An Improved MPPT Scheme for Photovoltaic Systems Using a Novel MRAC-FUZZY Controller

Original Scientific Paper

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Abstract *– This paper presents a novel and highly effective fuzzy model reference adaptive control for MPPT based on a boost converter. The design of Model-Referenced Adaptive Control (MRAC) and the adaptive gain selection are discussed. The adjustment of the adaptation gains by a fuzzy logic subsystem and a simplified fuzzy MRAC procedure are presented. The suggested algorithm is assessed through a comprehensive simulation in MATLAB/Simulink. Various scenarios and environmental conditions are considered to assess its robustness and adaptability. The results indicate that the suggested MRAC-Fuzzy MPPT control is extremely robust, with tracking efficiency that can reach 99.97%. Furthermore, it consistently operates the photovoltaic system at or around the MPP, effectively reducing oscillations, improving energy efficiency, and enhancing power production. Under real operating conditions, this new controller can be used for photovoltaic pumping applications.*

Keywords*:* *Photovoltaic System, MPPT, Fuzzy Model Reference Adaptive Control, MIT Rule*

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1. INTRODUCTION

Energy production represents a significant challenge for the years ahead. Furthermore, developing countries will increasingly require energy to enhance their development. Energy sources can be divided roughly into two groups: renewable and non-renewable energies. The first category includes sources such as wind, hydro, waste, biomass, geothermal energy and solar, while the second category comprises uranium, gas, oil, coal, and similar resources. Consumption of fossil fuels from the second category results in greenhouse gas emissions, leading to an increase in atmospheric pollution. Additionally, these fossil fuel resources are exhaustible [1, 2]. Consequently, numerous countries are dedicated to exploring alternative, sustainable, and profitable renewable energy sources. In contrast to fossil fuels, these new energy sources are non-polluting, emitting no greenhouse gases, and pose no inherent danger [3]. The use and advancement of photovoltaic energy are on the rise globally. One of the most promising applications of this renewable energy source is photovoltaic pumping, which is particularly beneficial in rural areas with high levels of sunlight and no access to an electric grid [4]. Solar energy refers to the portion of electromagnetic energy extracted by photosensitive cells from the radiation emitted by the sun. It involves converting electromagnetic radiation into electricity through the photovoltaic effect. Based on the photovoltaic cells' electrical properties and their configuration, the efficiency of PV systems can be enhanced through techniques known as Maximum Power Point Tracking (MPPT) [5].

Indeed, numerous research studies on MPPT algorithms have been conducted and documented in the literature. Traditional methods like the Incremental Conductance (INC) algorithm [6] and the Perturb and Observe (P&O) algorithm [7] are among the most commonly used techniques. In spite of their simple and functional design, conventional approaches were only adept to follow the maximum power point (MPP) when weather conditions stayed constant. Moreover, conventional MPPT algorithms often demonstrate ripples in the vicinity of the MPP and may not be optimal for extensive solar power installations. Given these limitations mentioned above, researchers worldwide are actively devising innovative approaches to MPPT control in solar systems. Advanced MPPT techniques, including heuristic approaches like genetic algorithm, Fuzzy Logic Control (FL) [8], Particle Swarm Optimization (PSO) [9, 10], and Artificial Neural Network (ANN) [11], are widely used as some of the most prevalent enhanced MPPT control techniques, which guarantee a remarkable capability to track the MPP. MPPT methodology based on soft computing is widely regarded as one of the most powerful approaches for addressing nonlinear problems. The realm of literature abounds with research endeavors focused on enhancing existing methodologies and surmounting their inherent constraints. [12] have presented a novel method called perturbation and observation approach, which has been optimized using Neural Network (NN) technology to achieve MPPT. To validate the effectiveness of this system, simulation tests were conducted, considering various solar radiation levels. The findings of this research suggest that the approach excels in varying light intensities and temperature, the P&O approach optimized by NN is more efficient than traditional INC approaches. This controller demonstrates the ability to generate approximately 99% of the real maximum power. In contrast to the Incremental Conductance approach, which requires approximately 0.3 seconds to attain the reference value, the NN method requires approximately 0.025 seconds to execute, exhibiting minimal overshoot. An efficient and rapid method for MPPT has been devised by employing FL without the need for an expert to construct the membership functions. Using MATLAB, the methodology is put into practice and its effectiveness is assessed by analyzing the results obtained, fuzzy logic significantly outperforms ANN optimized with PSO, ANN-GA (Genetic Algorithm), and ANN-ICA (Imperialist Competitive Algorithm) in terms of stability, precision, rapidity and simplicity of installation in the face of environmental fluctuations, as reported by [13]. In order to tackle the issue of chattering, a novel super-twist sliding-mode controller was proposed and integrated into the system. Additionally, a Type 2 fuzzy set (STSMC-T2FC) was employed to further enhance the performance of the system. The algorithm proposed has been developed using MATLAB and then assessed against both STSMC and traditional SMC methodologies across different radiation scenarios. The efficiency of the STSMC-T2FC MPPT stands at 99.59%, surpassing both STSMC with 99.33% and SMC with 99.20%. Despite the closely matched efficiency performances, STSMC-T2FC emerged as the superior choice, as indicated by [14]. A two-stage global MPPT control mechanism has been proposed to guarantee the utilization of all power generated by the PV for the load [15]. The initial stage employs global perturbation-based extremum seeking control (GPESC) to pinpoint the global Maximum Power Point (MPP). The second stage involves Model Reference Adaptive Control (MRAC), which is utilized to regulate the dynamics of the DC-DC converter. The simulation evaluates the effectiveness of the suggested controller in terms of tracking speed, efficiency, and accuracy under different radiation conditions. The GPESE and GPESC-PID controllers are utilized for comparative analysis. A newly developed high-frequency learning-based adjustable gain Model Reference Adaptive Control (HFLAG-MRAC) system, as proposed by [16], designed for a two-level MPPT control structure in PV systems. This approach aims to optimize power distribution to the load, particularly in the face of rapidly changing environmental conditions. The adaptive principle for the HFLAG-MRAC is formulated through Lyapunov theory, ensuring that the control system is theoretically robust and stable. However, there are several efforts still to be resolved in order to enhance the effectiveness of MPPT control. These efforts involve reducing response times, monitoring MPP, optimizing design parameters, attenuating steady-state oscillations, minimizing the sensor costs involved, and simplifying complexity.

Another issue is the aleatory behavior of optimization approaches in one-shot design methods, with MPPT MRAC control, system performance is affected by the adaptation gain of the adjustment mechanism: a high value of adaptation gain can cause system instability. This implies that the adaptation gain should be selected optimally to minimize this problem. In this context, a novel adaptive MPPT controller have been proposed, whose adaptation gain is defined heuristically using an adequate heuristic method for setting the adaptation gain based on fuzzy logic.

