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Research Paper

Improvement of the energy production of a photovoltaic-wind hybrid system using NF-PSO MPPT

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ABSTRACT

This manuscript gives a contribution to the optimization of a hybrid Photovoltaic-Wind Turbine system with a storage system. In order to capture the maximum power that can be produced by each source, while maintaining the rotor speed of the wind turbine at its maximum values according to wind variations, the Neuro-Fuzzy-Particle Swarm Optimization (NF-PSO) controller is proposed. The Neuro-Fuzzy method is used here because it allows an automatic generation of fuzzy rules, and the Particle Swarm Optimization to find an optimal gain allowing to readjust the dynamics of the fuzzy rules by reducing the power losses (oscillations). For the proper functioning of such a system, we have developed a fuzzy supervisor in order to have an optimal control of the system according to the variations of the requested load and the produced power by considering the storage system and the load shedding. The simulation results of the system confirmed the better performance of this method in terms of speed with a response time of 0.2s on the wind side and 0.025s on the side photovoltaic, of efficiency with 99.87% on the photovoltaic side and 99.6% on the wind side, and above all in term of oscillation reduction with practically a negligible oscillation rate compared to the NF and the Cuckoo algorithm.

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1. Introduction

The use of energy produced by renewable sources is a promising energy option that meets the growing demand for energy in the world [1]. However, these sources have the disadvantage of being dependent on weather conditions. In order to reduce the fluctuations in production caused by the random nature of these resources and to meet the load requirements, the solution to be retained is the assembly of different sources of electrical energy production [1-3]. In addition, the periods of the year with low insolation correspond to those with a better wind potential. It is therefore consistent that a complementarity between wind and solar energy is desirable and that the coupling of these two energy sources is the safest and least expensive solution for autonomous electrification systems [2]. The interest of such a coupling is to have more energy and a continuity of service, but, as for any hybrid PV-E system, the risk remains to have too much energy at some times and not enough at others. Therefore, it is necessary to use a storage system to store the excess energy when it exists and to release it during periods of insufficient supply [4, 5]. In order to be used in a wide range of applications and to satisfy the economic constraints, the conversion chain of these energies must be robust and reliable but it must also present a high performance at low cost. For this, it is necessary to extract the maximum power from renewable sources while taking into account the management of the storage system, by proposing a supervisor, which would have the advantage of extending the life of the devices. This has motivated several researchers to focus on the development of hybrid MPPT methods and intelligent supervisors such as: [6,7] who used a fuzzy logic (FL) supervisor for hybrid system management; [8] worked on a hybrid MPPT by combining Perturb and Observe and Artificial Neural Networks (P&O-RNA) methods; [9] worked on a hybrid system using a Neuro-Fuzzy (NF) MPPT algorithm for PV and for wind the Radial Basis Function Network-Sliding Mode (RBFNSM) algorithm; [10] worked on the Genetic Algorithm (GA) and PSO; [11] used three control strategies for hybrid system management, and in [12-14] improved MPPT algorithms are presented. For all these MPPT controls developed in the literature, the output power oscillates hence the power losses, in addition to that these methods do not manage to work well in a PV generator as well as in a wind generator while keeping the speed of rotation of the latter in its maximum values according to the wind variations.

The objective of this manuscript is to optimize the energy efficiency of a PV-WT hybrid system by combining RNs while equipping it with a PSO compensator in order to readjust the fuzzy rule dynamics to accelerate the convergence towards the desired performance, and to keep the rotor speed at its optimal values according to the wind variations.

This paper includes the following parts: the second section of the paper will be dedicated to the modeling of our study system, namely the PV model, the wind turbine model, the Permanent magnet synchronous generator (PMSG) model, the battery model and the DC/DC boost converter model. A third section is reserved for the presentation of the proposed MPPT method and the energy management algorithm. The different simulations done and the discussion of the results found will be the subject of the fourth section. In the fifth section a conclusion is presented.

2. Study System

In this section we present our studied system which consists of a Photovoltaic (PV) panel, a Wind Turbine (WT), a Permanent Magnet Synchronous Generator (PMSG), a storage battery, a supervisor, a variable load and two static converters figure1.

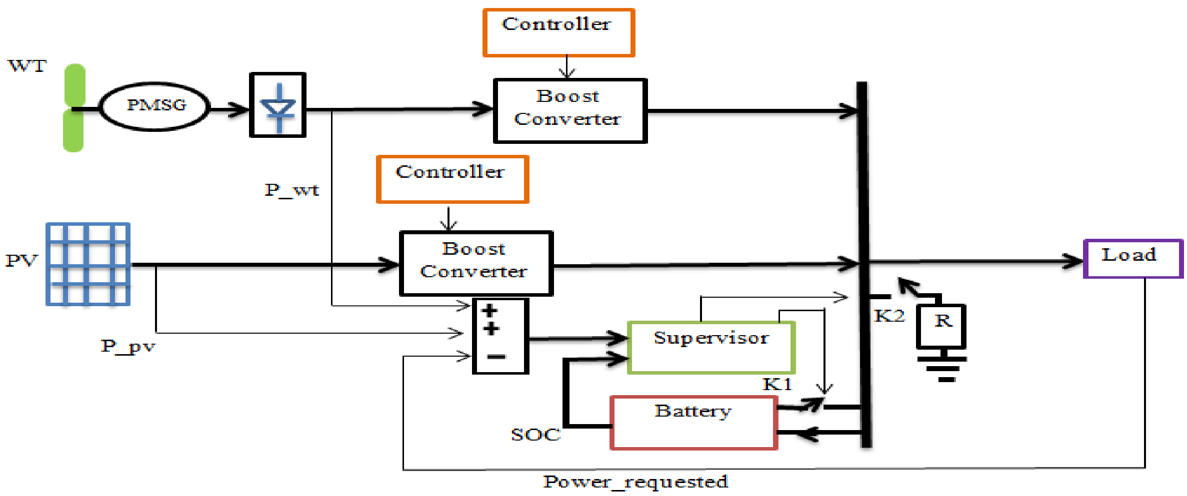


Fig 1. Structure of the studied system

2.1 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 [15] (Figure 2).

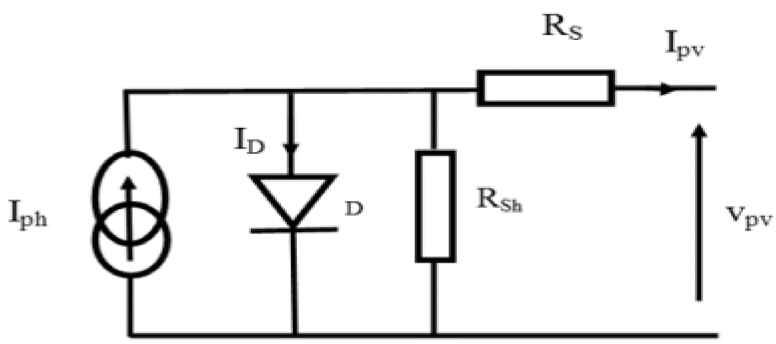


Fig 2. Single diode model of a PV cell

In this model, the photovoltaic cell is represented by a current source which 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 [16]:

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

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:

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

The electrical characteristics under standard conditions (G= 1000W/m2, and T=25C°) of the photovoltaic module used for the simulations are presented in Table 1. Figure 3 shows the typical current/voltage and power/voltage curves for the photovoltaic panel.

