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Original Article

A Novel Optimized Fuzzy Interfaced PID Controller MPPT Technique for Photovoltaic Systems under Unpredictable Environment

Rajesh Kumar K[1*], R. Sripriya[2], S.K. Bikshapathy[3]

[1,2]Department of Electrical Engineering, Faculty of Engineering and Technology, Tamilnadu, India.
[3]Department of Electrical and Electronics Engineering, Visvesvaraya College of Engineering and Technology, Ibrahimpatnam, India.

[*]Corresponding Author : krajeshk230@gmail.com

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Abstract - *This paper explores, evaluates, and enhances Maximum Power Point Tracking (MPPT) strategies for Photovoltaic (PV) units working under highly changing atmospheric conditions. Although conventional techniques like Search and Rescue (SRA), Model Predictive Control (MPC), and sliding-mode control can be slow in converging, have more oscillations, or are computationally heavy, this paper presents an improved Fuzzy PID-based MPPT controller integrated with a Genetic Algorithm (GA) for the self-tuning of membership functions and PID parameters. The new controller achieves a remarkable improvement in the dynamic response by reaching the maximum power point in a shorter time, lowering the oscillations at steady state, and showing great flexibility to sudden changes in light intensity. Results of simulations performed with MATLAB/Simulink indicate that the proposed approach delivers an MPPT efficiency of 96.98%, which is better than the usual ones, like Fuzzy (96.28%), GA-Fuzzy (96.72%), ANFIS (96.58%), and DC-DC boost-based MPPT methods. The authors assert that the introduced improvements demonstrate the controller's capability to improve the stability, reliability, and energy production of current solar PV systems, particularly in outdoor situations where the weather is highly changeable.*

Keywords - *Maximum Power Point Tracking, Solar Photovoltaic System, Fuzzy PID-Controller, DC-DC Controllers, Irradiance, Voltage.*

1. Introduction

The world's rising dependency on energy is rather worrying and requires quick immersion; it must be constant and reliable because everything is changing thanks to the internet, and because energy is the basis of everything. Every important segment of a nation is so reliant on energy that even a small blackout might have a domino effect, causing issues with the power grid, communications, and even national security [1].

Conventional energy origins like coal, gas, and fossil fuels are quickly running out, and the impact they have on the environment are grave, implying a desperate essential for option energy origins including solar, wind, and geothermal. Renewable energies, each having a unique set of disadvantages and advantages, have emerged as a hot area of study for numerous scholars throughout the world in recent decades [2]. Particularly when the cost-benefit ratio of renewables is comparable to that of coal and gas [3]. The availability of solar energy makes it the most favoured alternative energy source, with its cleanliness and lack of noise. Because of these features, several nations throughout the world have adopted both independent and grid-connected PV systems [4]. The use of solar energy has numerous advantages, as previously said, one of the biggest drawbacks is its dependence on climate variables, namely temperature and irradiance levels. PV systems' output is non-linear as a result of this tendency [5]. Furthermore, efficiency might suffer as a result of load circumstances, PV module temperature, or reductions in solar insulation. A PV module must function at its optimal power point to provide the maximum rated power.

For this, an extremely powerful point tracker controller was needed. PV modules are non-linear power sources, with terminal operating voltage controlling output power [6]. PV panels, on the other hand, get consistent irradiation values. MPP changes in response to modifications in the external environment. It is consequently critical to monitor MPP to get the most power out of PV systems [7]. PV systems, which transform solar energy into electrical energy, are becoming more popular. PV systems are utilised in small devices such as calculators, and might be utilised in bigger and more intricate systems like water and communication satellites network applications, lighting applications, and pumps [8]. Conversely, the primary disadvantages of PV systems are high manufacturing costs and low energy conversion efficiency.

In order to get beyond these drawbacks and boost system efficiency, the MPPT controller must be used to extract the maximum produced power from the PV systems [9]. As a result, the MPPT compensates for the fluctuating current-voltage features of the solar cell. To determine the operating point that will produce the most electricity, the MPPT modifies the PV module's output current and voltage. The MPPT must be able to accurately identify the continuously variable operating point where the most electricity is generated if the PV module is to operate as efficiently as possible [10].

Traditionally, linear control method-based MPPT algorithms do not produce improved results. On the other hand, this linearized control system has weak yields and a medium dynamic response [11]. The traditional controller MPPT approach lags in monitoring performance, so output effectiveness is heavily dependent on the engineer's technical understanding [12]. Optimization strategies for PV module MPPT may function with variable inputs, do not need flawless mathematical frameworks, and are self-convergent and capable of self-learning [13].

Despite the extensive development of MPPT algorithms, many existing approaches, including SRA, MPC, sliding-mode control, ANN-based techniques, and GA-enhanced fuzzy controllers, continue to exhibit notable limitations under unpredictable irradiance and temperature variations. Such issues that frequently occur include: slow convergence, sensitivity to local minimum, depending on large training datasets, and the instability related to the chattering effect as the non-linear characteristic of the photovoltaic system.

Besides, traditional fuzzy and PID-based MPPT controllers usually do not have the ability to adapt in real time, which results in increased oscillations in the steady state and a delay in tracking when the environment changes rapidly. However, these drawbacks indicate a research gap in designing an MPPT approach that, at the same time, provides high accuracy in the tracking, quick dynamic response, and stable operation under highly fluctuating conditions.

To fill this void, the article suggests an improved Fuzzy PID-based MPPT controller refined with a genetic algorithm-driven optimization method that automatically adjusts fuzzy membership functions and PID parameters. Previous GA-optimized fuzzy MPPT methods are mainly rule-based tuning and still keep some residual oscillations, and have limited dynamic robustness. Meanwhile, the new hybrid controller merges PID dynamics directly within the fuzzy inference system to enhance transient damping, steady-state stability, and duty-cycle consistency. Consequently, the proposed technology results in quicker convergence, lower oscillations, and a better MPPT efficiency of 96.98% during the rapidly changing irradiance situations.

By merging smart fuzzy logic with PID control and genetic optimization, the presented method is able to offer a more stable, adaptive, and practically installable MPPT solution, thereby moving forward the state of the art in photovoltaic energy conversion systems. Please find below the concepts employed in the present methodology:

The main goal of this study is to identify and evaluate a suitable Maximum Power Point Tracking method to get the most out of the solar modules/solar arrays.

- To get the best controller tuning parameters, a Fuzzy GA optimization method is adopted in this research.
- An optimization method coupled with an optimized Fuzzy PID controller for the proposed method has been exploited to upgrade the capability of the MPPT controller embedded in the Solar PV system so as to keep the KP maximum power from PV and to enhance the MPPT controller's efficiency and accuracy.

The proposed controller not only accomplishes the best MPPT efficiency with the least oscillations, but also converges faster, thus it can be considered as a better approach in terms of adaptability when compared to GAFLC and conventional intelligent MPPT techniques. Together, these contributions significantly enhance the design of MPPT controllers by making available a hybrid control strategy that is more stable, interpretable, and can be easily implemented in real-world photovoltaic systems.

An outline of the suggested study paper is provided below: The literature review for the current articles is considered in Segment 2, and the suggested technique was thoroughly summarised in Segment 3. Segment 4 provides the details of the simulation and results in Segment 5. The discussion of the proposed method is shown in Segment 6, and the research is concluded in Segment 7.

2. Literature Review

Muhammad Hamza Zafar & colleagues [14] suggest an innovative Search and Rescue (SRA) optimization technique utilizing MPPT control of PV systems. The suggested approach improves PV system performance by allowing for quicker and more precise monitoring of GM with extremely low oscillations at GM. The suggested SRA increases power and energy by a particular proportion. Furthermore, the settling and tracking times are reduced. The suggested SRA control technique is notable for its ease of implementation, robustness, and optimal power tracking efficiency in steady-state. SRA has limitations, including being stuck in minimal local areas and consuming an inefficient balance between the exploitation and exploration stages.

Zain Ahmad Khan and colleagues [15] developed, for maximal power extraction, a non-linear Back-Stepping Terminal Sliding Mode Control (BTSMC) is developed in the study. The capacity is powered by PV using a DC-DC buck-boost converter. The suggested controller produces reference voltages using a Radial Basis Function Neural Network (RBFNN). The results demonstrate that under rapidly varying environmental conditions, the suggested controller offers better tracking & faster merge in a fixed time. The chattering effect is an undesired phenomenon caused by oscillations with limited frequency and amplitude. It is quite difficult to implement.

Panagiotis E et al. [16] suggested a Fixed Step-Model Predictive Controller (FS MPC) implementation with a Maximum Power Point Tracker of a Photovoltaic (PV) array. It depends on the two-step horizon FS MPC in conjunction with the modified INC approach.

To allow concurrent communication between the MPPT and the controller while acquiring appropriate data in a single sample period, the current-based INC approach has undergone main alterations. The efficiency of PV system use and the ability to optimize system performance was increased. MPC has a complicated algorithm. As a result, it takes more time than the other controller.

Jean de Dieu Nguimfack and colleagues [17] An adaptive non-linear approach for MPPT control & voltage stabilization of a Single-Ended Primary Inductance Converter was created in the suggested research. The Radial Basis Function (RBF)-based neural network control approach was also utilized to estimate unmeasurable or unmeasured variables in the PV system.

The constancy of the controller’s closed loop is confirmed by Lyapunov’s theory. As the total number of neurons in the hidden layer rises, the RBF network’s complexity rises, and the standard RBF has various issues with its structure and training process, preventing it from modeling a severely non-linear system.

Badreddine Babes et al. [18] to maximize power in grid-connected solar systems, a study created a multilayer feed-forward ANN, MPPT controller employing metaheuristic optimization. In comparison to the INC method, the ANN-ACO controller provides faster MPP tracking, greater robustness, and reduced steady-state oscillation. A lot of input and target pairs are needed during the training process.

Catalina Gonzalez Castano et al [19] suggested a unique Artificial Bee Colony method for the photovoltaic system MPPT employing a DC-DC converter. The ABC MPPT method uses information values from the PV module to identify the P-V characteristic & pick the best voltage. The voltage reference for the outer PI control loop, which acts as the current reference for the predictive digital current programmed control, is then acquired using the MPPT technique. The overall system has a low computational cost. The main disadvantage of the ABC Method is its large amount of objective function evaluations, which causes it to slow down when employed in sequential processing.

