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Bio-Inspired Approach for MPPT Optimization in Solar PV Systems

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KEYWORDS

Photovoltaic, MPPT, Optimization, Metaheuristic, PSO, MATLAB/SIMULINK, PSIM.

ABSTRACT

The significant developments in solar photovoltaic (PV) technology have led to a strong push toward the development of new Maximum Power Point Tracking (MPPT) methods. Hence, various MPPT techniques have been applied to enhance the efficiency of PV technology. In addition, metaheuristic algorithms are widely used in various scientific and technical fields for problem-solving purposes. A majority of these techniques are inspired by natural phenomena, such as physical laws or biological processes.

In the present study, the effectiveness of a smart MPPT technique utilizing Particle Swarm Optimization (PSO) has been evaluated to enhance the efficiency of the photovoltaic system. To achieve this, a mathematical model has been developed and implemented within the MATLAB/ SIMULINK environment. One of the objectives was to minimizing the execution time of the algorithm. PSIM tools were then used to verify and analyze the results. The findings obtained indicated the high similarity of optimization in terms of maximum photovoltaic generator power, with an error of less than 1.8%.

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نهج مستوحى من الطبيعة لتحسين تتبع نقطة القدرة القصوى في أنظمة الطاقة الشمسية الكهروضوئية

اليعقوبي ياسين، أمين تيليوا، عيسى صابري

ملخــص: أدت التطورات الكبيرة في تكنولوجيا الطاقة الشمسية الكهروضوئية إلى دفع قوي نحو تطوير طرق جديدة لتتبع نقاط الطاقة القصوى (MPPT) وبالتالي تم تطبيق العديد من تقنيات MPPT لتعزيز كفاءة الطاقة الكهروضوئية. بالإضافة إلى ذلك، تُستخدم الخوارزميات الفوقية على نطاق واسع في مختلف المجالات العلمية والتقنية لأغراض حل المشكلات. والواقع أن غالبية هذه التقنيات مستوحاة من الظواهر الطبيعية، مثل القوانين الفيزيائية أو العمليات البيولوجية.

في هذه الدراسة، تم تقييم فعالية تقنية MPPT الذكية التي تستخدم تقنية تحسين سرب الجسيمات (PSO) لتعزيز كفاءة النظام الكهروضوئي.

لتحقيق هذا الهدف، تم تصميم نموذج رياضي وتنفيذه باستخدام بيئة MATLAB/SIMULINK. بعد ذلك، تم استخدام أدوات PSIM للتحقق من النتائج وتحليلها. أظهرت النتائج أن هناك تشابهاً كبيراً في التحسين فيما يتعلق بالحد الأقصى للطاقة المنتجة من المولدات الكهروضوئية، مع خطأ لا يتجاوز 1.8%.

الكلماتالمفتاحية - الطاقة الشمسية الكهروضوئية، تتبّع نقطة القدرة القُصوى، التحسين الخوارزميات فوقية الاستدلال، تحسين سرب الجسيمات برنامج ماتلاب/سيميولينك .

1. INTRODUCTION

Among the renewable energy sources, photovoltaic technology stands out as one of the most promising and most encouraging. Photovoltaic electricity is generated through the direct conversion of solar radiation into electrical power using photovoltaic cells. These cells are composed of semiconductor materials arranged in a PN junction [1]. The arrangement of photovoltaic cells serves as a method for constructing a module, and photovoltaic arrays can be established by clustering multiple modules together. Generally, a photovoltaic system (consisting of several cells connected in series or parallel) is referred to as a module. A photovoltaic system, often referred to as a solar power system, is composed of multiple individual photovoltaic (PV) cells that are connected together to generate electrical energy from sunlight. These PV cells are made of semiconductor materials, typically silicon, that convert sunlight into electricity through the photovoltaic effect. When these cells are connected in series, the voltage output of the system increases, as the voltages of individual cells add up, while the current remains the same as that of a single cell. When photovoltaic panel cells are connected in parallel, the current output increases as the individual cell currents are added up, while the voltage remains constant at the level of a unique cell. Several photovoltaic cells are connected in series or parallel to form a module to increase energy production. These modules are then grouped to form an array, constituting the complete solar panel system used for energy production. Each module is usually enclosed in a protective frame, designed to resist and withstand environmental conditions such as rain, dust, wind, and temperature fluctuations. These modules are important components of larger solar energy systems, commonly used in residential, commercial, and industrial installations, especially for autonomous sites (desalination plant) [2],[3].

