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A novel fast maximum power point tracking for a PV system using hybrid PSO-ANFIS algorithm under partial shading conditions

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ABSTRACT

It is highly expected that partially shaded condition (PSC) occurs due to the moving clouds in a large photovoltaic (PV) generation system (PGS). Several peaks can be seen in the P-V curve of a PGS under such PSC which decreases the efficiency of conventional maximum power point tracking (MPPT) methods. In this paper, an adaptive neuro-fuzzy inference system (ANFIS) is proposed based on particle swarm optimization (PSO) for MPPT of PV modules. After tuning the parameters of the fuzzy system, including membership function parameters and consequent part parameters, to obtain maximum power point (MPP), a DC/DC boost converter connects the PV array to a resistive load. ANFIS reference model is used to control duty cycle of the DC/DC boost converter, so that maximum power is transferred to the resistive load. Comparing the proposed method with PSO alone method and firefly algorithm (FA) alone shows its efficacy and high speed tracking of MPP under PSC. Due to the fact that these optimization algorithms have online applications, the convergence time of the algorithms is very important. The simulation results show that the convergence time for the proposed ANFIS-based method is lower than 0.15 second, while it is nearly three second for PSO and FA methods.

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I. INTRODUCTION

Due to the increase in electrical energy demands in industrial and individual sectors, more and more electrical power is required. However, since fossil fuels such as coal, oil, and etc. pollute the environment and increases the global temperature, the demand for renewable and sustainable energy increases every day. Since one of the most available energy resources is solar energy, PGS is one of the most frequently used technologies with rapid grown in the past decades. The advantages of PGS include low maintenance requirements and capability of operation without consumption of fuel which results in low cost and less environmental pollutions. The most important drawback of employing PGS is that its efficiency is low and has higher costs [1-4].

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The main challenge in application of PGS is to deal with its nonlinear current–voltage (I–V) characteristics where its MPP changes with temperature and irradiance. The typical power-voltage (P–V) and (I-V) curves of PV module indicate a unique MPP at one specific operating point including irradiance and temperature conditions. PV module usually generates intermittent power mainly due to the time-varying solar radiation and panel temperature [5-7], therefore it is indispensable to develop online MPPT algorithm able to find MPP of the PV module in the real time. There are many approaches in the literature that extract the MPP of a PGS. Examples of such approaches include incremental conductance (INC) [8], perturb and observe (P&O) [9], fuzzy logic [10], and ripple correlation approaches [11]. These methods try to increase the efficiency and reduce the time under identical solar irradiance. Among aforementioned methods, perturb and observe method is most widely used.

This method is based on perturbation of voltage using the present P and previous operating power P_{old}, if the generated

power by PV system increases, that is, the operational point moves towards the maximum power point, therefore in the next exploitation voltage, perturbation is created in direction of the previous exploitation voltage. This operation continues until MPP is reached, but if the power received from the PV system decreases, it means that it is far from MPP and therefore direction of the perturbation should be changed [12-14]. Although this method is very simple but its efficiency highly depends on the convergence speed and fluctuations around MPP, because if convergence speed increases, convergence accuracy decreases and fluctuations around MPP increase, thus parameters should be adjusted such that neither convergence speed is low nor fluctuation around MPP is high [15]. Rapid change of irradiance is another major challenge for P&O method which will probably lose its direction instead of tracking the true MPP. Such techniques are not fully adaptive and not very effective. Furthermore, most methods fail to track the true MPP under PSC and this is because multiple peaks (local and global peaks) specify the PV curves [16-18]. It is highly expected that the P&O algorithm get trapped in a local optimum and is not able to distinguish between local optimum and global optimum [19]. Having several peaks significantly decrease the efficiency of conventional MPPT methods, because probability of PSC occurrence is very high, thus it is required to develop appropriate MPPT methods which can track global MPP (GMPP) under PSC. To eliminate the barriers of GMPP tracking, meta-heuristic algorithms have also been used, such as Ant-colony optimization (ACO), firefly algorithm, artificial bee colony algorithm, particle swarm optimization, genetic algorithm, cuckoo search, grey wolf optimization, etc. [18, 20-27]. Several GMPP tracking methods are proposed for PGS operating under PSC. Authors of [28] used a scanning process to identify the regions in which there is a GMPP at the first step. Then, they applied P&O method to find the GMPP. Although this method can find GMPP efficiently, tracking speed is limited because almost all local maximum peaks (LMPs) must be found and checked to obtain the GMPP. In [29], in order to increase the convergence speed of PSO, the authors combined PSO with P&O. In this hybrid algorithm, P&O method first detects the nearest local MPP, and then PSO starts searching to find the global MPP. Merit of this method is the limited search space. In order to find GMPP of a modular PV system, ACO method is used [21]. The proposed method is able to track the global MPP with a single-current sensor at the output. In such situation, initial conditions specify the convergence speed of this method. Daraban integrated genetic algorithm (GA) with P&O method and makes one algorithm [22]. One benefit of this method is that it reduces the population size which decreases the number of iterations and results in faster detection of Global MPP. In [30], an artificial neural network (ANN) based MPPT is proposed whose parameters are optimized using a GA procedure for different irradiance and temperatures conditions. The results are used for offline training of the ANN and this method tracking MPP under uniform irradiance. In [31], an adaptive Neuro-fuzzy inference system-based MPP tracker for PV module is proposed, where the tracking MPP is in uniform irradiance conditions and cannot track the global MPP in PSC. In [32], a MPPT for PV system using adaptive neuro-fuzzy inference system was proposed. In order to train ANFIS, incremental conductance method based on uniform irradiance approach was used. In [33] at first a wide range is overviewed to locate the MPP range over the voltage axis. Then a detailed search around the maximum point obtained in previous step is performed to locate GMPP. Even though this method is capable of tracking MPP under PSC, it has low speed due to overviewing all P-V curves in the first stage. Reference [16] tries to extract the maximum power in PSC by combining gray wolf algorithm and P&O method; firstly, by using gray wolf algorithm the range of global maximum power point is determined and then by using P&O method it tracks the MPP. Because of using P&O method in the second stage, speed of this method is acceptable but since this method works based on perturbation of voltage or current, fluctuations around the MPP are very high and this leads to loss of power.

