An LS-Based Improvement of Conventional MPPT Techniques for Photovoltaic Systems Under Varying Conditions

Borni Boughdiri[1], Mohamed Hechmi Bouazizi[2] and Ali Hmidet[3]

Abstract— **Although conventional MPPT algorithms, such as Incremental Conductance (INC), Fractional Open Circuit Voltage (FOCV), and Perturb and Observe (P&O), are extensively employed in both scientific research and industrial applications because of their ease of implementation and reduced cost, they exhibit several inherent drawbacks. Indeed, these methods generally exhibit persistent oscillations around the maximum power point, a relatively slow convergence speed and an increased sensitivity to rapid variations in environmental conditions. In this work, an analytical enhancement of these MPPT techniques is proposed through the integration of the least squares (LS) method. For voltage-based method such as "FOCV", The LS approach is partially applied to approximate the power-voltage (P-V) characteristic with a parabolic model in order to estimate the MPP voltage, thereby replacing the fixed empirical relationships commonly employed in conventional schemes. For perturbative and derivative-based methods such as "P&O" and "INC", the full LS formulation is adopted to accurately identify the MPP by fitting the PV characteristic and analytically computing the optimal operating voltage. The estimated MPP voltage is subsequently exploited to directly regulate the duty cycle of the DC–DC boost converter. MATLAB/Simulink-based simulations demonstrate that the proposed LS-based MPPT methods substantially decrease oscillations around the maximum power point, improve convergence speed, enhance tracking accuracy and improve overall efficiency, particularly under varying irradiance and partial shading conditions. Finally, the proposed algorithms effectively overcome the drawbacks of the FOCV, INC, and P&O methods, reaching an efficiency higher than 98%.**

Keywords— Maximum Power Point Tracking (MPPT), FOCV MPPT, P&O MPPT, INC MPPT, LS Method.

I. Introduction

Maximum Power Point Tracking (MPPT) methods are applied in photovoltaic (PV) systems to maintain optimal energy extraction despite continuously changing operating conditions [1]. Although the rapid advancements in artificial intelligence-based MPPT techniques, classical approaches remain the most widely used in industrial applications. Among these methods, the most prominent are: FOCV, INC and P&O techniques [2].

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These classical methods are characterized by their simplicity, low implementation cost, high reliability and strong compatibility in embedded systems [3].

Despite these advantages, conventional MPPT methods have several inherent limitations that degrade the global efficiency of PV systems. In steady state, heuristic algorithms such as P&O and INC exhibit significant oscillatory behavior near the maximum power point (MPP), resulting in significant energy wastage [4]. Moreover, their convergence time can be significantly rised under fast-varying irradiance and temperature conditions. On the other hand, empirical methods such as FOCV rely on fixed fractional coefficient, whose accuracy is strongly affected by environmental variations and aging effects.

Under partial shading conditions, these drawbacks become even more critical as the power-voltage (P-V) characteristic presents multiple local maxima [5]. In such scenarios, conventional MPPT techniques generally fail to distinguish the global maximum power point (GMPP), leading a sub-optimal operation and reduced energy yield [6].

To overcome these limitations, the Least Squares (LS) method represents an effective solution for improving MPPT performance. By utilizing multiple voltage and current measurements, the LS technique enables an accurate local approximation of P-V curve, allowing a more precise estimation of the MPP. The integration of the LS method with conventional MPPT algorithms significantly reduces steady-state oscillations, accelerates convergence time, and enhance tracking accuracy, while maintaining a reasonable computational complexity [7].

The proposed system includes a 250 W photovoltaic (PV) generator, a DC–DC boost converter, a conventional MPPT algorithm improved by the least squares (LS) method and a resistive load operating under continuous conditions. MATLAB/Simulink is used to evaluate the effectiveness of the proposed structure under different irradiance levels, including conditions of partial module shading.

