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Theoretical and experimental analysis of genetic algorithms based MPPT for PV systems

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Abstract

This paper presents a theoretical and experimental analysis of Maximum Power Point Tracking (MPPT) method for photovoltaic (PV) systems based on Genetic Algorithms (GAs). The proposed algorithm is based on Genetic Algorithms (GAs) and it can estimate the current (Imp) and voltage (Vmp) at maximum power point by measuring the open circuit voltage (Voc) and the short circuit current (Isc) without knowing the irradiance and the cell temperature. The principle of GAs is searching for the maximum of fitness function and not for the minimum of power derivation; this gives more stability and minimize oscillation of output power around the maximum power point (MPP).
We expose the method with a few tests; then a comparison with the famous Perturb and Observe (P&O) and Incremental Conductance (Inc-Cond) is given. We tested stability (power oscillation) with real panels. To compare response time (rapidity) we used a PV emulator (realized by Kadri et al.), so we can inject the same irradiance profile and see output PV power evolution. The response time of P&O and Inc-Cond, and the PV power oscillation varies with the duty cycle increment step; with a small step, we get less power oscillation but this needs an important time response, we can improve system rapidity with a bigger duty increment step but important power oscillation will result. With GAs based MPPT we can get more stability with rapid response time. The results obtained show better stability and less oscillation around the MPP with the new method.

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Keywords: MPPT; Photovoltaic; Genetic Algorithms; Perturb and Observe; Incremental Conductance; power oscillation; Matlab/Simulink.

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1. Introduction

Because of the rapid growth in industries and the important place of energy in our model lifestyle, the world demand of energy continues to increase. Using conventional energy resources has a great undesirable impact on environment (greenhouse effect) and security (nuclear accidents). Therefore, it is very important to invest in alternative energy resources. Renewable energies are the best solution for our health and the health of our earth; it is certainly one of the future main energy sources. PV systems are one of energy renewable sources, the annual growth of PV industry rate has been more than 40% for the last decade [1] and the PV prices are declining. The International Energy Agency projects that solar power could provide "a third" of the global final energy demand after 2060 [2]. But this source of energy has a little power rate and it changes with atmospheric conditions (irradiance and temperature), so to improve the rate and optimize this source it is very interesting to make PV systems working with their optimal efficiency so with their maximum power, this is the objective of Maximum Power Point Tracking (MPPT).

There are many methods of MPPT [3-8] but in this paper we make comparison between AGs method with the two conventional methods Perturb and Observe (P&O) and Incremental Conductance (Inc-Cond) [9-16]. The two algorithms use the P(V) curve to give the MPPT search direction by incrementing/decrementing the array voltage (or dec/inc duty cycle); they use different techniques observe if the operating point is left or right of the MPP.

These algorithms give good results and are widely used in MPPT, but they present the drawback of oscillating around the MPP and difficulty to adjust the search step. In addition to converge to a local optimum.

By maximizing a fitness function, with GAs based MPPT, we can obtain a solution to the perturbations effect around the MPP. So with the proposed algorithm, the MPP is only moving to get more power, the oscillations problem around the MPP is minimized. This Method gives optimal current Imp (current at maximum power) by measuring the short circuit current Isc and open circuit voltage Voc. The proposed algorithm can efficiently follow the variation of irradiance and temperature (climatic conditions) and not P-V evolution curve.

With GAs, the solution doesn't depend on initial conditions because this method works with a population of individuals randomly generated and chooses the best ones, so searching for the real maximum point and not for the nearest one.

2. MPPT with P&O

P&O algorithm [9-13] operates by periodically perturbing (i.e. incrementing or decrementing) the array terminal voltage and comparing the PV output power and voltage values with the previous perturbation cycle values. If the PV output power is increasing, the perturbation will continue with the same direction in the next cycle, otherwise the perturbation direction will be reversed, we can write:

- $\Delta P > 0$ → Continues changing with the original direction
- $\Delta P < 0$ → Changes to the opposite direction
- $\Delta P = 0$ → Doesn't change (theoretical case)

We create a Simulink block for the conventional P&O algorithm [17] with an embedded function.

The various P&O algorithms are widely used in MPPT because of their simple structure and the few required measured parameters. Therefore, when the MPP is reached, the P&O algorithm will oscillate around it resulting in a loss of PV power. We can reduce the power loss around the MPP by decreasing the perturbation step, however, the algorithm will be slow in following the MPP when the atmospheric conditions start to vary and more power will be lost.

Also, in rapidly changing atmospheric conditions the P&O algorithm can deviate from the MPP sometimes even taking a wrong direction. We can observe this in Fig. 1. When searching for MPP and we are in point (*a*) going right, if atmospheric conditions do not change we will be in (*b*) and the output power increases ($\Delta P > 0$), so we are still going right; but if the output power decreases ($\Delta P < 0$) by irradiance decreasing, the operating point is located in (*c*), the searching direction changes and we go away from the MPP.

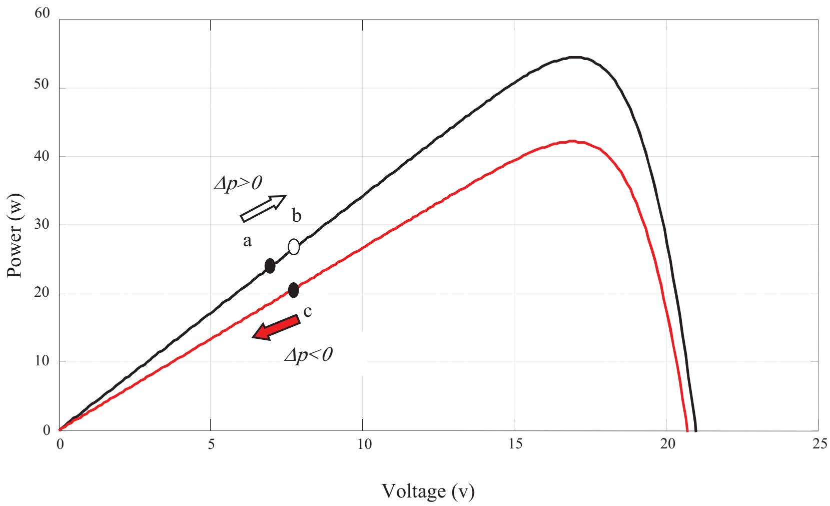

Fig. 1. Rapidly changing atmospheric conditions in P&O

3. MPPT with Inc-Cond

The basic idea of this method [11-16] is that the array terminal voltage always adjusted according to its value relative to the MPP voltage.

