Implementation of Genetic Algorithm-based MPPT For PV System In Tropical Climate: Study And Comparison With Conventional Method

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***Abstract*— This paper presents a computationally efficient and simple genetic algorithm-based maximum power point tracking (MPPT) technique for photovoltaic (PV) systems. The non-linear mathematical model of solar panels makes intelligent search algorithms, such as genetic algorithms, well-suited for MPPT applications. The proposed method is compared to the traditional perturb and observe (P&O) technique under distinctive data measured on the Sonapi site in Haiti. Simulation results using MATLAB/SIMULINK demonstrate that the proposed genetic algorithm-based MPPT outperforms the conventional P&O technique in several aspects such as fast-tracking of the MPP, stable functioning, robust performance, and reducing the overall steady-state oscillation. Experimental results further confirm the superiority of the proposed method over the conventional method.**

Keywords*— *Photovoltaic panels; genetic algorithm; P&O; MPPT; boost converter

I. INTRODUCTION

Renewable energies are becoming more and more the subject of research to substitute fossil fuels, which are conventionally used to generate electrical power [1][2][4]. Due to its numerous benefits, the decreasing cost of PV panels, and the increasing global energy demand, the utilization of PV energy has significantly expanded in recent years.

While solar energy systems may face limitations in terms of the efficiency of PV arrays in harnessing solar energy, it is imperative to implement the MPPT algorithm to ensure a more effective energy conversion [3]. Furthermore, remote tropical insular regions, such as the Caribbean islands, experience multiple micro-climates, leading to fast-changing meteorological conditions [5]. Additionally, the cost of producing electrical power is higher in these regions. Consequently, the implemented MPPT algorithm needs to be as efficient as possible in order to harvest maximum power and minimize losses.

The MPP of a PV array can be defined by a certain value of the output PV voltage at specific irradiation and temperature [6], therefore, MPPT algorithms are designed to reach eventually, this specific voltage [9].

Various types of algorithms have been proposed and can be classified as follows [5]:

Conventional algorithms: These include the perturb and observe (P&O) [12], incremental conductance (IC) [13], and hill-climbing (HC) [14] methods. However, their performance tends to be suboptimal during transient regimes.

Metaheuristic algorithms: This category includes particle swarm optimization (PSO) [15] and genetic algorithms (GA) [3]. The performance of these algorithms relies on the initial conditions and design parameters chosen.

Artificial intelligence algorithms: Fuzzy logic (FL) [16] and neural networks (NN) [17] fall under this category. The performance of these algorithms largely depends on the expertise of the human involved.

Non-linear algorithms: Sliding mode [18] and backstepping [19] are examples of non-linear algorithms. They exhibit good performance in terms of robustness and stability, making them more suitable for controlling and optimizing non-linear PV generator systems.

Hybrid algorithms: These involve the combination of two or more MPPT approaches mentioned above [20].

In this study, we will focus on two algorithms, which are the well-known P&O algorithm and a developed variant of a genetic algorithm, then compare their performances in terms of stability, rapidity, accuracy, and robustness.

The P&O algorithm is often employed in PV power systems mainly for its simplicity, and easy implementation. However, the biggest challenge of this method is the step size of the perturbation. With a large step, the system approaches the MPP quickly, but at the expense of big oscillation around the MPP. Reducing the step size, on the other hand, will solve the oscillation problem, and render the system more stable, but the convergence speed is reduced. So in both situations, the overall efficiency of the system is reduced.

The proposed method in this work is a genetic-based MPPT algorithm, which is simple, easy to implement, and designed to improve rapidity and stability when reaching MPP. The main idea of this method is the employment of the basic genetic algorithm steps (evaluation, selection, crossover, mutation, and insertion) to produce the best-fit operating voltage corresponding to the PV array's MPP.

The MPP in similar genetic algorithms is obtained using the mathematical model of the PV array, which includes the determination of different parameters experimentally [3].