In this paper, a hybrid method based on PSO-ANFIS is used to track GMPP under PSC in PGS. PSO is well-known as an optimization algorithm that finds the optimum point of a function. The inputs of fuzzy system are temperature and irradiation of each panel. The main objective is to achieve a system for finding the global MPP without the need to search the space and try several different points. The simulation results indicate that the convergence speed is very high and this hybrid method can find global MPP under PSCs.

This paper is organized in seven sections. In Section II characteristic of the PGS under PSC is explained. In Section III the FA method is described. In Section IV, the PSO method is briefly reviewed, and the Overview of ANFIS is described in V. In Section VI the application of PSO toward MPPT is described. In section VII the proposed hybrid PSO-ANFIS method is described. The simulation results are presented in Section VIII. Finally, the concluding marks are provided in Section IX.

II. CHARACTERISTICS OF THE PGS UNDER PSC

A. Basic Characteristics of a PV Array

PV cells include p-n junctions which generate electric power using photons. When a resistive load is connected to the PV cell, a direct current flows through a cell comprised of charges and the current terminates whenever the irradiance is terminated. The single-diode model of PV cell is used for modeling and simulation of the PV module. In order to boost the total efficiency of the system and increase the output power, cells of the PV array should be connected either in series or in

parallel. In order to increase voltage, current and power, the PV cells need to be connected together. The output equation for the entire module in Fig. 1 can be written [34].

$$I = I_{PV} - I_0 * [\exp\left(\frac{(V+IR_S)}{V_t A}\right) - 1] - \frac{(V+IR_S)}{R_p} \quad (1)$$

$$V_t = \frac{N_S KT}{q} \quad (2)$$

where

I_{PV} Photocurrent [A].
V Terminal voltage of PV module [V].
I_o Diode Saturation current [A].
q Charge of the electron [C] Maintaining the Integrity.
K Boltzmann's constant (J/K).
T Junction temperature [K].
N_s Number of cells in series.
R_p Parallel resistance of PV module (Ω).
R_s Series resistance of PV module (Ω).
A Diode ideality constant.

The characteristics of the PV module are given in Table I.

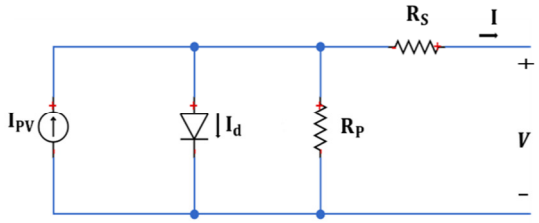


Fig. 1: Single-diode model of PV module

TABLE I.
Parameters of single PV module

Maximum Power	200W
Nominal open circuit voltage (V_{ocn})	32.9V
Maximum power voltage (V_{MP})	26.3V
Nominal short circuit current (I_{ocn})	8.21A
Maximum power current (I_{MP})	7.61A
Number of cells in series (N_s)	54

B. Effects of Solar Irradiance and Temperature

One of the important factors which affect power generation is solar irradiance. As solar irradiance increases, generated power also increases and as irradiance decreases, generated power also decreases. Fig. 2 (a) shows P-V curve and (b) I-V curve for irradiances of $1000\ W/m^2$, $800W/m^2$, $600W/m^2$ and $400\ W/m^2$. Fig. 2 shows that as irradiance increases, short circuit current increases and consequently increases the output power [35]. Temperature also affects generated power. As temperature increases, output power decreases and as temperature decreases power increases. It can be seen in Fig. 2 (c) shows P-V curve and (d) I-V curve that by increasing temperature from $25°C$ to $50°C$, open voltage decreases, therefore power generated by the solar panel decreases [36].

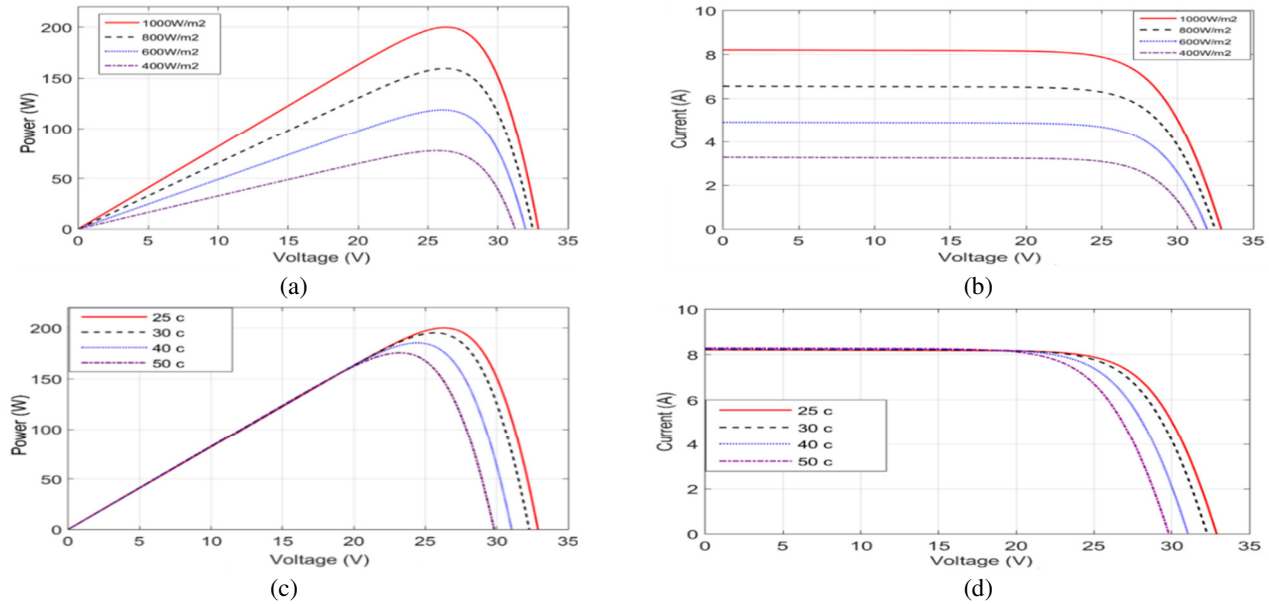


Fig. 2. (a) P–V and (b) I-V characteristics for different irradiation levels for constant temperature.
(c) P–V and (d) I-V characteristics for different temperature levels and constant irradiance

