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Development of an MPPT-Based Genetic Algorithm for Photovoltaic Systems versus Classical MPPT Techniques in Scenarios with Partial Shading

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Abstract: Photovoltaic (PV) systems face challenges in achieving maximum energy extraction due to the non-linear nature of their current versus voltage (I*x*V) characteristics, which are influenced by temperature and solar irradiation. These factors lead to variations in power generation. The situation becomes even more complex under partial shading conditions, causing distortion in the characteristic curve and creating discrepancies between local and global maximum power points. Achieving the highest output is crucial to enhancing energy efficiency in such systems. However, conventional maximum power point tracking (MPPT) techniques often struggle to locate the global maximum point required to extract the maximum power from the PV system. This study employs genetic algorithms (GAs) to address this issue. The system can efficiently search for the global maximum point using genetic algorithms, maximizing power extraction from the PV arrangements. The proposed approach is compared with the traditional Perturb and Observe (P&O) method through simulations, demonstrating its superior effectiveness in achieving optimal power generation.

Keywords: MPPT; partial shading; genetic algorithms; photovoltaic system; electronic converter

Citation: de Oliveira, F.M.; Brandt, M.H.M.; Salvadori, F.; Izquierdo, J.E.E.; Cavallari, M.R.; Ando Junior, O.H. Development of an MPPT-Based Genetic Algorithm for Photovoltaic Systems versus Classical MPPT Techniques in Scenarios with Partial Shading. *Inventions* **2024**, *9*, 64. https://doi.org/10.3390/inventions9030064

Academic Editor: Om P. Malik

Received: 3 May 2024
Revised: 21 May 2024
Accepted: 27 May 2024
Published: 30 May 2024

1. Introduction

With technological development and the advancement of industry, there is a growing increase in energy demand worldwide [1–3]. Photovoltaic (PV) energy derived from solar power is gaining prominence in this context due to its clean and emission-free primary source, making it a viable option for electrical systems [4,5]. Solar energy is free of generation costs, non-polluting, and requires low maintenance [6,7]. Due to the high initial investment cost, the energy produced by photovoltaic systems is more expensive than that produced by other energy production systems [6,7]. There is a wide variety of applications for photovoltaic energy; some examples are in homes, cars, charging stations, water pumping stations, and rural area electrification, improving domestic, medical care, agriculture, and education sectors [3–5].

Due to the varying solar incidence during the day and partial or total shading effects, photovoltaic panels often do not operate at their maximum capacity [8,9]. Different voltage and current levels are observed based on the configurations adopted in a photovoltaic arrangement. When there is partial shading on a photovoltaic array, the current versus voltage (I*x*V) characteristics change due to the system's dependence on solar radiation and temperature. An escalation in shading induces a decline in the current of the PV array [9]. Simultaneously, a temperature increase reduces the PV array voltage [7]. Consequently, points with different solar radiation and temperatures may exist in a given photovoltaic arrangement, reducing the PV's total generation capacity [10,11]. The characteristics of partial shading can be observed in strings installed in urban environments, where partial shading can be caused by trees, towers, buildings, and structures obstructing solar radiation [12,13]. Another way to obtain partial shade points in a string relates to positioning when installing the panels [14].

To tackle this challenge, the widely used solution is the implementation of MPPT (Maximum Power Point Tracking) systems [6,7,15,16]. Conventional tracking algorithms cannot effectively mitigate the challenges posed by partial shading, causing the panel to operate within local maximum bands and thereby reducing the overall efficiency of the photovoltaic array [9,17]. Two of the most commonly employed MPPT techniques, renowned for their simple implementation and minimal sensor requirements, are the Perturb and Observe (P&O) and Hill Climbing (HC) methods [18].

P&O continuously perturbs the operating point and observes the resulting change in power, making it suitable for various applications despite its susceptibility to rapid environmental changes. Building upon the simplicity of P&O, Incremental Conductance (INC) considers the instantaneous change in power concerning voltage, offering adaptability to rapidly changing solar irradiance conditions, rendering it effective in dynamic environments [19]. In addition to P&O and INC, Fractional Open-Circuit Voltage (FOCV) is another approach that utilizes a fraction of the open-circuit voltage to estimate the optimal operating point. Particularly effective under partially shaded conditions, FOCV addresses scenarios where traditional methods may fail [20].

In response to the limitations of conventional MPPT algorithms, the development of stochastic algorithms and artificial intelligence techniques has been pivotal. For instance, Model Predictive Control (MPC) employs a mathematical model of the PV system to predict future behavior and determine the optimal operating point. MPC handles dynamic and varying environmental conditions, providing an effective control strategy [21]. Artificial intelligence (AI) and machine learning (ML) techniques, including Differential Evolution (DE), genetic algorithms (GAs), Particle Swarm Optimization (PSO), and Artificial Neural Networks (ANNs), offer adaptive and self-learning capabilities [15,16,22]. These approaches optimize MPPT in real time and exhibit promising results under diverse conditions. Fuzzy Logic Control introduces linguistic rules to adapt to changing environmental conditions, providing robustness and the ability to handle uncertainties. Fuzzy logic-based MPPT systems demonstrate effectiveness in various operational scenarios [23].

The Ripple Correlation Control (RCC) technique is noteworthy for its performance under high-solar-irradiance conditions; however, its tracking efficiency experiences a drop at low solar irradiance [18]. The main drawback of conventional Maximum Power Point Tracking (MPPT) algorithms is their inefficiency under rapidly changing environmental conditions, such as fluctuations in solar irradiance and temperature. Traditional MPPT methods, like Perturb and Observe (P&O) or Incremental Conductance (IC), rely on steady-state conditions to accurately track the maximum power point (MPP). However, in dynamic conditions, these algorithms can fail to track the true MPP accurately and quickly, leading to power losses. This limitation arises because conventional MPPT algorithms typically use fixed step sizes or response times, making them slow to adapt to sudden changes, thus resulting in suboptimal performance and reduced energy harvest from the solar panels.

Introducing more intricate approaches, Hybrid MPPT Systems integrate multiple MPPT algorithms, combining the strengths of different techniques to enhance overall system performance—particularly valuable in conditions where individual methods may fall short [24]. Complementing this, Distributed MPPT techniques allocate control across multiple inverters in grid-connected PV systems, optimizing power extraction for large-scale installations while enhancing efficiency and minimizing losses [25].