However, the developed algorithm does not rely on the parameters of the PV array to determine the MPP, instead, a linear interpolation of the optimal current Ipp in terms of the solar irradiation is performed and fed to the algorithm.

After obtaining the optimal voltage, a PI controller is used to maintain the PV array's voltage equal to the reference produced by the developed algorithm. The controller gives the corresponding duty cycle needed to control the boost converter.

This paper is organized as follows: the second section presents a brief description of the system's overall structure and all the associated hardware. The third section is aiming to describe the steps needed to perform the proposed method. Simulation results are presented in the fourth section with an interpretation of the obtained results. The fifth section presents the test bench and the experimental results with an interpretation of the results. Finally, in the sixth section, the conclusion and some perspectives are presented

II. DESCRIPTION OF THE PROPOSED SYSTEM

In this section, the mathematical modeling of the parts composing the proposed system is presented. Fig.1 represents the overall schematic of the system

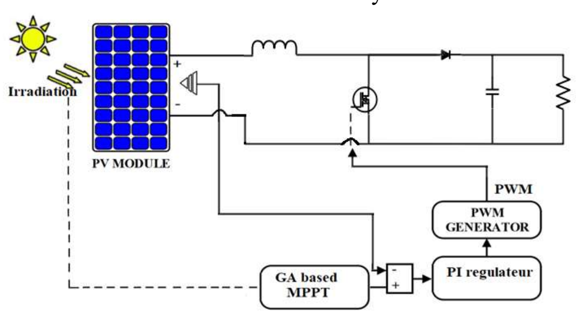

Fig.1 The global structure of the proposed system.

A. PV array Model

The mathematical model of a photovoltaic (PV) array is typically represented by a current-voltage (I-V) characteristic curve, the I-V characteristic curve describes the relationship between the current (I) and voltage (V) output of the PV array at a given irradiance level and temperature. It is often represented graphically as a curve. The general form of the I-V curve is as follows [7][8]:

$$I_{pv} = I_{ph} - I_0\left(e^{\frac{V_{pv}+R_S I_{pv}}{N.V_t}} - 1\right) - \frac{V_{pv}+R_S I_{pv}}{R_{sh}} \quad (1)$$

$$I_{ph} = \frac{G}{G_{ref}}\left(I_{phref} + \mu_{isc}\left(T - T_{ref}\right)\right) \quad (2)$$

$$I_0 = I_{0ref}\left(\frac{T}{T_{ref}}\right)^3 e^{\frac{qE_G}{k\gamma}\left(\frac{1}{T_{ref}} - \frac{1}{T_{ref}}\right)} \quad (3)$$

$$V_t = \frac{k.T}{q} \quad (4)$$

Where:

I_{pv}Is the output current of the PV array, V_{pv} is the output voltage of the PV array, I_{ph} is the photocurrent (current generated by incident light), I_0 is the diode saturation current, R_s is the series resistance of the PV array, N is the diode ideality factor, V_t is the thermal voltage, k is Boltzmann's constant, T is the temperature in Kelvin, q is the elementary charge, R_{sh} is the shunt resistance of the PV array. The I-V characteristic curve is influenced by various factors, including solar irradiance, temperature, and the electrical parameters of the PV array. These parameters can be determined experimentally or through manufacturer specifications.

B. The DC-DC converter

The boost converters are widely used in renewable energy systems. Their main use in these applications is the adaptation between the load and generated voltage.

