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Comparative Study Between Three Methods for Optimizing the Power Produced from Photovoltaic Generator

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The technics of maximum power point tracking is widely used in solar photovoltaic energy and electric power system applications. Traditionally, these technics are based on conventional methods like perturb and observe and incremental conductance. In this work, three methods based on particle swarms optimization, incremental conductance and adaptive neuro fuzzy inference system are presented. A comparative study is carried out. The study of this paper shows that there is a limitation in the incremental conductance method. To overcome the shortage of this last method, particle swarms and adaptive neuro fuzzy optimization methods are used. The behaviors of the three methods are compared and evaluated in simulation under matlab/simulink. Results demonstrate that the adaptive neuro fuzzy inference system is effective for photovoltaic power optimization even for non-uniform climatic conditions. It has the best performances followed by the particle swarms method.

NOMENCLATURE

ANFIS	Adaptive Neuro Fuzzy Inference System	Ipv [A]	PV current
PVS	Photovoltaic Solar	RMSE [-]	Root Mean Square Error
MPP	Maximum Power Point	MSE [-]	Mean Square Error
InC	Incrementale Conductance	MAPE [%]	*Mean Absolute Percentage Error*
PI	Proportional Integral	AIC [-]	Akaike Information Criterion
PID	Proportional Integral Derivated	C1 [µF]	Boost input capacity
MsF	Membership	C2 [µF]	Boost output capacity
MPPT	MPP Tracking	f [kHz]	Frequency of switching the Mosfet
P&O	Perturb and Observ	α [-]	Duty cycle
PVM	Photovoltaic Module	L [mH]	Inductance
GA	Genetic Algorithm	Vpv [V]	PV voltage
FIS	Fuzzy Inference System	Pref [W]	Mesured Power
FL	Fuzzy Logic	Imax [A]	Current at Maximum Power
STC	Standard Test Condition	Vmax [V]	Voltage at Maximum Power
PWM	Pulse Width Modulation	Popt [W]	Optimized Power with ANFIS
PSO	Particle Swarm Optimization	m [-]	coefficient of inertia
ANN	Artificial Neural Network	Q_i [-]	acceleration coefficient
ACO	Ant Colony Optimization	r_i [-]	random number
AI	Artificial Intelligence	Ir [W/m²]	Irradiation
DC	Direct Current	T [°C]	Temperature
Ppv [W]	Photovoltaic power	F [W]	Fitness function
		R_{MPPT} [%]	MPPT efficiency

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1. Introduction

Today's world sees rapid industry development and this makes us more energy dependent. Fossil sources occupy the largest share of electricity production [1], [2]. The use of conventional energies (around 87% of global energy consumption) has an undesirable impact on the environment in terms of greenhouse gas (GHG) emissions and safety (nuclear accidents). 36.5 billion tons of CO_2 is emitted in 2020 [3]. To overcome these problems, it is necessary to resort to alternative energies [4–9]. Among them is Photovoltaic Modules (PVM) solar energy. Its annual growth rate over the last ten years is estimated at more than 40% [10]. Despite their low efficiency, PVM still have a high price. To get around this efficiency problem, techniques for optimizing the power generated by the PVM are proposed [11], [12–16]. This technique, makes it possible to run after the maximum power that the module is capable of supplying [17]. The generated power depends on weather conditions irradiation and temperature [18–20]. Under these latter conditions, the electrical characteristics of the PVM have only one optimal. So not too much trouble for the technique to converge the system to the MPP. Under non-uniform conditions of irradiation and temperature, the electrical characteristics of the PVM present several optimal points. The algorithm used must therefore be able to distinguish the global optimum from the local optima [21]. It therefore requires a sophisticated algorithm which will be able to make a global exploration of the search space in order to make the system converge towards the global MPP [22].