C. Effect of PSC on PV Array

In high dimensions, some part of the PV system might be shaded by clouds, trees or other objects and this created partial shading because irradiance is not uniform. When this condition occurs, since flow in series configuration is fixed, cells which are shaded should be biased inversely to generate the current which other cells generate, in PSC, shaded cells operate like load instead of generating power thus hot spot is

created and burns the part of the module which is shaded and creates open voltage. To avoid this problem the bypass diodes perch parallel with modules and these bypass diodes allow the current to flow in one direction [37]. In case of partial shading, current can pass from diode. This prevents the power loss in the panel and prevents the problem like hot spot. When there is a bypass diode in the system and under partial shading condition, PV curve becomes more complicated and several peaks are observed (one global and several local) [38]. In Fig. 3, four PV modules are connected in series in which various radiations reach them.

In Fig. 4, photovoltaic system P-V, P-I & I-V curve for various radiations are shown. In this curve uniform irradiance of $1000\mathrm{W/m^2}$ and two samples under PSC are drawn. In sample 1 (case 1) $1000\ \mathrm{W/m^2}, 900\mathrm{W/m^2}, 800\mathrm{W/m^2}$ and $700\ \mathrm{W/m^2}$ radiations and in second sample $1000\mathrm{W/m^2}$, $800\mathrm{W/m^2}$ $600\mathrm{W/m^2}$, $400\mathrm{W/m^2}$ are given. Global MPP under PSCs are specified in picture.

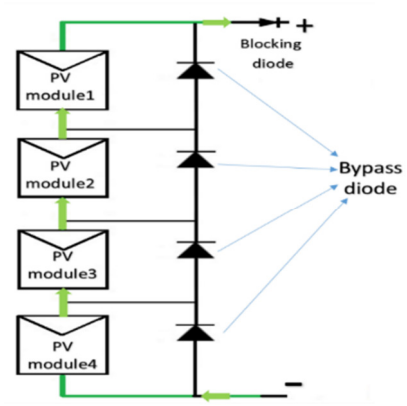
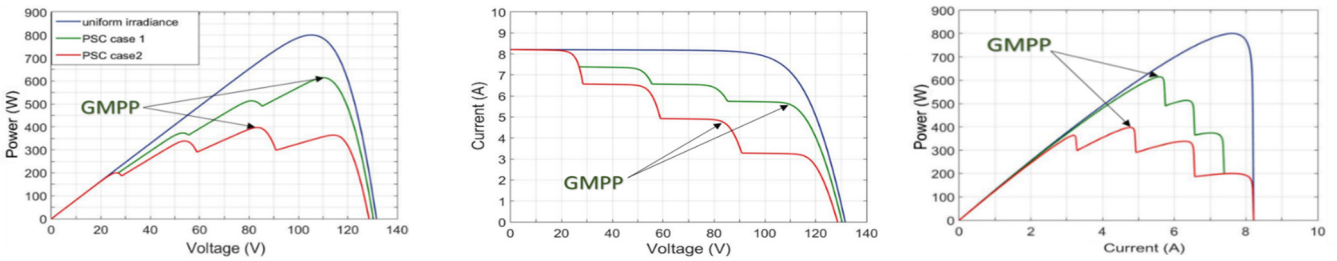


Fig. 3. Four series (4S) configuration under various irradiance.



(a) (b) (c)

Fig. 4. (a) P-V, (b) I-V, (c) P-I curve in uniform radiation and partial shading condition

III. General Overview of FA

One of the meta-heuristic algorithms is the Firefly algorithm which was proposed by Tung from Cambridge University in 2007 [39]. This algorithm is based on swarm like PSO. This algorithm employs an iterative process based on population with a high number of agents called firefly. These agents are allowed to search the search space better than distributed random search. For simplicity, three following rules are used to describe firefly algorithm:

1) All fireflies are unisex, such that a firefly is attracted to other fireflies regardless of its sex.

2) Attractiveness is proportional to their luminosity, therefore in each couple, the one with less luminosity moves towards the one with higher luminosity. Attractiveness is proportional to luminosity and both decrease as distance increases. If none of the fireflies has higher luminosity compared to the other one, movement would be random.

3) Luminosity of a firefly is determined or affected by perspective of the objective function.

There are two major problems in firefly algorithm: variations of luminosity and attraction formula. For simplicity, it can be assumed that attractiveness of a firefly is determined by its luminosity which is related to objective function. Since attractiveness of the firefly is proportional to luminosity viewed by the adjacent firefly, attractiveness of a firefly can be defined as follows:

$$\beta = \beta_0 e^{-\gamma r^2} \quad (3)$$

attractiveness at r = 0 and γ is attractiveness coefficient. Distance between each two fireflies i and j at x_i and x_j would be as follows.

$$r_{ij} = || x_i - x_j || = \sqrt{\sum_{k=1}^{d} (x_{i,k} - x_{j,k})^2} \quad (4)$$

Movement of a firefly i attracted by a brighter firefly j is as follows.

$$x_i^{t+1} = x_i^t + \beta_0 e^{-\gamma r^2} (x_j - x_i) + \alpha \varepsilon_i \quad (5)$$

The second term is in relationship with attractiveness. Third term is randomization operation in which α is randomization operation and i is a vector of random numbers obtained from a Gaussian distribution or a uniform distribution.