The state space model of the boost converter is expressed as follows: [10] [11]

- When the switch is ON:

$$\begin{cases} \frac{d}{dt}\begin{bmatrix} I_L \\ V_{out} \end{bmatrix} = \begin{bmatrix} 0 & 0 \\ 0 & \frac{-1}{RC} \end{bmatrix}\begin{bmatrix} I_L \\ V_{out} \end{bmatrix} + \begin{bmatrix} \frac{V_{in}}{L} \\ 0 \end{bmatrix} \\ Y = V_{out} \end{cases} \quad (5)$$

- When the switch is OFF:

$$\begin{cases} \frac{d}{dt}\begin{bmatrix} I_L \\ V_{out} \end{bmatrix} = \begin{bmatrix} 0 & \frac{-1}{L} \\ \frac{1}{C} & \frac{-1}{RC} \end{bmatrix}\begin{bmatrix} I_L \\ V_{out} \end{bmatrix} + \begin{bmatrix} \frac{V_{in}}{L} \\ 0 \end{bmatrix} \\ Y = V_{out} \end{cases} \quad (6)$$

By applying the average between the two modes, we can obtain the following state space system:

$$\begin{cases} \frac{d}{dt}\begin{bmatrix} I_L \\ V_{out} \end{bmatrix} = \begin{bmatrix} 0 & \frac{-(1-D)}{L} \\ \frac{1-D}{C} & \frac{-1}{RC} \end{bmatrix}\begin{bmatrix} I_L \\ V_{out} \end{bmatrix} + \begin{bmatrix} \frac{V_{in}}{L} \\ 0 \end{bmatrix} \\ Y = V_{out} \end{cases} \quad (7)$$

The boost converter circuit diagram is shown bellow

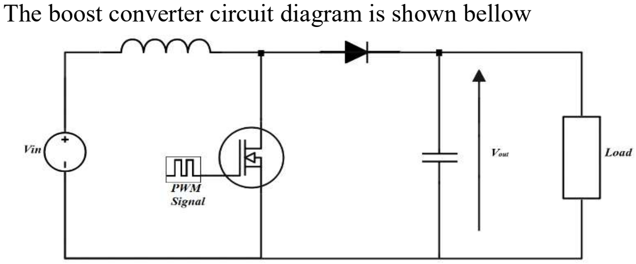

Fig.2. The circuit diagram of the boost converter.

III. DESCRIPTION OF THE PROPOSED METHOD

The MPP in the PV system corresponds to the optimal voltage and current Vpp and Ipp. Therefore, if we command the boost converter to maintain the output voltage of the panel equal to the optimal voltage, we can assure that the system is operating at the MPP. Since the photovoltaic cell is by definition a current source, we can observe a linear relation between the Ipp and the irradiation as shown in the figure below:

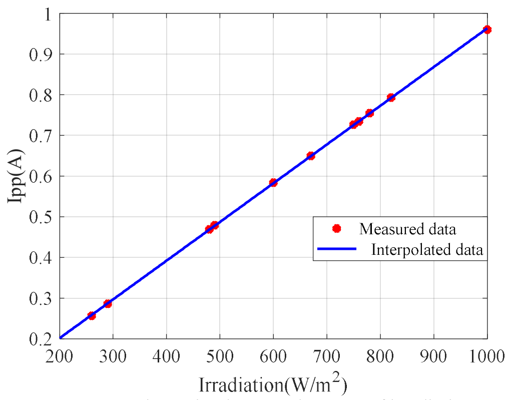

Fig.3. The optimal current in terms of irradiation.

From this interpolation, we can determine the optimal current online from the measurement of the irradiation. This interpolation can be written as:

$$I_{pp}(G) = a.G + b \quad (8)$$

With a, b are the constants of the interpolation. After the interpolation, the genetic algorithm's role is to determine the optimal voltage.

The biggest advantage of this method in comparison with the other genetic algorithm-based MPPT is we don't need the complex mathematical model of the PV, nor do we need to determine its parameters. The primary concept is to apply a basic genetic manipulation (Selection, crossover, mutation, and insertion) to a group of individuals to eventually obtain an ideal individual that corresponds to the maximum output power [3]. Fig.4.represents the flow chart of the proposed genetic algorithm.

