

## Maximum Power Extraction in Partial Shaded Grid-Connected PV System Using Hybrid Fuzzy Logic/Neural Network-Based Variable Step Size MPPT

Sanam Kouser<sup>1</sup>, G. Raam Dheep<sup>1</sup>, Ramesh C. Bansal<sup>2,3,\*</sup>

<sup>1</sup> School of Electronics and Electrical Engineering, Lovely Professional University, Phagwara, Punjab, India

<sup>2</sup> Department of Electrical Engineering, University of Sharjah, Sharjah, United Arab Emirates

<sup>3</sup> Department of Electrical Electronic & Computer Engineering, University of Pretoria, Pretoria, South Africa

\*Correspondence to Ramesh C. Bansal. Email: rcbansal@ieee.org

Sanam Kouser. Email: er.sanammirza@gmail.com

G. Raam Dheep. Email: raam.25227@lpu.co.in

### Abstract

The photovoltaic (PV) system's output power varies owing to solar radiation's irregularity, which confines their usage for various applications. Implementation of maximum power tracking (MPT) algorithms increases the efficiency and power generated from solar cells. When the array is partially obscured by clouds or structures, several local maximum power peaks (LMPPs) appear in the solar cell characteristics. Traditional MPPT algorithms, rather than following the global peak power point (GPPP), are preferable to following the local peak power point. If partial shading causes numerous LPPPs, it is necessary to look into how the MPPT technique can keep track of GPPP. Employing soft computing approaches such as the hybrid neural network/fuzzy method with variable step size perturb and observing MPPT, it is possible to trace the GPPP and also augment solar energy extraction. The present research paper focuses on hybrid fuzzy/neural network MPPT integrated with a high-step-up DC-DC converter to harvest the utmost power from the solar PV array. The voltage transients are reduced by controlling the DC link voltage along with solar radiation and temperature variations. The proposed MPPT technique is shown to be effective under both uniform and partial shade conditions in a series of simulations. From the test results, the efficiency of the overall system has increased from 91 to 98% for partial shading and uniform operating conditions.

**Keywords:** Photovoltaic; Peak power point algorithm; Fuzzy Logic Controller

## Abbreviations

PV	Photovoltaic	PSO	Particle swarm optimization
MPPT	Maximum power point tracking	PVH	Positive very high
LPPP	Local peak power point	ANFIS	Adaptive neuro-fuzzy inference system
GPPP	Global peak power-point	P&O	Perturb and Observe
ANN	Artificial neural network	PS	Positive small
DG	Distributed Generation	IC	Incremental conductance
PM	Positive medium	PVS	Positive very small
		PH	Positive high
		PLL	Phase-locked loop

## Introduction

Increasing demand for electricity in recent decades has necessitated the search for renewable energy sources, resulting in considerable interest in power plant diversification. Additionally, the growth of non-conventional energy has been remarkable, in part because these energy sources are the leading competitors to harmful fossil fuel-based power systems, which are becoming more and more popular. For distributed energy generation systems, solar and wind power emerged as the most important sources of green energy in this context (DGs). To be more explicit, photovoltaic cell-based solar energy generation has become a necessity for DG system improvement [1,2,3,4,5]. Electrical energy is generated by photovoltaic panels (PV modules). Several PV cells are coupled to produce these modules, which give a practical voltage and electric current value as well as a set that adequately protects the cells.

Solar cells created in the laboratory and built of monocrystalline silicon have a conversion efficiency of around 25%, which is a low figure when compared to supplementary sources of current energy generation, such as hydropower and wind power. [6]. In addition, ecological parameters such as the intensity of solar radiation and temperature have an impact on the voltage and output current of PV modules, which is a significant consideration. MPPT is a technique for pulling out the most energy from a panel while taking into account variables such as voltage and current. Increased study of maximum power point (MPP) search algorithms has led to increased efficiency and improved utilization of power production throughout the day as a consequence of the increase in research into MPP search algorithms. [7]. There are many issues associated with PV systems that go beyond simply supplying energy to grids, such as finding the most efficient way to get the most energy from solar PV configurations. For the MPP, several methods have been used [8]. However, the quantity of energy produced by PV systems may be negatively affected by partial shading. To deal with this problem, most PV systems linked to the network have adopted control approaches and converter topologies.

MPPT approaches can be categorized into four groups [9,10,11,12,13,14,15,16,17,18,19,20,21,22,23,24,25,26], such as model-based techniques, heuristic techniques, intelligent prediction-based techniques, and hybrid techniques. The model-based techniques have the following methods: constant current, constant voltage, look-up table technique, gradient descent method, curve fitting method, and optimal fixed voltage method. The incremental conductance (IC) technique, perturb and observe (P&O) technique, modified P&O technique, modified IC method, hill-climbing method, and beta method are all heuristic techniques. Intelligent prediction-based techniques have the

following methods: artificial neural networks (ANN), fuzzy logic control, particle swarm optimization (PSO), and the adaptive neuro-fuzzy inference system (ANFIS).

The open-circuit voltage ( $V_{oc}$ ) fraction strategy is a model-based, or fixed-step approach that predicts the peak power point value by using the open-circuit voltage value as a reference, supposing it is linearly proportional to  $V_{max}$ . A voltage sensor must be added to use this method, which is quite simple to do. The maximum power output is never even close to being reached in an assessed solar PV system that would be continuously shut down to verify the current value of the open circuit voltage. P&O [7,8,9] or incremental conductance [10, 11] are two search-based methods that use perturbing tactics to enhance the efficiency of MPPT methods. Other model-based techniques that use these perturbing strategies include P&O. Since they do not need any information about the short-circuit current or open-circuit voltage, they may be employed in any solar PV system. The process of making these devices comes with several critical issues. When irradiance or partial shading fluctuates continuously and rapidly, these algorithms' peak point of processing may fail due to a drop in the local peak power. Fuzzy logic and ANN were also developed to improve the search for the MPP's performance. However, there are some advantages to using smart controls, such as the fuzzy logic control, over the standard P&O control. There are also some benefits to a neuro-fuzzy hybrid intelligent control system related to the P&O technique.

A further way to speed up the search for the location of optimum power is to use ANN. As a result of training a neural network using P&O's method for finding the highest power point, an ideal increase or decrease in the duty ratio was generated [15,16,17]. Even though standard MPPT algorithm methods work well when PV panels are uniformly exposed to the sun, their efficiency can suffer when they are subject to partial shadowing. MPPT techniques listed above are typically only capable of delivering power to the local peak power point (LPPP) rather than the global peak power point (GPPP) [18]. Partial shading challenges in the hunt for MPP are being dealt with using bioinspired optimization algorithms because of these restrictions. Consequently, the MPPT approaches efficiency has deteriorated. As a result, meta-heuristic optimization methods are often used to identify the GPPP in the literature [18]. PSO (Particle Swarm Optimization) is one of the methods among them [19] because of its balance between performance, complexity, and maturity compared to numerical or heuristic optimization methods [20, 21]. Because the BAT-based MPPT method always reaches the GPPP, it can decrease the effects of partial shading, thus enhancing PV system performance [22, 23]. The combination of the P&O method and ant colony optimization was found in [24] to have faster GPPP convergence and reduced steady-state fluctuations than similar algorithms based on the PSO algorithm. Thus, new techniques for addressing partial shading and LMPP optimization are required. It is required to set up the PV system in such a way that it may be used to compare the MPPT algorithms described above [25, 26] before making a decision. The optimization-based MPPT algorithm is taking a long time to find the global power point because it depends on the number of populations and iterations used in the algorithm. Maximum power is trapped at the local peak if conventional MPPT algorithms like P&O MPPT and incremental conductance MPPT are used. The main reason for this problem is a fixed step size or a changed duty cycle. Variable step size MPPT has been developed to avoid this problem [27], but another issue arises, namely, power oscillation around the global peak point, as a result of using two fixed step sizes and a step size

determined by changing the power and voltage. In addition, various conditions must be met for the techniques to work properly:

- The system should be able to monitor and respond to changes in energy as quickly as possible.
- For the PV system to work better, the MPPT control needs to respond quickly and dynamically.
- After reaching the MPP, for any MPPT method's tracker, it is difficult to keep it in a fixed location. Maintaining a constant rate of operation is essential for minimizing the steady-state error.
- When making an MPPT control system, you have to make sure it can handle disturbances like input noise or inaccurate measurements.
- MPPT control systems must be efficient in both low and high irradiance circumstances, as this is critical to their overall performance. Many MPPTs are less efficient when there isn't a lot of light because the controller parameters were set for the rated power and a high level of irradiance.
- The above requirement has been addressed by the hybrid MPPT, i.e., by combining concepts of fuzzy logic and neural networks to provide variable step size that automatically changes based on the power and voltage of the PV panel. As an example of how important this work is, analytical and simulation results are shown for a solar PV system with a two-stage power transfer using an MPPT approach built on the hybrid fuzzy/neural variable step size PO method to achieve GPPP when the solar PV is exposed to both continuous sunlight and partial shade.

The organization of the paper is as follows: PV array modeling is presented in the second section. The third section describes the concept of partial shading. High-step-up DC-DC converter operation is presented in the fourth section. The proposed Hybrid Fuzzy Logical/Neural Network-Based Variable Step Size P&O MPPT Algorithm is explained in the fifth section. The sixth section provides a comprehensive analysis of the simulation of the proposed system. Experimental verification of the proposed work is presented in the seventh section. Concluding remarks on the proposed work are presented in the eight section.