The rest of this paper is structured as follows. Section II presents the modeling of the proposed system implemented in MATLAB/Simulink. Section III represents the generalized LS formulation. Section IV describes the conventional MPPT methods and details the enhancements introduced by the least square (LS) technique. Section V discusses several simulation scenarios under varying irradiance levels and partial shading conditions. Finally, Section VI concludes the paper by presenting a summary of the main results and suggesting future research directions.

II. DESCRIPTION OF THE PROPOSED SOLAR PHOTOVOLTAIC SYSTEM

The proposed photovoltaic (PV) system is composed of five series connected PV modules providing a peak output power of 250 W. The modules operate under both uniformly illuminated and partially shaded conditions. The PV array is interfaced with a DC–DC boost converter and supply a continuous resistive load. A dedicated control unit integrates three conventional MPPT algorithms enhanced by an analytical least squares (LS) method to improve the accuracy of maximum power point estimation. The overall structure is depicted in Fig.1.

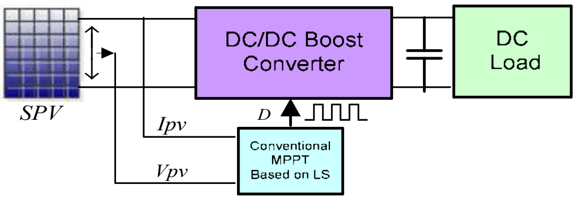

Fig.1. Topology of photovoltaic systems with partial shading

A. Equivalent Solar Cell Circuit Model

Solar cells generate electrical energy from incident solar radiation through the photovoltaic effect. A photovoltaic module consists of multiple interconnected solar cells electrically interconnected in series and parallel combinations to increase the output voltage and current to the desired levels. The equivalent single diode circuit is composed of a current source in parallel with a diode, and includes a shunt resistor and a series resistance [6]. The mathematical model is given in (1).

$$I_{pv} = I_{Ph} - I_s[e^{\frac{q[V_{pv}+R_S I_{pv}]}{NKT}} - 1] - \frac{V_{pv}+R_S.I_{pv}}{R_{sh}} . \quad (1)$$

Fig. 2 presents the equivalent circuit of a single-diode PV cell model, while Fig. 3 depicts the corresponding I–V and P–V characteristics at T = 25°C.

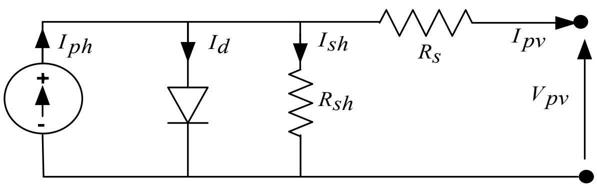

Fig.2. Solar cell equivalent circuit

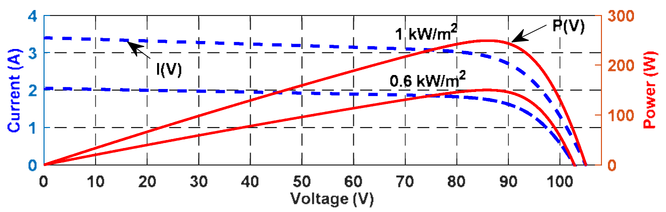

Fig.3. I–V and P–V characteristics (T=25°)

B. DC/DC Boost Converter

In photovoltaic (PV) systems, a DC–DC boost converter is typically used to increase the low output voltage of the PV array. By adjusting the duty cycle of the power switch, the Boost converter controls the input impedance seen by the PV generator, which enables effective MPPT.

Under continuous conduction mode (CCM) and assuming ideal components, the mathematical equations of the output current I_{out}, the optimum load R_{load}, the inductance L , the input capacitance C_{inp} and the output capacitance C_{out} of the boost converter are cited in [8] [9]. The duty cycle D is represented in (2).

$$D = 1 - \frac{V_{pv}}{V_{out}} , \quad (2)$$

Where V_{pv} characterizes the PV generator output voltage and V_{out} represents the output load terminals voltage. The adopted values are: $= 0.1\, mH$, $C1 = 220\mu F$, $C2 = 110\mu F$ and $R = 200\Omega$. The schematic diagram of DC/DC boost converter is shown in Fig.4.