The main contributions of the current study are described as follow:

- A new Fuzzy Model Reference Adaptive controller (MRAC-FUZZY) is suggested for photovoltaic systems in order to obtain an optimal MPP.
- The proposed algorithm reduces complexity by minimizing the adaptation equations mechanism and subsequently the controller.

- MRAC-FUZZY MPPT is intended to provide an adaptive control strategy that optimizes the power output of photovoltaic systems by dynamically adjusting control parameters to track the MPP under varying environmental conditions while maintaining stability and eliminating ripples. This leads to increased energy efficiency and improved performance of PV systems.
- The proposed algorithm reduces response time: by approximately 11 times, 5 times and 2 times, faster than P&O, FL and PSO respectively.
- A comparative study involving simulation is conducted to assess the efficiency of the suggested MPPT controller.

This research is structured as outlined below: In Section 2, we present the photovoltaic system's mathematical model. Section 3 outlines the procedure design of the proposed MRAC-Fuzzy MPPT control algorithm. Section 4 illustrates the simulation outcomes regarding the performance of the photovoltaic systems. These results are obtained by implementing the MRAC-Fuzzy MPPT control algorithm, which is proposed in this study. Furthermore, a comparison is made between the performance of this algorithm and three conventional controllers namely, "MPPT PSO," "MPPT Fuzzy Logic," and "MPPT P&O." Additionally, we evaluate the performance of each MPP controller in comparison to the proposed MRAC-Fuzzy MPPT algorithm. Finally, we conclude with some remarks and a summary of our findings.

2. MODELING OF THE PHOTOVOLTAIC SYSTEM

2.1. PHOTOVOLTAIC CELL MODELING

The typical composition of a photovoltaic cell consists of components depicted in Fig. 1, comprising a current generator, a diode, and a combination of resistors connected in series and parallel [17].

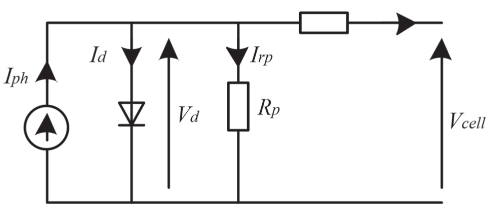


Fig. 1. PV circuit equivalent model

The equation below can be used to calculate the current delivered by a solar panel.

$$I_{cell} = I_{ph} - I_d[exp(\mu) - 1] - \frac{V_{pv} + R_s I_{pv}}{R_p} \tag{1}$$

With

$$\mu = \frac{V_{PV} + R_S I_{pv}}{N_s \frac{\mathrm{Ak_b}}{\mathrm{e}} T} \tag{2}$$

$$I_{ph} = \left(I_{sc} + \mathrm{k_i}(T - 270)\right)\frac{G}{1000} \tag{3}$$

$$I_d = I_0 \left(\frac{T}{298}\right)^3 \exp\left(\frac{\mathrm{qE_q}}{\mathrm{k_b} V_t}\left(\frac{1}{298} - \frac{1}{T}\right)\right) \tag{4}$$

Icell (I_{pv}) and V_{pv} represent the output current and voltage of the PV system, respectively, I_{ph} is the photocurrent, Id designates the diode current, I_0 is the inverse saturation current. The short-circuit current is designated by I_{sc}, the series resistance is indicated by R_s, the parallel resistance is noted as R_p. k_i is the temperature coefficient of the short circuit current. T, q, kb, and A correspond to the temperature, the electronic charge, the Boltzmann constant, and the diode factor respectively [18]. T is the temperature of Solar Cells and G is the irradiance and the irradiance reference (kW/m^2).

2.2. BOOST CONVERTER

Fig. 2 depicts the DC-DC converter responsible for optimizing the power transfer from the PV array to the load. This converter plays a crucial role in MPPT by dynamically adjusting the voltage and current levels between the PV source and the load. This allows the system to operate at the Maximum Power Point (MPP) of the PV array, maximizing power extraction under varying environmental conditions.

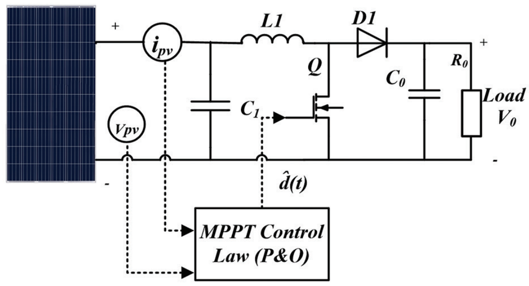


Fig. 2. Photovoltaic system schematic diagram

The fundamental connection between converter duty cycle and mains voltage is given by:

$$V_{pv} = i_{pv} R_0 (1 - d)^2$$

It is essential to consider the interaction among the duty cycle and the grid voltage in MPPT control to improve the transitional response [19]. To facilitate the analysis of the system's transient behavior, we examine a small equivalent signal similar to the one depicted in Fig. 2, as illustrated in Fig. 3.

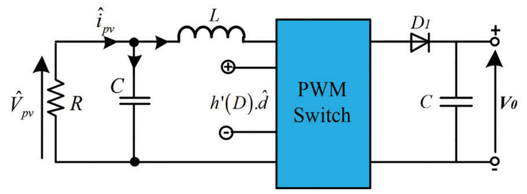


Fig. 3. Small-signal model of the photovoltaic output converter circuit

The duty cycle transfer function at mains voltage in small signal mode is calculated using an operating point [20]. As shown in Fig. 4, the equation between the mains voltage $\hat{V}_{pv}$ and the variation of the small pulse around the duty cycle $\hat{d}$ of the inverter can be determined in the Laplace domain as below:

$$\frac{\hat{V}_{pv}(s)}{R} + \hat{V}_{pv}(s)Cs = \frac{h'(D)\hat{d}(s) - \hat{V}_{pv}(s)}{sL} \tag{6}$$

with $\hat{d}(s)$ denoting the smaller signal variation near the duty cycle D, $h(d)$ represents the relationship among V_{pv} and D. $h'(D)$ the derivative of $h(D)$. According to Eq. (6), we get:

$$\frac{\hat{V}_{pv}(s)}{\hat{d}(s)} = \frac{h'(D)}{\mathrm{L}Cs^2 + \frac{\mathrm{L}}{\mathrm{R}}s + 1} \tag{7}$$

As defined above, $h(D)$ can be written as the following equation:

$$h(D) = V_{PV} = (1 - D)V_0 \tag{8}$$

V_0 represents the output of the boost converter. We simply derive $h(d)$ with regard to the duty cycle D, we obtain:

$$h'(D) = -V_0 \tag{9}$$

The output of the boost converter in a steady-state condition, designated as V_0, is represented by Eq. (8) under the assumption that transient switching behavior does not influence $h(d)$ and V_0. This leads to the derivation of $h'(D) = -V_0$. Consequently, Eq. (7) will be formulated as follows:

$$\frac{\hat{V}_{pv}(s)}{\hat{d}(s)} = \frac{\frac{-V_0}{\mathrm{LC}}}{\mathrm{s}^2 + \frac{1}{\mathrm{RC}}\mathrm{s} + \frac{1}{\mathrm{LC}}} \tag{10}$$

3. MAXIMUM POWER POINT TRACKER DESIGN

This section introduces the concept of the MRAC-FUZZY, which aims to optimize the power generated by a photovoltaic array. The complete framework of the suggested control methodology is depicted in Fig. 4.