According to [4] and [5], the efficiency of a solar system depends largely on its ability to continuously track the Maximum Power Point. The MPP is at which the solar panel system generates the maximum possible power under all operating conditions. [4],[5]. The control efficiency of Maximum Power Point Tracking is therefore crucial to ensure optimal energy conversion. Although classical MPPT techniques have proven effective, they often fall short in responding to rapidly changing weather conditions, maintaining tracking precision, and adapting to harsh or unpredictable environmental scenarios [6]. To overcome these limitations, bio- inspired optimization algorithms are emerging as a promising alternative. These methods draw inspiration from patterns and behaviors observed in nature (such as bees, birds, and wolves) and are designed to develop more robust, flexible, and adaptive algorithms. By mimicking natural processes such as evolution, cooperation among organisms, and environmental adaptation, these approaches offer new possibilities for optimizing solar energy production [7], [8].

In [9] and [10], the authors provide an overview of various bio-inspired algorithms that have been applied to MPPT control in photovoltaic (PV) panel systems. The most studied approaches include GA (Genetic Algorithms), PSO (Particle Swarm Optimization), ACO (Ant Colony Optimization), and ABC (Artificial Bee Colony). These different algorithms have demonstrated strong capabilities in addressing challenges related to rapidly changing weather conditions, the non-linear behavior of solar panels, and power fluctuations in the grid (due to variability in energy demand). The application of metaheuristic optimization algorithms for Maximum Power Point Tracking (MPPT) offers a novel approach to enhancing the energy efficiency of photovoltaic systems by ensuring the extraction of maximum power [11].

The MPPT aims to dynamically adjust the operating parameters of solar panels to optimize the conversion of solar energy to electricity in real time. Also, the PSO, inspired by the social behavior of bird or insect staves, is an evolutionary optimization algorithm that can be applied to effectively search for the space of possible solutions. In this paper, we will emphasize the unique benefits of each bio-inspired method, examining how they are applied to optimize maximum power point tracking using MATLAB/SIMULINK software. These results have been validated using the PSIM simulation tool.

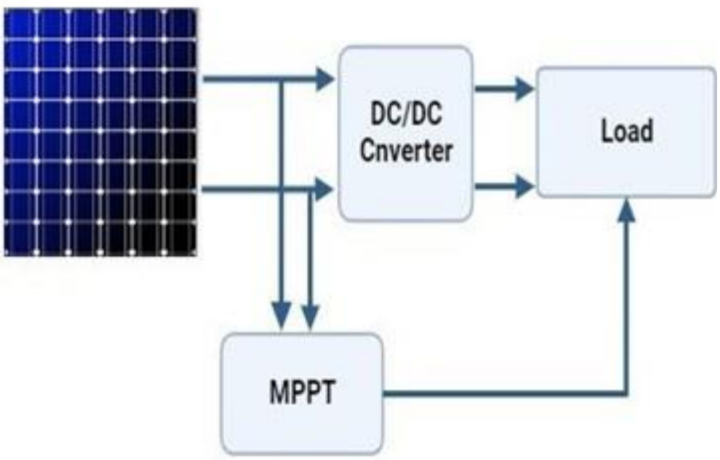

Figure1.ActualmethodtomaximizetheenergyofPVpanels.

2. METHODS

2.1. System architecture

main components: the energy conversion unit, the primary control unit, and the PV simulator.

