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# ADAPTIVE NEURAL CONTROL FOR MAXIMUM POWER EXTRACTION IN PHOTOVOLTAIC SYSTEMS

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**Key words: Adaptive neural control, Maximum power point tracking, Perturb and observe algorithm, Photovoltaic system.**

**This paper proposes a new adaptive neural control (ANC) based strategy for maximum power point tracking (MPPT) in a photovoltaic (PV) system. The proposed strategy exploits the online trained adaptive linear neuron (ADALINE) technique. This results in a simple, fast and accurate MPPT algorithm which is easy for implementation. The ANC method is based on the incremental conductance and implemented in direct control mode. Tracking performances of the proposal are experimentally assessed using the EN 50530 standard dynamic tests. A comparison with perturb and observe algorithm is achieved. Superiority of the suggested method in terms of tracking features, convergence speed and oscillatory behaviors reduction is proven. The originality of this work is the design of an efficient and simple ADALINE based MPPT algorithm that reaches very quickly the maximum power point. Moreover, the proposal is experimentally tested in a real PV system according to the EN 50530 standard.**

## 1. INTRODUCTION

Electricity generation through photovoltaic (PV) sources has seen a boost in the past decades. However, power-versus-voltage (*P-V*) characteristic of a PV panel is nonlinear and depends on the irradiance, ambient temperature, and load. Hence, maximum power point tracking (MPPT) algorithms have been proposed to keep the PV system at its maximum power point (MPP) [1].

So far, various MPPT strategies have been published in the literature. These algorithms are usually classified into two groups; conventional and soft computing methods. Among the conventional MPPTs, perturb and observe (P and O) [1] and incremental conductance (IC) [2] based algorithms are the most popular. Due to their robustness and ease of implementation, these algorithms are largely used in commercial products [3]. MPPT algorithms based on open-circuit voltage [4], fractional short-circuit current [5] and hill climbing [6] can also be mentioned. Under stable climatic conditions, these algorithms exhibit satisfactory performances with low implementation cost. However, under variable climatic conditions, they lose ability to keep working around the MPP [7]. For improvement, advanced soft computing methods have been proposed. Accordingly, MPPT methods based on artificial neural networks (ANNs) [8, 9, 10, 11], fuzzy logic [3, 12], particle swarm optimization [13], intelligent monkey king evolution [14], differential evolution [15], predictive control [16], and sliding mode control [17] are published.

ANNs based MPPT algorithms are the most investigated and suggested techniques. Their attractiveness is due to the ANNs advantages, such as robust operation, fast tracking, tolerance to nonlinear systems, and no requirement of accurate models [8]. In addition, the ANNs training can be performed off-line or it can be achieved online which gives more adaptability to the ANNs regarding to changes in the system parameters. Recently published studies have exploited feed-forward back propagation ANNs with offline training [8]. Single adaptive neurons with an online training [9] and with a combined online and offline training [10] are also used. Although these strategies have shown good performances, some of them are trained offline [8] which require repetitive offline training. Others suffer from their complexity [8, 10], required irradiance and temperature sensors [8], and not verified experimentally [9, 10]. Hence, these drawbacks contribute to increase costs of the system and complicate their implementation. On the other hand, even for the proposals based on other concepts, the majority has been verified only through simulations [11, 15], tested under simple irradiance profiles [4, 5, 13], or validated on PV simulators which remain non-real PV systems [7, 13, 14, 16]. At the best of our knowledge, an adaptive MPPT based on the simple online trained adaptive linear neuron (ADALINE) with an experimental validation in a real PV system using the EN 50530 standard dynamic tests [18], have not been proposed yet.

In this paper, a new direct adaptive neural control (ANC) based strategy is proposed for maximum power extraction in a PV system. The suggested method is based on the IC and exploited the ADALINE technique [19]. Mainly, the ADALINE advantages are its simple structure, convergence speed, and ability to be trained online [20]. Actually, the proposed ANC method presents a very simple structure compared to other ANCs and ANNs based MPPTs [8, 9, 10], since the ADALINE requires only one parameter (a learning rate) for tuning. Moreover, due to the fact that the ADALINE uses only one layer for operation, its online training is very fast which leads to reach very quickly the MPP. On the other hand, the use of an ADALINE that is characterized by a high filtering capability [20] is another benefit of the proposal. Indeed, this allows having filtered measurement signals. So, the control is less exposed to measurement noises, which makes the system more stable. The ANC method is implemented in direct control mode for simplifying the control loop. For validation purpose, an experimental test bench is implemented and different irradiance profiles according to the EN 50530 standard are reproduced. This standard is very rigorous since it requests to tests the MPPT methods under steady state (low and high irradiance levels) as well as dynamically changing conditions (strong irradiance instability). These conditions are characterized by using consecutive increasing and decreasing ramps of irradiance with different irradiance levels as well as gradients. A comparison with the P and O algorithm is performed under the same conditions.