So, $\frac{dP}{dV} > 0$ to the left of MPP and $\frac{dP}{dV} < 0$ to the right, as illustrated on Fig. 2.

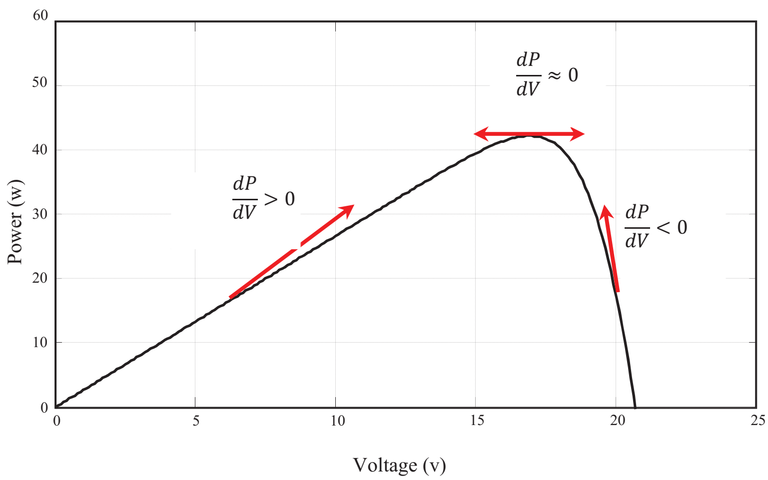

Fig. 2. MPPT with Incremental Conductance

$\frac{dP}{dV} = \frac{d(I.V)}{dV} = V.\frac{dI}{dV} + I$, so this can be written by:

$\frac{dI}{dV} > -\frac{I}{V}$ $\rightarrow$ In the left of the MPP

$\frac{dI}{dV} < -\frac{I}{V}$ $\rightarrow$ In the right of the MPP

$\frac{dI}{dV} \approx -\frac{I}{V}$ $\leftrightarrow$ At the MPP

We can say that the MPP of a PV can be tracked by comparing the incremental and instantaneous conductances, (dI/dV) and (I/V) , of the PV array.

This algorithm gives the real search direction of MPP and can follow rapidly the varying atmospheric conditions, but it presents oscillations around the MPP and sensitivity to the perturbations because one can try to obtain $dP/dV = 0$. So a small undesirable perturbation can move away from MPP. On the other hand, incremental conductance method presents difficulties to adjust the step. The size of the step will determine the tracking speed, when the step size is large, the system response is fast, but the solar system may work around the real maximum power point and cause oscillations like P&O method.

We also created a Matlab embedded function for Inc-Cond algorithm and inserted it in a similar architecture of the Photovoltaic (PV) system so the three methods can be compared.

4. GAs based MPPT

4.1. The proposed method

GAs is an optimization stochastic algorithm based on natural genetic selection [18], its principal advantages:

- It uses its codes instead of parameters;
- It does not work with a point but with a population of points;
- It just needs function values and does not have to calculate any other value (for instance differential).

The steps of Genetic Algorithms are:

a. Initialization:

At first, we should create a random population with $Nind$ binary individuals, with a choice of the length (bits number S, precision). A population is a binary matrix where the number of rows represents the number of individuals and column number represents the length of individuals. The population is formed by cell currents that might give the maximum power.

$$population(I) = \underbrace{\begin{bmatrix} & \cdots & \\ \vdots & \ddots & \vdots \\ & \cdots & \end{bmatrix}}_{S\ bits} \left.\vphantom{\begin{bmatrix} \cdots \\ \vdots \\ \cdots \end{bmatrix}}\right\} Nind\ individuals$$

b. Evaluation:

It is a very important step because it gives the chance of an individual to be selected, the evaluation is given by the value of individuals fitness function. It is a positive function and the individual is optimum for maximum value of its fitness function value; in our case, the fitness function is simply based on power:

$$P = V.I \tag{1}$$

An individual (current) is most important if the corresponding power is bigger.

To evaluate an individual, we use the one-diode cell model shown by the circuit in Fig. 3 [19-21]; where Rs and Rp are respectively series and parallel resistances of the cell.

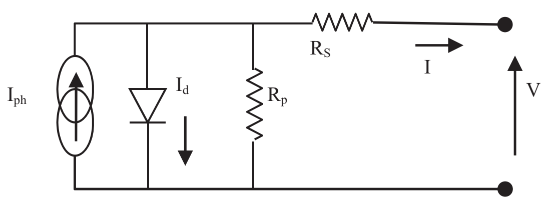

Fig. 3. Equivalent circuit of solar cell with single diode

Usually the value of Rp is very large, so the equation for the output current can be given by:

$$I = I_{ph} - I_d \tag{2}$$

With:

$$I_d = I_{rs}\left[exp\left(\frac{q}{kTA}(V + R_s I)\right) - 1\right] \tag{3}$$

Where, I: Output current (A), V: Output Voltage (V), I_d: Current through the intrinsic diode, I_{ph}: Cell photocurrent, I_{rs}: Cell reverse saturation current, q: The charge of an electron, k: Bolzmann's constant, A: The p-n junction ideality factor, T: Cell temperature, V_{oc}: Open-circuit voltage, I_{sc}: Short-circuit current, R_S: Series resistances of the cell.

Making the approximation that $Iph \approx Isc$, (2) becomes:

$$I = I_{sc} - I_{rs}\left[exp\left(\frac{V + R_s I}{V_T}\right) - 1\right] \tag{4}$$

With,

$$V_T = \frac{kTA}{q} \tag{5}$$

The temperature is considered by the following equations [22]:

$$T = \frac{V_{oc} - V_{ocr}}{K_v} - T_r \tag{6}$$

With, T_r and V_{ocr} the cell temperature and open circuit voltage are respectively at standard test conditions (STC), V_{oc} is the open circuit voltage at operating conditions, and K_v is the temperature coefficient of V_{oc}.

