

Performance Evaluation of PV MPPT Using ANFIS Subtractive Clustering, GWO, and IT2FL: A Comparative Study

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ABSTRACT

Solar energy is eco-friendly nature. To maximize its utilization, this paper presents a comparative performance evaluation of four advanced maximum power point tracking (MPPT) techniques for photovoltaic (PV) systems: ANFIS subtractive clustering, Interval Type-2 Fuzzy Logic (IT2FL), and Grey Wolf Optimization (GWO)-based MPPT. The proposed ANFIS approach leverages subtractive clustering (ANFIS-SC), which offers significant advantages over conventional grid partitioning, including adaptability to complex data structures, automatic identification of optimal cluster centers, and reduced computational complexity by focusing on high-density regions. The resulting Sugeno-type ANFIS-SC MPPT system employs a single rule and one membership function per input, achieving simplicity, fast dynamic response, and superior tracking precision compared to traditional P&O methods. To further benchmark performance, an IT2FL-based MPPT is implemented, leveraging its inherent robustness to system uncertainties, while the GWO-based MPPT is introduced for its exceptional global search capability and adaptability to PV system. The three techniques are rigorously compared in terms of power extraction efficiency, voltage stability, and current dynamics under varying irradiance and temperature conditions. Simulation results demonstrate that while all intelligent methods outperform conventional P&O. This study provides critical insights for selecting MPPT strategies based on operational priorities, paving the way for optimized PV system.

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1. INTRODUCTION

The distance from central power grids and the cost of infrastructure are primary obstacles to electrification in remote areas, where load demand is often too low to justify traditional grid expansion. Coupled with challenges like frequent power outages, grid instability, and environmental concerns (e.g., CO₂ emissions [1- 3], ozone depletion, and global warming), these limitations have intensified the need for decentralized network.

Among renewables, PV energy stands out due to its minimal operating costs, pollution-free operation, and direct electricity generation capability. However, PV systems face significant challenges, including nonlinear power-output characteristics and dependence on environmental conditions [4- 8]. To maximize efficiency, MPPT is essential. Conventional MPPT methods offer simplicity but suffer from oscillations and slow convergence under dynamic conditions.

Modern MPPT controllers typically integrate a DC-DC converter driven by advanced algorithms. Artificial Intelligence (AI) based approaches, such as ANFIS, IT2FL, and GWO have demonstrated superior performance, combining robustness, fast tracking, and adaptability to nonlinearities. This paper advances the field by proposing three advanced AI-MPPT techniques:

- ANFIS with subtractive clustering, which eliminates the need for manual grid partitioning, reduces computational overhead, and improves adaptability to complex data patterns.
- Interval Type-2 Fuzzy Logic (IT2FL), which enhances uncertainty handling in fluctuating irradiance/temperature conditions.
- GWO-based MPPT is introduced for its exceptional global search capability and adaptability to PV system.

The paper is organized as follows: Section 2 introduces the PV system modeling, while Section 3 details the MPPT methodologies, including the conventional Perturb & Observe (P&O) method, ANFIS-based subtractive clustering (ANFIS-SC), Grey Wolf Optimization (GWO), and Interval Type-2 Fuzzy Logic (IT2FL). Section 4 depicts the simulation results and a comparative performance analysis under environmental conditions. Finally, Section 5 concludes the study with key findings and insights. The results demonstrate that ANFIS-SC, GWO, and IT2FL consistently outperform P&O in terms of tracking efficiency, dynamic response, and PV power output.

2. PV MODELING

The solar system under consideration, seen in Figure 1, employs the PV system, whose electrical properties are listed in Table 1.

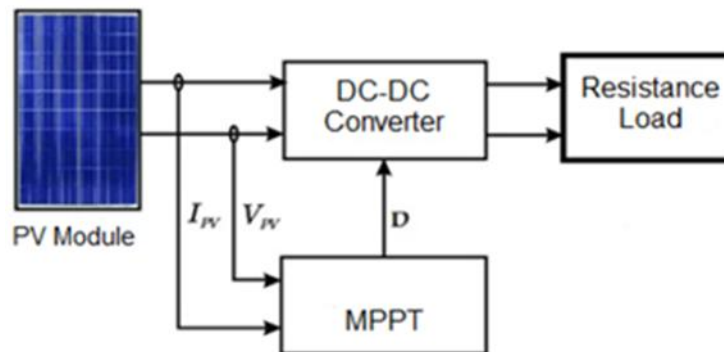


Fig. 1. PV system.

The single-diode model is a suitable compromise between simplicity and accuracy. A photocurrent source in parallel with a single nonlinear diode, a shunt resistor, and a series resistor are depicted in Figure 2. The photocurrent source is primarily determined by the amount of solar irradiation and the cell's operating temperature. These equations define the model of the PV cell:

$$I = I_{ph} - I_D - I_{sh}$$

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

$$I = [I_{sc} + K_1(T_c - T_r)]\lambda$$

Where,

I_{ph} : photocurrent current, I_D : diode current, I : output current from the cell, I_{sh} : shunt resistor current, I_s : diode saturation current, K_1 : Boltzmann constant, q : electron charge, T_c : actual cell temperature, R_{sh} : shunt resistance, and I_{sc} : short-circuit current, T : reference temperature, λ : irradiance and R_s : series resistance, V and I are the output voltage and output current of the PV module respectively.