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Obtained experimental results shown superiority of the ANC method. Indeed, the use of ADALINE leads to reach very quickly the MPP and allows extracting more power.

This paper is organized as follows. The PV system is introduced in Section 2. In Section 3, the proposed ANC method is developed. Section 4 presented the experimental setup and the test conditions. Obtained experimental results are discussed in Section 5. Section 6 concludes this paper.

## 2. PV SYSTEM DESCRIPTION

Simplified block diagram of the controlled PV system is depicted in Fig. 1 where a PV panel of IFRI260-60 type is used. Electrical specifications of the PV panel at standard test conditions (STC) are summarized in Table 1 [21]. Its characteristics at 25°C are plotted in Fig. 2.

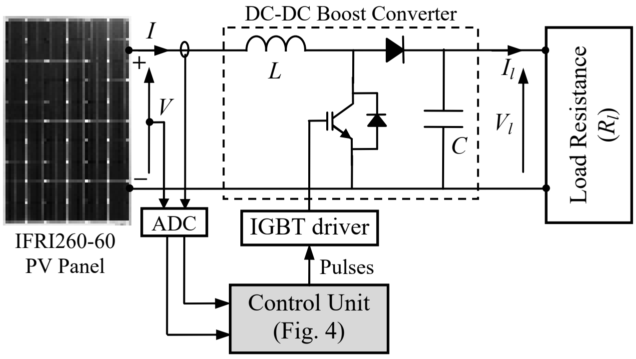


Fig. 1 – Simplified block diagram of the controlled PV system.

*Table 1*

Electrical specifications of the IFRI260-60 PV panel at STC

| | |
|---|---|
| Current at the MPP $I_{mp}$ | 8.1 A |
| Voltage at the MPP $V_{mp}$ | 32.05 V |
| Maximal power $P_{max}$ | 260 W |
| Short-circuit current $I_{sc}$ | 8.65 A |
| Open-circuit voltage $V_{oc}$ | 38.1 V |
| Number of cells connected in series $N_s$ | 60 |

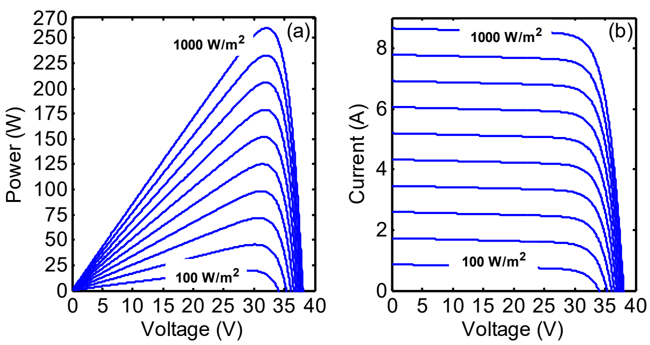


Fig. 2 – Characteristics of the used IFRI260-60 PV panel at 25°C for different irradiance levels (graphs plotted with step of 100 W/m$^2$): (a) power-voltage (*P-V*) curves; and (b) current-voltage (*I-V*) curves.

In continuous conduction mode, the average model of the used dc-dc boost converter can be expressed as

$$\frac{\mathrm{d}I}{\mathrm{d}t}=\frac{V}{L}-\frac{V_l}{L}(1-\alpha), \tag{1.a}$$

$$\frac{\mathrm{d}V_l}{\mathrm{d}t}=\frac{I}{C}(1-\alpha)-\frac{V_l}{R_l C}, \tag{1.b}$$

where $I$ and $V$ are, respectively, the output current and voltage of the PV panel. α is the duty cycle. $V_l$ is the output voltage and $R_l$ is the load resistance. $L$ is the input inductance and $C$ is the output capacitance.