### **Modeling of the PV Cell Array**

The equivalent circuit of the PV system is depicted in Fig. 1. The leaking resistance  $R_{sh}$ , which exceeds the ideal diode properties, is represented by a continuous resistance [25]. It is necessary to first model the PV to execute a comprehensive system simulation with precise system characteristics because the voltage-current relation is exceedingly nonlinear.

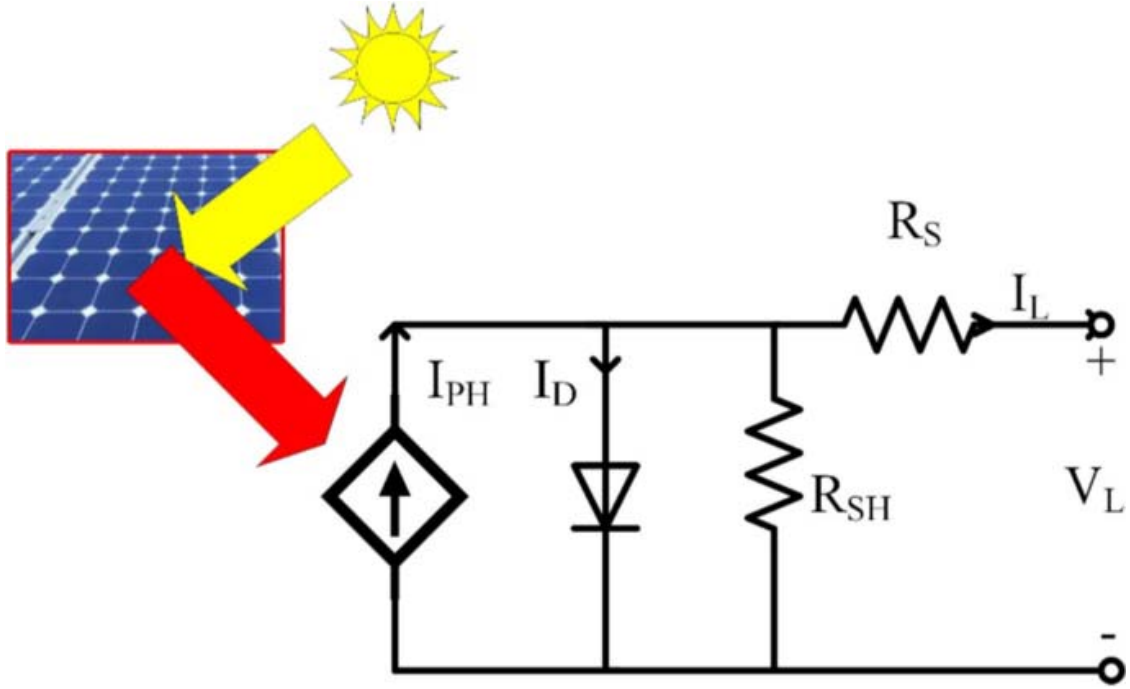


Fig. 1. PV array equivalent circuit [25]

The short-circuit current and open-circuit voltage are determined by the arrangement of PV array cells in series and parallel.

$$V_{OC} = N_s \times V_{oc} \quad (1)$$

$$I_{SC} = N_p \times I_{sc} \quad V_{OC} = N_s \times V_{oc} \quad (2)$$

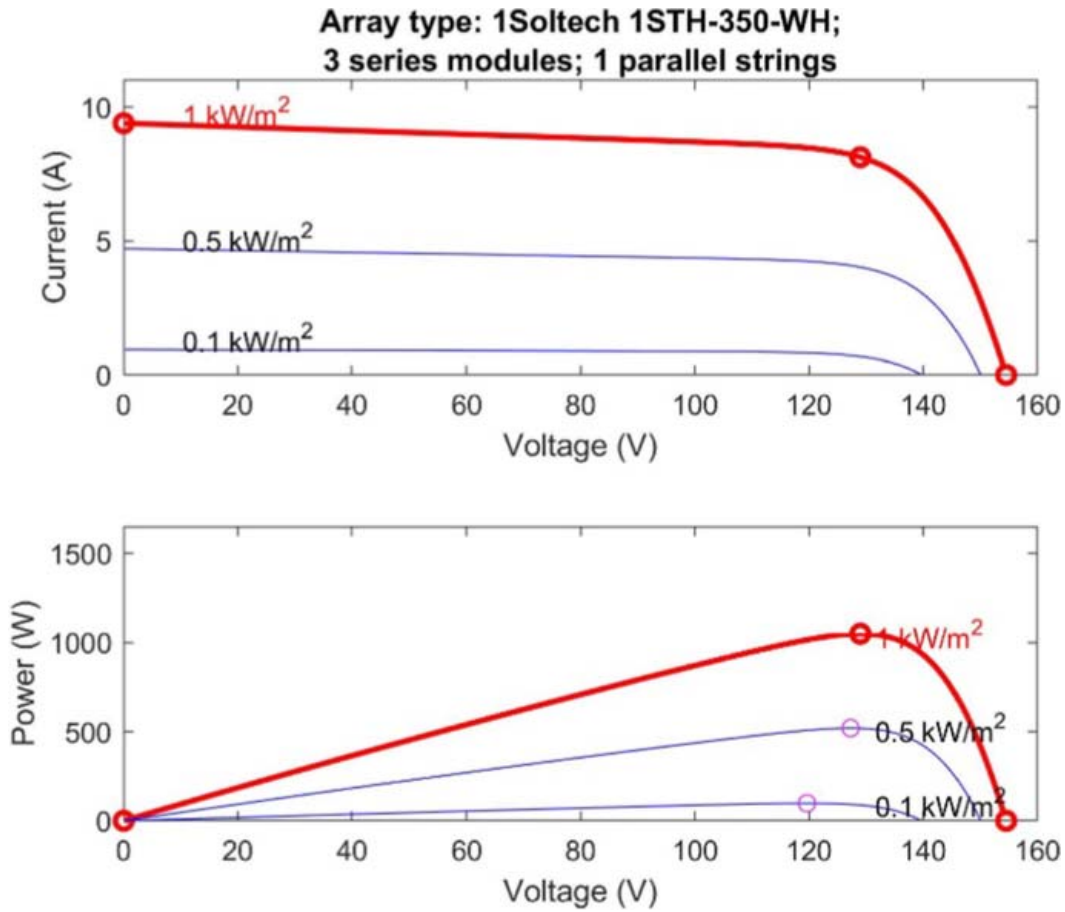
According to [26, 28], It is possible to calculate the PV's P-V and I-V characteristics as follows.

$$I_{PH} = I_{SC} \times S_N + I_t (T_C - T_t) \quad (3)$$

$$I_d = I_O \times \left( \exp\left(\frac{q(V_L + I_L \times R_S)}{A \times K \times T}\right) - 1 \right) \quad (4)$$

$$I_O = I_{Or} \left( \frac{T_C}{T_r} \right) \times \exp\left(\frac{qE_g}{B \times K} \left( \frac{1}{T_r} - \frac{1}{T_C} \right)\right) \quad (5)$$

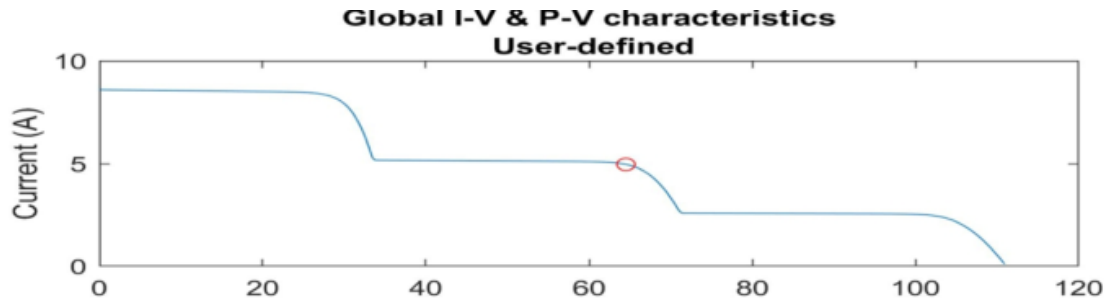
$$I_L = I_{PH} - I_d - \frac{V_L + I_L \times R_S}{R_{SH}} \quad (6)$$



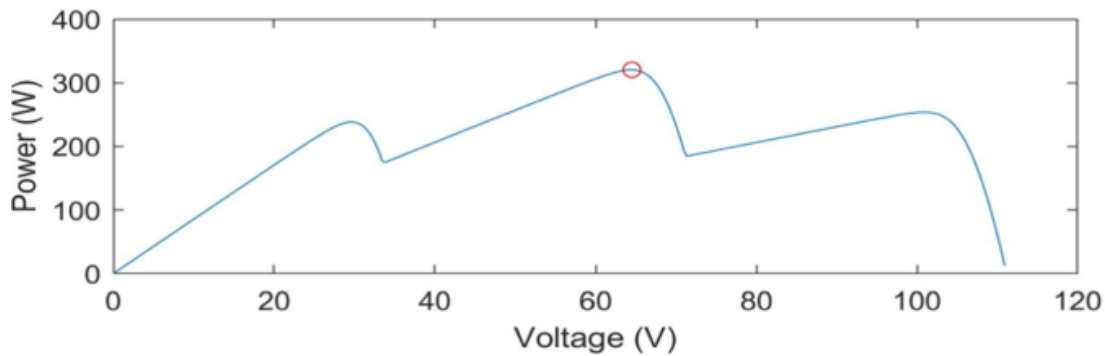
**Fig. 2. a and b** IV and PV characteristics of the PV Array

Equation (3) is used, when the irradiation level is set to  $S_N$  and the operating cell temperature is set to  $T_c$ . When irradiation levels are varied while the cell temperature remains constant, it is likely to obtain the I-V and P-V characteristics by calculating PV current, power, and voltage, as depicted in Fig. 2a and b.