To address challenges related to the partial shading of strings, intelligent or bio-inspired algorithms offer effective solutions [26]. Among these, GAs stand out, developed based on Darwin's theory of the evolution of species. GAs distinguish themselves from traditional search and optimization techniques by working with a population of potential candidates rather than a single point. The GAs are an adaptive search mechanism based on the Darwinian principle of natural selection and genetic reproduction, where their main task is to efficiently search for solutions that are in line with the problem's objective. This characteristic makes GAs efficient for finding optimal or approximate solutions to various problems [27,28]. These algorithms play a crucial role in overcoming issues associated with partial shading in photovoltaic arrays, providing robust optimization strategies that contribute to improved energy extraction in varying environmental conditions.

In this context, an investigation was conducted into applying two MPPT methods—the widely used P&O and the bio-inspired GA—to a photovoltaic system consisting of three modules. The analysis was executed using MATLAB as the simulation tool. Various partial shading scenarios were simulated to assess the efficacy of these methods in addressing shading issues. Some works in the literature, such as [29,30], present an MPPT method based on genetic algorithms. However, the system topology and the algorithm approach differ from the proposal in this work. Previous studies have explored the application of GAs for MPPT to address some of the limitations of conventional methods. These studies have shown that GAs can effectively adapt to rapidly changing environmental conditions by optimizing the tracking process through evolutionary techniques, thereby improving the efficiency and accuracy of MPPT. It would be beneficial to include and discuss these prior studies in the current work to provide a comprehensive context and highlight the advancements and unique contributions of your research [29,30].

The primary objective was to validate the MPPT techniques and observe their performance in tracking the maximum power point (MPP) under challenging conditions. Particular emphasis was placed on comparing the two methods under diverse operating conditions. Comprehensive analyses were performed on the data obtained from these experiments to discern the advantages of GA over conventional MPPT methods. These findings contribute to ongoing efforts to optimize energy extraction in varying environmental conditions and underscore the potential of bio-inspired approaches in overcoming challenges associated with solar panel shading.

2. Power Converters and MPPT Algorithms

To optimize the efficiency of the photovoltaic system, incorporating a power converter between the panels and the electric grid is indispensable. Nevertheless, it is essential to acknowledge that the current generation of these converters presents efficiency limitations [31]. Given the uncontrollable nature of environmental conditions, the focus naturally shifts towards effectively managing the dynamic load variations experienced by the panel. In addressing this challenge, DC-DC or DC-AC converters are pivotal in the control strategy.

The literature reveals a diverse array of converters [32,33]. Notable among these for photovoltaic projects are (i) buck, (ii) boost, and (iii) buck-boost DC-DC converters. DC-DC converters, also known as choppers, function as devices capable of converting a fixed voltage source into a variable voltage source or a variable source into a fixed source. This conversion involves passive elements in the system, such as an inductor and capacitor, and a solid-state device that operates through high-frequency switching, utilizing the pulse-width modulation (PWM) technique.

Power converters typically demonstrate efficiency levels from 90% to 95% [31–34]. The nuanced performance within this range is intricately tied to the converter's topology, design elements, the quality of components, and operating conditions, such as input and output voltage specifications, as well as load characteristics [30–33]. These diverse factors collectively contribute to the dynamic efficiency variations observed across different operational scenarios. Ongoing research and developments in power electronics continue to refine and optimize converter efficiency over time [34–37].

The conventional boost converter topology is often employed in photovoltaic systems to increase the output voltage beyond the input voltage, effectively regulating and stabilizing the panel voltage, ensuring optimal photovoltaic system operation [37]. This configuration presents some positive aspects, such as simplicity, ease of implementation, and suitability for low- to moderate-power applications. However, it comes with limitations, including higher ripple currents, potential reliability issues, and reduced efficiency, particularly in scenarios with rapid changes in environmental conditions [32,37].

In contrast, while associated with high-power, high-current applications, the interleaved boost converter offers several advantages over conventional boost converters [38]. It excels in distributing the load current across multiple phases, thereby reducing individual current stress on each phase. This distributed current handling results in lower component stresses, improved reliability, and increased power processing capability. The interleaved boost converter also helps mitigate ripple currents, enhances system reliability, and improves overall efficiency [38]. Despite these benefits, its implementation might be overly complex for low- to moderate-power applications.

Considering the specific requirements and operational conditions of the photovoltaic system, the conventional boost converter was chosen to prioritize simplicity and ease of implementation, given the lower power range involved in this work. Figure 1 illustrates a basic boost converter or voltage lifter. It operates through a two-stage process: (1) the conduction of the transistor (S), and (2) the conduction of the diode (D).

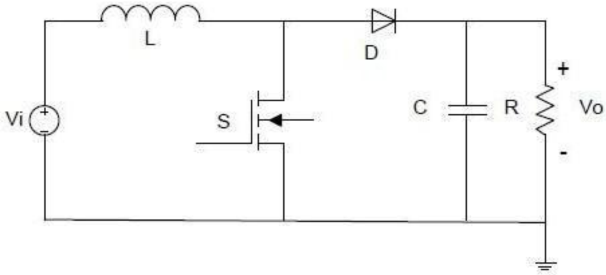
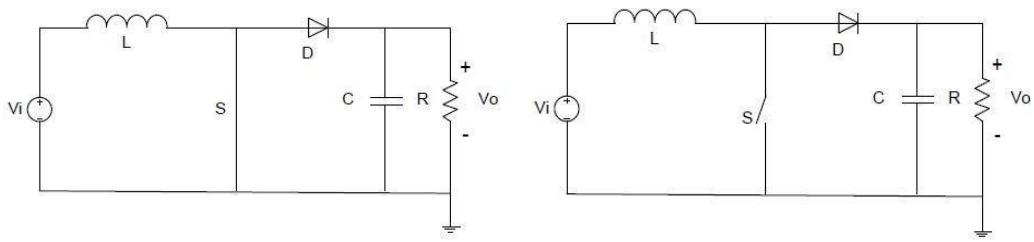


Figure 1. Boost converter circuit schematic.

In the initial stage, depicted in Figure 2a, the transistor conducts while the diode remains blocked. During this phase, the inductor L is charged directly by the input voltage V_i. It is important to note that the output voltage V_o exceeds V_i, resulting in the diode being inversely biased since it does not conduct current to the load R.



(**a**) (**b**)

Figure 2. Simplified circuit schematic of the boost converter, showcasing configurations with (**a**) the switch closed and the diode open, and (**b**) the switch open and the diode closed.

