Photovoltaic power optimization based on artificial intelligence method

El Hadji Mbaye Ndiaye [1], Alphousseyni Ndiaye [1,2], Mactar Faye [1,2]

[1] Research team energetic system and efficiency, Alioune Diop University of Bambey, BP 30.

[2] Laboratory of Water, Energy, Environment and Industrial Processes, ESP, S-10700, Dakar-Fann, Senegal.

elhadjimbaye.ndiaye@uadb.edu.sn, alphousseyni.ndiaye@uadb.edu.sn, mactar.faye@uadb.edu.sn

Abstract

This paper presents a new hybrid approach based on the combination of Adaptive Neuro Fuzzy Inference System (ANFIS) and Genetic Algorithm (GA) for the continuation of the Maximum Power Point (MPP) of a Photovoltaic Generator (PVG). PVG considered too dependent on the climatic conditions, need tools allowing them to deliver at any moment the maximum of available power. For this purpose, a combination between GA and ANFIS is performed for better optimization of the power of the PVG. The GA is used in this work to optimize the choice of membership functions (MsF) of ANFIS to optimize photovoltaic power. This proposed method outperforms non-optimized ANFIS methods found in the literature with a shorter response time (8.24 ms versus 83 ms for a non-optimized ANFIS controller). An experimental validation of the proposed methods is also carried out.

Keywords: *Power Optimization, ANFIS, GA, MPPT, Artificial Intelligence*

1. Introduction

High energy consumption has become a major concern for the energy sector [1], [2]. Most of this consumption is of fossil origin. The use of conventional energies has an undesirable impact on the environment in terms of greenhouse gas (GHG) emissions and safety (nuclear accidents). To overcome these problems, it is necessary to resort to alternative energies [3]. Among them is photovoltaic solar energy. Its annual growth rate over the last ten years is estimated at more than 40% [4]. The major drawbacks of solar photovoltaic (PV) energy are the price of the generator which remains high and the energy efficiency relatively low. To overcome these problems, two ways are often used: to increase the energy efficiency by adopting technologies of very high level or to maximize the power delivered by the Photovoltaic Generator (PVG) [5]. To optimize the power delivered by the PVG, a Maximum Power Point Tracking (MPPT) command is used [6], [7]. There are several MPPT techniques that can be grouped into three categories: classical methods, Artificial Intelligence (AI) based methods, and evolutionary methods. These techniques vary in complexity, speed, robustness, and stability. They aim to reduce the response time and improve the dynamic response of the system [8], [9].
Perturb and Observ (P&O) and Incremental Conductance (InC) methods are the most used among the classical methods. This is largely due to their simplicity of implementation and the non-complexity of their algorithm [9]. The recurring problem with P&O is the permanent disruption of voltage that negatively impacts the power of the system [10]. These power losses pass through the multiple oscillations around the MPP. To solve this problem, the method based on the increment of conductance has been proposed. It has fewer oscillations around the MPP, Perturb and Observ (P&O) and Incremental Conductance (InC) methods are the most used among the classical methods. This is largely due to their simplicity of implementation and the non-complexity of their algorithm [9]. The recurring problem with P&O is the permanent disruption of voltage that negatively impacts the power of the system [10]. These power losses pass through the multiple oscillations around the MPP. To solve this problem, the method based on the increment of

conductance has been proposed. It has fewer oscillations around the MPP, but their performance remains almost identical [11] because of its relatively high response time. These methods are thus easy to implement, but have high costs and control complexity [10]. The AI methods were then introduced. As part of the control of PV systems, Fuzzy Logic (FL), Artificial Neural Networks (ANN) and Adaptive Neuro Fuzzy Inference System (ANFIS) are the most widespread. ANN have a very high learning ability [11], [12]. FL is often used in complex systems to overcome the limitations of conventional mathematical tools. However, it has limits including the accuracy of information expressed in natural language and thus a certain margin of instability. To overcome these drawbacks, the current trend is to integrate these tools into hybrid architectures to take advantage of the advantages of FL and ANN [13]. Thus, the ANFIS method has been proposed [14], [9].

In [15], ANFIS is used to control a boost converter. The method used consists of simulating with an insolation of 500 W/m² and one of 600 W/m². The comparison of the results shows that the power of the PVG increases by 83% for an insolation of 500 W/m² and 97% for an insolation of 600 W/m² with the MPPT command type ANFIS.

In reference [9], the ANFIS model is presented as part of the continuation of the MPP of a PV pumping system. An evaluation of the system with or without ANFIS is performed. The results show that the ANFIS command increases PVG power from 20.1% to 82.7%.

El Hadji and al [16] used ANFIS to extract the maximum power available across the PVG. The results obtained show the robustness and performance of the ANFIS command compared to the InC with response times of 2.4 ms and 401 ms respectively.

In reference [17], ANFIS is proposed for controlling the charging and discharging of a battery for a PV system connected to the three-phase grid. The first model is used to control the charging process of the battery while the second manages the injection to the grid. The results show that the control manages the charge-discharge cycle of the battery with successive stages of connection-disconnections of the load and regulates the injection to the grid.

ANFIS is compared with the MPPT P&O command in [18]. Used to extract the maximum power from a PV system, the results showed that under varying climatic conditions, the best performances are obtained with ANFIS. The latter has fewer oscillations than P&O and its convergence speed is smaller.

Five MPPT techniques are proposed in [19]. These include FL methods, P&O and ANFIS. The results indicate that ANFIS is better than the others with an efficiency of 99.4%, FL 98.1% and P&O 97.5%.