The most used of the classical methods are the P&O method and the InC method [5], [23–26]. Several researchers have used the P&O technique in their work. This method, based on the voltage disturbance and the observation of the variation of the power, is very widespread in the literature. Originally, it was designed to exceed the limits of other types of deterministic controls such as Hill Climbing, Open Circuit Voltage Fraction, etc. It also presents limits linked mainly to the response time and the numerous oscillations around the MPP. The InC method is proposed [3, 18, 25]. In [27], according to the results, the incremental conductance algorithm performs better than the perturb and observe algorithm. To overcome the problems linked to the limits of the methods mentioned above under variable of climatic conditions, Soft-Computing methods based on Meta-heuristic algorithms and Artificial Intelligence (AI) algorithms are proposed. MPPT techniques are based almost exclusively on these techniques. They are very numerous and diverse. They range from Evolutionary Algorithms (Genetic Algorithm), Meta-heuristic algorithms (Optimization by Particle Swarms) and AI algorithms (Artificial Neural Networks, Fuzzy Logic, ANFIS) [21], [10, 11, 28–31].

Artificial Neural Networks (ANN) have been used in several works to optimize the power delivered by a PVM. Its operating principle is inspired by that of the human brain. With their great generalization capacity, they are used for solving complex optimization problems [32], [33]. This is the case in [34] where MPPT method based on ANN is compared to MPPT method based on P&O. The results show that ANN method is more robust than P&O method, regardless of the operating conditions of the PVM. Its limits lie in its lack of interpretation and the difficulty of determining the appropriate number of Layer/Neurons. In addition, these latter limits represent strong points for the Fuzzy Logic (FL) algorithm. The interpretive inability encountered with ANN is resolved by the use of LF. It uses its linguistic variables to overcome this problem [35], [36]. Using the classical logic process, it has facility for extension and interaction [37], [38].

FL also has limits which can be circumvented. Which makes them two complementary techniques and the combination of which gives the Neuro-Fuzzy technique including ANFIS.

In reference [39], two ANFIS models are proposed for grid-connected PV system current injection and battery control. The results show that the proposed the models offered allow the battery charging/discharging process to be supervised and at the same time injecting good quality energy into the grid.

In [40] two MPPT techniques based on ANFIS and P&O are compared. Comparison results show that the technique based on the ANFIS algorithm is more robust.

In [5] Five MPPT techniques are proposed. A comparative study is carried out between them. The simulation results show that the best performances are obtain with ANFIS with an efficiency of 99.4%, against 98.1% and 97.5% respectively for FL and P&O.

The power optimization technique using the ANFIS algorithm is more robust than other techniques such as FL, ANN, InC and P&O. It overcomes the problems encountered with ANN and FL as it is a complementary technique linking the two [28, 38, 41].

Other types of techniques based on algorithms whose principle is inspired by the evolution of nature are presented in the literature [11, 42]. Among them there are methods based on the Particle Swarms Optimization (PSO) algorithm [43, 44].

In [45], a comparative study between techniques using PSO, InC and P&O is carried out. Results of simulation show that the PSO technique is the more robust with the most low response time compared to the two others techniques (InC and P&O). In [46], authors proposed a comparative study between PSO, P&O and FL techniques to optimize the MPP of the PVM. Results show that the MPPT technique based on PSO outperformed FL and P&O techniques.

The work in this paper is consisting to do a comparative study between MPPT techniques based on ANFIS, PSO and InC algorithms put under the same conditions in order to indicate the most efficient and the most robust for power optimization problems. A validation of these three commands is done using an experimental database. The scientific contribution of this paper is to design a MPPT technique based on ANFIS algorithm using database collected to solar power plant in tropical zone.

The rest of the article is organized as follows. Section II presents the MPPT proposed approaches. Section III the proposed approach for the MPPT techniques. Section IV presents the results of simulations and discussions. Finally, a conclusion is made in section V.

2. Proposed approach

In solar PV system, power delivered by the PVM is not always the maximum. This is due to the phenomenon of intermittence. As a result, the operating point of the PVM is not even the MPP. It so requires a technique which is able to extract the MPP of the PVM. This technique, called MPPT optimizes the power through the generation of a duty cycle for controlling the static converter.

The block diagram of the studied system is given in Figure 1.