The transistor is open in the second stage of the boost converter circuit, as illustrated in Figure 2b. During this phase, the stored energy in the inductor is released. Having accumulated energy during the transistor's conduction phase, the inductor maintains the circuit's I_o current flow. With the switch S opens, the diode D conducts, providing a path for the inductor's stored energy to discharge.

As the energy is released, the voltage across the inductor reverses, causing a voltage drop across the diode. This allows the energy to flow from the inductor to the load resistor R, effectively boosting the output voltage beyond the input voltage V_i. In general, the capacitor C helps smooth out any voltage ripples, contributing to a more stable output voltage. This two-stage boost converter operation enables the system to step up the input voltage to a higher level, making it a valuable component in power electronics applications, including photovoltaic systems.

The converter's inductance, capacitance, and output-to-input voltage ratio can be determined using Equations (1) to (3), respectively [39].

$$L = \frac{V_i \cdot \delta}{f_S \cdot \Delta I_L} \tag{1}$$

$$C = \frac{I_o \cdot \delta}{f_S \cdot \Delta V_C} \tag{2}$$

$$\frac{V_O}{V_i} = \frac{1}{1-\delta} \tag{3}$$

These parameters are a function of the transistor's duty cycle δ and switching frequency f_S, as well as the current ripple in the inductor ΔI_L and the voltage ripple across the capacitor ΔV_C. Adjusting the duty cycle allows the converter to optimize its operation for maximum power extraction from the PV system. Duty cycle control can be achieved through an MPPT algorithm or a dedicated controller [40,41].

2.1. Perturbation and Observation (P&O)

A visual representation of the flowchart outlining the P&O method is given in Figure 3. It involves systematically perturbing the array voltage, either by increasing or decreasing it, and monitoring the resulting output power. In the event of a power increase, the perturbation continues in the same direction; otherwise, it reverses direction.

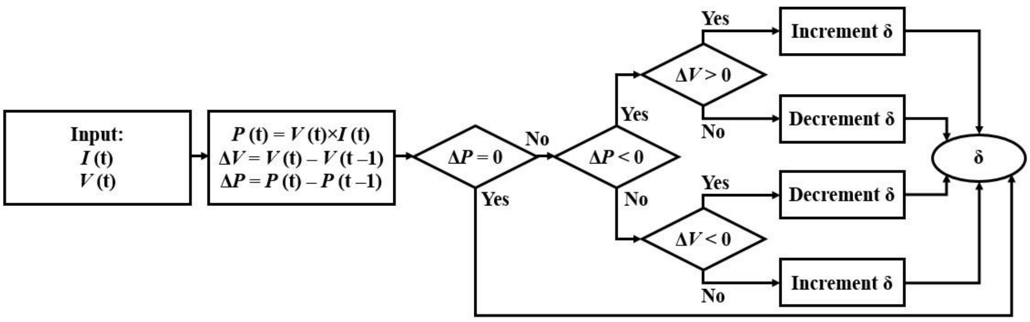


Figure 3. Flowchart of the P&O MPPT method.

This iterative process periodically updates itself, leading to oscillations around the MPP rather than stabilization at the precise MPP [42–44]. As will be shown later, an inherent challenge of the P&O method arises when the system operates under partial shading conditions, potentially causing it to converge to local maxima instead of reaching its maximum efficiency [6,7].

2.2. Genetic Algorithm (GA)

In the 1950s and 1960s, scientists independently studied evolutionary systems with the idea that evolution could be used as a tool for optimizing engineering problems [30]. The main idea in all the systems was to evolve an original population of candidate solutions to a given problem, using operators inspired by natural genetic variation and natural selection.

Genetic algorithms, or GAs, were created by John Holland in the 1960s and developed by Holland and his students and colleagues at the University of Michigan [31].

In contrast to evolution and evolutionary programming strategies, Holland's original goal was not to design algorithms to solve specific problems, but rather to formally study the phenomenon of natural adaptation and how it could be imported into computer systems; thus, the genetic algorithm was presented as an abstraction of biological evolution, where it is a method for transforming a population of chromosomes, which can be represented as a chain of 1's and 0's, into a new population using a kind of natural selection in conjunction with the operators of crossover, mutation, and inversion of inspired genetics.

As illustrated in the flowchart of Figure 4, genetic algorithms represent an adaptive search mechanism grounded in the Darwinian principles of natural selection and genetic reproduction. The primary objective is to explore solutions aligned with the problem's objectives efficiently.

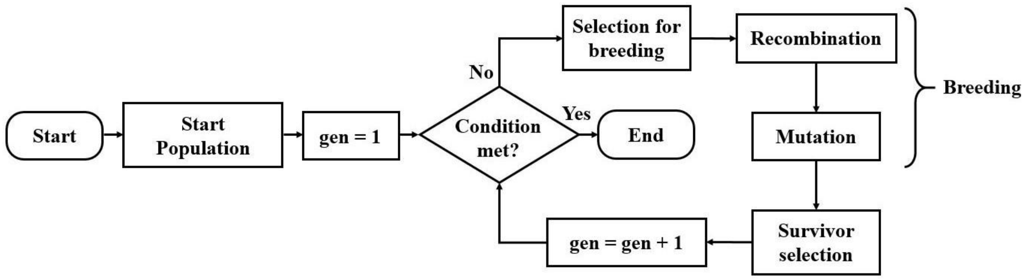


Figure 4. Typical GA-based MPPT flowchart.

The GA unfolds through the following key steps:

(i) Initialization: An initial generation population is randomly created.

(ii) Generation Iteration: Maintaining a population of potential solutions denoted as P(gen) = $(x_1 \ldots x_n)$.

(iii) Evaluation: Each individual (x_i) in the population undergoes evaluation through a fitness function, determining its fitness measure.

(iv) Selection: New individuals are generated from μ individuals in the current population, selected for breeding based on their fitness measures. Preferential treatment is given to the best-performing individuals.

(v) Recombination and Mutation: Some individuals undergo changes through recombination and mutation processes, forming new potential solutions.

(vi) Next Generation Selection: Individuals from the old and newly formed solutions are chosen for the next generation (gen + 1).

This iterative process continues until a predefined stopping condition is met. The stopping condition is often based on achieving a desired fitness level for the solutions [15,16]. The repetition continues until the specified condition, an expected fitness level or a maximum number of iterations, is satisfied.

