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Research article

A new neuro-fuzzy controller based maximum power point tracking for a partially shaded grid-connected photovoltaic system

Saeed Danyali [a,*], Mohammad Babaeifard [a], Mohammadamin Shirkhani [a], Amirreza Azizi [b], Jafar Tavoosi [a], Zohreh Dadvand [a]

[a] Department of Electrical Engineering, Ilam University, Ilam, Iran
[b] Department of Electrical Enigeering, Shahed University, Tehran, Iran

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ABSTRACT

Today, renewable energy systems like photovoltaic system are widely used in various applications. Among the different types of microgrids, hybrid microgrids are the most used type, therefore, inverters should be used to exchange power between DC and AC sides. According to the existing economic issues, extracting the maximum possible power from these systems are an important issue. This paper presents a new neuro-fuzzy controller for achieving maximum power point tracking (MPPT) in a grid-connected PV system under partially shaded conditions. This controller uses the Gravity Search Algorithm (GSA) to track the global maximum power point (GMPP) of the presented grid-connected PV system. The method controls the grid-connected inverter at the desired voltage to achieve maximum power after receiving its required specifications from the system. The Matlab/Simulink software is used to evaluate the performance of the proposed method. The results show that the proposed method can track the maximum power point under uniform and partial shading conditions with high speed and accuracy. Specifically, the proposed algorithm improves the tracking speed and increases the power output compared to traditional methods. The neuro-fuzzy controller's adaptive capabilities allow it to respond efficiently to dynamic changes in shading, ensuring stable and optimal power output. These advantages make the proposed method a significant improvement over existing MPPT techniques.

1. Introduction

The increasing use of distributed generations (DGS) and renewable energy around the world for various reasons such as economic and environmental reasons have attracted the attention of many researchers to this type of energies [1,2]. Ditribution network is transformed from a passive network to an active network by addition of DGs, therefore the management of these resources is necessary to increase reliability and power quality and also, reduce losses and costs [3,4]. The output power of Photovoltaic (PV) system, which is one of the main renewable energy systems, is depended on various factors such as temperature and sun's irradiations [5]. To extract the maximum power from photovoltaic (PV) systems, a Maximum Power Point Tracking (MPPT) controller is integrated. This controller optimizes the power output by continuously adjusting the system to operate at its peak efficiency [6,7].

* Corresponding author.
E-mail addresses: s.danyali@ilam.ac.ir (S. Danyali), mohammad.babaifard@gmail.com (M. Babaeifard), mohammadaminshirkhani77@gmail.com, ma.shirkhani@ilam.ac.ir (M. Shirkhani), amirreza.azizi9615@gmail.com, amirreza.azizi@shahed.ac.ir (A. Azizi), j.tavoosi@ilam.ac.ir (J. Tavoosi), zohreh.dadvand@gmail.com (Z. Dadvand).

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Several methods have been proposed to improve the efficiency of MPPT. For instance, a fuzzy logic-based MPPT utilizing the Incremental Conductance (INC) method was introduced to improve static and dynamic responses and increase the output DC power in PV systems [8,9]. This method demonstrated improved performance but faced challenges with variable step size optimization. To address this, a control scheme combining the Golden Section Search (GSS) algorithm with both P&O and INC algorithms was proposed to enhance MPPT convergence and reduce oscillations [10,11]. This combination showed better stability but added computational complexity. In order to improve the static and dynamic responses and increase the output DC power in PV systems, compared to traditional methods, a new fuzzy logic-based MPPT was proposed in Ref. [12]. A new control scheme was introduced in Ref. [13] by combining the Golden Section Search (GSS) algorithm with both P&O and INC algorithms to enhance MPP convergence and reduce oscillations. The presented method improves MPPT convergence speed under fluctuations by receiving and analyzing input and output data from the DC-AC inverter. However, it still faces challenges such as precise optimization. In Ref. [14], an optimized fuzzy logic MPPT technique was proposed based on combining the Particle Swarm Optimization (PSO) and Genetic Algorithm (GA). Given the combination of several algorithms, this method involves complex computation. In Ref. [15], two AI-based control schemes were proposed to improve MPPT performance in variable weather conditions. This study investigates two scenarios: in the first scenario, PSO, GA, and a fuzzy logic-based controller perform the calculations, and in the second scenario, an improved genetic algorithm (IGA) performs the calculations. Two different MPPT algorithms, Quadratic Maximum (QM) and Steep Descent (SD), were evaluated in two different scenarios with a PV system consisting of four amorphous silicon panels in Ref. [16]. More recently, novel algorithms like Quadratic Maximum (QM) and Steep Descent (SD) have been evaluated for their effectiveness in various scenarios, particularly in PV systems with amorphous silicon panels [17–19]. These algorithms showed promise in specific applications but needed further refinement for broader applicability. An approach using resistive fluctuations to track global maximum power point (GMPP) under partially shaded conditions was introduced, demonstrating effectiveness in diverse PSC scenarios. However, the complexity of resistive fluctuation measurement limited its practical implementation [20,21]. In Ref. [22], a new approach for tracking the GMPP in partially shaded conditions is presented. The assessment of resistive fluctuations along with GMPP across diverse PSC scenarios is conducted using both static and dynamic loads. In Ref. [23], an MPPT technique that combines the Simple Accelerated Particle Swarm Optimization (SAPSO) algorithm and the classical Hill Climbing (HC) algorithm is presented for a PV system under partial shade conditions. Due to the combination of two algorithms, this method involves complex computation. To increase the speed and accuracy of MPPT and enhance its matching with GMPP for PV systems, an intelligent technique using power voltage (P-V) curves is presented in Ref. [24]. This method tracks the GMPP by combining the real power and the estimated power in different PV parts. To solve common challenges in other evolutionary algorithms, such as longer convergence times, a high number of search particles, and stable state oscillations, a whale optimization with differential evolution (WODE) algorithm is proposed in Ref. [25] for MPPT in partially shaded conditions. Inspired by the amberjack hunting behavior, this algorithm facilitates rapid and oscillation-free tracking of the optimal global peak in multiple stages.

In [26], to improve the performance of the MPPT in a partial shaded condition and address the challenges of GMPP, a fuzzy sliding mode control (FSMC) scheme with fuzzy proportional integral (FPI) control is proposed. This study technique accurately tracks the reference voltage and maximum power in partially shaded conditions and also, ensuring the system stability. The proper functioning of the sensors has a great impact on the efficiency of this method. In Ref. [27], by using an adaptive fuzzy logic controller (AFLC), the accuracy and tracking speed of MPPT are improved under both partial and overall shading conditions. The proposed method utilizes the Grey Wolf Optimization (GWO) algorithm in four shading scenarios to determine the duty ratio and evaluate the performance of AFLC. The adaptability to dynamic changes during sudden environmental variations is considered as a weakness in AFLC. To solve the non-linear challenges in MPPT adjustment, an algorithm based on artificial neural network (ANN) with a variable step size is presented in Ref. [28]. This technique has a complex computation and require a large number of input data. In Ref. [29], probability estimation algorithm for tracking GMPP is presented, which enhances the tracking speed for GMPP by sampling data obtained in partial shading conditions using an intelligent probability estimation algorithm process. Finally, by utilizing the P&O algorithm, it improves the accuracy of the results, although this algorithm has a complex computation. Various types of fuzzy logic controller are used recently to achieve a high efficiency MPPT algorithm in PSCs. An asymmetrical interval type-2 fuzzy logic control (IT-2 AFLC) algorithm based GMPPT is presented in Ref. [30] under PSCs.