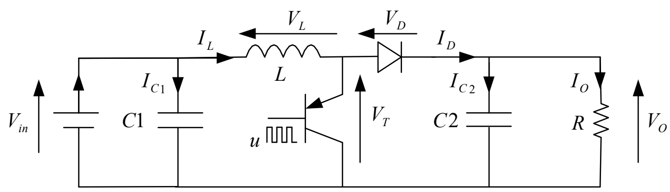

Fig.4. Circuit diagram of DC/DC boost converter

III. GENERALIZED LEAST SQUARES FORMULATION

The least squares method is a mathematical approach used to determine the best-fitting curve by minimizing the sum of squared errors. The output $y_i(x_i)$ can be approximated by a polynomial function of degree m, given by [10]:

$$y_i(x_i) = a_0 + a_1 x_i^1 + a_2 x_i^2 + \cdots + a_{m-1} x_i^{m-1} + a_m x_i^m \quad (3)$$

$i \in \{1, \ldots n\}$, this expression can be reformulated as follows:

$$Y = X * \theta , \quad (4)$$

Where θ: is the vector of parameters, Y: denotes the vector of measured data and X: represents the design matrix.
In the case of a photovoltaic (PV) system, the least squares model is formulated by considering the input variable x_i as the voltage samples v_i and the output vector $y_i(x_i)$ as the corresponding power measurements $P_i(V_i)$. The PV power can be approximated by a polynomial of degree m [11] .

$$P_i(V_i) = \sum_{k=0}^{m} a_k V_i^k , \quad (5)$$

Where $P_i(V_i)$ is the output power, V_i is the PV voltage, a_k are the unknown coefficients to be estimated and m is the polynomial order (typically $m = 2$ for MPPT applications).
The LS estimation minimizes the squared error:

$$J = \sum_{i=1}^{n} \left(P_i - \hat{P}_i\right)^2 , \quad (6)$$

Where P_i is the measured value of power at the i^{-th} sample. $\hat{P}_i$ is the estimated power value at the i^{-th} sample obtained from the model. The optimal parameter vector is obtained by:

$$\theta = (X^T * X)^{-1} * X^T * P . \quad (7)$$

IV. CONVENTIONALS MPPT BASED ON LS METHOD

Conventional MPPT methods including FOCV, P&O, and INC are frequently applied in photovoltaic systems due to their simplicity. However, these techniques suffer from steady-state oscillations, slow convergence speed and limited accuracy under dynamic and partial shading conditions. To overcome these drawbacks, the Least Squares (LS) technique is integrated with conventional MPPT algorithms to enhance their tracking performance.

A. Principle of the FOCV Method

The Fractional Open Circuit Voltage (FOCV) algorithm is one of the simplest MPPT control methods and widely used for estimating the MPP in photovoltaic system. This technique is also known as constant voltage method. This method relies on the near-linear relationship between the open-circuit voltage V_{oc} and the MPP voltage V_{mp} under varying insolation. V_{mp} can be computed as follows:

$$V_{mp} \cong K.V_{oc} \,, \tag{8}$$

Where K is a parameter dependent on the PV cell type, with values ranging from 71% up to 78% [12].

B. Principle of the FOCV Method Based on LS

In the proposed FOCV based on LS approach, the photovoltaic output power is first computed from a sliding window containing the 10 most recent measurements of the voltage and current. The output power is given by (9).

$$P_{pv} = V_{pv} * I_{pv} \,, \tag{9}$$

The P–V characteristic is then approximated using a second-order polynomial model.

$$P_i(V_i) \cong aV_i^2 + bV_i + c \,, \tag{10}$$

The polynomial fitting problem can be expressed in a compact matrix form as:

$$[X] * \theta = (P) \,, \tag{11}$$

Where (P) is the vector of measured power values, $\theta = [a \quad b \quad c]^T$ is the coefficient vector, and $[X]$ is the regression matrix derived from the corresponding voltage samples [13]. The least-squares solution can be analytically derived from (7). Once the polynomial approximation of the P–V curve is identified, the MPP voltage is found analytically by satisfying the condition.