As can be seen in Fig. 2, *P-V* curves of the PV panel are hardly nonlinear and exhibit a unique MPP for each irradiance level [22]. So, a dynamic tracking algorithm is necessary to extract the available maximum power under any operating conditions. The developed ANC method as well as its learning rule will be presented in what follows.

## 3. PROPOSED ANC METHOD FOR MPPT

### 3.1. ADALINE THEORY

Topology of an ADALINE is shown in Fig. 3. It is composed by an input vector $X(k)=[x_1(k) \;\cdots\; x_m(k)]$, an adjustable weight vector $W(k)=[w_1(k) \;\cdots\; w_m(k)]^{\mathrm{T}}$, a linear activation function and a single output (estimated output) $y_{est}(k)$. The ADALINE weights are updated online in order to minimize the estimation error $e(k)$. Usually, the weights are iteratively updated using the μ-least mean square (μ-LMS) learning rule as follows [20]:

$$W(k+1)=W(k)+2\mu\, e(k)X(k), \tag{2}$$

where μ is the learning rate. The value of μ affects directly accuracy, convergence speed and stability of the ADALINE. Indeed, low value of μ leads to increase the accuracy and stability at the cost of slower convergence speed. On the other side, high value of μ leads to high convergence speed but with less accuracy and stability.

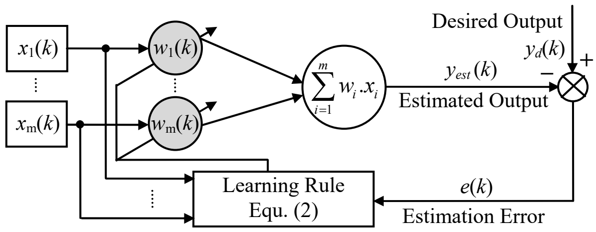


Fig. 3 – ADALINE topology.

### 3.2. PROPOSED ANC METHOD

The principle of the proposed ANC method consists in comparing the PV panel instantaneous conductance ($I/V$) and its incremental conductance ($\Delta I/\Delta V$) to determine whether to increase or decrease the PV panel voltage in order to reach the MPP. The sum of these quantities is positive on the left side of the MPP and negative on its right side. Hence, the MPP is reached when this sum is null and the following equality is verified:

$$\frac{\mathrm{d}I}{\mathrm{d}V}=-\frac{I}{V}. \tag{3}$$

On the other side, the instantaneous conductance of the dc-dc boost converter can be derived from (1.a) as

$$\frac{\mathrm{d}I}{\mathrm{d}V}=\frac{\mathrm{d}t}{L\,\mathrm{d}V}\left[V-V_l(1-\alpha)\right]. \tag{4}$$

The MPP is reached when (3) and (4) are equal. Hence:

$$\frac{\mathrm{d}t}{L\,\mathrm{d}V}\left[V - V_l\left(1-\alpha\right)\right] = -\frac{I}{V}\,. \quad (5)$$

In its discrete form, the equality (5) can be written as

$$\frac{L}{T_s}\frac{\Delta V(k) I(k)}{V(k)} + V(k) = V_l(k)\left(1-\alpha(k)\right), \quad (6)$$

where $\Delta V(k) = V(k) - V(k-1)$ is the variation of the PV panel output voltage. $T_s$ is the sampling period. From (6) and Fig. 3, an ADALINE structure can be derived as

$$V(k) + \frac{L}{T_s}\frac{\Delta V(k) I(k)}{V(k)} = y_d(k), \quad (7.a)$$

$$V_l(k)\left(1-\alpha(k)\right) = W(k) = y_{est}(k), \quad (7.b)$$

where its input $X(k)$ is equal to 1 and $W(k)$ is its unique weight. After the learning process, $W(k)$ will converge to $V_l(k)\left(1-\alpha(k)\right)$. Therefore, the optimal voltage $V_{ref}(k)$ can be calculated in the following way:

$$V_{ref}(k) = L\frac{\Delta I(k)}{T_s} + W(k), \quad (8)$$

where $\Delta I(k) = I(k) - I(k-1)$ is the variation of the output current.

### 3.3. MODIFIED LEARNING RULE

As previously stated, ADALINE is usually trained using the μ-LMS learning rule. Besides, in nonlinear systems, a modified learning rule with hard limit function is used [20]. As our controlled system is specifically nonlinear, a hard limit function is cascaded with the estimation error. Moreover, experimental tests are shown that the following modified μ-LMS learning rule achieves best performances in term of convergence speed, stability and oscillations in the PV panel output current and voltage:

$$W(k+1) = W(k) + \mu\,\mathrm{sign}\{e(k)\}X(k)\,. \quad (9)$$

Block diagram of the ANC strategy is given in Fig. 4.