Table 1. Parameters of PV

Parameters	Values
Maximum Power	218.871 W
Optimum operating voltage	29.3 V
Optimum operating current	7.47 A
Open circuit voltage	36.6 V
Schort-circuit current	7.97 A

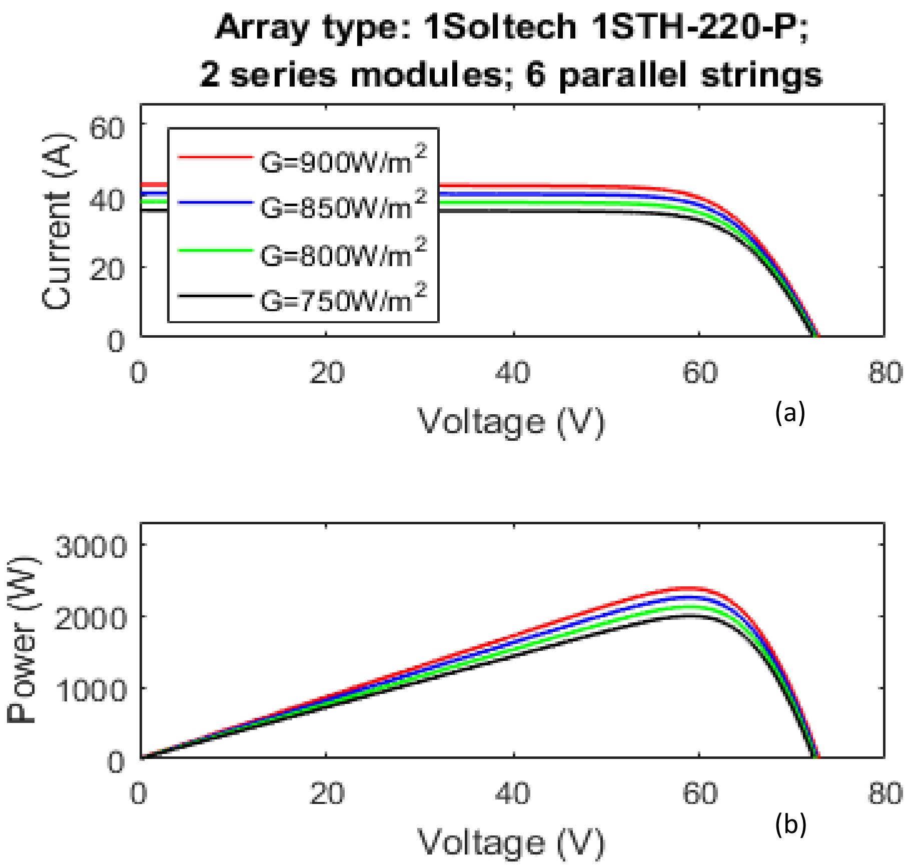


Fig 3. Current/voltage (a) and power/voltage (b) characteristics of the photovoltaic panel according to irradiation variations

2.2 Wind turbine model

The aerodynamic power collected by a wind turbine is written in the following form [17]:

$$P_{aero} = \frac{1}{2} C_p(\lambda, \beta)\rho S V^3 \quad (6)$$

With:

ρ: the air density (kg/m^3) ; V: wind speed (m / s); S: the useful surface crossed by the wind given by S= πR^2; R: the radius of the blades; $C_p(\lambda, \beta)$ **:** Power coefficient.

The power coefficient Cp (λ, β) i given by [18]:

$$C_p(\lambda, \beta) \ = 0.5(\frac{98}{\lambda_i} - 0.4\beta - 5)\exp(-16/\lambda_i) \quad (7)$$

$$\frac{1}{\lambda_i} = \frac{1}{\lambda + 0.08\beta} - \frac{0.035}{\beta^3 + 1} \quad (8)$$

$$\lambda = \frac{R\omega_m}{V} \quad (9)$$

The aerodynamic torque appearing at the level of the turbine is therefore a function of this power:

$$\Gamma_{aero} = \frac{P_{aero}}{\omega_m} = \frac{1}{2\omega_m} C_p(\lambda, \beta)\rho\pi R^2 V^3 \quad (10)$$

Where: ω_m is the rotor speed of a wind turbine.

Table 2 recapitulates the parameters of the wind turbine used for the numerical simulations.

Table 2. Wind turbine parameters

Parameters	Values
Nominal mechanical output power	1300W
pitch angle	0°
air density	1.22 kg/m^3
Blade radius	0.68 m
Wind speed	9m/s

For each wind speed, there is a maximum power of the wind turbine which is obtained according to the rotor speed figure 4.

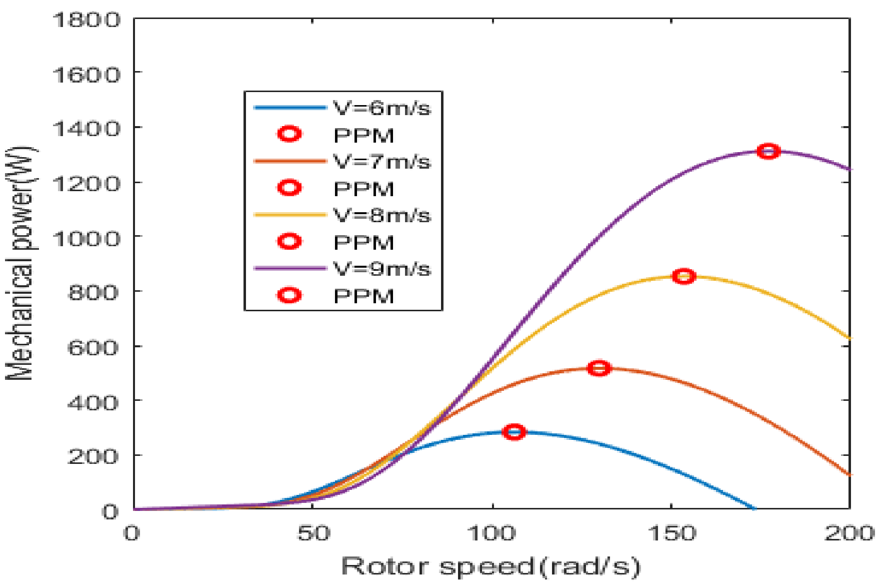


Fig 4. Mechanical power/speed characteristic

2.3 Permanent magnet synchronous generator model

For applications autonomous of wind energy transformation, the PMSG are used the most considering their reliabilities and robustnesses. We used the referential d-q transform of park for modeling. The voltage of axis d and q is obtained by the system of equation (11) [17].

$$\begin{cases} v_{ds} = R_s i_{ds} + L_d \frac{di_{ds}}{dt} - L_q \omega_r i_{qs} \\ v_{qs} = R_s . i_{qs} + L_q \frac{di_{qs}}{dt} + L_d \omega_r i_{ds} + \omega_r \Psi_r \end{cases} \quad (11)$$

The equation (12) gives the electromagnetic torque of PMSG.

$$\Gamma_e = 1.5p[(L_d - L_q)i_{qs}i_{ds} - \Psi_{qr}i_{dr} - \Psi_r i_{qs}] \quad (12)$$

With: i_{ds} and $v_{ds}$the current and voltage of the axis d; i_{qs} and v_{qs} the current and voltages of the axis q; ω_r the angular frequency of generator; L_q, and L_d are the inductances of the generator; Ψ_r the permanent flux; Rs the stator resistance and P is the Pole pairs.

Table 3 recapitulates the parameters of the PMSG used for the numerical simulations.

Table 3. PMSG parameters

Parameters	Values
Rated power	1300W
Stator phase resistance	0.425 Ω
Machine inertia	0.01197 kg.m^2
Armature inductance	0.0082 H
Friction factor	0.001189N.m/s
Pole pairs	5

2.4 Battery model

We used the equivalent series model to represent the battery, Figure 5. It is composed of an ideal voltage U_{oc} a series resistance R_{bat} and the battery voltage which is given by:

$$V_{bat} = U_{oc} - R_{bat}.I_{bat} \quad (13)$$

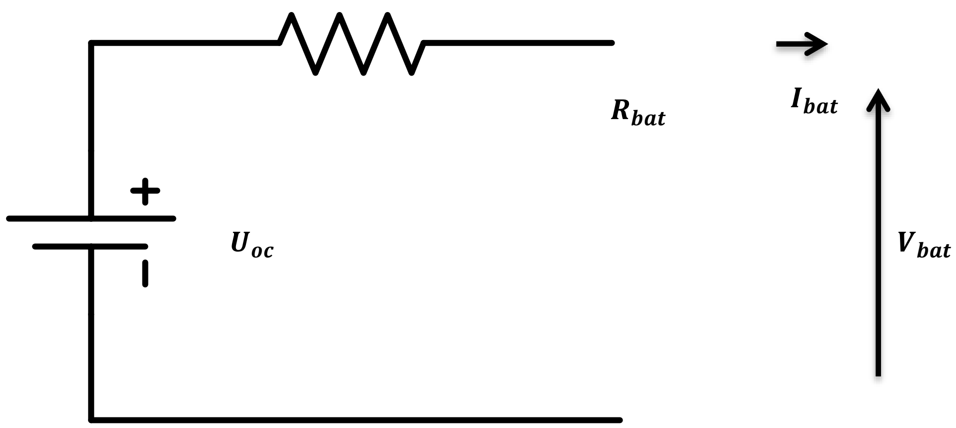


Fig 5. Equivalent circuit model of the battery

In order to avoid degradation of the battery and prolong its life, their state of charge must be maintained within a certain interval defined as follows

$$SOC_{min}(t) \leq SOC\,(t) \leq SOC_{max}(t) \quad (14)$$

The expression of the evolution of the State of Charge (SOC) of the battery as a function of its current is given by:

$$SOC(t) = SOC(t-1) + \int_{t-1}^{t} I_{bat}\, dt \tag{15}$$

Table 4 recapitulates the parameters of the battery used for the numerical simulations.

