Journal of Solar Energy Research (JSER)

Journal homepage: www.jser.ut.ac.ir

Meta-Heuristic Optimization of the Neuro-Fuzzy MPPT Controller for PV Systems Under Partial Shading Conditions

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Received: 21-09-2022
Accepted: 19-11-2022

Abstract

The main challenge of photovoltaic (PV) systems is to extract the maximum power from the array, especially when it is partially shaded and subjected to variable weather conditions (sunshine and temperature). To address this challenge, this manuscript proposes a new method based on the Neuro-Fuzzy- Particle Swarm Optimization (NF-PSO) combination. The NF method is used here because it allows an automatic generation of fuzzy rules, and we inject the PSO meta-heuristic at the input of the Neuro-fuzzy to find an optimal gain allowing not only to convert the real input values into fuzzy quantities and to readjust the dynamics of the fuzzy rules by reducing the power losses (oscillations), this combination also provides a simple and robust MPPT scheme to manage efficiently the partial shading, and its convergence to the global maximum power point (GMPP) is independent of the initial conditions of the search process. To confirm the NF-PSO as a viable MPPT option a comprehensive evaluation is performed against two other methods, namely the cuckoo algorithm and the original Neuro-Fuzzy. The simulation results of the system confirmed the better performance of this method in terms of speed with a response time of 0.044s, efficiency with 99.94%, and especially in terms of oscillation reduction with practically a negligible oscillation rate compared to the NF and the Cuckoo algorithm.

Keywords: NF-PSO, Cuckoo, meta-heuristics, partial shading, GMPP

DOI:10.22059/jser.2022.349012.1255 DOR: 20.1001.1.25883097.2023.8.1.2.8

1. Introduction

With the increasing demand for energy in the world, and the associated polluting effects, mainly caused by the combustion of fossil fuels that leads to global warming, the use of energy produced by renewable sources is becoming promptly a solution for the global energy plan [1, 2]. Among the renewable energies we have solar energy, which is currently the easiest energy system to install, the most reliable, the most abundant, and most importantly, with the advances in technology, a significant reduction in the costs of the components of this energy [2]. Notwithstanding these advantages, solar power systems have a major issue of optimizing

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energy recovery, which is why these systems must include maximum power point tracking (MPPT) controllers. In addition to that the power generated by PV modules depends on environmental factors, namely solar radiation and atmospheric temperature [3]. All these drawbacks affect the characteristic curves of a PV system, because for a constant irradiance the characteristic curves of a PV system have only one maximum power point (MPP), while for a varied irradiance like the partial shading of some cells, these curves have several MPPs, among which the local points (LMPP) and the global point (GMPP). Therefore, an MPPT method must be able to extract the optimal power available under all operating conditions [4, 5]. This has motivated several researchers to focus on the development of MPPT methods capable of extracting the GMPP regardless of the operating conditions. In [2] Jubaer Ahmed *et al* present the Cuckoo Search (CS) algorithm; this algorithm is very efficient but has a convergence rate that is affected by the Levy flight and can be slower. Smail C. *et al* in [6], a new hybrid GWO-PSO method is proposed; in this hybridization, GWO search agents explore the search space deeply to avoid LMPPs, and thus can converge to GMPP and this exploration is controlled by the PSO algorithm, which in turn improves the solutions This exploration is controlled by the PSO algorithm, which in turn improves the obtained solutions as the process goes on in order to accelerate the convergence to GMPP in the exploitation phase. This method is efficient and converges quickly on the GMPP, but its concern is that it presents some oscillations in steady state which can lead to power losses. Similarly in [7], Makhloufi *et al* propose a global/local maximum power point tracker based on the logarithmic PSO for partially shaded PV systems. The authors of [8] recently improved the EGWO algorithm by adding a new wolf hopping procedure, they show that the developed EGWO can reduce the tracking time up to 45.5% and increase the dynamic efficiency by more than 2%, compared to the original GWO. In [9-10] the authors present an improved gray wolf algorithm; in [11] Eltamaly *et al* present a GWO hybridization with fuzzy logic controller (GWO-FLC). In [12, 13] respectively, perturb-and-observe (P & O), and incremental conductance (INC), presented known classical methods, the problem with these methods is that they are often trapped in a local maximum power point (LMPP) without reaching the GMPP. In [14-16], a modification of the P&O is performed and the defect of this method is that there is always the possibility that it is trapped in the LMPP. In [17] Claude Bertin N. *et al* made a comparative study between six MPPT methods, where they showed the superiority of fuzzy logic over the other five MPPT methods Fractional Short-Circuit Current (FSCC), Fractional Open-Circuit Voltage (FOCV), Perturb and Observe (P&O), Incremental Conductance (INC) and Hill Climbing (HC). In [18-20], respectively two modified methods Hill-Climbing (HC) and Incremental Conductance (INC) are presented, their disadvantage is that they require to perform several iterations. In [21], Özgür C. *et al* worked on a hybrid MPPT by combining Perturb and Observe and Artificial Neural Networks (P&O-RNA) methods; in [22] Alireza R. *et al* worked on a Fuzzy-Neural (FN) MPPT algorithm for PV. In [23] also Alireza Z. *et al* developed a partial shading algorithm for sensing that requires only the available measurements of row voltage and current. Ahmad R. *et al* in [24], they worked on Genetic Algorithm (GA) and PSO; all these hybridizations are known for their performance, but most of them still have steady state oscillations in the power output, which leads to power losses. In [25] Shams I. *et al* presented a modified butterfly optimization algorithm. In [26] Raeisi H. *et al* proposed a new set of relations to simulate the performance of a panel under partial shading conditions and a simulator is constructed accordingly. Mazaheri Salehi *et al* in [27] presented a state of the art on mppt methods and their applications. In [28] Venkateswari R. *et al* carried out a critical analysis of the factors improving the efficiency of a photovoltaic solar system. In [29] Oulcaid M. *et al* show that so far very little attention has been paid to the evaluation of MPPT methods, so they develop a method that can improve the performance of an MPPT. In [30] Syafaruddin *et al* a MPPT system is proposed for a partially shaded PV generator using neural networks and fuzzy logic with a polar information controller. The main drawback of this method is the high cost and complexity, due to the combination of two intelligent methods. The objective of this manuscript is to introduce a PSO algorithm that improves the performance of NF. PSO readjusts the dynamics of the fuzzy rules in order to accelerate the convergence to the desired performance. Moreover, this hybridization allows the GMPP to be reached in only a few steps, thus making the MPPT controller more efficient.