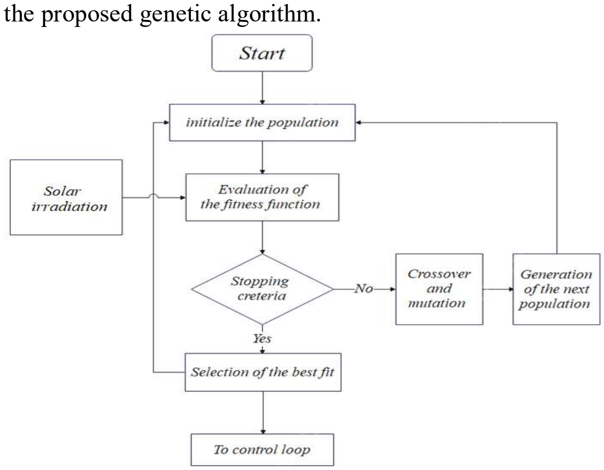

Fig.4. The flowchart of the genetic algorithm.

The steps of the genetic algorithm are presented as follows [3]:

1-choosing the fitness function: is the function that is required to be optimized, in this particular case, to maximize the output power of the PV array.

2-Initialization: the initial population consists of 4 individuals created randomly. The population remains constant during the entire trails.

3-Evaluation: Evaluation ensures the survival of an optimal individual. This can be done by evaluating which chromosome gives the optimal solution for the corresponding fitness function and then sorting them descending. In this particular application, the population represents potential PV array voltage. From solar irradiation G, we can estimate the optimal current using (12). Then, the algorithm will calculate the output power for each individual and sort them.

4-Selection: After evaluating the 4 chromosomes in the fitness functions, the chromosome corresponding to the maximum of the target function is selected as the algorithm's output.

5-Crossover: After selecting the best-fit chromosome, the algorithm should yield 3 more chromosomes produced from the best-fit chromosome, and discard the old unfit chromosomes. In this method, we tried the self-reproducing approach, which means we only need one chromosome to produce the other two our case, the next generation chromosome increases and decreases the best fit of 1%.

6-Mutation: After crossover, the last step is to insert at least one chromosome from a random number generator, thus, with the last chromosome crossed randomly, the condition of keeping the same number of population is fulfilled.

The algorithm keeps updating the best-fit solution for every value of the optimal voltage and for each sampling time.

The output of the algorithm is a referential speed, which is then regulated using a PI controller with anti-wind-up action. This controller was selected for its simplicity and robustness and is expected to provide acceptable performance for this application. The final output of the controller is the duty cycle that drives the boost converter [12].

IV. SIMULATION RESULTS

The tests were conducted in Matlab/Simulink environment, with a sampling time of $T_s = 10^{-5}$s, the used load was a 400Ω resistor, the switching frequency is $1000H_z$, the boost converter inductance is $L = 10^{-3}H$, the boost converter capacitor is $C_{out} = 10^{-3}F$, and the input capacitor is $C_{in} = 10^{-3}F$ One must mention, that the proposed method doesn't take into account the variation of the temperature in the process of searching the MPP.

In this study, we used 4 parallel connected PV arrays of the "Baoding Tianwei Solarfilms TWSF-W-aSi-100W-1" reference model.

In the tropical context of our study and based on solar measurements, a solar irradiance profile was established. This profile consists of 11 sampling values distributed over one year (2011) of measured data at the Sonapi site (Port-au-Prince, Haiti). It shows significant variability in solar irradiance [9].

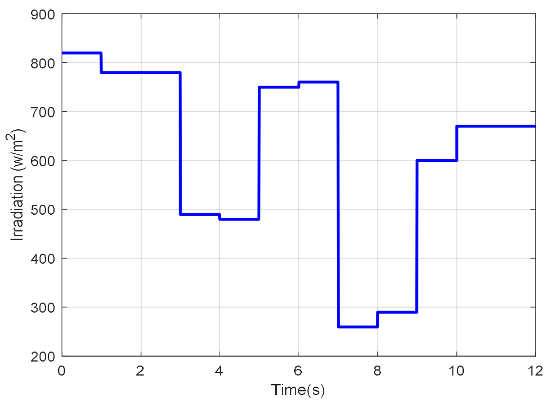

Fig.5. Solr irradiation profile.