$$\frac{dP(V)}{dV} = 0 \,, \tag{12}$$

Thus, the voltage at MPP can be calculated as:

$$V_{mp} = -\frac{b}{2a} \,, \tag{13}$$

The analytically estimated V_{mp} replaces the empirical relationship $V_{mp} \cong K.V_{oc}$ employed in the conventional FOCV method. The typical block diagram of the FOCV based on LS technique is depicted in Fig.5. (PI gains: $K_p = 0.05$, $K_i = 3$).

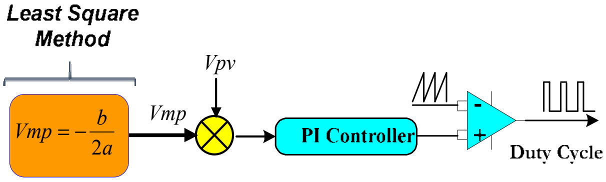

Fig.5. Block Diagram of the FOCV-LS

C. Principle of the P&O Method

The Perturb and Observe (P&O) approach is one of the most widely used methods for MPPT in PV systems. Its simplicity of implementation and low cost make it attractive for industrial applications [14]. The algorithm relies on perturbing the voltage by small increments or decrements around its initial value. Once a perturbation is applied, the power varies. If the new power exceeds the previous value, the perturbation continues in the same direction; otherwise, it is reversed. This process is repeated until the MPP is reached. The output power of a PV generator is expressed as:

$$P = V * I \,. \tag{14}$$

Since the analytical derivative is not directly available, the P&O algorithm uses a discrete approximation:

$$\Delta P = P(k) - P(k-1), \quad \Delta V = V(k) - V(k-1) \,, \tag{15}$$

The slope of the P–V curve is approximated by:

$$\frac{dP}{dV} \approx \frac{\Delta P}{\Delta V} \,, \tag{16}$$

The sign of ΔP and ΔV is used to define the perturbation direction [15].

D. Principle of the P&O Method based on LS

To overcome the drawbacks located in classical P&O, an enhanced hybrid approach combining the P&O algorithm with the Least Squares (LS) technique. The LS method is used to approximate the local behavior of the (P–V) characteristic by fitting a polynomial model over a sliding window of measured data.

$$P_i(V_i) \cong aV_i^2 + bV_i + c \,, \tag{17}$$

Based on this quadratic approximation, the voltage corresponding to the maximum power can be estimated as:

$$V_{mp} = -\frac{b}{2a} \,, \tag{18}$$

The duty cycle D_{ls} is then computed using the boost converter, by replacing the PV voltage with its optimal estimated value V_{mp}.

$$D_{ls} = 1 - \frac{Vmp}{Vout} \,, \tag{19}$$

The duty cycle D is determined by combining the outputs of both methods using a mixing factor α.

$$D = \alpha.D_{ls} + (1-\alpha).D_{P\&O} \,, \tag{20}$$

The mixing factor is fixed at $\alpha = 0.5$, D_{ls} represents the duty cycle estimated by the least squares method, $D_{P\&O}$ corresponds to the duty cycle provided by the P&O algorithm and D is the final duty cycle applied to the system. The flowchart of the enhanced P&O is shown in Fig.6.