Power, voltage, and current all change as a result of the changing temperature and irradiance. The change in current and power concerning irradiance is shown in Figs. 2 and 3.



(a). I-V characteristics of PV cell Array due to partial shading conditions.



(b). PV characteristics of PV cell Array under the influence of partial shading

**Fig. 3.** **a** I-V characteristics of PV cell Array due to partial shading conditions. **b** PV characteristics of PV cell Array under the influence of partial shading conditions

### Operation of Partial Shading Systems with Maximum Power

The kind of Photo-Voltaic module, the bypass diode design details, the string layout, and the nature of the shadow all have an impact on shading. The energy lost due to shading is compounded by a mismatch in alignment between the current flowing through a single string of modules and a loss resulting from an array's parallel strings having electrical voltages that are not aligned properly [29].

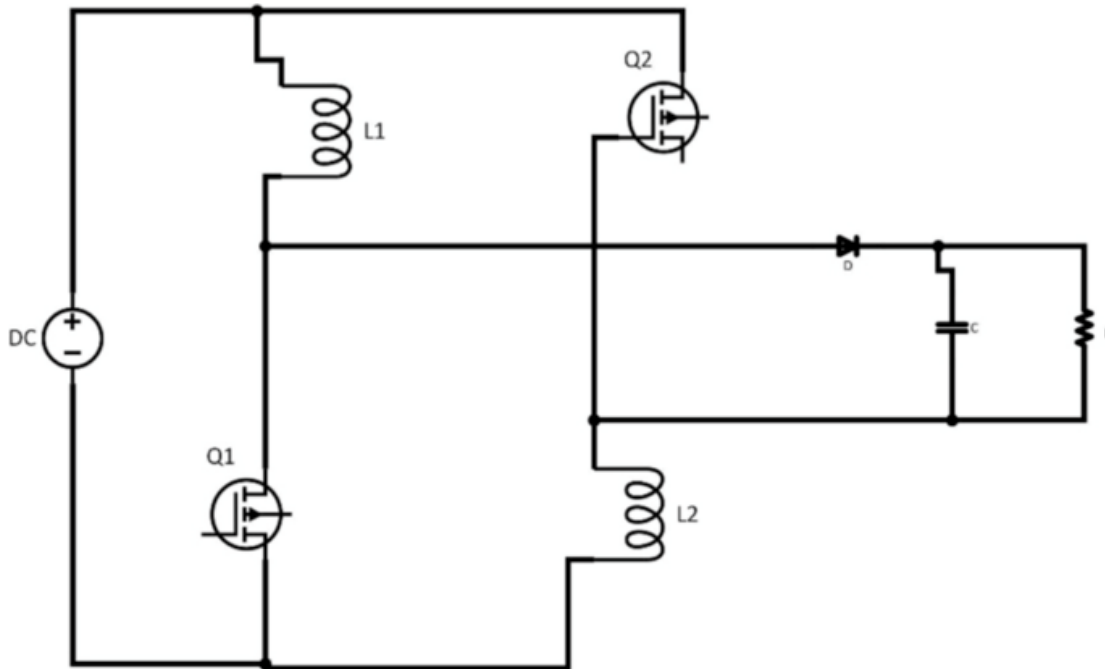
When polarized, the diodes divert the current from that substring, reducing the impact of shadowing on power generation in a PV system. While shading a cell, the cell's electrical current decreases, and since that current is incompatible with the electrical current of the substring, the current must be reverse polarized for the diode to work correctly (acting as a charge). For a cell to operate near its voltage, a substring's total voltage must be greater than zero. Many factors contribute to the overall current-voltage curve, including individual substring curves, as well as the series-shunt configuration of individual strings.

During partial shading situations, the converter's global peak power point tracking process, also known as GPPPT, seeks to calculate the optimum global power production value from between the many I-V curves of the unit that emerge from the various partial shading conditions. Once the DC-DC converter is optimized, it can supply the highest power output independent of the PV panels' partial shading. While PV systems can be partially shaded, the

DC-DC converter and GPPP must operate with agility and precision, regardless of irradiance, to provide maximum power generation at all times and under all irradiance conditions [30,31,32,33].

**High Step-Up DC-DC Converter**

To achieve the needed DC bus voltage for the system, a high-step-up DC-DC converter with an active switching LC-network is employed in this study, which makes use of the front-end stage of a photovoltaic (PV) system to provide the requisite DC bus voltage for the system. In this transformer-less DC-DC converter, just a single capacitor and a single diode are needed, but the voltage gain is greatly enhanced by combining the ASL (active switched inductor) and ASC (active switched capacitor) networks, which are connected in a compound configuration. By using a switched capacitor instead of a capacitor, this converter avoids the high instantaneous currents created by the capacitor, which is a disadvantage of traditional voltage-boosting devices that employ a capacitor. Figure 4 depicts the topology of the active switching LC network in the high-step-up DC-DC converter with active switching.



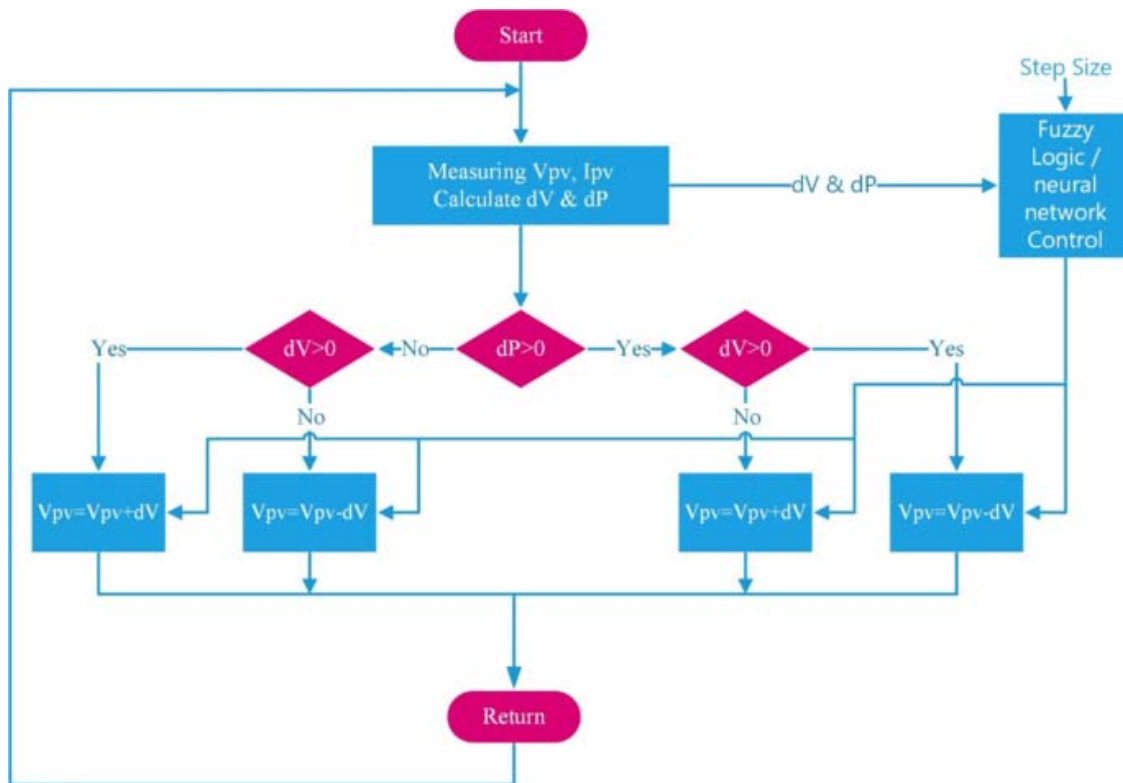
**Fig. 4.** DC-DC converter with a high step-up ratio and an active switching LC-network

The ASLC converter topology combines an ASC system network with an original ASL system network. There is a common switch S1 between the original ASL and ASC networks, which includes inductors L1 and L2 as well as switches Q1 and Q2. Because only a single diode and a single capacitor are added, the basic structure is maintained.