The simulation results for the PV array's voltage and the output power of the boost converter are shown below:

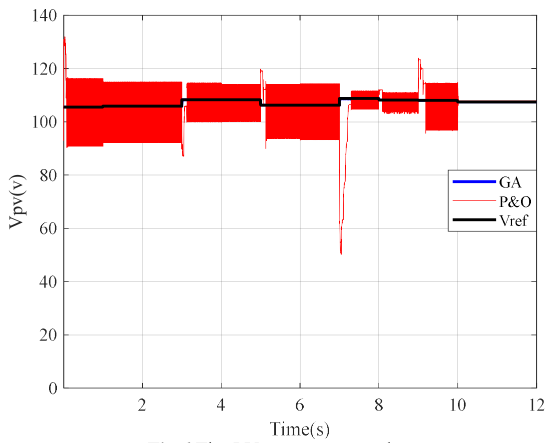

Fig.6. The PV array output voltage.

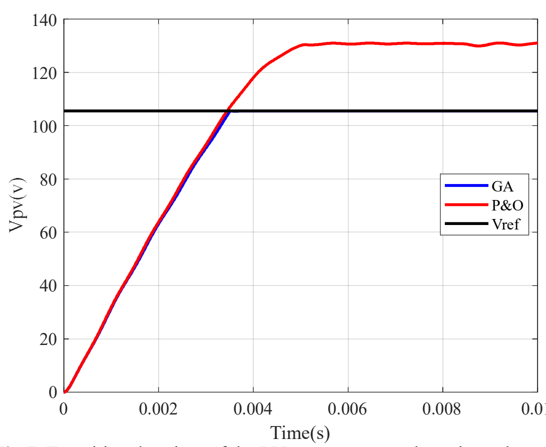

Fig.7. Transitional regime of the PV array output voltage in each method.

The figures above represent the output voltage of the PV array. It is evident that the proposed method achieves the optimal value for Vpv within a short duration of 3.5ms, accompanied by a minor voltage oscillation of ΔV=0.02v. In contrast, the P&O method takes significantly longer, around 70ms, to reach the optimal value and exhibits a much larger voltage oscillation of ΔV=25v. As a result, the proposed method demonstrates superior performance by maintaining stable and accurate functioning around the optimal PV voltage.

The next, results are about the boost converter output power for each method.

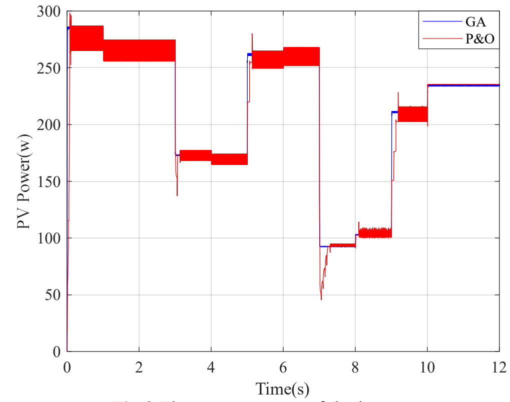

Fig.8. The output power of the boost converter.

The proposed method showcases the accurate and stable functioning of the PV array output voltage, consistently staying close to the reference voltage. This characteristic is reflected in the output power of the boost converter, which rapidly achieves steady-state operation, maintains stability at the maximum power point (MPP), and exhibits robustness in response to changes in solar irradiation. Furthermore, the average power output of the boost converter using the proposed method reaches 214.08W, with minimal oscillations (ΔP=1.75W). In comparison, the P&O algorithm yields a slightly lower average power output of 209.74W, accompanied by significantly higher fluctuations (ΔP=20W).