In this paper, a new neuro-fuzzy based MPPT agorithm is presented which track the global maximum power point in PV system in the partially shaded conditions. By using parallel bidirectional DC-AC inverter in the simulated systems, voltage control is performed at different voltage levels. Then, a neuro-fuzzy control is implemented on a grid-connected DC-AC inverter, which can achieve power control for various generaton and consumption values. This caontrol method can track the global maximum power point of the PV system under partially shaded conditions with Gravity Search Algorithm (GSA) and deliver the maximum received power from PV system to the AC grid.

The rest of the paper are organized as follows: overview structure of the grid-connected PV system and MPPTs methods are introdued in section 2 and 3, respectively. Section 4 presented the proposed neuro-fuzzy controller and also, the simulation results is fully presented in section 5. Finally, the conclusion is given in section 6.

2. MPPT methods

High cost and low conversion efficiency, making necessary to use MPPTs algorithm in PV systems even in partially shading conditions (PSCs) which is a phenomenon that happens when the light exposure unevenly on the PV panels. Considering that based on different environmental conditions, PV cells and modules generate different power, there are several MPPT algorithms that can track the maximum power point under different conditions. MPPT algorithms can be classified into classical, optimization and intelligent

MPPT.

Classical MPPT algorithms are include Incremental Conductance (IC), Perturband Observe (P & O), Fractional Short Circuit Current (FSCC), Constant Voltage (CV), Adaptive Reference Voltage (ARV), Ripple Correlation Control (RCC), Hill Climbing (HC), DC- link capacitor droop control based MPPT, online-MPP searchalgorithm, look uptable method and Fractional Open-Circuit Voltage (FOCV) (see Fig. 1). These algorithms have a simple structure but they don't consider the partial shadow effect. Figs. 2 and 3 shows the flowchart of two popular algorithms, the IC and P&O MPPT algorithms, respectively. The P&O MPPT algorithm operates on PV voltage or DC/DC converter's duty ratio for track the MPPT [31–33].

As shown in Fig. 3, the IC algorithm use PV voltage and current to locate PV MPPT. By comparing ∂I/∂V with I/V, the status of MPPTPV is determined as follows:

$$\frac{\partial I}{\partial V}=0 \text{ at MPPT} \tag{1}$$

$$\frac{\partial I}{\partial V}<-\frac{I}{V} \text{ at the right hand of MPP} \tag{2}$$

$$\frac{\partial I}{\partial V}>-\frac{I}{V} \text{ at the left hand of MPP} \tag{3}$$

Optimization-based MPPT algorithms, like classical MPPT algorithm are include several methods such as grey wolf optimization (GWO) and particle swarm optimization (PSO). In these methods, MPP is tracked in a dynamic condition. Fig. 4 shows the flowchart of the PSO-based MPPT method. Given that this method deals with the basis of the search method, it can easily track the MPP.

Intelligent-based MPPT algorithms which is used in this paper, usually used in dynamic wheather conditions and has high tracking efficiency and speed. fuzzy logic control (FLC) is among these methods which, no system knowledgement is required for implementation of FLC-based MPPT. Artificial neural network (ANN) and sliding mode control (SMC) can be mention for another intelligent-based MPPT algorithms. In traditional techniques, to design a controller for tracking the MPP, the PV system should be modeled in mathematical form, which is very difficult in partially shaded conditions [13,34,35]. In intelligent-based algorithms, there is no need to mathematical modeiling of the system, therefore, using these algorithms get increased recently. In FLC, in addition to doesn't require to mathematical model of the PV system, the controller settings can be adjusted by the operator.

By comparision between voltage error and reference voltage, FLCs continuosely change the dytu ratio in converters to achieve maximum voltage (V_{mpp}). In this comparision, reference voltage is the V_{mpp} and voltage error is obtained by comparision the PV instantaneous voltage with the reference voltage. Usually, the inputs of the FLC-based MPPT are E (error) and ΔE (change in error) which given in following equations:

$$E(n)=\frac{\Delta P}{\Delta V}=\frac{V_{PV}(n)*I_{PV}(n)-V_{PV}(n-1)*I_{PV}(n-1)}{V_{PV}(n)-V_{PV}(n-1)} \tag{4}$$

$$\Delta E(n)=E(n)-E(n-1) \tag{5}$$

Fig. 4 shows the control scheme of the FLC. The voltage error is given to the FLC as an input and Δδ, which is change in load angle is the output of the system. Appropriate selection of membership functions as well as rule base table of fuzzy system can improve its efficiency. Also, the use of FLC-based methods such as Adaptive Neuro-Fuzzy Inference Systems (ANFIS) can help increase the tracking speed and improve the efficiency of the system [36–38]. Fig. 5 shows the simple structure of the ANFIS for tracking the MPP.

3. System component modeling

Structure of the simulated system in this paper is shown in Fig. 6. In this system, DG unit (PV system) is connected to the AC grid via a DC-DC boost coverter and a DC-AC inverter. AC microgrids can supply the single-phase loads which created unbalanced voltage in the AC side, resulting power fluctuations in DC side and increase its Instability, but the DC-AC buck-boost converter prevent from transfer these fluctuations to DC side [39–41]. To regulate the output voltage and current of the module to achieve the PV MPP (V_{max}^{global}, P_{max}^{global}), a boost controller circuit is needed as shown in Fig. 7. In this converter, the output voltage of the PV module is always adjusted in MPP. Fig. 6 shows the paper's used inverter in the simulated system. Also, as showon in Fig. 7, by using voltage controller unit which used several inputs, PWM signal is generated in such a way that MPPT is achieved. The control form of signal generation using PI

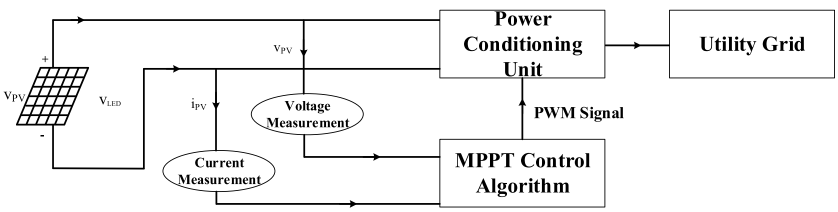

Fig. 1. Block diagram of a grid-connected solar PV system MPPT controller.