The ANFIS method gives good results compared to the methods mentioned above [19]. Its advantage is that it allows to integrate the knowledge that the user has on the inputs and outputs. This being the case, the implementation of an ANFIS system comes up against some difficulties, in particular concerning the choice of optimization parameters [13], [16] and the complexity of its structure [20]. Consequently, there are other types of command whose principle is inspired by the evolution of nature [21], [22]. These are commands based on evolutionary algorithms. Among these algorithms, the Genetic Algorithm (GA) is studied in this work. It has been the subject of several studies for the order MPPT.

Slimani and al [23], [4], [24] developed the MPPT-GA approach. Comparing the results obtained with those of the classical P&O and InC methods shows that the MPPT-AG control has a higher convergence speed and makes it possible to solve the oscillation problems observed with the P&O around the MPP.

Paul and al [1] presents a new neuronal MPPT control optimized by GA. They do a comparative study with the InC and find that the proposed method offers the best results.

Semero and al [20] proposed an approach based on GA and PSO (Particle Swarm Optimization). They first use the GA for the identification of the PVG parameters. Then they combine GA and PSO to optimize the structure of the MPPT ANFIS command. The performance of the proposed optimization method is compared with that of Artificial Neural Networks (ANN) and classical methods (P&O and InC). The GA-PSO-ANFIS command offers better performances with a RMSE (Root Mean Square Error) criterion of 10.95% against 30.3% for ANN and 25.5% for conventional methods.

The bibliographic review presented reveals that there is no work that corresponds to the GA-ANFIS combination alone for ordering a boost converter. Thus, assuming that the use of a new approach based on the GA would be relevant insofar as it would make it possible to make a good choice of the parameters of membership functions and fuzzy rules of ANFIS, the object of this paper is then to design an ANFIS command optimized by GA to continue the maximum power delivered by the PVG at any time.

This article is structured in three parts. First an introduction is made. The proposed optimization method is then presented in the second part followed by simulation results. Finally, a conclusion completes this work.

2. GA-ANFIS method

2.1 ANFIS

Neuro-fuzzy systems are fuzzy systems formed by a learning algorithm inspired by the theory of neural networks. The learning technique operates according to local information and produces only local changes in the system [25], [26], [16], [27], [28]. The proposed ANFIS model has two inputs (current and voltage of the PVG) and a single output (power of the PVG). It implements a Takagi Sugeno Fuzzy Inference System (FIS) (Eq. (1) and Eq.(2)).

If Vpv is A1 and Ipv is B1 then:

$P_{pv\text{-}opt}=A1V_{pv}+B1I_{pv}+C1$ (1)

If Vpv is A2 and Ipv is B2 then:

$P_{pv\text{-}opt}=A2V_{pv}+B2I_{pv}+C2$ (2)

Its structure is composed of five layers and it is given in figure 1 with two inputs (Vpv and Ipv) and one output (Ppv-opt): Fuzzification, Fuzzy rules, Normalization, Defuzzification and summation. They are given by the Eq.s 3 to 7.

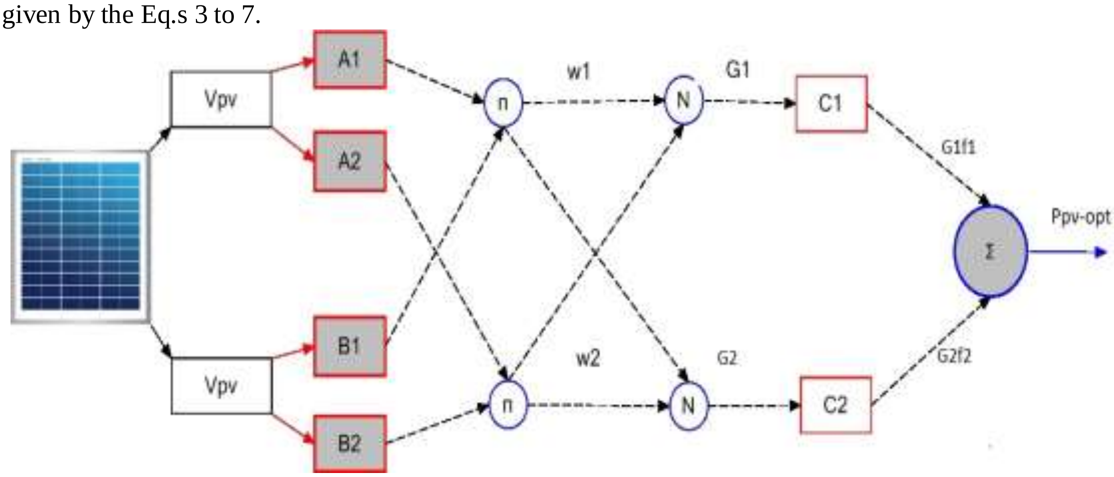

Fig.1. Structure of ANFIS

Layer 1: Fuzzification

The neurons of this layer realize the fuzzy sets that will serve in the antecedents of the rules (Eq. 3).

$O_i^k = \mu_{Ai}(V_{pv})$ (3)

Eq. 4 gives the Gaussian type membership function.

$\mu_{Ai}(V_{pv}) = exp\left[-\left(\frac{Vpv-a_i}{b_i}\right)^2\right]$ (4)

Layer 2: Fuzzy rules

Each neuron in this layer corresponds to a rule of Sugeno-Takagi. It receives the outputs of fuzzification neurons and calculates its activation. It is modeled by Eq. 5.