E. Principle of the INC Method

The Incremental Conductance (INC) method finds the MPP by comparing the array's incremental conductance $\frac{dI}{dV}$ with its instantaneous conductance $-\frac{I}{V}$. This approach is based on the fact that at the MPP, the PV array's power slope is zero ($\frac{dP}{dV} = 0$); to the right of the MPP, it is negative ($\frac{dP}{dV} < 0$); and to the left, it is positive ($\frac{dP}{dV} > 0$) [14]. The slope of the P–V curve can be computed as follow:

$$\frac{dP}{dV} = \frac{d(V.I)}{dV} = I + V.\frac{dI}{dV} \ . \quad (21)$$

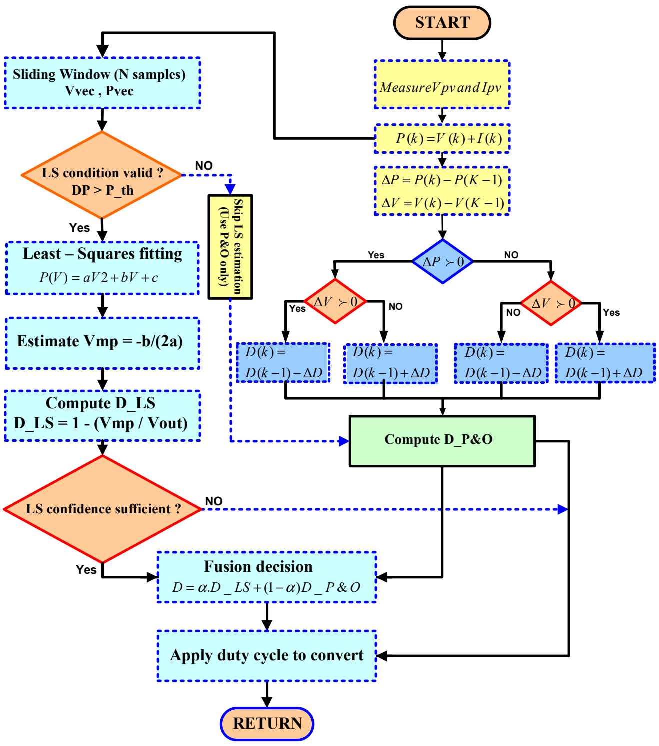

Fig.6. Flowchart of P&O-LS

F. Principle of the INC based on LS Method

The flowchart of the enhanced INC is shown in Fig.7.

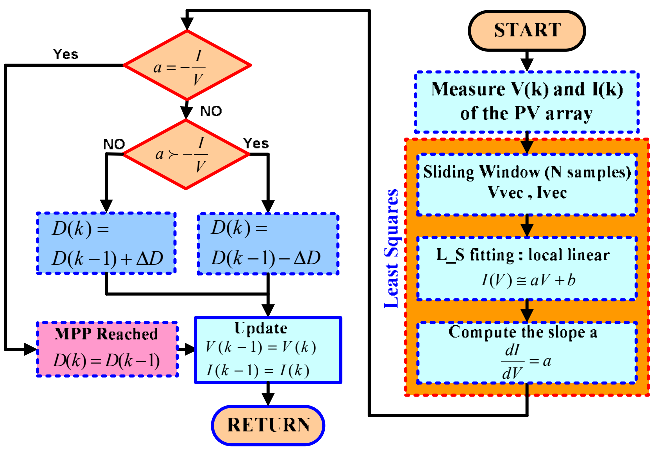

Fig.7. Flowchart of the INC based on LS.

To overcome the limitations located in conventional INC, the Least Squares technique is integrated with the INC method. Although the photovoltaic current–voltage characteristic is inherently nonlinear, the MPPT process operates within a narrow voltage range around the operating point. Therefore, a first-order Taylor series of $I(V)$ can be used to represent the PV current.

$$I(V) = a.V + b \ , \quad (22)$$

The estimated coefficient a directly provides a robust approximation of the incremental conductance:

$$\frac{dI}{dV} = a \ , \quad (23)$$

At the MPP, the following condition holds:

$$a = -\frac{I}{V} \ , \quad (24)$$

V. INTERPRETATION AND DISCUSSION OF SIMULATION OUTCOMES

The FOCV, FOCV-LS, P&O, P&O-LS, INC and INC-LS MPPT methods are implemented in MATLAB Simulink. Table I presents the characteristics of the PV module employed in the simulation. Table II summarizes the different irradiance scenarios applied. Each scenario represents a specific operating condition. Scenario S1 corresponds to uniform irradiance under standard test conditions (STC), whereas S4 represents a uniform low irradiance level of 200 W/m². The other two scenarios, S2 and S3 correspond to weak and strong partial shading conditions, respectively.