Table 4. Parameters of battery

Parameters	Values
Nominal capacity	100 Ah
Nominal voltage	48 V
Internal resistance	0.08 Ω

2.5 DC/DC boost Converter model

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]).

$$V_{out} = \frac{V_{in}}{1-D} \tag{16}$$

Where: V_{out}: Output voltage; V_{in} : input voltage; D: duty cycle.

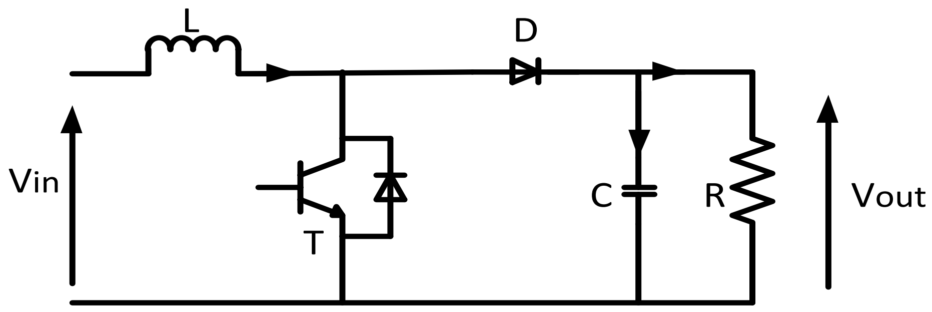


Fig 6. Boost converter

The converter parameters are given in table 5.

Table 5. Converter parameters

Parameters	Values
Load	30 Ω
Inductor	3 mH
Capacitor	100µF

The authors in [18] have shown that the output voltage of the chopper is proportional to the speed of the machine. This means that if we act on this voltage, we also act on the speed of the machine. Therefore, if a MPPT method is good at ensuring the maximum extraction of power from the wind turbine, it will always be able to keep the speed of the machine at its optimal values.

3. Methods used

In this section, we present the MPPT method used and the energy management method.

3.1 MPPT Method

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 architecture composed of five layers as shown in Figure 7 [19]. 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).

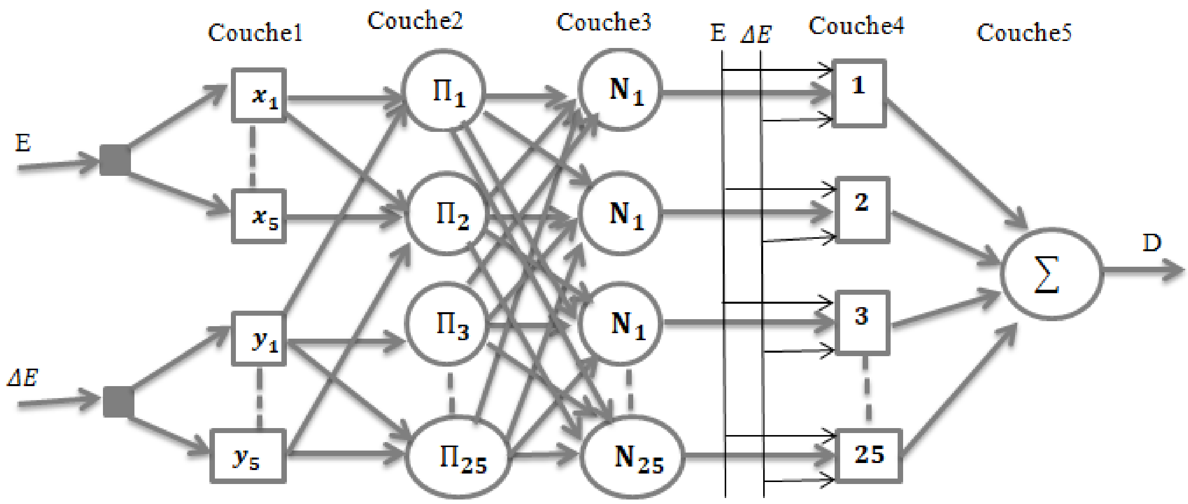


Fig 7. Architecture of ANFIS used.

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 equation 17), forward the numerical data to the nodes of the second layer representing the fuzzy subsets that calculate the membership function value (equation 19). The nodes in the third layer perform the fuzzy operations (equation 20). The nodes of the fourth layer perform the operation of calculating the weighted consequence of the rule (equation 21) [19]. Finally the fifth layer (equation 22) performs the defuzzification operation.

$$o^1_{k_{x_i}} = \mu_{xi}(E)\,, \quad k_{x_i}=1, 2, 3, 4, 5; \qquad x_i = MN, LN, Z, \ LP, MP$$
$$o^1_{k_{y_i}} = \mu_{yi}(\Delta E) \quad k_{y_i}=1,2, 3, 4, 5; \qquad y_i = MN, LN, Z, \ LP, MP \tag{17}$$

$$E = \frac{I(k)-I(k-1)}{V(k)-V(k-1)}$$
$$\Delta E = E(k) - E(k-1) \tag{18}$$

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)

$$w_k = \mu_{Ai}(E).\mu_{Bi}(\Delta E) \tag{19}$$

Where w_k is the output of layer 2.

$$v_k = \frac{w_k}{w_1+w_2+w_3+\cdots w_{25}} \tag{20}$$

The membership functions obtained for each input are given below:

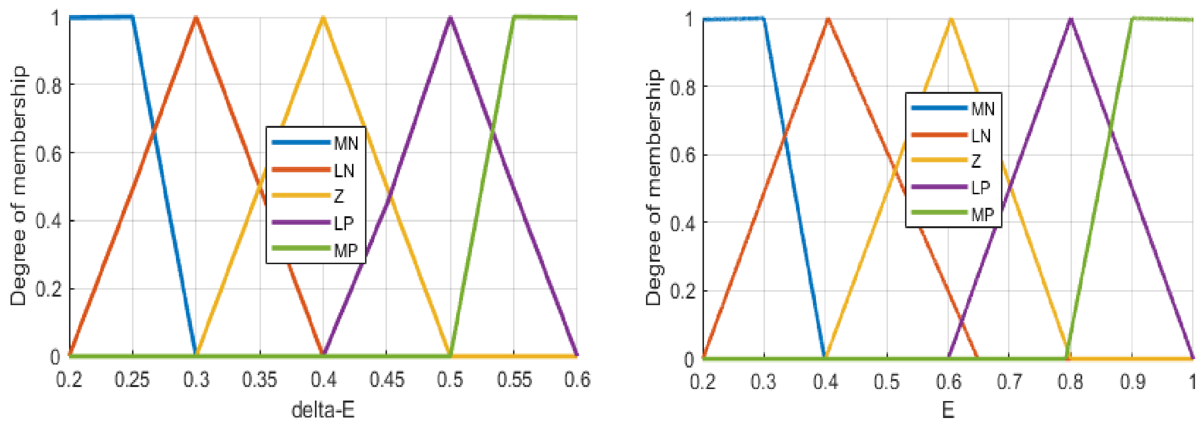


Fig 8. Membership functions of the inputs obtained

$$o_k^4 = v_k.f_k = v_k(a_k.E + b_k.\Delta E + m_k) \tag{21}$$

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:

$$o_k^5 = \sum_{k=1}^{4} o_k^4.v_k \tag{22}$$

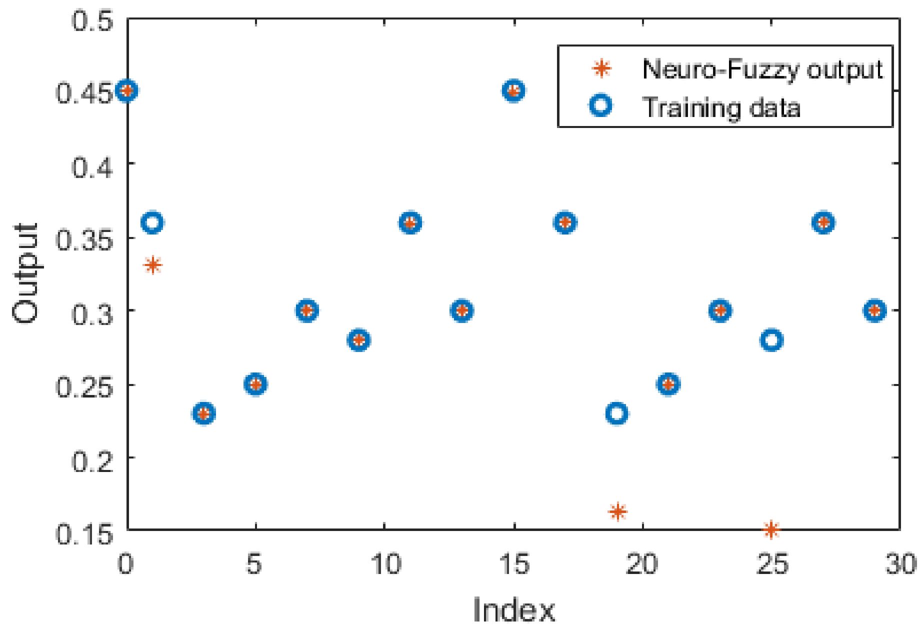


Fig 9. Training of the neuro-fuzzy network.