IV. General Overview of PSO

PSO is an advanced calculation method based on swarm intelligence [40]. In this method, each particle is determined based on its velocity and position. Behavior of particles is affected by experiences of neighboring particles. Each particle follows the particle with best performance to find its solution.

Distribution of particles in the solution space is random. In each iteration, particles employ two final values to update themselves. Desired solution in the first value which the particle finds and it is called the best personal value, second final value is the desired solution which is identified by all particles and it is called the best global value. When the best solutions are found, particles update their acceleration and position according to the following equations.

$$V_i^{k+1} = WV_i^k + C_1\,rand_1^k\left(pbest_i^k - x_i^k\right) + C_2\,rand_2^k\left(gbest_i^k - x_i^k\right) \quad (6)$$

$$x_i^{k+1} = x_i^k + v_i^{k+1} \quad (7)$$

where V_i^k is acceleration of particle i^{th} from k^{th} iteration, W is weight, C_1 and C_2 are acceleration coefficients which are used to guide the search towards the personal and global solutions, $rand_1$ and $rand_2$ are random numbers between 0 and 1. Among all evolutionary methods, PSO is mainly used to track GMPP because this method is optimized based on swarm.

V. Overview of ANFIS

Neuro-fuzzy models which were developed by Jang in 1993, combine fuzzy logic and artificial neural networks to facilitate the learning and adaptation processes [41]. In fact, in neuro-fuzzy models, an adaptive network which is the general form of a multi-layer pioneer neural network is used to resolve the problem of identifying parameters of fuzzy inference system. An adaptive network is a multi-layer pioneer structure where its output behavior is determined through a set of modifiable parameters. Using such an adaptive neural network, the main problem of using fuzzy inference system which is obtaining "if-then" rules and optimizing parameters of the model is solved. Most commonly used fuzzy inference system which can be used in an adaptive network is Takagi-Sugeno fuzzy system the output of which is a linear relation and its parameters can be estimated through combining mean square error and back-propagation error based on gradient reduction.

Membership functions of x are in A_1 and A_2, membership functions of y are in B_1 and B_2 and p_1, q_1, r_1, p_2, q_2, r_2 are parameters of the output function. Fig. 5 shows ANFIS structure equivalent to the mentioned inference system.

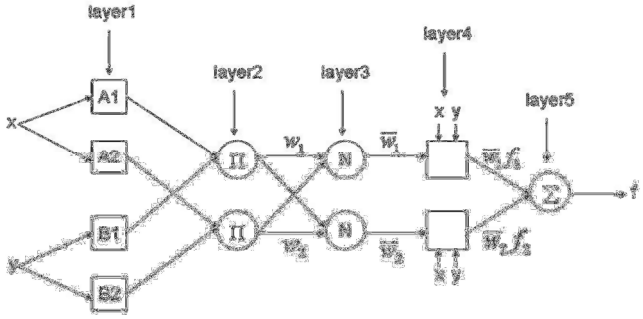


Fig. 5: ANFIS configuration

VI. Application of PSO for MPPT

Fig. 6 shows a block diagram of MPPT scheme based on PSO method. The intended system has PV modules and a DC-DC boost converter is used as interface between load and PV system. The steps of tracking MPP based on PSO are described below.Step.1: Parameter selection. In the proposed system the position of particles are defined as the duty cycle DC-DC converter and all the power produced by PV systems is considered as a merit. A point to note is that if we consider a large number of particles, MPP tracking will guarantee the accuracy even under complex light patterns, but it increases the calculation time. So the number of particles should be considered in a way that we face neither an increase in the calculation time nor the accuracy cut. To achieve this aim we consider one particle for each module.

Step. 2: Initializing PSO. In the initialization phase of PSO, the particles in search space randomly are between d_{min} and d_{max} values. d_{max} and d_{min} are maximum and minimum duty cycle value for dc-dc converter, in this paper they have been considered between 0.1 and 0.9 respectively.

Step. 3: Calculation merit. After the PWM command was given to the DC-DC converter based on the position of the particle i, during the specified time that fluctuations became stable, the PV's voltage and current are measured. This value is calculated as the amount of particle's merit.

Step. 4: Updating values of gbest and pbest. If for a specific particle, its merit is better than its pbest, the merit value will be saved and replaced. If this amount is also better than gbest, this value will replace the gbest's value.

Step. 5: When all particles are evaluated, position and velocity of all particles of the population should be updated.

Step. 6: Determining convergence. Here, the simulation time is selected 3 sec for all methodologies, so after this time the algorithms will stop. But for evaluation, the number of repetitions of each algorithm is recorded when the average relative change in the best fitness function value over the 3 sec is less than or equal to a specific value.

Step. 7: Due to changes in solar radiation and temperature, the output power of photovoltaic system varies, in this situation particles swarm algorithm automatically runs again to track new optimum operating point.

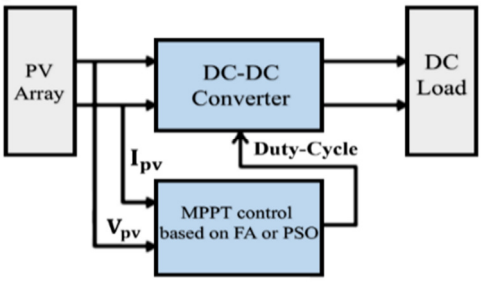


Fig. 6. Block diagram of FA and PSO based MPPT scheme

VII. PROPOSED HYBRID PSO-ANFIS

The block diagram of the proposed methodology is illustrated in Fig.7. PV system is connected to load through a boost converter. Irradiance level and operating temperature and their corresponding optimal duty cycle value of PV module are taken as the input-output training data set for the ANFIS. Optimal duty cycle is obtained by using PSO optimization algorithm for different operating scenarios. Temperatures as 10, 25 and 40° C and radiation on 200, 500 and 800 W/m^2 are considered for each panel, which obtained $3 \times 3 \times 3 \times 3 \times 3 = 243$ duty cycles totally. In Table II, some of operating scenarios which apply to ANFIS are illustrated. For the studied problem in this paper, the best value for the number of membership functions is obtained 5 by trial and error. After selection the best number of membership functions, the training procedure is started. Here, 80% of all input-output datasets as training and the rest of them as the test data are randomly selected. Such as any neural network training procedure there is a validation data, which is normally selected 5% of the training data. If the accuracy over the training data set increases, but the accuracy over that validation data set stays the same or decreases, then the training program will be stopped.