At open circuit ($I = 0$ and $V = V_{oc}$) using (4), the cell reverse saturation current can be written:

$$I_{rs} = \frac{I_{sc}}{exp\left(\frac{V_{oc}}{V_T}\right) - 1} \tag{7}$$

Equation (4) can give the expression of the cell output voltage, using (7) we can write:

$$V = V_T\, Ln\left[\left(1 - \frac{I}{I_{sc}}\right)\left(exp\left(\frac{V_{oc}}{V_T}\right) - 1\right) + 1\right] - R_s I \tag{8}$$

Finally, the power equation (fitness function) can be given:

$$P = \left(V_T\, Ln\left[\left(1 - \frac{I}{I_{sc}}\right)\left(exp\left(\frac{V_{oc}}{V_T}\right) - 1\right) + 1\right] - R_s I\right).I \tag{9}$$

Using this equation, power (fitness function) is calculated for each individual, this value will be used in genetic operations to create a novel population and this one will be inserted in the population of parents according to their fitness function.

c. Genetic operations

They are the base of GAs, they do not exclude probability theories but they give very interesting results, these operations are:

1. **Selection**: To select, with a rate T_{sel}, a part of the population corresponding to the optimum fitness function. The selection method used is 'fitness proportionate selection' (also called: roulette wheel selection), so in a population with N_{ind} individuals and if f_i is the fitness of an individual i, its probability of being selected is: $p_i = \frac{f_i}{\sum_{j=1}^{N_{ind}} f_j}$
2. **Crossover**: Cross pairs of individuals (parents) to get the novel ones (children), with T_{rcm} probability that parents have children.
3. **Mutation**: After crossover, we apply a mutation. It is analogous to biological mutation; it alters one or more gene values in a chromosome with P_m (low) probability that an arbitrary bit will be changed from its original state ($bit \leftarrow \overline{bit}$).
4. **Insertion**: The new population will be integrated to the old population to replace individuals with minimum fitness function.

d. Program termination

Executing program creates new best individuals, the program terminates according to the iterations number so we obtain a constant executing time.

4.2. Testing of the algorithm

Fig. 4 shows the flow chart of the algorithm, variable N_{gen} represents the number of generations (repetition of the loop).

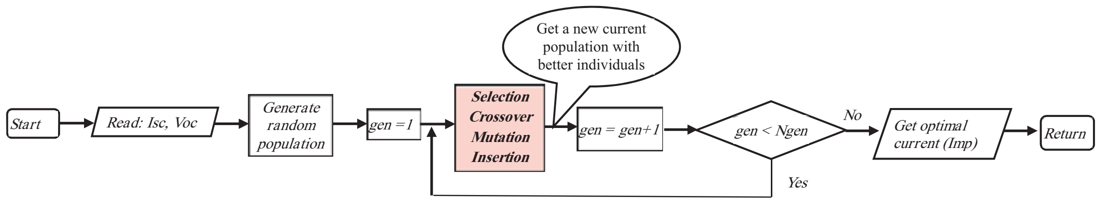

Fig. 4. Flow chart of Genetic Algorithms

Using this flow chart, an algorithm is written as an embedded function in the *MPPT_GAs* Simulink bloc with the necessary Matlab functions (Fig. 5), with *GAs_parameters* and *PV_parameters* are GAs and PV panel parameters respectively.

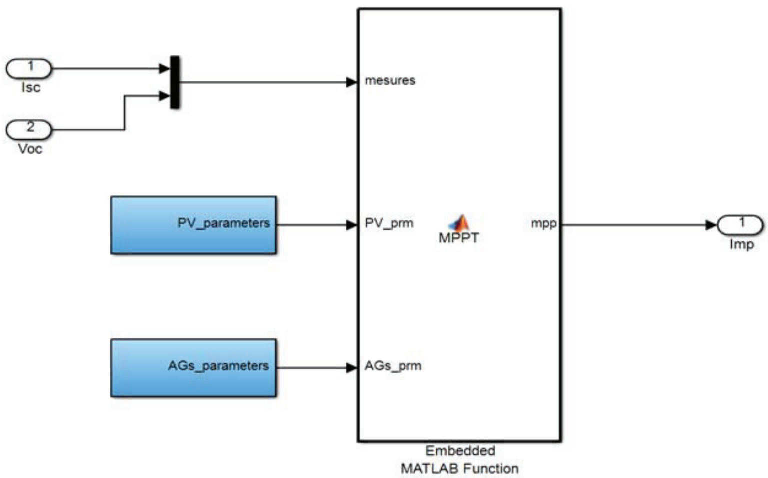

Fig. 5. MPPT_GAs block function

To optimize the algorithm, it was tested with different genetic parameters (T_{sel}, T_{rcm} , and P_m), number of individuals N_{ind} , and their length S (precision).

4.2.1. Changing number of individuals:

Fig. 6 and Fig. 7 show the maximum power evolution with number of generations using 10 and 30 individuals respectively. (with, $S = 16$ bits, $T_{sel} = 0.8$, $T_{rcm} = 0.8$, $P_m = 0.01$).

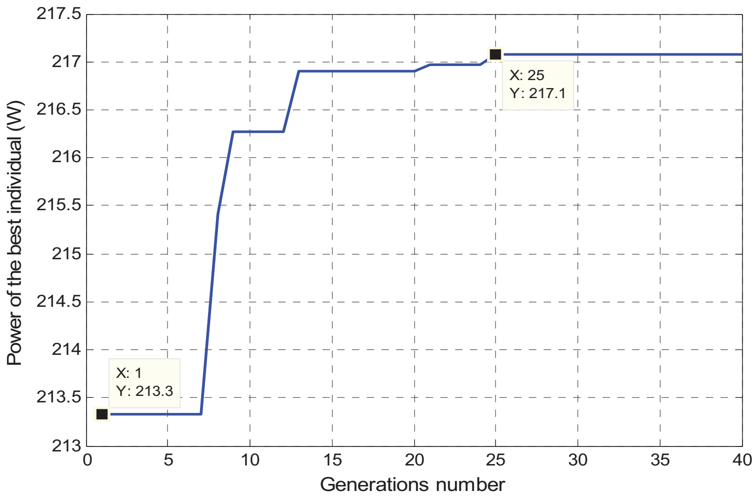

Fig. 6. Maximum power evolution using 10 individuals

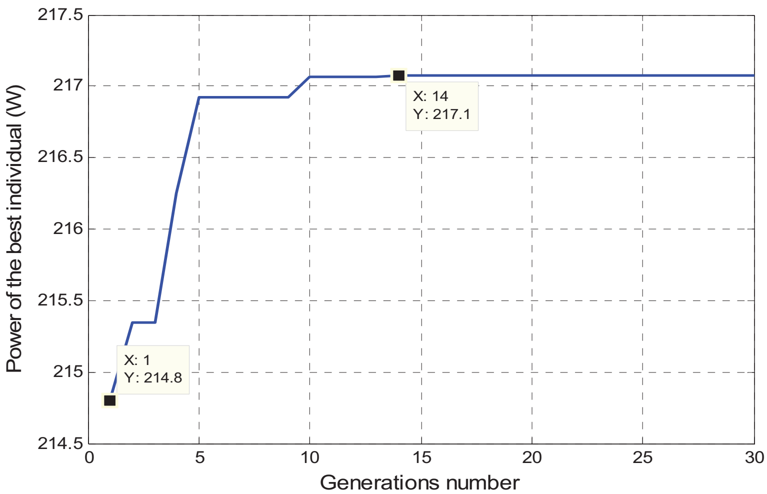

Fig. 7. Maximum power evolution using 30 individuals

When using 10 individuals we get the MPP after 25 generations but when using 30 individuals the MPP appears after only 14 generations. In addition, the power of the first generation is often bigger with wide generation. With a big number of individuals (large population) the maximum power is given in less generations but it needs more execution time, to decrease it we should take a small number of generations (in termination condition).

