COMPARATIVE PERFORMANCE ANALYSIS OF THE FUZZY LOGIC AND INCREMENTAL CONDUCTANCE MPPT TECHNIQUE IN RAPIDLY CHANGING IRRADIANCE CONDITIONS

ANALIZA COMPARATIVĂ A PERFORMANȚEI TEHNICII MPPT BAZATE PE LOGICA FUZZY ȘI A METODEI DE CONDUCTANȚĂ INCREMENTALĂ ÎN CONDIȚII DE IRADIERE VARIABILĂ RAPID ….

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Abstract: *This paper presents a comparative evaluation of two Maximum Power Point Tracking (MPPT) techniques, Fuzzy Logic (FL) and Incremental Conductance (INC), under varying irradiance conditions. providing a cross-comparison between a soft-computing-based FL controller and the traditional INC method in order to highlight performance differences between intelligent and conventional MPPT strategies. The analysis is conducted over a very short time interval of 1 second, allowing the dynamic response of each controller to be assessed under a sudden and abrupt change in solar irradiance , with the objective of improving photovoltaic (PV) energy extraction and reducing power loss. Both controllers were designed and tested in MATLAB/Simulink using a single-diode PV module model. Simulation results show that the FL controller achieves faster dynamic response and lower steady-state oscillation than the INC technique, particularly under rapidly changing irradiance. In addition to performance analysis, the study assesses the practical feasibility of*

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each method by estimating their computational requirements and structural complexity. The INC algorithm demonstrates low processing cost and straightforward implementation, making it suitable for low-resource embedded systems. Conversely, FL exhibits superior tracking quality at the expense of higher computational load due to fuzzification, rule evaluation, and defuzzification. This trade-off highlights that algorithm selection must balance tracking accuracy with execution cost depending on the target hardware constraints.

Keywords: MPPT, boost converter, fuzzy logic, incremental conductance

Rezumat: *Acest articol prezintă o evaluare comparativă a două tehnici de urmărire a punctului de putere maximă (MPPT), Logica Fuzzy (FL) și Conductanța Incrementală (INC), în condiții variabile de iradiere solară, realizând o analiză paralelă între un controler FL bazat pe soft-computing și metoda tradițională INC, cu scopul de a evidenția diferențele de performanță dintre strategiile MPPT inteligente și cele convenționale. Analiza este efectuată pe un interval foarte scurt de 1 secundă, permițând evaluarea răspunsului dinamic al fiecărui controler în cazul unei modificări bruște și instantanee a iradierii solare, având ca obiectiv îmbunătățirea extracției de energie fotovoltaică (PV) și reducerea pierderilor de putere. Ambele controlere au fost proiectate și testate în MATLAB/Simulink utilizând un model cu o singură diodă al modulului PV. Rezultatele simulărilor arată că regulatorul FL obține un răspuns dinamic mai rapid și oscilații în regim staționar mai reduse decât tehnica INC, în special în condiții de variație rapidă a iradierii. Pe lângă analiza performanței, studiul examinează și fezabilitatea practică a fiecărei metode prin estimarea necesarului de calcul și a complexității structurale. Algoritmul INC prezintă un cost de procesare redus și o implementare simplă, fiind adecvat pentru sisteme embedded cu resurse limitate. În schimb, metoda FL oferă o calitate superioară a urmăririi punctului de putere, însă la prețul unei încărcări computaționale mai mari, datorită etapei de fuzzificare, evaluării regulilor și defuzzificării. Acest compromis evidențiază necesitatea de a echilibra precizia urmăririi cu costul de execuție, în funcție de constrângerile hardware ale aplicației vizate*

Cuvinte cheie: MPPT, convertor boost, logica fuzzy, conductanța incrementală

1. Introduction

Modern times have seen the widespread use of renewable energy sources like photovoltaic (PV) energy in several nations. Two layers comprise mobile carriers in a silicon semiconductor solar PV cell [1]: holes in the valence band and electrons in the conduction band [2]. Although a single PV cell produces a limited amount of power, a panel made up of several cells connected in series can generate a higher overall PV voltage. Then, in order to increase the panel's current, these panels are connected in parallel to create arrays [3]. It is crucial to take advantage of the nonlinear properties of PV cells since they react to variations in temperature and irradiance. An elevation in ambient temperature triggers a decrease in PV voltage due to its negative coefficient associated with ambient temperature, resulting in a decline in PV power. Conversely, heightened ambient temperatures marginally raise the current. Conversely, an increase in irradiation leads to a substantial surge in current, consequently amplifying the extracted PV power output. PV voltage is, however, minimal affected by changes in irradiance [4]. Because of the PV module's nonlinear properties, a robust controller is required to identify the optimal position on the power-voltage (P-V) and current-voltage (I-V) curves under the influence of changing weather [5]. Many researchers have recently proposed and evaluated various types of MPPT approaches. However, there may be challenges to using an MPPT technique, including expense, complexity, response time, and oscillations at the Maximum Power Point (MPP). Nevertheless, there are minimal efficiency gains to the new MPPT methods existent on the market, such as fractional open-circuit voltage [6], incremental conductance (INC) [7], and perturb and observe (P&O) [8]. on the other hand, artificial intelligence methods including adaptive fuzzy-neural networks, fuzzy logic systems, and neural networks have been suggested to be attractive choices for this use [9]. In contrast to incremental conductance MPPT. in this study, the Fuzzy Logic MPPT technique is employed, and it is demonstrated to be more efficient. In this paper, MATLAB/Simulink software is used to simulate and validate the whole system, to improve the MPPT methods a theoretical analysis of the DC/DC boost converter is also carried out. The FL-MPPT technique is then used to maximize the PV system's output powerand it’s especially appropriate for quickly changing solar irradiance values.