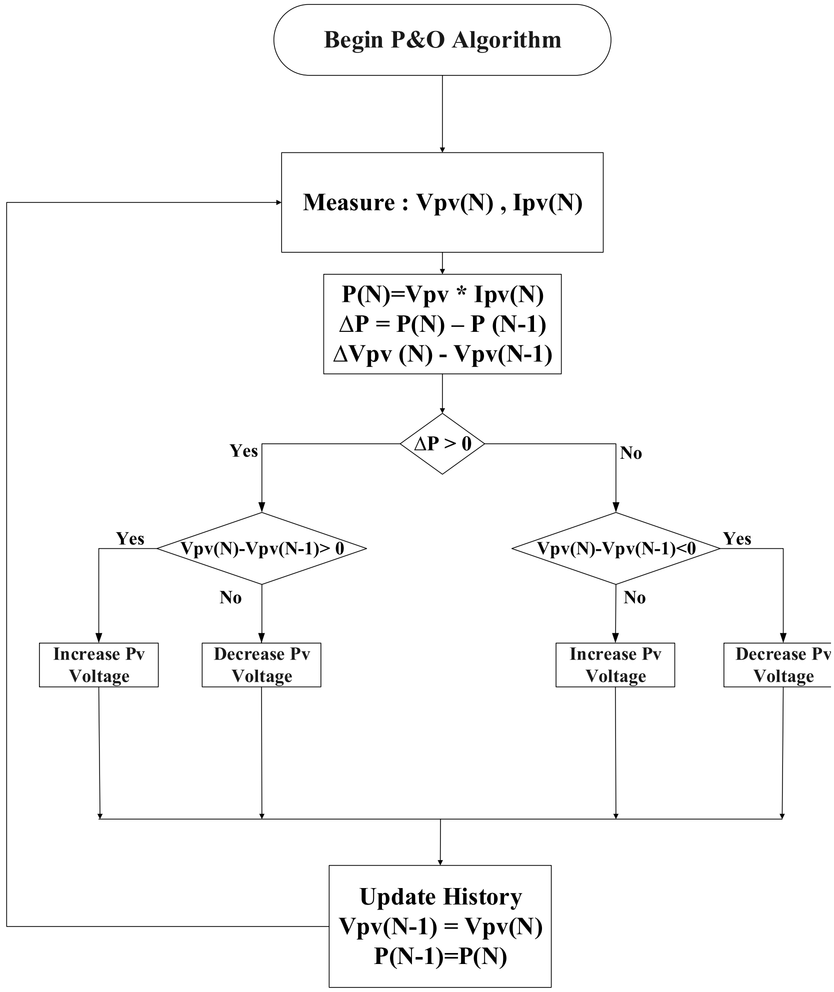

Fig. 2. P&O algorithm flowchart.

controller is shown in Fig. 8. The schematic of this method by adding the GSA MPPT algorithm used in this paper is shown in Fig. 9.

To achieve V_{max}^{global} in the output of the PV module, the PI controller which is shown in Fig. 8, is always regulated the duty ratio. This controller circuit is shown in Fig. 9.

Fig. 10 shows the PWM control signal block of the converter switches. In the proposed interface converter, the voltage and current at the connection point of the converter and grid are sampled continuously. The sampled voltage and current then enter the frame conversion device. The reference values are synchronized, and the instantaneous real and reactive powers are calculated. Subsequently, the line-to-line reference voltage and the reference current in the synchronous reference frame device are determined. Next, the reference voltage and reference current are compared with the voltage and current at the point of common coupling, and the resulting error values are fed into the voltage and current controllers. After comparing the output of the controllers with the tooth wave and generating a zero pulse, the switching circuit, based on the pulse width modulation method, switches continuously to minimize the voltage and current error values, ensuring that the voltage and current at the junction of the converter align closely with the reference values.

4. Neuro-fuzzy based MPPT controller for partially shaded condition using Gravity Search Algorithm

In PSCs, each part of PV modules has its own MPP based on its temperatures and irradiations, so for a PV module with three different shading part, Fig. 12 shows the three separate MPP. As shown in this figure, in the partially shaded condition, the PV module has three local maximum power point, which only one of them is the global maximum power point (GMPPT). So, the proposed algorithm must always track the GMPPT. In this paper, a Gravity Search Algorithm (GSA) is proposed to track the GMPP in PSCs. Fig. 11 shows the proposed algorithm flowchart.

First, in the GSA, for each part of the PV modules under a certain temperature and solar radiation, the local MPP is determind. Then by use this local MPP, the proposed algorithm determind the global point of maximum power. With this approach, the GMPP of a PV

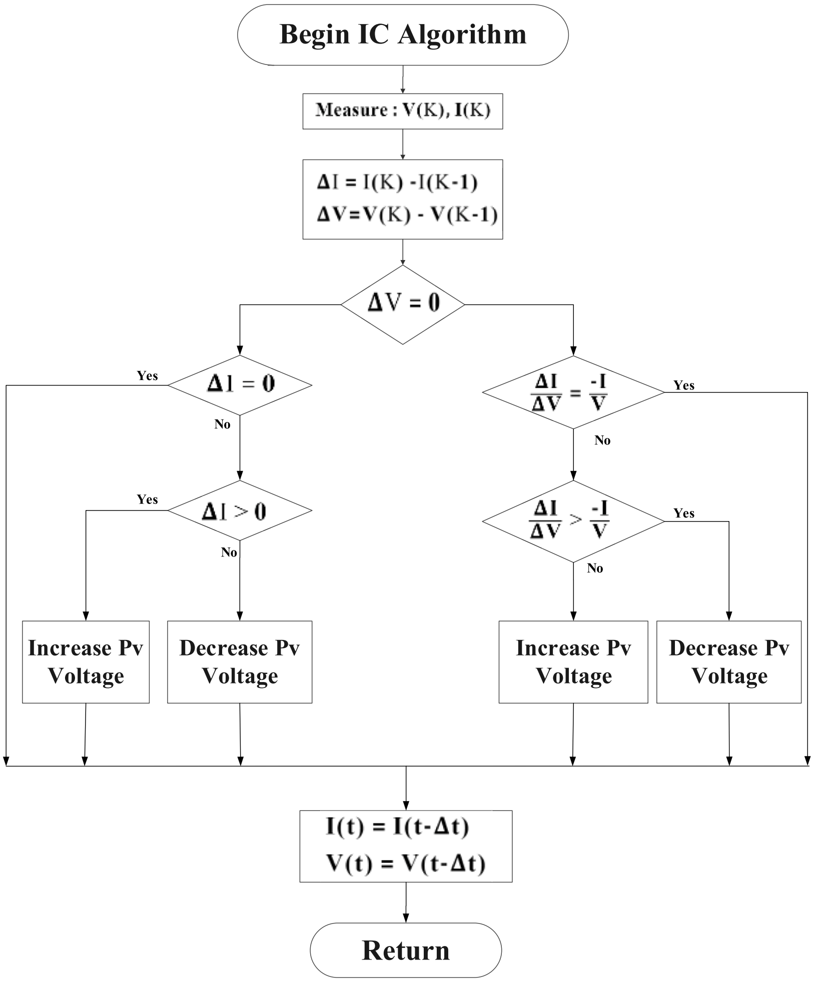

Fig. 3. IC algorithm flowchart.

module (V_{max}^{global}, P_{max}^{global}) can be determind quickly and with high accuracy.

In the presented MPPT algorithm, the objective funcion for optimization of each PV module is as follows:

$$P_{PV} = V_{PV} \times I_{PV} = \frac{T_{cell}}{q/nk} \times Ln\left(\frac{I_{ph} - I_{PV} + I_S}{I_S}\right) I_{PV} - r_S I_{PV}^2 \tag{6}$$

If the PV modules are considered in parallel ($V_{PV1} = V_{PV2} = V_{PV3} = V_{PV\ total}$), then the total PV power is obtained as follows:

$$P_{PV\ total} = P_{PV1} + P_{PV2} + P_{PV3} \tag{7}$$

$$P_{PV\ total} = V_{PV\ total} \times I_{PV1} + V_{PV\ total} \times I_{PV2} + V_{PV\ total} \times I_{PV3} \tag{8}$$

By inserting (4) in (6), the following eauation is obtained:

$$P_{PV,total} = \frac{T_{cell1}}{q/nk} \times Ln\left(\frac{I_{ph1} - I_{PV1} + I_{S1}}{I_{S1}}\right) I_{PV1} - r_{S1} I_{PV1}^2 + \frac{T_{cell2}}{q/nk} \times Ln\left(\frac{I_{ph2} - I_{PV2} + I_{S2}}{I_{S2}}\right) I_{PV2} - r_{S2} I_{PV2}^2 + \frac{T_{cell3}}{q/nk} \times Ln\left(\frac{I_{ph3} - I_{PV3} + I_{S3}}{I_{S3}}\right) I_{PV3} - r_{S3} I_{PV3}^2 \tag{9}$$