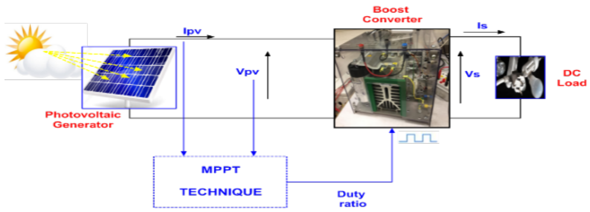


Figure 1: Schematic diagram of the MPPT technique

2.1. Incremental Conductance method based MPPT

The InC algorithm is among the most efficient of the classical algorithms. It is based on the cycle of the change in pressure to the change in voltage of the PVM (equation 1). At MPP, the slope is zero. The tracking is done according to the position of the operational point (or slope) (dPpv / dVpv) relative to the MPP (equation (3)). The latter depends on the value of the conductance (Ipv / Vpv). The sign of the latter indicates whether the MPP is reached or not (equation (2)). It is compared to its increment. This amounts to saying that the MPP depends on the voltage variation and that of the current [18,26],[47,48]. Thus, the algorithm increments or decrements the duty cycle of the static converter to continue the MPP. The flowchart is shown in Figure 2.

$$\frac{dP_{pv}}{dV_{pv}} = I_{pv} + V_{pv}\frac{dI_{pv}}{dV_{pv}} \quad (1)$$

The MPP is found when:

$$\frac{dP_{pv}}{dV_{pv}} = 0 \rightarrow \frac{dI_{pv}}{dV_{pv}} = -\frac{I_{pv}}{V_{pv}} \quad (2)$$

The sign of the slope indicates the direction of evolution of the MPP according to equation (3).

$$\begin{aligned} &\frac{dP_{pv}}{dV_{pv}} > 0, left\ side\ of\ MPP \\ &\frac{dP_{pv}}{dV_{pv}} < 0, for\ V_{pv} > V_{MPP}, right\ side\ of\ MPP \\ &\frac{dP_{pv}}{dV_{pv}} = 0, on\ the\ MPP \end{aligned} \quad (3)$$

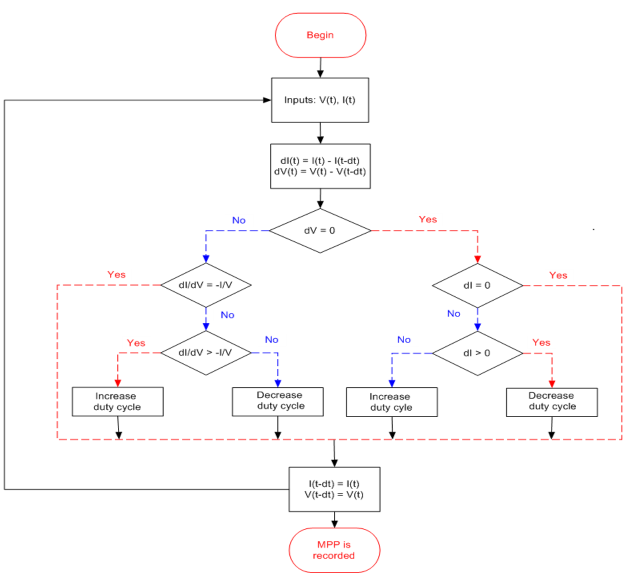


Figure 2: Incremental Conductance flowchart based MPPT

2.2. PSO method based MPPT

Particle Swarm Optimization is an evolutionary meta-heuristic approach. It is used for solving optimization problems. Its principle is based on the behavior of particles (individuals) [49]. In this paper we use a swarm of birds (Figure 3). In this type of swarm, collective intelligence is involved. Particles converge towards those with the best performance [50].

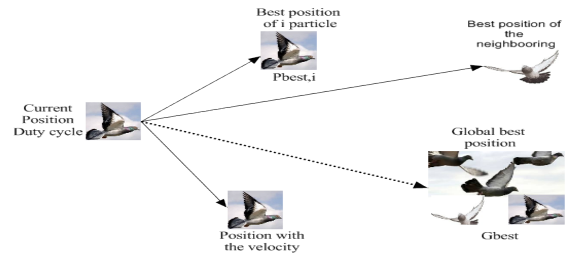


Figure 3: Movement of a particle in the swarm of birds

The duty cycle α of the boost converter represents the particles. Velocity and position are initialized to begin and the movement of the particles are described by equations (4) and (5). For evaluating the best position of the particles, fitness function is calculated according to the equation (6). Vpv and Ipv are calculated for each particle i with a fixed position in the search space [αmin, αmax]. The algorithm converges the system towards the global optimum. For this the duty cycle is initiated. This ratio, depending on P_{besti} and G_{best}, is corrected if it deviates from the best overall duty cycle as in the principle of Figure 3. The particles are then evaluated in terms of position and velocity according to equations (7) and (8). Updates are made to re-evaluate the optimum duty cycle for controlling the boost converter. Table 1 gives the parameters of the PSO. These parameters are defined for the PSO simulations. The flowchart is shown in Figure 4.