The proposed algorithm consists of two levels. First level presents an MPPT control law based on P&O technique, as shown in Fig. 5. A voltage reference (vref) is set by this control block for any given MPP voltage. In the second level, a proposed MRAC-Fuzzy MPPT controller is developed which is illustrated in Fig. 6.

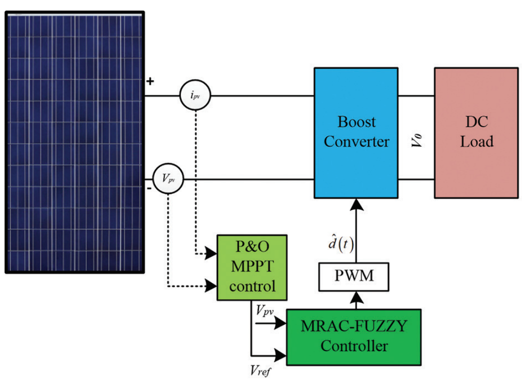


Fig. 4. Photovoltaic system with the suggested MPPT control configuration

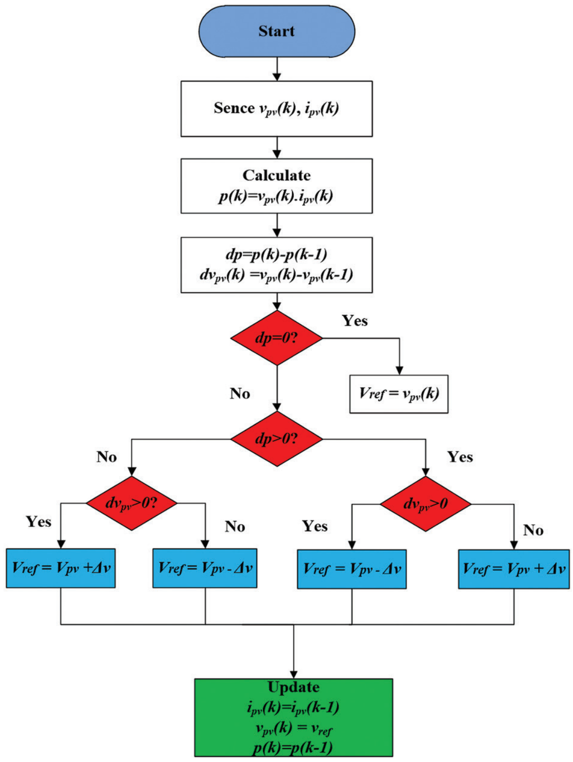


Fig. 5. Voltage Setpoint calculation

The new adaptive MPPT controller has only two inputs: voltage array and reference voltage. Its architecture is based on a reference model, a plant, and an adaptation gain (γ) as shown in Fig. 6.

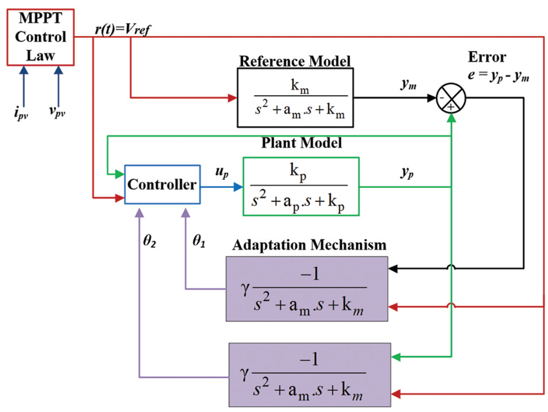


Fig. 6. Proposed MRAC controller architecture

The aim of the MRAC is to ensure that the output of the plant produces the output of the reference model by using γ. To achieve optimal output measurement, it is crucial to select a reference model as the initial step in implementing an MRAC, Additionally, a controller should be formulated to minimize the error (e) among reference and plant value. The Massachusetts Institute of Technology (MIT) law, which employs a gradient strategy, is considered one of the most fundamental adaptive approaches. Developed at MIT in the 1960s for aerospace uses, the MRAC controller enhances this technique by adjusting the adaptation laws to minimize the disparity among the reference and system output.

Conventional MRAC feedback is not sufficient for second-order systems. The second-order system control law and the first to second-order extension of MRAC-FUZZY are described in this section.

The plant model is defined with the following equation:

$$\frac{d^2 y_p(t)}{dt^2} = -\mathrm{a_p}\frac{dy_p(t)}{dt} - \mathrm{b_p} y_p(t) + \mathrm{k_p} u_p(t) \tag{11}$$

$$G_p(s) = \frac{y_p(s)}{u_p(s)} = \frac{\mathrm{k_p}}{s^2 + \mathrm{a_p} s + \mathrm{b_p}} \tag{12}$$

a_p, b_p and k_p are plant coefficients which can be determined using equation (9). The reference model has been specially adapted to define the required output $y_m(t)$ for the input $r(t)$ in the next equation.

$$\frac{d^2 y_m(t)}{dt^2} = -\mathrm{a_m}\frac{dy_m(t)}{dt} - \mathrm{b_m} y_m(t) + \mathrm{k_m} r(t) \tag{13}$$

$$G_m(s) = \frac{y_m(s)}{r(s)} = \frac{\mathrm{k_m}}{s^2 + \mathrm{a_m} s + \mathrm{b_m}} \tag{14}$$

k_m exhibits a positive gain, a_m and b_m are determined to ensure that the reference model produces a step response that is critically attenuated. The purpose of the control system is to create $y_p(t)$ in a manner that the later proceeds $y_m(t)$.