Utilizing a DC-DC buck-boost converter, Izhar Ul Haq et al [20], to get the most power out of a PV array, a non-linear generalized global sliding mode controller (GGSMC) was presented. Utilizing a Feed-Forward Neural Network (FFNN), a reference voltage was provided. When the temperature and amount of sunlight fluctuate, a GGSMC is supposed to keep up with the reference created by the FFNN.

There is no chattering or harmonic distortion in the system response. The suggested control technique eliminates the reaching phase, resulting in increased durability and accuracy, as well as faster tracking. The chattering effect is an undesired phenomenon caused by oscillations with limited frequency and amplitude. It is quite difficult to implement. Implementation of FFNN results in loss of neighborhood information; additional parameters must be optimized. Translation invariance is not the case.

D. Devaraj et al. [21] suggested a paper that provides a Fuzzy-based MPPT approach that is optimized utilizing the Genetic Algorithm (GA). The suggested GA concurrently creates the fuzzy rule base and optimized ranges for both membership functions. Online training is done by running the PV system under various situations. After training, GA offers FLC’s optimized membership criteria and regulation framework. In all weather conditions, the GA-optimized FLC-based MPP tracking technique surpasses competitors in terms of precise tracking and response time. Voltage variation is more common in FLC.

In their study [22], Po-Chen Cheng et al developed an asymmetrical Fuzzy Logic Control (FLC) using a PSO technique-based approach for MPPT for photovoltaic technology. To boost efficacy, a Membership Function (MF) model was developed. Both the PSO approach and technique are utilised to optimise a cost function and the input MF setting values. FLC-based MPPT has the potential to enhance transient time and tracking accuracy. The PSO method frequently converges to some local optimization.

Roshan Pradhan and colleagues [23] presented a study that investigated the use of model predictive Control (MPC) techniques to collect power from photovoltaic systems-using MPC’s capacity to forecast the future state of controllable variables. It had been discovered, resulting in faster tracking of MPP in constantly changing air circumstances, resulting in an efficient system. It aids in the reduction of undesired oscillations by increasing tracking speed. MPC has a complicated mechanism. As a result, it takes more time than the other controller does.

Zaghba et al.[24] present a hybrid control strategy combining fuzzy logic and sliding mode control to enhance the performance of grid-connected photovoltaic systems under rapidly changing atmospheric conditions. The approach improves uncertainty management and power extraction stability, while PSO and GA algorithms optimally tune the PI current controller on the grid side. However, current THD values (8.33%–10.63%) exceed IEEE standards, indicating a need for further refinement in inverter control strategies.

Elbaksawi et al [25] present a metaheuristic-based Maximum Power Point Tracking (MPPT) strategy that combines Improved Grey Wolf Optimization (IGWO) and the BAT algorithm, named Improved Grey Wolf BAT Optimization (IGWBO). This approach enhances power extraction in photovoltaic systems, overcoming the convergence delays and oscillatory tracking of the individual algorithms. However, the method's reliance on algorithmic tuning poses challenges for adaptability across different photovoltaic system configurations.

Elmi and Yildirim [26] proposed a chaos-based non-linear model predictive control method to enhance power extraction from Organic Photovoltaic (OPV) Systems. This approach is based on a feedback-guided recursive plan to quickly locate the best functioning point with the least cost. There is a Lagrange-based optimizer to get a reference, and the chaotic-neural-network-based predictive control that is used to change the operating point with the help of a boost converter.

According to the results, overvoltage events were reduced by more than 1.3%, the capacity of the feeder was improved, network losses were reduced, and the efficiency of the system was increased. However, the fact that this method is very computationally intensive makes it very difficult to be used in low-cost or real-time OPV control scenarios.

Naima et al [27] proposed a hybrid Maximum Power Point Tracking (MPPT) method that combines a Modified Finite Control Set Model Predictive Control (MFCS-MPC) with the adaptive P&O algorithm to pump up photovoltaic inverter performance.

This approach hastened the tracking response time by 35%, decreased overshoot by 28%, and switching losses by 15% with the help of a weighted cost function. However, due to its dependence on complicated predictive modeling, it is difficult to implement in a low-cost inverter system. Siddique et al [28] developed a 33 multi-string solar panel setup combined with a modified boost converter and an Adapted Perturb-And-Observe Model Predictive Control (APO-MPC) technique to enhance Global Maximum Power Point tracking (GMPP).

Their simulation and physical experiments reveal that the system is capable of effectively extracting power and being cost-efficient in different partial shading scenarios. Yet, the dependence on precise predictive modeling might influence the robustness when there are noisy measurements.

Gundogdu et al. [29] came up with an enhanced grey wolf optimization technique for GMPPT that is capable of faster convergence, reaching a higher tracking accuracy, and betterly handling uniform and non-uniform conditions. It achieved a 76% decrease in runtime and a 2.3% increase in energy harvesting. On the downside, the performance of the method still hinges on the careful tuning of the algorithm in a variety of PV configurations.

Guntupalli et al [30] propose a deep CNN coupled with a modified coati optimization algorithm for dynamic GMPPT. The new method tracks faster, is more efficient, and causes less oscillations in the output compared to traditional methods. However, it is so computationally intensive that it might be difficult to deploy in cheap PV controllers.

Melhaoui et al [31] came up with a hybrid Incremental Conductance Fuzzy Logic MPPT that uses SInC and CSI as new inputs. According to their models, the system was running at a 97.7% efficiency level and took 53.5 ms for convergence time under changing conditions of irradiance and load, better than conventional hybrids. However, relying on fuzzy rules that are accurately calibrated may restrict the system's ability to adapt to different PV system settings.

In previous methods, the pitch adjustment rate value is very close to zero, which is the cause of stagnation in the algorithmic convergence and the limitation of the dynamic response of the system. Besides these, control of converter levels is made even more difficult by capacitor imbalance, restriction of voltage gain, and problems with regulating reference signals. Most of the current methods do not work for non-linear or time-varying systems, need a lot of computer power, or are very dependent on precise tuning parameters.

On the other hand, predictive and hybrid methods suffer from such problems as too much THD, complex modeling, and being highly sensitive to tuning of the algorithm.

ANN- and fuzzy-based systems, on the other hand, need a great deal of training data and carefully calibrated rule sets. Even though a lot of research has been done on MPPT and fuzzy-based optimization strategies, these limitations, such as slow global search capability and high implementation complexity, still hamper their practical robustness. To overcome the above constraints, a novel strategy is proposed in the next section.

3. Proposed Methodology

This study aims to analyze and optimize MPPT techniques for solar PV systems. Regular control methods like Search and Rescue, Model predictive control, and sliding mode control have drawbacks like trapped SRA, improper balance between exploitation and exploration phases, and complex implementation.

Optimized control techniques like the ABC Algorithm, PSO algorithm, Multilayer feed-forward ANN, and FLC without optimization control are analyzed. A proposed technique combines an optimized Fuzzy PID controller with an optimized Genetic algorithm to develop the presentation and accuracy of MPPT controllers in solar PV systems.

Problem Representation: A typical technique is used to simulate a photovoltaic system, and the associated Duty Cycle (D) is generated by applying random Values of Temperature (T_{cell}) and Irradiance(G_{cell}). A dataset consisting of(T_{cell}), (G_{cell}), and D is constructed using the collected values [32].

Fitness Function: The Solar Photovoltaic structure must convey the most power possible to the load. As a result, the goal is to reduce the difference between the power supplied by the PV module and the power absorbed by the load under the specified parameters.

$$\min(error) = P_{\max(pv)} - P_{actual(pv)} \tag{1}$$

$P_{\max(pv)}$ is the maximum power under the PV module's Standard Test Conditions (STC). This information is often included in the manufacturer's datasheet.

The following is a description of the fitness function [33]:

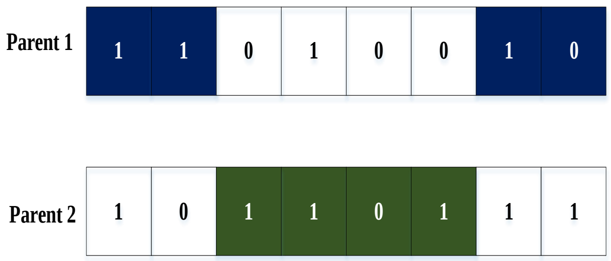
$$F = \frac{k}{error} \tag{2}$$

Where k is the fitness value's amplifying factor. To generate a variety of fitness ratings for chromosomes, the K value was often kept as modest as feasible. Once the fitness function has been determined, the approach will proceed to locate the best-fit reproduction options. The next section explains how to select the best-suited solutions.

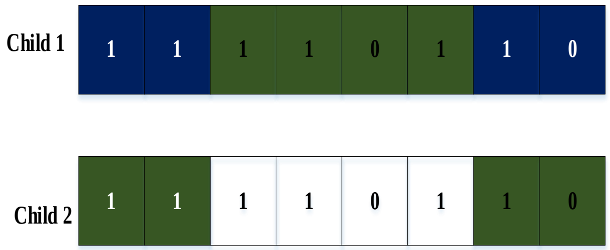
Selection: Each new generation (genetic process) is made by a selected group of people. In GA, the choice of these people is crucial. A new population is created throughout the selection process, usually with the same number of people as the previous population. Chromosomes are designated from the modern populace using a specific system. For the next generation, the most compatible chromosomes will be picked.

Crossover Operator: The GA's global search characteristic is mostly due to the crossover operator, a recombination operator. The children are formed by substituting a few of the parent chromosomes with the quantified possibility after the crossover operator chooses two parents from the mating pool.

The two-point crossover operator chooses two cross-over sites from the parents, as exposed in Figure 1(a). The parent's binary string has been highlighted. The novel characteristics (child) created by the two-point crossover technique are exposed in Figure 1(b).