Table 1: PSO implementation parameters

Parameters	Values
Q_1	1,2000
Q_2	2
m	0,4000
Iterations	25

$$\alpha_i^{t+1} = \alpha_i^t + \left(\frac{d\alpha}{dt}\right)_i^{t+1} \quad (4)$$

$$\left(\frac{d\alpha}{dt}\right)_i^{t+1} = w\left(\frac{d\alpha}{dt}\right)_i^t + Q_1 r_1 (P_{besti} - \alpha_i^t) + Q_2 r_2 (G_{best} - \alpha_i^t) \quad (5)$$

$$F_i(\alpha^t) = P_{pv,i}^t \quad (6)$$

$$P_{besti} = \alpha_i^t \qquad if \quad F_i(\alpha^t) \geq F_i(P_{besti}) \quad (7)$$

$$G_{best} = \max(P_{besti}) \quad (8)$$

F is the fitness function,

α is the duty cycle of the boost converter,

t is the time of simulation

r_1 and r_2: uniformly pull in [0,1].

w: coefficient of inertia.

Qi: acceleration coefficient

P_{best_i} is the personal best position of particle *i*

G_{best} is the best position of the particles in the entire population.The MPPT technique based on PSO algorithm is described by equations (4) to (8).

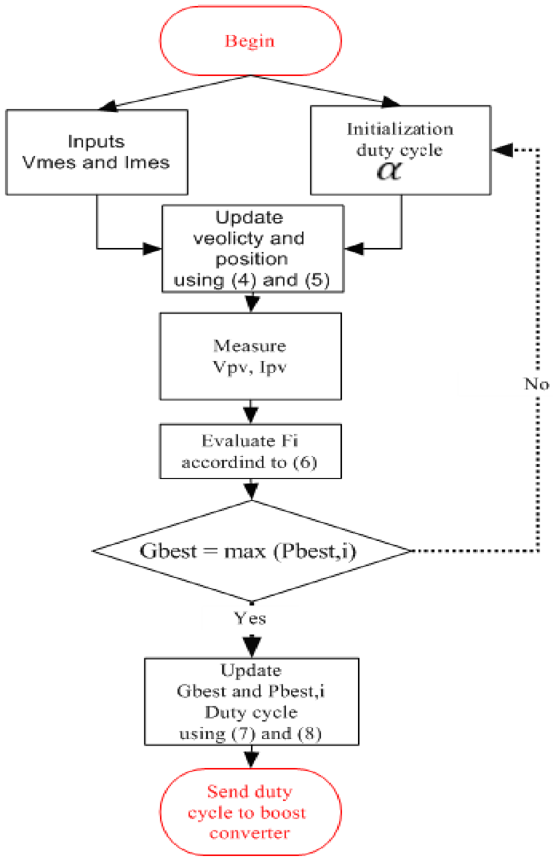


Figure 4: PSO flowchart based MPPT

2.3. ANFIS method based MPPT

ANFIS is an adaptive neuro-fuzzy inference system that has five layers in its structure. These layers refine the fuzzy rules already established by human experts and readjust the overlap between the different fuzzy subsets [51–54].

The neural structure replaces the hidden layers with fuzzy rules. This further simplifies learning and interpreting the results obtained. The structure proposed in this work receives the voltage and current from the PVM as inputs and supplies the output with an optimal power comparable to that of the PVM.

The architecture of the MPPT ANFIS technique is given in Figure 5.