This paper includes the following parts: the second section of the paper will be dedicated to the modeling of the PV generator and the boost converter. A third section is reserved for the presentation of the method used. The different simulations made as well as the discussion of the results found will be the subject of the fourth section. In the fifth section a conclusion is presented.

2. Materials and methods

2.1. Materials

In this part we present our studied system which consists of a Photovoltaic (PV) panel, and a boost converter.

2.1.1. Photovoltaic panel model

The scientific community offers several models to model a photovoltaic panel. The most widely used model, for its simplicity and accuracy, is the one with one diode [31] (Figure 1).

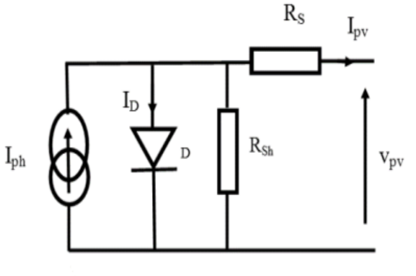

Figure 1. Single diode model of a PV cell

In this model, the photovoltaic cell is represented by a current source that generates a current Iph proportional to the solar radiation. The shunt resistance Rsh characterizes the leakage current at the junction and the resistance Rs represents the various contact and connection resistances. The current supplied by the cell Ipv is modeled by the following equation [32]:

$$I_{pv} = N_p I_{ph} - N_p I_0 \left[\exp\left(\frac{qV_{pv}}{N_s nKT}\right) - 1\right] \quad (1)$$

The inverse saturation current Io is:

$$Io = Ior \left(\frac{T}{Tr}\right)^3 \exp\left(\frac{qE_g}{nKT}\left(\frac{1}{Tr} - \frac{1}{T}\right)\right) \quad (2)$$

The inverse saturation current at Tr is:

$$Ior = \frac{I_{scr}}{exp\left(\frac{qV_{oc}}{nKTN_s}\right) - 1} \quad (3)$$

$$Iph = [I_{scr} + (K_i(T - Tr))] \frac{E}{100} \quad (4)$$

PV module power can therefore be obtained as follows:

$$P_{pv} = V_{pv} I_{pv} = N_p V_{pv} I_{ph} - V_{pv} N_p I_0 \left[\exp\left(\frac{qV_{pv}}{N_s nKT}\right) - 1\right] \quad (5)$$

Knowing that a PV generator has several PV modules associated in series and/or parallel, in our work, each PV generator consists of four Canadian Solar CS5C-80M modules connected in series. Figure 2 shows the four shaded PV arrays used in this paper. The electrical parameters under standard conditions (G= 1000W/m2, and T=25C°) of the PV module used for the simulations are presented in Table 1. Figure 3 shows the typical power-voltage and current-voltage curve for the shaded PV array.