TABLE I. Specification of the PV module

Parameter	***Value***
Maximum power (Pmax)	49.88 W
Voltage at MPP (V_{mp})	17.2 V
Cells per module (Ncell)	36
Short-circuit current (Isc)	3.4 A
Current at maximum power point (Imp)	2.9A
Open circuit voltage Voc	21V
Number of PV modules linked in series	5

TABLE II. The five PV modules for different irradiances

Insolation (W/m²)							
Scenarios	**Time (s)**	**M1**	**M2**	**M3**	**M4**	**M5**	**Rated Power (W)**
S1	**(0 - 0.15)**	1000	1000	1000	1000	1000	249.5
S2	**(0.15 -0.25)**	1000	1000	1000	800	700	194.7
S3	**(0.25 - 0.35)**	800	600	600	500	500	133.9
S4	**(0.35 - 0.45)**	200	200	200	200	200	48.87

A. Simulation of the FOCV and FOCV-LS Method

In Scenario 1, the simulation results of the conventional FOCV MPPT and the proposed FOCV-LS algorithm are illustrated in Figs. 8 and 9. The comparison clearly indicates the superiority of the FOCV-LS approach in terms of dynamic and steady-state performance. The proposed method achieves a tracking efficiency of approximately 98.55%, exceeding that of the conventional FOCV (97.396%) by more than 1%.

Moreover, the convergence time is significantly reduced from 0.08 s (FOCV) to 0.01 s (FOCV-LS), corresponding to a convergence speed nearly eight times faster. In addition, the power ripple is significantly reduced from 1.5% with the FOCV to 0.71% using the FOCV-LS approach, leading to negligible steady-state oscillations. Both methods can track the maximum power point (MPP), however, the FOCV-LS reaches a higher power level (249.454 W) compared to the FOCV (248.806 W), confirming its improved tracking capability.

Under Scenario 2 (weak partial shading), a similar performance trend is observed. The FOCV-LS converges to a higher power level (192.433 W) than the FOCV (190.74 W) within the same settling time (0.15 s), while delivering superior tracking efficiency (98.598% versus 97.229%).

Despite severe variations in operating conditions, including partial shading (S3) and uniform irradiance (S4), similar performance improvements are consistently observed.

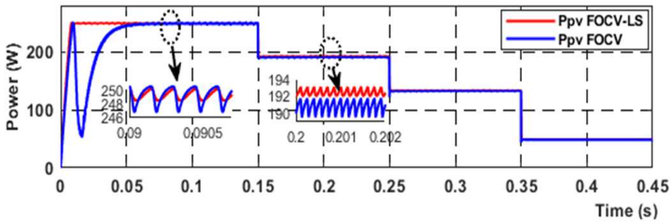

Fig.8. Input power curves (Ppv) at the boost of FOCV and FOCV-LS

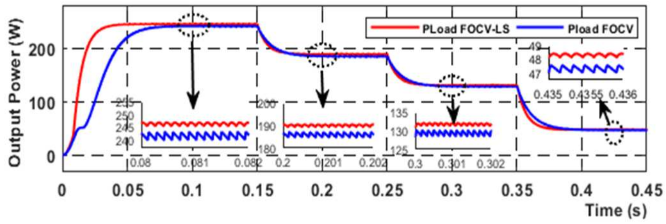

Fig.9. Output power curves (Pload) at the boost of FOCV and FOCV-LS

It can be observed in scenario 1 that the measured P-V data obtained from the sliding window are highly concentrated around the maximum power point at $V_{mp} = 86.6\ V$ and $P_{mp} \approx 250\ W$. The polynomial is depicted on Fig.10.