4.2.2. Changing bits number:

The number of bits S represents the length of individuals (precision). The power evolution using $S = 20$ and $S = 5$ is shown on Fig. 8 and Fig. 9 respectively, we can note that high S value gives more precision (power changes) but needs bigger number of generations, we can also see more power changes (diversity) with $S = 20$ than with $S = 5$ (longer individuals help appearance of new ones), it is a good thing but the executing time increases.

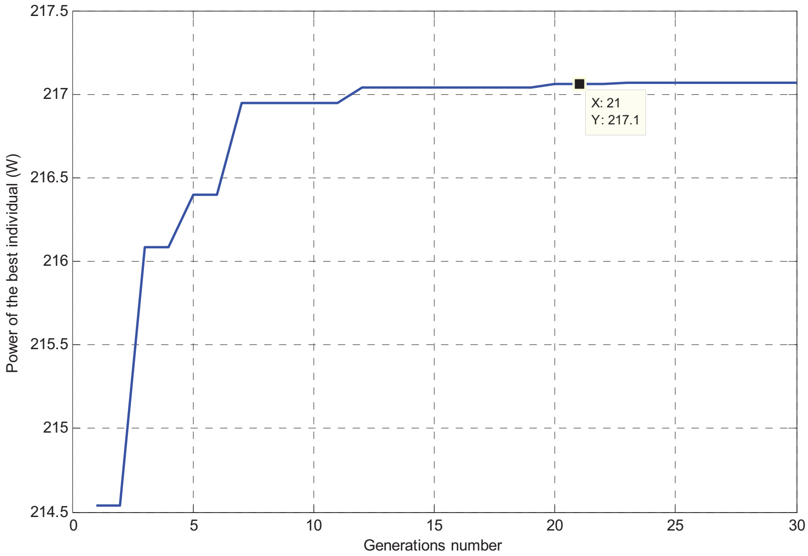

Fig. 8. Power evolution with S=20

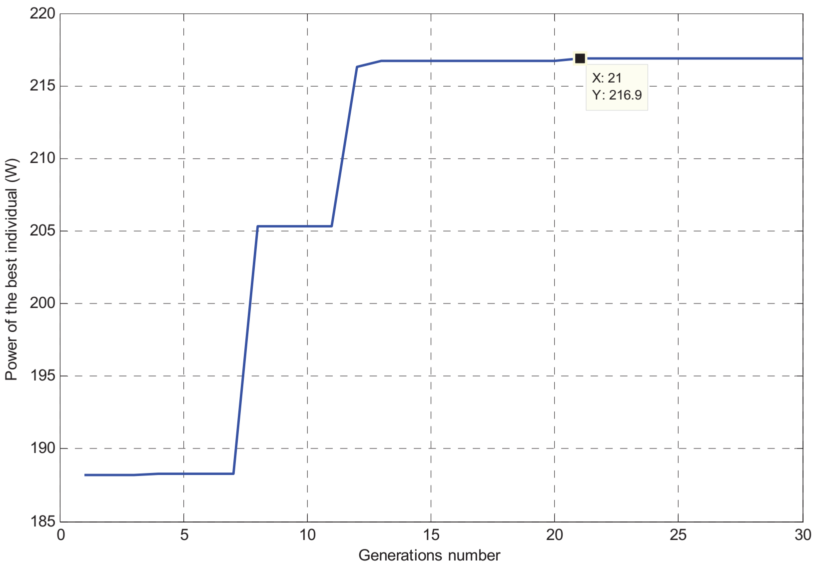

Fig. 9. Power evolution with S=5

5. Experimental results

The tests are made in LIAS laboratory (Laboratoire d'Informatique et d'Automatique pour les Systèmes) of Poitiers university (France), Fig. 10 shows the architecture of the experimental PV system, and Fig. 11 a photograph of the experimental test bench.

We used Conergy PowerPlus 214P Photovoltaic panels [23], two panels are used to measure Isc and Voc (we can use instead a pilot cell), a boost converter DC/DC is placed between the PV panels and a resistive load.

The object is to generate a PWM signal to the boost in order to make the PV panels working with their maximum power (around the MPP).