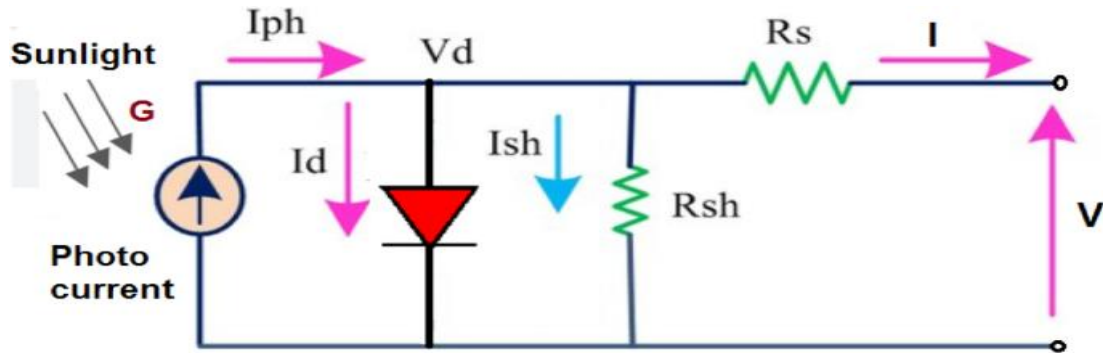


Fig. 2. PV cell equivalent circuit

Table 1. PV module electrical characteristics values

Power maximum power point (Pmpp) W	200.143
Voltage maximum power point (Vmpp) V	28.7
Current maximum power point (Impp) A	7.61
Open Circuit Voltage (Voc) V	32.9
Short Circuit Current (Isc) A	8.21
Number of cells connected in series	54
Number of cells connected in parallel	1

3. Methodology

This study evaluates and compares four MPPT

3.1. Perturb and Observe

At the first step, the PV system is implemented via P&O MPPT [9-14] for collecting the dataset of PV voltage, PV current, and the duty cycle. The PV MPPT P&O is implemented according to the algorithm below:

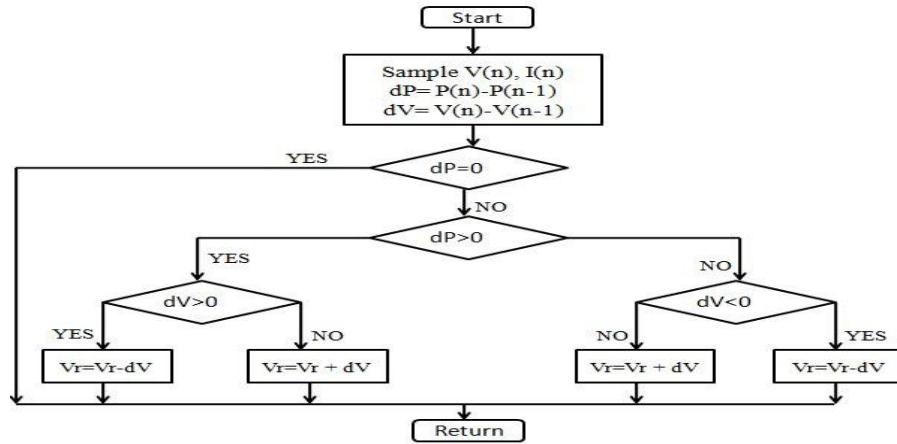


Fig.3. Flowchart of P&O MPPT algorithm

3.2. Adaptive Neuro-Fuzzy Inference System

ANFIS controller combines the strengths of artificial neural networks (ANN) and fuzzy logic control (FLC), making it highly effective for nonlinear systems such as PV modules. It offers fast response times and high efficiency, even under varying weather conditions. By leveraging ANN's learning ability and FLC's interpretability, ANFIS efficiently manages fluctuations in irradiance and temperature.

3.2.1. Working principle of ANFIS

The ANFIS model uses PV voltage and current as inputs. The ANN component helps optimize the fuzzy rule base and membership functions, creating an adaptive inference system. Through iterative learning, ANFIS fine-tunes nonlinear functions using a set of fuzzy rules [15- 23].

Fig. 5 illustrates the ANFIS control flow. For a two-input (x, y) and one-output system, the fuzzy rules can be expressed as:

If x is A_1 and y is B_1 , then f_1

$$f_1 = p_1x + q_1x + r_1$$

If x is A_2 and y is B_2 then, f_2 (2)

$$f_2 = p_2x + q_2x + r_2$$

And the output function is given by equation,

$$f = \frac{w_1f_1 + w_2f_2}{w_1 + w_2} \quad (3)$$

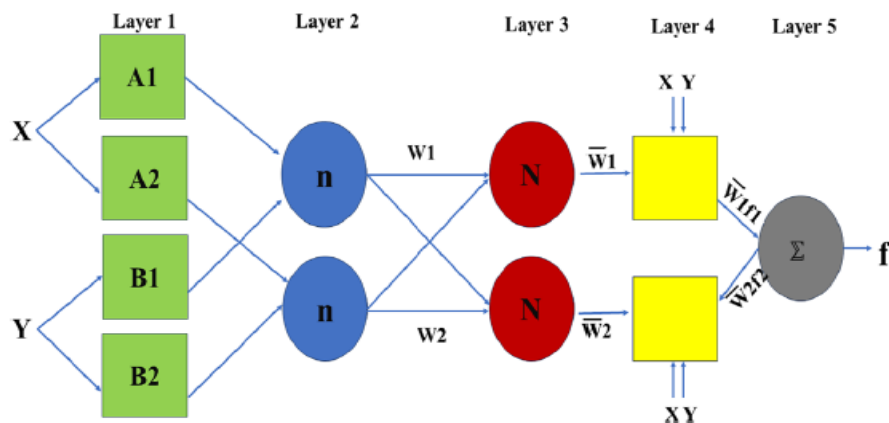


Fig. 4. Flow diagram of ANFIS

3.2.2 Subtractive Clustering Algorithm

Subtractive clustering treats each data point as a potential cluster center. The algorithm works as follows:

- A. **Potential Calculation**– Evaluate each point’s likelihood of being a cluster center based on nearby data density.
- B. **First Cluster Selection**– The point with the highest potential becomes the first cluster center.
- C. **Neighbor Removal**– Exclude points within a defined range (clusterInfluenceRange) of the selected center.
- D. **Iterative Process**– Repeat steps 2–3 for remaining points until all data falls within a cluster’s influence range.