$w_i = \mu_{Ai}(V_{pv}) * \mu_{Bi}(I_{pv})$ (5)

Layer 3: Normalization
Each neuron calculates the normalized degree of truth of a given fuzzy rule. The value obtained represents the contribution of the fuzzy rule to the final result. It is modeled by Eq. 6.

$$G_i = \frac{w_i}{w1+w2} \quad (6)$$

Layer 4: Defuzzification
Each neuron i of this layer is connected to a normalization neuron corresponding to the initial inputs of the network. It calculates the weighted consequence of the rule.
Layer 5: Summation
It includes a single neuron that provides the output of ANFIS while calculating the sum of all outputs of defuzzification neurons (Eq. 7).

$$P_{pv\_opt} = \sum_i P_{pv\_opt_i} G_i \quad (7)$$

Ai, Bi and Ci: linguistic terms;
ai, bi: parameters of the membership functions. ai is the center of the Gaussian function and bi is the slope of the function (variance);
µ: Gaussian membership function (Eq. 5);
wi: activation functions;
Gi: normalization functions;
Ppv_opt: summation function.

2.2 Genetic Algorithm

GA are optimization algorithms based on techniques derived from genetics and mechanisms of evolution of nature: selection and reproduction or recombination (crossing and mutation) [29]. They are part of the evolutionary algorithms and they use iteratively random processes for the search of solution to a problem whatever its degree of complexity. They massively use pseudorandom numbers to perform the exploration of solutions. Unlike other algorithms, GA does not stop in local extrema [20], [30], [31].
Genetic operations are the base of GA. They do not exclude probability theories. These operations are: selection, mutation and crossover. The selection operation is applied on a population of chromosomes and forms a mating pool. The crossover operator is applied next to produce new chromosomes. Like in nature, crossover produces new individuals having some parts of both parent's genetically material. The mutation is a genetic operation used to maintain genetic diversity from one generation of a population of GA chromosomes to the next one.
The goal of GA is to define an approximate solution to an optimization problem in a reasonable time. In an optimization problem, each variable corresponds to a gene in the chromosome. An individual is a set of chromosomes and the effectiveness of the GA will depend on their coding choices. An evolving set of individuals forms a population.
To find the minimum of the fitness function, in the interval [0, t_S], with a precision of x significant digits, we will precede as follows: $2^{n-1} \leq 10^x . t_S \leq 2^n$
With n the number of bits. The code of each chromosome corresponds to its value P_{max}. The Eq. (8) gives the number of each chromosome in real encoding.

$$Pr = \left(\frac{2}{2^n} - 1\right) . Pmax \quad (8)$$

3. Proposed Approach

In this work, the GA is used to optimize the choice of parameters of the membership functions of ANFIS. Indeed, learning an ANFIS requires a number of choices. It is necessary to choose the number of inputs and output, the number and type of membership functions (MsF) and the type of structure (Sugeno or Mamdani). These choices may compromise the effectiveness of the order. For example, a bad choice of MsF parameters makes the command less efficient by decreasing its speed of convergence. Thus, to circumvent all these problems, the GA is used for the choice of membership functions parameters.

In the developed algorithm, individuals represent the power of the PVG (Eq. 9) and the number of bits (binary coding) gives the precision. To code the power in binary, the algorithm sets its maximum value which is in our case Pmax (Eq. 10).

$$Population(P) = \begin{bmatrix} P_1 \\ \vdots \\ P_N \end{bmatrix} \quad (9)$$

$$P_{max} = \overbrace{110.....1}^{n\ bits} \quad (10)$$

In STC, the value of maximum power is given by Eq. (11). Its binary equivalent is given by Eq. (12).

$$P_r = 6430\ W \quad (11)$$

$$P_{max} = 1100100011110 \quad (12)$$

The evaluation of an individual is then done by calculating the power. The performance function, must be able to attribute to each individual a indicator representing its relevance to the problem we are trying to solve. In this work, for an optimization, this performance function is represented by the fitness function (F) (Eq. (14)).
The wheel roulette method is the best known and the most used. With this method each individual has a chance to be selected proportional to his performance, therefore, the more individuals are adapted to the problem, the more likely they are to be selected. To use the image of the "fairground wheel", each individual is assigned a sector whose angle is proportional to its adaptation. The principle of this method is to associate with each individual Pi (of a population size Nind) a probability J proportional to its performance F (Eq. 13).

$$J = \frac{F(Pi)}{\sum_i^{Nind} F(Pi)} \quad (13)$$

We turn the wheel and when it stops turning we select the individual corresponding to the sector designated by a kind of cursor that points to a particular sector of it after she stopped turning.
For any two values of powers, the algorithm after binary coding performs a crossing operation with a probability Pcr.

$$\left\{\begin{matrix} 110000 \,|\, 110100 \\ 100111 \,|\, 110010 \end{matrix}\right\} \begin{matrix} \downarrow \\ \uparrow \end{matrix} \rightarrow \left\{\begin{matrix} 110000 \,|\, 110010 \\ 100111 \,|\, 110100 \end{matrix}\right\}$$

After crossover, we apply a mutation, with a small probability Pmut.

$$\left\{\begin{matrix} \qquad\quad \downarrow \\ 1000011\mathbf{0}0111 \end{matrix}\right\} \rightarrow \left\{\begin{matrix} \qquad\quad \downarrow \\ 1000011\mathbf{1}0111 \end{matrix}\right\}$$

The parameters for mutation and crossing are given in Table 1.