2.2.1. Representation or Encoding

Genetic algorithms commonly employ binary or floating-point representations. Binary representation consists of a fixed vector formed by concatenating "0" and "1", and it is direct if solutions are binary or indirect if conversion is needed. Floating-point representation, associating a vector of real numbers with a defined size, offers advantages such as smaller chromosome size, reduced CPU and memory consumption, and simplified representation [15,16]. However, it does not facilitate the direct use of building blocks for demonstrating convergence [45,46].

2.2.2. Fitness of Individuals

The fitness function establishes a direct link between the GA and the problem characteristics, mimicking nature where fitness measures a population's environmental adaptation. For the proposed work, focusing on maximizing power output, fitness is determined by the individuals who contribute to this objective [47,48].

2.2.3. Selection Methods

Selection mimics genetic evolution's reproduction phase, favoring the fittest individuals as progenitors for generating a new candidate population. Various selection methods exist, including the Roulette Method, tournament selection, and linear or exponential sorting [49–51].

2.2.4. Genetic Reproduction

The chosen coding method for individual representation guides the application of genetic operators. Genetic reproduction can occur asexually, where an individual independently generates a descendant through mutation. Alternatively, sexual reproduction involves two individuals contributing to creating one or more offspring through processes like genetic recombination, crossbreeding, or crossover [51].

The crossover operator is a pivotal component of genetic reproduction, involving the exchange of genetic material between two individuals. This process generates two new individuals formed by combining information from the pair of progenitor individuals. Various standard crossover operators exist, including those with one cutoff point, two cutoff points, multipoint or uniform, and heuristic approaches [52]. This critical phase plays a key role in shaping the population's genetic diversity and influencing the evolutionary process's convergence speed.

2.2.5. Mutation

The mutation operator randomly modifies one or more chromosome genes, generating a new individual. The mutation rate, representing the mutation probability, is generally small to avoid potential fitness reduction [51].

2.2.6. Evolution Parameters

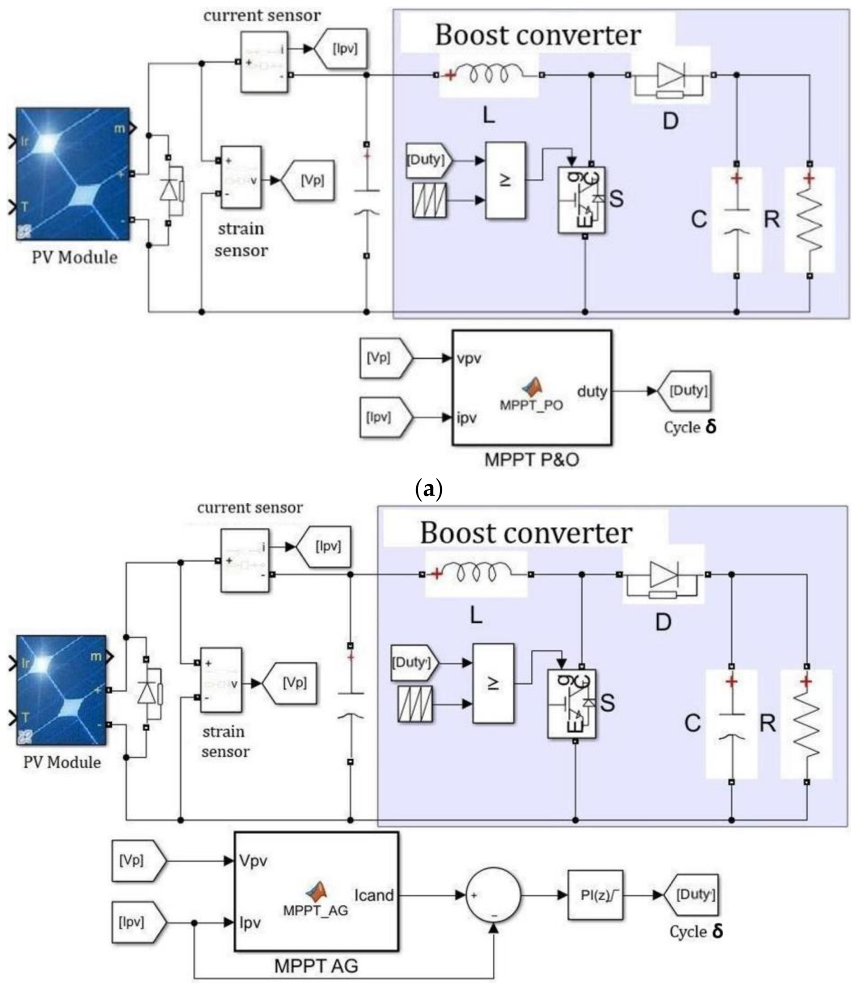
Implementing a genetic algorithm requires carefully considering several critical parameters that collectively shape the algorithm's overall performance. These parameters include population size, crossover rate, generation interval, number of generations, convergence of the evaluation function, number of rounds, and seeding rate [53,54].

Population size, representing the number of individuals in a population, directly influences the diversity and exploration capacity of the algorithm. The crossover rate, determining the probability of two individuals undergoing crossover, balances exploration and exploitation [53,54]. The generation interval, closely tied to population size, defines the percentage of the population replaced in each new generation. A higher rate can expedite the algorithm but may risk losing high-fitness individuals, while a lower rate slows the algorithm but retains individuals with superior fitness levels. The number of generations is a crucial stopping criterion, indicating the total cycles or new populations generated. A low value may lead to premature convergence, while a high value extends processing time but allows for a more thorough exploration of the search space. To ensure convergence to an optimal solution, the convergence of the evaluation function is vital. The number of rounds dictates the total iterations of the algorithm, contributing to its overall performance. The seeding rate influences the diversity and exploration capacity of the initial population. Optimal values for these parameters must be judiciously adjusted, considering the specific characteristics of the population. Genetic algorithms involve a dynamic process, and parameter tuning is essential for achieving optimal results [55,56].

In the proposed work, a meticulous examination and comparison of these evolution parameters are conducted to assess their impact on the performance of two maximum power tracking techniques for a photovoltaic system—conventional P&O and the innovative GA. This comprehensive analysis unfolds under simulated conditions, encompassing normal and partially shaded operating scenarios. The systematic evaluation aims to ascertain the effectiveness and efficiency of these methods in optimizing power output for photovoltaic applications.

3. PV System Model

The power converter and the tracking algorithm are primarily linked through the duty cycle (δ). The tracking algorithm assesses voltage and current data from the system, dynamically adjusting the duty cycle to optimize extracted power [26]. Figure 5 depicts the boost converter models utilized for the P&O and GA tracking algorithms. In both cases, the dimensioned boost converter maintains consistent values, with inductance and capacitance data determined by Equations (1) and (2). Simultaneously, duty cycle determination is executed through Equation (3), thereby isolating the δ parameter. All simulations for both algorithms are conducted within the Matlab/Simulink computing environment.