Clustering Parameters

Squash Factor– Scales cluster influence range. Smaller values produce more, smaller clusters.

Acceptance Ratio– Minimum potential (relative to the first cluster) to accept a new center. **Rejection**

Ratio– Maximum potential (relative to the first cluster) to reject a point as a center.

3.3. Grey Wolf Optimizer

Grey wolf optimization is an intelligent swarm technique developed by [24- 26], which mimics the leadership hierarchy of wolves well known for their group hunting. Grey wolves belong to the canid family and mostly prefer to live in packs. They have a strict dominant social hierarchy; the leader is a male or female, called Alpha (α). The alpha is primarily responsible for decision-making. The dominant wolf’s orders must be followed by the pack. Betas (β) are subordinate wolves that assist the alpha in decision-making. The beta is an advisor to alpha and organizer for the pack. The delta (δ) wolves have to submit to the alpha and beta, but they dominate the omega. There are different categories of delta-like Scouts, Sentinels, Elders, Hunters, Caretakers etc. The lowest-ranking gray wolf is Omega (ω) who must submit to all other dominant wolves. Fig. 5 describes the hunting techniques and social hierarchy of wolves.

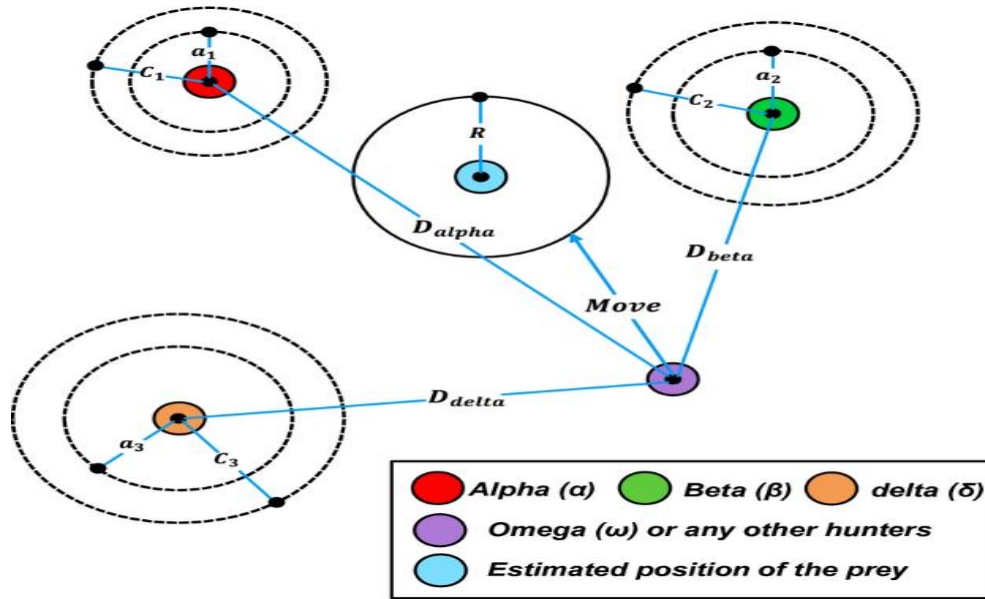


Fig. 5. GWO strategy

3.3.1. Algorithm steps

The GWO algorithm is briefly described in the following steps:

- Step 1: Reset GWO parameters such as search agents (G_s), design variable size (G_d), vectors a , A , C and maximum number of iterations.

$$\vec{A} = 2\vec{a}r_1 - \vec{a} \quad (4)$$

$$\vec{C} = 2r_2 \quad (5)$$

The values of $\vec{a}$ are decreased linearly from 2 to 0 during the iterations.

- Step 2: Generate random wolves based on pack size. Mathematically, these wolves can be expressed as,

$$Wolves = \begin{bmatrix} G_1^1 & G_{G_d-1}^1 & G_{G_d}^1 \\ G_1^{G_s} & G_{G_d-1}^{G_s} & G_{G_d}^{G_s} \end{bmatrix} \quad (6)$$

Where, G_{ij} is the initial value of the i th pack of the i th wolves.

- Step 3: Estimate the fitness value of each hunting agent.

$$\vec{D} = |\vec{C}\vec{G}_p(t) - \vec{G}(t)| \quad (7)$$

$$\vec{C}(t+1) = \vec{G}_p(t) - \vec{A}\vec{D} \quad (8)$$

- Step 4: Recognize the best hunting (G_α), the second best hunting (G_β) and the third best hunting (G_δ).

$$\vec{D}_\alpha = |\vec{C}_1\vec{G}_\alpha - \vec{G}| \quad (9)$$

$$\vec{D}_\beta = |\vec{C}_2\vec{G}_\beta - \vec{G}| \quad (10)$$

$$\vec{D}_\delta = |\vec{C}_3\vec{G}_\delta - \vec{G}| \quad (11)$$

$$\vec{D}_1 = \vec{G}_\alpha - \vec{A}_1(\vec{D}_\alpha) \quad (12)$$

$$\vec{D}_2 = \vec{G}_\beta - \vec{A}_2(\vec{D}_\beta) \quad (13)$$

$$\vec{D}_3 = \vec{G}_\delta - \vec{A}_3(\vec{D}_\delta) \quad (14)$$

- Step 5: Renew the current search agent location using the following equation:

$$\vec{G} = \frac{\vec{G}_1 + \vec{G}_2 + \vec{G}_3}{3} \quad (15)$$

3.4. Interval Type 2 Fuzzy Logic

Zadeh developed fuzzy set theory [27- 29], an approach widely used. It has the ability to operate without requiring a precise mathematical model. The controllers based on fuzzy logic replicate human reasoning to make control decisions, converting linguistic instructions into precise numerical actions. The FLC has three stages:

- Fuzzification: Converting the crisp inputs into fuzzy membership values.
- Fuzzy Inference: Applying the rule base to map the fuzzy inputs to the fuzzy output.
- Defuzzification: Translating the fuzzy output to a crisp control output value.