Figure 2 illustrates the block diagram of the proposed system [11]. The system consists of three

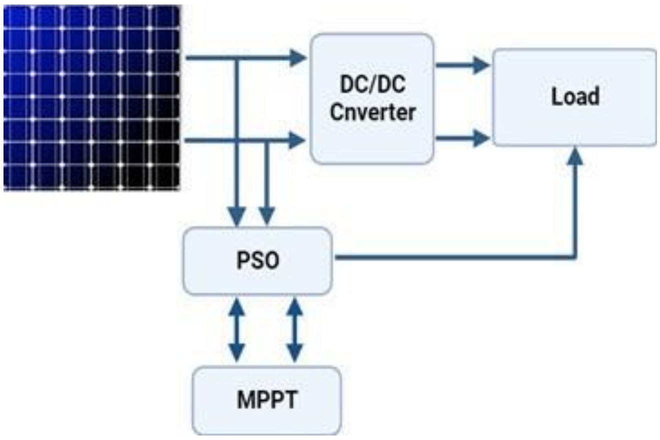

Figure2.Blockdiagramoftheproposedmethod.

2.2. PV panel model

Several solar cells connected in parallel or series make up a photovoltaic module. Series connections increase the voltage, while parallel connections boost the current. The module is made up of various components, which can differ based on the type of solar panel technology, such as amorphous, polycrystalline, or monocrystalline panels. Regarding cost, effectiveness, and general performance, each variety has pros and cons of its own.

The equivalent electrical circuit of a photovoltaic cell can be represented in Figure 3 [11]. It consists of a serial resistor, a diode, a power supply, and a resistor shunt.

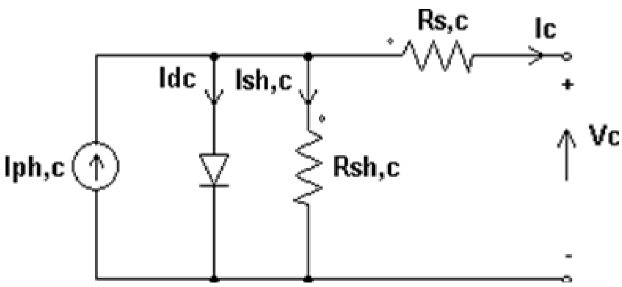

Figure3.ElectricalmodelofaPVcell.

From the equivalent circuit, the current produced by the photovoltaic cell can be expressed using the following equation [12]:

$$I_c = I_{ph,c} - I_{0,c}\left(e^{\frac{q(V_c+R_{s,c}I_c)}{\propto KT}} - 1\right) - \frac{(V_c+R_{s,c}I_c)}{R_{sh,c}} \quad (1)$$

Iph,c is a cell's photocurrent, *I0,c* is the reverse saturation current of the diode of a cell, and *q, a, K* and *T* respectively designate the charge of the electron, diode ideality factor, Boltzmann constant, and cell temperature. *V,c* is the cell end voltage, *Ic* is the cell current, and *Rs,c* and

Rsh,c are the cell series and shunt resistors.

In this equation, *Iph,c* represents the photocurrent generated by the cell, while *I0,cI* denotes the reverse saturation current of the cell's diode. The symbols *q, k,* and *T* refer respectively to the electron charge, diode ideality factor, Boltzmann constant, and the temperature of the cell. *Vc* stands for the cell voltage, *Ic* is the output current, and Rs,c and Rsh,c represent the series and shunt resistances within the cell.

2.3. Description of PSO algorithm

Eberhart and Kennedy developed the particle swarm optimization technique in the year of 1995. This is a population-based stochastic optimization technique [13]. The PSO approach creates a set of random particles first in order to find the optimal solution. The two best values are applied to each particle at the end of each generation. Thus far, the most successful option has been the first one. The maximum value that a population particle has ever reached is another. The best value in the world is this. When a particle utilizes the population as its topological neighbors, the best value is the local best. It is possible to alter a particle's speed and position once you are aware of its two optimal values. By multiplying the present position by the velocity, vi(z), one can determine the position of xi(z) [14]:

$$X_i(z) = X_i(z-1) + v_i(z) \tag{2}$$

$$vi(z) = wv_i(z-1) + C_{1r1}[P_{best} - X_I(z)] + C_{2r2}[G_{best} - X_i(z)] \tag{3}$$