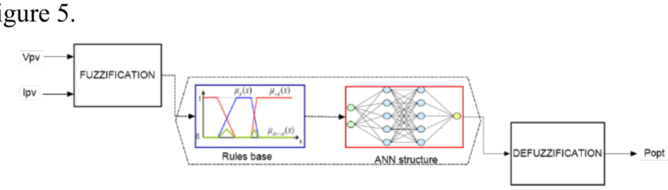


Figure 5. Architecture of the MPPT ANFIS technique

Layer 1: Each Neuron calculates the degree of truth of a fuzzy subset by its transfer function. It is called fuzzification layer. Numeric input values are converted to linguistic variables (equations 9 and 10) for high interpretability.

$$O_i^1 = \begin{cases} \mu_{Ai}(V_{pv}) & for \quad i = 1,2 \\ \mu_{B(i-2)}(I_{pv}) & for \ i = 3,4 \end{cases} \tag{9}$$

With:

$$\mu_{Ai}(V_{pv}) = exp\left[-\left(\frac{Vpv-a_i}{b_i}\right)^2\right] \tag{10}$$

Layer 2: It calculates the degree of activation of antecedents (premises). This is the layer of fuzzy rules (equation 11).

$$w_i = \mu_{Ai}(V_{pv}) * \mu_{Bi}(I_{pv}) \tag{11}$$

Layer 3: It normalizes the degree of activation of the rules: it is the normalization layer (equation 12).

$$G_i = \frac{w_i}{w1+w2} \tag{12}$$

Layer 4: It determines the parameters of the consequence of the fuzzy rules. Previous linguistic variables will be translated again into numeric values before being sent to the last layer. It is defuzzification (equation13).

$$O_i^4 = \frac{\sum_i w_i f_i}{\sum_i w_i} \tag{13}$$

Layer 5: It calculates the overall output of the system: it is the output layer. Equation (14) gives the expression of the optimal power generated by the PVM with the ANFIS technique for three fuzzy subsets.

$$P_{opt} = \sum_{i=1}^{nit}\left\{P_{opt,i}\cdot\frac{e^{-\left[\left(\frac{Vpv-a_i}{b_i}\right)^2+\left(\frac{Ipv-a_{i-2}}{b_{i-2}}\right)^2\right]}}{\sum_{i=1}^{3}\left(e^{-\left[\left(\frac{Vpv-a_i}{b_i}\right)^2+\left(\frac{Ipv-a_{i-2}}{b_{i-2}}\right)^2\right]}\right)}\right\} \tag{14}$$

where ai and bi are the parameters of the premise of the MsF, and Popt is the optimal power delivered by the ANFIS controller.

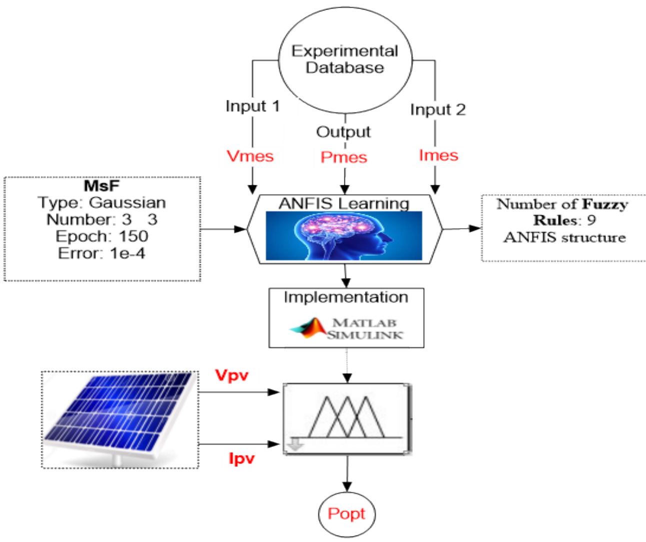
With nit the number of iterations when learning the ANFIS algorithm. Figure 6 gives the flowchart of the technique implemented in simulink and table 2 the learning parameters. The matlab "anfisedit" interface is used for learning the MPPT ANFIS command with a real database made up of two inputs (Vpv and Ipv) and one output. The number and type of MsF are fixed as well as the number of iterations. The hybrid learning algorithm is used and an error tolerance of 1e-4 is arbitrarily set.

Table 2 : ANFIS learning parameters

Parameters	Values
FIS	Takagui-Sugeno
MsF (Type)	Gaussian
MsF (Number)	3 3
Fuzzy rules	9
Epochs	10
RMSE (Training)	0.000123
RMSE (Checking)	0.002012

3. Simulation Results and Discussions

In this section, the results of simulations under matlab/simulink are presented. These simulations are performed with a real database. The latter first allowed to digitally characterize the PVM before being used for the validation of the three techniques presented in previous sections. The PVM consists of two PVs in series. The photovoltaic platform shown in Figure 7 is used in this study. The characteristics of the photovoltaic system being identified (Sharp Module) are given in Table 3. This platform is located at the Polytechnic high school of Cheikh Anta Diop University, Dakar, Senegal. This country is a tropical zone with an adequate rate of sunshine (5.7 kWh/m²/day) for the installation of solar PV plant.