Table 1. Parameters of PV

Parameters	Values
Maximum Power	80.15 W
Optimum operating voltage	17.5 V
Optimum operating current	4.58 A
Open circuit voltage	21.8 V
Schort-circuit current	4.97 A

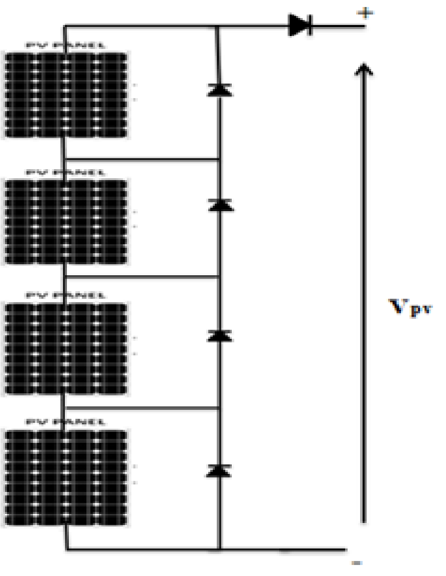

Figure 2. Structure of the PV array use

Table 2. Shading patterns used [5]

Pattern number	Irradiance variations (W/m2) for each sub-module				GMPP(W/m^2)
SP1	1000	1000	1000	1000	320.6
SP2	1000	500	1000	1000	236.7
SP3	1000	700	100	1000	183
SP4	1000	700	500	250	132

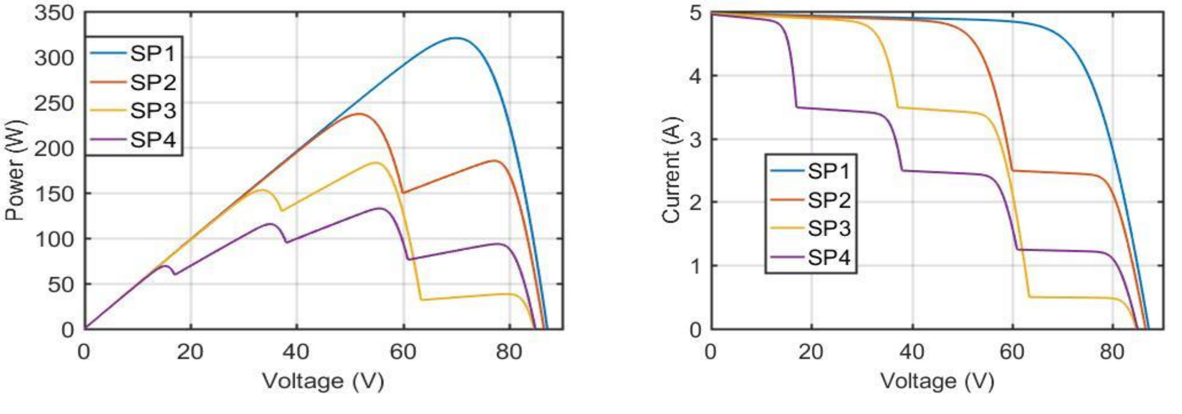

Figure 3. Power-Voltage and Current-Voltage characteristics of the models used

2.1.2. Boost converter

Static converters are essential parts of the variable speed wind power conversion system. In this document, a boost converter is used here. During operation of the chopper, the switch is closed with a closing time equal to (D.T), and it is opened in an opening time ((1-D) .T), with: T is the switching period and D the duty cycle of the switch (D∈ [0,1]).

$$V_{out} = \frac{V_{in}}{1-D} \quad (6)$$

Where:

V_{out}: Output voltage;

V_{in} : input voltage;

D: duty cycle.

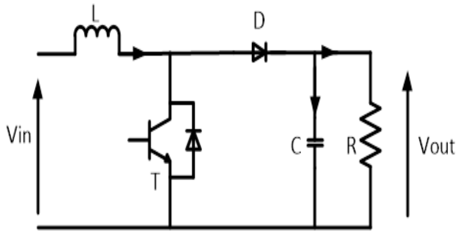

Figure 4. Boost converter

The converter parameters are given in table 3.

Table 3. Converter parameters

Parameters	Values
Load	30 Ω
Inductor	3 mH
Capacitor	100µF

2.2. Methods

In this section, we present the method used which consists of NF controller and the determination of offset gains by the PSO

2.2.1. NF Controller

The NF method developed here is based on the ANFIS (Adaptive Neuro-Fuzzy Inference System) model with the difference that our membership functions used here are triangular and not Gaussian. ANFIS implements a Takagi Sugeno type fuzzy inference system and has an architecture composed of five layers as shown in Figure 5 [33]. Our method contains two inputs: the error (E) and the variation of the error (ΔE), and a single output which is the variation of the duty cycle (D).

