiation and noise in its electrical connections. It has been demonstrated that the efficiency of the system based on the proposed method offers improved performance in terms of dynamics, with a smoother curve, faster response and better tracking of the reference trajectory.

Another performance measure that is suggested in this study to demonstrate the efficacy of the suggested strategy when comparing MPPT approaches during a dynamic radiation profile is the response of the battery connected to the photovoltaic system (SOC%). Figures 7 and 10 show the SOC profile during charge and discharge states. It can be noted that the SOC of a battery might vary greatly according to the degree of irradiation and the ambient temperature. The SOC curves are impacted by how closely the suggested technique follows the MPPT. The recommended approach may select the relevant MPP to provide the greatest energy output for battery charging.

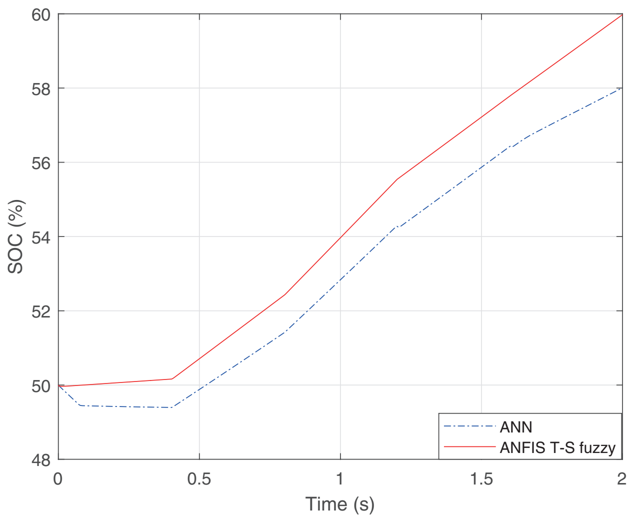

Figure 7. The battery charging curve under variable weather circumstances

A comparison of ANFIS T-S fuzzy MPPT with the various MPPT methods available in the literature is presented in Table 5. This comparison highlights that our fuzzy ANFIS T-S approach offers even higher energy efficiency and better susceptibility to adaptation to environmental changes. In addition, its algorithmic complexity remains rather medium compared to other algorithms, making it more accessible for real-time implementations on photovoltaic systems.

Figure 8 illustrates the suggested ramp variations of G and T, which are used to demonstrate how the proposed algorithm can accommodate various fluctuations in the atmospheric conditions taken into account. In Figure 9, a comparison of DC power output using the ANN approach, the P&O method and ANFIS based on T-S fuzzy is shown. The results demonstrate that the suggested hybrid MPPT outperforms the others. The P_{pv} of the suggested hybrid MPPT approach grows (decreases) linearly when radiation increases (decreases), but the P&O technique deviates considerably from the MPP and loses its tracking direction multiple times, which is illustrated in Figure 9. Furthermore, the suggested hybrid approach has a very tiny oscillation amplitude and never loses its tracking location. The ANN, on the other hand, has a huge oscillation amplitude and loses its tracking direction multiple times, as illustrated in Figure 9. In addition, radiation transients have no effect on tracking because of the quick reaction of the ANFIS approach at the initial step of the suggested hybrid technique.

Table 5. A comparison of the performance of ANFIS T-S flou-based MPPT with other MPPT algorithms

MPPT algorithms	Complexity of implementation	Convergence speed	Tracking efficiency	Adaptability to changing conditions
P&O [36]	Easy	Varies	Very low	Medium
INC [37]	Easy	High	Low	Medium
ANN [38]	High	High	Medium	Excellent
Fuzzy Logic [39]	High	High	Medium	Excellent
PSO [40]	Medium	Moderate	Medium	Excellent
GWO [41]	Medium	Medium	High	Excellent
ANFIS T-S fuzzy	Medium	Very high	Very high	Excellent