The MIT rule (The MIT law employs a gradient approach in its implementation) is applied to build the adaptation law of the controller parameters for the MRAC. Using the MIT rule, the cost function is given by:

$$J(\theta) = \frac{e^2}{2} \tag{15}$$

$$e = y_p - y_m \tag{16}$$

Where e represents the error between the plant and the reference model, θ is an adjustable control parameter. Based on the MIT rule, we can write:

$$\frac{d\theta}{dt} = -\gamma\frac{\delta J}{\delta\theta} = -\gamma e\frac{\delta e}{\delta\theta} \tag{17}$$

Where γ is an adaptation gain.

In the proposed algorithm, the equation (17) is used for the controller. In contrast to the MRAC developed by [21], we have streamlined the equations governing the adaptation mechanism and subsequently optimized the controller.

$$u_p = \theta_1 r - \theta_2 y_p = \theta^T \varphi \tag{18}$$

With φ expressed as $[r, y_p]\ T$ and $[\theta_1, \theta_2]\ T$ denotes the estimation vector of the controller variables. Replacing Eq. (18) with Eq. (11), we obtain:

$$\frac{d^2 y_p(t)}{dt^2} = -\mathrm{a_p}\frac{dy_p(t)}{dt} - (\mathrm{b_p} + \mathrm{k_p}\theta_2) y_p(t) + \mathrm{k_p}\theta_1 r(t) \tag{19}$$

Based on Eqs.13 and 19, we can get:

$$\mathrm{k_p}\theta_1 = \mathrm{k_m} \tag{20}$$

$$\mathrm{b_p} + \mathrm{k_p}\theta_2 = \mathrm{b_m} \tag{21}$$

$$\mathrm{a_p} = \mathrm{a_m} \tag{22}$$

θ_1, θ_2 converge as follows:

$$\theta_1 = \frac{\mathrm{k_m}}{\mathrm{k_p}} \tag{23}$$

$$\theta_2 = \frac{\mathrm{b_m} - \mathrm{b_p}}{\mathrm{k_p}} \tag{24}$$

Using Laplace, the Eq. 23 become:

$$\frac{y_p(s)}{r(s)} = \frac{\mathrm{k_p}\theta_1}{s^2 + \mathrm{a_p}s + (\mathrm{b_p} + \mathrm{k_p}\theta_2)} \tag{25}$$

According to the error in Eq. (16), we can define:

$$e = \left(\frac{\mathrm{k_p}\theta_1}{s^2 + \mathrm{a_p}s + (\mathrm{b_p} + \mathrm{k_p}\theta_1)} - \frac{\mathrm{k_m}}{s^2 + \mathrm{a_m}s + \mathrm{b_m}}\right) r(s) \tag{26}$$

In order to determine the derivatives of sensitivity ($\delta e/\delta\theta_1$ and $\delta e/\delta\theta_2$), and with the use of Eqs.17 and 26, we obtain:

$$\frac{\delta e}{\delta\theta_1} = \frac{\mathrm{k_p} r}{s^2 + \mathrm{a_p}s + \mathrm{b_p} + \mathrm{k_p}\theta_2} \tag{27}$$

$$\frac{\delta e}{\delta\theta_2} = \frac{-\mathrm{k_p} y_p}{s^2 + \mathrm{a_p}s + \mathrm{b_p} + \mathrm{k_p}\theta_2} \tag{28}$$

As mentioned previously that $s^2 + a_m.s + b_m = s^2 + a_p.s + b_p + k_p\theta_2$, and according to the MIT law and utilizing equations (27) and (28), we can conclude the expressions of θ_1 and θ_2.

$$\frac{d\theta_1(t)}{dt} = -\gamma\left(\frac{1}{s^2 + \mathrm{a_m}s + \mathrm{b_m}} r(t)\right) e(t) \tag{29}$$

$$\frac{d\theta_2(t)}{dt} = \gamma\left(\frac{1}{s^2 + \mathrm{a_m}s + \mathrm{b_m}} y_p(t)\right) e(t) \tag{30}$$

The adaptation gain γ dictates the system's performance and is typically determined heuristically. In order to guarantee an optimum performance, the gain γ in the proposed algorithm is determined using a fuzzy logic controller. As defined previously, the fuzzy controller must contain two inputs and a single output as illustrated in Fig. 7.

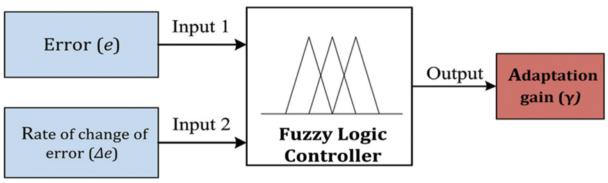


Fig. 7. Fuzzy control input and output variables

We have assigned five triangular membership functions to each fuzzy controller variable as indicated in Fig. 8, resulting in a total of 25 inference rules. The fuzzification method employed is the Max-Min method (Mamdani). These distributions are depicted in the following figures.

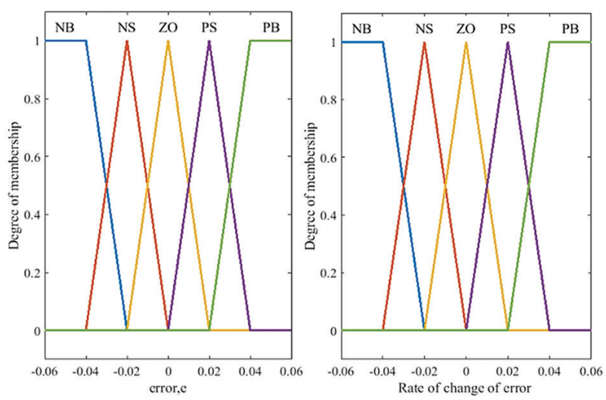


Fig. 8. Membership functions of two inputs

With NB: Negative Big; NS: Negative Small; ZO: Approximately Zero; PS: Positive Small; PB: Positive Big.

Inputs and output are linked by rules called inference rules, which enable conclusions to be executed. The typical form of a fuzzy rule is:

If <Conditions linked by fuzzy operators> Then <Action >

The following table illustrates the representation of inference rules (used to determine the adaptation gain) in matrix form, commonly referred to as the "Inference Matrix".

Table 1. Inference matrix

				e		
	γ	NB	NS	ZO	PS	PB
Δe	NB	Z	Z	B	B	B
	NS	Z	Z	S	S	S
	ZO	S	Z	Z	Z	S
	PS	S	S	S	Z	Z
	PB	B	B	B	Z	Z

For instance, the rules corresponding to the red cell in the table is interpreted as follows: if error is NB and rate of change of error is ZO, then the adaptation gain is small (S).