Table 1. Genetic Algorithm parameters

Parameters	Values
Population size (Nind)	1000
Selection rate (J)	0.8
Crossing probability(Pcr)	0.03
Mutation probability (Pmut)	0.05
Number of generation (Ngen)	100

Figure 2 shows the power section and the control part using GA-ANFIS. The flowchart of the optimal control based on GA-ANFIS is shown in Figure 3.

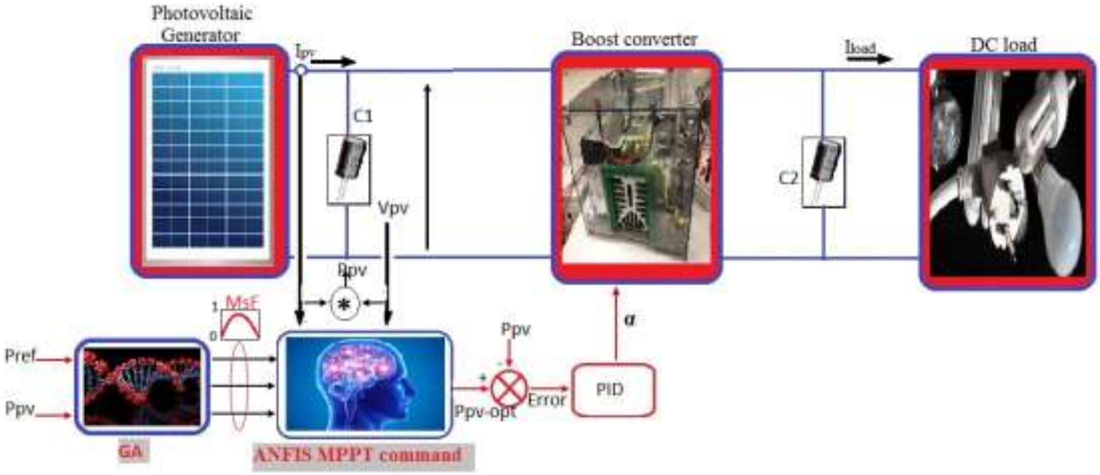

Fig.2. Block diagram of the system studied with the MPPT GA-ANFIS command

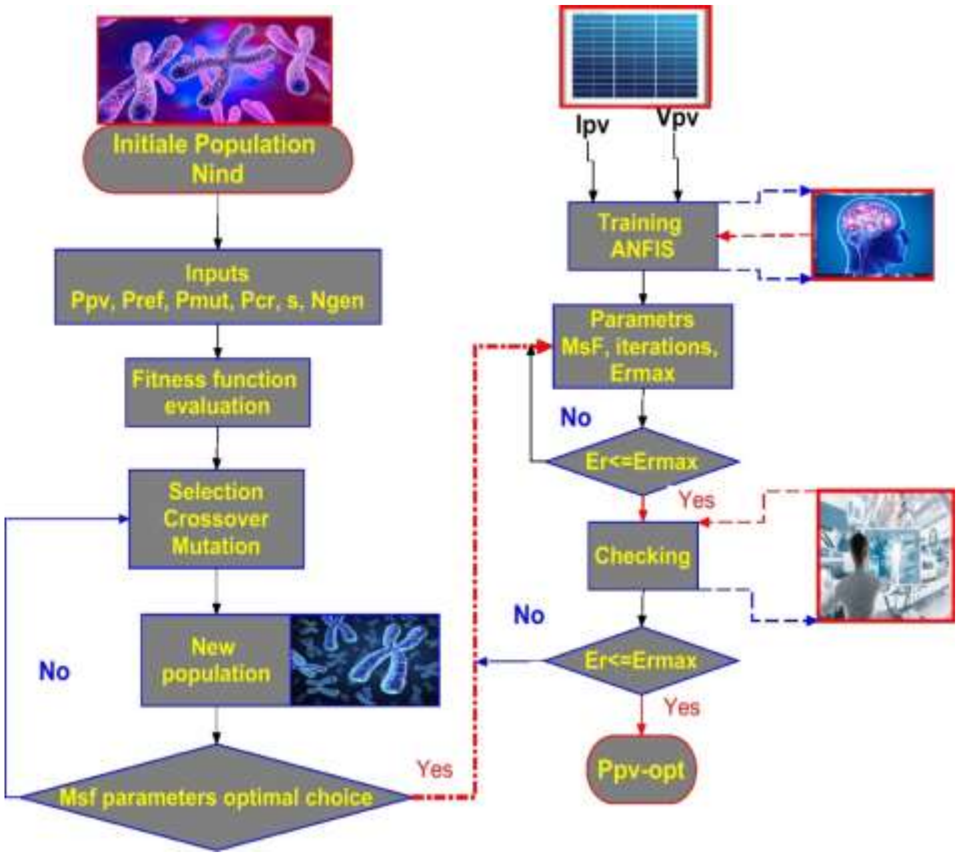

Fig.3: Flowchart of the optimal GA-ANFIS control

An interval of variation is defined for the maximum power of the PVG. Then this parameter is created randomly in this interval and the population consists of a set of chromosomes (PVG Power). To evaluate the chromosomes at each generation, we used the Fitness function given by Eq. (14). The evaluation of an individual is done by calculating his power.

$$F = \int_0^{ts} (Pref - Ppv)^2 dt \qquad (14)$$

With Pref, the optimal power of the PVG for given climatic conditions and ts, time of simulation.
By minimizing the criterion (Fitness function), it is possible to improve response time and reduce power fluctuations. This optimized power will then be sent to the ANFIS input with the voltage and current of the PVG. For learning ANFIS, a database of 150000 data is used of which 60% (90000) are for training and 40% (60000) for checking.