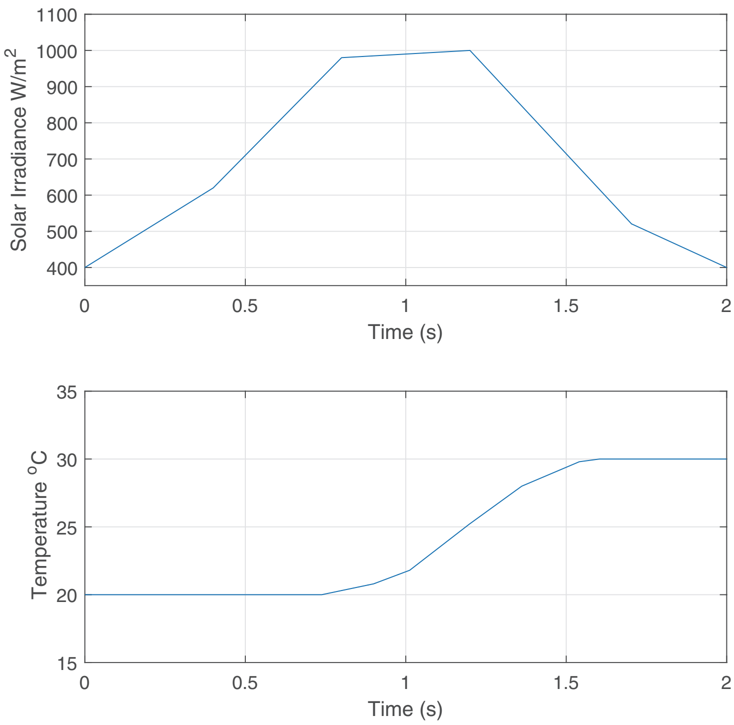

Figure 8. Solar irradiance G ramp variations and cell temperature T ramp variations used to test methods

In other words, the classic P&O approach is susceptible to oscillation around the MPP, which results in cumulative energy losses due to its perturbative nature. It continually adjusts the voltage in pursuit of the MPP, never obtaining maximum accuracy. Furthermore, because of its iterative working, P&O reacts more slowly, taking many cycles before reaching the MPP, especially under quickly changing weather circumstances. Moreover, the quality of the training data is crucial to the performance of the ANN approach. Without adequate training with varied data, the model can be ineffective in the face of abrupt meteorological variations. In addition, the operations required to generalize the model can sometimes slow down its responsiveness. The two methods are outperformed by ANFIS T-S, which employs a hybrid neuro-fuzzy approach to rapidly predict the optimal trajectory and adjust system parameters in real time. Thanks to this mechanism, it is possible to overcome the constraints of the other methods by offering higher accuracy and greater energy efficiency, particularly in dynamic contexts.

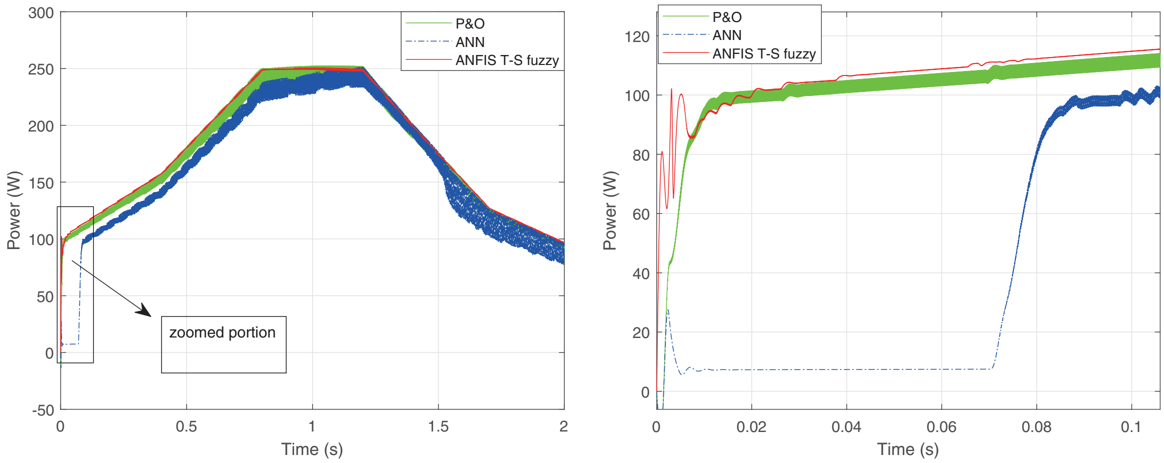

FIGURE 9. Comparing the performance of DC power production through using traditional ANN, traditional P&O MPPT, and ANFIS based on T-S fuzzy for ramp changes of G and T