Fig. 13 shows the structure of used neural network. According to takagi-suggeno, if in this model, x and y are the inputs of the ANFIS labeled A and B, and also, and f is the output, following equations can be written:

$$if\ x \quad is \quad A_1\ and\ y \quad is \quad B_1\ then\ f_1 = p_1 x + q_1 x + r_1 \tag{10}$$

$$if\ x \quad is \quad A_2\ and\ y \quad is \quad B_2\ then\ f_2 = p_2 x + q_2 x + r_2 \tag{11}$$

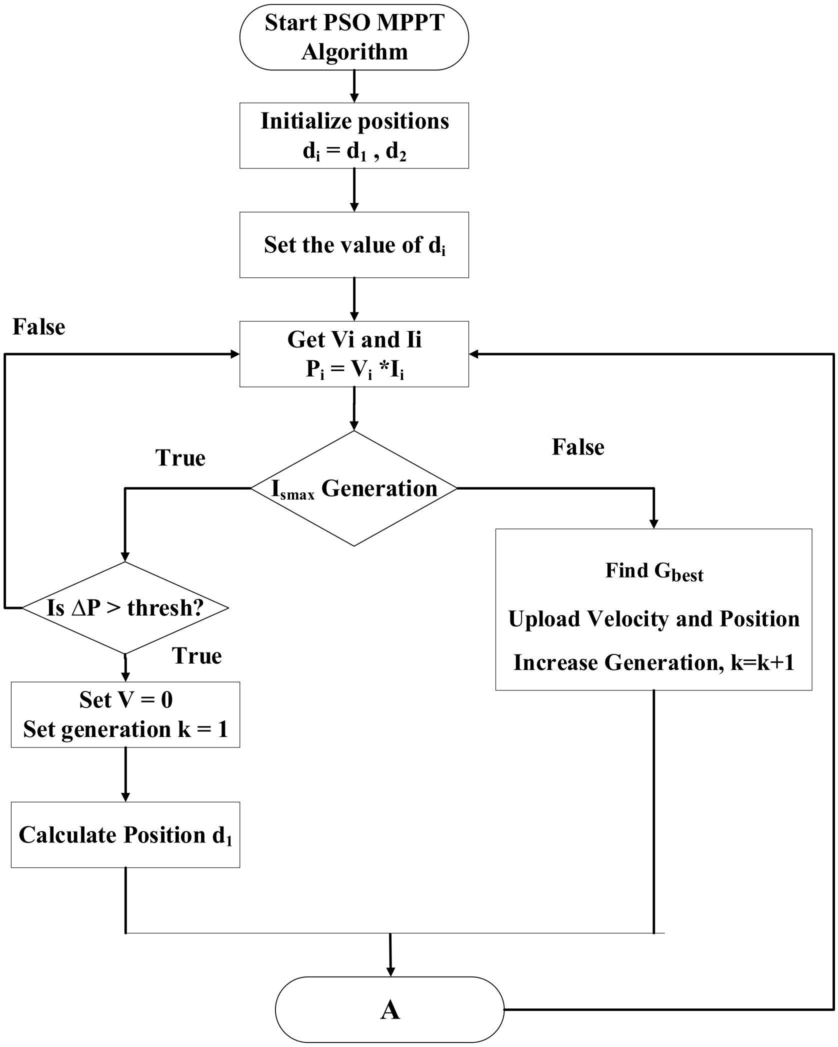

Fig. 4. PSO-based MPPT algorithm flowchart.

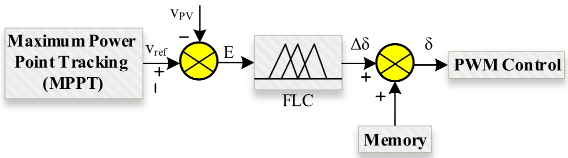

Fig. 5. FLC-based MPPT controler block diagram.

where p_1, p_2, q_1, q_2, r_1 and r_2 are linear parameters. This neural network has three layers which, first layer membership function (μ) is calculated as follows:

$$O_{1,i} = \mu_{Ai}(x), i = 1, 2 \tag{12}$$

$$O_{1,i} = \mu_{Bi}(x), i = 3, 4 \tag{13}$$

Also, for each rules the weight cofficient (w_i) are calculated as follows in second layer nodes:

$$O_{2,i} = w_i = \mu_{Ai}(x) \times \mu_{Bi}(y) \tag{14}$$

In layer 3, which is a non-adaptive layer, the weight cofficient of each node is calculating as follows according to the weighted sum

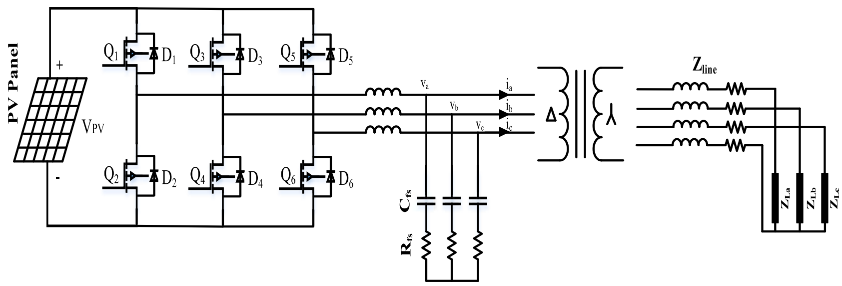

Fig. 6. The structure of used DC/AC inverter.

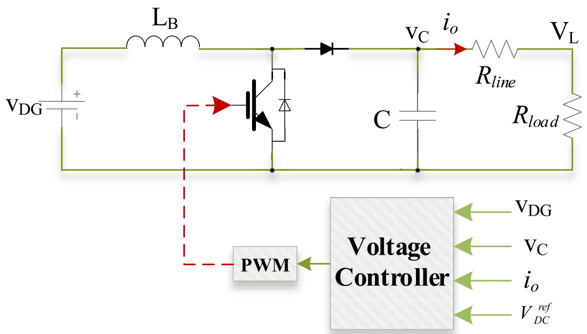

Fig. 7. A boost converter structure.

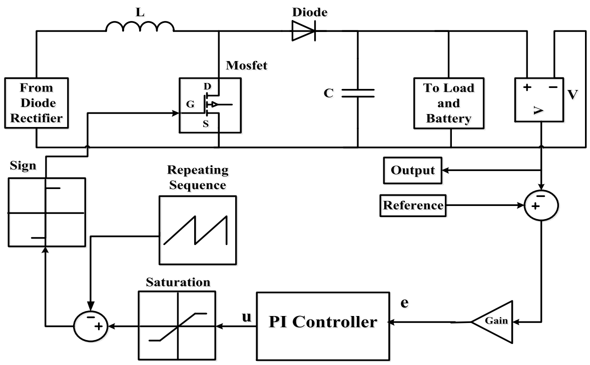

Fig. 8. The internal circuit of the controller of the boost converter.

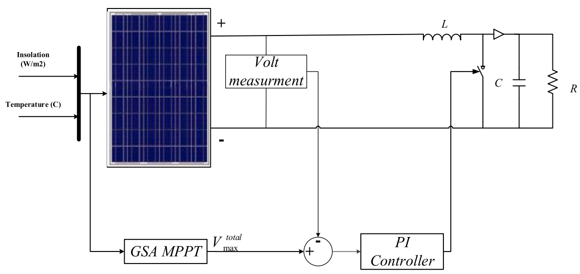

Fig. 9. Schematic of the circuit to track the maximum power point.