2. Photovoltaic Module Modeling

The Single-Diode model is commonly acknowledged for its balance between simplicity and accuracy. Figure 1. illustrates an electrical circuit representing a solar cell, incorporating a photocurrent source (Iph) in parallel with a nonlinear single diode, alongside a series resistor (Rs) and shunt resistor (Rp). The Iph source is predominantly influenced by both the sunlight intensity and the cell's operating temperature. The PV cell's behavior is mathematically described by the subsequent equations:

$$I = I_{ph} - I_0 \left[exp\left(\frac{(V + R_s.I)}{n \times V_{th}}\right) - 1\right] - \frac{V + R_s.I}{R_p}, \tag{1}$$

$$I_{ph} = (I_{sc} + a.(\mathrm{T}\text{-}T_n))\frac{G}{G_n}, \tag{2}$$

$$I_0 = I_{0,n}\left(\frac{T}{T_n}\right)^3 exp\left[\frac{q \times E_g}{n \times K}\left(\frac{1}{T_n} - \frac{1}{T}\right)\right], \tag{3}$$

$$I_{0,n} = \frac{I_{sc}}{exp\left(\frac{V_{oc}}{nV_{th}}\right) - 1} \tag{4}$$

I_{ph} : generated current of solar cells under a given insolation;
I : output current of the module PV.
V: Solar module voltage (V)
V_{th}: the thermal voltage $V_{th} = \frac{NsKT}{q}$
N_s : Number of cells connected in series.
I_0 : diode reverse saturation current.
$I_{0,n}$: Nominal saturation current.
G: Irradiation at STC conditions
q : Electron charge (q=1· 60217646×$10^{-19}C$);
n : Diode identity factor (n=1.3).
K : Boltzmann constant (K=1.38.$10^{-23}J/K$).
T : Temperature of the p-n junction (in *Kelvin*).
T_n : cell temperature at reference condition (T_n = 25°C).
E_g : band gap energy (≈1.1 *eV*)
R_s : solar cell's series resistance (Ω).
R_p: solar cell's parallel resistance (Ω).
a : the coefficient for the temperature in the case of short circuit current.

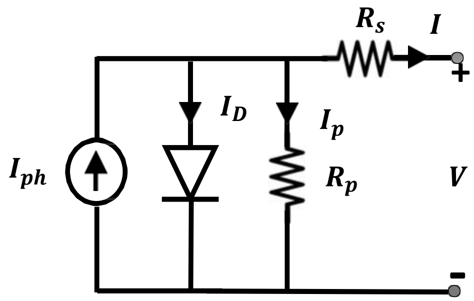


Figure 1. Equivalent circuit of a solar cell.

Table 1. **Specifications of the PV panel in STC conditions**

Rated Power (Pmp)	**Voltage at maximum power (Vmp)**	**Current at maximum power (Imp)**	**Open circuit voltage (Voc)**	**Short circuit current**	**Total number of cells in series (Ns)**	**Total number of cells in parallel (Np)**
200W	26,35V	7,59A	32,9V	8,21A	54	1

3. Incremental Conductance (INC) Method

The incremental conductance method [10] (INC) works by contrasting the incremental and instantaneous conductance of the PV module in order to determine its terminal voltage. The optimum power point has been found when the incremental conductance and instantaneous conductance equal. When the PV module's terminal voltage increases (dP/dV>0), there is an apparent rise in output power within operating boundaries. On the other hand, as the terminal voltage rises over the MPP, the output power decreases (dP/dV< 0). Figure 7. illustrates the flow architecture of the INC controller.