Type-2 fuzzy sets provide greater flexibility compared to type-1 sets (Fig. 6) by incorporating an additional degree of freedom in the fuzzy inference process (Fig. 7). This feature makes them particularly effective in environments with uncertainty and ambiguity, thereby enhancing system performance.

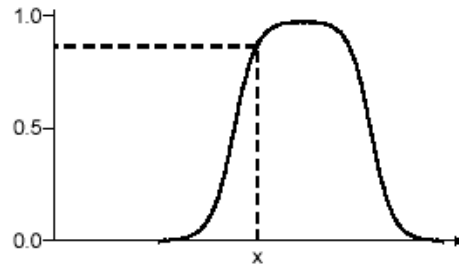


Fig. 6. Fuzzy Type 1

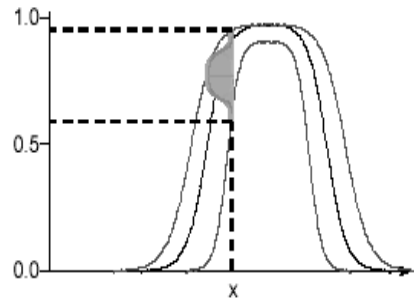


Fig. 7. Fuzzy Type 2

The interval type-2 fuzzy logic controller, denoted as $\tilde{X}$, is defined by a type-2 membership function, $\mu_{\tilde{X}}(x,u)$, where $x \in X$ (X being the universe of discourse) and $u \in J$ $x \subseteq [0,1]$, as described in [14].

$$\tilde{X} = \{(x,u), \mu_x(x,u)\} \mid \forall u \in J \in [0,1] \quad (16)$$

The representation of $\tilde{X}$ set can also be given by[15]:

$$\tilde{X} = \int_{x \in X} \int_{u \in J} \frac{\mu_{\tilde{X}}(x,u)}{(x,u)} J \in [0,1] \quad (17)$$

3.3.1. Footprint of Uncertainty

FOU represents the aggregation of all primary membership functions.

$$FOU(\tilde{X}) = \cup_{x \in X} J_x \quad (18)$$

It is bounded by:

- Upper membership function (UMF): $\bar{\mu}_{\bar{X}}(x)$.
- Lower membership function (LMF): $\underline{\mu}_{\bar{X}}(x)$.

Type-2 Fuzzy Inference System (FIS)

The IT2FL controller is composed of four basic elements (Fig. 8)

a. Fuzzification

Transform a precise input x' into an IT2FS by computing its associated Upper and Lower Membership Functions (UMF and LMF), thereby capturing the uncertainty inherent in the membership grades.

$$\bar{X}(x') = [\underline{\mu}_{\bar{X}}(x'), \bar{\mu}_{\bar{X}}(x')] \quad (19)$$

b. Inference

If x_1 is $\bar{X}_1$ and x_2 is $\bar{X}_2$, then y is $(\bar{C})$

The firing strength is determined by applying a t-norm operator, which aggregates the membership values of the antecedent conditions.

$$F_i = [\underline{f}_i, \bar{f}_i] \quad (20)$$

Where,

$$\underline{f}_i = t\text{-norm}(\underline{\mu}_{\bar{X}_1}(x_1), \underline{\mu}_{\bar{X}_2}(x_2)) \quad (21)$$

$$\bar{f}_i = t\text{-norm}(\bar{\mu}_{\bar{X}_1}(x_1), \bar{\mu}_{\bar{X}_2}(x_2)) \quad (22)$$

c. Type Reduction

IT2FS can be reduced to a T1FS through type-reduction techniques, such as the Karnik–Mendel (KM) algorithm, which is commonly used to compute the centroid of the IT2FS.

The KM Algorithm calculates the switch points iteratively according to the equations below:

$$y_L = \frac{\sum_{i=1}^L x_i \bar{\mu}(x_i) + \sum_{i=L+1}^N x_i \underline{\mu}(x_i)}{\sum_{i=1}^L \bar{\mu}(x_i) + \sum_{i=L+1}^N \underline{\mu}(x_i)} \quad (23)$$

$$y_r = \frac{\sum_{i=1}^R x_i \underline{\mu}(x_i) + \sum_{i=R+1}^N x_i \bar{\mu}(x_i)}{\sum_{i=1}^R \underline{\mu}(x_i) + \sum_{i=R+1}^N \bar{\mu}(x_i)} \quad (24)$$

$$Y_c = [y_L, y_r] = \text{Centroid}(\bar{C}) \quad (25)$$

Where y_L and y_r are endpoints of the type-reduced set.

d. Defuzzification

Defuzzification is the final stage in a fuzzy inference system, where a crisp output is derived by averaging the bounds of the type-reduced set, typically obtained via centroid-based methods.

$$y = \frac{y_L + y_r}{2} \quad (26)$$

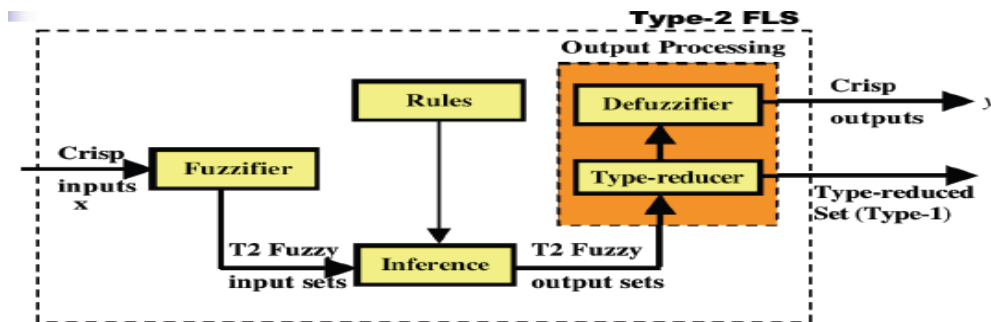


Fig.8 Architecture of IT2FLC.