ANFIS flowchart based MPPT

Table 3: Characteristics of the PV

Parameters	Values
V_{CO}	20 V
V_{MPP}	16 V
I_{SC}	2.5600 A
I_{MPP}	2.4300 A
P_{MPP}	38.3800 W

Experimental bench

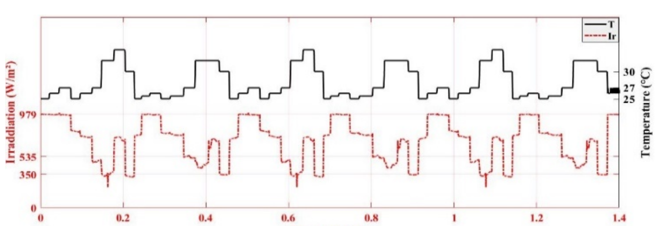


Figure 8: Experimental database of irradiation and temperature

In this subsection, the results obtained by the three MPPT methods are visualized. A comparative study is then carried out in order to detect the best order. Table 4 shows the simulation parameters and the Figure 9 gives the Simulink model.

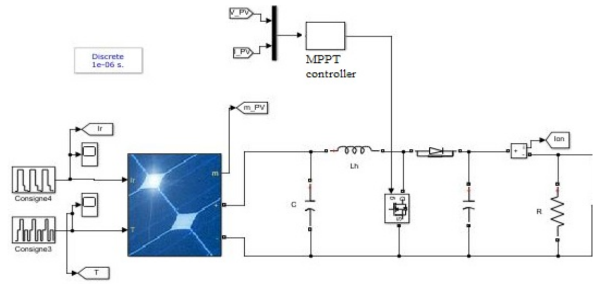


Figure 9: System simulated under matlab/simulink

Table 4: System electrical parameters

Parameters	Values
Input capacity	200.6230 µF
Inductance	1 mH
Output capacity	480 µF
Load	34.8000 Ω
Switching frequence	15 kHz

The RMSE and MAPE criteria are evaluated at the level of equations (17) and (18). They characterize the difference between the power generated by the control and the real power (Figure 14). The efficiency of the MPPT technique is given by equation (19).

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(P_{ref} - P_{pv_i}\right)^2} \quad (17)$$

$$MAPE = 100 * \frac{1}{n}\sum_{i=1}^{n}\left|\frac{P_{ref}-P_{pv_i}}{P_{ref}}\right| \quad (18)$$

$$E_{MPPT}(\%) = \frac{P_{PV,MPPT}}{P_{Mesure}} \quad (19)$$

Figure 12 and Figure 13 respectively show the currents and voltages of the PVM obtained with the different MPPT techniques. They follow changes in weather conditions (Figure 8) which have a considerable influence on the point of operation of the PVM. In Figure 12, we see that the currents obtained with the PSO and ANFIS techniques are almost identical while that obtained with the InC technique is much lower. The opposite phenomenon is observed on the voltage curves in Figure 13. Indeed, the MPPT InC technique pursues the MPP first by comparing the voltage and the current of the PVM. Then, as the principle is based on conductance, the control performs compensation to achieve the desired MPP. Only, as it evaluates each time the variation of the power compared to the voltage, it often diverges with an enormous overshoot of the voltage. In addition, being also a static control, it takes a relatively long time to adapt to a climatic disturbance. This induces a small and slow variation in its duty cycle (Figure 10). As a result, it has difficulty extracting maximum power for these non-uniform irradiation and temperature conditions. Figure 11 represents the power curves of the three controls with respect to the measured power (reference). It reveals overruns for the PSO and InC techniques while the ANFIS technique follows the set-point with an accuracy of 93.46%.

Furthermore, the performance criteria presented in Figure 14 show that the ANFIS technique is better with an extremely low RMSE (0.0194), no overshoot (D=0) and a higher efficiency of around 99.9984%. It is followed by the PSO technique with a RMSE of 1.7235 and an efficiency of 94.8748%.