(a) Parent chromosomes



(b) Two-point crossover new features

Fig. 1(a) Parent chromosomes, and (b) Two-point crossover new features.

Mutation Operator: A local optimal value cannot be reached because the mutation operator presents novel substantial information into the populace, allowing for more quick and accurate convergence.

The rule set employs a bit-wise mutation, which swaps a small number of randomly selected bits from 1 to 0 or from 0 to 1 with a low mutation frequency between 0.0001 and 0.1. By imitating the natural processes of evolution and natural selection, GA is frequently utilized as a metaheuristic optimizer or a classifier. GAs are more frequently used in hybrid MPPT approaches than as a standalone MPPT technique.

Under dynamic situations, the use of GA improves tracking response properties & reduces SS oscillations. GA-based MPPT approaches' processing requirements and implementation complexity, however, can be viewed as drawbacks [34, 35]. Figure 2 shows a flowchart for the general GA-based MPPT method.

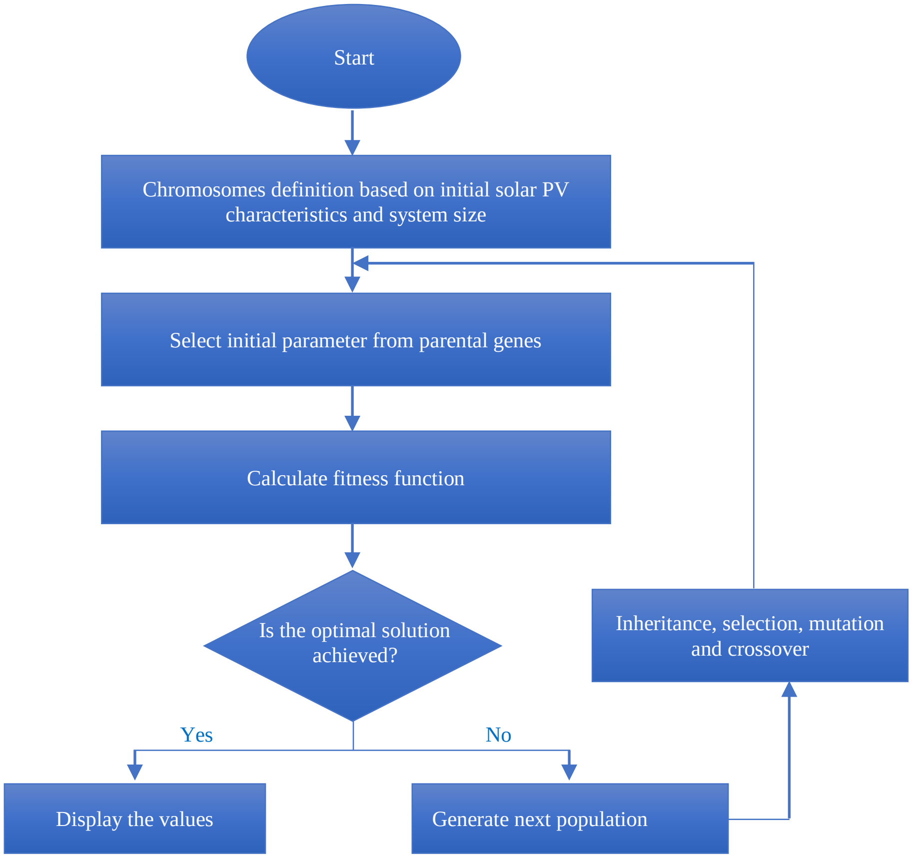


Fig. 2 General GA-based MPPT algorithm

Maximum Power Point Tracking Systems: Maximum power tracking's main objective is to get as much electricity as possible from the PV model. Many MPPT methods are utilized to track the maximum power point [36].

In photovoltaic systems, extreme power point tracking is a helpful technique for maximizing the output power of standalone PV panels. The MPPT techniques was utilized to wrest the most power possible from a standalone PV panel under a variety of environmental circumstances, including conversion in temperature, partial cloud cover, masking, and sun irradiation [37, 38]. This technique overcomes this because PV output varies continuously with irradiance and temperature, and conventional controllers cannot maintain accurate tracking under these fluctuations. MPPT ensures that the system consistently operates at its maximum power point, enabling higher efficiency and stable performance in all environmental conditions.

Optimized Fuzzy Interfaced PID Controller MPPT Technique: Advanced MPPT algorithms for photovoltaic systems have been extensively researched to overcome negative performance issues. The main problem with conventional techniques is slower tracking and requiring a complex control circuit. Compared to conventional INC techniques, the ANN-based ACO algorithm tracks MPP effectively below changing radioactivity conditions. The development of intelligent algorithms has greatly benefited MPPT control systems. Due to daily variations in temperature and radiation, the MPP system must run continuously in real time.

Optimized algorithms have higher efficiency against these conditions. A new Enriched Fuzzy PID (EF-PID) controller was proposed in the MPPT technique to overcome the demerits of existing techniques.

A genetic-based enriched algorithm is proposed to optimize fuzzy PID controllers, recommending the best membership functions and fuzzy rules for PID parameter adjustment to follow the maximum power point in standalone solar PV systems.

This optimized approach achieves excellent tracking, higher efficiency, and faster response under varying environmental conditions. This technique overcomes slow tracking and poor adaptability of existing methods. By using genetically tuned fuzzy-PID parameters, the controller achieves faster response, better stability, and higher accuracy under rapidly changing environmental conditions. Figure 3 shows the proposed fuzzy PID-based MPPT controller.

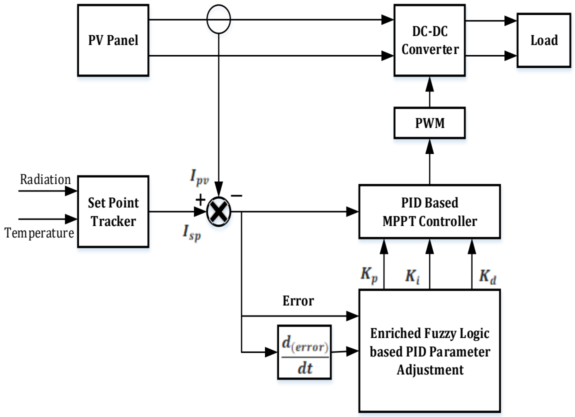


Fig. 3 Fuzzy-PID-based MPPT controller

4. Simulation Parameters and System Modeling

To ensure reproducibility and facilitate independent validation of the proposed optimized Fuzzy PID-based MPPT controller, this section presents the detailed simulation environment, photovoltaic system modeling, DC–DC converter specifications, and control parameter settings used in this study.

4.1. Simulation Environment and General Settings

All simulations were carried out using MATLAB/Simulink R2023a under identical operating conditions to ensure fair comparison among MPPT techniques. A standalone photovoltaic system connected to a DC–DC boost converter supplying a resistive load was considered. The MPPT controller was implemented in discrete-time with a fixed sampling period. Simulation parameters are summarized in Table 1.

Table 1. General simulation parameters

Parameter	Value
Simulation software	MATLAB/Simulink R2023a
Solver type	Discrete (ode3)
Sampling time	1×10^{-4} s
Switching frequency	20 kHz
Load type	Resistive
Operating mode	Standalone PV system
Temperature	25 °C (constant)
Irradiance levels	500 W/m², 1000 W/m²

4.2. Photovoltaic System Modelling

The photovoltaic module is modeled using the single-diode equivalent circuit, which provides a good trade-off between modeling accuracy and computational complexity. The output current of the PV module is expressed as:

$$I_{pv} = I_{ph} - I_0\left(e^{\frac{V_{pv}+I_{pv}R_s}{nV_t}} - 1\right) - \frac{V_{pv}+I_{pv}R_s}{R_{sh}} \qquad (3)$$

Where I_{ph} is the photo generated current $I_0$is the diode saturation current, R_s and R_{sh} represent the series and shunt resistances, n is the diode ideality factor, and V_t is thermal voltage.

Photo-generated output is linearly dependent on irradiance and temperature, which makes it possible to accurately simulate changes in the environment. Table 2 lists the parameters of the PV module, which were chosen from the typical values of datasheets.

Table 2. PV Module electrical parameters

Parameter	Value
Maximum power (Pmax)	315 W
Open-circuit voltage (Voc)	44.7 V
Short-circuit current (Isc)	9.1 A
Voltage at MPP (Vmp)	37.2 V
Current at MPP (Imp)	8.47 A
Series resistance (Rs)	0.35 Ω
Shunt resistance (Rsh)	820 Ω

4.3. DC-DC Boost Converter Modelling

To connect the PV panel to the load and adjust the working voltage following the MPPT set point, a DC-DC boost converter is used. The averaged state-space model of the boost converter is:

$$\frac{dI_L}{dt} = \frac{1}{L}\left(V_{pv} - (1-D)V_0\right) \qquad (4)$$

$$\frac{dV_0}{dt} = \frac{1}{C}\left((1-D)I_L - \frac{V_0}{R}\right) \qquad (5)$$

Here, D denotes the duty cycle output or generated by the MPPT controller, L stands for the inductor, C represents the output capacitor, and R is the load resistance.

The parameters of the converter were determined with the aim of achieving Continuous Conduction Mode (CCM) and the smallest possible output ripple. The parameters of the DC-DC converter are shown in Table 3.

Table 3. DC-DC boost converter parameters

Parameter	Value
Inductance (L)	2 mH
Output capacitance (C)	2200 µF
Switching frequency	20 kHz
Load resistance (R)	25 Ω
Input voltage range	20-45 V
Output voltage range	40-80 V

4.4. Fuzzy PID and Genetic Algorithm Parameters

The proposed controller integrates a fuzzy inference system with PID control, whose parameters are optimized using a genetic algorithm in Table 4.

The GA minimizes tracking error and steady-state oscillations by tuning fuzzy membership functions and PID gains.

Table 4. GA and controller parameters

Parameter	Value
Population size	30
Number of generations	50
Crossover probability	0.8
Mutation probability	0.02
PID gains	Optimized by GA
Fuzzy MF types	Triangular
Linguistic variables	NB, NS, ZE, PS, PB

All parameters, models, and controller settings presented above were used consistently throughout the simulation study. By providing explicit PV modeling equations, converter state-space formulations, and controller specifications, the proposed framework can be directly reproduced and extended by other researchers for comparative or hardware-oriented studies.