PSO algorithm parameters are as follows: $C_1 = 1.2$, $C_2 = 1.7$, $W = 0.97$ and size of swarm are four. In order to regulate membership functions for ANFIS, 243 operating scenarios are considered by simulation results to trace maximum power of three collections, membership functions are on Fig. 8 for two inputs. Since membership functions are equal for radiation, only, one of them enters which is seen in Fig. 8(a). Fig. 8 shows (a) membership functions of ANFIS input (irradiance level) after learning and (b) Membership functions of ANFIS input (temperature) after learning. The proposed ANFIS controller is considered to have five inputs (one for temperature and four irradiances for each PV modules). By ignoring the slight differences of the temperature value among each PV modules, we would have one T parameter and four magnitude of radiations illustrated as Ir1 to Ir4 in Fig. 7.

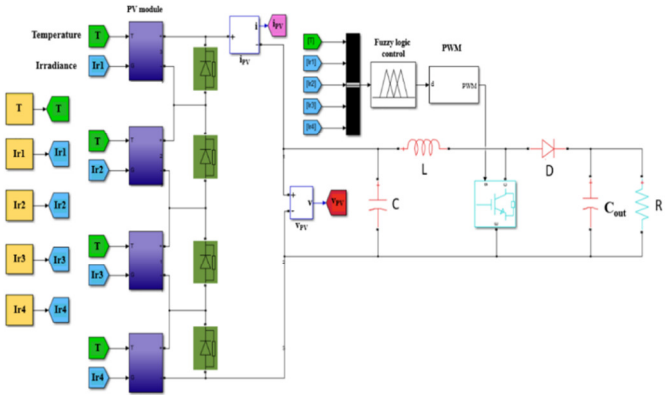
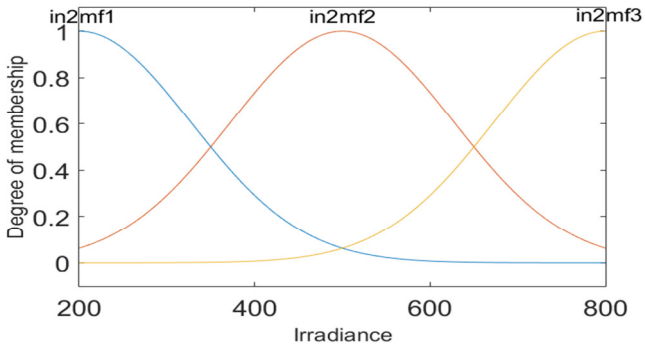
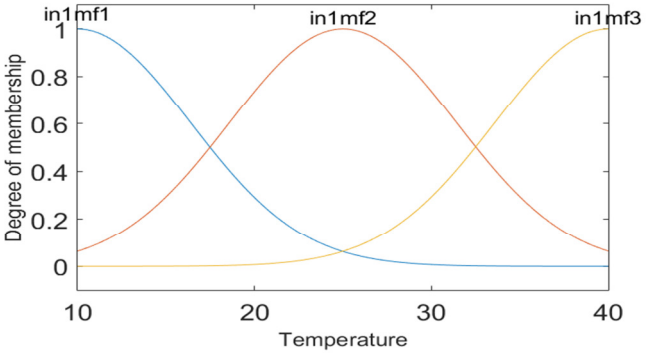


Fig. 7. Matlab/Simulink model of hybrid PSO-ANFIS MPPT scheme



(a)



(b)

Fig. 8. (a) Membership functions of ANFIS input (irradiance level) after learning. (b) Membership functions of ANFIS input (temperature level) after learning

Table II
Some of modes which apply to training anfis

T(c)	Ir 1 (W/m^2)	Ir 2 (W/m^2)	Ir 3 (W/m^2)	Ir 4 (W/m^2)	Duty cycle
10	200	200	500	800	0.5342
10	200	500	500	800	0.4293
25	500	200	800	200	0.5517
25	800	800	800	800	0.4967
40	800	800	200	200	0.6578
40	500	800	500	800	0.3878

VIII. SIMULATION RESULTS

For analyzing MPPT methods, general comparisons have been done among FA, PSO and the proposed method. Extensive studies have also been done in Matlab/Simulink under different patterns of PSC. PV module, KC200GT has been used in simulation of solar panel. PV system, shown in Fig.7, has a DC-DC boost converter with four PV modules which have been interconnected in series. The components for the designed boost converter are chosen as $L = 10$ mH. $C_{in} = 100\mu F$, $C = 330$ µF, $V_{in} = (0–130$ V), $V_{out} = 300$ V, $f_s = 25$ kHz, $R = 70\ \Omega$ and output voltage ripple is $\leq 1\%$. For the proposed method, one

radiation sensor is used for each panel, and one temperature sensor for whole system as shown in Fig. 7. Sensors are the input of ANFIS system. In different situations of PSC and also sudden changes of radiation, ANFIS system gives out a proper duty cycle for MPPT as an output. For PSO and FA methods, voltage and current of the PV system are sampled for the MPPT block as shown in Fig. 6, then after a specified time, output power of the system is calculated and then duty cycle is calculated and applied to the circuit. This procedure is repeated several times and eventually, optimized duty cycle is achieved and DC-DC boost converter works based on that. In Fig. 6 block diagram of the control system based on PSO and FA methods is given.