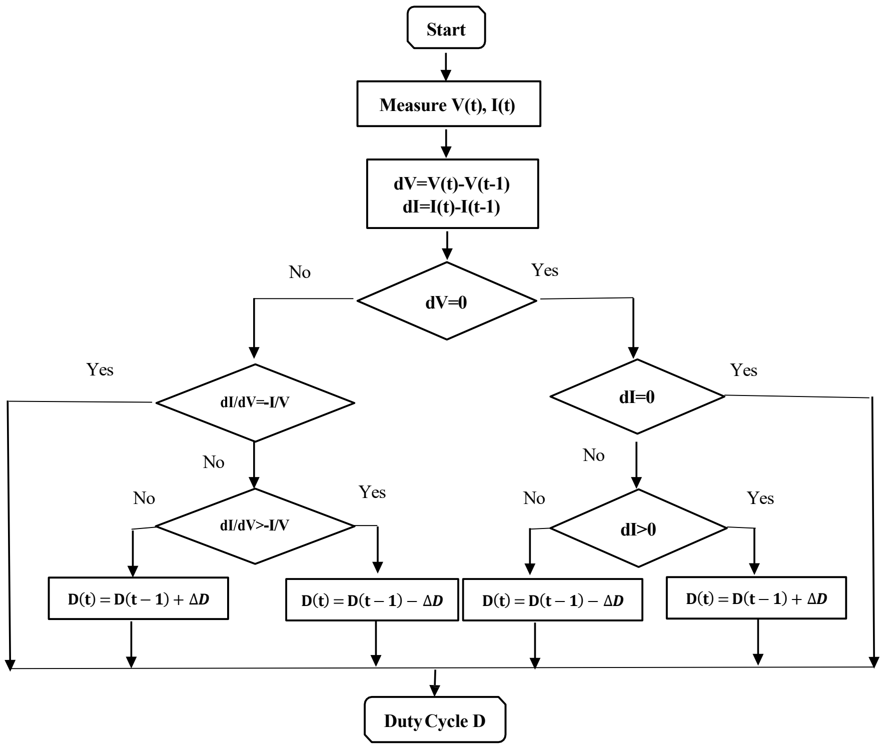


Figure 2. INC Flow chart

4. Fuzzy Logic (FL) Method

Fuzzy logic was used to track the MPP of the PV module. due to its advantages of robustness, simplicity in design [11], and independence from the precise knowledge of the PV model. Typically, a fuzzy logic control system comprises four fundamental components: a fuzzification module, rule base unit, a fuzzy inference engine, and a defuzzification module, as illustrated in Figure 3. Within this paper, the FL-MPPT utilizes the error E and its variation ΔE as inputs to execute the FL algorithm, enabling the tracking of the MPP throughout the simulation. Moreover, the sole output variable in the FL system is the change in the boost converter's duty cycle ΔD. the error and the change in error can therefore be expressed as follows:

$$E = \frac{P_n - P_{n-1}}{V_n - V_{n-1}} = \frac{\triangle P}{\triangle V} \tag{5}$$

$$\triangle E = E_n - E_{n-1} \tag{6}$$

where $P_n$and V_n are the power and voltage of the PV panel.

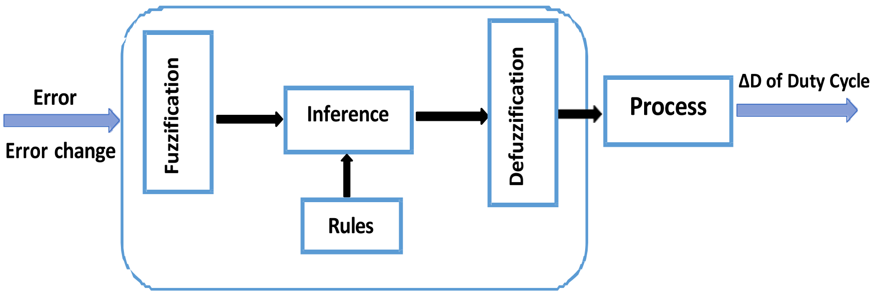


Figure 3. Block diagram for a fuzzy controller.

5. DC/DC Boost Converter

In PV application systems, the boost converter is commonly utilized, most notably for the MPPT controller, as seen in Figure 4. Therefore, the considered input parameters of the converter are $V_{pv} = V_{mpp}$ and $I_{pv} = I_{mpp}$ and $P_{pv} = P_{mpp}$,The output voltage (Vo) of the converter is determined for load resistance (R) of 36.12 Ω, assuming a loss less converter. Therefore, Vo and duty ratio (D) are determined as

$$V_0 = \sqrt{P_0 \times R} = 85\text{ V} \tag{7}$$

$$D = 1 - \frac{V_{pv}}{V_0} = 0.69 \tag{8}$$

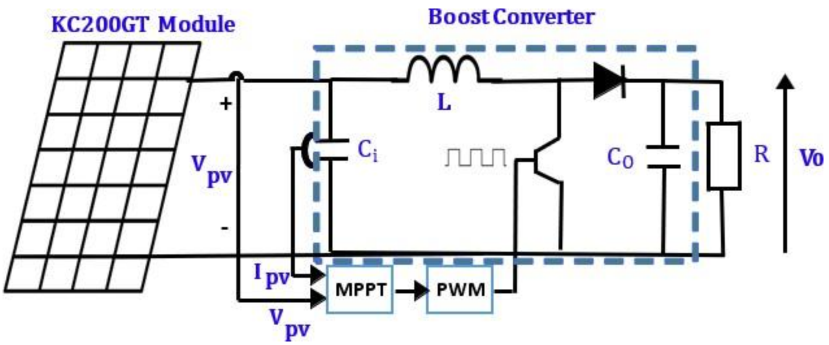


Figure 4. Boost converter with MPPT controller.