The impact of the particle's prior velocity on its current velocity is adjusted by the inertia weight, w. The cognitive learning factor, or C*1*, indicates a particle's level of interest in its own accomplishment. The social learning factor, or C*2*, indicates a particle's level of interest in the prosperity of its neighbors. C*1* and C*2*, positive constants, are frequently employed. In addition, two separate random number sequences, r*1* and r*2* , € [0, 1], are employed to prevent entrapment on local minimums and to permit a small number of particles to diverge in a more exhaustive search of the search space; P*best* and G*best* represent the local and global best positions.

The velocity and location updates of the particle swarm optimization technique are explained in [13].

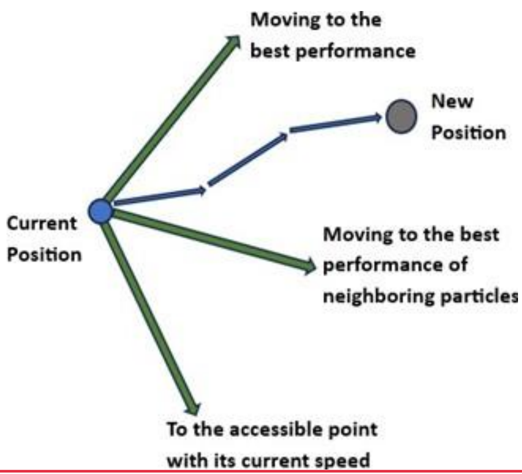

Figure4.Theparticlevelocityupdatesmethod.

Particle Swarm Optimization is often preferred over other bio-inspired optimization methods, such as Genetic Algorithms and Ant Colony Optimization, due to its distinct advantages shown in Table 1.

According to [18], PSO is very efficient because it works collaboratively. Each particle in the swarm maintains its own best-known solution while taking into account the best overall solution found by the swarm as a whole. This dual learning mechanism often leads to better overall solutions.

Table 1. PSO advantages.

	PSO	GA
Why PSO is chosen?	- Simplicity of design (reduced number of parameters) and its wide application in different fields [15]. - PSO Also employs more intuitive working principle (reduced computation time) [16]. - Faster convergence rate. By leveraging swarm intelligence and collective learning [17]	- Requires fewer parameters to configure, which makes it easier to implement and adapt to a wide range of fields [15]. - Relies on more complex biologically inspired operations like crossover and mutation [16]. -Depends on random evolutionary changes [17].

Additionally, PSO is highly versatile. It can be applied to a wide range of optimization problems and has broad applications across various fields, including energy, water, biomedical electronics, and more. [15], [16].

Additionally, PSO requires fewer computational resources than GA and ACO due to its streamlined approach. The absence of intricate genetic operations and pheromone-based strategies significantly reduces computational overhead, making PSO an efficient choice for large-scale optimization tasks [19].

2.4. Adaptation of the algorithm

When PSO is applied to MPPT controllers, xk represents the current value of the fill factor d of the transistor key, while the particle velocity vk corresponds to the rate of change of d for the sampling time ts−Δt. The objective function is the output electrical power of the SB-PPV.

The key parameters of PSO are w, C_1, and C_2, as Table 2 shows. To optimize the algorithm's efficiency, it is crucial to identify the best combination of these parameters. However, since both different numerical values and variation laws for these parameters can be used, finding the optimal combination requires extensive experimentation and remains a challenging task.

The results from the search for the ideal parameter set highlight that there is currently no definitive solution to this problem.

The version of the PSO algorithm proposed in Figure 5 is a modified approach that shows promising potential for use in MPPT controllers.