(**a**)

(**b**)

Figure 5. MPPT controller configurations for the duty cycle to the boost converters, depicting (**a**) the P&O method and (**b**) the GA-based method.

Table 1 presents the solar plate data utilized as the foundation for the simulations. The plate model adopted for this purpose is the Soltech 1STH-FRL-4H-260-M60-BLK.

Table 1. Key parameters of the solar plate used as the basis for simulations.

Parameter	Average Value
Maximum Power	259.44 W
Open Circuit Voltage (V_{OC})	38.6 V
Voltage at Maximum Power Point	31.6 V
Temperature Coefficient in V_{OC}	−0.356%/°C
Number of Cells per Module	60
Short Circuit Current (I_{SC})	8.93 A
Current at Maximum Power Point	8.21 A
Temperature Coefficient in I_{SC}	0.102%/°C

Each of the three panels experienced a uniform light intensity of 1000 W/m^2 under a constant temperature of 25 °C. The simulations encompass three distinct scenarios. In the initial simulation, no partial shading was introduced, allowing all three panels to receive the full 1000 W/m^2. In the second simulation, partial shading was applied to one solar panel, reducing its irradiance to 500 W/m^2. Finally, the third simulation involved partial shading on two solar panels. The first panel maintained an irradiance of 1000 W/m^2, the second panel experienced shading with 900 W/m^2, and the third panel with 500 W/m^2.

The boost converter was engineered to manage the diverse power characteristics of the solar plate, with a primary emphasis on accommodating the highest voltage (38.6 V) and current levels (8.93 A), while operating at 20 kHz. The calculated simulation model parameters included an inductance of 1.5 mH and a capacitance of 36 µF, considering a load of 100 Ω. The transistor and diode models were selected as ideal switches, exhibiting zero or infinite resistance depending on the switch's state.

4. Results

4.1. Case Study 1

When partial shading is not applied, and the maximum power point is determined to be 778.19 W, both techniques demonstrate satisfactory performance under steady-state conditions. Figures 6 and 7 depict the power, voltage, and current plots corresponding to the P&O and GA-based MPPT techniques, respectively.

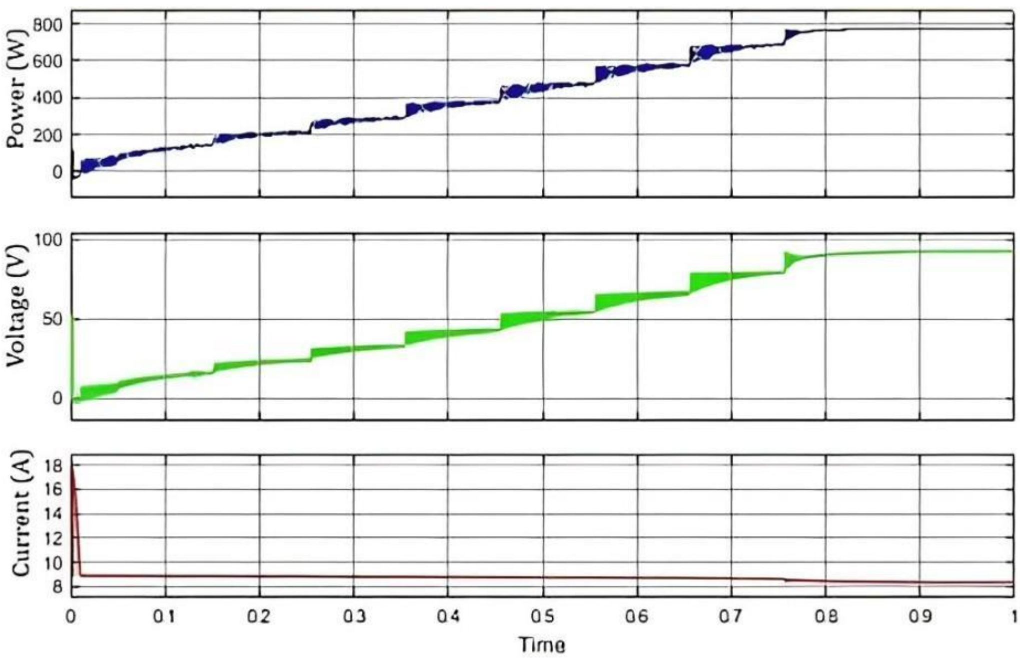


Figure 6. Case 1: power, voltage, and current versus time for the P&O MPPT method.

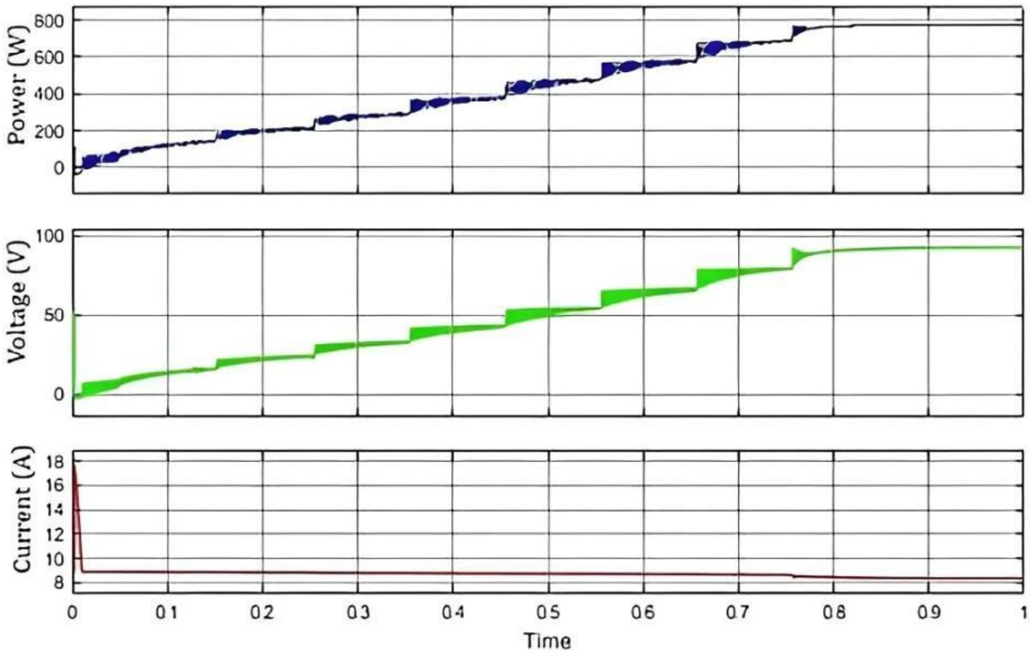


Figure 7. Case 1: power, voltage, and current versus time for the GA-based MPPT technique.