4. Simulation and discussion

The implementation of ANFIS, and IT2FL PV MPPT has been achieved on the dataset of the PV MPPT

based on P&O. The figures below show The I–V and P–V curves of the simulated MATLAB model of the PV module at 25°C and different solar irradiance, and the Simulink simulation of the system.

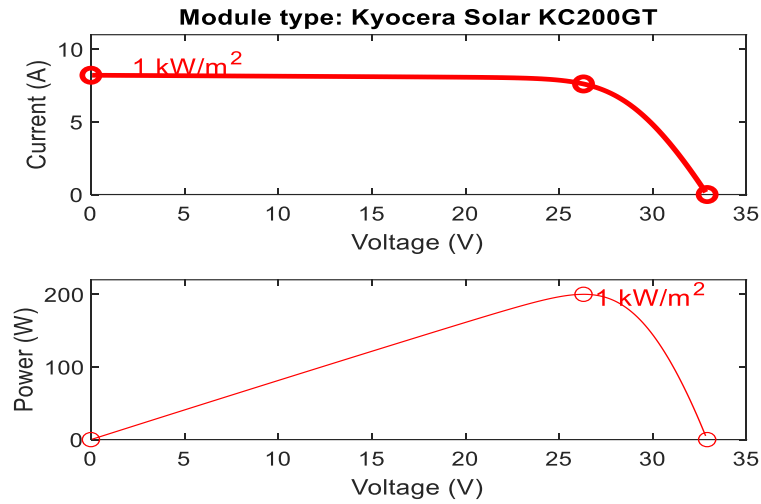


Fig. 9. The I–V and P–V curves of the simulated MATLAB model

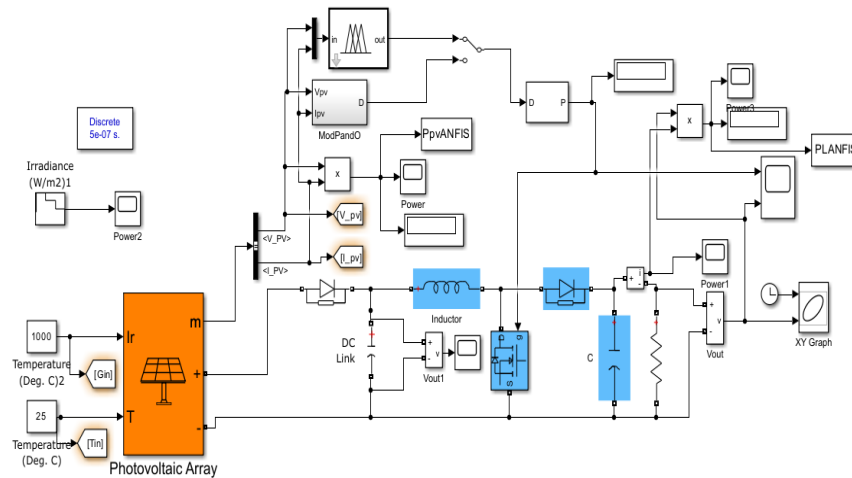


Fig. 10. Simulink of the proposed system

The ANFIS training using subtractive clustering partition has generated one cluster for each input, as is shown on Fig. 11.

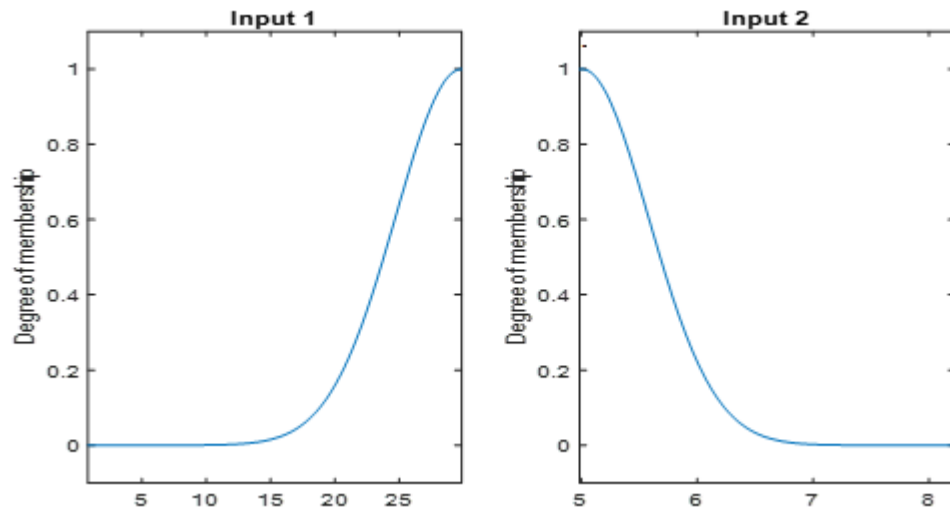


Fig. 11. Input Membership functions

The ANFIS-SC parameters are presented below:

Table 2. ANFIS-SC parameters based on subtractive clustering

Range of influence	0.5
Squash factor	1.25
Accept ratio	0.5
Reject ratio	0.15

The GWO parameters are below:

- Dimension of the problem (Duty cycle): 1
- Number of search agents (wolf population): 7
- Iteration number: 100

The Interval Type-2 Fuzzy Logic parameters are below:

- Type reducer: Karnik-Mendel
- Scale factor: 0.6
- Lower lag: 0.4.