5. Result

Simulation of a standalone PV panels system utilizing an improved genetic algorithm fuzzy PID MPPT controller is done, and results are recorded. The proposed method's performance is examined using MATLAB/Simulink. A DC-DC Fuzzy Logic control with an advanced boost converter connects the PV module to the load. DC-DC Fuzzy Logic control with an advanced Boost converter is used as a power-conditioning unit. The results of a simulation of a standalone Solar PV system with an improved Genetic algorithm fuzzy PID MPPT controller were obtained. Power conditioning equipment is a DC-DC Fuzzy Logic control with an advanced Boost converter. This section provides power, voltage, & current in graphical and waveform, as well as duty cycle for irradiance (G_{cell}) 500 and 1000 at temperature (T_{cell}) $25°C$.

The numerous parameters were recorded after modeling the PV system under typical test settings. The PV system simulation with a maximum power point tracker at 500 w/m2 at 25 C is shown in Figure 4.

Figure 5 shows a solar photovoltaic system for specified input circumstances using chosen MPPT techniques at 500 w/m2 at 25 C. Power output from the PV system swung wildly up and down. According to Figure 5(a), the power generated rises from 0 to 90 Watts. The profile of the input voltage from 0V to 22V is illustrated in Figure 5(b). Figure 5(c) demonstrates how the PV array's current sharply lessened from 4.3 A to 4.26 A.

The output duty cycle of fuzzy PID systems for input power is shown in Figure 6. The converter models determine the current duty cycle for maximum power output under typical test conditions. The duty cycle produced by the enhanced Genetic Algorithm Fuzzy PID MPPTs coincides very fit, leading to the production of output power.

Figure 7 shows the input power for PV solar systems in the waveform. This waveform also generates a power of 95.83 watts. The seconds are displayed on the X-axis while the watts are displayed on the Y-axis.

The waveform of the input voltage for solar photovoltaic systems is depicted in Figure 8. This waveform also generates the voltage 22.52 watts as mentioned earlier in graph form. The X-axis demonstrates time in seconds, and the Y-axis demonstrates voltage in volts.

Figure 9 shows the input current for solar photovoltaic systems in the waveform. This waveform also generates the voltage 4.25A as mentioned earlier in graph form. The X-axis demonstrates the time in seconds, while the Y-axis demonstrates the current in amps.

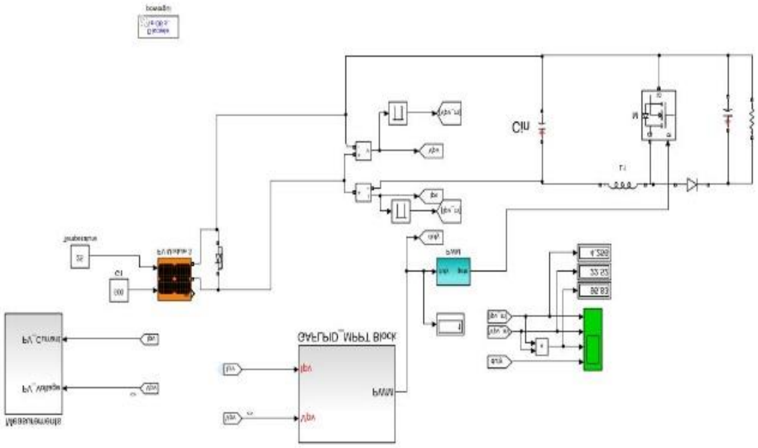
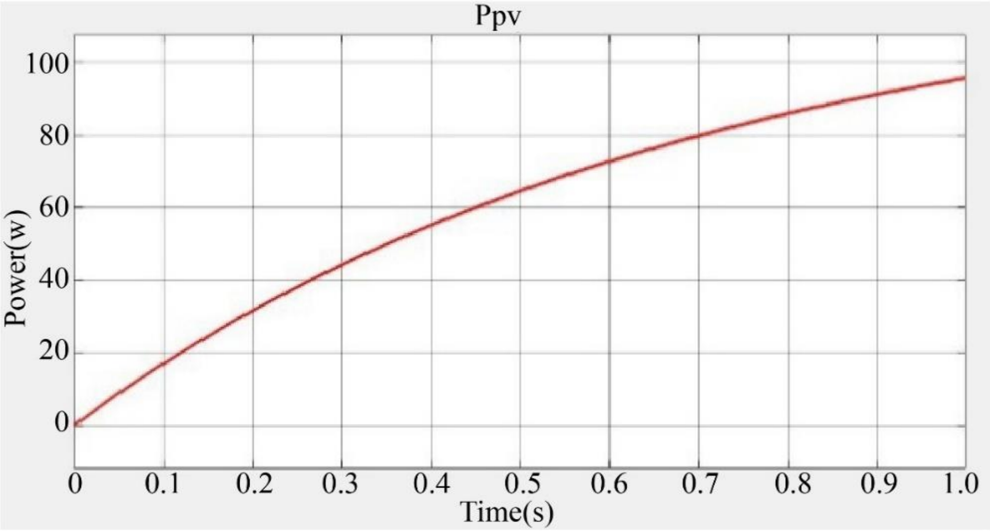
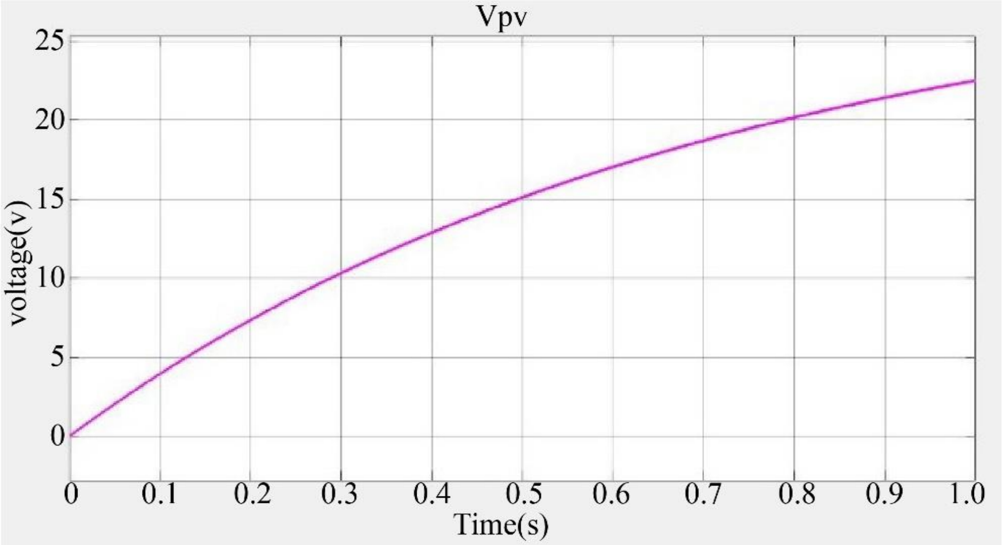

PV system at $500\ \mathrm{w/m^2}$ at $25°\mathrm{C}$

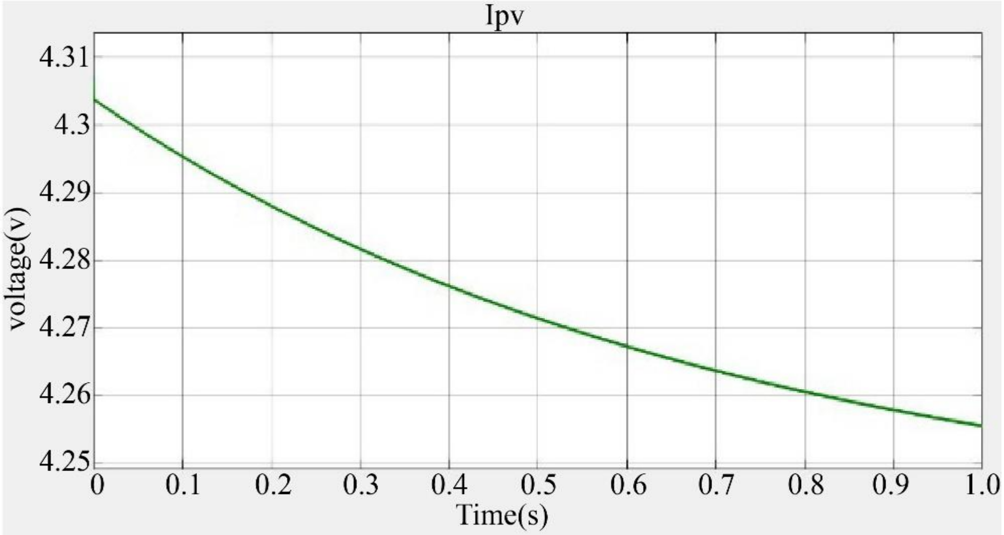
Fig. 4 Simulation diagram for PV system at $500\ w/m^2$ at $25°C$