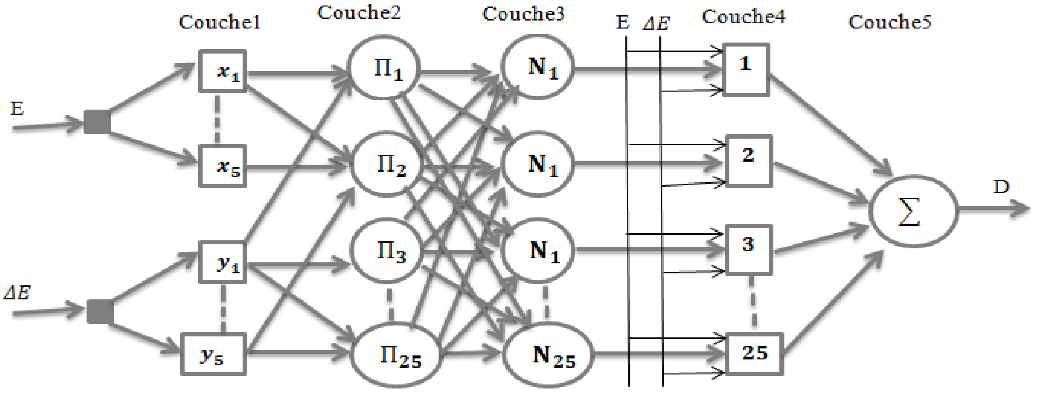

Figure 5. Architecture of ANFIS used.

The nodes of the input layer, whose number is equal to the number of linguistic terms (calculate the membership degrees of the input values by equations 7 and 8), forward the numerical data to the nodes of the second layer representing the fuzzy subsets that calculate the membership function value (equation 11). The nodes in the third layer perform the fuzzy operations (equation 12). The nodes of the fourth layer perform the operation of calculating the weighted consequent of the rule (equation 13) [33-34]. Finally the fifth layer (equation 14) performs the defuzzification operation.

$$o^1_{k_{x_i}} = \mu_{xi}(E)\ ,\quad k_{x_i}=1, 2, 3, 4, 5$$
(7)

$$x_i\ = MN, LN, Z,\ LP, MP$$

$$o^1_{k_{y_i}} = \mu_{yi}(\Delta E)\quad k_{y_i}=1,2, 3, 4, 5$$
(8)

$$y_i\ = MN, LN, Z,\ LP, MP$$

$$E = \frac{I(k)-I(k-1)}{V(k)-V(k-1)}$$

(9)

$$\Delta E = E(k) - E(k-1)$$

(10)

Where E and ΔE are respectively the inputs of nodes k_{x_i} and k_{y_i} of layer1. x_i and y_i are the linguistic terms associated with membership functions μ_{xi} and μ_{yi}. In our case the linguistic terms used are Most Negative (MN), Least Negative (LN), Zero (Z), Least Positive LP), and Most Positive (MP)

$$w_k = \mu_{Ai}(E).\mu_{Bi}(\Delta E)$$
(11)

Where w_k is the output of layer 2.

$$v_k = \frac{w_k}{w_1+w_2+w_3+\cdots w_{25}}$$
(12)

The membership functions obtained for each input are given below:

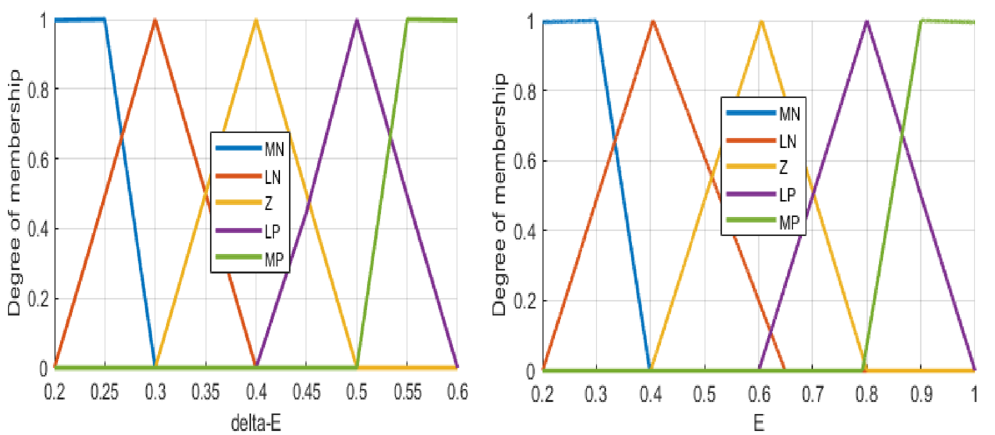

Figure 6. Membership functions of the inputs obtained.

$$o^4_k = v_k.f_k = v_k(a_k.E + b_k.\Delta E + m_k)$$
(13)

Where v_k is the output of layer 3, and (a_k, b_k, m_k) is the set of output parameters of rule k.