To minimize the oscillations at MPP, the output capacitor is designed for 0.2% output voltage ripple *(ΔVo)* and the inductor value is designed for 40% input current ripple (ΔIpv) at switching frequency fs = 20 kHz as given [12]-[13]

$$L = \frac{V_{pv} \times D}{2\Delta I_{pv} \times f_s} = 0.15 \text{ mH} \tag{9}$$

$$C = \frac{V_0 \times D}{2\Delta V_0 \times R \times f_s} = 240\ \mu\text{F} \tag{10}$$

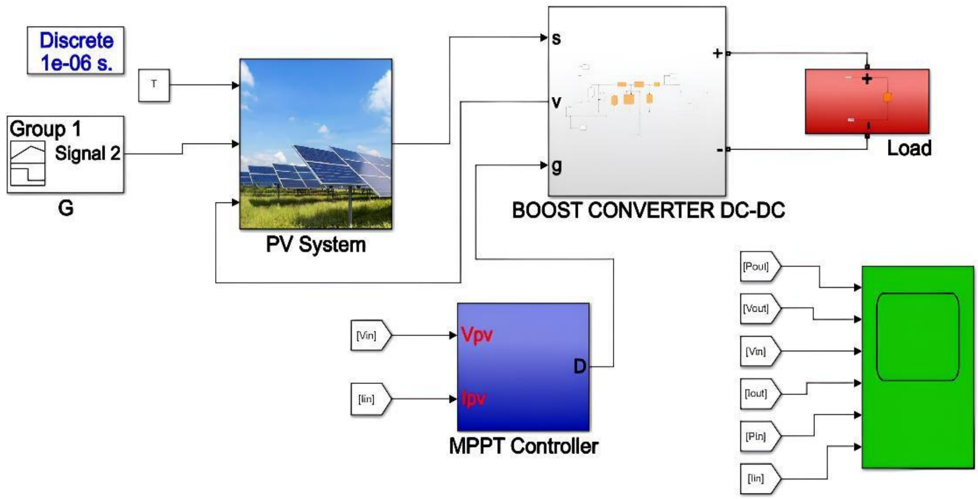


Figure 5. Proposed PV system with MPPT techniques.

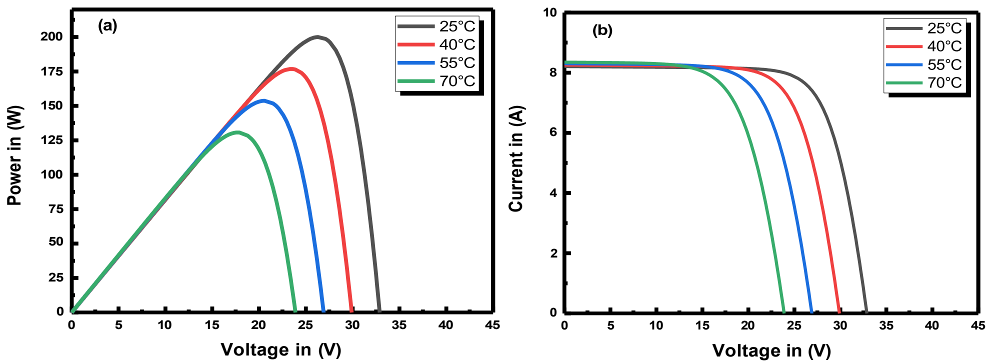


Figure 6. P-V(a) and I-V(b) curves at different Temperatures (25, 40,55 and 75°C) at fixed irradiation (1000W/m²)

At 132 V, there is a practical capacitance of 300 μF which is capable of supporting the output voltage of 85 V. Two capacitors are linked in parallel to reduce the ESR effect. Thus, at 132V, the effective capacitance is C= = 600 μF

6. Results and Discussion

The suggested PV system is validated and tested using the MATLAB/Simulink software employing the MPPT methods shown in Figure 5. In this study, the output power of the PV module is tracked under a variety of meteorological conditions using both the INC and FL MPPT methods. The PV module curves for different temperatures and constant irradiation are displayed in Figure 6. The PV module curves under various irradiation values and fixed temperatures are shown in Figure 7.