It is well-known that the choice of the controlling parameters for a heuristic-based algorithm is performed based-on **trial and error** methodologies over numerous independent trials and observing the performance of the algorithm. Therefore, for the studied problem domain, the best values of the parameters involved in the PSO, FA or ANFIS for a number of trial runs are selected. For example, in PSO algorithm, $C_1 = 1.2, C_2 = 1.6, W = 0.97$ are selected by trial and error, and the number of repetition to the determining convergence is obtained 16 times. The number of particles is chosen as 4. Also for FA method $\beta_0 = 2, \alpha = 0.35,\ \gamma = 1$ and number of repetition is obtained 6 times. In this paper, the number of fireflies is chosen as 4. Three techniques of MPPT are used as a controller for DC-DC boost converter with proper duty cycle for study and dynamic comparison of PV system's responses in PS conditions. These methods are studied in terms of tracking time, convergence speed, oscillations around MPPT and tracking efficiency in different conditions of partial shading. Two different patterns of partial shading have been used in tracking efficiency. As first example, under PSC, radiation for each PV module is considered 1000 W/m^2, 900 W/m^2, 600 W/m^2, and 300 W/m^2 respectively. P-V curve is represented in Fig. 9(a). In this case, there are four peaks that GMPP is 400.92 W and its location is third peak in the curve. Fig.9(b) represents output power of the PV system for study case methods. According to this figure, it can be seen that all three methods, have succeeded to achieve GMPP. Details of the simulation results (i.e. power, voltage, current, and duty cycle of DC-DC boost converter) are given in Fig.10. with different MPPT techniques under PSC. As is shown in Fig 10 tracking based on PSO and FA started with random initial values. FA and PSO methods have tracked the GMPP at times 2.65sec and 2.85sec and have converged at powers equal to 400.25W and 400.13W respectively. The proposed method has tracked the GMPP in less than 0.15sec and converged at power 397.4W. In second investigated pattern of PSC, solar radiations are considered 800 W/m^2. 800 W/m^2, 800 $W/m^2$and 500 W/m^2, respectively. P-V diagram is represented in Fig 9(a). In this condition, global MPP is equal to 478.75W which has occurred at first peak of the P-V diagram. Output power of the PV system for three methods is represented in Fig. 9(b). FA and PSO methods have been able to identify GMPP. FA and PSO methods have tracked the global maximum power at times 2.7sec and 2.9sec and have converged at powers equal to 478.23W and 478.05W respectively. The proposed method has also tracked the GMPP in less than 0.15sec and converged at power 477.65W. Details of the simulation results for PV system are shown in Fig. 11 with different MPPT techniques under second PSC pattern. Finally, it can be concluded that all the three algorithms are able to track GMPP, and also the efficiency of the proposed method is much better in comparison with FA and PSO, because it tracks the global MPP and converges in a very short time. Accuracy of the proposed method also can increase, if we increase the number of data, used in neural network training. Results of the simulation are given briefly in the Table III and also a qualitative comparison has been performed among different investigated methods of MPPT in the Table IV.

It should be noticed that, in addition to the sampling time, the number of solar panels, the number of particles and iterations considered for the PSO, so the time consumption for each iteration, the tracking time and the MPP obtained in experiment is actually influenced by the speed of the employed digital controller and the program statements written for the MPPT algorithms. Therefore, a comprehensive comparison between the time consuming and other performance evaluations achieved using different algorithms is not reasonable. But for a rough compare, and also to improve the results obtained by the proposed algorithm, the results are compared with the recently-published closely-related papers [42] and [43]. In [42], a novel Overall Distribution (OD) MPPT algorithm to rapidly search the area near the global maximum power points, which is further integrated with the PSO, has been proposed. From the results reported in [42], in the best situation, it takes in 0.210s, 4 iterations to reach the GMPP in Case I (with three panels) using the proposed Overall Distribution-PSO (OD-PSO) MPPT algorithm, it is 0.206s for FA. In [43], a study of the proposed optimization technique based on PSO has been performed against two conventional P&O and INC algorithms. Results confirm that the PSO algorithm guarantees fast convergence to GMPP and has better performance in comparison with the conventional ones. In this paper, after PSC occurrence the proposed algorithm could manage to find the global MPP in 0.17s. Therefore, simulation results based on Table III, show that the convergence time for the proposed ANFIS-based method is lower than 0.15 second, while it is more for improved version of PSO such as OD-PSO and FA methods suggested in [42] and [43].

TABLE III
Performance comparison of PSO, FA methods and proposed method

Shading pattern	Tracking Methods	Power (Watts)	Tracking Speed (Second)	Maximum power from P-V curve	%Tracking Efficiency
First case	PSO	400.13	2.85	400.92	99.80
	FA	400.25	2.65		99.83
	Proposed method	397.4	0.15		99.12
Second case	PSO	478.05	2.9	478.75	99.85
	FA	478.23	2.7		99.89
	Proposed method	477.65	0.15		99.75

TABLE IV
Qualitative comparison among different methods

Type	PSO	FA	Proposed Method
Periodic Tuning	Not required	Not required	Not required
Tracking Speed	Medium	Medium	Very fast
Tracking Accuracy	Highly Accurate	Highly Accurate	Accurate
Steady state oscillation	Zero	Zero	Zero