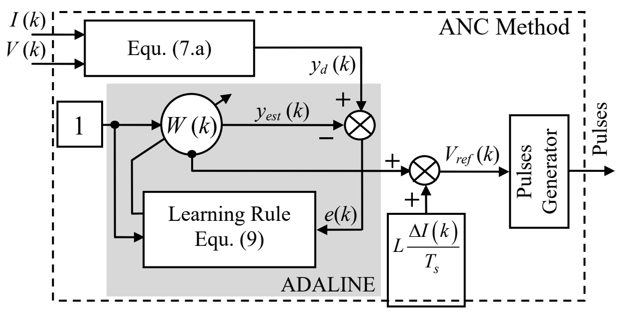


Fig. 4 – Block diagram of the proposed ANC method.

## 4. EXPERIMENTAL SETUP AND TEST CONDITIONS

### 4.1. DESCRIPTION OF THE EXPERIMENTAL SETUP

A view of the experimental setup used for verifying the feseability and effectiveness of the proposed ANC method is shown in Fig. 5. Its control and power circuit parameters are given in Table 2. The experimental setup mainly contains an insulated-gate bipolar transistor (IGBT)-based dc-dc boost converter with a high power IGBT driver. A Hall-effect voltage sensor of LV25-P type and a Hall-effect current sensor of LA55-P type are, respectively, used to measure the output voltage and current of the PV panel. On the PV panel side, the applied irradiance profiles are provided by four halogen lamps. Their luminous intensity is controlled using a single-phase power controller. A light radiation detector of RG100 type is used for irradiance measurement on the PV panel surface.

The developed ANC strategy as well as the P and O algorithm are implemented under MATLAB-Simulink environment and executed on a dSPACE DS1104 board using Euler resolution method. The P and O algorithm is implemented with a fixed step size of 0.001. This value is optimized through several experimental tests in order to achieve fast transients and reduced steady state oscillations. On the other hand, the ANC mehtod is implemented with a learning rate μ equal to 0.5. Also, these value is experimentally adjusted to ensure stability and optimal speed of weight convergence.

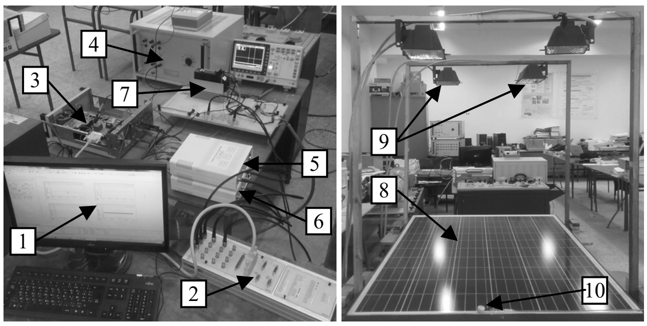


Fig. 5 – View of the experimental test bench: 1) PC-Pentium + dSPACE board + ControlDesk; 2) dSPACE input/output connectors; 3) dc-dc boost converter; 4) load resistance; 5) voltage sensor; 6) current sensor; 7) single-phase power controller; 8) IFRI260-60 PV panel; 9) halogen lamps; and 10) irradiance sensor.

*Table 2*

Control and power circuit parameters of the test bench

| | |
|---|---|
| Switching frequency $f_{sw}$ | 100 kHz |
| Input inductor $L$ | 10 mH |
| Output capacitor $C$ | 3.3 mF |
| Load resistance $R_l$ | 220 Ω |
| Sampling period $T_s$ | 100 μs |

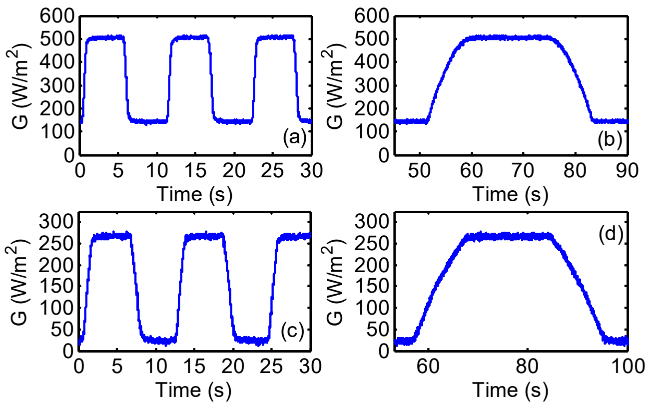


Fig. 6 – Irradiance profiles: (a) medium to high level with fast profile; (b) medium to high level with slow profile; (c) low to medium level with fast profile; and (d) low to medium level with slow profile.