4. RESULTS AND DISCUSSION

The MATLAB-Simulink software is utilized to perform various simulations. Table 2, 3 and 4 presents the PV panel parameters, the boost converter data, and the coefficients of the suggested methodology. To assess the performance of our approach, we compare it with other classical MPPT control methods such as Perturb and Observe, fuzzy logic, and metaheuristic PSO controllers under dynamic temperature and irradiation profiles.

To simulate a photovoltaic (PV) system with MPPT control in MATLAB/Simulink, several settings need to be adjusted in the blocks to ensure correct simulation and accurate results. Below are the key block parameters and model settings for running a PV system with a boost converter and MPPT controller.

- **PV Generator (Photovoltaic Array) Settings**

The photovoltaic array block is typically found in the Simscape Electrical library. Key parameters adjusted:

- Irradiation (Ir): We use a standard value for solar irradiance, such as 1000 W/m² (under standard test conditions), or modify it based on real-time weather data or dynamic inputs. Example: Irradiance = 1000 W/m².
- Temperature (T): We set the ambient temperature to a typical value, like 25°C, or adjust it according to simulation parameters (e.g., dynamic temperature changes).
- Number of Series and Parallel Modules: These affect the voltage and current characteristics of the PV system. Adjust based on our desired output. In our case Series = 2 modules, Parallel = 2 string (these values vary depending on the panel's specifications).

- **Boost Converter Settings. Key Parameters to Adjust are given in Table 3.**
  - Duty Cycle (D): The duty cycle is controlled by the MPPT algorithm and adjusts based on the MPPT feedback.
- **Simulation Settings**
  - Solver: We used ode45 (Variable step size).
  - Simulation Time: Simulation time = 1 seconds.
  - Time Step (Sampling Time): The time step should be small enough to capture system dynamics accurately. A typical value might be 0.01 to 0.1 seconds. In our case: Time step = 10^{-6} seconds.
- **Test Cases for Different Conditions. To test various conditions of your system, we modify the following parameters:**
  - We vary the Irradiation: we test our system under different light conditions [800 W/m2 700w/m2 600W/m2 800W/m2 900W/m2].
  - We vary the Temperature: we test for different ambient temperatures (as shown in figure 13) to observe the system's response to temperature changes.

Table 2. PV Model Parameters

DC-DC Boost Parameters	Value
C1	100 µF
VIN	56.6-60.3 V
L	2 mH
R0	20 Ω
C0	100 µF
V0	112.5-129.1 V

Table 3. DC-DC boost converter Parameters

PV Model Parameters	Value	PV Model Parameters	Value
Maximum power	213.15W	PV cell Rpe	100 µF
Maximum current	35 A	PV cell Rse	56.6-60.3 V
Maximum voltage	29 V	Cells per module	2 mH
Short-circuit current (Isc)	7.84 A	R	20 Ω
Open-circuit voltage (Voc)	36.3 V		

Table 4. MRAC-FUZZY control parameters

MRAC_FUZZY Parameters	Value
$a_p = a_m$	8.17 × 103 (rad/s)
$b_p = b_m = 1/L \times C1$	1.67 × 107 (rad/s)^2
$k_p = V0/L \times C1$	6.45 × 108V (rad/s)^2
Simulation step time (Ts)	1 µs
Switching frequency (fs)	20 kHz
k_m	5.75 ×108V (rad/s)^2

The proposed MRAC-FUZZY based MPPT control has been verified by simulations under MATLAB/Simulink using the control scheme illustrated in Fig. 9.

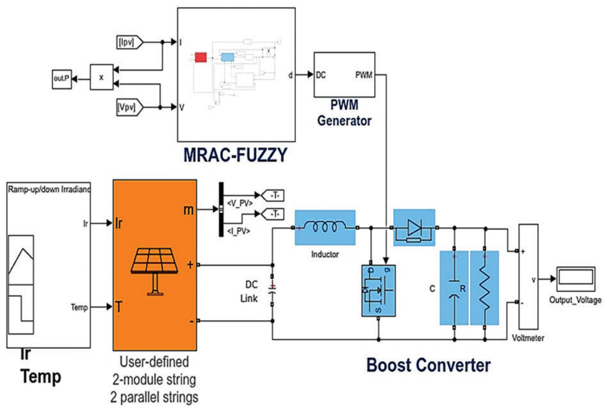


Fig. 9. Block diagram of the photovoltaic system

4.1. CONTROLLER BEHAVIOR IN CASE OF IRRADIATION VARIATION

The efficacy of the proposed MRAC-FUZZY MPPT has been validated through simulations under diverse operating conditions using MATLAB/Simulink software. Initially, we conducted an irradiation test as illustrated in Fig. 10. The irradiance profile begins with an initial irradiance of 800W/m^2. At t=0.2s, the irradiance gradually decreases to 700W/m^2 over a duration of 0.2 seconds. Following this, starting at t=0.6s, the irradiance rises to 600W/m^2, then increases further to 800W/m^2, and finally to 900W/m^2. The temperature remains constant at 25°C throughout the used profile.

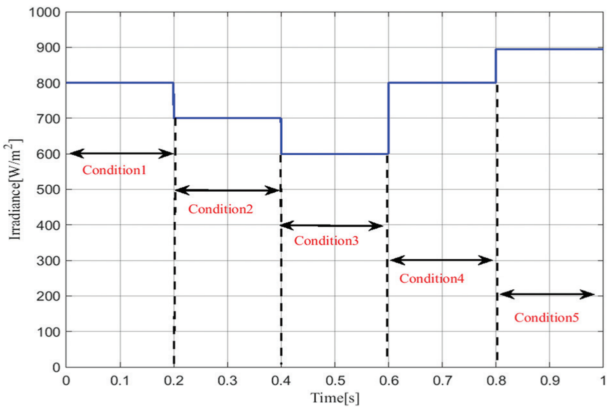


Fig. 10. Variable irradiation profile

Fig. 11 illustrate the photovoltaic output power using the proposed MRAC-FUZZY, PSO, P&O, and Fuzzy Logic controllers. Zooms are applied: one focusing on the transient mode to enhance response time and another on the steady-state mode to illustrate ripples in the MPP. Fig. 10 shows that the P&O technique has a maximum time to reach MPP which about 0.046s, followed by the FL technique at 0.016s, and the PSO at 0.0095s, while the proposed technique takes only 0.0034s to reach the MPP.

The FL and P&O methods show a significant ripple around the MPP but do not reach it. The PSO algorithm presents less ripples, compared with the MRAC-FUZZY method, which has practically no ripple and follows the MPP easily over all five irradiation conditions.