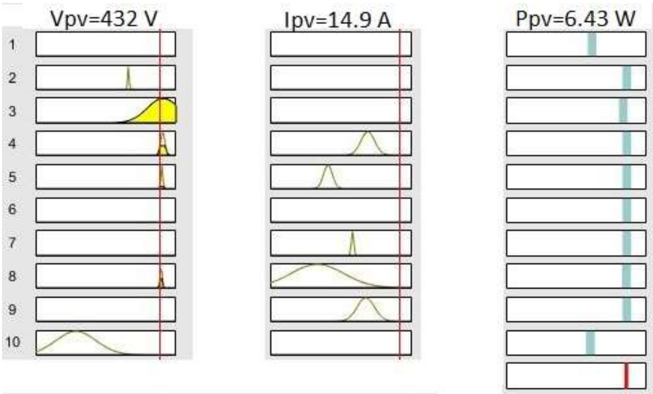

Fig.4. Fuzzy rules and membership functions

In Figure 4, the fuzzy rules and MsF are represented. Each input has ten fuzzy rules. MsF are of the Gaussian type (Eq. 5). There are six for the voltage and five for the current. For the output, MsF are linear (Eq..7).
Figure 5 gives the power characteristic as a function of the voltage and current as a function of the voltage of the PVG. The principle of the MPPT command is based on the position of the operating point with respect to the MPP. These two, which may not be the same, the algorithm used always converge the operating point to the MPP.

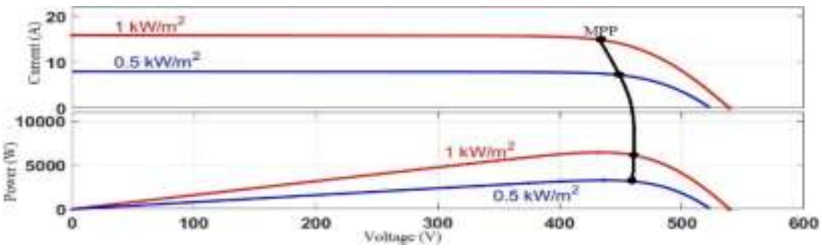

Fig.5. I-V and P-V characteristics of the PVG

For the corrector, we had a first choice on the PI corrector, but the results obtained were not at all satisfactory. This is how we turned to the PID which gives a good compromise between stability and response time. The transfer function of the boost converter is obtained with a digital program implemented on matlab. This made it possible to obtain the values of the terms of the PID corrector.
The values of the different terms are presented in Table 2.The parameters of the PVG are given in Table 3 under optimal conditions. The PVG consisting of 15 modules in series and 2 modules in parallel.

Table 2. Values of the PID corrector parameters

Parameters	K_p	K_i (min^{-1})	K_d (s)
Values	10	5	0.01

Table 3. PVG parameters

Parameters	Pmax (W)	Vmax (V)	Imax (A)
Values	6430	432	14.9

Figure 6 below shows the profiles of sunshine and temperature. These last two are the parameters that have the greatest influence on PVG performance [33],[34].

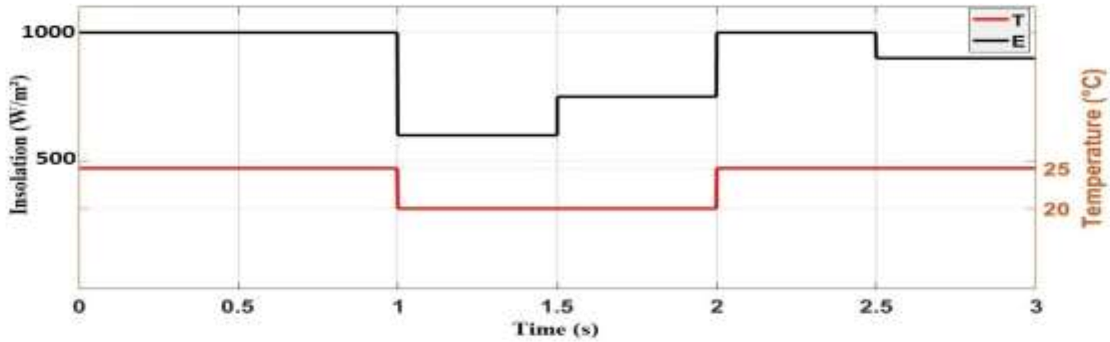

Fig.6: Variation of insolation and temperature

4. Results

4.1 Simulation Results and Discussions

Figure 7 shows the model simulated under Matlab/Simulink with the MPPT GA-ANFIS and ANFIS commands. For the first time, a matlab program was developed to learn how to optimize ANFIS with the GA. In the latter, learning is done in the anfisedit interface of matlab.