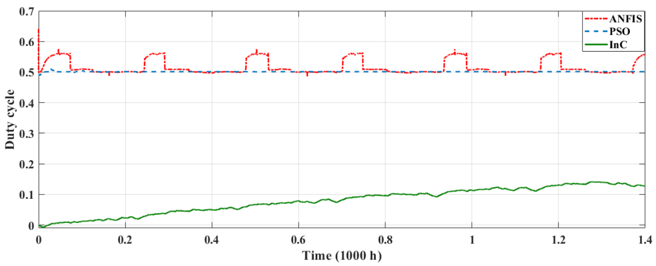


Figure 10: Variation in the duty cycle

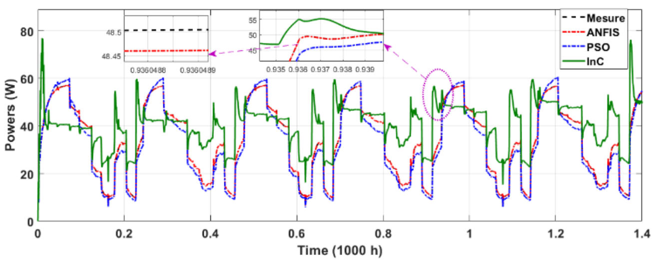


Figure 11: PVM powers

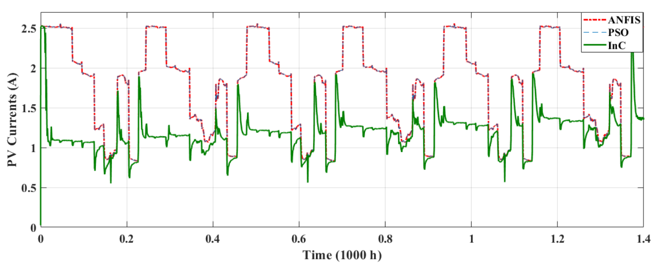


Figure 12: Currents of the PVM

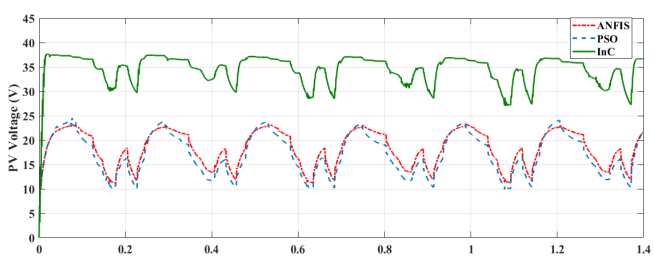


Figure 13: PVM voltages

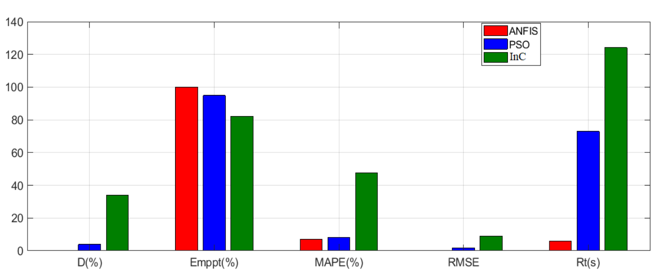


Figure 14: MPPT controller's performance parameters

These results corroborate those found in the literature which highlight the oscillating nature of the power obtained with the InC technique due to their inability to detect with precision the overall maximum in a situation of non-uniform climatic conditions [3]. They also confirm the results presented in [38] where the authors made a comparison between ANFIS and InC.

4. Conclusion

MPPT techniques are used to optimize power generated by PVM. In this work, a comparative studied between PSO, ANFIS and InC is done. An experimental validation of these MPPT techniques is also done using real database. The simulation results show that the MPPT technique based on ANFIS algorithm has the best performances. However, if we have to choose between these methods, the two parameters to consider are the complexity of the implementation and the performance of the method. For the first criterion, the choice will be relatively focused on the InC because of its great ease of implementation. For the second criterion, ANFIS will be chosen because of its best performance in terms of response time and accuracy. But we can conclude that the ANFIS and PSO methods give good results compared to the InC method.

Conflict of Interest

The authors declared that there is no conflict of interest.

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