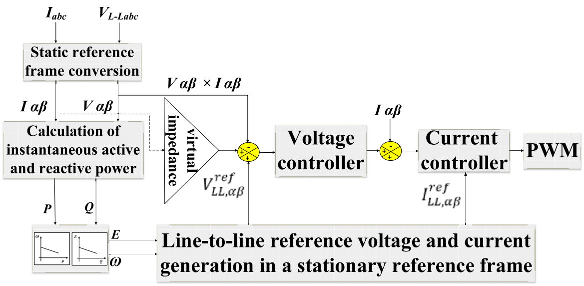

Fig. 10. PWM control signal block diagram.

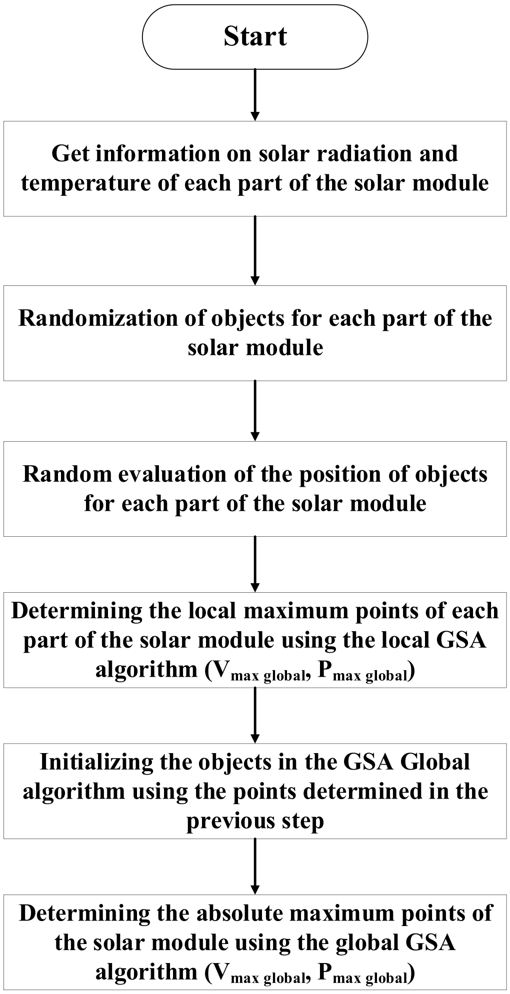

Fig. 11. Proposed GSA flowchart.

rule:

$$O_{3,i} = \acute{w}_i = \frac{w_i}{\sum_i w_i} \tag{15}$$

The fourth layer is defined as follows:

$$O_{4,i} = \acute{w}_i \times (p_i x + q_i y + r_i) \tag{16}$$

Also, layer 5 has a single non-adaptive node which calcylates the output according to the followin equation:

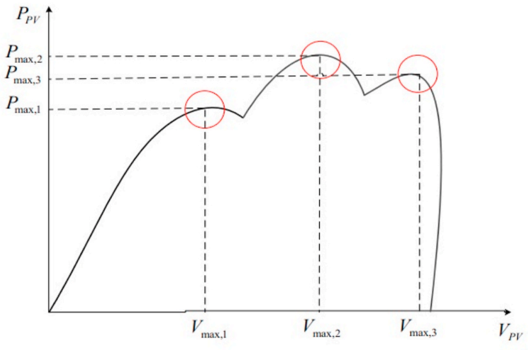

Fig. 12. MPP in three shading conditions.

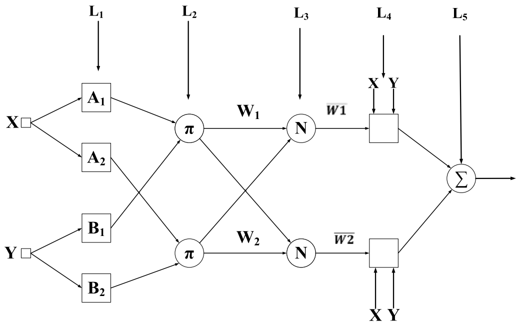

Fig. 13. The desired neural network structure.

$$O_{5,i} = \sum_i \acute{w_i} f_i = \frac{\sum_i w_i f_i}{\sum_i w_i} \tag{17}$$

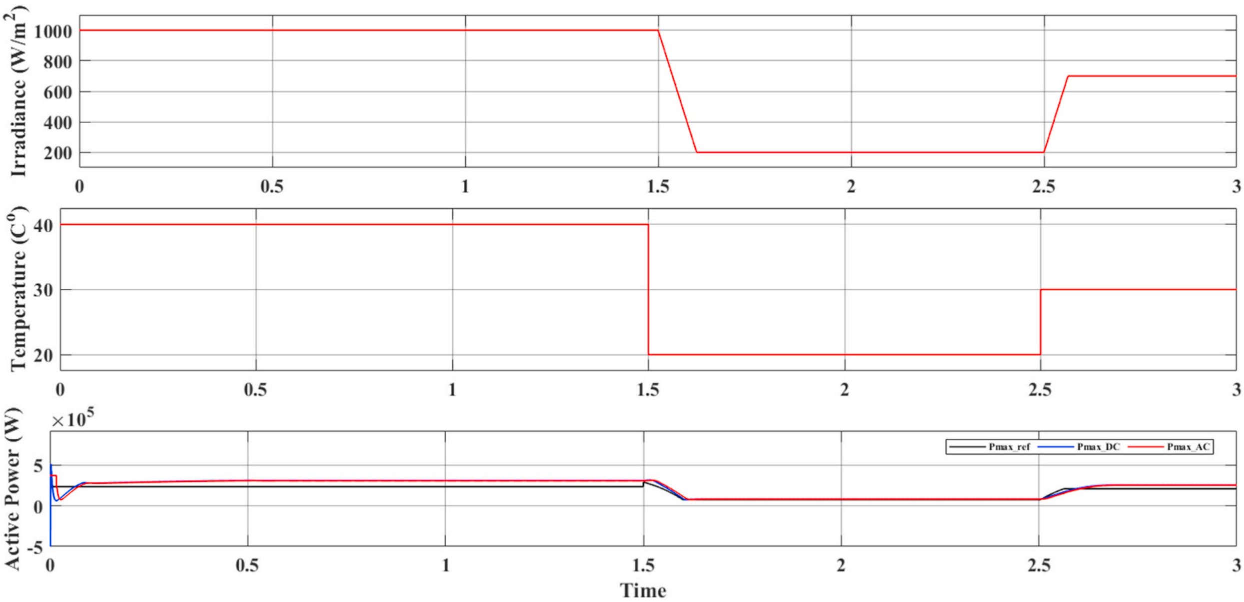

Fig. 14. Tracking the MPPT point and its corresponding voltage in uniform radiation and temperature state.

5. Simulation results

In this section, to analyze and validate the proposed method, the simulation of the proposed algorithm is performed to control the output active power in a grid-connected PV system and tracking the point of receiving the maximum power in partially shaded conditions. At first, the performance of the proposed method has been investigated under uniform temperature and radiation conditions.

According to Fig. 14, the temperature and irradiation are same and uniformly for all three parts of the solar panel at any moment. In this regard, for validating the proposed algorithm, the radiation and temperature received by the solar panel are reduced from 1000 W/m^2 and 40 °C to 200 W/m^2 and 20 °C, and in continue, these two parameters will be reduced again to 700 W/m2 and 30 °C respectively. As seen from this figure, with the change of radiation and temperature every second, the output power of the DC and AC sections follows the maximum reference power point with high accuracy and fast speed. Fig. 15 shows the changes in the output voltage and current of the photovoltaic system at the point of common coupling (PCC). According to this figure, the proposed method has a proper and optimal performance in maintaining the DC link voltage in PCC.