3.2 Determination of the compensation gain 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 [20-23]. 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 [23]. It is an iterative algorithm. 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:

$$V_{i+1} = w.V_i + c_1.r_1.\left(x_{ip} - x_i\right) + c_2.r_2.\left(x_g - x_i\right) \tag{23}$$

$$x_{i+1} = x_i + V_{i+1} \tag{24}$$

With:

$$w = w_{max} - iter.(w_{max} - w_{min})/iter\_max \tag{25}$$

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 10.

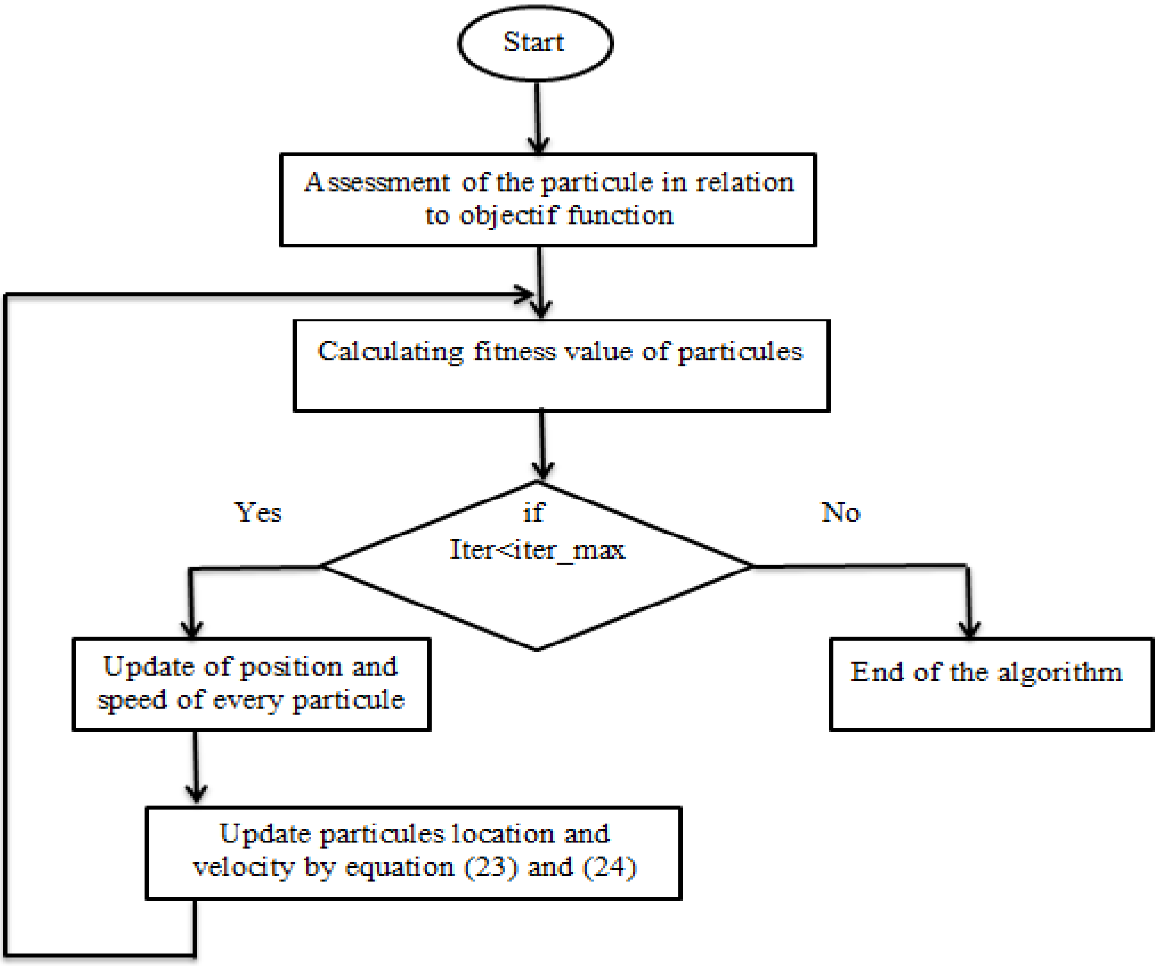
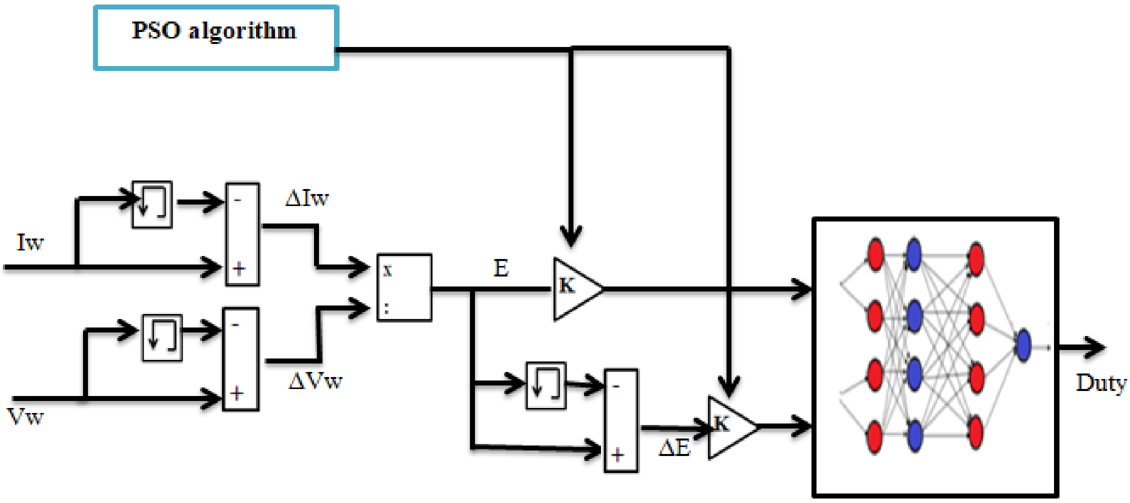


Fig 10. Flowchart of PSO algorithm

After realizing all the components of our method, we obtain the structure given in figure 11.



Fig

Fig 11. Design process of the hybrid method of MPPT developed

3.3 Energy management

The role of the supervisor is to optimize the use of the energy produced and that of the battery. If the renewable sources do not provide enough power and the battery capacity is sufficient, the battery will provide the missing power. If the hybrid power exceeds the load demand, the excess will be stored in the battery and if the battery is full, the excess will be dissipated in a load shedding system (in this case a resistor). Thus, the battery is not the main supplier, its charge/discharge rate is reduced, and therefore the battery life is extended.

The inputs of our supervisor are the state of charge of the battery (SOC), and the difference between the power supplied and the power of the load (delta_P). The outputs are the commands of switches K1 and K2.

The fuzzy variables used to realize our fuzzy supervisor are:

Negative (N), significantly Zero (Z) and Positive (P) for Delta_p

Empty battery (Emin), medium full battery (E) and full battery (Emax) for SOC

On and Off for switches K1 and K2.