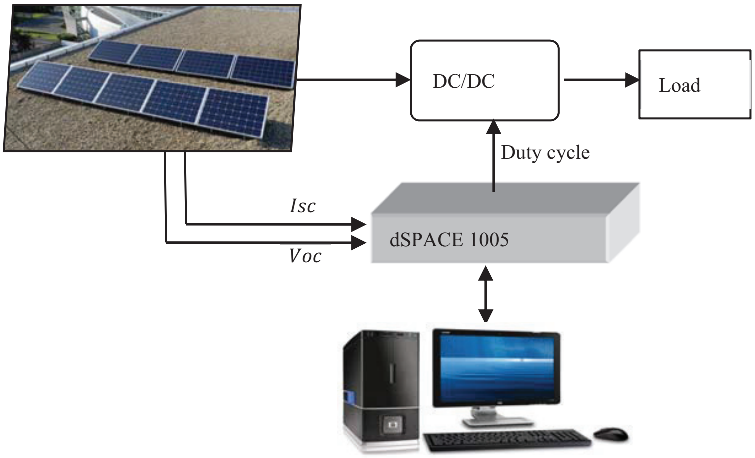

Fig. 10. PV system with MPPT

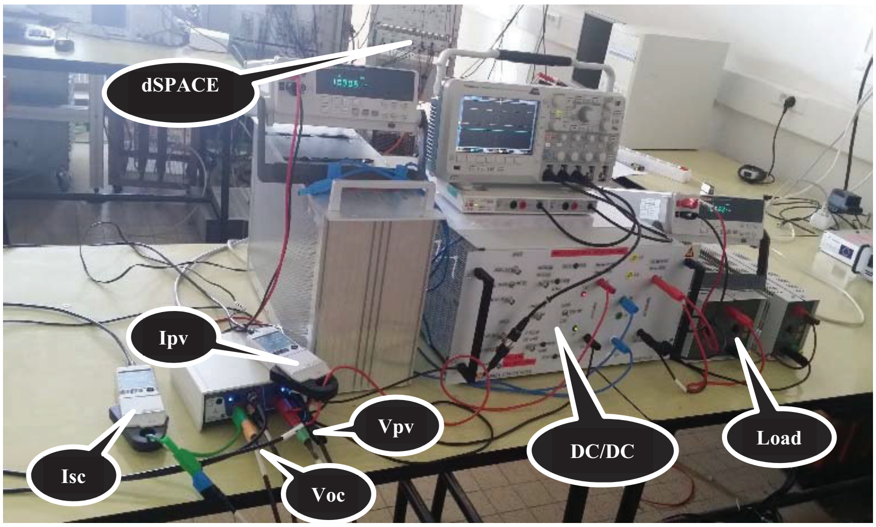

Fig. 11. The experimental test bench of the PV system

The algorithms (P&O, Inc-Cond, and AGs) are separately implemented in the dSPACE1005 using Matlab/Simulink® (see Fig. 12 for AGs method), all data and results tests are collected from ControlDesk®.

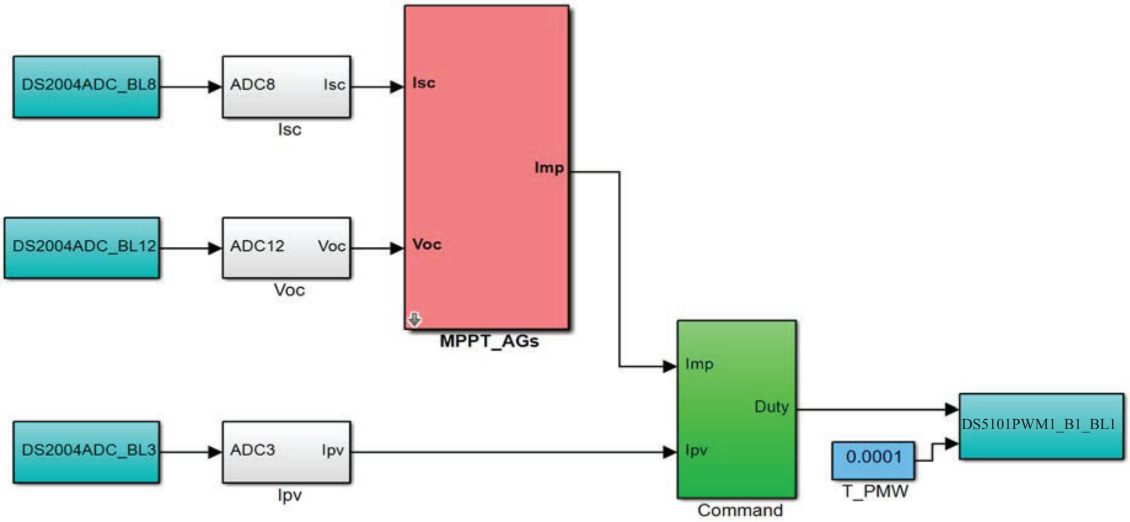

Fig. 12. Simulink implementation of MPPT based GAs

PV Panels are used to compare the stability (oscillation), for rapidity (response time) we used a PV emulator[24,25] (Fig. 13). Thus, we can inject the same irradiance profile and observe the power evolution for each algorithm.

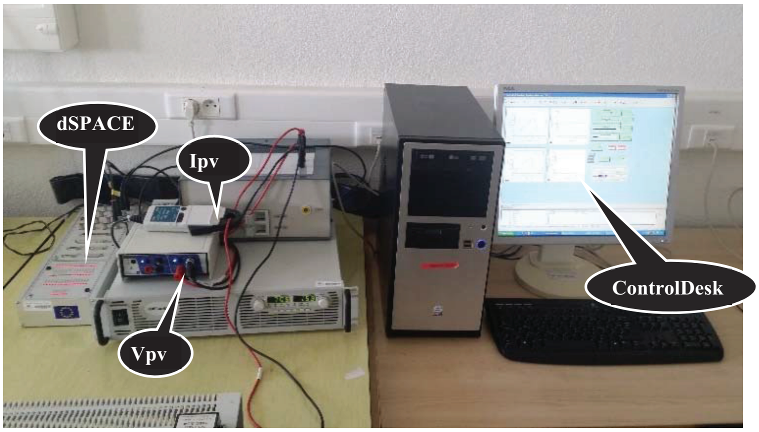

Fig. 13. The experimental test bench of the emulator

5.1. Testing with PV panels

Both AGs, P&O, and Inc-Cond are implemented with Simulink, a test is made separately for each method (one after another) so a small global power different can be seen due to the changing of irradiance level (measurement not at the same time).

We made tests using GAs and P&O (Fig.14) then using Inc-Cond and AGs (Fig.15), with duty cycle increment $\Delta D = 0.01$. We can clearly observe less power oscillation with GAs than P&O or Inc-Cond methods, so we get more stability.