Figure 8. displays the boost converter circuit used in Simulink. Furthermore, the FL-MPPT technique is utilized as shown in Figure 9. Consequently, the PV system's current and voltage are monitored with the goal to calculate the PV panel’s power, error, and error change.

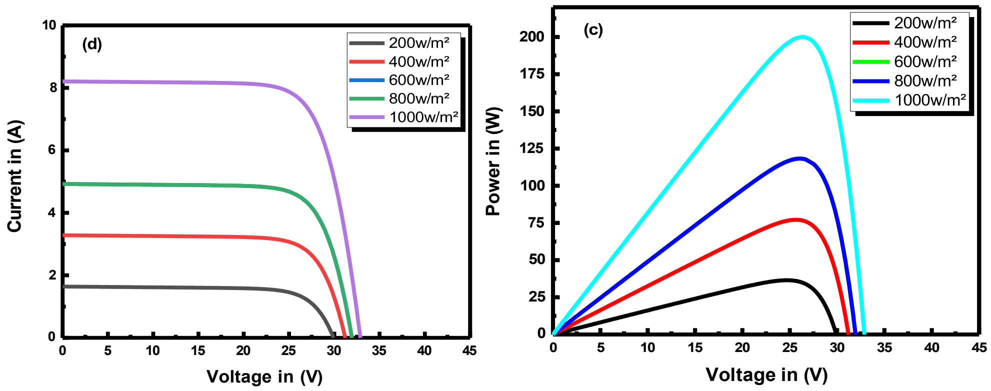


Figure 7. P-V (c) and I-V (d) curves at different irradiations (1000, 800,600,400 and 200W/m²) at constant temperature (T=25°C)

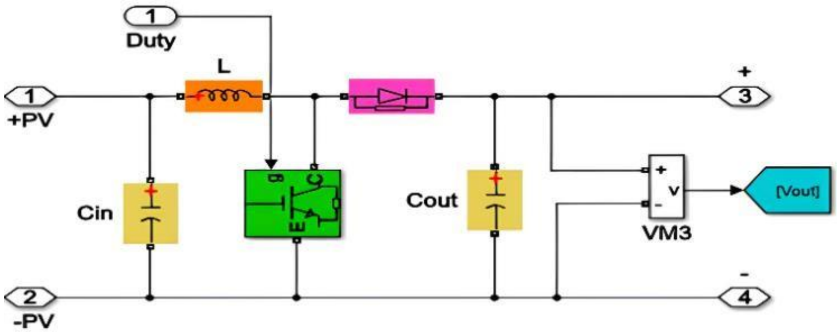


Figure 8. schematic of Boost converter in Simulink.

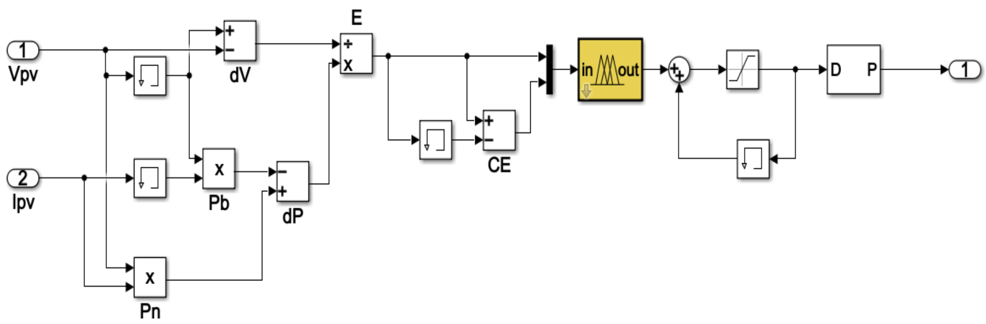


Figure 9. The Simulink model of MPPT by FL method.

To validate our model, the simulated single-diode representation of the KC200GT module was compared with the manufacturer's datasheet values under STC. Figure 10 illustrates the P–V characteristics generated by the model against the datasheet reference curve, while Figure 11 displays the corresponding I–V profiles. The strong agreement observed between the simulated results and the datasheet measurements confirms the accuracy of the proposed model, offering a reliable basis for subsequent MPPT performance assessment under variable irradiance and temperature.