(a) Input power



(b) Input voltage



(c) Input current

Fig. 5 Simulation of PV systems

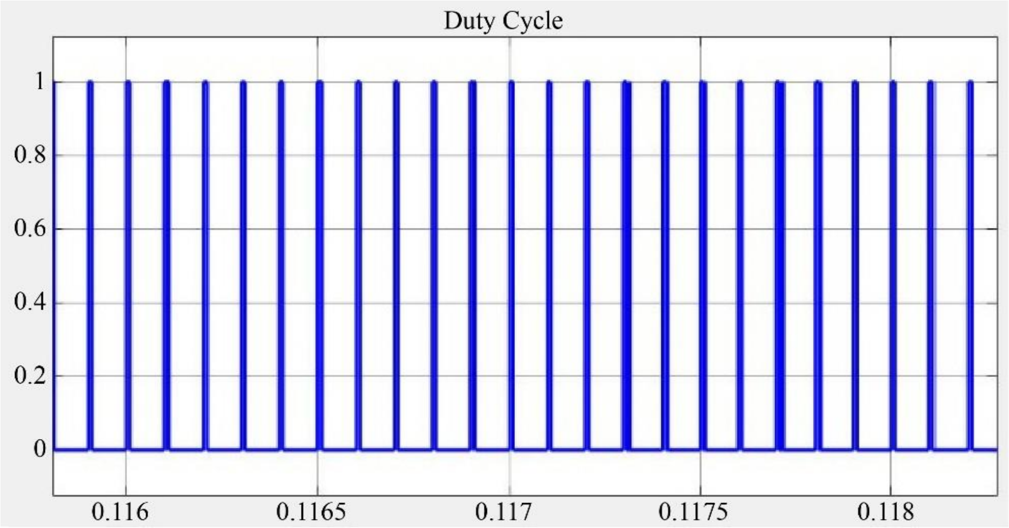


Fig. 6 Duty cycle

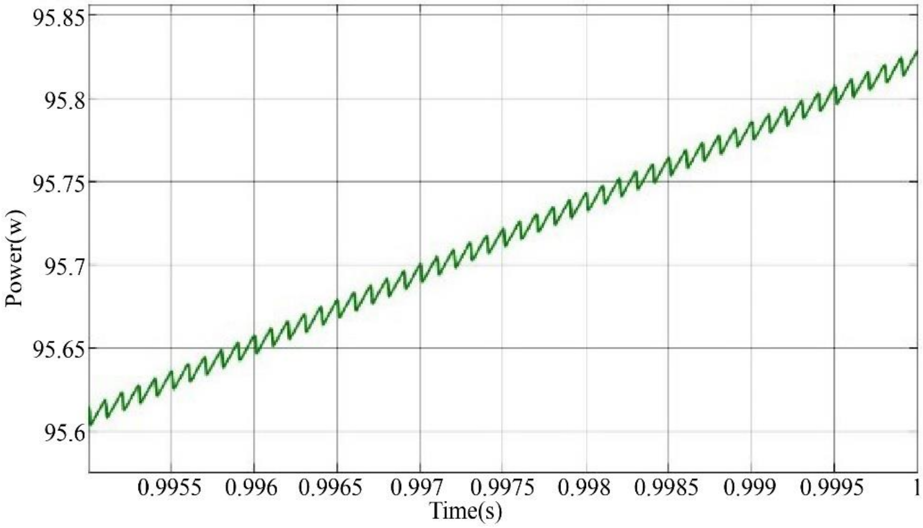


Fig. 7 Input power

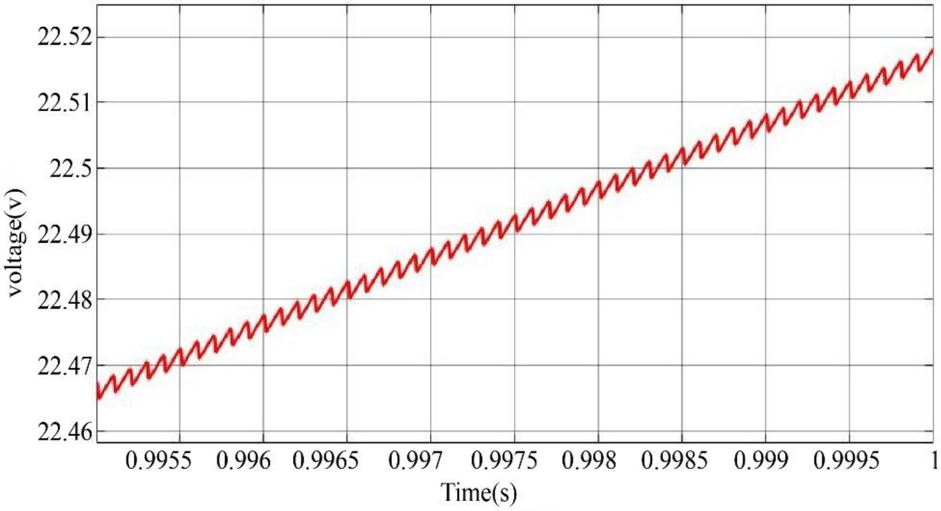


Fig. 8 Input voltage

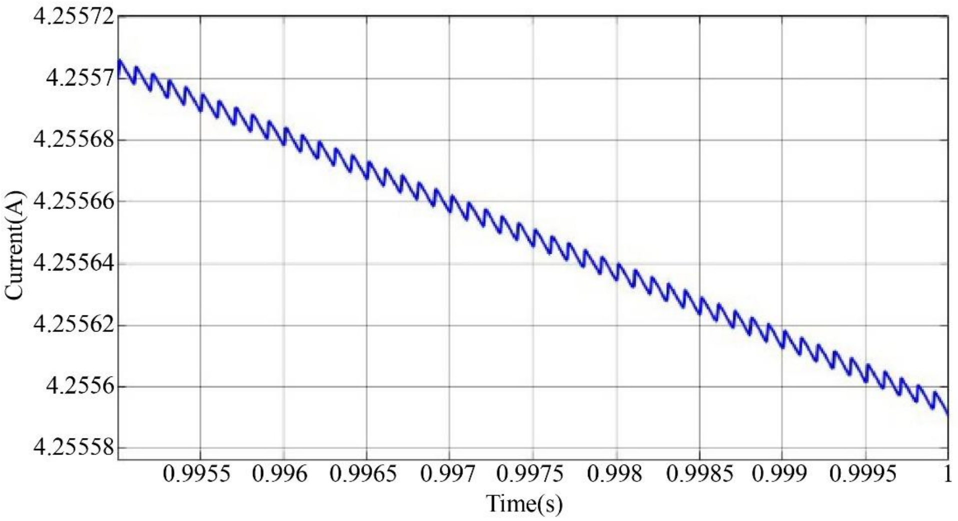


Fig. 9 Input current

PV system at $1000\ w/m^2$ at $25°C$

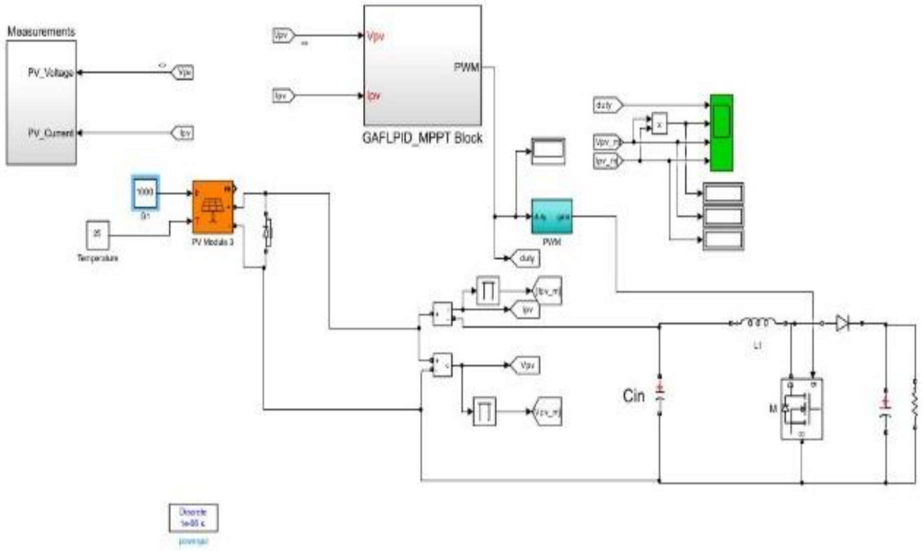


Fig. 10 Simulation diagram for PV system at $1000\ w/m^2$ at $25°C$

Figure 10 shows the simulation diagram for the PV system at $1000\ w/m^2$ at $25°C$. The numerous parameters were noted down after modeling the PV system under typical test settings. The PV system simulation with a maximum power point tracker at $1000\ w/m^2$ at $25°C$ is shown in Figure 11.

Figure 11 shows a solar photovoltaic system for specified input circumstances using chosen MPPT techniques at $1000\ w/m^2$ at $25°C$. The power produced by the PV system increased suddenly.

Based on Figure 11(a), the power generated rises from 0 to 300 Watts. The profile of the input voltage from 0V to 40V is depicted in Figure 11(b). As seen in Figure 11(c), the PV array's current sharply reduced from 8.6A to 7.54A.

The duty cycle output of fuzzy PID systems for input power is shown in Figure 12. Under typical test conditions, the converter model establishes the duty cycle for maximum power output. The output power was generated as a result of the enhanced Genetic Algorithm Fuzzy PID MPPTs' extremely strong duty cycle generating correlation.

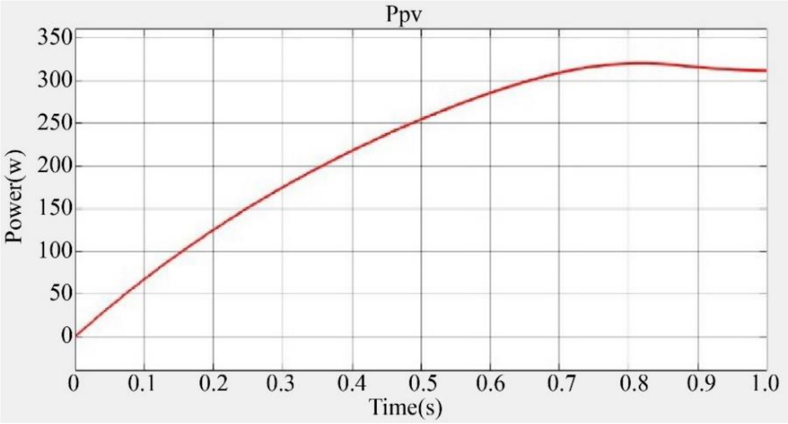
Figure 13 shows the input power for PV solar systems in a waveform. This waveform generates a power of 314.7 watts. The X-axis demonstrates the time in seconds, while the Y-axis demonstrates the power in watts.

Figure 14 shows the input voltage for PV solar systems in the waveform. This waveform also generates a voltage of 41.72 volts. The seconds are demonstrated on the X-axis while the volts are demonstrated on the Y-axis.