### 4.2. TEST CONDITIONS

To test the efficiency of the implemented methods, experiments are carried out under various irradiance (*G*) profiles. The used dynamic test conditions are based on the EN 50530 standard [18]. However, in this work, this standard is used in a slightly modified form. Indeed, due to the current limitation of the used power source (less than 20 A) to feed the halogen lamps, the number of the used lamps is limited to four (see Fig. 5). Thus, the obtained maximum irradiance at the PV panel surface is around 510 W/m$^2$. The four irradiance profiles reproduced in the laboratory are illustrated in Fig. 6. For medium to high level, the irradiance varies between 150 and 510 W/m$^2$ (Figs. 6(a) and (b)), and for low to medium level, the irradiance varies between 30 and 270 W/m$^2$ (Figs. 6(c) and (d)). For fast profiles, the slopes are 360 W/m$^2$/s (Fig. 6(a)) and 145 W/m$^2$/s (Fig. 6(c)) and for slow profiles, the slopes are 42 W/m$^2$/s (Fig. 6(b)) and 20 W/m$^2$/s (Fig. 6(d)). All the experiments are realized under a temperature around 25°C.

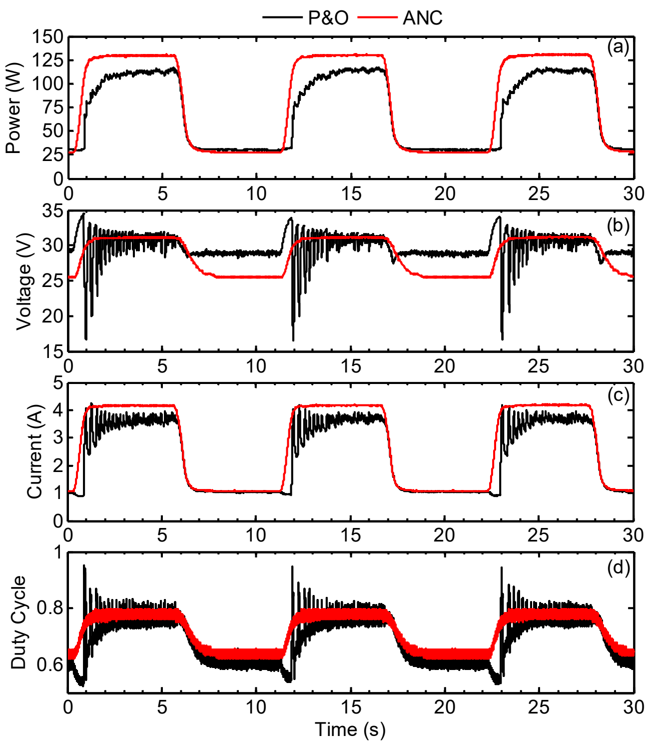


Fig. 7 – Tracking performances under medium to high irradiance with fast profile: (a) power; (b) voltage; (c) current; and (d) duty cycle.

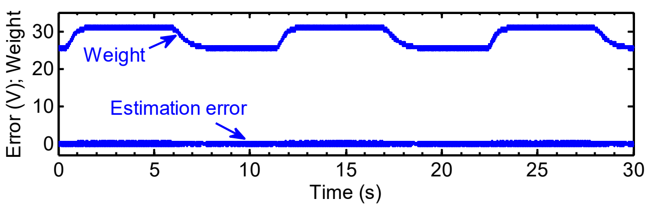


Fig. 8 – Evolution of the weight and estimation error in the ANC method under medium to high irradiance with fast profile.

## 5. EXPERIMENTAL RESULTS AND DISCUSSIONS

To show best tracking performances of the proposed ANC method, a comparison with the P and O algorithm is achieved. The obtained experimental results are illustrated and analyzed. Four tests are realized according to the irradiance profiles shown in Fig. 6 and two additional tests are performed when step changes in irradiance are applied.