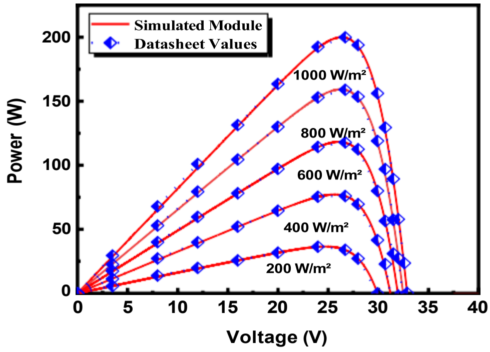


Figure 10. Evaluation of P–V Characteristics for the KC200GT PV Module using simulated and Datasheet curves

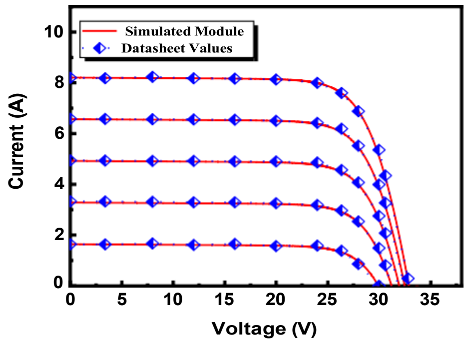


Figure 11. Evaluation of I–V Characteristics for the KC200GT PV Module using simulated and Datasheet curves

By using the rules and associated membership functions, the inference mechanism interprets the data. To provide effective process control, the defuzzification block converts the fuzzy output from the inference mechanism into non-fuzzy data. The fuzzy algorithm's control rules make it easy to implement and largely unaffected by variations in solar characteristics .Table 2, which contains 49 fuzzy control rules, presents the rules governing the control mechanism.

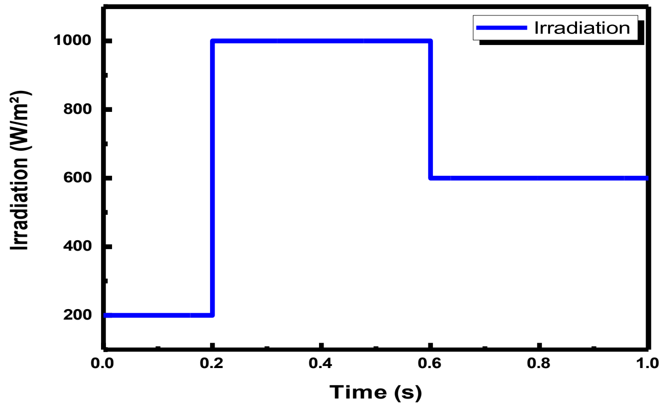


Figure 12. Irradiance profile

Table 2. **The rules implemented in the FLC.**

CE \ E	NB	NM	NS	Z	PS	PM	PB
NB	NB	NB	NB	NM	NS	NS	Z
NM	NB	NB	NM	NM	NS	Z	PS
NS	NB	NM	NS	NS	Z	PS	PM
Z	NB	NM	NS	Z	PS	PM	PB
PS	NM	NS	Z	PS	PS	PM	PB
PM	NS	Z	PS	PM	PM	PB	PB
PB	Z	PS	PM	PB	PB	PB	PB

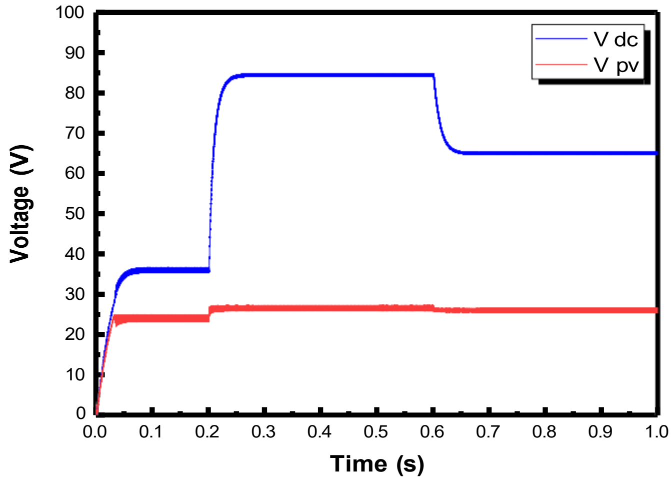
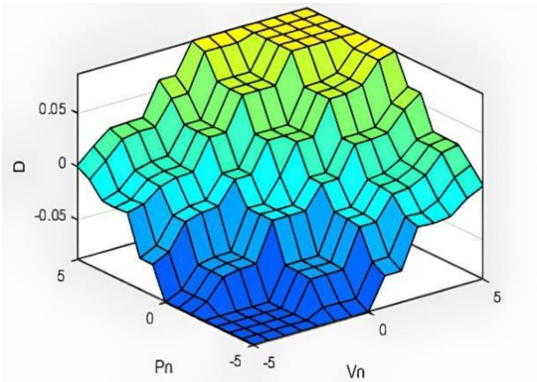


Figure 13. The variation of the Voltage in Boost Converter

The simulation was performed using the two algorithms previously mentioned. The step change in solar irradiance G is applied while the temperature stays constant at T = 25°C. The solar irradiance, as shown in Figure 12. increases from a value of 200 W/m^2 at time t=0.2s to 1000 W/m^2 at t=0.6s and falls at t=0.6s from 1000 W/m^2 to 600 W/m^2 at t=1s, and the boost converter increases and decreases in response to variations in irradiance between 40 and 85 volts and between 85 and 65 volts as illustrated in Figure 13.