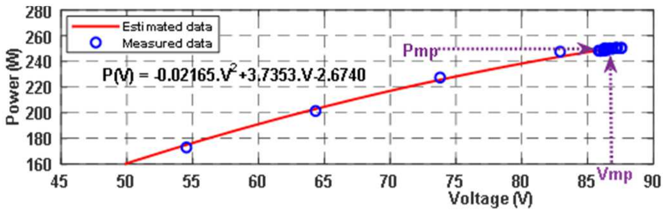

Fig.10. Measured data from the sliding window

B. Simulation of the INC and INC-LS Method

Figures 11 and 12 present the comparative results of the INC and the proposed INC-LS MPPT algorithms proposed.

In Scenario 1, the proposed approach successfully reaches the MPP of 247.68 W with a settling time of 0.013 s, corresponding to a convergence speed approximately 3.5 times faster than that of the INC method (0.0455 s). The INC-LS achieves an efficiency of 97.048% in Scenario 1, increasing to 98.36% in Scenario 4, whereas the conventional INC is limited to 95.54% under the same initial conditions. Moreover, the proposed method exhibits a notable reduction in steady-state oscillations. The power ripple is effectively minimized from 2.43% with the INC to 1.3% using the INC-LS approach, confirming its improved stability around the MPP. In Scenario 2, the proposed method successfully reaches the global maximum point (GMP) at 194 W, achieving an efficiency of approximately 97.39% within a settling time of 0.165 s. In contrast, the conventional INC algorithm fails in locating the global maximum; rather, it settles on a local maximum point (LMP) at an average power of 172 W, with an efficiency of 96% and a tracking time of 0.17 s.

A zoomed-in view of this region further confirms that the proposed INC-LS approach exhibits negligible power oscillations compared to the conventional INC algorithm.

In Scenario 3, the INC-LS method successfully tracks the global maximum point at 133.6 W, whereas the INC fails to reach this level and converges to a lower power value of 91.5 W. The same analysis and performance trends are observed in scenario 4.

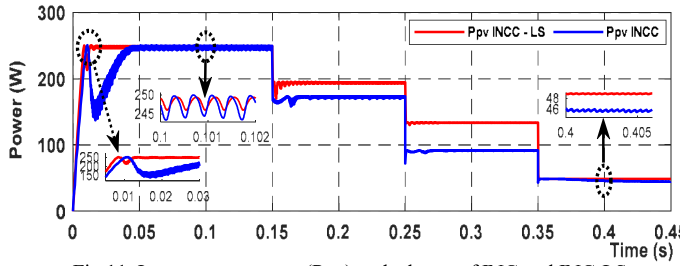

Fig.11. Input power curves (Ppv) at the boost of INC and INC-LS

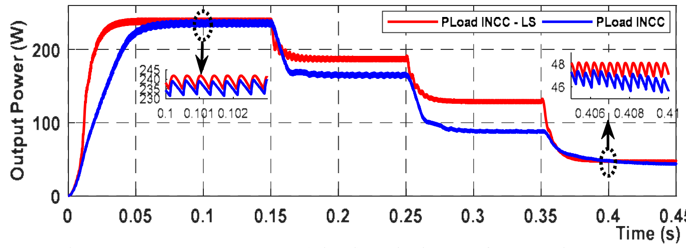

Fig.12. Output power curves (Pload) at the boost of INC and INC-LS

C. Simulation of the P&O and P&O-LS Method

Figures 13 and 14 show the simulation outcomes for the standard P&O and the suggested P&O-LS MPPT algorithms. In Scenario 1, the P&O-LS algorithm exhibits significantly reduced oscillations once the MPP is reached, with the power ripple decreasing from 3.17% for the conventional P&O method to 1.47%.

The proposed P&O-LS MPPT reaches the maximum power point in 0.018 s, corresponding to a convergence speed approximately 1.5 times higher than that of the P&O method (0.027 s). Furthermore, under partial shading conditions, the P&O-LS strategy successfully tracks the global maximum point at 193.75 W in Scenario 2 and 133.5 W in Scenario 3, achieving a tracking efficiency of approximately 98.20%. Conversely, the P&O algorithm converges to 172 W in Scenario 2 and 91.5 W in Scenario 3, with an efficiency of approximately 96.89%, indicating that it's trapped at a local maximum point.