The last layer is obtained by:

$$o^5_k = \sum_{k=1}^{4} o^4_k.v_k$$
(14)

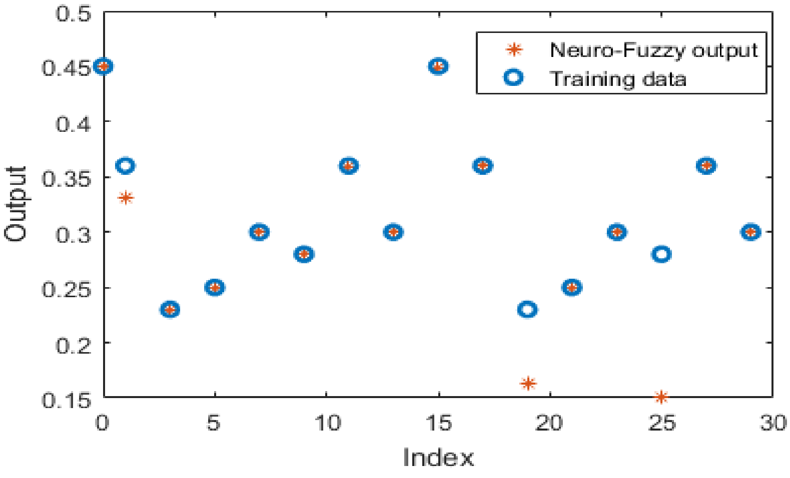

Figure 7. Training of the neuro-fuzzy network.

2.2.2. Determination of offset gains by the PSO

Particle swarm optimization (PSO) is an evolutionary computation technique developed by Eberhart and Kennedy (1995). This algorithm is inspired from the social behavior of animals, such as the flocking of birds and the schooling of fish, and the swarm theory. It has been proven to be efficient in solving optimization problem especially for non-linearity and non-differentiability, multiple optimum and high dimensionality [35-38]. The many applications of this algorithm in several fields and particularly in the field of technology shows its superiority compared with other stochastic methods such as the genetic algorithm, biogeography, and the colony of the ants [38]. It is an algorithm itératif. À each stage of calculation which the values of the individuals are compared according to the function objectifies to place the new guides then are select. During its execution, the algorithm passes by the stages grouped in the following flow chart:

The position and velocity of each particle are updated by applying the following equations:

$$V_{i+1} = w.V_i + c_1.r_1.(x_{ip} - x_i) + c_2.r_2.(x_g - x_i) \quad (15)$$

$$x_{i+1} = x_i + V_{i+1} \quad (16)$$

With:

$$w = w_{max} - iter.(w_{max} - w_{min})/iter\_max \quad (17)$$

x_{ip} and x_g respectively the best position of a particle i since the first iteration, and the best overall position of the swarm;

c_1 and c_2 are acceleration coefficients with a typical value of 2;

r_1 and r_2 are random numbers within [0, 1];

w is the coefficient of the inertia weight, iter is the present iteration number, max and min subtitles stand for maximum and minimum, respectively. In addition, “iter_max” have been selected such that the best fitness function with a suitable convergence capability can be achieved. This value is 1000 in the simulation. Supporting the above mentioned PSO technique, the procedure of the PSO can be described by the flowchart shown in Figure 8.