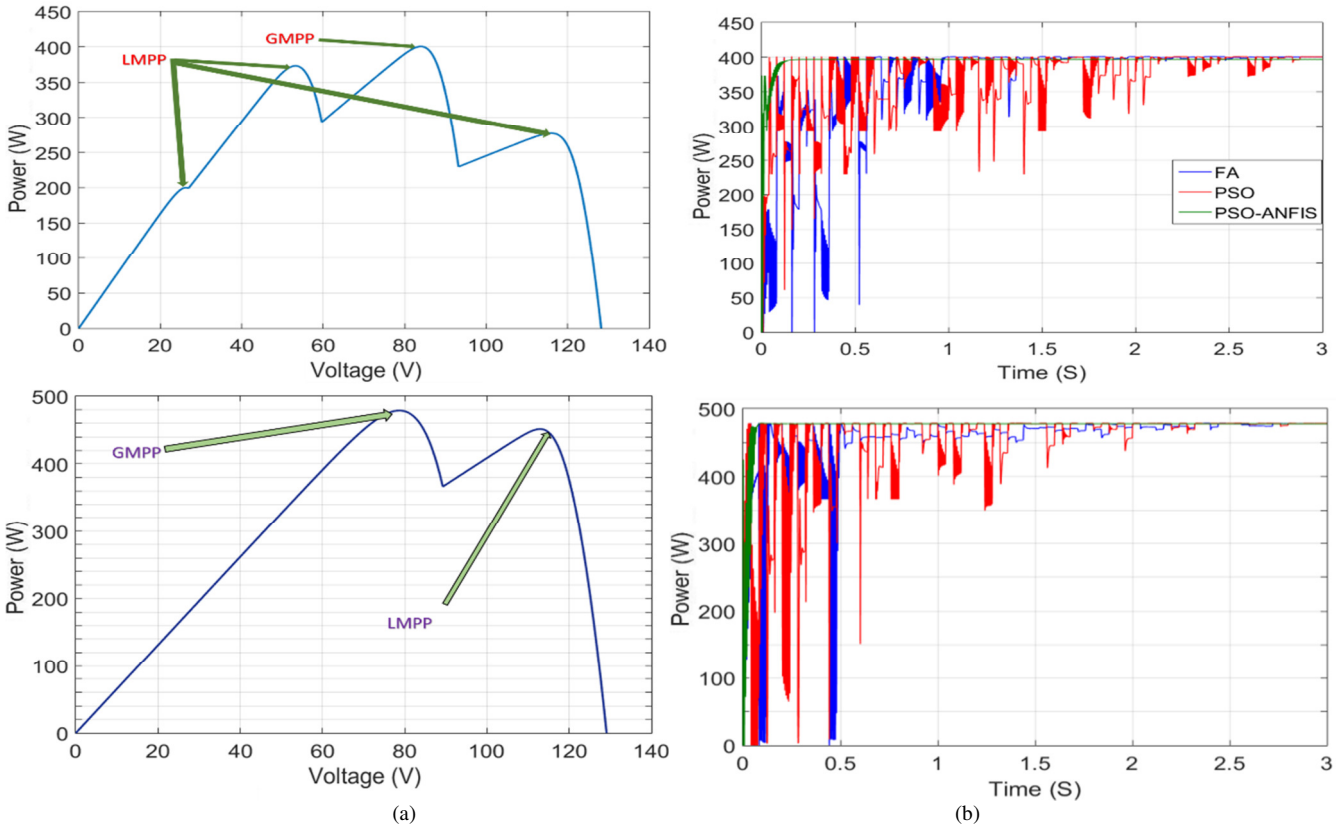


Fig. 9. (a) P–V curve (b) PV output power for PSO, FA and proposed method under different two partial shading patterns.