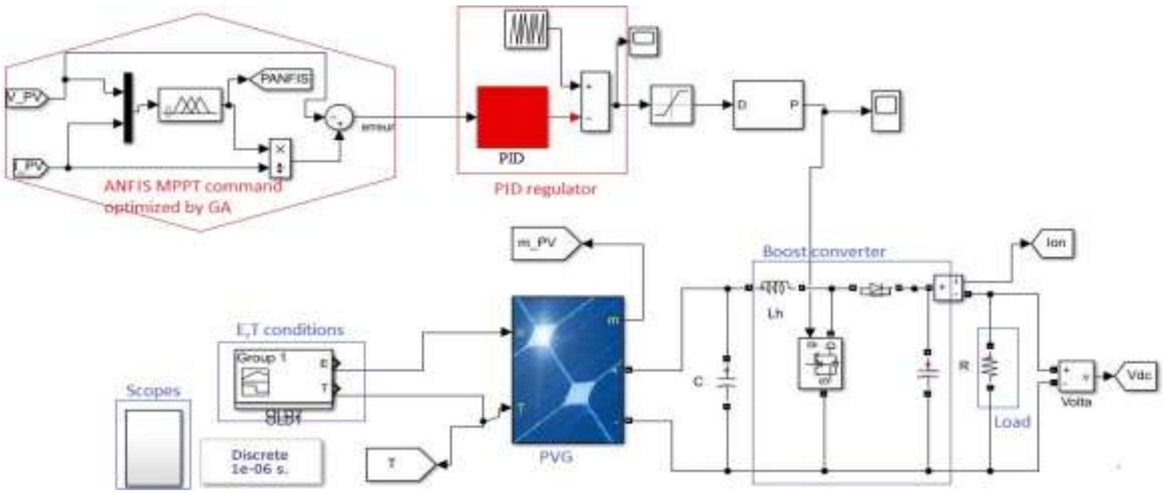

Fig.7.Simulink model

The figures below are the simulation results.

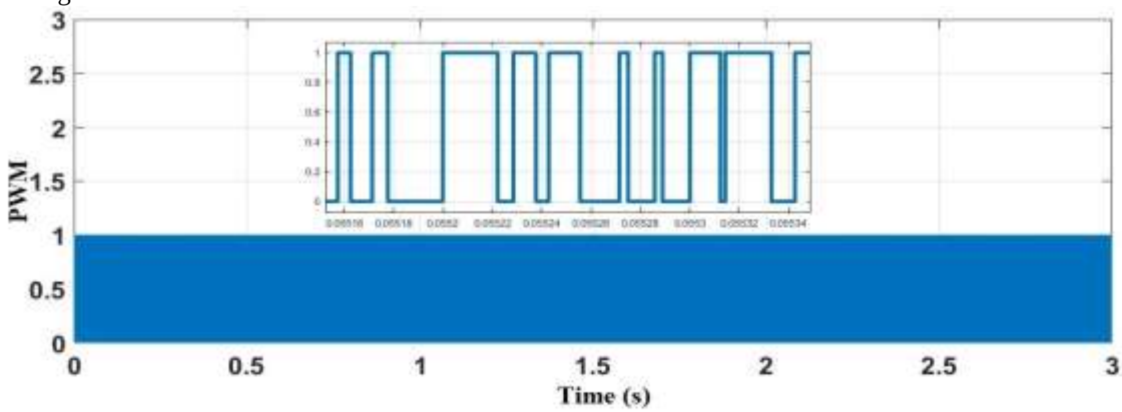

Fig.8. PWM control signal

Figure 8 shows the control signal of the boost converter. This signal controls the opening and closing of the power switch (Mosfet) [32].

Performance test

In this part, a performance study is performed. It is carried out under standard conditions (1000 W / m², 25 °C and AM = 1.5) with a reference power of 6.430 kW.

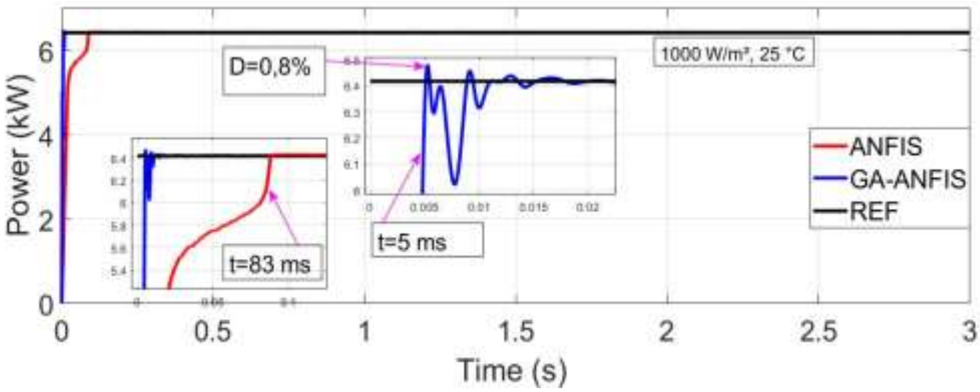

Fig.9. Powers under standard conditions

Table 4. Performance Parameters for GA-ANFIS and ANFIS Controllers

Controllers	Response time (ms)	Overflow (%)	Precision	Stability
ANFIS	83	0	Precise	Stable
GA-ANFIS	5	0.6	Precise	Stable

Figure 9 shows that GA-ANFIS is faster but has an overflow of 0.8%. From a stability and precision point of view, the two commands are equal (Table 4).

Robustness test

The robustness of the PVG is tested under varying climatic conditions.