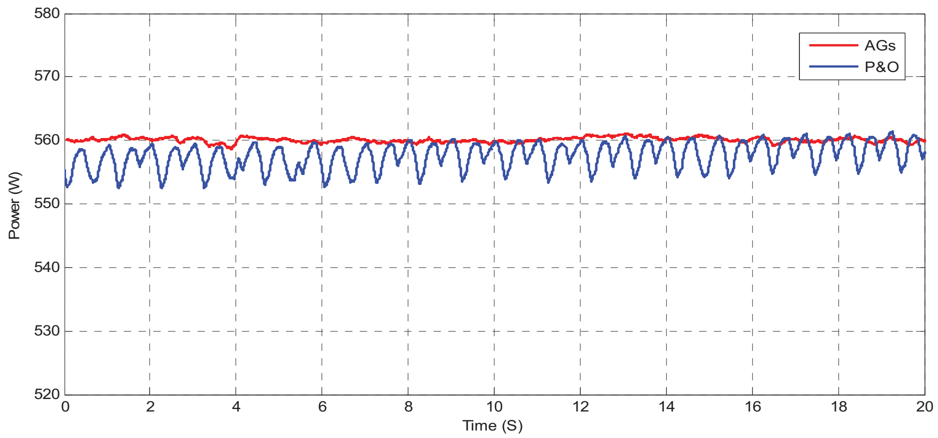

Fig. 14. PV power evolution with P&O and GA using $\Delta D = 0.01$

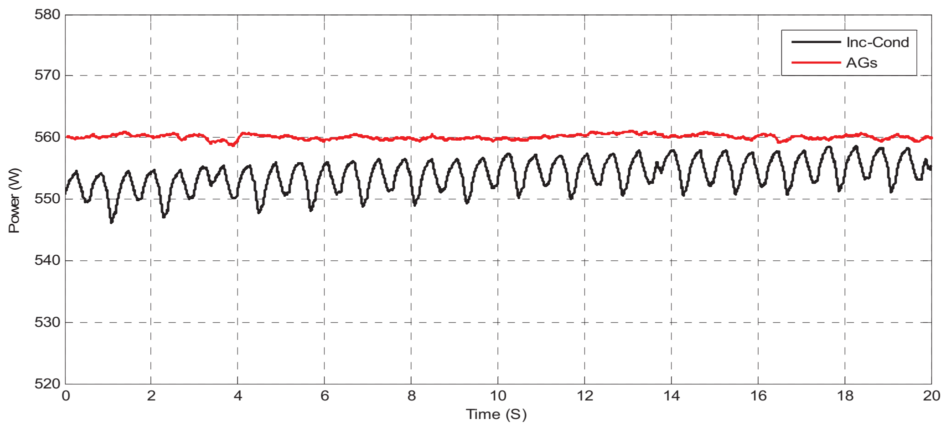

Fig. 15. PV power evolution with Inc-Cond and GA using $\Delta D = 0.01$

The next figures (Fig.16 and Fig. 17) show experimental tests with $\Delta D = 0.02$ (note the little changing in global PV power due to irradiance changing between tests). We can see higher oscillation level with $\Delta D = 0.02$ than $\Delta D = 0.01$ using P&O and Inc-Cond so more power oscillation, while with AGs method the power is stable.

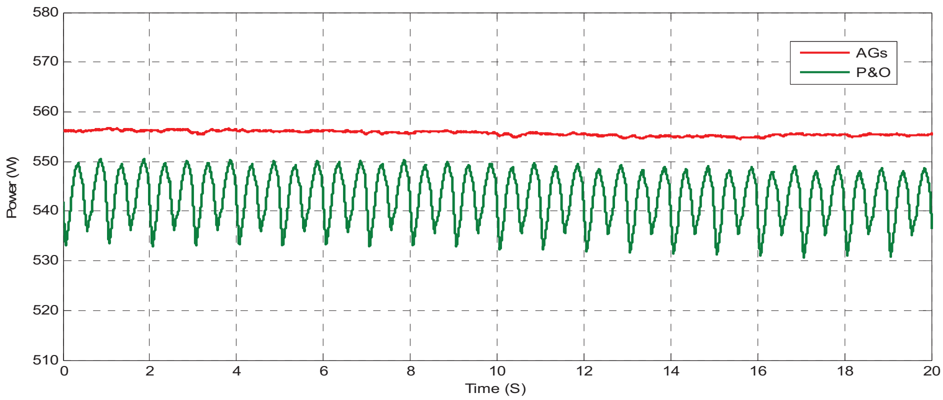

Fig. 16. PV power evolution with P&O and GAs with $\Delta D = 0.02$

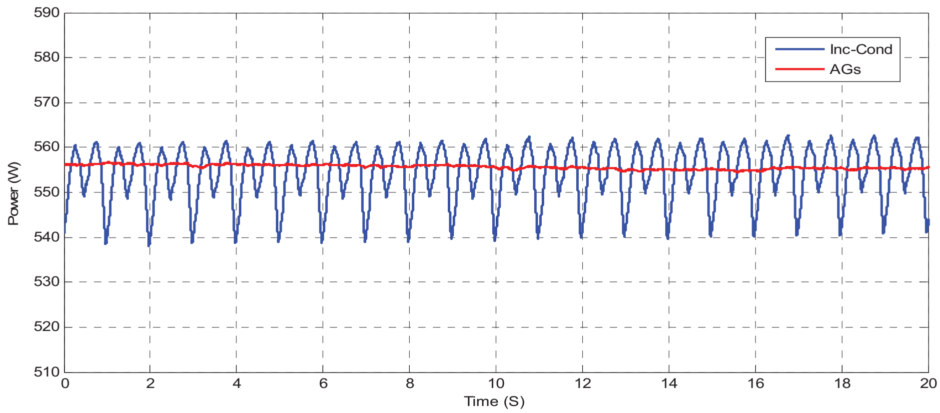

Fig. 17. PV power evolution with GAs and Inc-Cond with $\Delta D = 0.02$

We present by the next figures (Fig. 18 and Fig. 19) the duty evolution with GAs and Inc-Cond methods with $\Delta D = 0.01$ and $\Delta D = 0.02$ repectively, we can observe that duty cycle with GAs is approximately constant so the power is more stable. With duty increment $\Delta D = 0.02$ we can improve the response time (next section) of P&O and Inc-Cond methods but the power oscillation is more important.