The membership functions corresponding to each fuzzy set are given in Figure12:

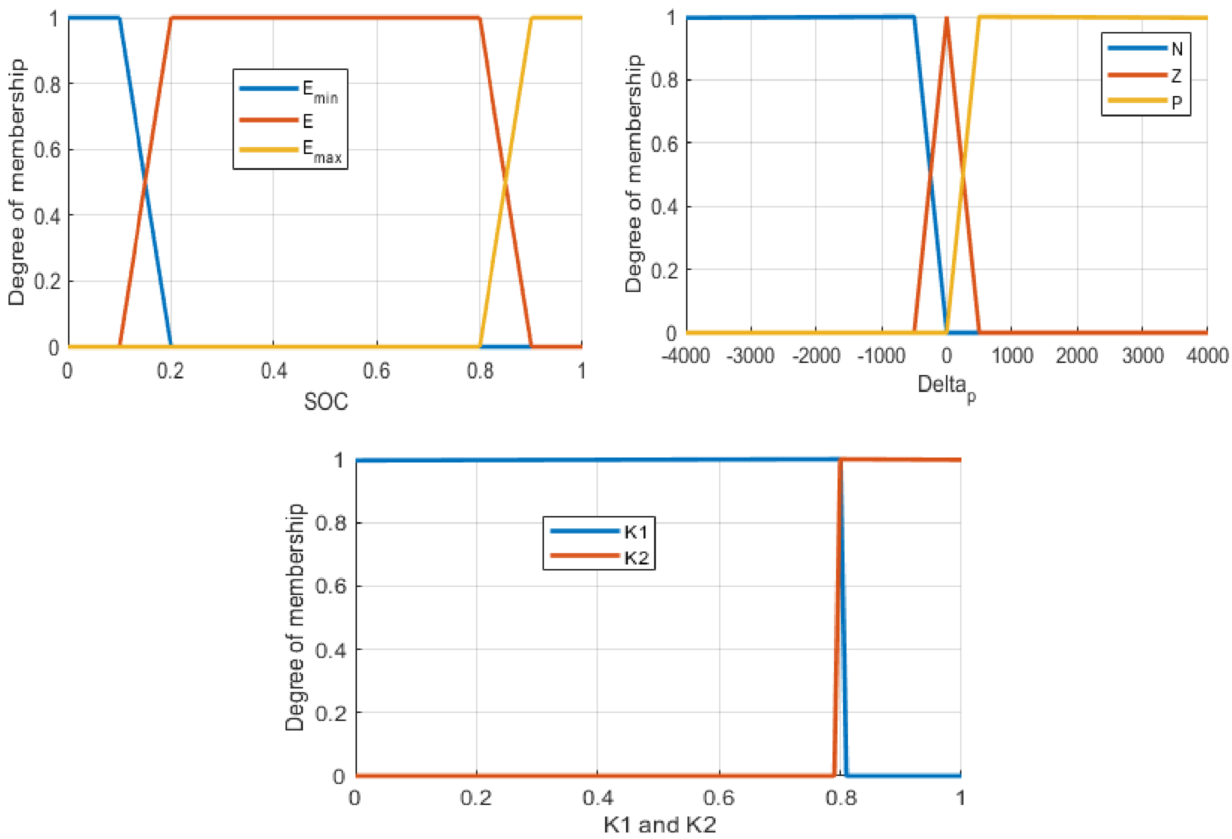


Fig 12. Membership functions

The different fuzzy rules used are given in the tables below:

Table 6. Fuzzy rules for K1

K1		SOC		
		Emin	E	Emax
Delta_P	N	on	on	on
	Z	on	on	on
	P	on	on	off

Table 7. Fuzzy rules for K2

K2		SOC		
		Emin	E	Emax
Delta_P	N	off	off	off
	Z	off	off	off
	P	off	off	on

For the implementation of all the fuzzy rules used here, we used Mamdani type fuzzy rules. Flow chart of the algorithm of energy management is given below

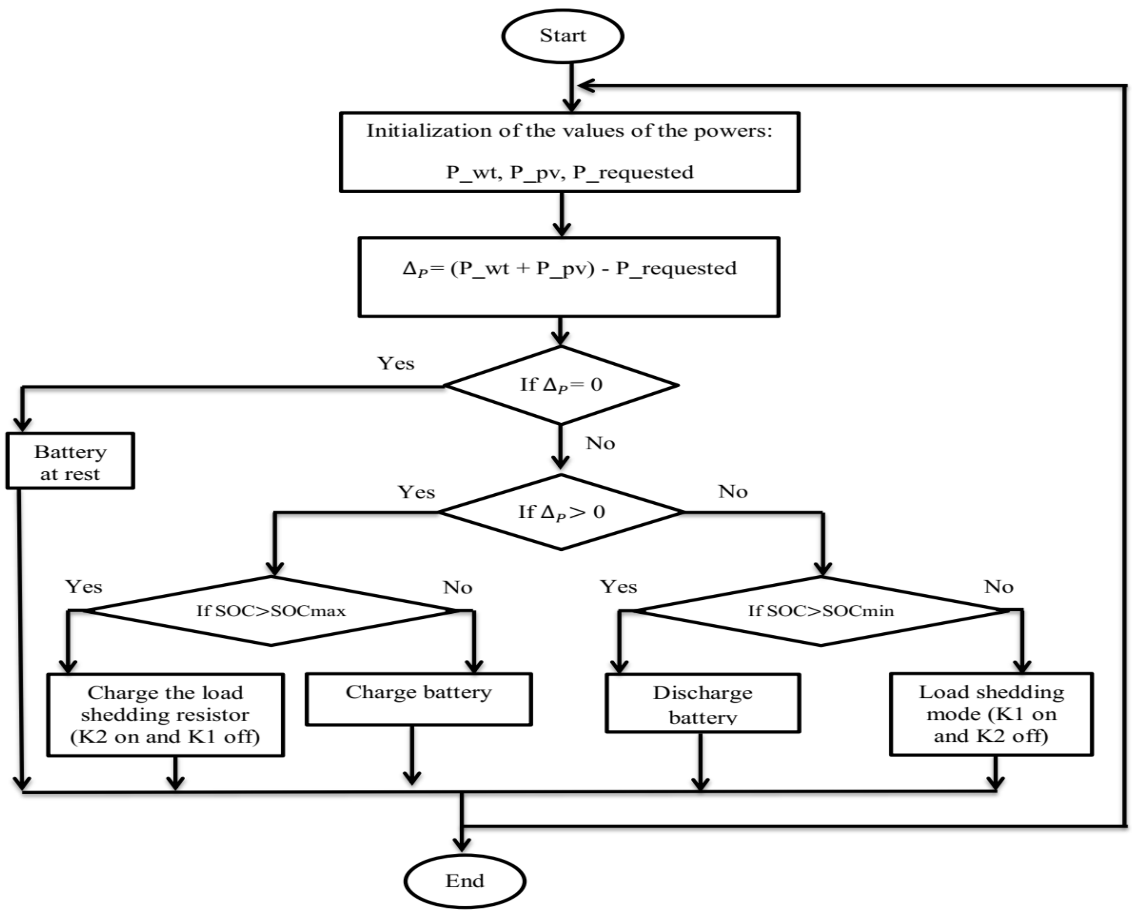


Fig 13. flowchart of the algorithm of energy management

4. Results and discussions

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 simulation was performed with Matlab/Simulink software and a comparison was made with MPPT, NF and Cuckoo algorithm controllers.