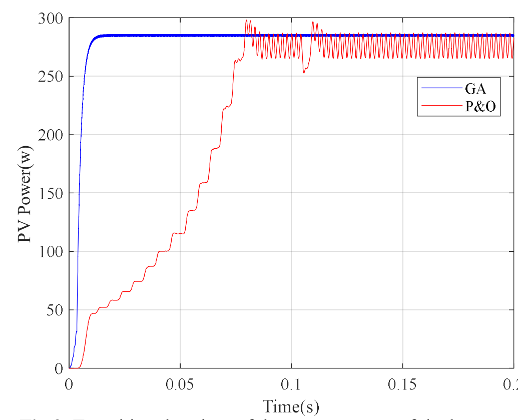

Fig.9. Transitional regime of the output power of the boost converter.

These results reinforce the superiority of the proposed method in terms of stable and precise functioning, leading to higher average power output and reduced power fluctuations when compared to the P&O algorithm.

After simulation using the data of the solar irradiation across a typical day, we obtain the results illustrated in the table below:

TABLE I. THE STATISTICAL ANALYSIS OF THE OBTAINED RESULTS FOR A TYPICAL DAY.

The parameters	**Genetic algorithm**	**P&O**
Average converted Power(w)	217.244	205.40
The harvested energy(MJ)	12.817	12.118
Standard deviation (%)	1.073	2.078

The obtained results demonstrate a significant difference between the two methods, particularly in terms of converted power. The crucial aspect highlighted by these results is the efficiency of the power conversion, which serves as a clear indication of the superiority of the tested algorithm. Furthermore, the results also reveal a higher stability level in the proposed method's functioning. This is evident from the lower standard deviation observed in the efficiency of the proposed method compared to the P&O algorithm, signifying a more consistent and smooth operation.

V. EXPERIMENTAL RESULTS

The final stage of this work is to present the experimental results. The equipment used in this experiment are PV simulator in which the same solar irradiation profile is used, two voltage sensors, one current sensor, one resistive load, and a Dspace 1104 board in which all the data from the sensors are collected. The sampling frequency used in this experiment is 10000Hz the same parameters used in the simulation

Fig.10. The experimental test bench.

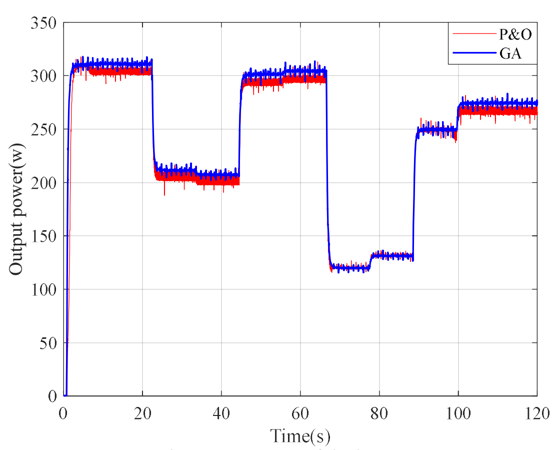

Fig.11. The output power of the boost converter.

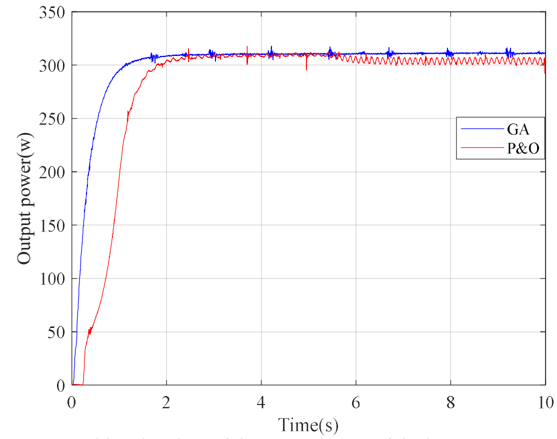

Fig.12. Transitional regime of the output power of the boost converter.