4.2. Case Study 2

Figure 8 offers a comprehensive insight into the photovoltaic arrangement's P-I curve under partial shading conditions. The intricate curve presents two noteworthy maximum points, contributing to the nuanced system performance analysis. Notably, a local maximum lies at 436.97 W, while a global maximum is at 512.29 W.

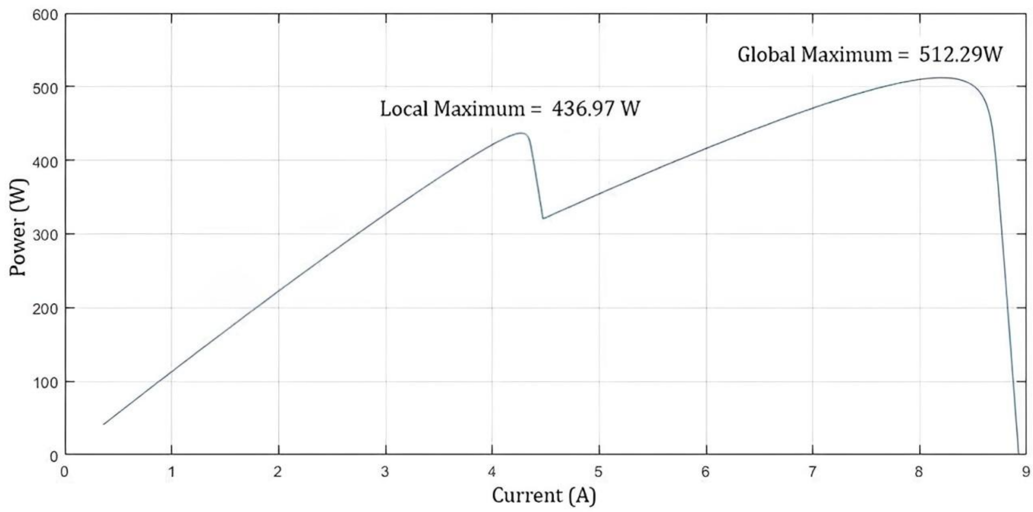


Figure 8. Case 2: power versus current characteristic curve.

The P&O algorithm exhibits a limitation in reaching the maximum power point, settling in proximity to a local maximum. The resultant tracking efficiency is quantified at 85.19 percent, as meticulously portrayed in the graphical representation offered in Figure 9. Conversely, the GA-based MPPT technique emerges as a contrasting protagonist in this scenario. It not only attains the coveted maximum power point but sustains a stable power output of 508.80 W in the permanent regime. The accompanying illustration in Figure 10 vividly captures this triumph, emphasizing a remarkable efficiency of 99.32%.

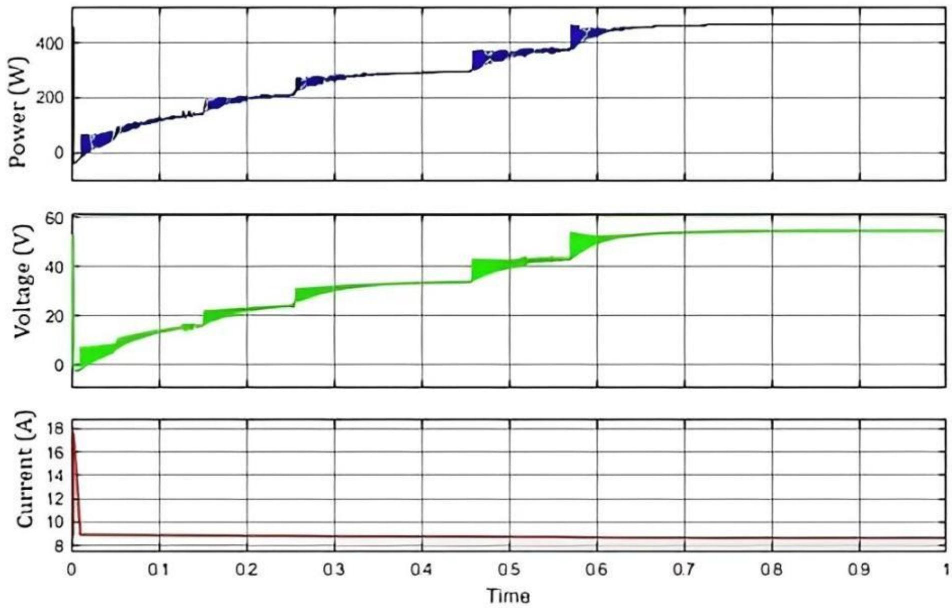


Figure 9. Case 2: power, voltage, and current versus time for the P&O MPPT method.

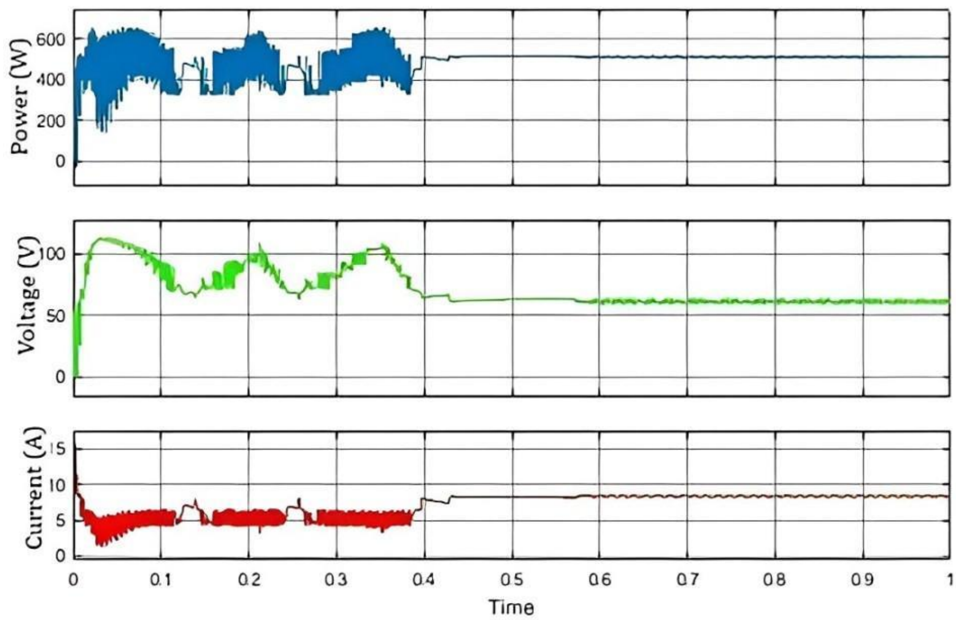


Figure 10. Case 2: power, voltage, and current versus time for the GA-based MPPT technique.