The power demand, the wind speed and the sunshine are variable to test the operation of the proposed controllers in various climatic conditions

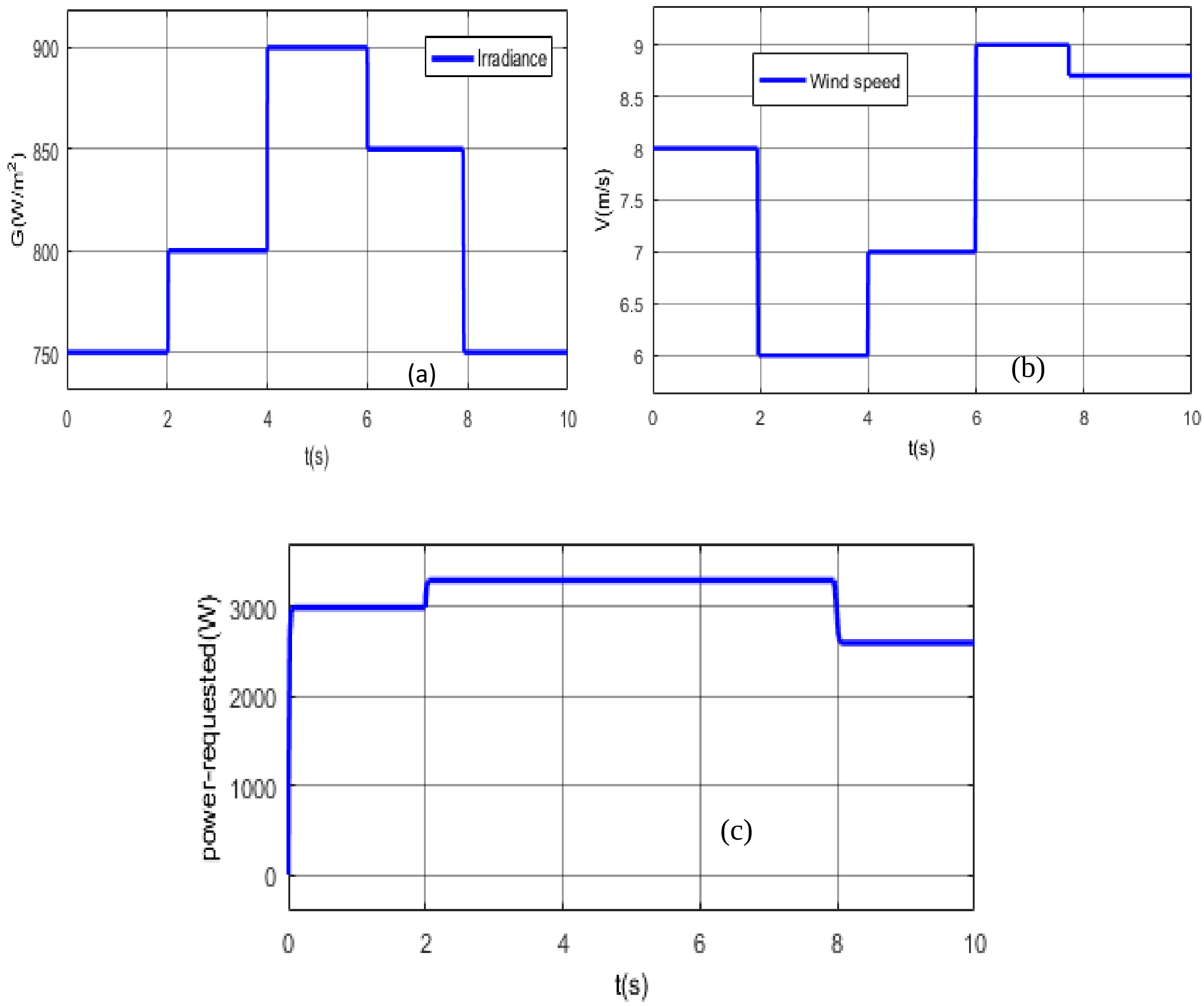


Fig 14. Irradiance (a), wind speed (b) and power demand (c).

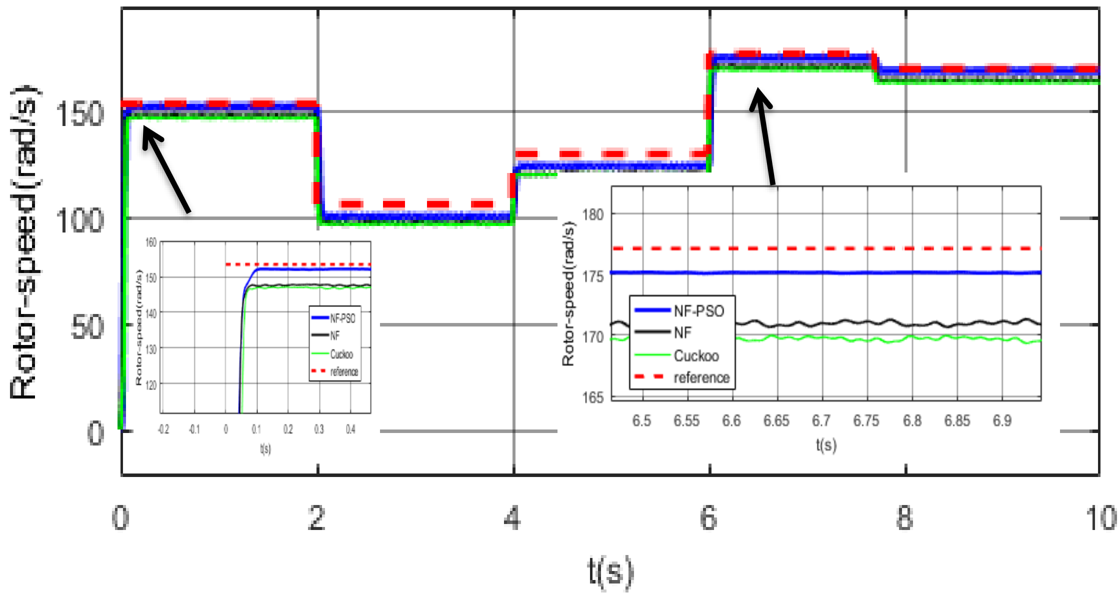


Fig 15. Rotor speed

In figure 15, we notice that the results obtained with our method are favorable compared to the compared methods, with a presence of undulations which prevents to keep the rotor speed at its maximum values.