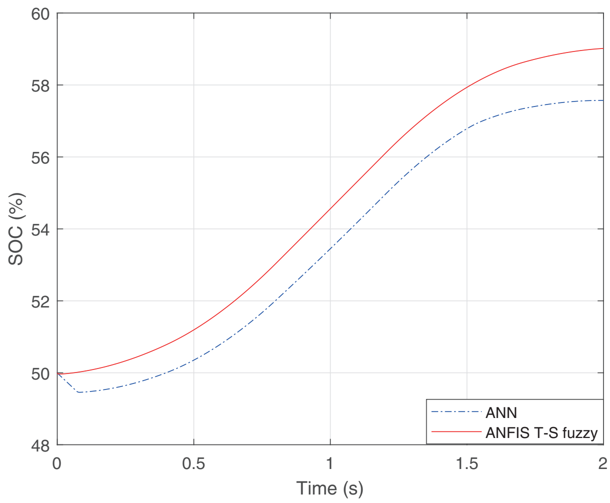

FIGURE 10. The charging profile of batteries according to various weather scenarios

Figure 10 depicts the SOC profile under varied irradiation and temperatures. As can be seen, temperature has a significant impact on the battery's level of charge. At higher temperatures, the SOC grows more slowly, resulting in slower charging.

The performance of solar photovoltaic (PV) systems is greatly influenced by two key factors: ambient temperature and solar radiation. As temperature increases, the open-circuit voltage (V_{oc}) of the panels decreases, leading to a reduction in their overall efficiency. At the same time, solar radiation, has a direct impact on energy generation. At low irradiance, the maximum power available decreases, making it more difficult to track the maximum power point (MPP). Above 25°C (Figures 5, 6 and 9), the P&O method is confronted with intense oscillations around the maximum power point (MPP), resulting in energy losses. By contrast, the ANN method has difficulty adapting quickly to rapid fluctuations in temperature and irradiance, necessitating frequent recalibration. The ANFIS T-S fuzzy method stands out for its robustness to changes in temperature and irradiance. Moreover, it automatically modifies fuzzy parameters based on real-time and historical data, ensuring precise MPP tracking even when environmental disturbances occur.

5. **Concluding Remarks.** In this study, we introduced a novel adaptive neuro-fuzzy inference system designed for PV battery systems operating in non-uniform conditions. The approach employs a maximum power point method based on the T-S fuzzy model. We provided comprehensive mathematical models for various system parameters, with a focus on the photovoltaic panel, boost converter, and storage battery. These models are utilized to validate the feasibility and effectiveness of the proposed method. The ANFIS-based learning is employed to calculate the estimated MPP current, and the high precision of the T-S reference model was used to determine the optimal trajectory for operating at maximum power. The ultimate power control problem is then framed as a manageable optimization problem under linear matrix inequality (LMI) constraints. Simulation results illustrate that the proposed MPPT method enhances the DC power output and reduces the time required to achieve a steady state in changing environmental conditions. Despite the increase in the number of operation steps, the suggested technique eliminates unnecessary data through the selected dataset. The performance of the T-S fuzzy system proposed in this work suggests that it is a promising approach for MPPT in photovoltaic arrays. The suggested ANFIS T-S fuzzy approach can potentially transform intelligent energy management in photovoltaic systems. Its long-term impact is expected to be particularly important, increasing the efficiency of solar systems in areas with variable weather conditions and lowering energy losses and maintenance costs on a wide scale. Although the results already show an improvement in performance with this method, there are still several possibilities for optimization. Firstly, implementing a continuous self-learning strategy would enable ANFIS to adjust in real time to environmental changes. In addition, its combination with smart grids would enable optimal energy distribution, boosting the stability and efficiency of power grids.

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