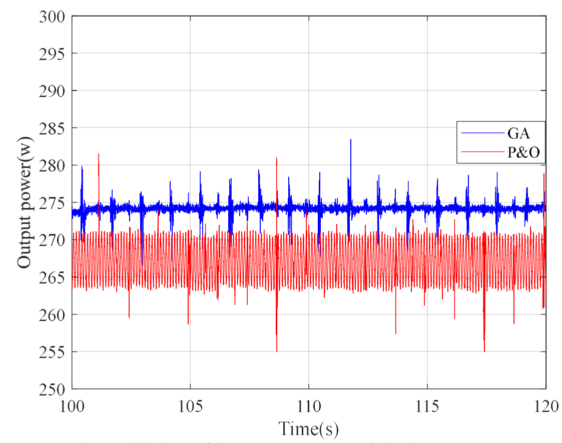

Fig.13. The oscillation of the output power of the boost converter.

From the figures provided, it is evident that the proposed method exhibits clear superiority over the P&O algorithm. In Fig11, a higher output power can be observed when utilizing the proposed method compared to the P&O algorithm. Specifically, the average power achieved using the genetic algorithm is 224.96W, whereas the average power with the P&O algorithm is 217.42W.

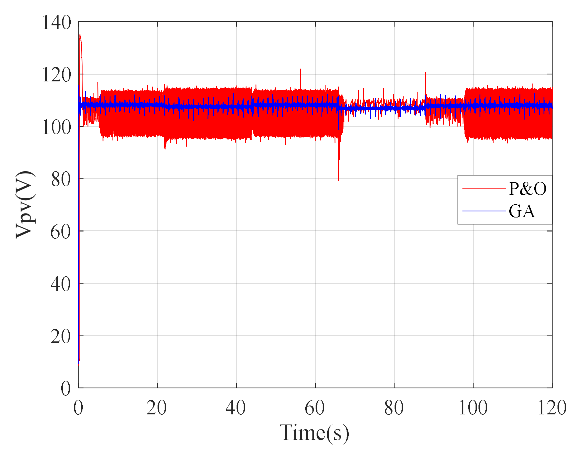

Fig.14. The PV array output voltage.

The reason behind this disparity in average power is illustrated in Fig.14. It is apparent that the proposed method effectively maintains the output voltage of the PV array at the optimal level, unlike the P&O method. As a result, we can conclude that the proposed method offers higher accuracy in achieving the optimal voltage compared to the P&O method. As a result, we can confidently state that the proposed method achieves higher efficiency.

In Fig.12, it is evident that the proposed method exhibits a faster rise time of 1.2s, while the P&O algorithm takes 2.5s. This indicates the rapid functioning of the proposed method in comparison to the P&O algorithm.Fig.13 further supports the superiority of the proposed method, as it demonstrates fewer fluctuations in the output power when utilizing the genetic algorithm compared to the P&O algorithm. The standard deviation using the proposed method is 0.56W, while the P&O algorithm yields a higher standard deviation of 2.54W. Consequently, the proposed method ensures a more stable functioning around the maximum power point (MPP), resulting in reduced power fluctuations. Therefore, based on the provided data, it is reasonable to conclude that the proposed method achieves higher efficiency, faster response time, and improved stability around the MPP compared to the P&O algorithm.

VI. Conclusion

In this study, we investigated a GA-based MPPT algorithm applied to a PV conversion system. We provided a comprehensive description of the system components and presented the mathematical model associated with these components. Subsequently, we introduced the proposed method and highlighted its unique characteristics. Through simulation and experimental comparisons with the well-known P&O algorithm, the performance of the proposed method was evaluated. The results of the performance tests clearly demonstrated the superiority of the proposed method over the conventional approach. This superiority was evident in various aspects, including stable functioning around the maximum power point, rapid convergence, robustness, and higher levels of converted power and efficiency.

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