In the following, the performance of the proposed method has been investigated under partially shade conditions. In the simulated system, a PV module with three shading conditions is investigated. Figs. 16 and 17 shows the irradiance and temperature of these three shaded conditions, respectively. As shown in these two figures, the simulated system has a three different stage of irradiance and temperatures.

As can be seen in Fig. 18, with the changes of partial shaded conditions, the proposed algorithm quickly and with high accuracy follows the output voltage and power of the solar panel towards the maximum voltage and power point. In this regard, the proposed GSA algorithm immediately determines the voltage value, which can obtain the maximum power from the solar panel. Then, by control the inverter with the neuro-fuzzy controller, the maximum power obtained in the DC side is transfer to the AC side.

Figs. 19–24shows the changes in the output voltage and current of the photovoltaic system at the point of common coupling (PCC) in partially shaded condition. According to theses figures, the proposed method has a proper and optimal performance in maintaining the DC link voltage in PCC.

Fig. 25 shows the power changes of each part of the photovoltaic system with radiation and temperature changes in each part. As can be seen in this figure, due to the different input radiation and temperature in each section, the output power of all three sections is always different, but their sum is equal to the maximum tracking power.

In Fig. 26, the speed and accuracy of the proposed method in the maximum power point tracking are compared with traditional PID controller in the partially shaded condition. As can be seen from the figure, the PID controller tracks and follows the maximum power point when the radiation and temperature change with a much greater delay and much less accuracy than the neuro-fuzzy controller. Also, Fig. 27 shows a closer look from Fig. 26.

Table 1, shows the coparision between the proposed method in this paper and other methods. As its clear from this table, the proposed method has higher accuracy and lower convergence time compared to other mentioned methods, so it has a better operation.

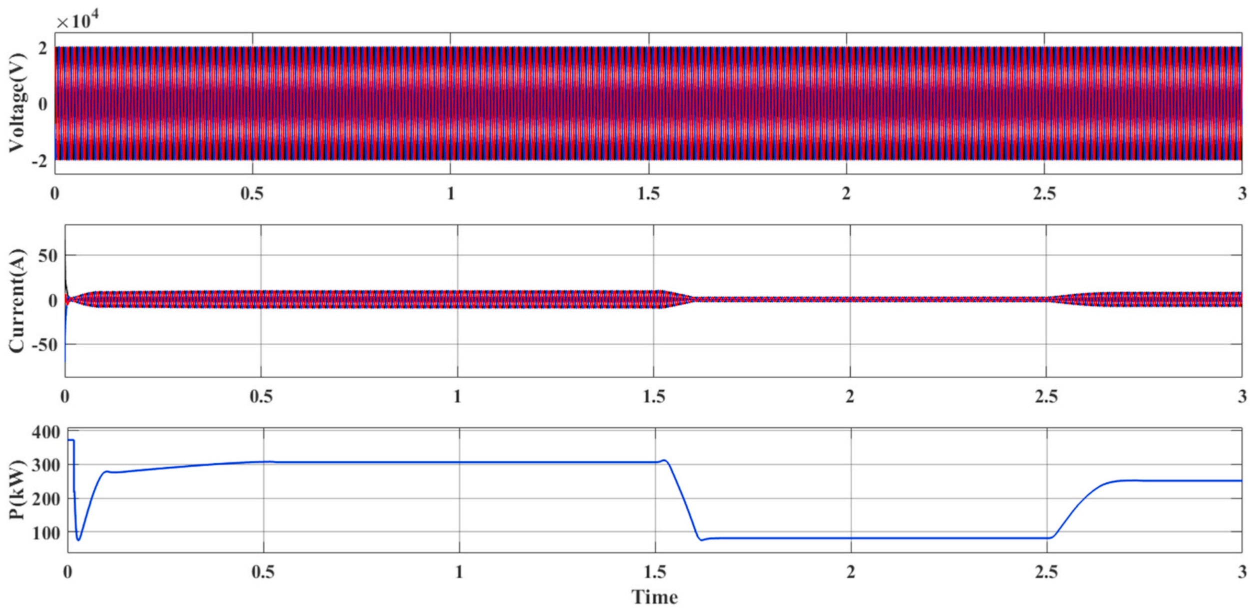

Fig. 15. Changes in voltage, current and power output of the photovoltaic system in the AC side.

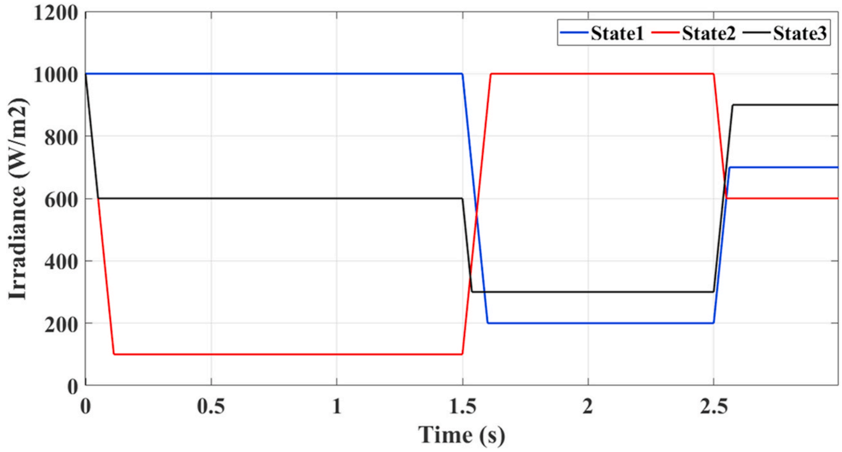

Fig. 16. Changes in irradiation in three different states.

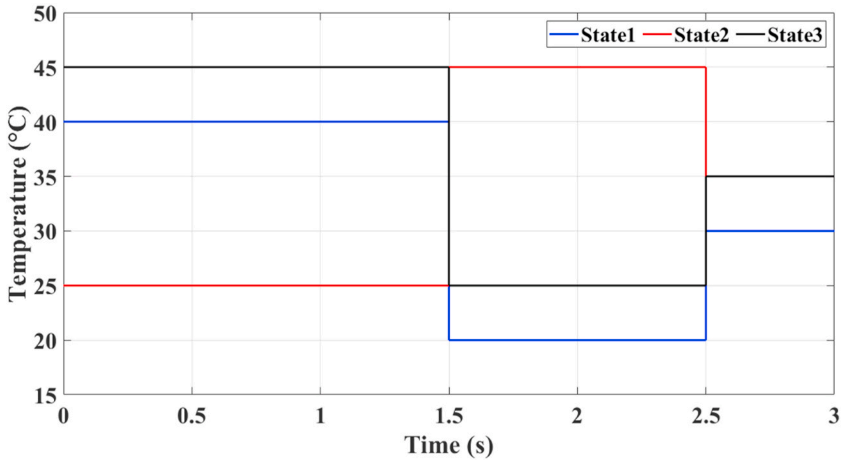

Fig. 17. Changes in temperature in three different states.

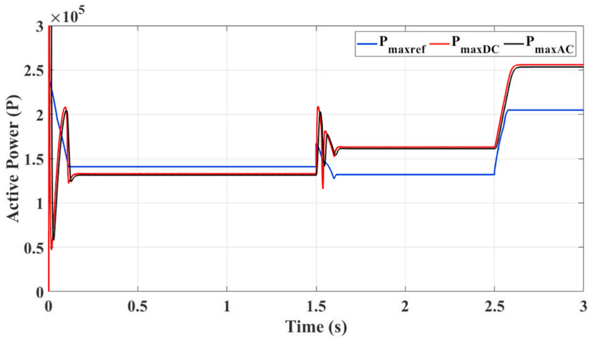

Fig. 18. Power changes in DC and AC sides for three different sections of the solar panel.