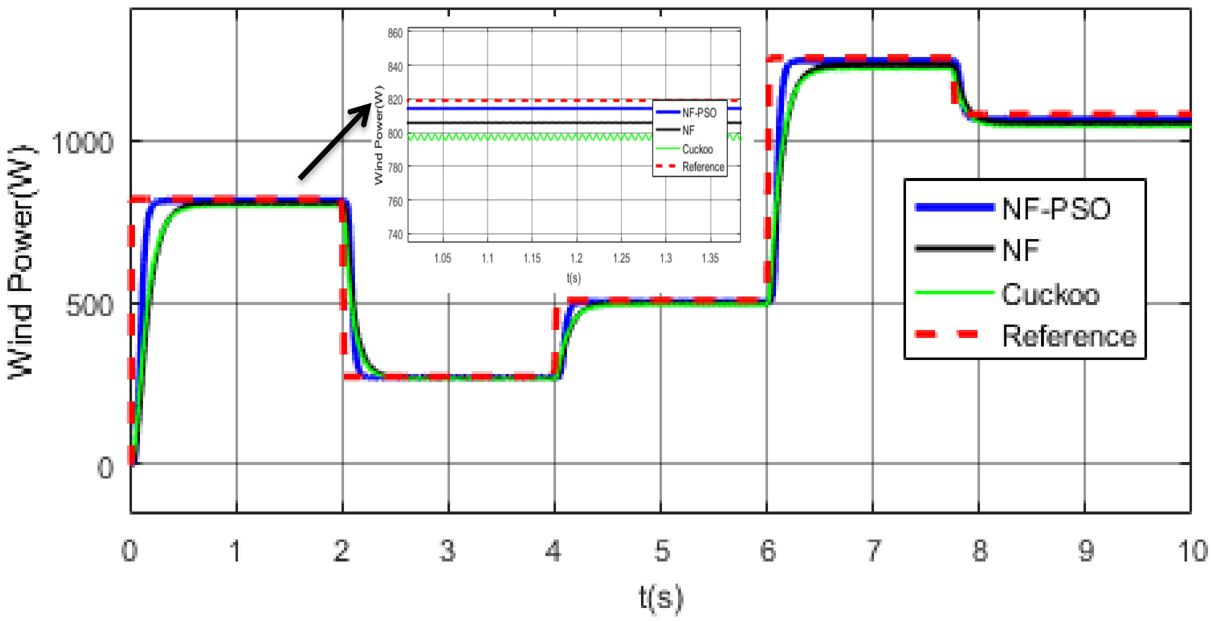


Fig 16. Wind power

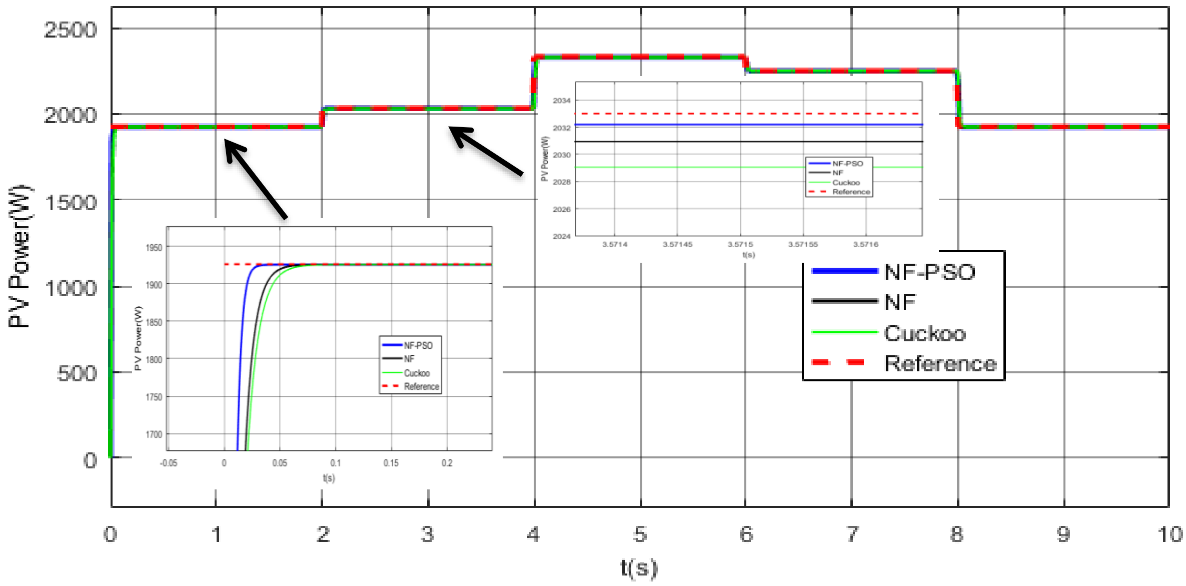


Fig 17. Photovoltaic panel power

Figures 16 and 17 show the results obtained using our NF-PSO approach and compared with the NF and Cuckoo. From these curves, we can see that the NF-PSO controller has contributed in a more efficient way to the extraction of the maximum power compared to the MPPT strategies based on the NF and Cuckoo approach because it has a better rise time, and response hence its fast convergence compared to the compared approaches (see comparison table below) and it is very simple to implement. Thus, we can say that our controller has contributed to the improvement of the production of a PV-WT system.

Table 8. Comparison of the results

Algorithm	Tracking efficiency (%)		Response time (s)		Steady state oscillation (%/W)	Rising time(s)	
	WT	PV	WT	PV		WT	PV
NF-PSO	99.6	99.87	0.2	0.025	No	0.1014	0.00140
NF	98.1	99.78	0.5	0.06	Less	0.1026	0.00142
CUCKOO	97.5	99.74	0.51	0.07	Less	0.1068	0.02

After maximizing the production of both sources, we need to ensure energy management so that there is continuity of service.

We assume that the state of charge of the battery is 90% (Full) to be able to check all the cases of operation.

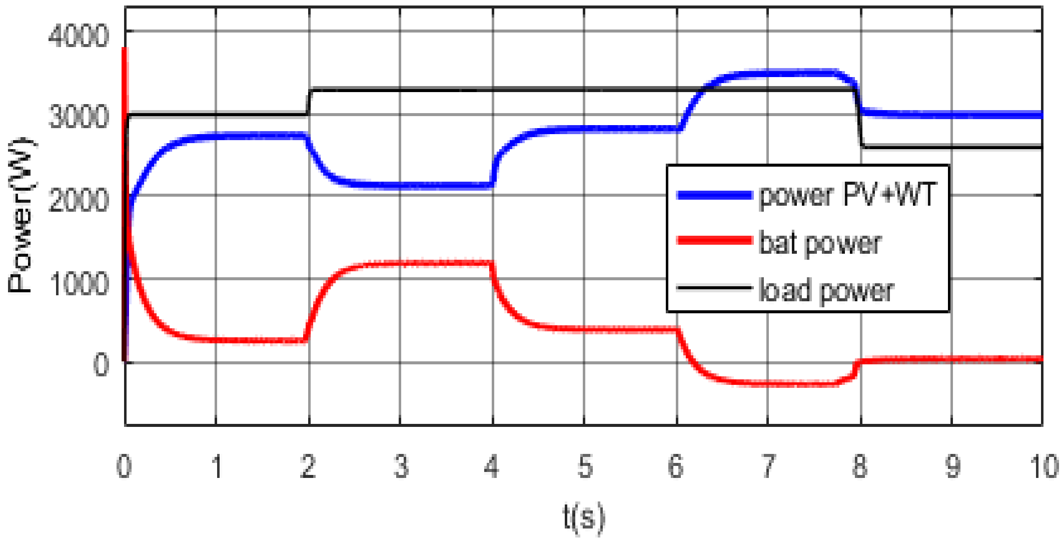


Fig 18. Power of the two sources, power of the battery and power demand

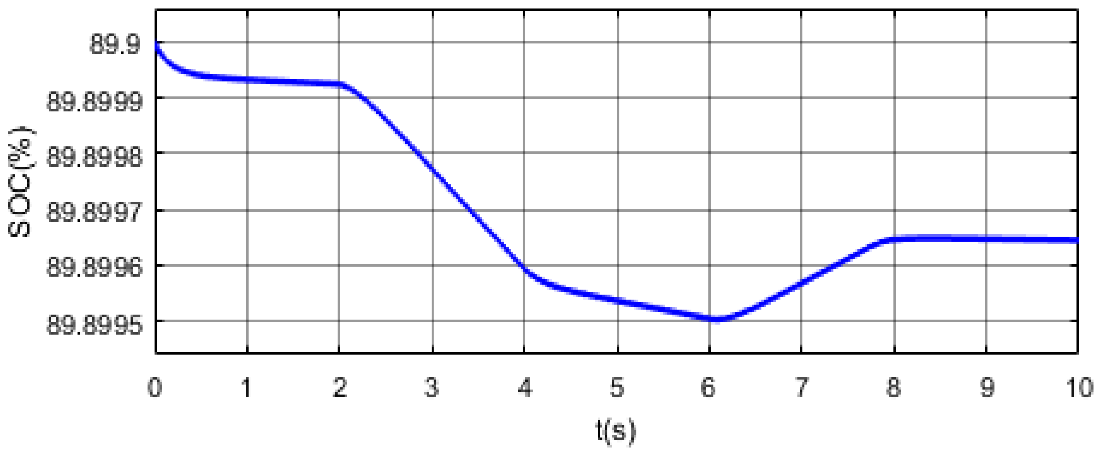


Fig 19. State of charge of battery

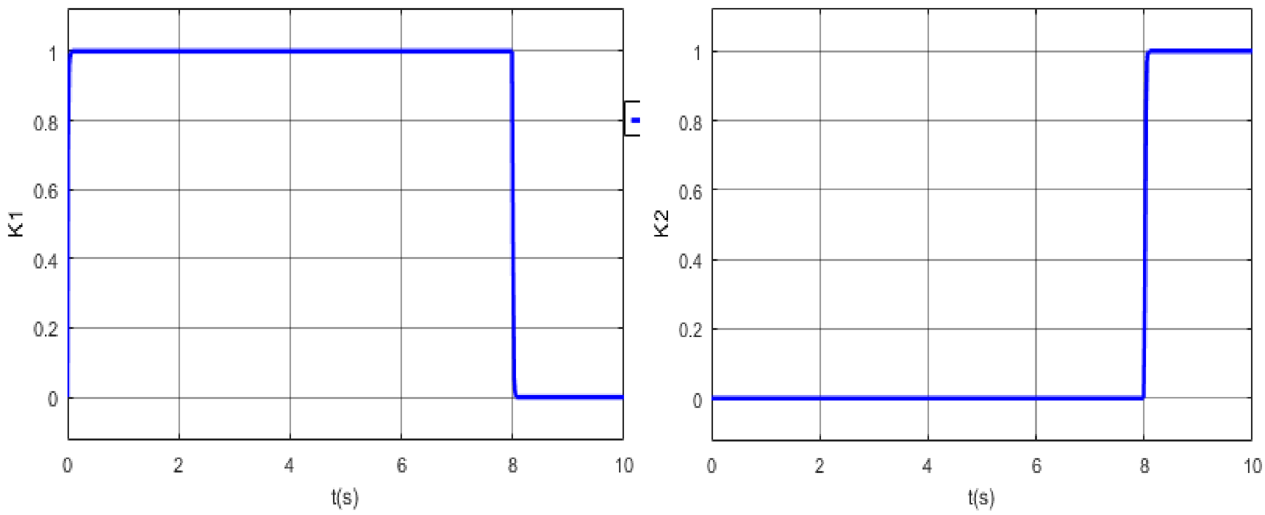


Fig 20. Switch K1 and K2

In the time interval t= [0-6], the two renewable sources do not manage to satisfy the demand, so the battery intervenes to ensure the demand, hence the presence of a positive power (K1=1). In the time interval t= [6-8], the battery is charged and reaches its maximum state of charge, because there is an excess of energy: the two sources completely satisfy the demand. In the interval t= [8-10], the battery is charged, so to avoid its deterioration, the switch K2 turns on (K2=1) and the excess power is transmitted to the resistor.