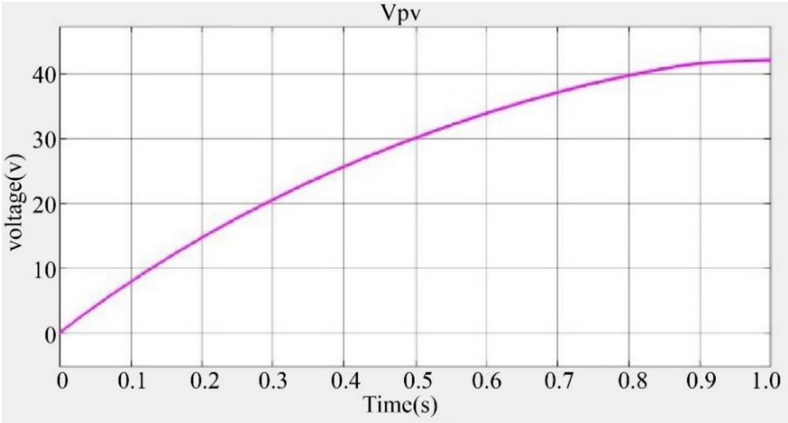
Figure 15 shows the input current for PV solar systems in the waveform. This waveform generates a current of 7.54 amperes. The X-axis demonstrates the time in seconds, while the Y-axis demonstrates the current in amps.

Table 5. Result comparison of PV system with varying irradiance

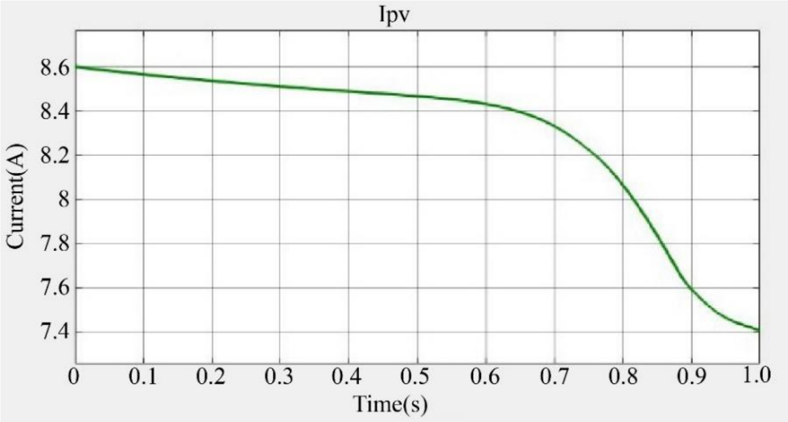
Irradiance level	Power P_{pv}	Voltage V_{pv}	Current I_{pv}	Duty Cycle (D)
500 w/m^2 at 25°C	95.83	22.52	4.25	0.11
1000 w/m^2 at 25°C	314.7	41.72	7.54	0.2



(a) Input power



(b) Input voltage



(c) Input current

Fig. 11 Simulation of PV

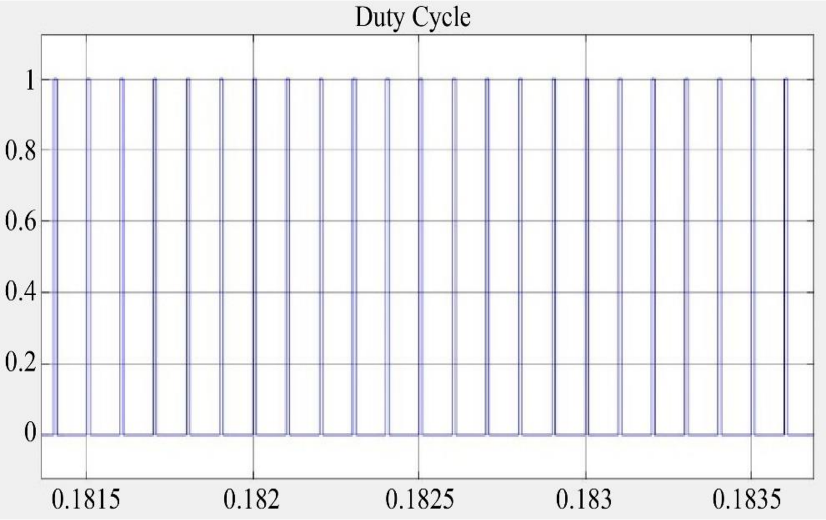


Fig. 12 Duty cycle

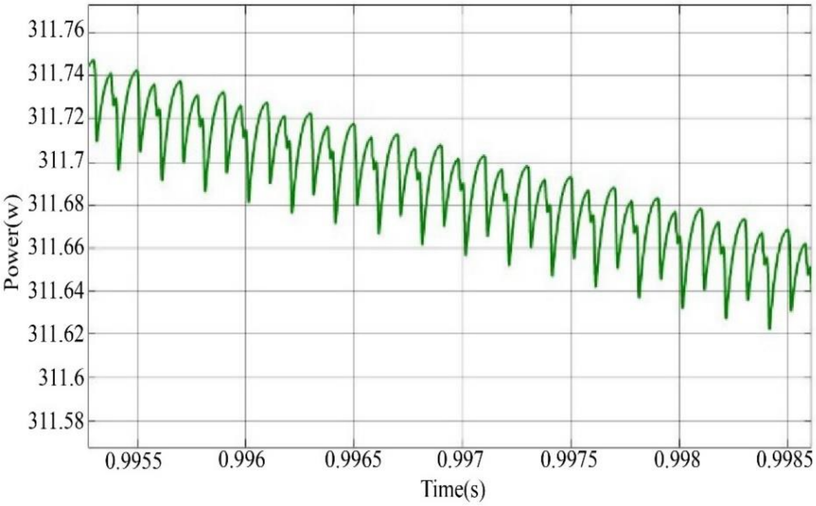


Fig. 13 Input power

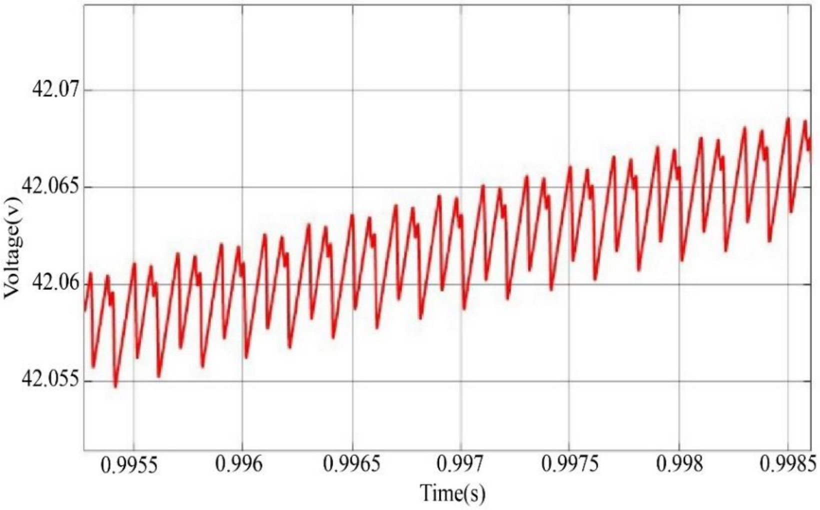


Fig. 14 Input voltage

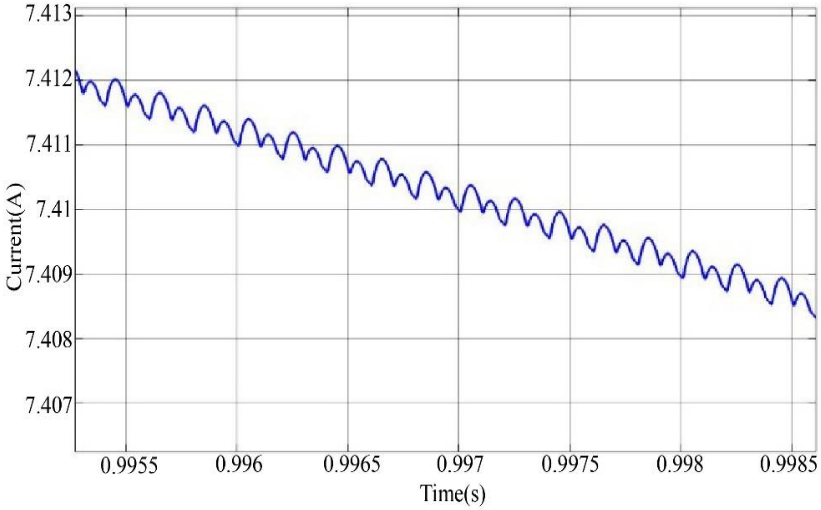
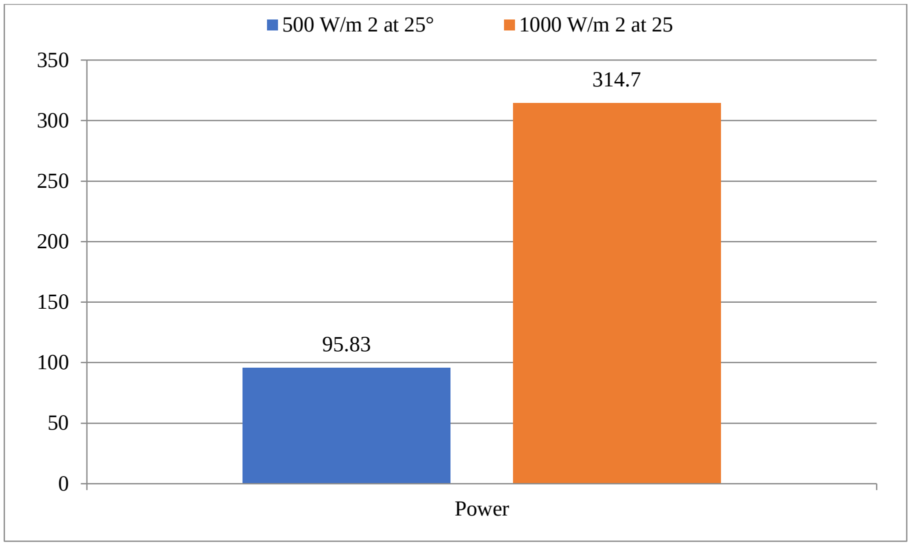
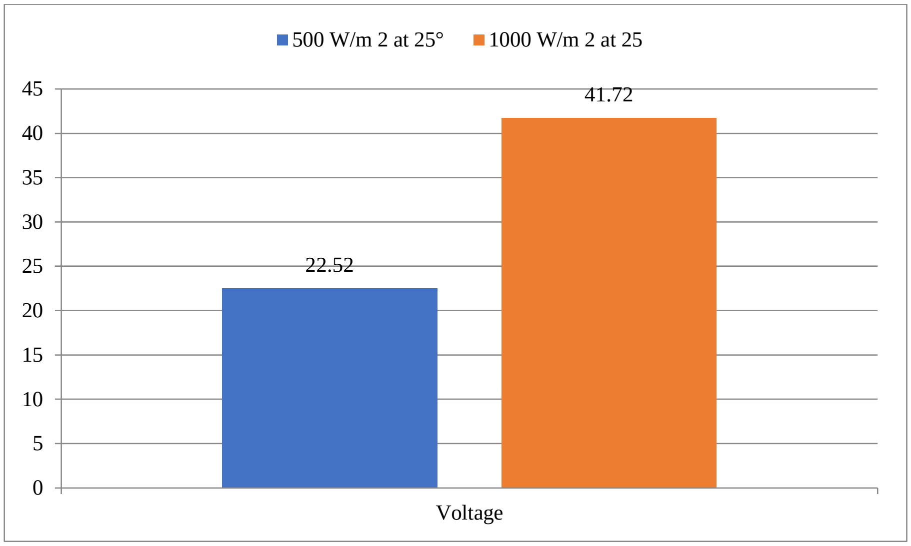