**Proposed Hybrid Fuzzy Logical/Neural Network-Based Variable Step Size P&O MPPT Algorithm**

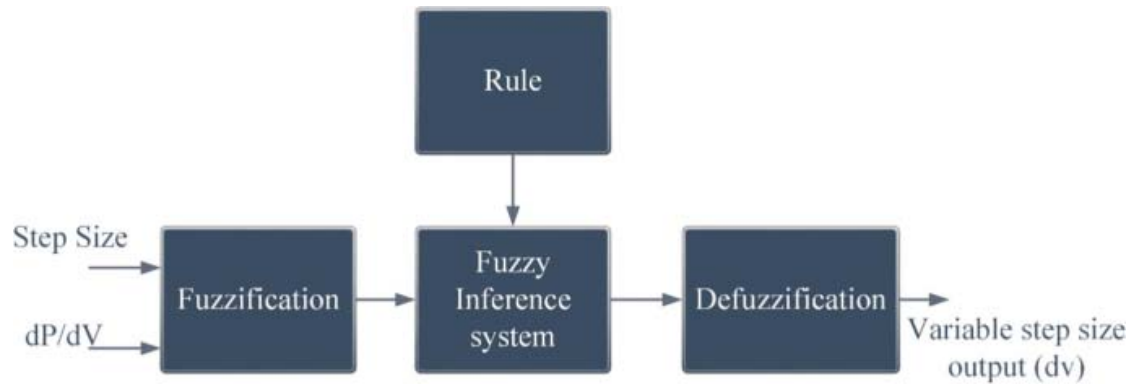


Traditional perturb and observe methods often use constant step-size perturbations, resulting in a struggle between reducing PV array power output oscillations about the peak power point and achieving a convergent increasing time towards the peak power point (MPP). A large step-size allows a quick dynamic reaction to abrupt changes in irradiance but results in significant steady-state fluctuation of the PV array's power output near the peak power point and power loss. Smaller step sizes help to reduce the fluctuation of the PV array's power output about the peak power point; however, this results in a slower response to abrupt changes in solar irradiance because of their slower dynamic response. Minimum steady-state oscillations and quick dynamic responsiveness necessitate a variable step-size MPPT. In order to address the restrictions of the typical fixed step-size P&O MPPT algorithm, the hybrid fuzzy logic/neural network approach has been used here to control the step size. Figure 5 depicts a hybrid fuzzy logic/neural network-based variable step-size P&O MPPT algorithm.



**Fig. 5.** Flowchart for hybrid fuzzy logic/neural network variable step size MPPT

The PV array's terminal current and voltage are  $I_{pv}$  and  $V_{pv}$ , respectively. The proposed method works by providing a variable step-size reference voltage  $V_{pv}$  to the associated power converter. Based on Mamdani's fuzzy logic rules, the variable step-size control action was determined using a framework of Max-Min operations. There are four main components to the fuzzy logic controller, as depicted in Fig. 6. The controller, which consists of 25 rules, was built using "if/then" logic. As stated in Table 1, the fuzzy rule labels are as follows: "positive medium (PM)," "positive very small (PVS)," "positive small (PS)," "positive very high (PVH)," and "positive high (PH)."

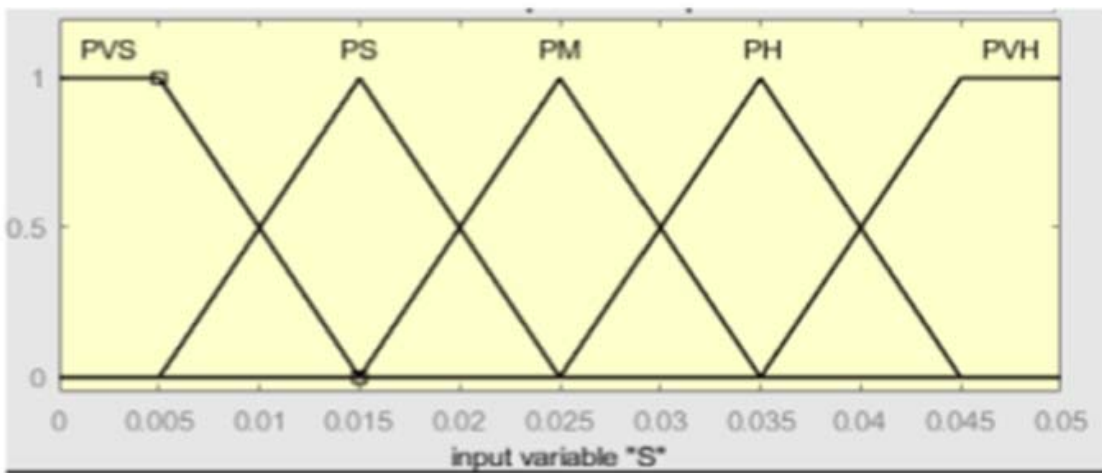
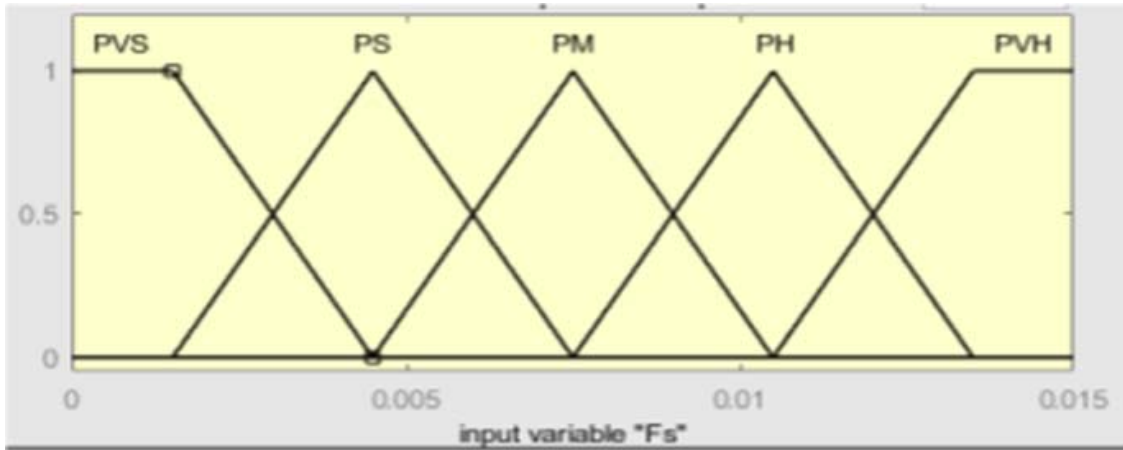


**Fig. 6.** FLC-based variable step size control

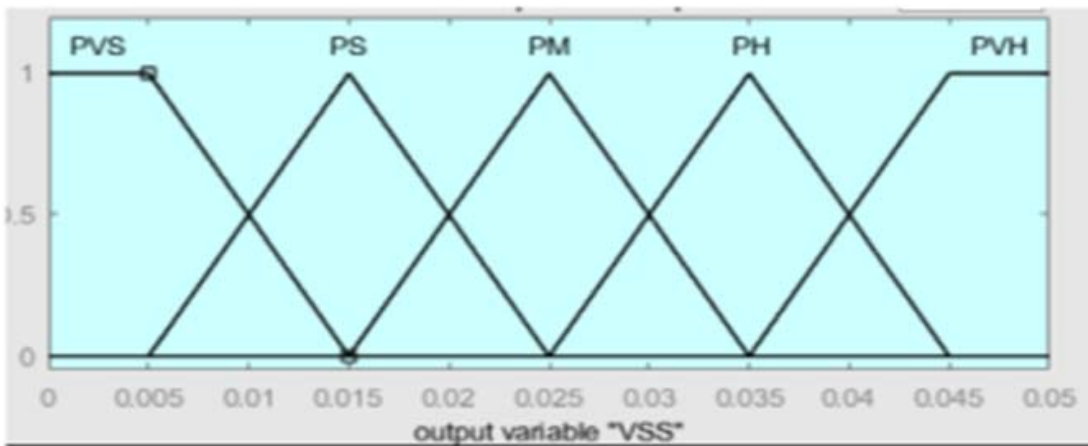
**Table 1.** Fuzzy step size control rules

		Step Size				
		PVSs	PSs	MPp	HPp	PVHh
dP/dV	PVSs	PVHh	PVSs	PVSs	PSs	PSs
	PSs	PVHh	PVSs	PVSs	PSs	PSs
	MPpp	PSs	PSs	PSs	PVHh	PVHh
	HPp	PSs	PVH	PSs	PVSs	PVHh
	PVHh	PVSs	PVSs	PVHh	PHh	PVHh

The FLC has two inputs: the variable perturbation step size and the fixed perturbation step-size of the PV voltage. Using the rules laid out in Table 1, the fuzzification block assesses the P-V curve's slope and the perturbation step size, and the rules are used to make inferences. Figure 7a and b show that defuzzing the fuzzy sets generated by the inference process using membership functions results in a variable step size controller control signal. The fuzzy logic controller's output variable step size "dv" is the specified outcome of each of the 25 rules it implements.