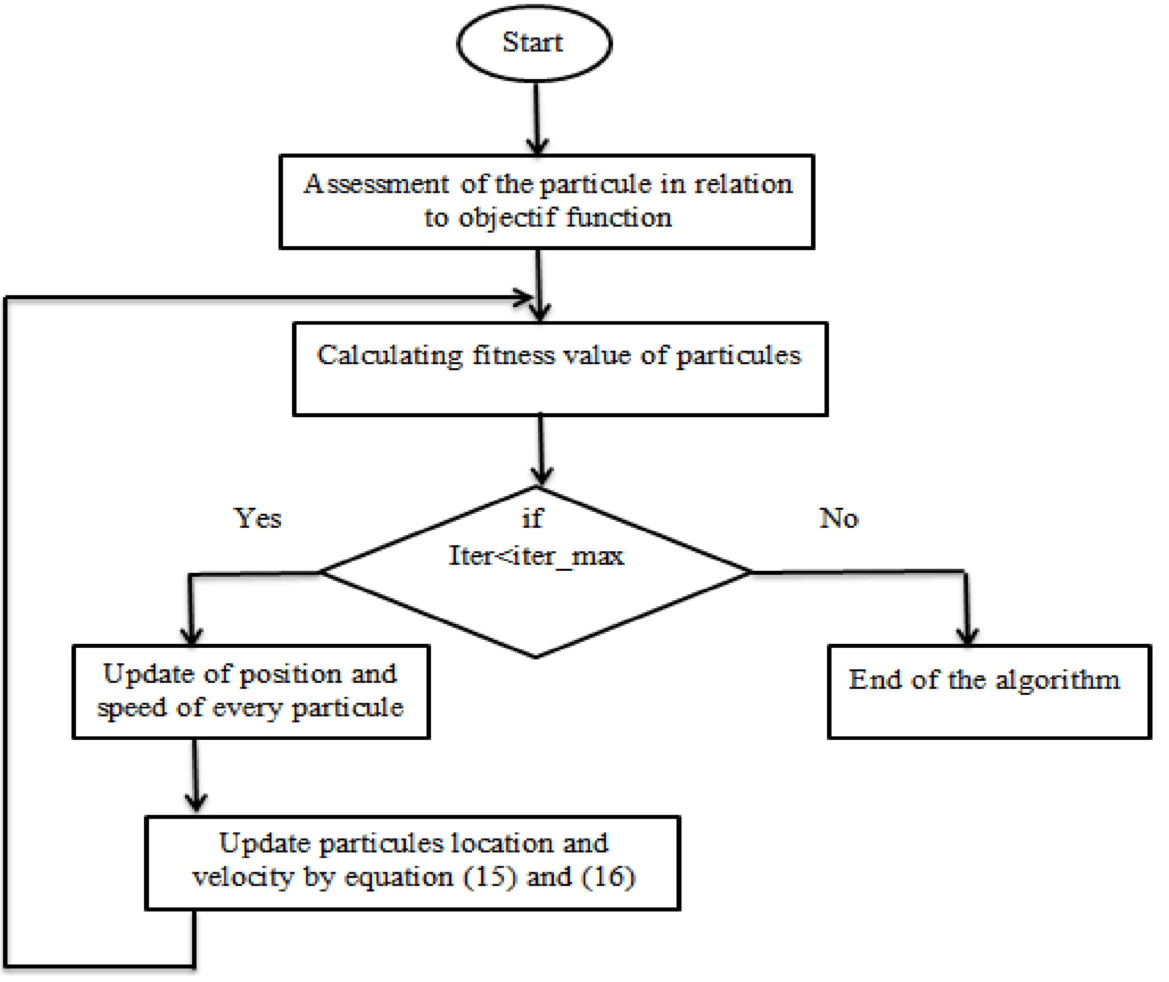

Figure 8. Flow chart of PSO algorithm

After realizing all the components of our method, we obtain the synoptic diagram of our method is presented in figure 9. We have combined Neuro-Fuzzy and PSO. Neuro-fuzzy is a hybrid artificial intelligence system that combines fuzzy logic and a learning algorithm derived from neural networks to determine the parameters of fuzzy sets and fuzzy rules from data; it is used because it can automatically generate the fuzzy rules. The PSO is a meta-heuristic; it is used here to determine the normalization gains, allowing to convert the real input values into fuzzy quantities, to readjust the dynamics of the fuzzy rules.