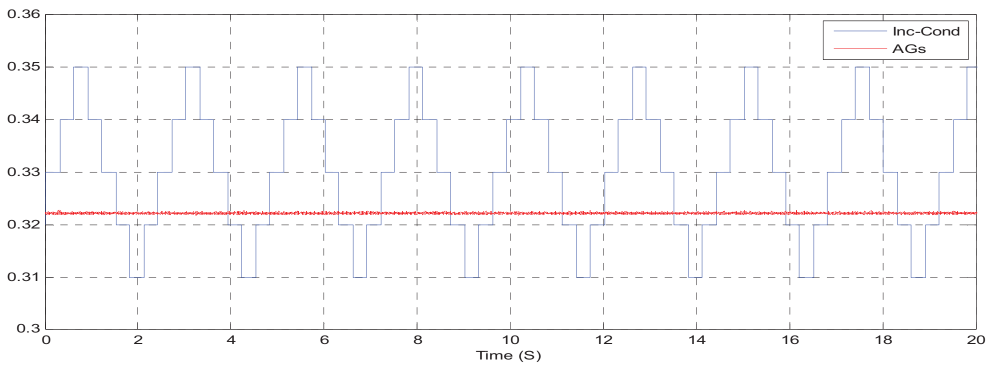

Fig. 18. Duty cycle evolution with GAs and Inc-Cond using $\Delta D = 0.01$

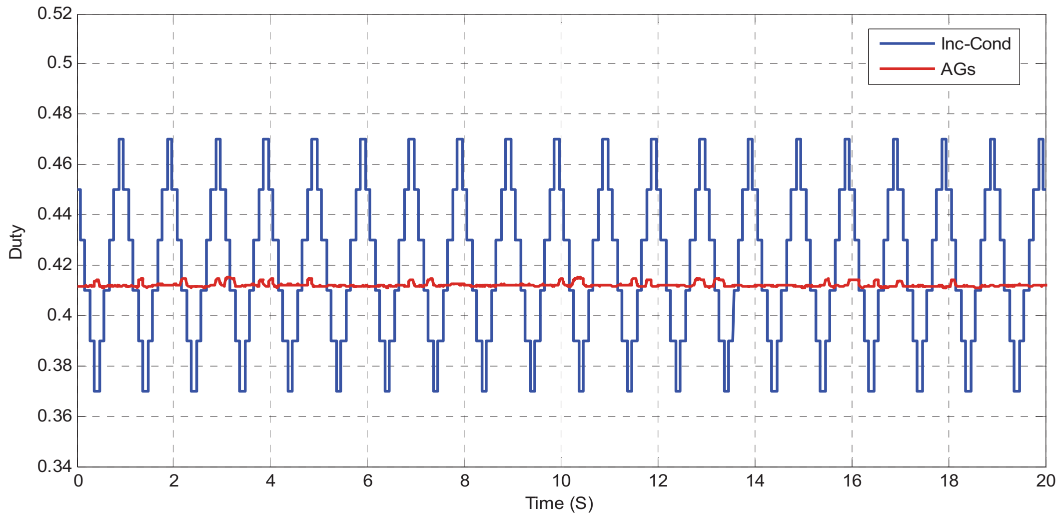

Fig. 19. Duty cycle evolution with GAs and Inc-Cond using $\Delta D = 0.02$

5.2. Testing with PV emulator

A PV emulator realized by Kadri et al. [24,25] in LIAS laboratory allowed us to define an irradiance profile changing (Fig. 20), so we can test the tracking of the MPP by the three methods.

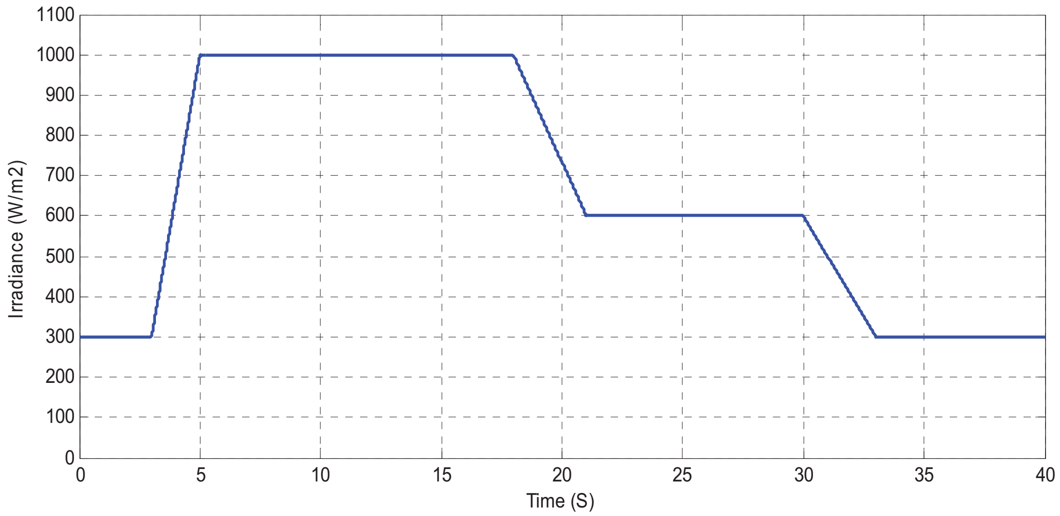

Fig. 20. Profile irradiance

We observe (on the next figures) that both P&O, Inc-Cond, and GAs methods track the PV maximum power. With Inc-Cond and P&O we get less power oscillation with $\Delta D = 0.01$ (Fig. 21 and Fig. 23) than with $\Delta D = 0.02$ (Fig. 22 and Fig. 24) respectively, but the MPP tracked slower; On the contrary it is clear that the AGs method tracks rapidly the MPP (red curve) and solves the problem of power oscillation around it.