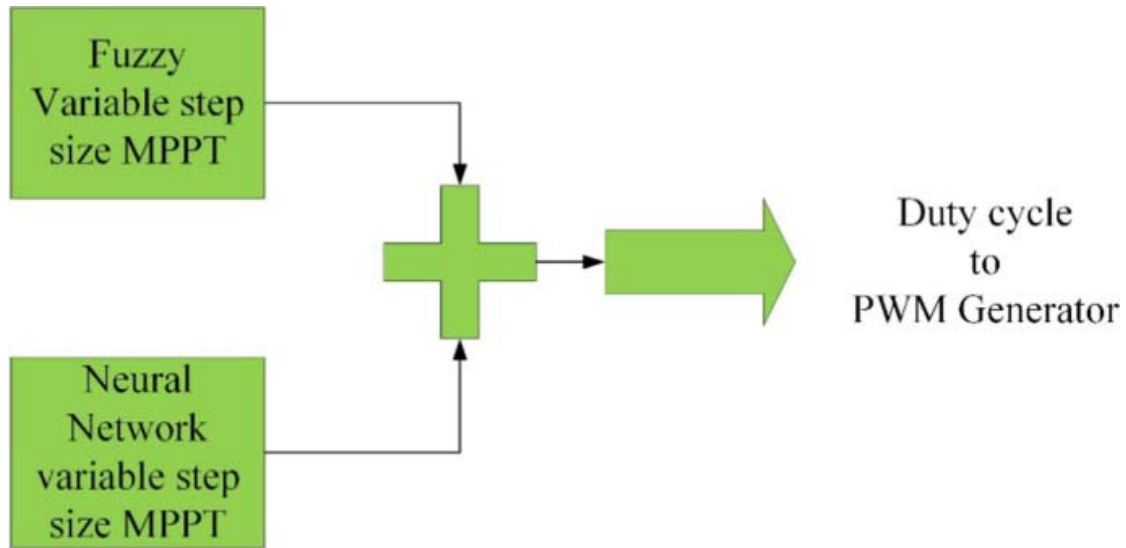
(a) The FLC's input membership function



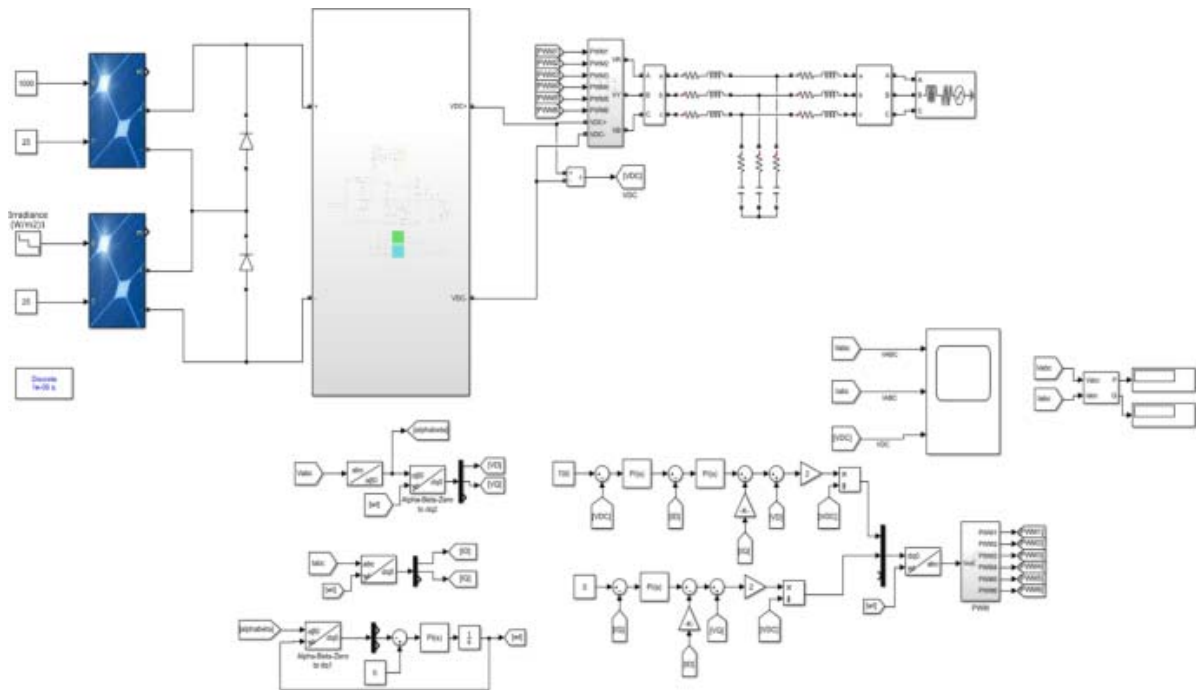
(b) The FLC's output membership function

Fig. 7. a The FLC's input membership function. b The FLC's output membership function

The data collected from the fuzzy logic-based variable step-size MPPT is used to train the artificial neural network variable step-size MPPT. Finally, the output of the FL variable step-size MPPT and neural-network variable step-size MPPT is averaged and given to the PWM generator to control the DC-DC converter, which is used to harvest the highest amount of energy possible from the PV cell array. Figure 8 depicts a hybrid fuzzy/neural network MPPT with variable step size.



**Fig. 8.** Hybrid fuzzy logic / neural network variable step size MPPT



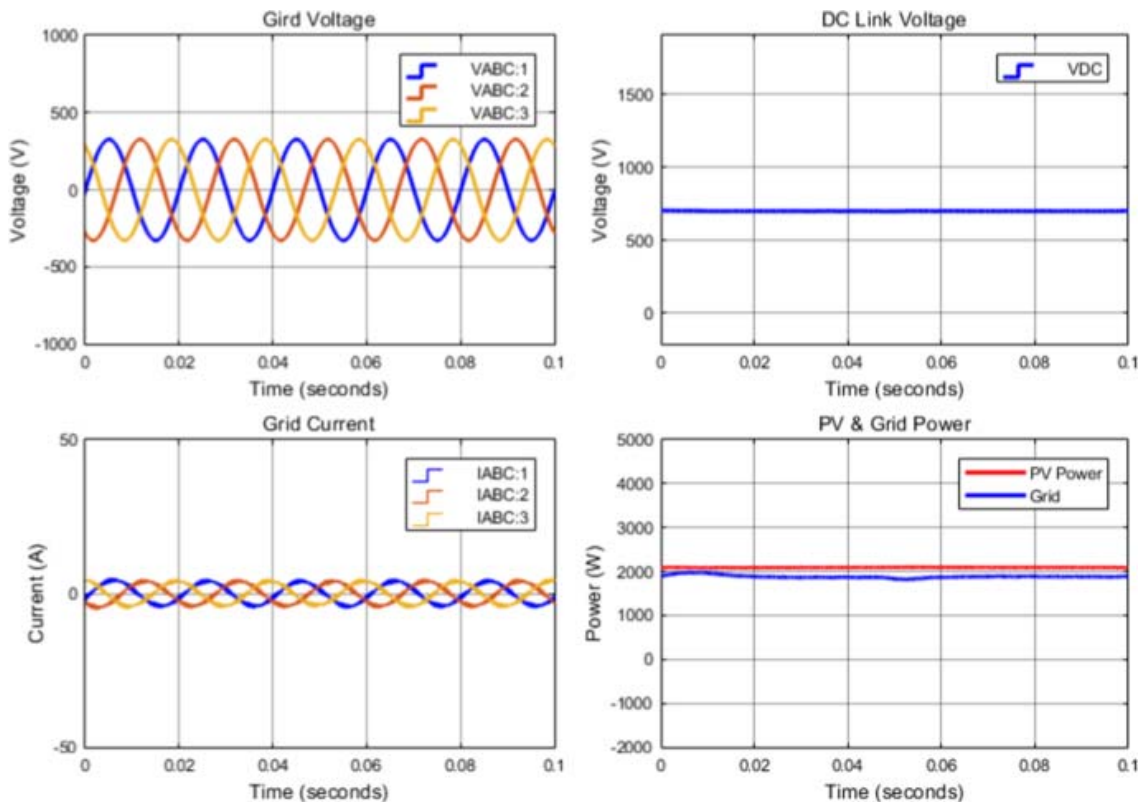
**Fig. 9.** Simulink model of the solar PV three-phase grid system

## Results and Discussion

A Simulink diagram of a PV system coupled to the three-phase network is depicted in Fig. 9. A DC-DC converter as well as a three-phase full-bridge inverter are used to link the solar panels to the grid for power generation. The control algorithm consists of one MPPT and one phase-locked loop (PLL) and all of the controllers, including the inverter DC bus controller, boost converter, and an MPPT controller.

The output terminal current of the grid-connected inverter and the DC link voltage are both managed by the grid. The duty cycle generated as a result of the hybrid (fuzzy logic and neural network) MPPT algorithm is followed by the controller of the high-gain boost converter.

DC energy is converted to AC energy by an inverter that also manages the synchronization of the current output with the grid voltage and DC-link voltage. The controller has a voltage-regulating outer loop and a current-controlling inner loop. To maintain a constant DC-link voltage and keep the output current synchronized with the grid voltage, the inverter performs a crucial job. The power rating of the two series-connected PV panels is 2100 W at 258 V, and the grid rating is 400 V at 50 Hz.



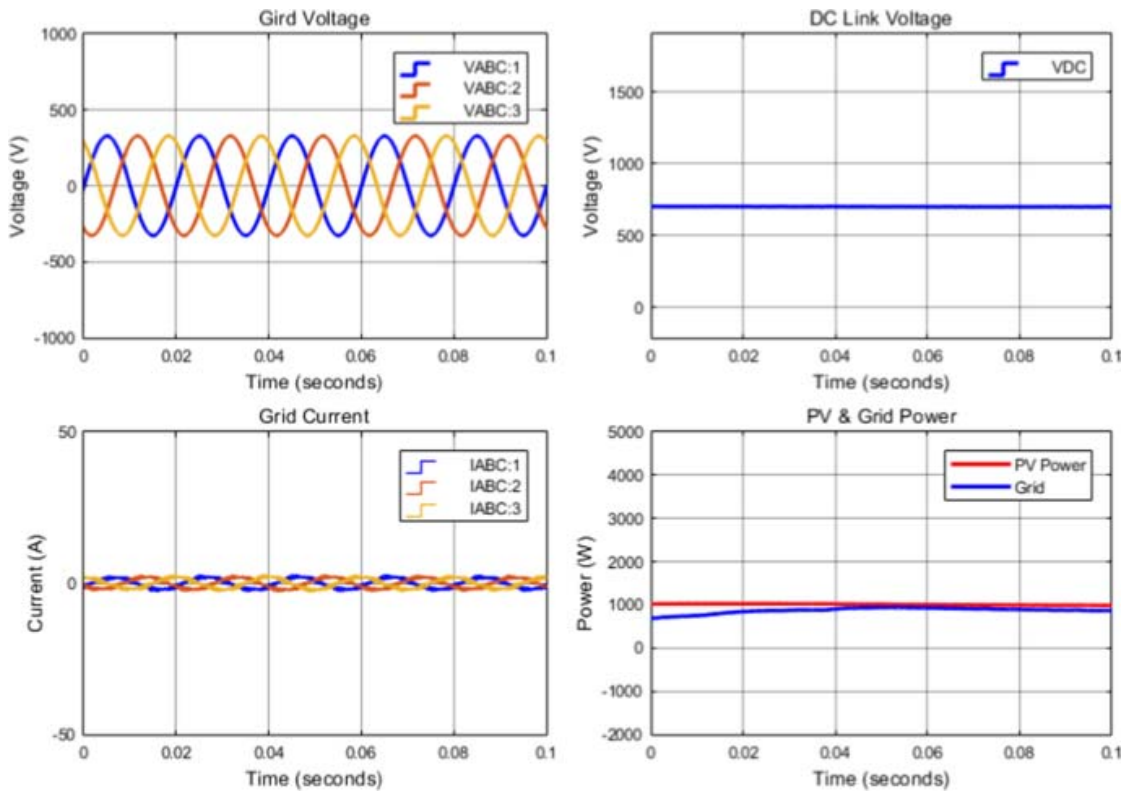
**Fig. 10.** Simulation results at  $1000 \text{ W/m}^2$