Fig. 15 Input current





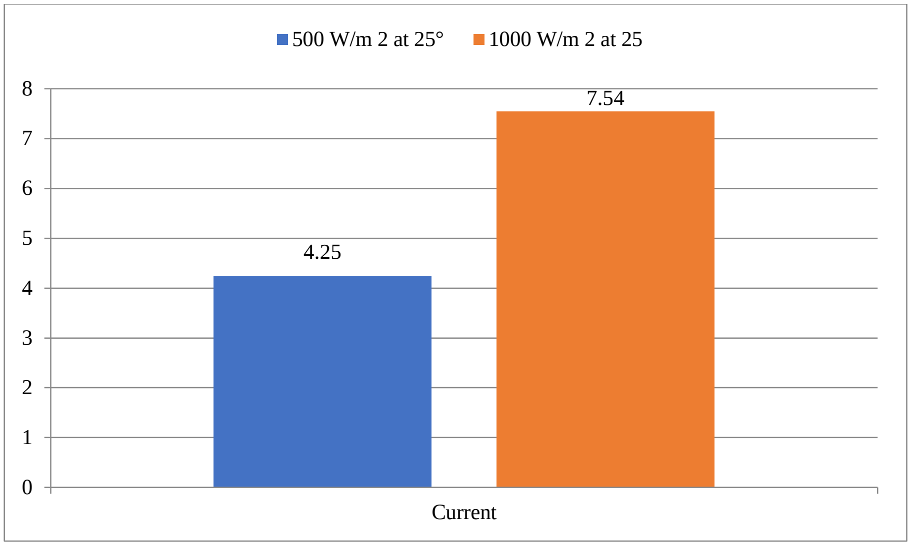


Fig. 16 Result comparison of PV system with varying irradiance

Figure 16 shows the result comparison of the PV system with varying irradiance. This figure is concluded from the above Table 5 that increasing the irradiance increases the input power, voltage, & also the input current at $25°C$.

The simulation is run with different irradiances and a constant temperature of $25°C$. Table 1 shows temperatures and varied irradiances used in the simulation. The temperature was held constant at $25°C$ despite shifting solar irradiation. With a constant temperature, solar irradiance was controlled at 500 and 1000 w/m^2.

Efficiency: Table 6 thoroughly compares the efficiency produced by PV. Efficiency analysis in the context of the proposed converter involves a comprehensive examination of its performance using mathematically based equations. Efficiency, typically denoted by η, is calculated as the ratio of output power to input power, expressed as a percentage. In the case of a solar PV system with MPPT control, the efficiency can be mathematically represented as:

$$\eta = \frac{P_{out}}{P_{in}} \times 100\% \tag{6}$$

P_{out} Signifies the output power generated by the solar PV system and P_{in} represents input power absorbed from solar irradiance. The output power P_{out} is influenced by factors such as solar irradiance, temperature, shading, and the efficiency of the power conversion process. The input power P_{in}, on the other hand, depends on the intensity of solar radiation incident on the photovoltaic modules. Additional equations can be used to evaluate the effectiveness of the MPPT control algorithm and the system as a whole, looking deeper into efficiency analysis.

$$Efficiency = \frac{P_{actual}}{P_{maximum}} \times 100\% \tag{7}$$

P_{actual} is the PV system's actual power output under particular circumstances. $P_{maximum}$ is the maximum power that the PV system, operating at its maximum power point, could generate under those exact conditions.

Under specific input conditions, the proposed MPPT controller has enhanced tracing performance, and the total efficiency of the solar PV system is comparable to or even higher than that of modern MPPT-based systems, as can be seen from the table. Table 6 presents a comparative efficiency analysis of the proposed optimized Fuzzy PID-based MPPT controller against several widely reported MPPT techniques.

While a few techniques, like conventional MPPT and fuzzy logic controllers, show that the peak efficiencies are very slightly higher (97%), these methods usually perform at this level only when the operating conditions are quite stable, and they are often unable to cope with changes in irradiance and temperature that occur very quickly.

On the other hand, the new controller (PMCC) delivers 96.98% efficiency in rapidly changing environmental conditions, which is quite superior to fuzzy (96.28%), GAfuzzy (96.72%), ANFIS (96.58%), and DCDC boost-based MPPT methods (96.02%) traditionally used in the solar power generation sector.

Furthermore, it is the capacity of the proposed method to accurately track changes dynamically, minimize steady-state oscillations, and stabilize the duty-cycle that are fundamentally important rather than just achieving peak efficiency. The incorporation of PID behavior within the fuzzy framework, which has been genetically optimized, leads to quicker convergence and better transient performance, which are not factors considered by previous GAFLC based methods. Hence, even though from the quantitative point of view the difference in efficiency is quite minor, the optimized Fuzzy PID MPPT controller (PMCC) proposed here introduces a major advantage in terms of its ability to keep the efficiency level high most of the time, even that the irradiance conditions are random, thus delivering a more stable and reliable MPPT solution for actual photovoltaic installations.

Table 6. Efficiency comparison

Techniques	Efficiency
Fuzzy [21]	96.28%
GA Fuzzy [21]	96.72%
ANFIS [21]	96.58%
MPPT DC-DC boost converter [39]	96.02%
MPPT [40]	97%
Fuzzy Logic Controller [41]	97%
Proposed	96.98%

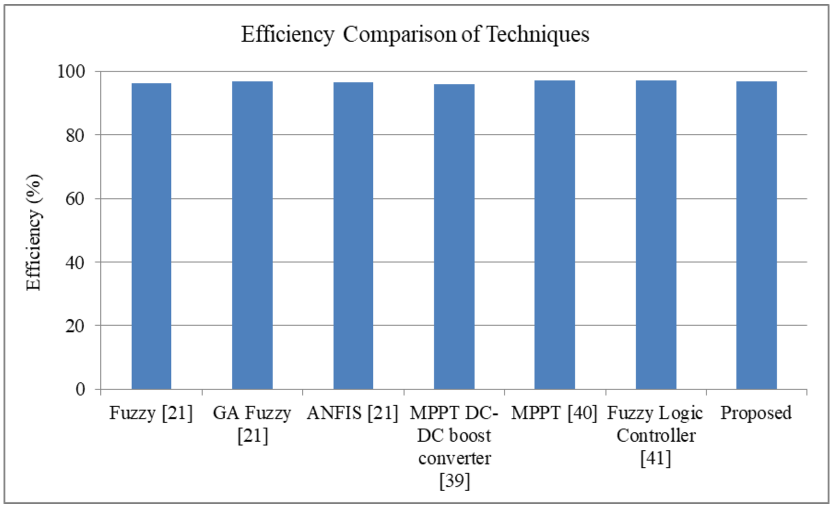


Fig. 17 Efficiency

Figure 17 shows the effectiveness of a solar PV system using a Fuzzy, ANFIS, and Ga-optimized fuzzy system below numerous scenarios. Based on the outcomes, it is possible to state that the suggested GA fuzzy-PID MPPT controller has been optimised and is capable of tracking precisely under the mentioned input conditions.

5.1. Membership Functions

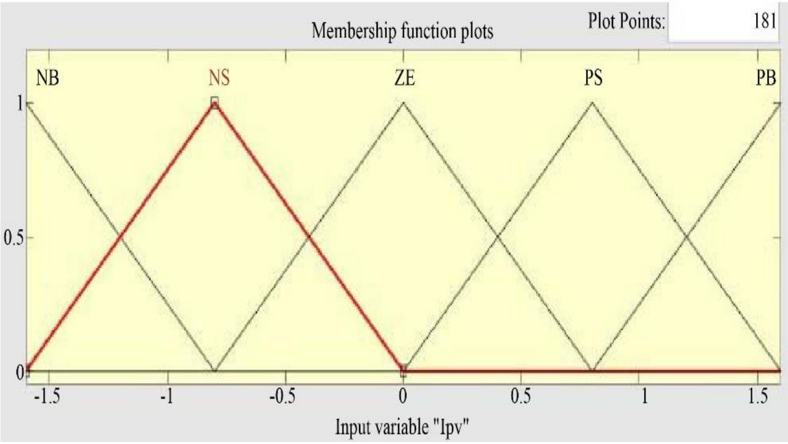
The membership function for Solar PV systems is shown in Figure 18. In response to the provided Membership Functions, GA produces optimum values. GA provides the best rules based on convergence. Figure 15(a)–(c), respectively, shows the membership function of Ipv, Vpv, and Ppv based on the GA optimization. Negative Big (NB), Negative Small (NS), Zero Equivalence (ZE), Positive Small (PS), and Positive Big (PB) are the different classifications for the membership functions. MF is small for power, zero equivalent for voltage, and small for positive current.