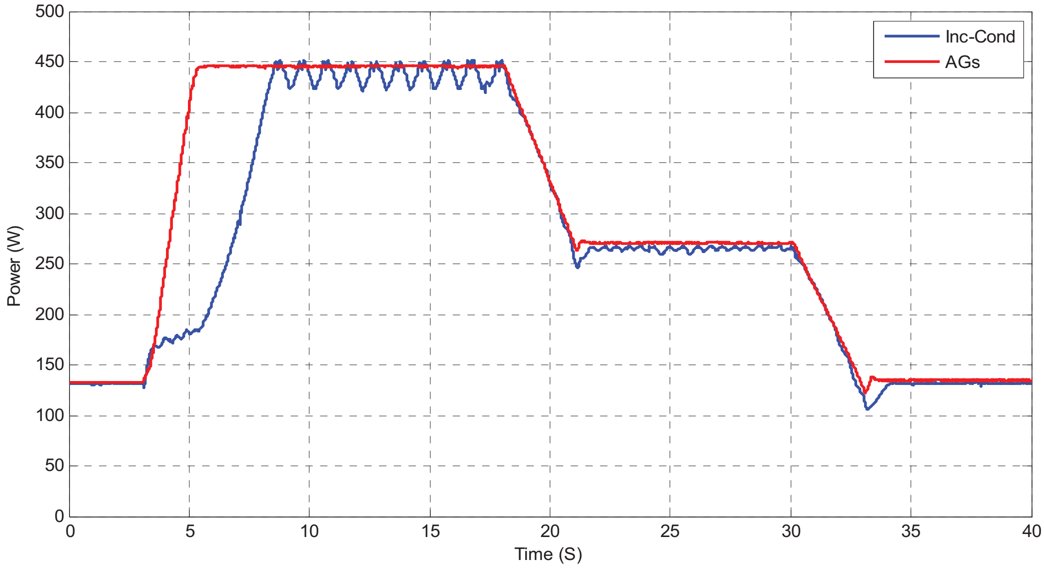

Fig. 21. PV power evolution with GAs and Inc-Cond using $\Delta D = 0.01$

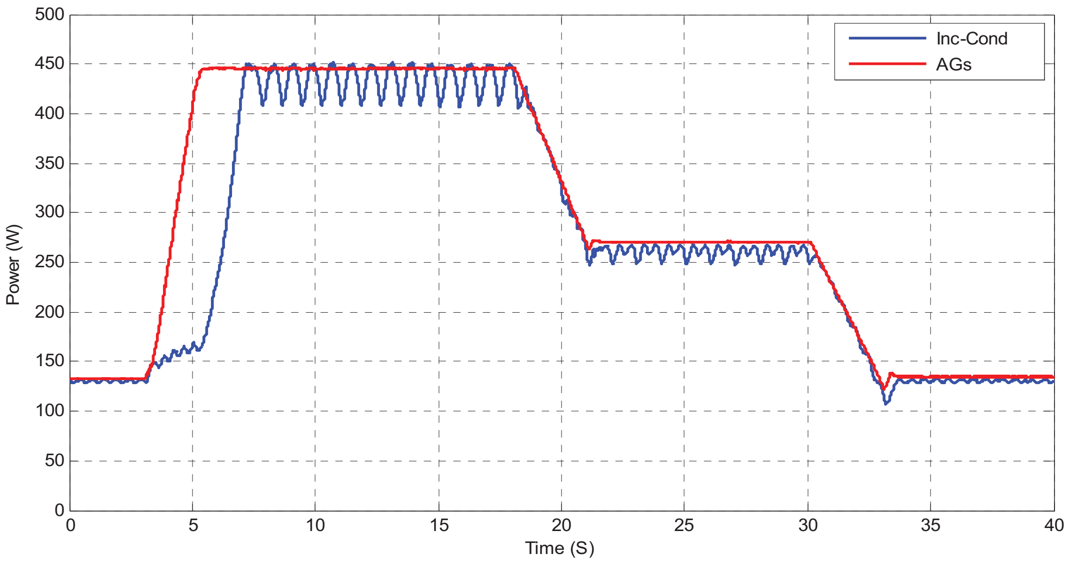

Fig. 22. PV power evolution with GAs and Inc-Cond using $\Delta D = 0.02$

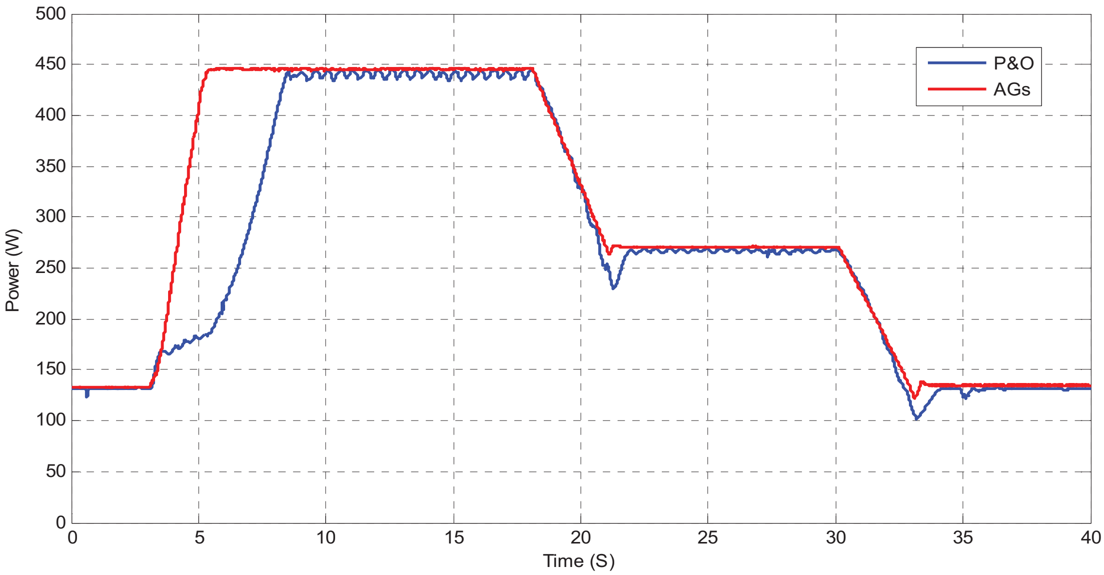

Fig. 23. PV power evolution with GAs and P&O using $\Delta D = 0.01$

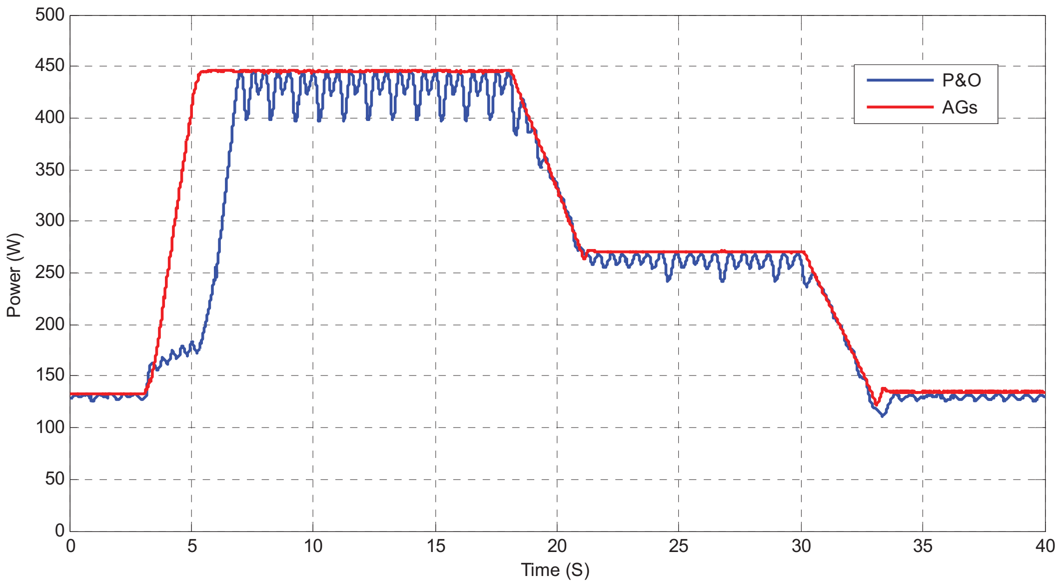

Fig. 24. PV power evolution with GAs and P&O using $\Delta D = 0.02$

6. Conclusion

This paper has proposed a GAs-MPPT control method for solar power generator systems, which tested theoretically (simulation) and experimentally (with emulator and real panels). The proposed method can generate more energy than traditional methods because these will lead to power oscillations or approximate MPPT. In addition, the proposed controller has a strict stability, good rapidity and accuracy, which are not provided by conventional techniques such as P&O and Inc-Cond.

In addition, with the proposed method the problem of oscillations around the MPP is solved as well as the sensitivity to noise because it searches the maximum and not the minimum (like minimum of power derivation) and follows rapidly varying atmospheric conditions. The disadvantage of the algorithm is using the PV panel model, which is not a perfect image of the panel, thus a small error is added to the result, that can be minimized by parameters identification of the PV panel.

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