Figure 14. shows the three-dimensional correlation between PV voltage, power, and duty cycle. The surface graph, as shown, illustrates the suggested MPPT-FLC tracker's best performance during the simulation. The comparison of the INC and FL MPPT methods during the rapid irradiance change is then shown in Figure 15. This outcome demonstrates that as compared to INC-MPPT, a more efficient power is acquired from FL-MPPT.

Figure 14. Rules surface viewer.



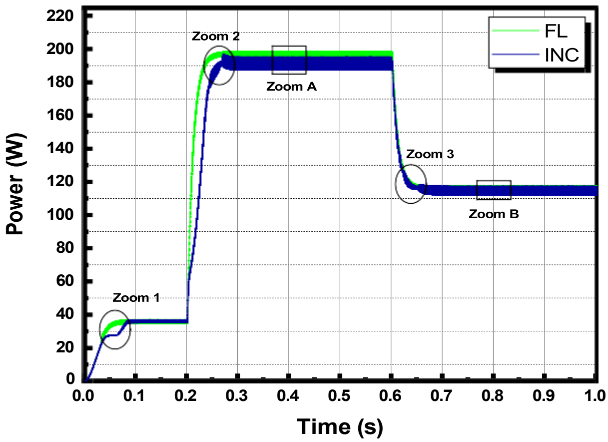


Figure 15. The evolution of the output power of different methods under varying irradiance and fixed Temperature (25°C) in Case 1

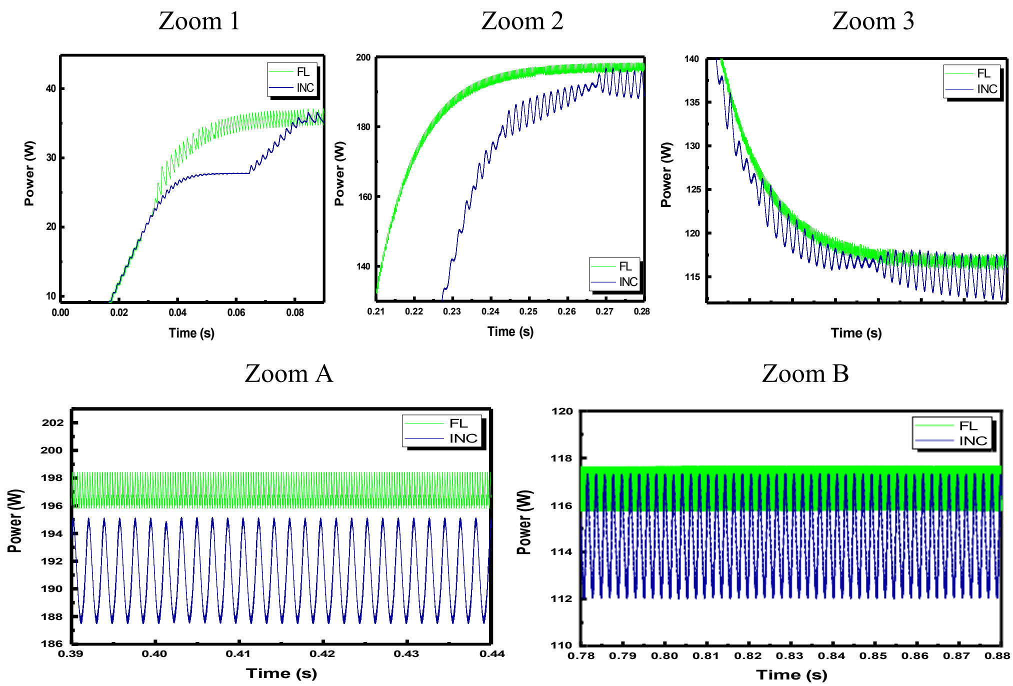


Figure 15. Zooms of power curves

It can be observed that power and irradiance are proportionally related, meaning that an increase in irradiation results in a rise in the photovoltaic power output. During the transient phase, the INC controller requires more time than the FL controller to achieve the optimal power level. this demonstrates that FL controller is faster than the INC controller, with response time of 0.085 s for the INC controller, and 0.065 s for the Fuzzy controller. This indicates that the FL controller is faster than the INC controller. moreover, The INC control has significant oscillations in the steady state and after stability, which implies large power losses; in contrast, the fuzzy controller has minimal oscillation.