Fig. 12 presents the IT2FL based PV MPPT controller membership functions according to the parameters above.

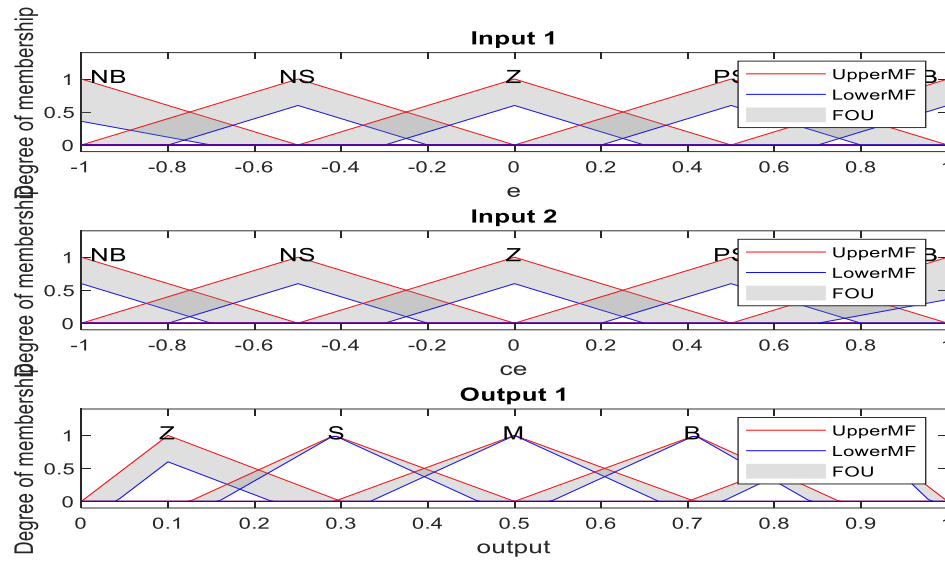


Fig. 12. Membership functions of IT2FL-based MPPT controllers

As shown in Figs. 13–18 and according to table 3, which presents the performance comparison results of the four MPPT controllers, the intelligent MPPT controllers—namely ANFIS-SC, GWO, and IT2FL—outperform the conventional P&O MPPT controller. Among the intelligent MPPT controllers, none completely dominates all performance criteria. However, it can be concluded that the IT2FL-based MPPT controller performs the best, as the GWO-based MPPT controller exhibits a slight dip in performance between 0.02s and 0.1s.

Under load conditions, the intelligent MPPT controllers surpass the P&O MPPT, though the GWO-based MPPT shows some power oscillations.

Figs. 19–20 illustrate the impact of wolf population size on the performance of the GWO-based MPPT. A wolf population of 7 enables the GWO algorithm to deliver maximum power compared to populations of 6 and 8.

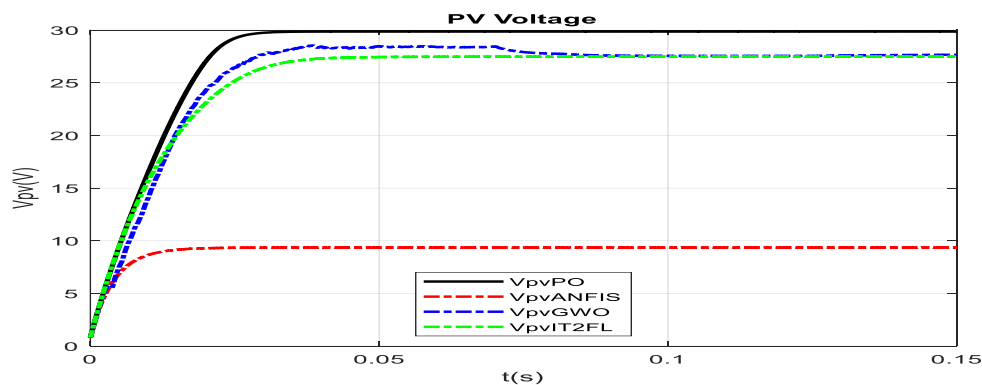


Fig. 13. Comparative analysis of PV voltage output using P&O, ANFIS-SC, GWO, and IT2FL-based MPPT controllers

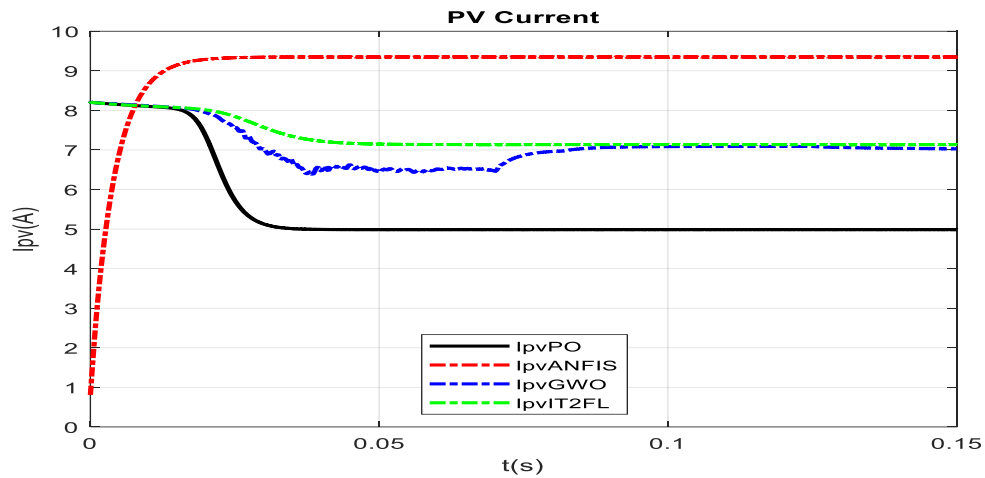


Fig. 14. Comparative analysis of PV current output using P&O, ANFIS-SC, GWO, and IT2FL -based MPPT controllers