5.1.1. Implementation Difficulties of Proposed Converter

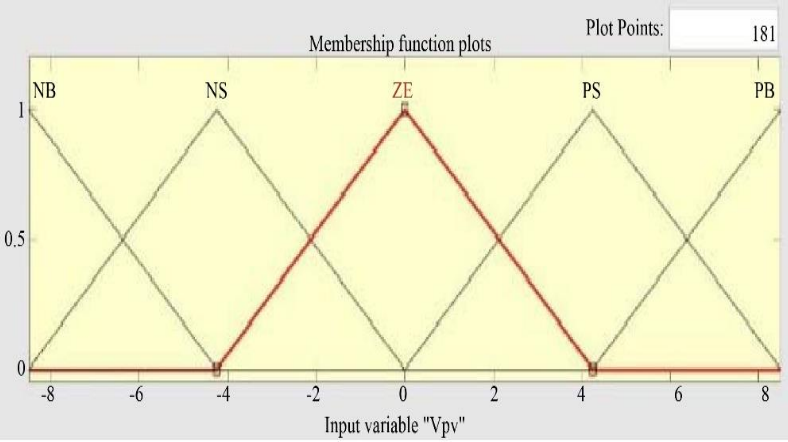
There are various difficulties and complexity involved in putting the proposed converter’s control mechanism into practice in a lab setting. First, in order to achieve the best performance, the improved Fuzzy PID controller must be integrated with the MPPT algorithm. This needs exact calibration and altering of several parameters. This is a laborious and technically complex operation, especially when working with genuine gear.

The controller circuit might also be quite a challenge to build. Designing such a complex circuit, which includes a Fuzzy PID controller, is no easy task as it demands very good knowledge of electrical engineering and control theory. Besides, in order to assure the control system’s stability and its capability to handle disturbances and varying operating conditions, detailed designing and testing are vitally important. Besides, there are several reasons why the researchers decided against the assembly of a hardware test and workbench in a laboratory environment for a conventional boost converter. First of all, the suggested converter topology can be capable of providing a higher level of flexibility and adaptability than traditional boost converters.

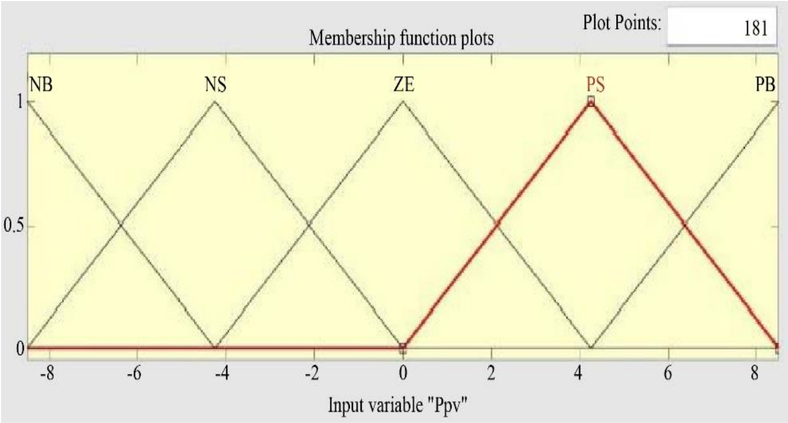
Due to their possible incompatibilities, it may be very difficult to evaluate the effectiveness of the higher optimization technique and the optimized Fuzzy PID controller in a standard boost converter layout. Besides, relying on regular boost converters for testing purposes in labs would still be a limited way of checking the efficiency and performance of the proposed control methods. The features and capabilities of the proposed converter topology are so unique that they require not only the integration of complex control algorithms and optimization methodologies but also some special testing and evaluation techniques.



(a) Membership function for current Ipv



(b) Membership function for voltage Vpv



(c) Membership function for power Ppv

Fig. 18 Membership functions

In addition, the choice to concentrate on simulations rather than hardware experiments might have been made because of such things as the availability of the material or equipment. Simulations are “cheap” and quick ways to check the effectiveness of the proposed control methods in various working conditions without the need for lots of hardware setup and testing. All in all, concentration on theoretical analysis and simulation-based assessments will provide a more detailed examination of the performance characteristics and control capabilities of the control procedures, despite the fact that the performance of the control process of the proposed converter in practice in a lab setting has its issues.

6. Ablation Study

The use of an ablation study here focuses on what each major element of the control system that the propose participate. (fuzzy logic controller, PID, and GA-based optimization) are the keys parts of the system as discussed in the coming Table 7. All the running of the various systems is based on the PV model, DCDC converter, and MATLAB/Simulink environment, as were explained before.

Table 7. Comparative performance of parameters for ablation study

Variant	Tracking Efficiency	Duty stability
Baseline PID	95.00	Low
Fuzzy (no PID)	96.28	Medium
Fuzzy-PID (no GA)	96.40	Medium
GA-PID (no fuzzy)	96.55	Medium
Proposed	96.98	High

7. Discussion

The performance evaluation of the proposed Fuzzy PID-GA-based MPPT controller, which is optimized, clearly shows the benefits of higher accuracy in tracking, better response to changes and higher stability under rapidly changing solar irradiance conditions, in fact regardless of the classic PID, fuzzy-only, or even GA-fuzzy MPPT approaches, the hybrid proposed here really is a combination of fuzzy reasoning, PID dynamics, and genetic optimization that is able to give solutions to both the transient and steady-state performance issues most commonly photovoltaic MPPT systems.

It should be pointed out that the references to ABC, PSO, and RBFNN-based MPPT techniques in this paper are, in fact, based on comparative understandings collected from the literature, as reviewed in Section 2, and not from direct simulation in the same MATLAB/Simulink environment. These techniques were brought up to show the contrast of the proposed method with the most advanced intelligent and metaheuristic MPPT strategies, whose reported drawbacks have been highlighted, e.g., slow convergence, getting stuck in local optima, heavy computational demand, chattering phenomenon, and the need for long training data or parameter tuning. On the other hand, the Results section of this paper is deliberately limited in scope to a quantitative and reproducible benchmarking of the proposed controller and the most related baseline methods, thus ensuring experimental uniformity.

The simulation outcomes have validated the proposed controller, which is capable of reaching an MPPT efficiency of 96.98%, thus surpassing traditional fuzzy, GA-fuzzy, ANFIS, and DC-DC boost-based MPPT methodologies in terms of performance under changing operating conditions. In fact, even though some traditional techniques claim slightly better peak efficiencies at steady-state, the proposed controller exhibits excellent robustness as it shows less steady-state oscillations, quicker tracking of the maximum power point, and higher duty-cycle stability during sudden changes in irradiance. Such features are very important in photovoltaic applications since the environmental conditions are always changing.

Also, as shown by the ablation study, this evidence is even more compelling since the impact of each element of the proposed control scheme is separately considered. Figures confirm performance rises from PID control alone, to PID control assisted by fuzzy, and finally to fully optimized Fuzzy PID-GA. This is proof that the performance improvements not just random but that they are the result of the synergistic interaction between the fuzzy inference, PID control action, and genetic optimization. Specifically, the PID element helps transient damping and steady-state accuracy, whereas GA-based tuning guarantees optimal parameter selection without the need for human intervention.

In terms of implementation, the new controller balances well performance and complexity. Compared to ANN- or deep-learning-based MPPT strategies, it does not require large training datasets and heavy computational resources. Also, it lessens the chattering and modeling sensitivity problems of sliding-mode and predictive control methods. These factors make the new method a better fit for real-world applications in standalone PV systems, rooftop PV systems, microgrids, and PV systems subject to partial shading and rapid irradiance changes.

Overall, the discussion shows that the major point of this paper is not just to reach the highest peak efficiency but to provide a stable, adaptive, and reproducible MPPT solution that can keep high performance at all times, even in the face of real-world and challenging conditions. By directly tackling the issues that have been pointed out in existing intelligent and metaheuristic MPPT techniques, the developed Fuzzy PID-GA controller pushes forward the practicability of MPPT methods in the photovoltaics energy conversion systems of the future.

8. Conclusion

This paper introduced an MPPT controller based on Fuzzy PID - an optimized one that overcomes the drawbacks of the existing ones, like SRA MPC, sliding-mode, ANN-based, and GA-FLC algorithms. After carrying out extensive MATLAB/Simulink simulation experiments, the proposed controller type has been proven to reach the point faster, produce fewer oscillations, be more accurate in tracking, and attain an efficiency of 96.98%, which is higher than that of many other modern MPPT methods. By means of GA optimization, the adaptation of fuzzy PID structure is improved, allowing stable and efficient operation under varying irradiance and temperature conditions. Besides making the performance better, this work also adds to the field of renewable energy at large through more dependable extraction of solar power, better stability of systems, and higher energy production even without extra hardware costs.

These innovations not only encourage energy practices based on sustainability but also boost solar PV as a source of energy for smart grids, rooftop installations, rural electrification, and other new applications like electric vehicle charging and microgrid integration. Although there are difficulties in implementation on hardware due to tuning and converter integration, the simulation outputs support a strong potential of the proposed approach when it comes to practical application. Further studies can look into real-time embedded applications, hardware-in-the-loop validation, and adaptive or neuro-fuzzy varieties to enhance robustness even more. In general, results show that an optimized Fuzzy PID MPPT controller could be a very good and widely scalable means of increasing not only the efficiency but also the reliability and sustainability of photovoltaic power systems over the long term.

Glossary section:

FLC - Fuzzy Logic Controller
MPPT - Maximum Power Point Tracking
GMPP - Global Maximum Power Point
PID - Proportional-Integral-Derivative.
PV - Photovoltaic
SRA - Search and Rescue Algorithm
MPC - Model Predictive Control
PID - Propotional-Integral-Derivative

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