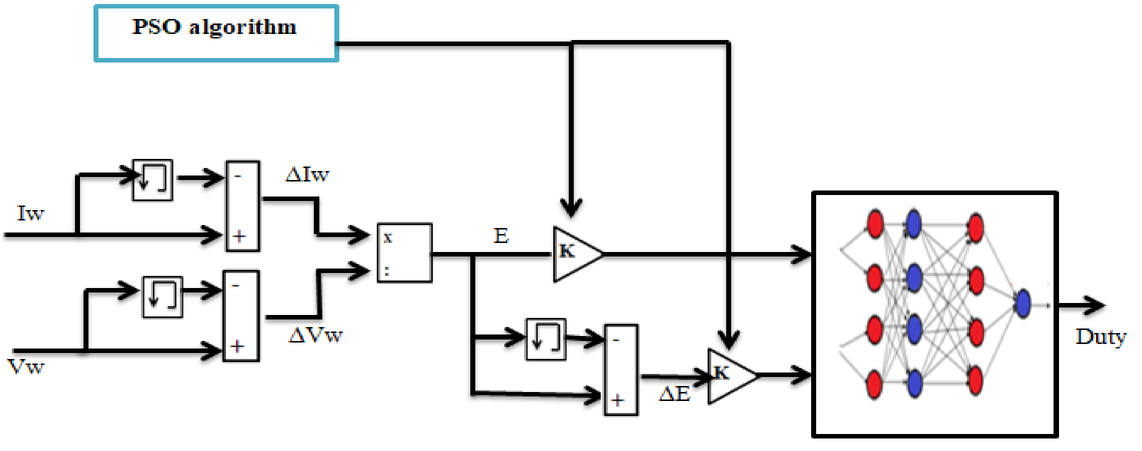

Figure 9. Design process of the hybrid method of MPPT developed

3. Results and discussion

In order to test the performance of the NF-PSO MPPT controller, we performed several simulation cases. To verify the theoretical study on the behavior of the MPPT controller a series of simulations was performed with Matlab/Simulink software and a comparison was made with the MPPT, NF and Cuckoo algorithm controllers

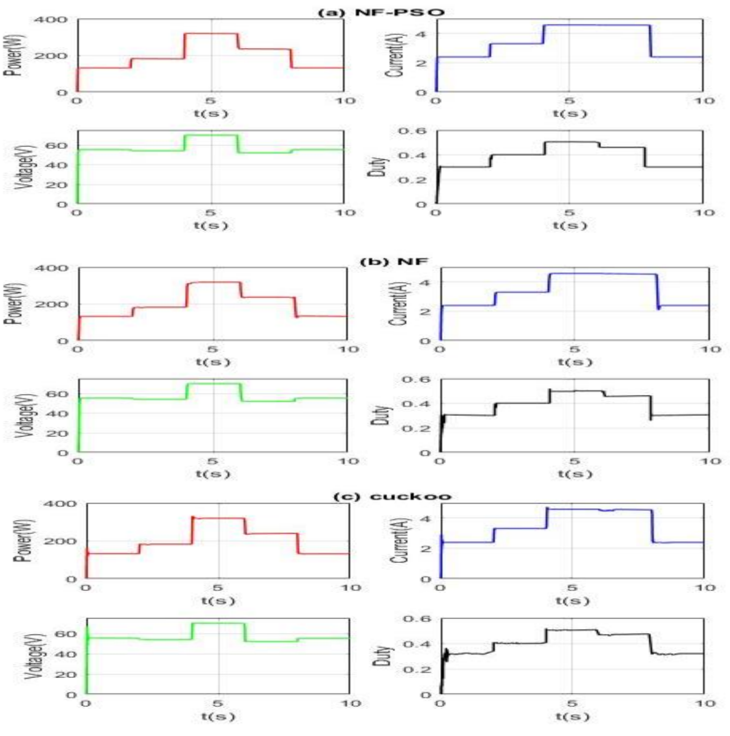

Figure 10. Curves obtained with different shading pattern variations using (a) NF-PSO, (b) NF, and (c) Cuckoo.

The simulation results in Figure 10 show the waveforms of power (red color), voltage (green color), current (blue color), and duty cycle (black color) obtained with the different methods. The results in Figure 10 confirm that the values of Ppv, Ipv, and Vpv reached the same values as those presented by the PV specifications in Table 1 and 2. To clearly see the effectiveness of our proposed MPPT method, we performed a co-simulation in Figure11.