(i) Under uniform irradiance

The PV panel is connected in series, and the irradiance is fixed at  $1000 \text{ W/m}^2$ . The corresponding PV power, grid voltage, grid current, DC link voltage, and grid power are shown

in Fig. 10. The simulated results show that the PV power is around 2080 W and the grid power is around 1990 W. The voltage across the DC connection is also kept at 700 volts, while the grid voltage and current are 400 volts and 4.975 a, respectively. The efficiency was calculated for the present operating condition and found to be 95.67%.

Similarly, in the second condition, the irradiance is fixed at 500 W/m<sup>2</sup> and results such as PV power, grid voltage, grid current, DC-link voltage, and electrical grid power are simulated. The simulated outputs are demonstrated in Fig. 11. The results report that the PV and grid powers are 1010 W and 990 W. The DC-link voltage is 700 V along with the electrical grid voltage and the current is 400 V and 2.52 A. Therefore, the efficiency of the system at 500 W/m<sup>2</sup> is 98.02%.



**Fig. 11.** Simulation results at 500 W/m<sup>2</sup>

(ii) Under partial shaded conditions

The first PV panel's irradiance is fixed at 1000 W/m<sup>2</sup> whereas the irradiance on the second PV panel is varied from 1000, 800, 600, and 400 W/m<sup>2</sup> every 0.2 s to create a partial shading effect. The corresponding results, such as PV power, grid voltage, grid current, DC link voltage, and grid power, are shown in Fig. 12. When the second PV panel's irradiance is 800 W/m<sup>2</sup>, the PV power is around 1700 W, the grid power is around 1600 W, the voltage of the DC connection is maintained at 700 V, the grid voltage is 400 V, and the grid current is 4 A. At this point, the efficiency is 94.11%. When the second PV panel's irradiance is 600 W/m<sup>2</sup>, the PV power is around 1400 W, the grid power is around 1300 W, the DC link voltage is maintained at 700 V, the grid voltage is 400 V, and the grid current is 3.125 A. The efficiency in this

condition is 92.85%. When the second PV panel's irradiance is 400 W/m<sup>2</sup>, the PV power is around 850 W, the grid power is around 780 W, the DC link voltage is maintained at 700 V, the grid voltage is 400 V, and the grid current is 1.95 A. The efficiency in this condition is 91.76%. The maximum power from the PV panel is effectively extracted to the maximum point employing hybrid fuzzy logic/neural network-based variable step size MPPT. Tables 2 and 3 demonstrate the output parameters and efficiency of the proposed MPPT under different operating conditions and with other MPPTs.

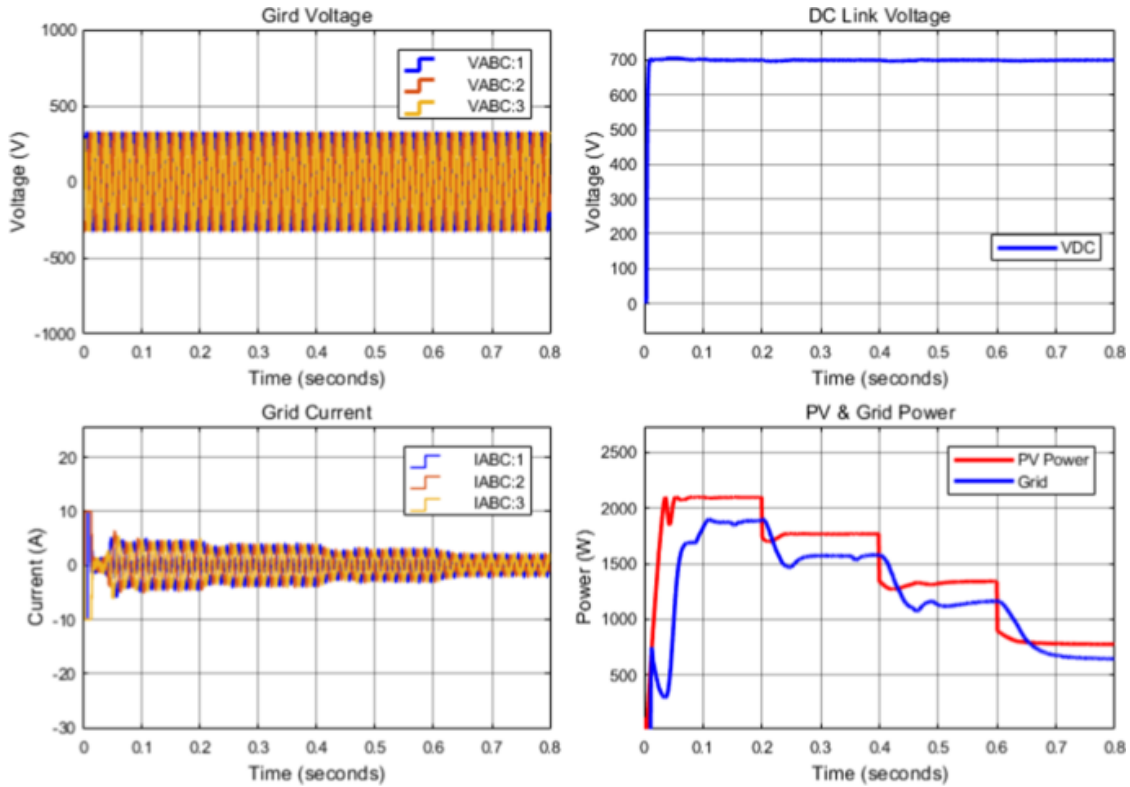


Fig. 12. Simulation results under partial shading effect

Table 2 The outcome of the proposed MPPT under different operating parameters

Operating Conditions	Parameters			Efficiency ( $\eta$ ) (%)
	PV Power (W)	Grid Power (W)	Grid current (A)	
Irradiance of Panel 1 and Panel 2: 1000 W/m <sup>2</sup>	2080	1990	4.975	95.67
The irradiance of Panel 1 and Panel 2: 500 W/m <sup>2</sup>	1010	990	2.4750	98.02
Irradiance of Panel-1: 1000 W/m <sup>2</sup> and Panel 2: 800 W/m <sup>2</sup>	1700	1600	4	94.11
Irradiance of Panel-1: 1000 W/m <sup>2m</sup> and Panel 2: 600 W/m <sup>2m</sup>	1400	1300	3.25	92.85
Irradiance of Panel-1: 1000 W/m <sup>2m</sup> and Panel 2: 400 W/m <sup>2m</sup>	850	780	1.95	91.76

**Table 3 Comparisons of proposed hybrid MPPT with other MPPTs**

References	MPPT Technique	Parameters			Efficiency ( $\eta$ ) (%)
		PV Power (W)	Grid Power (W)	Grid current (A)	
[15]	Fuzzy	2076	1978.4	4.94	95.3
[18]	Neural Network	2075	1975.4	4.93	95.2
[34]	Fuzzy	2070	1958.2	4.89	94.6
[35]	Fuzzy	2072	1966.3	4.91	94.9
[36]	Fuzzy	2071	1963.3	4.90	94.8
[37]	Fuzzy, Neural with evolutionary algorithms	2073	1971.4	4.92	95.1
[38]	Neural Network Estimator	2074	1968.2	4.92	94.9
[39]	fuzzy	2073	1965.2	4.91	94.8
[40]	SASV-MPPT approach and Lyapunov design method	2077	1981.4	4.98	95.39
Our Paper	Hybrid Fuzzy Neural Network	2080	1990	4.975	95.67

### Experimental Verification

The experimental hardware step up for the hybrid Fuzzy logic/neural network-based variable step size MPPT for grid-connected solar PV systems is shown in Fig. 13. The experimental setup consists of eight panels with a rating of 250 W installed on the rooftop, a high-step-up boost-converter, a DC-AC inverter, a single-phase AC grid, and a PIC microcontroller for implementing MPPT and grid inverter control.



**Fig. 13.** Hardware setup of the proposed work

The hardware model is tested under conditions of uniform irradiance and partial shading. Figure 14 shows the PV voltage and current for constant irradiance. PV voltage is 255 V, PV



current is 7.58 A, and PV power is 1932.9 W. Figure 15 shows the DC link voltage, grid phase “A” voltage, and current for the same conditions. The DC link voltage is kept at 698 volts, the phase “A” voltage is kept at 228 volts, the phase “A” current is kept at 2.56 a, and the inverter power is kept at 1766.4 watts. The efficiency of the system is 91.38%.