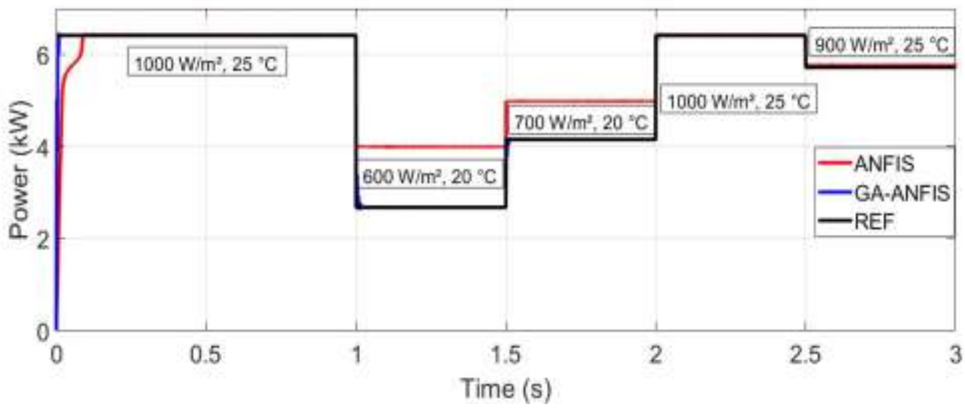

Fig.10. GA-ANFIS, ANFIS and REF powers

Figure 10 gives the ANFIS powers and that of the proposed method compared to the PVG reference power. It shows the difference between the responses of the two controllers. The proposed method is more precise and faster than the ANFIS controller but the latter has a zero overflow. The zoomed sections (Figure 9) show that the optimized controller follows the set-point with very small fluctuations while the non-optimized controller loses some time before continuing the instruction especially for the insolation of 600 and 700 W/m². Which explains their difference from the standpoint of robustness. Three error criteria are evaluated. These are the RMSE (Eq. 15), the MAPE absolute average error (Eq. 16), and the average absolute error MAE (Eq. 17). The results are shown in Figure 14.

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(P_{ref} - P_{pv_i}\right)^2} \qquad (15)$$

$$MAPE = 100 * \frac{1}{n}\sum_{i=1}^{n}\left|\frac{P_{ref}-P_{pv_i}}{P_{ref}}\right| \qquad (16)$$

$$MAE = \frac{1}{n}\sum_{i=1}^{n}\left|P_{ref} - P_{pv_i}\right| \qquad (17)$$

Table 5 gives the response times obtained with the ANFIS and GA-ANFIS commands as a function of the simulation time.

Table 5. Response time of the GA-ANFIS and ANFIS controllers

Controller	Response time (ms)	Simulation time (s)
ANFIS	83	3
GA-ANFIS	8.24	3

Table 6. Comparative study of GA-ANFIS and ANFIS controllers

E(W/m2) – T(°C)	Real time Power (W)	ANFIS Power (W)	GA-ANFIS Power (W)
1000-25	6430	6429	6430
600-20	3314	2598	3312.09
700-20	5000	4040	5000
1000-25	6430	6429	6430
900-25	6215	5634	6214.93

5. Experimental validation

The photovoltaic platform shown in Figure 11 is used in this study. He is installed at the Polytechnic high school of Cheikh Anta DIOP University, Dakar, Senegal. Senegal is located in extreme West Africa between 12.5 ° and 16.5 ° N latitude and 12 ° and 17 ° W longitude. It has a dry tropical climate characterized by two seasons: a dry season from November to June and a rainy season from July to October. Senegal has significant solar potential with an average annual radiation duration of about 3000 h and an exposure rate of 5,7 kWh/m²/day. This radiation varies between the northern sunniest part (5.8 kWh/m²/day in Dakar) and the southernmost part in terms of precipitation (4.3 kWh/m²/day in Ziguinchor). The temperature varies from 16 °C around Dakar (January) to 38 °C in the south (October). Rainfall increases from north to south with an annual average of 300 mm in the far north and 1500 mm in the extreme south. The relative humidity varies between 75 and 95%. The characteristics of the photovoltaic system being identified (Sharp Module) are given in Table 8 [3].