Figs. 7–14 presented tracking performances of the implemented algorithms when the irradiance profiles shown in Fig. 6 are applied. Figs. 7(a), 9(a), 11(a) and 13(a) present the PV output power waveforms. It is clear that the P and O exhibits important power losses unlike the proposed method where a maximum power is extracted. The P and O exhibits a time delay and takes long times to reach the steady states while the proposal tracks instantaneously the maximum power. PV output voltage and current waveforms are plotted in Figs. 7(b), 9(b), 11(b) and 13(b), and in Figs. 7(c), 9(c), 11(c) and 13(c), respectively. Important oscillations are clearly manifested in case of P and O especially during transient states. In case of the ANC method, the voltage and current waveforms are more stable and presented less oscillations. In Figs. 7(d), 9(d), 11(d) and 13(d), the duty cycles computed by the implemented strategies are given. The duty cycles seem to be stable, not saturated and present fewer oscillations in case of the ANC method. So, this indicates that the PV system is controlled in more stable way. However, in case of P and O, the duty cycles present important oscillations and tend to be saturated during transient states. This can conduct the PV system into instability.

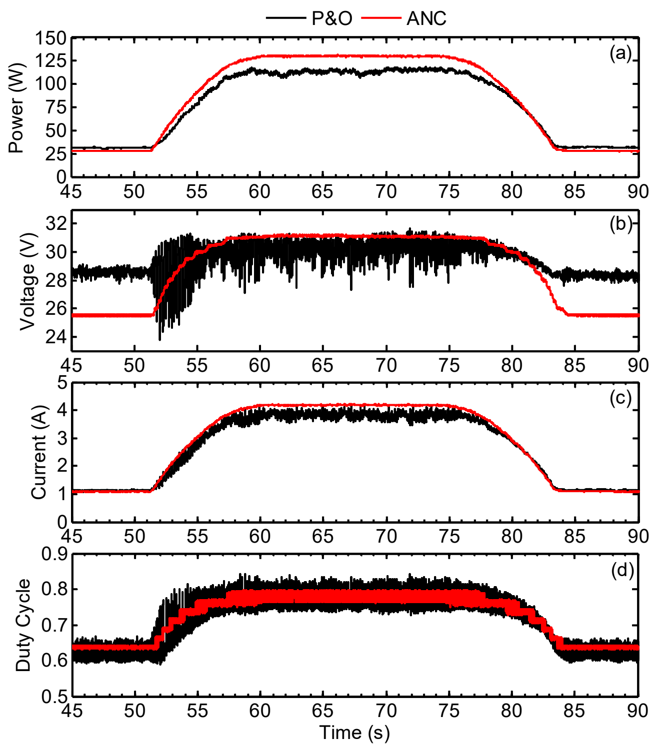


Fig. 9 – Tracking performances under medium to high irradiance with slow profile: (a) power; (b) voltage; (c) current; and (d) duty cycle.

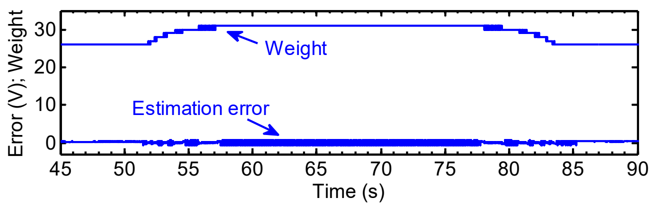


Fig. 10 – Evolution of the weight and estimation error in the ANC method under medium to high irradiance with slow profile.

To show the good performances of the used ADALINE technique, the weight and estimation error waveforms are presented in Figs. 8, 10, 12 and 14. It can be seen that the weights are well converged to their optimal values and the estimation errors are very small.