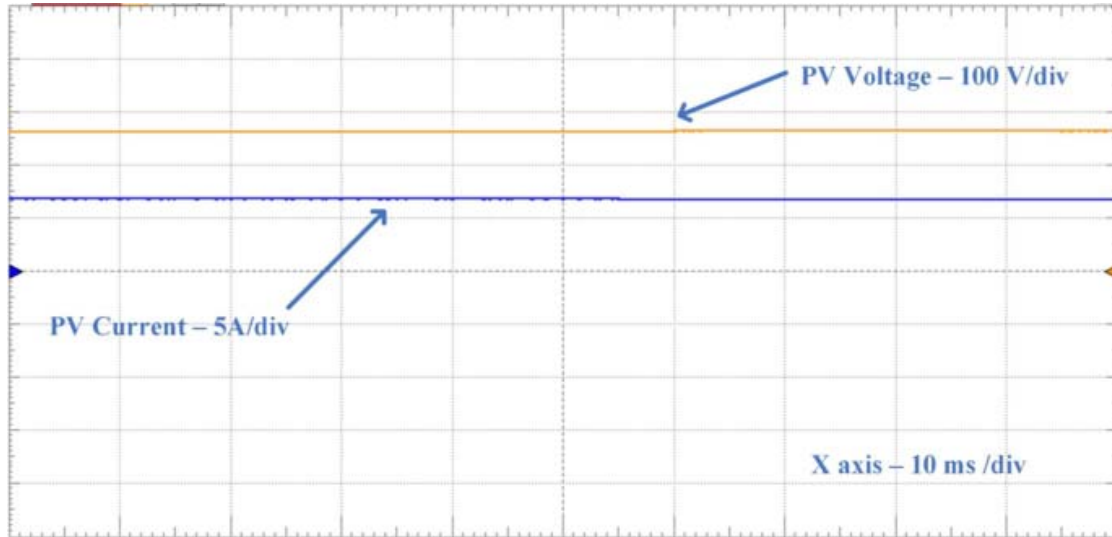


Fig. 14. PV voltage and current for constant irradiance

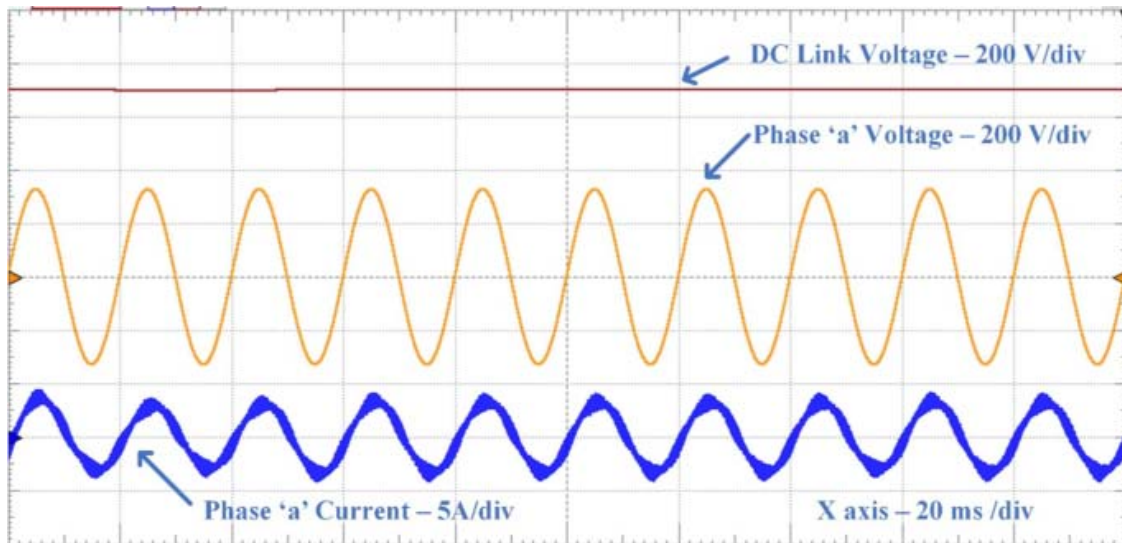


Fig. 15. DC link voltage, grid phase ‘a’ voltage and current for constant irradiance

By covering the four panels with metal sheets, partial shading conditions are created, and corresponding results are measured during the conditions. Figure 16 shows the PV voltage and current for partially shaded conditions. PV voltage, current, and power after partial shading are 210, 3.89 A, and 816.9 W, respectively. Figure 17 shows the DC link voltage, grid phase “A” voltage, and current for the same conditions. The DC link voltage, phase “A” voltage, current, and power from the inverter after partial shading are 697 V, 230 V, 1.1 A, and 759 W. The efficiency of the system is 92.91%.

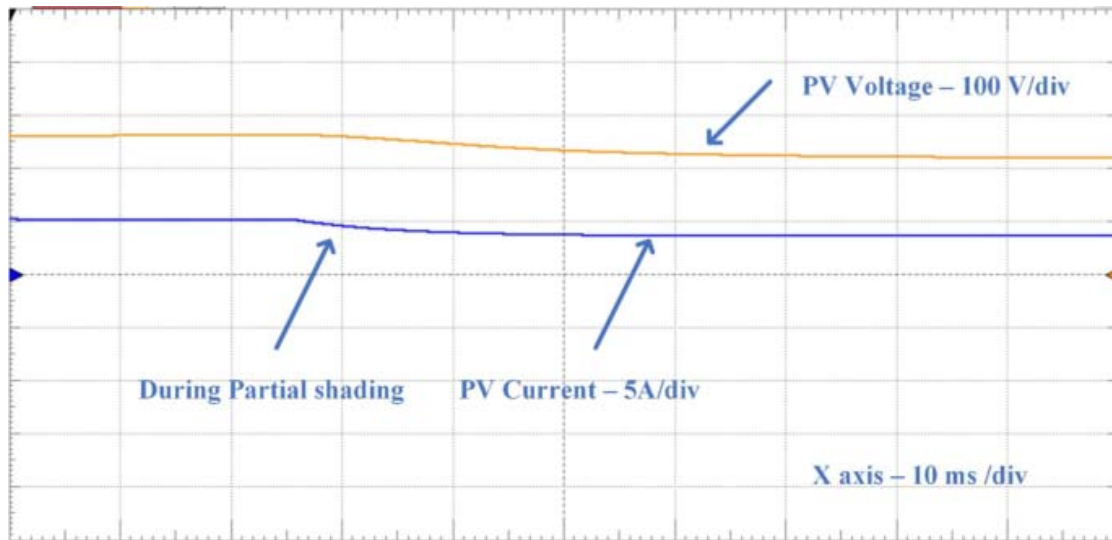


Fig. 16. PV voltage and current for partial shaded conditions

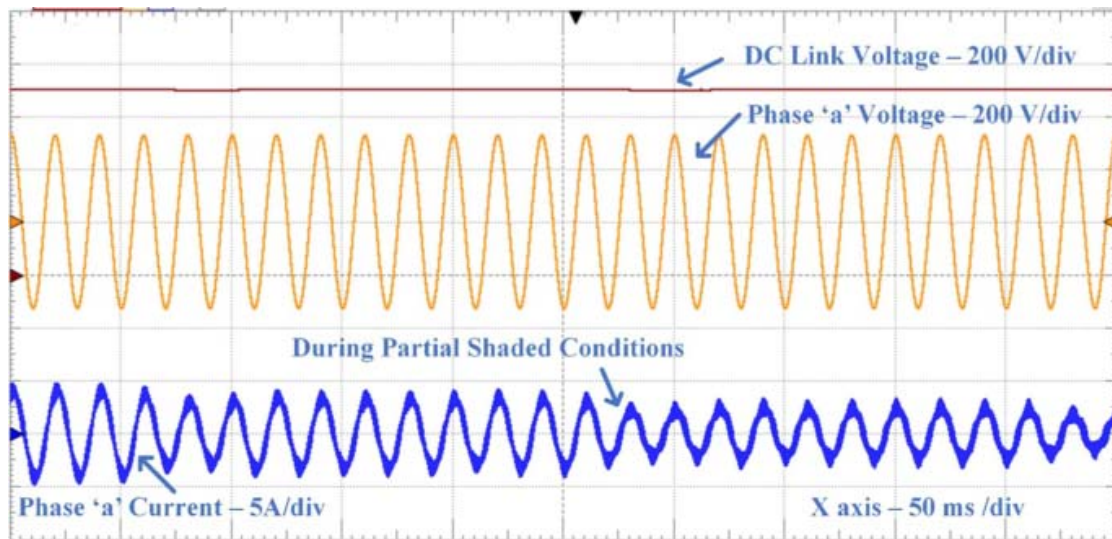


Fig. 17. DC link voltage, grid phase 'a' voltage and current for partial shaded conditions

### Conclusion

The hybrid Fuzzy logic/neural network-based variable step size approach is used to construct a global MPPT algorithm to optimize the max possible extraction of electrical energy available in PV installations connected to an electrical grid. A comparable circuit that operates similarly to a PV panel was used to better understand its operation. The panel's behavior was observed, and the current-voltage (I-V) and power-voltage (P-V) curves were plotted for various solar-radiation values. Partial shading seems to cause a significant shift in the characteristic curves. The full conversion system is explained and studied, from the solar panel through the grid connection. So, an MPPT controller based on a hybrid FLC/ANN-based variable step size was created to help the PV system approach GPPP. To make the proposed method as close to real-world operating conditions as possible. Several scenarios of the system were tested to better understand the hybrid Fuzzy logic/neural network-based

variable step size approach. The proposed MPPT is able to extract maximum power with a maximum power ratio of 95 to 99%. The overall efficiency of the system is around 91.76 to 95.67 for uniform and partially shaded conditions. but these factors are not favorable for the existing algorithm. The proposed algorithms are also capable of achieving convergence to the global point even when partial shading is applied to the PV array, with the shortest time and the least power variation in the steady-state. The optimization of fuzzy and neural networks can be adopted using the latest algorithm to improve the maximum power ratio and efficiency of the system, and it is considered a future scope for this work.