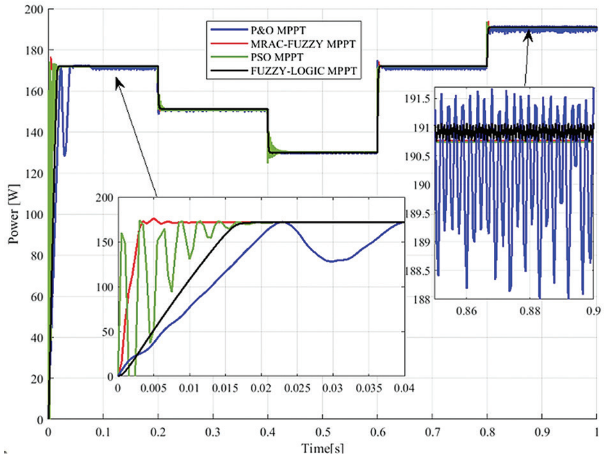


Fig. 11. Simulation results of four MPPT controllers with variable irradiation and constant temperature

To highlight the effectiveness of the proposed approach, in addition to response time and ripple, other performance criteria are calculated like energy losses and efficiency during five irradiation conditions, as shown in Table 5. As a result, the novel control algorithm can ensure the superior effectiveness compared to the other conventional MPPT control, FL and meta-heuristic controller under sudden change in irradiance conditions. It can be noted that the response time is minimal, ripple and energy losses are the lowest, and efficiency is the very highest in the event of the proposed MRAC-FUZZY MPPT.

Table 5. Performance comparison for the 4 algorithms

MPPT Techniques	Condition 1	Condition 2	Condition 3	Condition 4	Condition 5
Response time (s)					
P&O	0.046	0.043	0.049	0.046	0.044
FUZZY LOGIC	0.016	0.018	0.022	0.016	0.02
PSO	0.0095	0.0096	0.019	0.0095	0.01
MRAC_ FUZZY	0.0034	0.0036	0.004	0.0034	0.0038
Ripples (W)					
P&O	5.2	4.1	3	3.2	3.5
FUZZY LOGIC	2.6	3	2.3	2.6	2
PSO	1.4	1.6	1	1.4	1.3
MRAC_ FUZZY	0.05	0.01	0.01	0.01	0.02
Energy losses (%)					
P&O	3	3.7	2.30	1.86	1.81
FUZZY LOGIC	1.5	1.98	1.76	1.51	1.03
PSO	0.8	1.05	0.76	0.81	0.67
MRAC_ FUZZY	0.02	0.006	0.007	0.005	0.01
Efficiency (%)					
P&O	95.2	94.6	95.11	95.94	95.83
FUZZY LOGIC	96.41	95.73	96.42	96.58	96.94
PSO	97.92	97.25	98.2	97.6	98.1
MRAC_ FUZZY	99.88	99.97	99.86	99.98	98.87

4.2 CONTROLLER BEHAVIOR IN CASE OF TEMPERATURE VARIATION

The four MPPT controls are simulated under two variable profiles of temperature and constant irradiation as illustrated in Fig. 12. Firstly, it's evident from Fig. 13 and Fig. 14 that power varies inversely with temperature. The performance criteria are summarized in Table 6. It can be noted that the MPPT MRAC-FUZZY control has better PPM tracking performance with minimal response time, almost zero ripple around the MPP and very high efficiency with little energy loss compared to P&O, Fuzzy Logic and PSO MPPTs controllers.

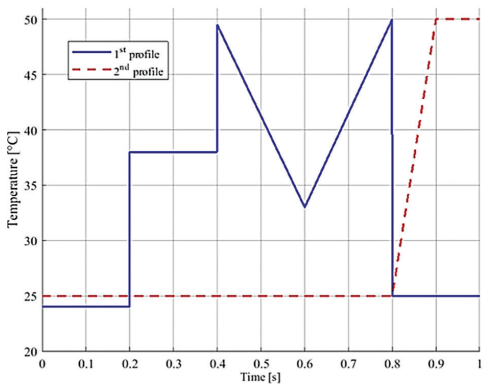


Fig. 12. Variable Temperature profiles

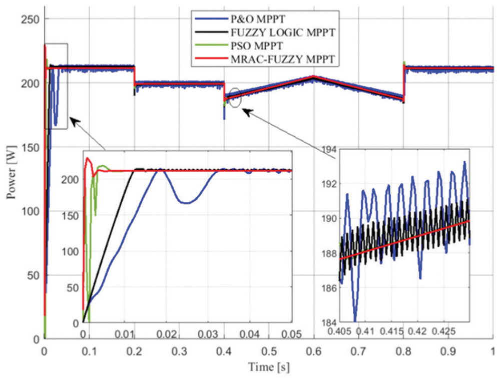


Fig. 13. Simulation results of four MPPT controllers with variable temperature and constant irradiation (1st profile)

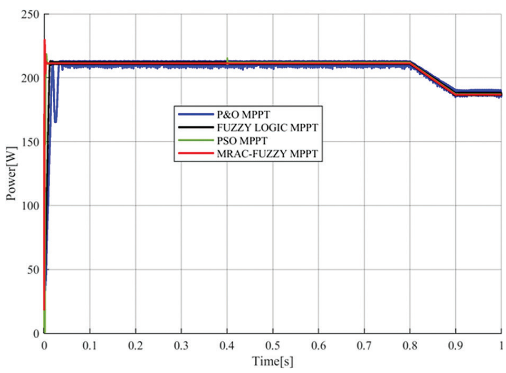


Fig. 14. Simulation results of four MPPT controllers with variable temperature and constant irradiation (2nd profile).

Table 6. Performance comparison for a variable temperature profile

MPPT techniques	P&O	FUZZY-LOGIC	PSO	MRAC-FUZZY
Response time (s)	0.034	0.015	0.005	0.0032
Ripple (W)	7.8	2.4	1.2	0.01
Energy loss (%)	4.53	1.93	0.69	0.005
Efficiency (%)	95.32	96.67	97.98	99.96

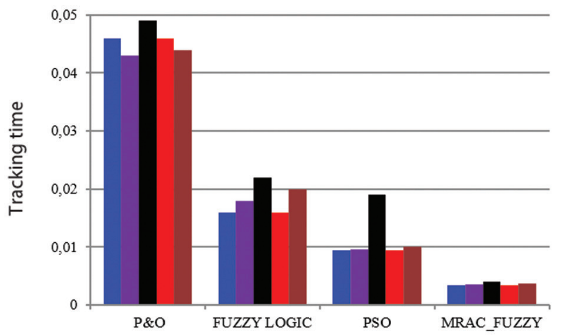
The results presented in Table 6 show that the P&O method has the highest response time to reach the Maximum Power Point (MPP), with a value of 0.034 s. This is followed by the FUZZY_LOGIC technique at 0.015 s, and the PSO method at 0.005 s. In contrast, the proposed technique captures the MPP in just

0.0032 s. Although the P&O, FUZZY_LOGIC, and PSO methods exhibit ripple content near the MPP, they fail to precisely achieve it. On the other hand, the MRAC-FUZZY method demonstrates nearly zero ripple content and tracks the MPP with high accuracy. Regarding energy losses, the P&O, FUZZY_LOGIC, and PSO methods experience losses of 4.53%, 1.93%, and 0.69%, respectively, while the proposed technique incurs virtually no energy losses. In terms of tracking efficiency, the P&O method achieves 95.32%, FUZZY_LOGIC achieves 96.67%, and PSO achieves 97.98%. In comparison, the proposed technique achieves an impressive tracking efficiency of 99.96%.