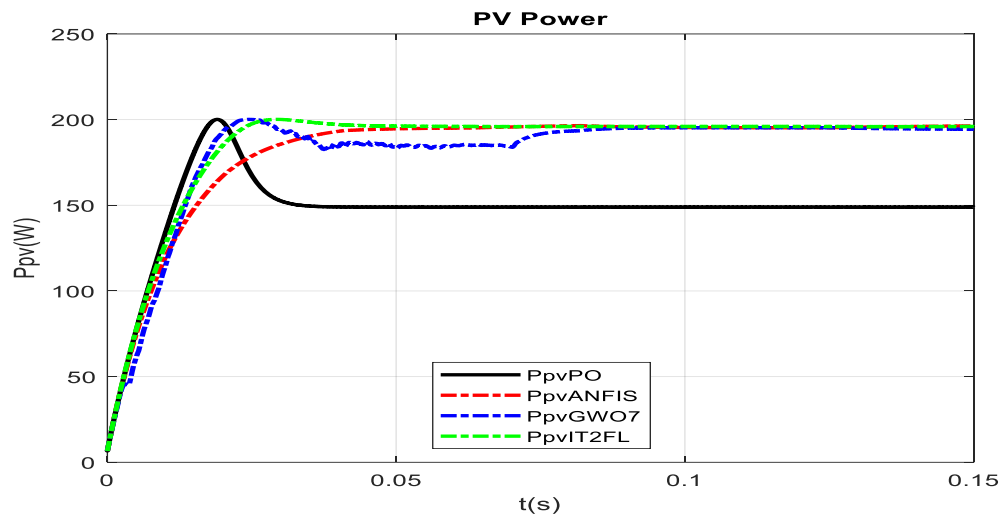


Fig. 15. Comparative analysis of PV power output using P&O, ANFIS-SC, GWO, and IT2FL -based MPPT controllers

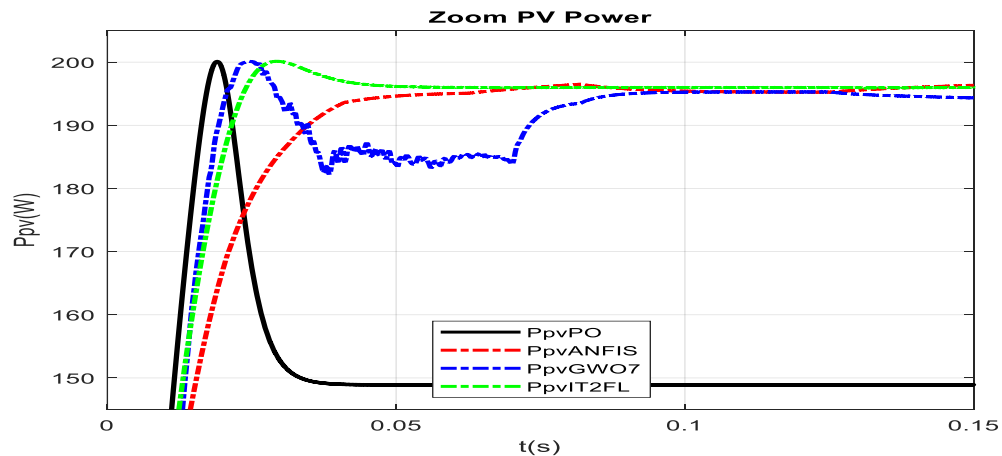


Fig. 16. Zoom of comparative analysis of PV power output using P&O, ANFIS-SC, GWO, and IT2FL -based MPPT controllers

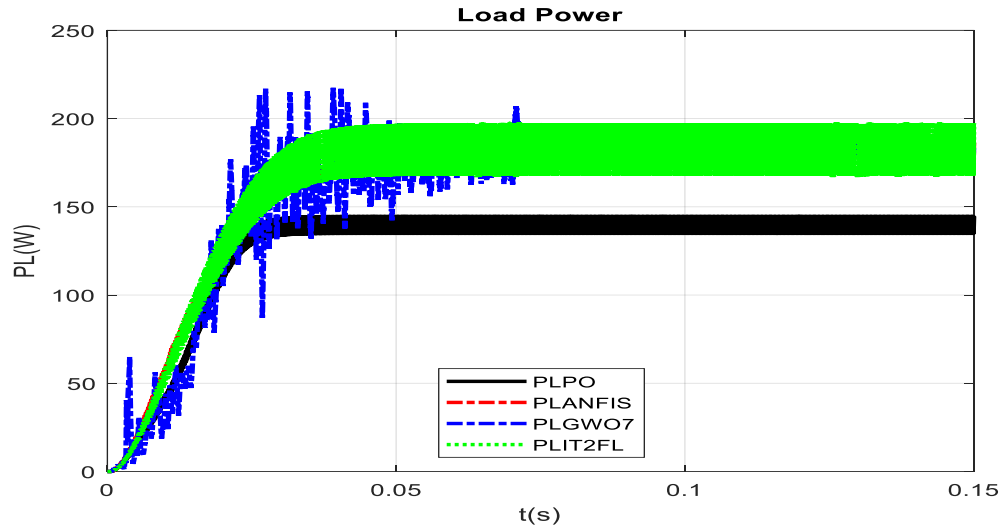


Fig. 17. Comparative analysis of Load power using P&O, ANFIS-SC, GWO, and IT2FL-based MPPT controllers