4.3. Case Study 3

Figure 11 portrays the P-I curve of the photovoltaic arrangement encountering partial shading conditions in Case 3. The intricacies of the curve unfold with three notable maxima points, featuring two local maxima at 435.49 W and 245.96 W, alongside the most significant power point that yields a power output of 477.55 W.

Within Case 3, the P&O method, once again, encounters challenges in reaching the global maximum point, as discerned from the P-I curve specific to this case. The resultant efficiency in the permanent regime is quantified at 51.22%, a finding prominently displayed in the graphical representation offered in Figure 12. In stark contrast, the GA-based MPPT technique stands out as a shining example of superior performance in Case 3. It not only achieves a commendable power output of 477.20 W in the permanent regime but also attains an enviable efficiency of 99.93% in accurately tracking the highest power point for this specific case. This is illustrated in the graphical representation provided in Figure 13.

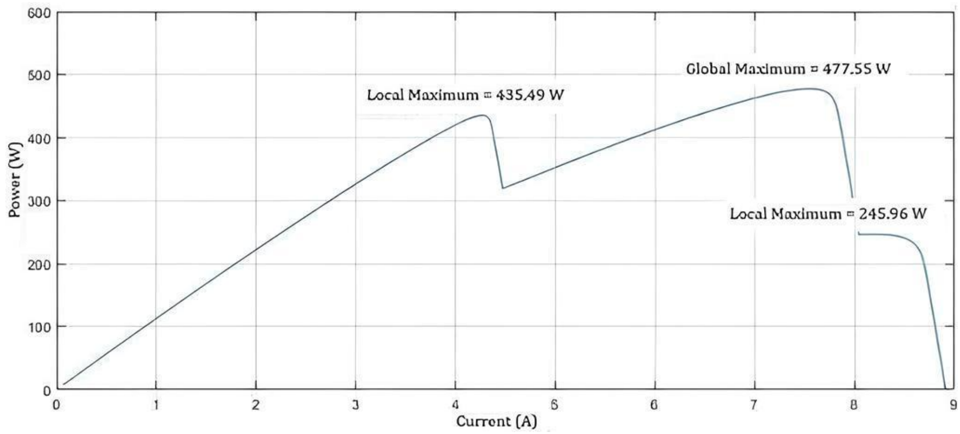


Figure 11. Case 3: power versus current characteristic curve.

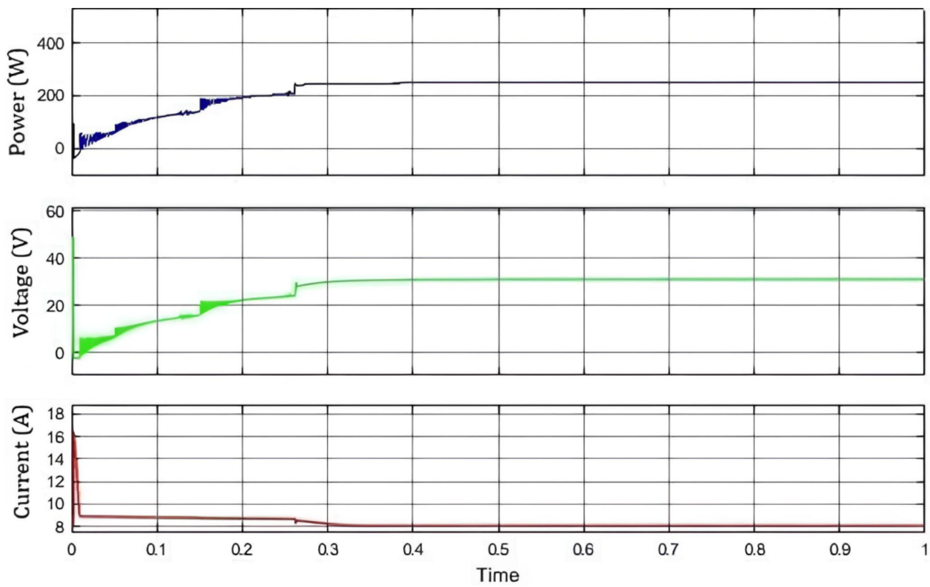


Figure 12. Case 3: power, voltage, and current versus time for the P&O MPPT method.

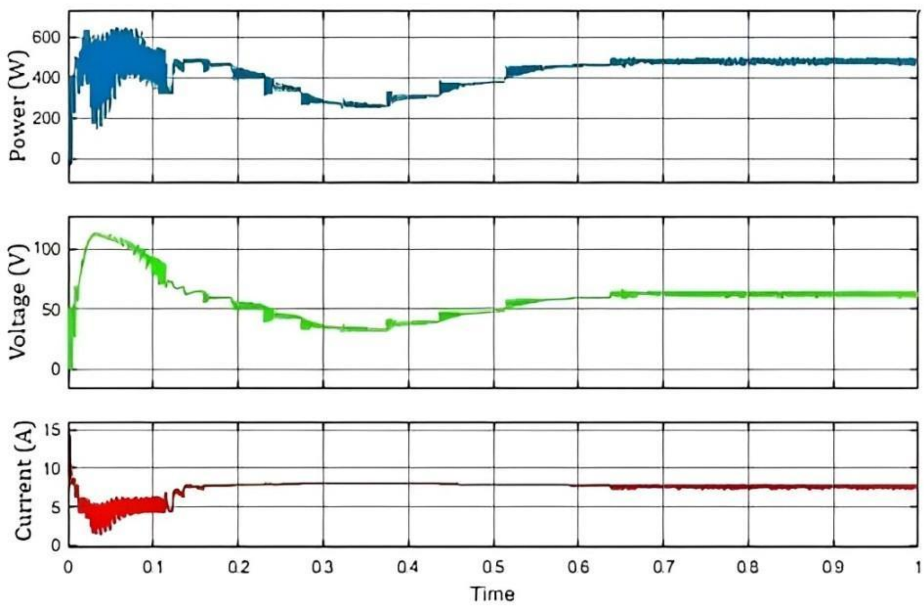


Figure 13. Case 3: power, voltage, and current versus time for the GA-based MPPT technique.