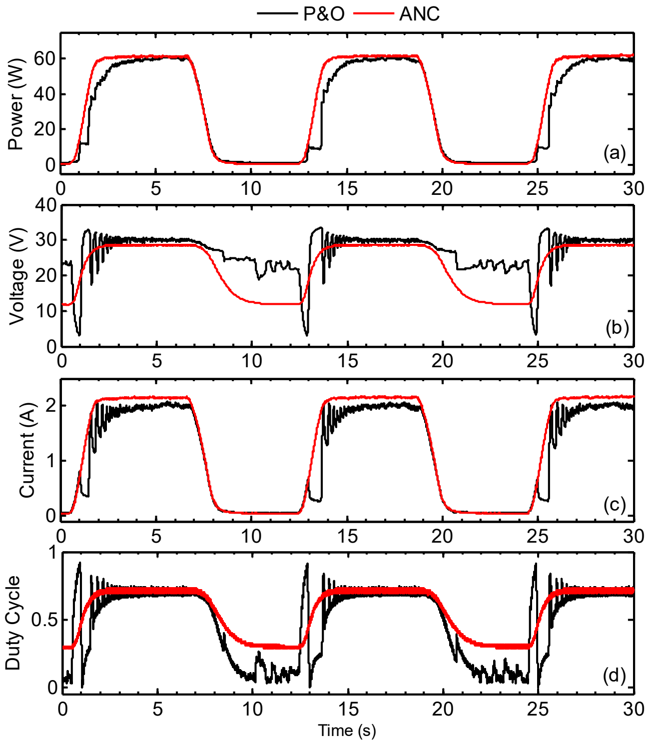


Fig. 11 – Tracking performances under low to medium irradiance with fast profile: (a) power; (b) voltage; (c) current; and (d) duty cycle.

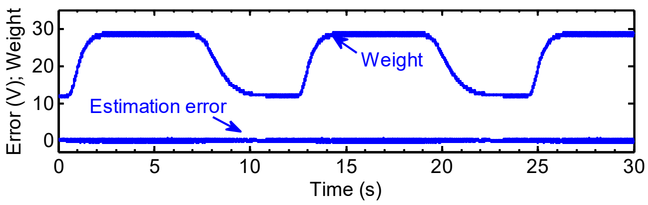


Fig. 12 – Evolution of the weight and estimation error in the ANC method under low to medium irradiance with fast profile.

Thereafter, a comparative study in term of response time is achieved. Two step changes in irradiance are applied. The power responses are plotted in Fig. 15 for medium to high irradiance (145 to 511 W/m$^2$), and in Fig. 16 for low to medium irradiance (24 to 260 W/m$^2$). The observed slopes in the reproduced irradiance profiles (plotted in green color) are due to the fact that the response of the halogen lamps is not instantaneous although step voltage references are applied using a robust single-phase power controller (see Section 4.1). This explains the obtained large time constants. In Figs. 15 and 16, the irradiances take 0.536 s and 0.66 s to attain 95 % of their final values, respectively. The response times of the implemented algorithms and lamps are indicated on the graphs. The response time in case of P and O is 3.5 times the response time needed by the proposed method for medium to high irradiance, and 2.5 times the response time needed by the proposed method for low to medium irradiance. So, the proposed method has proven a good tracking rapidity. This permits certainly to generate more important power regarding rapid changes in irradiance that can appear.

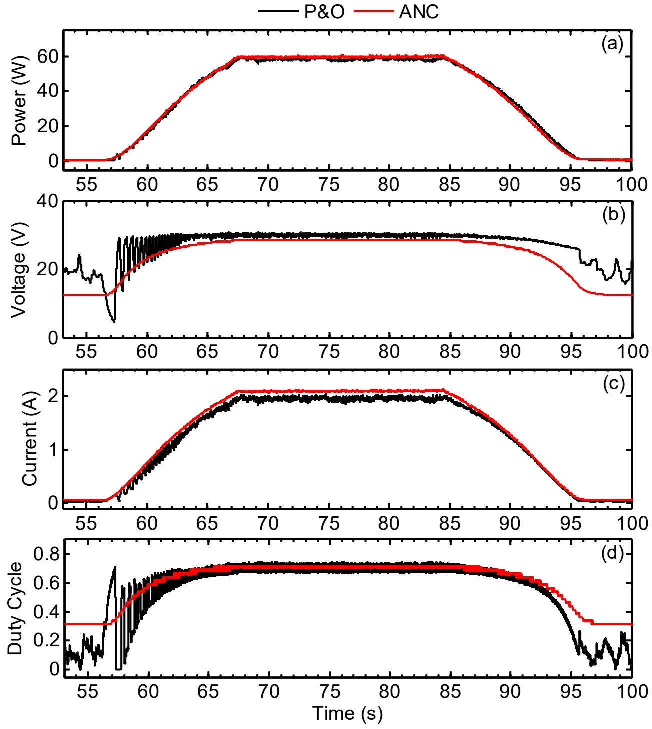


Fig. 13 – Tracking performances under low to medium irradiance with slow profile: (a) power; (b) voltage; (c) current; and (d) duty cycle.