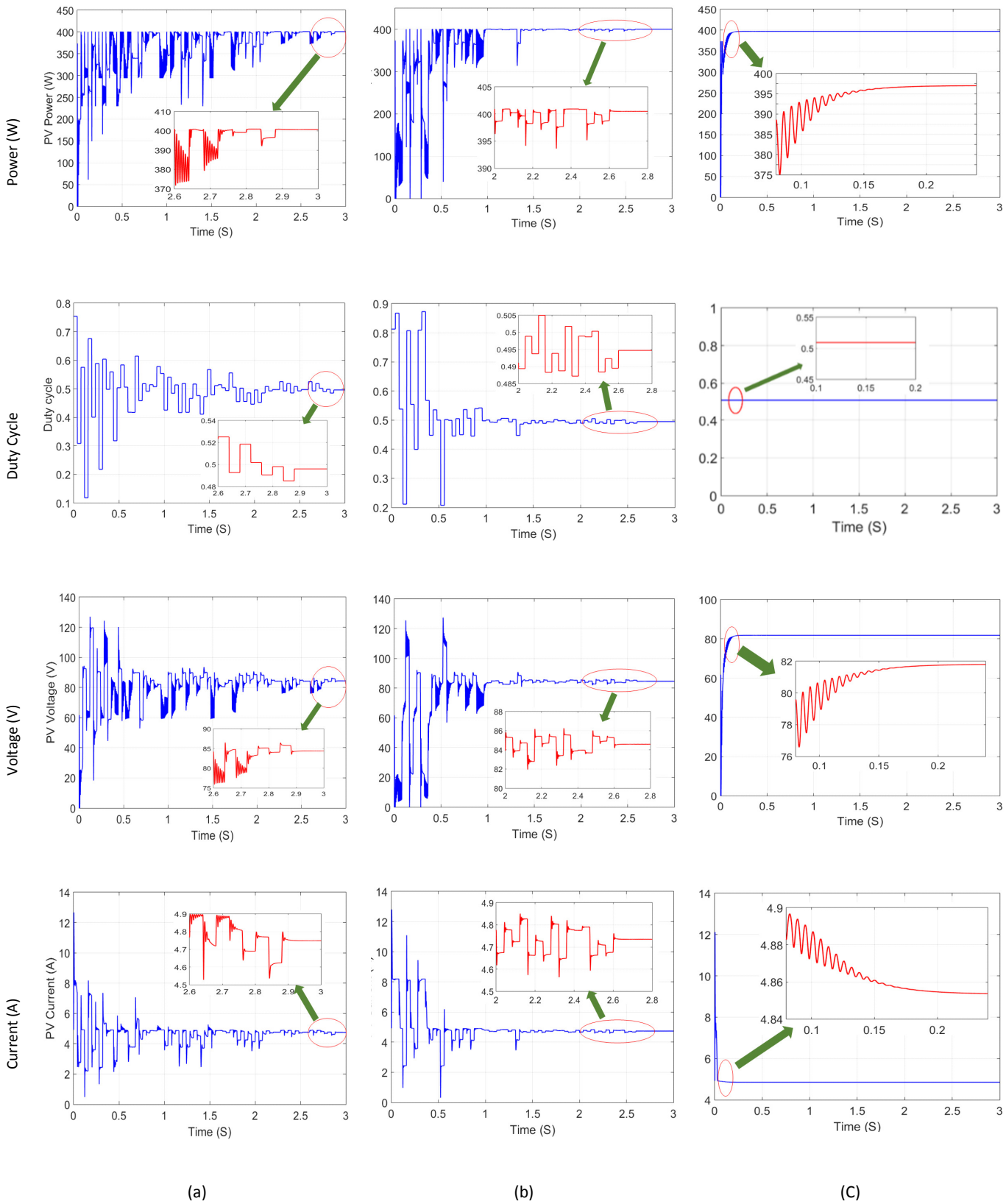


Fig. 10. MPP tracking under partial shading condition by (a) PSO method, (b) FA method, (c) proposed method

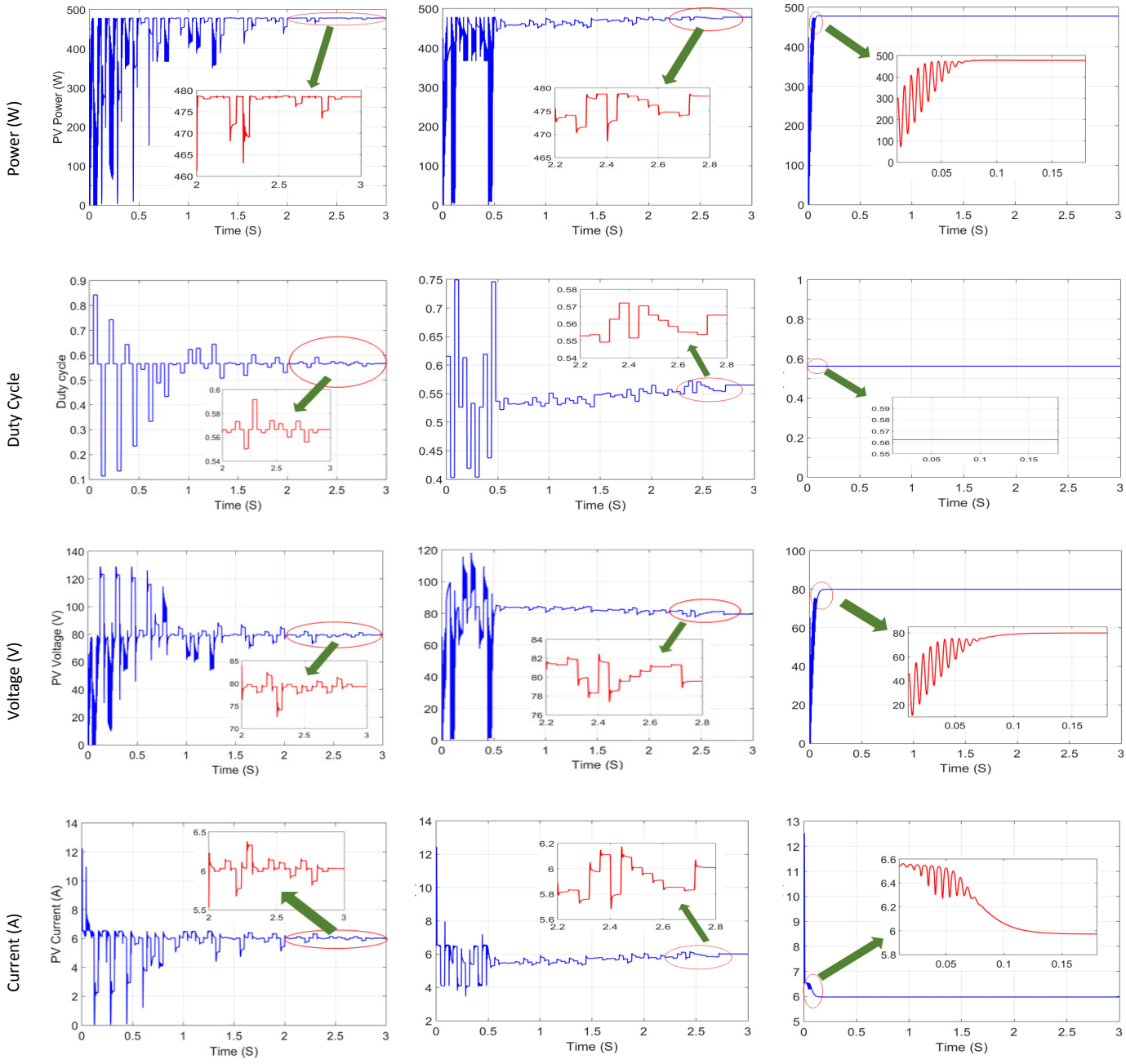


Fig. 11. MPP tracking under partial shading condition by (a) PSO method, (b) FA method, (c) proposed method

IX. Conclusion

In this paper, adaptive Neuro-fuzzy inference system based on PSO for maximum power point tracking controller is proposed under PSC for a PV system. The operation of PSO-ANFIS based MPPT controller is investigated under PSC. After proper training of the presented ANFIS model with PSO algorithm, the ANFIS-based MPPT controller successfully tracks the maximum available power under partial shading condition. The advantage of this hybrid method is the maximum value reached in a fast time with high gain. Therefore, the PSO-ANFIS based control is an efficient way for tracking the GMPP and in this hybrid method, oscillation around the MPP is zero. In large scale, the time of convergence is very important, therefore, this hybrid method is excellent for extracting the global MPP in a large photovoltaic power station.

Due to the nonlinear nature of our PSO-ANFIS approach, further studies need to comparison PSO-ANFIS with other nonlinear controllers like robust or sliding mode control techniques to improve the paper.

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