5. Discussion

Table 2 summarizes the P&O and GA-based MPPT technique performances in three distinct simulated cases, conducted under a constant light intensity of 1000 W/m^2 and a temperature of 25 °C, each characterized by specific shading conditions. In the first scenario, where no partial shading is applied, the algorithms showcase positive aspects, such as achieving the highest power point of 778.19 W, indicating efficient power generation. However, there is slight room for improvement in GA efficiency, which is 98.61%. Moving to the second case, involving partial shading of one panel, the GA efficiency excels at 99.93%, underscoring the algorithm's robustness in handling shading conditions. Conversely, the P&O efficiency drops significantly to 51.22%, signaling challenges in partial shading situations. In the third simulated case, with partial shading on two panels, while GA efficiency remains high at 99.93%, P&O efficiency drops to 51.22%. Once again, it indicates potential limitations of the P&O method in dealing with shading scenarios. Moreover, the highest power point slightly decreases to 477.55 W compared to the case with no partial shading.

Table 2. Comparative performance summary of P&O and GA-based MPPT techniques in three simulated photovoltaic cases under varying shading conditions.

Case Number	HPP (W)	Power (W)		Efficiency (%)	
		P&O	GA	P&O	GA
1	778.19	774.60	767.40	99.54	98.61
2	512.29	436.4	508.80	85.19	99.32
3	477.55	244.60	477.20	51.22	99.93

These simulations offer valuable insights into algorithmic adaptability in diverse shading conditions. The comparison between a genetic algorithm and the widely recognized P&O method reveals notable shortcomings in the latter. P&O demonstrates significant limitations in determining the global maximum power point under partial shading conditions. Additionally, the extracted power exhibits oscillatory behavior in response to rapid changes in weather conditions [18]. As da Luz and coauthors demonstrated in [57], future work should focus on experimental validation to corroborate these findings.

Addressing the challenge of partial shading is crucial for effectively utilizing flexible photovoltaics across various applications. These applications span from silicon-based technologies [58] to CIGS [59,60] and even organic thin films [60,61], finding applications in diverse areas such as mobility, electronic gadgets, furniture, and building façades. Expanding and diversifying the applications of flexible photovoltaics is an area that requires further exploration. Both hardware and software development are essential to enhance the performance and efficiency of these devices.

Moreover, understanding the mechanisms of degradation is paramount. In the case of organic thin-film modules, exposure to partial shading may lead to chemical degradation, impacting the structural integrity of the materials and potentially reducing their efficiency over time [62–64]. On the other hand, silicon-based flexible modules may face challenges such as increased series resistance and the risk of short circuits under partial shading conditions [62,63]. Investigating these degradation pathways is also crucial for developing mitigation strategies and ensuring the long-term reliability of flexible photovoltaic technologies and power quality [65–69].

6. Conclusions

This study examined and compared two MPPT methods, namely the P&O and GA techniques, in different configurations of a photovoltaic system. The comparison was conducted through three simulation cases using a photovoltaic system comprising three modules connected in series. In Case 1, all three modules received the same solar irradiation of 1000 W/m^2 without shading. In Case 2, two modules received 1000 W/m^2 while one received 500 W/m^2, representing partial shading. In the final case, the first module received 1000 W/m^2, the second received 900 W/m^2, and the third received 500 W/m^2. The temperature was kept constant at 25 °C throughout the simulations.

The two techniques were simulated for each case to track the maximum power point using P&O and GA MPPT techniques. The P&O method performed well in Case 1 without shading. However, in Cases 2 and 3, when partial shading was introduced, the technique encountered difficulties and remained stuck at local maximum points, hindering power generation. On the other hand, the GA-based MPPT technique successfully tracked the global maximum point in all three simulation cases, showcasing its effectiveness and accuracy in both shadeless and partially shaded systems. These findings validate the efficacy of GA-based MPPT compared to traditional methods and highlight its superiority in mitigating shading effects and optimizing energy extraction.

By shedding light on the advantages of bio-inspired approaches, particularly genetic algorithms, in overcoming the complexities associated with solar panel shading, this study contributes to the ongoing quest for enhanced efficiency and resilience in photovoltaic systems. These insights pave the way for the continued refinement of MPPT strategies, driving progress toward sustainable energy utilization in varying environmental contexts.

Author Contributions: Conceptualization: M.H.M.B., F.M.d.O. and O.H.A.J.; methodology: M.H.M.B., F.M.d.O., F.S., M.R.C. and O.H.A.J.; validation: F.M.d.O., F.S., J.E.E.I., M.R.C. and O.H.A.J.; investigation and simulation: M.H.M.B. and F.M.d.O.; writing—original draft preparation: M.H.M.B., F.M.d.O. and O.H.A.J.; writing—review and editing: F.M.d.O., F.S., J.E.E.I., M.R.C. and O.H.A.J.; project administration: F.M.d.O. and O.H.A.J.; funding acquisition: F.S., M.R.C. and O.H.A.J. All authors have read and agreed to the published version of the manuscript.

Funding: This research was partially supported by the FACEPE agency (Fundação de Amparo a Pesquisa de Pernambuco) throughout the project with references APQ-0616-9.25/21 and APQ-0642-9.25/22. O.H.A.J. was funded by the Brazilian National Council for Scientific and Technological Development (CNPq), grant numbers 407531/2018-1, 303293/2020-9, 405385/2022-6, 405350/2022-8 and 40666/2022-3, as well as the Program in Energy Systems Engineering (PPGESE) Academic Unit of Cabo de Santo Agostinho (UACSA), Federal Rural University of Pernambuco (UFRPE). M.H.M.B. and F.M.O. were funded by the Federal University of Latin American Integration (UNILA). M.R.C. was funded by UNICAMP (State University of Campinas) throughout the Auxílio Início de Carreira (Docente), FAEPEX, process number 2095/23, as well as the Programa de Incentivo a Novos Docentes (PIND), FAEPEX, process number 2419/23.

Data Availability Statement: The original contributions presented in the study are included in the article, further inquiries can be directed to the corresponding author/s.

Conflicts of Interest: The authors declare no conflicts of interest.

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