5. Conclusion

In order to improve the efficiency of PV-wind systems, especially their energy production, we have developed an intelligent and simple method based on NF and PSO. This strategy allows optimizing at each moment and for both sources the power output. Thus we started with the presentation of the system used. Then we presented the NF-PSO controller. The simulation results show the advantage of the adopted strategy because it is faster with a response time of 0.2s on the wind side and 0.025s on the photovoltaic side, more efficient with 99.87% on the photovoltaic side and 99.6% on the wind side, and above all it allows to keep the rotation speed of the machine always at its maximum values, it also allows the reduction of oscillation with practically a negligible rate of oscillation compared to that of the NF and the Cuckoo algorithm. To have an optimal behavior of the installation from a power flow point of view, we developed a fuzzy supervisor. This allows an efficient and rational management of the energy to satisfy the needs of the energy consumer. We plan in the near future to test our approach by taking into account the variation of the temperature on the PV side and the fast variation of wind on the wind turbine side; we also will apply our method in the case of partial shading and perform 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).

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7. References

[1] Krishna, K.S., and Kumar, K.S. A review on hybrid energy systems. Renewable and Sustainable Energy,Reviews, 2015; vol (52), 907 – 916. doi.org/10.1016/j.rser.2015.070187.

[2] Madan, A.S, S. Balasubramanian, and G. Arunkumar. Current Status of Research on Hybrid Power Generation Systems. *Res.* 1. Appl. Sei. Eng. Technol, 2014; vol. 8, no.14, pp. 1684-1690. Doi: 10.19026/rjaset.8.1150.

[3] Diaf. S, Diaf. D, M. Belhamed, M. Haddadi and A. Louche. A methodology for optimal sizing of autonomous hybrid PV/wind system. Energy Policy, 2007; vol 35(11), 5708–5718. doi: 10.1016/j.enpol.2007.06.020.

[4] M. Egido and E. Lorenzo. The Sizing of Stand-Alone PV-Systems: A Review and a Proposed New Method. Solar Energy Materials & Solar Cells, 1992; 26, pp. 51-69. doi.org/10.1016/0927-0248(92)90125-9.

[5] Hans Beyer and Christian Langer. A Method for the Identification of Configurations of PV/Wind Hybrid Systems for the Reliable Supply of Small Loads. Solar Energy, 1996; Vol. 57, pp. 381-391. doi:S0038-092X(96)00118-1.

[6] Bouthaina. M, Rachid. C and Kamel E.H. Energy Management of the Stand-alone Hybrid Power System by Fuzzy Logic. 6th Eur. Conf. Ren. Energy Sys. 25-27 june 2018. https://www.researchgate.net/publication/326711741.

[7] Courtecuisse. V, Srooten. J, and Robyns. B. A methodology to design a fuzzy logic based supervision of hybrid renewable energy systems. Mathematics and Computers in Simulation, 2010; 81: 208-224. doi: 0.1016/j.matcom.2010.03.003.

[8] Özgür Celik and Ahmet Teke. A Hybrid MPPT method for grid connected photovoltaic systems under rapidly changing atmospheric conditions. Electric Power Systems Research, 2017; 152, 194–210. doi.org/10.1016/j.epsr.2017.07.011.

[9] Alireza. R, Ali. E, Hasan. E and Mohammad. M. Intelligent hybrid power generation system using new hybrid fuzzy-neural for photovoltaic system and RBFNSM for Wind turbine in the grid connected mode. Front. Energy, 2017; DOI: 10.1007/s11708-017-0446-x.

[10] Ahmad. R, Hossein. K and Mahdi. M. A Comprehensive Method for Optimum Sizing of Hybrid Energy Systems using Intelligence Evolutionary Algorithms. Indian Journal of Science and Technology, 2013; Vol 6 (6), ISSN: 0974-6846.

[11] Malek Zaibi, Gerard. C, Xavier. R, Jamel. B and Bruno. S. Smart power management of a hybrid photovoltaic/wind stand-alone system coupling battery storage and hydraulic network. Mathematics and Computers in Simulation, 2016; vol 146.pp. 210-228. ISSN 0378-4754. doi.org/10.1016/j.matcom.2016.08.009.

[12] Sasan Moghaddam, Mehdi. B, Majid. M and Pierluigi. S. Designing of stand-alone hybrid PV/wind/battery system using improved crow search algorithm considering reliability index. International Journal of Energy and Environmental Engineering, 2019; 10:429–449. doi.org/10.1007/s40095-019-00319-y.

[13] Paul Abena, Philippe Djondine, P.N. Eloundou and H. Abena. A Novel Hybrid MPPT for Wind Energy Conversion Systems Operating under Low Variations in Wind Speed. Energy and

Power Engineering, 2020; 12, 716-728. doi.org/10.4236/epe.2020.1212042.

[14] Claude Bertin Nzoundja Fapi, Patrice Wira, Martin Kamta and Bruno Colicchio. Voltage Regulation Control with Adaptive Fuzzy Logic for a Stand-Alone Photovoltaic System. European Journal of Electrical Engineering, 2020; Vol. 22, No. 2, April, pp. 145-152. https://www.researchgate.net/publication/341622219.

[15] Mostefa Kermadi and El Madjid. B. Artificial intelligence-based maximum power point tracking controllers for Photovoltaic systems: Comparative study. Renewable and Sustainable Energy Reviews, 2017; vol. 69, p. 369–386. doi.org/10.1016/j.rser.2016.11.125.

[16] M. Premkumar and R. Sowmya. An effective maximum power point tracker for partially shaded solar photovoltaic systems. Energy Reports, 2019; 5, 1445–1462. doi.org/10.1016/j.egyr.2019.10.006.

[17] Ramji Tiwari and Babu, N. R. fuzzy logic based MPPT for permanent magnet synchronous generator in wind energy conversion system. IFAC-PapersOnLine, 2016; 49-1.462–467. doi:10.1016/j.ifacol.2016.03.097.

[18] Huynh, Q., Nollet, F., Essounbouli, N., and Hamzaoui, A. Fuzzy control of variable speed wind turbine using permanent magnet synchronous machine for stand-alone system. In Sustainability in Energy and Buildings. Proceedings of the 3rd International Conference in Sustainability in Energy and Buildings (SEB 11), 2012; vol 12, page 31-44. Springer Verlag.

[19] Jyh-Shing Roger Jang. ANFIS: Adaptive-Network-Based Fuzzy Inference System. IEEE Transactions on systems, Man, and Cybernetics, 1993; Vol 23, N°3, 665-685. doi: 0018-9472/93$03.00.

[20] Chiou, J.S. and Liu, M.T. Numerical simulation for Fuzzy-PID controllers and helping EP Reproduction with PSO hybrid algorithm, Simulation. Modelling Practice and Theory, 2009; Vol. 17, pp.1555–1565. doi: 10.1016/j.simpat2009.05.006.

[21] Bouarroudj, N., Boukhetala, D. and Boudjema, F. Tuning Fuzzy PD$^{\alpha}$ sliding mode controller using PSO algorithm for trajectory tracking of a chaotic system. Journal of Electrical Engineering, 2014; Vol. 14, N° 2, pp.378–385.

[22] Bouarroudj, N., Boukhetala, D. and Boudjema, F. A hybrid fuzzy fractional order PID Sliding-Mode controller design using PSO algorithm for interconnected Nonlinear Systems. Journal of Control Engineering and Applied Informatics, 2015; Vol. 17, No. 1, pp.41–51.

[23] Abdelhalim Borni, Noureddine Bouarroudj, Abdelhak Bouchakour and Layachi Zaghba. P&O-PI and fuzzy-PI MPPT Controllers and their time domain optimization using PSO and GA for grid-connected photovoltaic system: a comparative study. International Journal of Power Electronics, 2017; 8(4), 300-322.