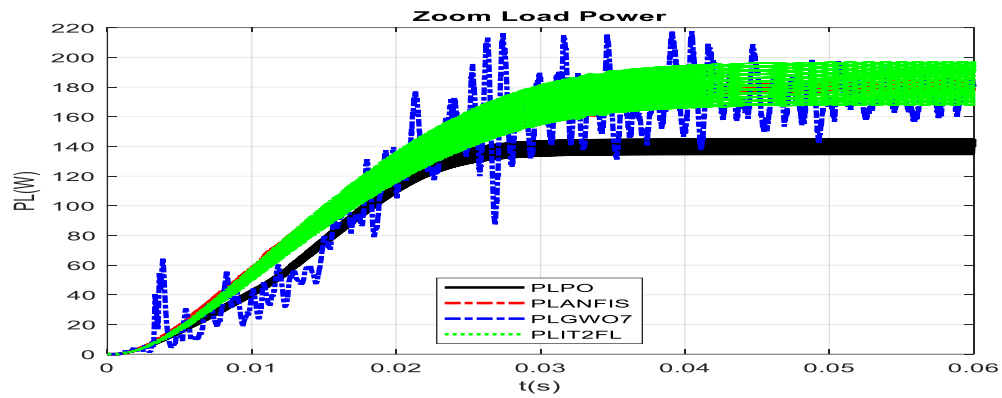


Fig. 18. Zoom of comparative analysis of Load power using P&O, ANFIS-SC, GWO, and IT2FL-based MPPT controllers

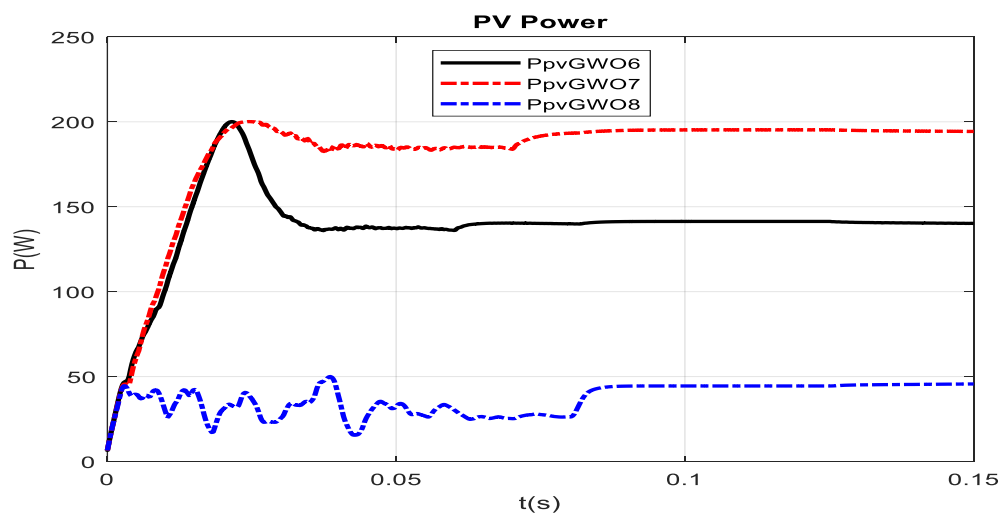


Fig. 19. Impact of wolf population size on GWO-Based MPPT performance: PV power output comparison

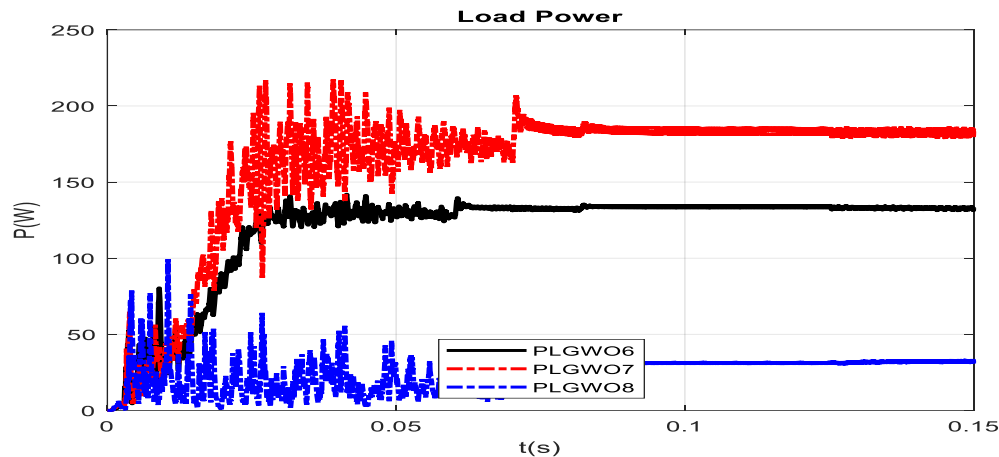


Fig. 20. Impact of wolf population size on GWO-Based MPPT performance: Load power comparison

Table 3. Comparative performance evaluation of four PV MPPT controllers

	P&O	ANFIS-SC	GWO	IT2FL
RiseTime	0.0141	0.0250	0.0165	0.0179
SettlingMin	148.8540	180.0000	180.0011	180.0026
SettlingMax	200.1382	196.5045	200.1372	200.1368
Overshoot	0	0	0.0686	0.0684
Undershoot	0	0	0	0
Peak	200.1382	196.5045	200.1372	200.1368
PeakTime	0.0190	0.0820	0.0245	0.0293

5. Conclusion

The comparative analysis underscores the limitations of classical P&O in dynamic environments and highlights the superiority of intelligent MPPT techniques. While ANFIS-SC excels in adaptability and learning, GWO offers rapid convergence (with minor oscillations), and IT2FL provides the highest stability under uncertainty. For optimal PV system performance, IT2FL is the most reliable choice, though GWO remains competitive when fine-tuned (e.g., wolf population optimization). Future work could explore hybrid approaches (e.g., ANFIS-GWO) to further enhance tracking precision and robustness.

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