6. Conclusion

In this paper, to control the active power of the grid-connected PV system, a new neuro-fuzzy MPPT method is presented. The introduced grid-connected inverter uses this neuro-fuzzy controller on the grid side, which is responsible for active power control. Also, this controller has an internal loop that keeps the DC link voltage at a constant value and avoids distortions on it. This feature prevents the distortion and minimizing the fluctuations on the output AC voltage of the inverter. This controller prevents the mutual

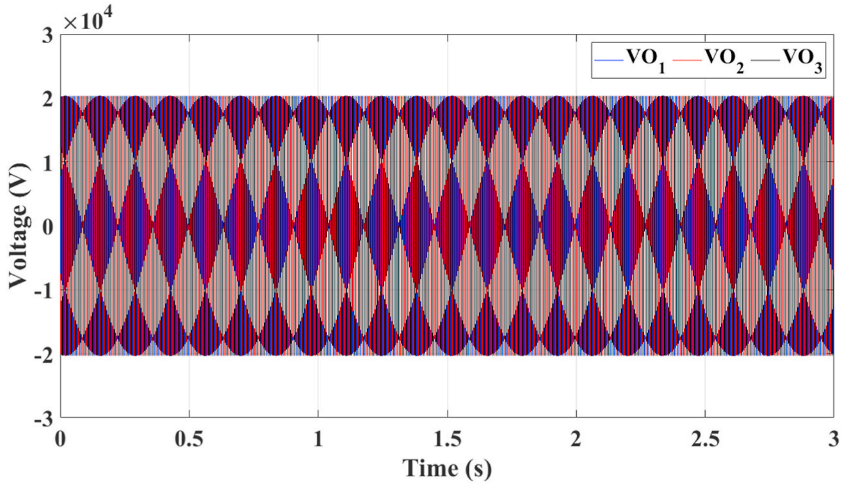

Fig. 19. Changes in the output voltage of the solar panel in the AC section in three different conditions.

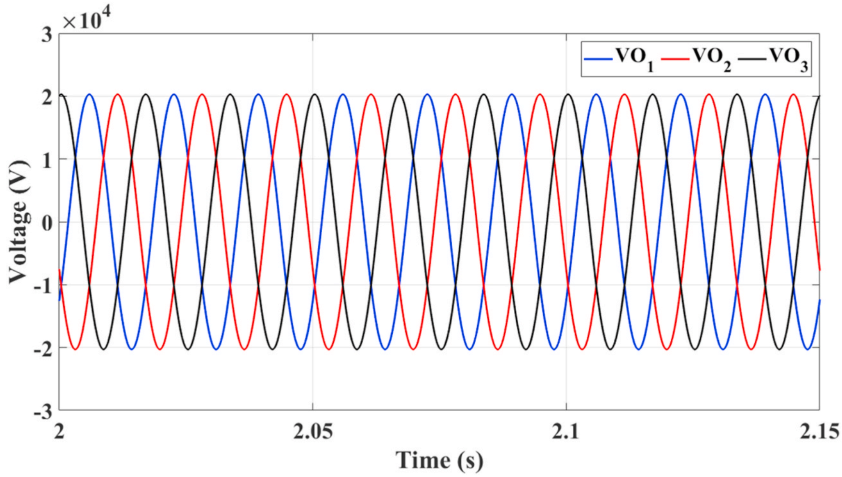

Fig. 20. Zoom of Fig. 18.

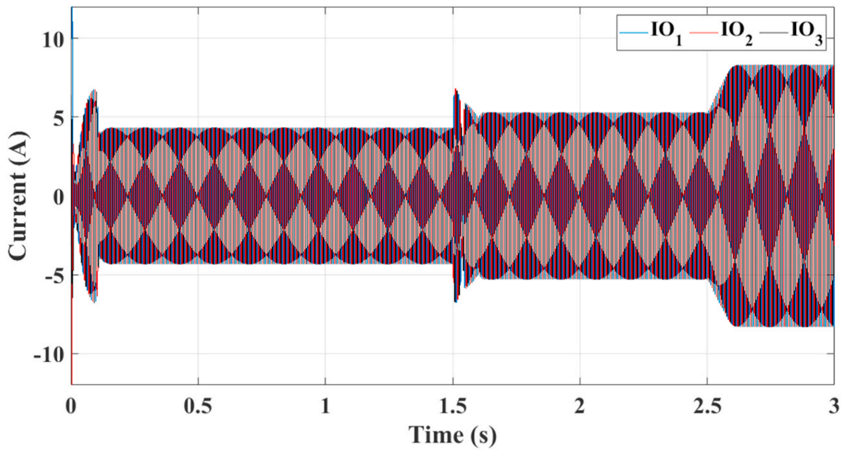

Fig. 21. Changes in the output current of the solar panel in the AC section in three different conditions.

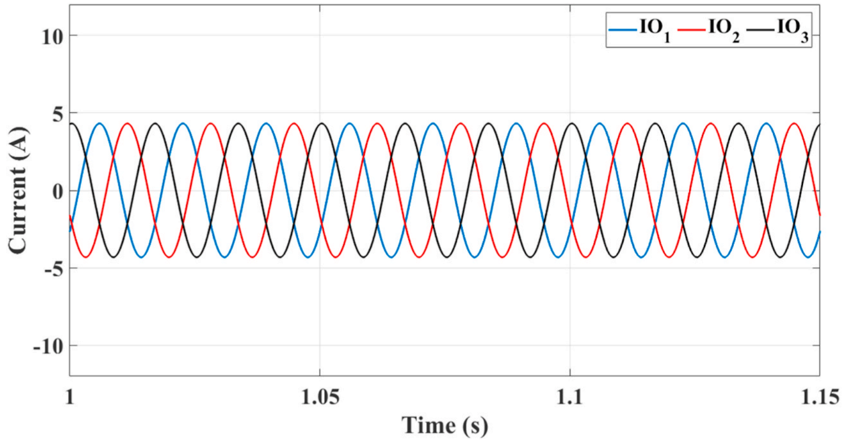

Fig. 22. The output current of the solar panel in the AC section in the first state.

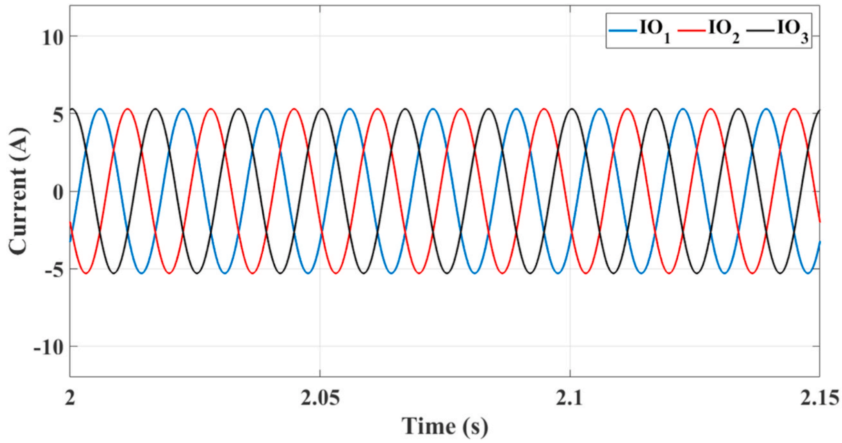

Fig. 23. The output current of the solar panel in the AC section in the second state.