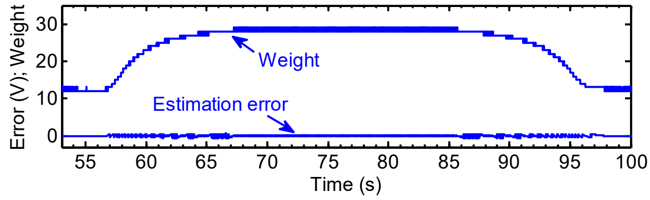


Fig. 14 – Evolution of the weight and estimation error in the ANC method under low to medium irradiance with slow profile.

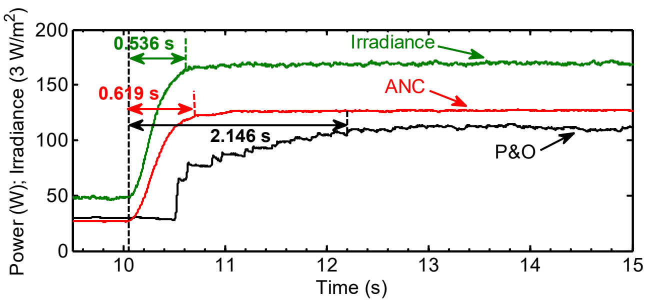


Fig. 15 – Comparison in term of response time when a step change in irradiance is applied – from medium to high level.

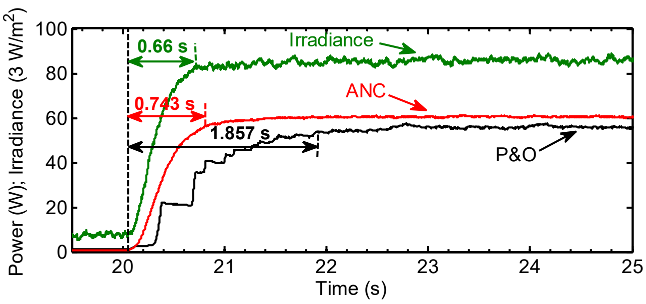


Fig. 16 – Comparison in term of response time when a step change in irradiance is applied – from low to medium level.

The reported results indicate that the generated powers using the proposed method are more important. P and O presented very low performances with important oscillations and power losses. This is due in part to its sensitivity to the measurements noises unlike the proposal which acts as an adaptive filter. In addition, the proposed method reaches very quickly the MPP.

For more readability, a brief comparative study, in term of efficiency and dynamic tracking, between the proposed ANC method, the baseline P and O and two others proposed ANC based MPPTs [9, 11] is reported in Table 3. From this comparison, superiority of the proposed ANC method is clearly established.

*Table 3*

Comparison between P and O, proposed methods in [9] and [11], and the proposed ANC method

| | Simulated Efficiency | Tracking Speed | Notes |
|---|---|---|---|
| P | 97.8 % | Slow | - Baseline comparison algorithm. |
| [9] | 98.02 % | Slow | - Based on direct adaptive neural control;<br>- Complex structure;<br>- Verified only through simulation. |
| [11] | 98.17 % | Fast | - Based on ADALINE which is trained with a real-time recurrent learning gradient;<br>- Verified only through simulation. |
| ANC | 99.98 % | Very Fast | - Based on the simple ADALINE;<br>- Verified under a real PV system. |

## 6. CONCLUSION

A new ANC method has been proposed in this paper for improving maximum power extraction in PV systems. The suggested online learning procedure has exploited the simple ADALINE technique. It has resulted in simple MPPT strategy which can be easily implemented in low-cost digital signal processors. Moreover, the proposal constitutes a direct control method for the converter which eliminates the need for an additional control loop. An experimental setup has been implemented and various irradiance profiles according to the EN50530 standard dynamic tests have been reproduced. A comparison with the P and O algorithm has been conducted under the same conditions. Obtained experimental results have shown that the proposed method has presented interesting tracking features with more extracted power; short time response in different irradiance dynamic conditions; and low steady-state oscillations, which enabled to a stable operation. Unlike the P and O algorithm which has illustrated a power loss, a slow response time and oscillations. Comparative study with two other ANC methods in term of efficiency and dynamic tracking is also achieved. It can be concluded that the suggested method leads to achieve a considerable amount of energy gain over the life cycle of the PV panel.

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