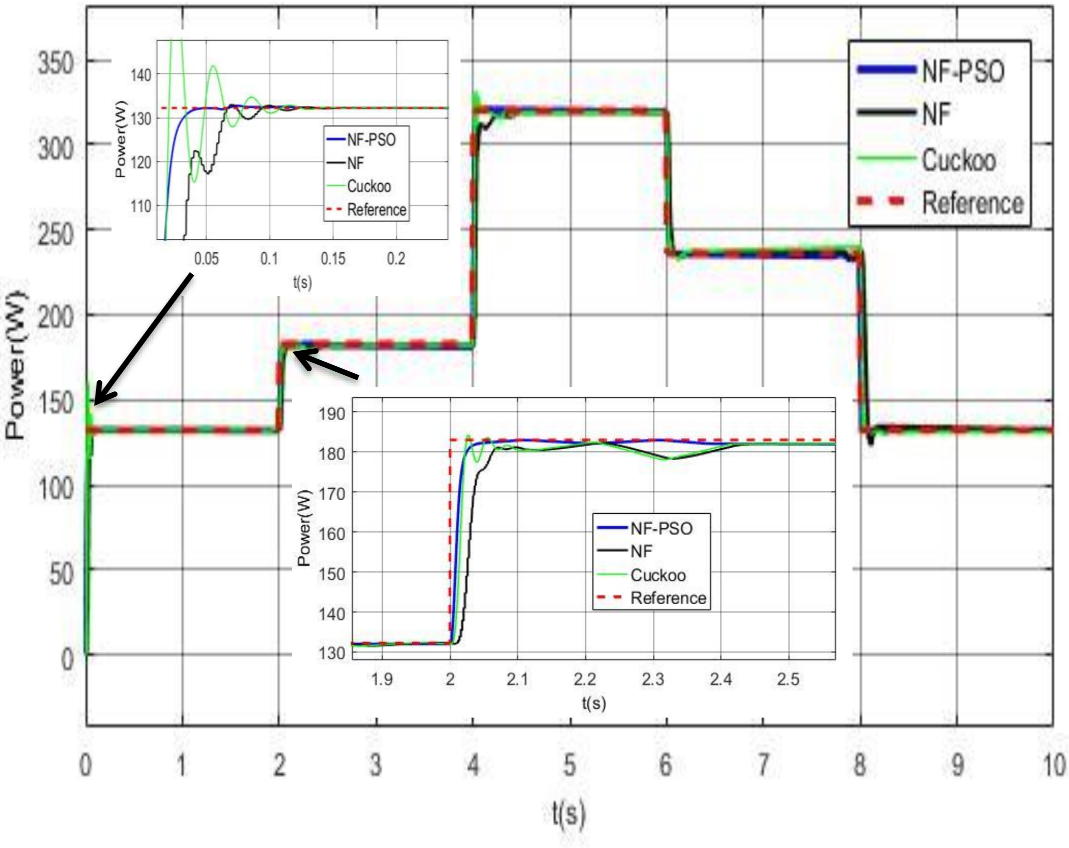

Figure 11. Co-simulation of the powers obtained with the different MPPT methods

For clarity, the performance of each method is summarized in Table 4. Although the numbers are not absolute, i.e., given in ranges, they can be considered reasonable indicators of the relative performance of these methods.

Table 4. Comparison of the different MPPT methods

Algorithm	Tracking efficiency (%)	Response time (s)	Steady state oscillation (%/W)
NF-PSO	99.94	0.044	0.0009
NF	98.90	0.138	0.0404
Cuckoo	98.96	0.155	0.041

We notice that for the initial power rise from zero to steady state, NF-PSO seems to be the fastest; In addition, Cuckoo shows larger fluctuations in the transient regime; in terms of tracking accuracy, our method is more efficient with 99.94% and a response time of 0.0009s.

4. Conclusion

In order to improve the efficiency of partially shaded PV systems, especially their energy production, we have developed an intelligent and simple method based on NF and PSO. This strategy allows to optimize at each moment the maximum power available in a PV array operating under partial shading. Thus we started with the presentation of the used equipment. Then we presented the NF-PSO controller. The simulation results under different scenarios of partial shading show the advantage of the adopted strategy because it is faster with a response time of 0.044s, more efficient with 99.94%, also allows the reduction of oscillation with a rate of oscillation of 0.0009 %/W. In our future work we will make a comparative study by optimizing the Neuro-Fuzzy with two other iterative algorithms among which: Grey Wolf Optimization (NF-GWO), Whale Optimization Algorithm (NF-WOA) and compare with Particle Swarm Optimization (NF-PSO).

5. Acknowledgements

The authors would like to thank the journal editor and all organizations that provided data for this research.

Nomenclature

n: Ideality factor of the PN junction

K= 1.3805 × 10-23 [J/K]: Boltzmann's constant

q = 1.6 × 10^{-19} [C]: Charge of the electrons

T[K]: Temperature of the cell

Eg = 1.12 [eV]: Band gap energy of the semiconductor used in the PV cell

Io: Inverse saturation current

Iph [A]: Photo-current

Ior: Inverse saturation current at Tr

Ipv[A]: Current of the PV module

Vpv[V]: Voltage of the PV module

Ppv[W]: Power of the PV module

Iscr [A]: Cell's short-circuit current at the reference irradiation and temperature

Np: Number of cells connected in parallel

Ns: Number of cells connected in series

Tr [K]: Reference temperature of the cell

Voc [V]: Open-circuit voltage

D: duty cycle

x_{ip} : Best position of the particle at iteration i

x_i : Position of the particle at iteration i

x_g : Best position of its neighborhood at iteration i

c_1 and c_2: Acceleration coefficients

r_1 and r_2: random numbers within [0, 1]

w : Coefficient of the mass of inertia

V_{i+1} and V_i: velocities of the particle at iteration i and i+1

μ_{xi} : Membership functions of the linguistic terms x_i

μ_{yi} : Membership functions of the linguistic terms y_i

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