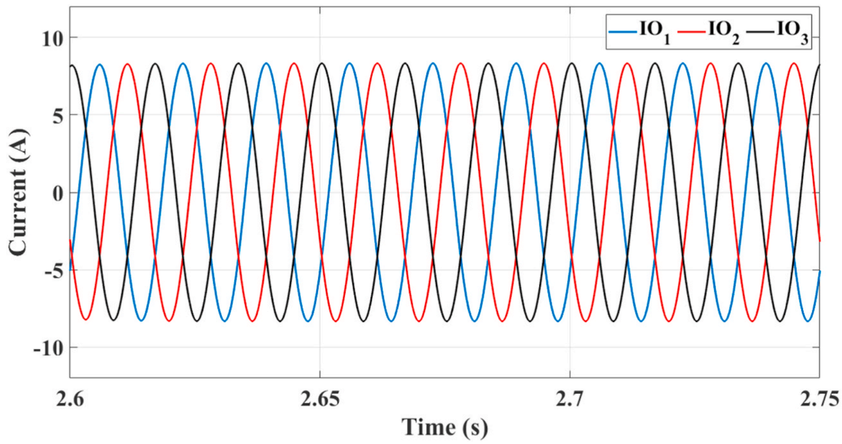

Fig. 24. The output current of the solar panel in the AC section in the third state.

effect of electrical parts on each other as much as possible, which minimizes the damage caused by disturbances of electrical parts on each other. In the simulation section, the optimal performance of this controller in tracking the maximum power point in different conditions of radiation and temperature, including partially shaded conditions, was discussed and investigated. The results of the

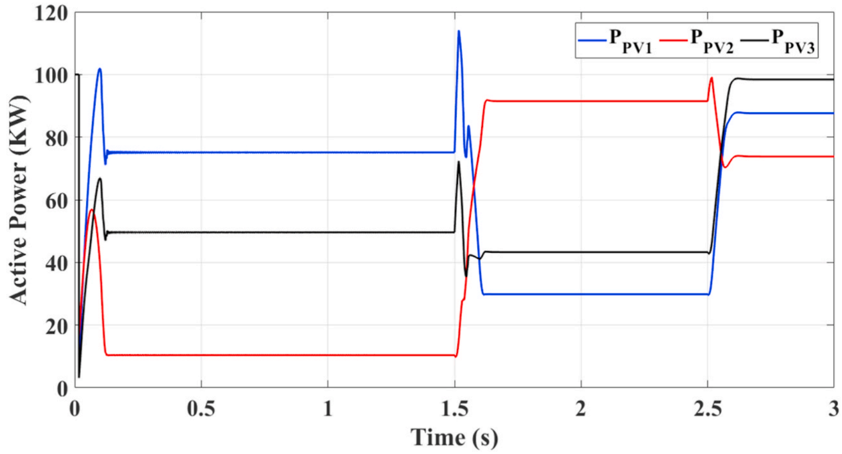

Fig. 25. Changes in the output power of each ice from the photovoltaic system in partially shaded conditions.

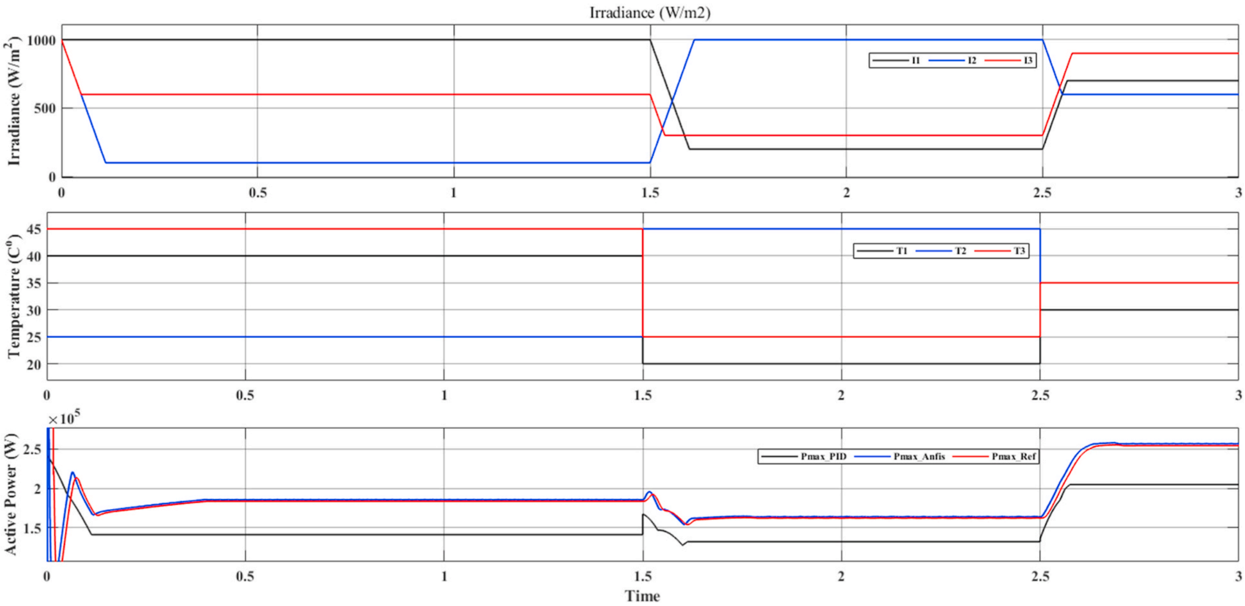

Fig. 26. Comparison of neuro-fuzzy controller and traditional PID in tracking the maximum power point.

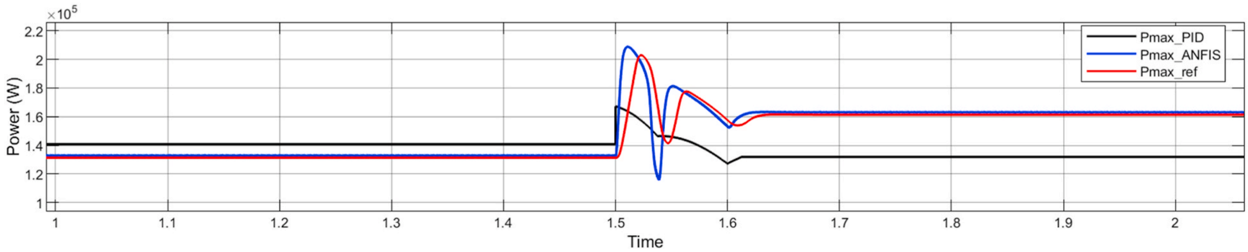

Fig. 27. Zoom of Fig. 26.

simulation show the efficiency and capability of the proposed method in controlling the active power in a grid-connected photovoltaic system. For future work, researchers can discuss and study the existing conditions for reactive power considering that much attention has been paid to inverter voltage and current control in this paper [42–44].

Table 1
A comparision between proposed method and other methods.

Method	Accuracy (%)	Convergence time(s)
Genetic algorithm-based PID	92	0.38
Partical swarm obtimization-based PID	94	0.25
Traditional fuzzy	95	1.2
Proposed Method	96	0.2

CRediT authorship contribution statement

Saeed Danyali: Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Software, Resources, Project administration, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Mohammad Babaeifard:** Writing – original draft, Visualization, Validation, Supervision, Software, Resources, Methodology, Investigation, Data curation, Conceptualization. **Mohammadamin Shirkhani:** Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Software, Resources, Project administration, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Amirreza Azizi:** Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Software, Resources, Project administration, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Jafar Tavoosi:** Writing – original draft, Visualization, Validation, Supervision, Software, Resources, Investigation, Formal analysis, Data curation, Conceptualization. **Zohreh Dadvand:** Writing – original draft, Validation, Software, Resources, Methodology, Investigation, Data curation, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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