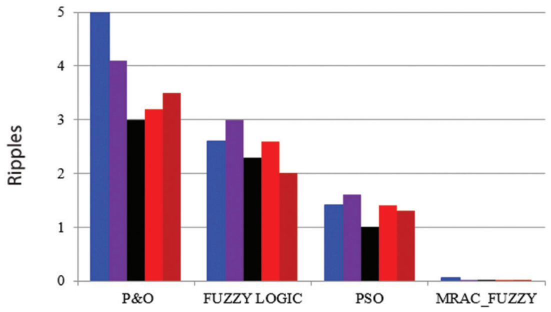
The results highlight the exceptional MPP tracking capability of the MRAC-FUZZY MPPT controller, excellent tracking of maximum power point with total elimination of ripples. In contrast, other MPPT controllers experience delays in reaching the MPP. Moreover, the time required to reach the MPP is 0.0034s, approximately 11 times faster than P&O, 5 times faster than FL, and 2 times faster than PSO. Figure 15 show the comparison between tracking time, ripples, and efficiency of proposed MRAC-FUZZY, PSO, Fuzzy Logic and P&O MPPT under variable condition as shown in Figure 9.

In comparison to other recent studies, the PV system's tracking efficiency has ultimately been improved, as outlined in Table 7.

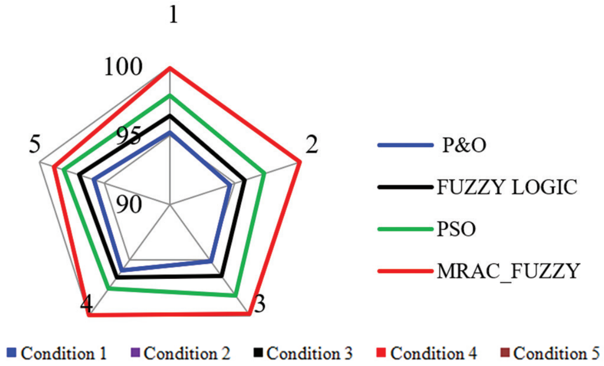
It can be seen that MRAC-FUZZY algorithm enhances the system's average efficiency from 95.32%, 96.67%, and 97.98 in comparison to the P&O, Fuzzy Logic and conventional PSO algorithms respectively, achieving a rate of 99.96%.



(a)



(b)



(c)

Fig. 15. Comparison evaluation. (**a**) Tracking time, (**b**) Ripples, (**c**) Efficiency.

Moreover, the MRAC-FUZZY algorithm, as proposed, exhibits superior accuracy in tracking maximum power following fluctuations in climatic conditions, with minimal observable oscillation around the MPP, distinguishing itself from other control methods, As observed in the zoomed-in views of Figs. 11 and 13, notable improvements are evident when comparing the results obtained with the PSO, Fuzzy Logic, and P&O MPPT algorithms. These enhancements are delineated below:

- The tracking time is notably shorter compared to other algorithms
- The power ripple has been significantly reduced

Table 7. An analysis comparing the suggested approach to other methods

Performance Parameters	Adaptive MPPT Controller [21]	ANFIS-TRSMC [19]	(PSO) [22]	(GWO)-PID [23]	Proposed MPPT
Tracking time	0.0036	0.04	0.012	0.018	0.0034
Oscillations at MPP	Low	Medium	Medium	No	No
Complexity	Medium	Medium	Medium	Medium	low
Efficiency	99.69%	98.9%	96.96%	99.50%	99.97%

5. CONCLUSION

In order to improve the photovoltaic system's efficiency, a new fuzzy model reference adaptive control based MPPT has been proposed. The proposed algorithm combines the strengths of the MRAC concept, which can handle non-linear systems adequately, and the advantages of fuzzy logic, which can determine the adaptation gain heuristically. In order to simulate the system behavior for MPP tracking, simulations were carried out in the MATLAB/Simulink environment. A comparative analysis was conducted again to the classical algorithms like (P&O), fuzzy logic, metaheuristic (PSO), according to different criteria (dynamic response time, low ripples, and efficiency). The simulation outcomes have confirmed the exceptional performance of the innovative controller, showcasing a reduction in response time (3.4ms to reach the MPP) it is around 11 times, 5 times and 2 times faster than P&O, FL and PSO respectively with high efficiency up to 99.97%. Also, the proposed MPPT algorithm based MRAC-Fuzzy can ensure good tracking of MPP without ripple.

The proposed MRAC-Fuzzy-based MPPT controller offers higher tracking efficiency, reduced ripple content, and lower energy losses compared to traditional MPPT techniques. However, successful implementation in a real PV system requires addressing challenges related to sensor accuracy, hardware limitations, environmental factors, and system stability. In the upcoming study, the proposed MPPT algorithm will be deployed in a real testing environment. This will include the setup of temperature and irradiation sensors, as well as instrumentation to measure the power and voltage generated by the photovoltaic panel. The MPPT controller will be integrated with an inverter or a battery charger to validate the effectiveness of the MPPT algorithm based MRAC-FUZZY controller. During the implementation of the developed MPPT controller, several challenges and potential issues may arise, including:

- Problems related to model parameter estimation: Photovoltaic system models may not be perfectly accurate. Real-world conditions can present unexpected variations compared to theoretical assumptions (e.g., shadows on the panels, dust, or panel degradation). This could lead to errors in adjusting the MRAC-FUZZY controller.
- Sensitivity to irradiation and temperature conditions: MPPT algorithms are sensitive to rapid variations in irradiation and temperature. In particular, sudden changes in irradiation due to clouds or shadows could disrupt the tracking efficiency. The fuzzy algorithm must be adjusted to handle these variations smoothly and stably.
- Control latency: In a real system, sensor and controller latency may introduce delays in adjusting the control, which could slow down the system's response. Our proposed algorithm needs to be designed to minimize this latency and ensure an appropriate real-time response.