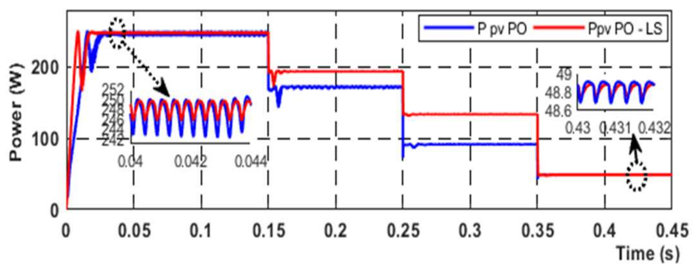

Fig.13. Input power curves (Ppv) at the boost of P&O and P&O-LS

These results confirm that the P&O-LS strategy provides higher accuracy and improved robustness compared to the conventional P&O technique. Similar behavior and performance pattern can be observed in Scenario 4.

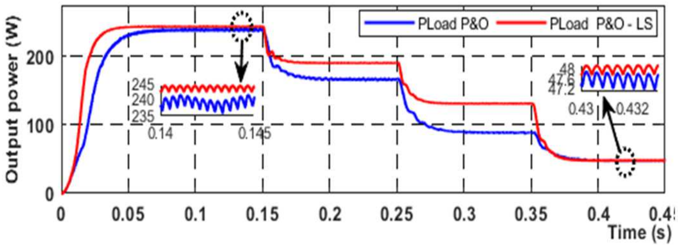

Fig.14. Output power curves (Pload) at the boost of P&O and P&O-LS

VI. SELECTION CRITERIA FOR THE MOST MPPT

It should be noted on table III that the results presented in this comparison are derived from Scenario 1, which is considered as the baseline case for performance evaluation.

TABLE III. The performance comparison table

Method	**Efficiency (%)**	**Convergence time (s)**	**Convergence Speed**	**Power ripple (%)**	**Tracking Global maxima (GM)**
FOCV-LS	98.55	0.01	8× faster than FOCV	0.71	Failed to detect GM
FOCV	97.39	0.08	Slow (reference)	1.5	Failed to detect GM
INC-LS	97.05	0.013	3.5× faster than INC	1.3	Successfully detected GM
INC	95.54	0.045	moderate	2.43	Trapped in LM
P&O-LS	98.26	0.018	1.5× faster than P&O	1.47	Successfully detected GM
P&O	96.72	0.027	moderate	3.17	Trapped in LM

Based on the comparative results, the P&O-LS method emerges as the most suitable technique for practical implementation. It offers an excellent trade-off between high efficiency, fast convergence speed and reduced power oscillations, while maintaining a relatively simple structure compared to INC-based approaches. Furthermore, it effectively locates the GMPP during partial shading scenarios.

VII. CONCLUSION

This study presents an enhanced MPPT technique based on the integration of the LS method with the conventional FOCV, INC and P&O algorithms. Findings from simulations validate that integrating the LS method improves total performance regarding reliability, convergence rate, and steady-state ripple. Nevertheless, for GMPP detection under partial shading conditions, only the INC-LS and P&O-LS methods successfully track the global maximum power point, whereas the FOCV-LS approach remains limited and converges to a lower power level. Therefore, the proposed P&O-LS technique emerges as an effective and practical solution for photovoltaic systems, offering an optimal trade-off between performance, robustness and implementation simplicity.

The impact of measurement noise, ADC quantization, sensor imperfections and experimental validation on a real-time platform have been identified as important future research directions. To further extend the practical relevance of this work, future investigations will focus on the experimental validation of the proposed approach under real operating conditions, as well as its implementation on real-time embedded platforms, including DSPs and microcontrollers.

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