Based on the performance results summarized in *Table 3*. below, which provides a statistical analysis of the two MPPT techniques under different irradiance conditions, we aim to better evaluate the overall effectiveness and robustness of each method. The tracking efficiency corresponding to each irradiance level is defined as:

$$\eta_i = \frac{P_{output,i}}{P_{mpp,i}} \tag{11}$$

Table 3. **Robustness and Efficiency Comparison of MPPT Controllers Under Solar Irradiance Variation at 25°C**

Irradiance (W/m2)/ Temperature (°C)	Maximum theoretical power output (W) $P_{mpp,i}$	Average Instantaneous Output Power $P_{output,i}$ (W)		Power Conversion Efficiency η_i (%)	
		FL	INC	FL	INC
1000/25	200	197.1	191.3	98.55	95.65
800/25	159.3	157.4	154.2	98.80	96.79
600/25	118.25	116.8	113.2	98.77	95.72
400/25	77.13	76.1	73.9	98.66	95.81
200/25	36.48	35.8	34.3	98.13	94.02

To evaluate the overall behavior of the MPPT techniques, both the average tracking efficiency and its dispersion were computed. The average efficiency is obtained as

$$\eta_{average} = \frac{1}{N} \sum_{i=1}^{N} \eta_i \tag{12}$$

while the associated variability is quantified through the standard deviation by the equation:

$$\sigma = \sqrt{\frac{1}{N-1} \sum_{i=1}^{N} (\eta_i - \eta_{average})^2} \tag{13}$$

with N=5 representing the total number of irradiance conditions evaluated.

The numerical outcomes are reported in *Table 4.*

Table 4. **Statistical Evaluation of Power Tracking Efficiency Across Different Irradiance Profiles**

MPPT Technique	Mean $\eta_{average}$(%)	σ Standard Deviation (%)
Fuzzy Logic	98.58	0. 07
Incremental Conductance	95.59	1.01

It is observed that the FL controller attains the greatest mean tracking efficiency combined with the smallest standard deviation, reflecting superior robustness and consistent performance under fluctuating irradiance. In contrast, the INC technique yields comparatively lower efficiency with a moderate level of variation, which highlights its reduced capability in maintaining optimal tracking accuracy across operating conditions.

The computational burden of the MPPT strategies was evaluated by estimating the number of floating-point operations (FLOPs) executed per sampling cycle. The analysis considers additions and multiplications as one FLOP each, while a division is approximated as eight FLOPs due to its higher execution cost. *Table 5.* summarizes the estimated processing effort for the two techniques. The results indicate that INC maintains a relatively low computational demand**,** as its operation relies primarily on simple arithmetic comparisons between the incremental variations of current and voltage. In contrast, FL requires a greater number of computations, attributed to the fuzzification stage, the evaluation of rule sets, and the final defuzzification procedure used to generate the control signal.

These observations highlight that although FL offers improved tracking robustness under dynamic conditions**,** its implementation requires more processing resources than INC—an important factor when targeting real-time embedded control or low-power MPPT hardware.

Table 5. **Comparative Computational Cost of MPPT Methods Expressed in FLOPs/Iteration**

MPPT Technique	Total FLOPs per Iteration (Approx.)	Main Contributors to Processing Cost
Fuzzy Logic	~ 120 FLOPs	Input fuzzification, rule-base processing,Mamdani inference, defuzzification process
Incremental Conductance	~ 35 FLOPs	dI/dV slope estimation, comparison logic, Duty cycle adjustment

Beyond performance assessment, the practical implementation of MPPT algorithms must also be taken into account. The Incremental Conductance technique is widely appreciated for its straightforward structure, modest computational load, and compatibility with low-cost microcontrollers. These advantages make it suitable for real-time applications, although its tracking accuracy may decrease when irradiance or temperature changes occur abruptly.Conversely, Fuzzy Logic control generally demands more memory, careful tuning of membership functions, and a well-designed rule base, which increases its implementation effort. Despite this additional complexity, FL offers high robustness and adaptability when dealing with non-linear photovoltaic characteristics, allowing it to maintain reliable MPPT performance under rapidly varying conditions—provided that its parameters are properly defined and validated.

7. Conclusions

This study involved modeling and evaluating the performance of MPPT techniques (INC and FL) through simulations conducted in the MATLAB/Simulink environment under various irradiation conditions. The initial focus was on examining the mathematical model of the PV circuit and analyzing the boost converter. Thereafter, the complete proposed system including the PV module, boost converter, and MPPT techniques was modeled and simulated in MATLAB/Simulink. The comparison results obtained from the MPPT control simulations indicate the behavior and characteristics of IN and FL techniques under different irradiation scenarios. In summary, selecting the appropriate MPPT method requires balancing tracking efficiency and implementation constraints: INC favors simplicity and low hardware cost, while FL offers improved dynamic behavior at the expense of higher computational requirements. In future work, we aim to develop a hybrid MPPT approach that combines the strengths of both INC and FL, seeking to achieve fast tracking response, reduced oscillation around the MPP, and robust performance under highly variable environmental conditions.

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