6. REFERENCES

[1] H. T. Pham, L. Dai, "A Feasible MPPT Algorithm for the DC/DC Boost Converter: An Applied Case for Stand-Alone Solar Photovoltaic Systems", Inter-

national Journal of Electrical and Computer Engineering Systems, Vol. 14, No. 6, 2023, pp. 713-724.

[2] M. Brahmi, C. B. Regaya, A. Zaafouri, "Comparative Study Of P&O and PSO Particle Swarm Optimization MPPT Controllers for Photovoltaic Systems", Proceedings of the 8th International Conference on Control, Decision and Information Technologies, Istanbul, Turkey, 17-20 May 2022, pp. 1608-1613.

[3] C. B. Regaya, H. Hamdi, F. Farhani, A. Marai, A. Zaafouri, A. Chaari, "Real-time implementation of a novel MPPT control based on the improved PSO algorithm using an adaptive factor selection strategy for photovoltaic systems", ISA Transactions, Vol. 146, 2022, pp. 496-510.

[4] A. Elgharbi, D. Mezghani, A. Mami, "Intelligent Control of a Photovoltaic Pumping System", Engineering, Technology & Applied Science Research, Vol. 9, No. 5, 2019, pp. 4689-4694.

[5] A. R. Danila, R. Roshini, E. Priyanka, M. Sindhuja, A. S. Jones, "Design and Implementation of Photovoltaic Powered SEPIC DC-DC Converter Using Particle Swarm Optimization (PSO) Technique", Computing and Social Networking. Lecture Notes in Networks and Systems, Vol. 317, Springer, 2022.

[6] M. Jagadeshwar, D. K. Das, "A novel adaptive model predictive control scheme with incremental conductance for extracting maximum power from a solar panel", Iranian Journal of Science and Technology, Transactions of Electrical Engineering, Vol. 46, 2022, pp. 653-664.

[7] M. Jagadeshwar, D. K. Das, "A novel MRAC-MPPT scheme to enhance speed and accuracy in PV systems", Iranian Journal of Science and Technology, Transactions of Electrical Engineering, Vol. 47, 2023, pp. 233-254.

[8] A. K. Mohaisen, "Artificial Intelligent Maximum Power Point Controller based Hybrid Photovoltaic/Battery System", International Journal of Electrical and Computer Engineering Systems, Vol. 14, No. 10, 2023, pp. 1183-1191.

[9] S. Saha, M. Cintury, C. Roy, "A PSO based MPPT controller for solar PV system at variable atmospheric conditions", Advanced Computational Paradigms and Hybrid Intelligent Computing, Advances in Intelligent Systems and Computing, Vol. 1373, Springer, 2022.

[10] B. Mahbouba, B. R. Chiheb, H. Hichem, Z. Abderrahmen, "Comparative Study Of P&O and PSO Particle Swarm Optimization MPPT Controllers Under Partial Shading", International Journal of Electrical Engineering and Computer Science, Vol. 4, 2022, pp. 45-50.

[11] Md. T. Hussain, A. Sarwar, M. Tariq, S. Urooj, A. BaQais, Md. A. Hossain, "An Evaluation of ANN Algorithm Performance for MPPT Energy Harvesting in Solar PV Systems", Sustainability, Vol. 15, No. 14, 2023, p. 11144.

[12] Y. El Aidi Idrissi, K. Assalaou, L. Elmahni, E. Aitiaz, "New improved MPPT based on artificial neural network and PI controller for photovoltaic applications", International Journal of Power Electronics and Drive Systems, Vol. 13, No. 3, 2022, pp. 1791-1801.

[13] M. Fathi, J. A. Parian, "Intelligent MPPT for photovoltaic panels using a novel fuzzy logic and artificial neural networks based on evolutionary algorithms", Energy Report, Vol. 7, 2021, pp. 1338-1348.

[14] K. Kayisli, "Super twisting sliding mode-type 2 fuzzy MPPT control of solar PV system with parameter optimization under variable irradiance conditions", Ain Shams Engineering Journal, Vol. 14, No. 1, 2023.

[15] R. D. Tehrani, F. Shabaninia, "Two-level control of photovoltaic systems using global perturbation-based extremum seeking control and model reference adaptive control", Transactions of the Institute of Measurement and Control, Vol. 40, No. 13, 2018, pp. 1-12.

[16] P. Sahu, R. Dey, "An improved 2-level MPPT scheme for photovoltaic systems using a novel high-frequency learning based adjustable gain-MRAC controller", Scientific Reports, Vol. 11, 2021.

[17] F. Z. Kebbab, L. Sabah, H. Nouri, "A Comparative Analysis of MPPT Techniques for Grid Connected PVs", Engineering, Technology & Applied Science Research, Vol. 12 No. 2, 2022, pp. 8228-8235.

[18] M. Brahmi, C. B. Regaya, H. Hamdi, A. Zaafouri, "MPPT Using PSO Technique Comparing to Fuzzy

Logic and P&O Algorithms for Photovoltaic System", Proceedings of the 9th International Conference on Control, Decision and Information Technologies, Rome, Italy, 3-6 July 2023, pp. 2457-2461.

[19] B. Mbarki, F. Fethi, J. Chrouta, A. Zaafouri, "Adaptive neuro-fuzzy inference system algorithm-based robust terminal sliding mode control MPPT for a photovoltaic system", Transactions of the Institute of Measurement and Control, Vol. 46, No. 2, 2023, pp. 316-325.

[20] C. B. Regaya, F. Farhani, H. Hamdi, A. Zaafouri, A. Chaari, "A new MPPT controller based on a modified multiswarm PSO algorithm using an adaptive factor selection strategy for partially shaded PV systems", Transactions of the Institute of Measurement and Control, Vol. 46, No. 10, 2023, pp. 1991-2000.

[21] S. Manna et al. "Design and implementation of a new adaptive MPPT controller for solar PV systems", Energy Reports, Vol. 9, 2023, pp.1818-1829.

[22] W. M. Ersalina, R. Agus, K. Ardath, D. Rudi, "Particle Swarm Optimization (PSO) based Photovoltaic MPPT Algorithm under the Partial Shading Condition", Journal Electronika Dan Telekominikasi, Vol. 23, No. 2, 2023, pp. 99-107.

[23] J. Aguila-Leon, C. Vargas-Salgado, C. Chinas-Palacios, D. Diaz-Bello, "Solar photovoltaic Maximum Power Point Tracking controller optimization using Grey Wolf Optimizer: A performance comparison between bio-inspired and traditional algorithms", Expert Systems with Applications, Vol. 211, 2023, p. 118700.