### **Data Availability**

The data that support the findings of this study are available from the corresponding author upon reasonable request.

### **Conflicts of Interest/Competing Interests**

There are no known conflicts of interest associated with this publication.

### **References**

1. Abo-Khalil AG, Berrouche Y, Barhoumi EM, Baseer AM, Praveen RP, Awan AB (2016) A low-cost PMSG topology and control strategy for small-scale wind power generation systems. *Int J Eng Sci Res Technol* 5:585–592
2. Morimoto S, Nakayama H, Sanada M, Takeda Y (2005) Sensorless output maximization control for variable-speed wind generation system using IPMSG. *IEEE Trans Ind Appl* 41:60–67
3. Li H, Chen Z (2008) Overview of different wind generator systems and their comparisons. *IET Renew Power Gener* 2:123–138
4. Kim HS, Lu DD (2010) Review on wind turbine generators and power electronic converters with the grid-connection issues. In: *Proceedings of the 2010 20th Australasian Universities Power Engineering Conference*, Christchurch, New Zealand, 5–8 December
5. Abo-Khalil AG, Awan AB (2018) Comparative study of passive and active islanding detection methods for PV grid-connected systems. *Sustainability* 10(6):1798
6. Tran TTD, Smith AD (2017) Evaluation of renewable energy technologies and their potential for technical integration and cost-effective use within the US energy sector. *Renew Sustain Energy Rev* 80:1372–1388
7. Karami, Nabil K, Moubayed N, Outbib R (2017) General review and classification of different MPPT techniques. *Renew Sustain Energy Rev* 68:1–18
8. Ahmed J, Salam Z (2018) An enhanced adaptive P&O MPPT for fast and efficient tracking under varying environmental conditions. *IEEE Trans Sustain Energy* 9:1487–1496
9. Elgendy MA, Zahawi B, Atkinson D (2012) Assessment of perturb and observe MPPT algorithm implementation techniques for PV pumping applications. *IEEE Trans Sustain Energy* 3:21–33

10. Femia N, Petrone G, Spagnuolo G, Vitelli M (2005) Optimization of Perturb and observe maximum power point tracking method. *IEEE Trans Power Electron* 20:963–973
11. Safari A, Mekhilef S (2011) Incremental conductance MPPT method for PV systems. In: *Proceedings of the 2011 24th Canadian Conference on Electrical and Computer Engineering (CCECE)*, Niagara Falls, ON, Canada, 8–11 May; 345–347
12. Hussein KH, Muta I, Hoshino T, Osakada M (1995) Maximum photovoltaic power tracking: an algorithm for rapidly changing atmospheric conditions. *IEE Proc Gener Transm Distrib* 142:59–64
13. Abo-Khalil AG, Lee DC, Choi JW, Kim H-G (2006) Maximum power point tracking controller connecting PV system to Grid. *J Power Electron* 6:226–234
14. Byunggyu YU, Abo-Khalil AG, Matsui M, Yu G. Sensorless fuzzy logic controller for maximum power point tracking of grid-connected PV system. In *Proceedings of the 12th International Conference on Electrical Machines and Systems ICEMS*, Tokyo, Japan, 15–18 November 2009
15. Kottas TL, Boutalis YS, Karlis AD (2006) New maximum power point tracker for PV arrays using fuzzy controller in close cooperation with fuzzy cognitive networks. *IEEE Trans Energy Convers* 21:793–803
16. Al-Amoudi A, Zhang LL (2000) Application of radial basis function networks for solar-array modeling and maximum power-point prediction. *IEE Proc Gener Transm Distrib* 147:310–316
17. Syafaruddin E, Hiyama T (2009) Artificial neural network-polar coordinated fuzzy controller based maximum power point tracking control under partially shaded conditions. *IET Renew Power Gener* 3:239–253
18. Veerachary M, Senjyu T, Uezato K (2003) Neural-network-based maximum-power-point tracking of coupled-inductor interleaved-boost converter-supplied PV system using fuzzy controller. *IEEE Trans Ind Electron* 50:749–758
19. Hohm DP, Ropp ME (2003) Comparative study of maximum power point tracking algorithms. *Prog Photovolt Res Appl* 11:47–62
20. Eltamaly AM, Al-Saud MS, Abo-Khalil AG, Farah H (2020) Simulation and experimental validation of fast adaptive particle swarm optimization strategy for photovoltaic global peak tracker under dynamic partial shading. *Renew Sustain Energy Rev* 124:109719
21. Eltamaly AM, Al-Saud MS, Abo-Khalil AG (2020) Performance improvement of PV systems' maximum power point tracker based on a scanning PSO particle strategy. *Sustainability* 12:1185
22. Eltamaly AM, Al-Saud MS, Abokhalil AG, Farh HM (2019) Photovoltaic maximum power point tracking under dynamic partial shading changes by novel adaptive particle swarm optimization strategy. *Trans Inst Meas Control* 42:104–115
23. Eltamaly AM, Al-Saud MS, Abokhalil AG (2020) A novel scanning bat algorithm strategy for maximum power point tracker of partially shaded photovoltaic energy systems. *Ain Shams Eng J* 11:1093–1103
24. Eltamaly AM, Al-Saud MS, Abo-Khalil AG (2020) A novel bat algorithm strategy for maximum power point tracker of photovoltaic energy systems under dynamic partial shading. *IEEE Access* 8:10048–10060
25. Sundareswaran K, Vigneshkumar V, Sankar P, Simon SP, Nayak PSR, Palani S (2016) Development of an improved P&O algorithm assisted through a colony of foraging ants for MPPT in PV system. *IEEE Trans Ind Inform* 12:187–200

26. Abo-Khalil AG (2020) Maximum power point tracking for a PV system using tuned support vector regression by particle swarm optimization. *J Eng Res* 8:139–152
27. Jusoh A, Alik R, Guan T, Sutikno T (2017) MPPT for PV system based on variable step size perturb and observe Algorithm. *TELKOMNIKA (Telecommunication Computing Electronics and Control)* 15:79. <https://doi.org/10.12928/telkomnika.v15i1.3160>
28. Yu B, Abo-Khalil AG, So J, Yu G (2009) Support vector regression based maximum power point tracking for PV grid-connected system. In: *Proceedings of the 2009 34th IEEE Photovoltaic Specialists Conference (PVSC)*, Philadelphia, PA, USA, 7–12 June; 002037–002042
29. Eltamaly AM, Farh HMH (2019) Dynamic global maximum power point tracking of the PV systems under variant partial shading using hybrid GWO-FLC. *Sol Energy* 177:306–316
30. Nasiruddin I, Khatoon S, Jalil MF, Bansal RC (2019) Shade diffusion of partial shaded PV array by using odd-even structure. *Sol Energy* 181:519–529
31. Jalil MF, Khatoon S, Nasiruddin I, Bansal RC (2021) An overview of PV array modelling, configuration and MPPT techniques. *Int J Model Simul* 42(4):533–550
32. Jalil MF, Nasiruddin I, Khatoon S, Bansal RC (2020) An improved photovoltaic array configurations and reconfiguration under partial shading conditions”. *Electr Power Compon Syst* 48:9–10
33. Bansal RC, Zobaa AF (eds) (2022) *Handbook of renewable energy technology*. World Scientific Publishers, Singapore
34. Narwat LK, Dhillon J (2021) Design and operation of fuzzy logic based MPPT controller under uncertain condition. *J Phys: Conf Ser* 1854(1):012035. IOP Publishing
35. Mahamudul H, Saad M, Henk MI (2013) Photovoltaic system modeling with fuzzy logic based maximum power point tracking algorithm. *Int J Photoenergy* 2013:10. <https://doi.org/10.1155/2013/762946>
36. Loukil K, Abbes H, Abid H, Abid M, Toumi A (2020) Design and implementation of reconfigurable MPPT fuzzy controller for photovoltaic systems. *Ain Shams Eng J* 11:319–328
37. Fathi M, Parian JA (2021) Intelligent MPPT for photovoltaic panels using a novel fuzzy logic and artificial neural networks based on evolutionary algorithms. *Energy Rep* 7:1338–1348
38. Saidi AS, Salah CB, Errachdi A, Azeem MF, Bhutto JK, Ijyas VPT (2021) A novel approach in stand-alone photovoltaic system using MPPT controllers & NNE. *Ain Shams Eng J* 12(2):1973–1984
39. Farajdadian S, Hosseini SMH (2019) Optimization of fuzzy-based MPPT controller via metaheuristic techniques for stand-alone PV systems. *Int J Hydrogen Energy* 44(47):25457–25472
40. M’Sirdi NK, Nehme B (2015) The VSAS approach gives the best MPPT for solar energy sources. *J Renew Energy Sustain Dev* 1. <https://doi.org/10.21622/resd.2015.01.1.060>