Fig. 11. Experimental device

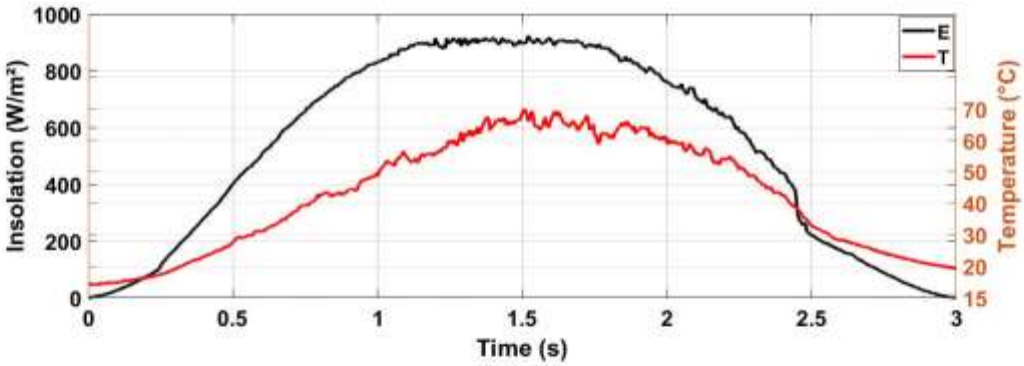

Fig.12. Variation of climatic conditions

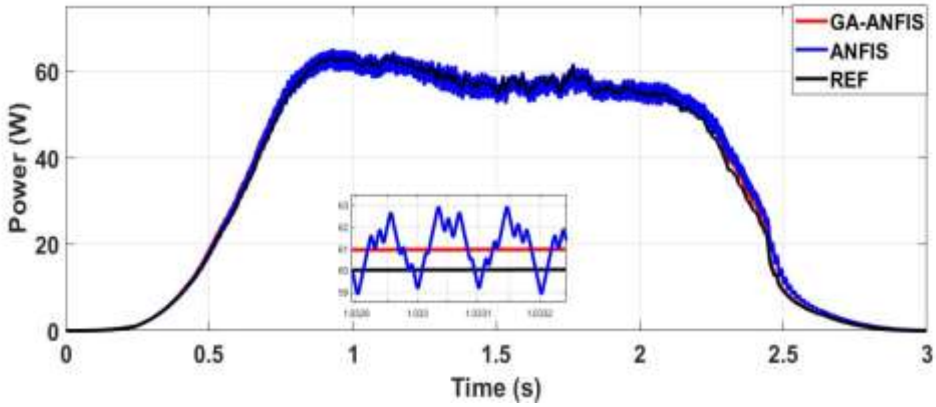

Fig.13. REF, GA-ANFIS and ANFIS powers

Figure 12 shows variations in site conditions. These variations correspond to different photovoltaic power values (see Figure 13). These data have created a basis for the validation of our models.
Therefore, the proposed method (GA-ANFIS) is more accurate than the ANFIS method because GA-ANFIS has a root mean squared error (RMSE) of 0.04 against 0.068 for ANFIS. The ANFIS power oscillates around the reference power (figure 13) while the power GA-ANFIS follows the reference with a great precision and a good stability. Table 7 gives the SPV parameters and Table 8 the robustness parameters for two different irradiation profiles.

Table 7. Characteristics of the PVG

Parameters	Voc (V)	Isc (A)	Pc (W)	Cell surface (cm²)	Number of cells
Value	22,5	2,24	30	49	36

Table 8. Robustness parameters of the GA-ANFIS and ANFIS controllers

E (W/m²)- T (°C)	Real time Power (W)	ANFIS Power (W)	GA-ANFIS Power (W)
877,4-57,60	58.92	58.71	58.86
588,8-50,68	46.74	47.26	45.31

Figure 14 presents three error criteria. These errors are evaluated against a reference. They testify to the performance of the GA-ANFIS controller.

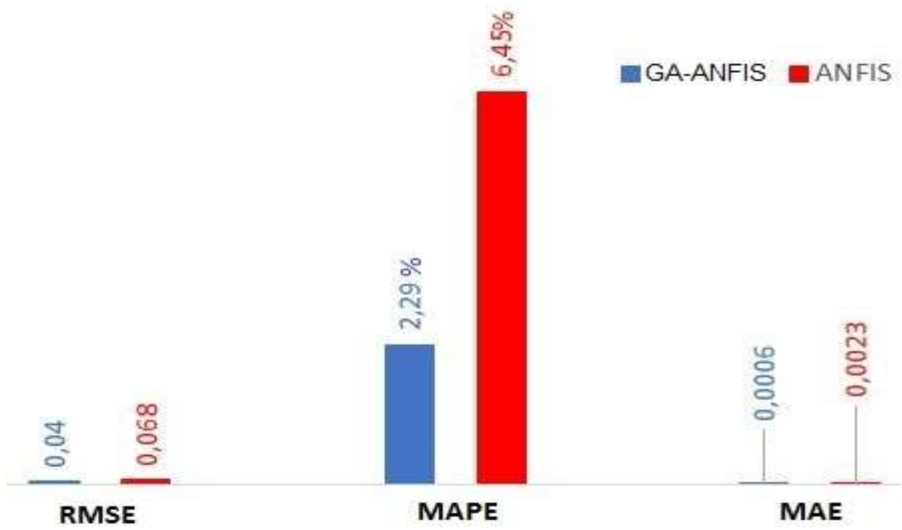

Fig 14: Evaluation of the error criteria for GA-ANFIS and ANFIS

6. Conclusion

In this work, the optimization of an MPPT command of type ANFIS by the GA is presented for the maximization of the power of a PVG. The results obtained have shown the effectiveness of GA in the research and optimization of a hybrid neuro-fuzzy controller type ANFIS. They show that the ANFIS optimized by GA is better than the non-optimized ANFIS. This is also the case with the experimental validation of the two MPPT models.

The performance and robustness of the controller is highly dependent on the choice of GA parameters (population size, selection rate, recombination rate and number of generations), but also ANFIS learning.

Conflict of Interest

The authors declare no conflict of interest.

Acknowledgements

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Acronyms	
ANFIS	Adaptive Neuro Fuzzy Inference System
PVS	Photovoltaic Solar
MPP	Maximum Power Point
InC	Incrementale Conductance
PID	Proportional Integral Derivative
MsF	Membership Function
MPPT	Maximum Power Point Tracking
P&O	Perturb and Observ
PVG	Photovoltaic Generator
GA	Genetic Algorithm
FIS	Fuzzy Inference System
GHG	Green House Gaz
FL	Fuzzy Logic
STC	Standard Test Conditions
PWM	Pulse Width Modulation
PSO	Particle Swarm Optimization
ANN	Artificial Neural Network

REF	Reference
Nomenclature	
AM [-]	Air Masse
Ipv [A]	PV current
Er [%]	Error
Pref [kW]	Maximum Power at STC
RMSE [%]	Root Mean Square Error
MAE [%]	Mean Absolute Error
MAPE [%]	Mean Absolute Percentage Error
C1 [µF]	Boost input capacity
C2 [µF]	Boost output capacity
Fc [kHz]	Frequency of switching the Mosfet
α [-]	Duty cycle
L [mH]	Inductance
Vpv [V]	PV voltage
Wi [-]	Activation function
µ [-]	Gaussian Membership function
Gi [-]	normalization function
Pmax [W]	Maximum Power
Imax [A]	Current at Maximum Power
Vmax [V]	Voltage at Maximum Power
Ppv-opt [kW]	Optimized Power with GA-ANFIS
Kp [-]	Proportional gain
Ki [min^{-1}]	Integral gain
Kd [s]	Derivative gain
E [W/m^2]	Insolation
T [°C]	Temperature
F	Fitness function
J	Probability of selection (GA)

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