Table 2. PSO Parameter Tuning

	Purpose	Challenges	Solutions
Inertia Weight (w)	Controls the balance between exploration (searching new areas) and exploitation (refining known solutions)	A large w promotes exploration but may prevent convergence, while a small w leads to premature convergence [20]	Adaptive or linearly decreasing inertia weight strategies are often used, where w starts high and decreases over iterations to enhance exploration in early stages and exploitation later [20].
C1 & C2	Controls the influence of a particle's personal experience (C1) and the swarm's collective knowledge (C2)	A high C1 makes particles too independent, reducing convergence speed, while a high C2 can lead to excessive clustering around the global best, causing stagnation [21].	A balanced approach, such as C1 = C2 = 2, is commonly used, but adaptive mechanisms (e.g., decreasing C1 while increasing C2) help maintain diversity in early stages while encouraging convergence later [21].
Velocity Clamping	Prevents particles from exceeding a maximum speed, ensuring stable exploration	If the velocity is too high, particles may overshoot good solutions; if too low, progress is slow [14].	Adaptive velocity limits based on the problem scale and dimensionality can be used [14].
r1 , r2	Introduce stochasticity to ensure diversity in search.	If these values are too small, the search becomes deterministic and may get trapped in local optima [22].	Typically, they are sampled from a uniform distribution between [0,1] in each iteration [22].

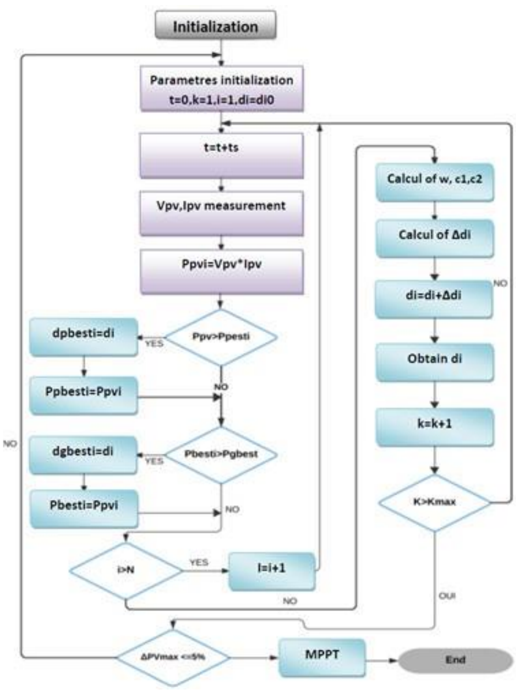

Figure 5. Flowchart of the proposed algorithm.

This algorithm uses a unique CF reduction factor, the numerical values of which are established using the following equation, to guarantee algorithm convergence:

$$CF = \frac{2}{\left|2 - \varphi - \sqrt{\varphi^2 - 4\varphi}\right|} \tag{4}$$

Where: $\varphi = c_1 + c_2$

The new coordinates of the particle (as applied to the MPPT controller, the values of the filling factor d) at each iteration of the algorithm are calculated by the equation:

$$dik+1=dik+CF.\ [\Delta dik+C_1.r_1.(Ppbesti-dik)+ C_2.r_2.(Pgbest-dik) \tag{5}$$

Finding the ideal values of C_1 and C_2 is made much easier by the use of PSO, which ensures algorithm convergence at any value of C_1 and C_2. The results confirm the possibility of using PSO for MPP tracking.

3. RESULTS & DISCUSSION

This crucial section is dedicated to analyzing the MPPT control solutions based on metaheuristic PSO (Particle Swarm Optimization) for the proposed objective functions. MATLAB was used to simulate and determine the optimal power output of the photovoltaic panel. To validate the theoretical approach, the corresponding circuit model was implemented and tested using PSIM simulation software.

3.1. Optimization results

After setting the parameters and technical data in MATLAB, the number of iterations was configured to 1000, with three distinct population sizes: P = 20, P = 50, and P = 100. The optimal power value obtained was 264.47 W, as shown in Figure 6 and summarized in Table 3. The objective function gradually converged to its optimum as the population size increased, primarily because the computation time decreased with larger populations. In order to examine the performance of the proposed method under changing conditions, the algorithm was run over thirty iterations, and the results were validated using a boxplot, as presented in Figure 7.

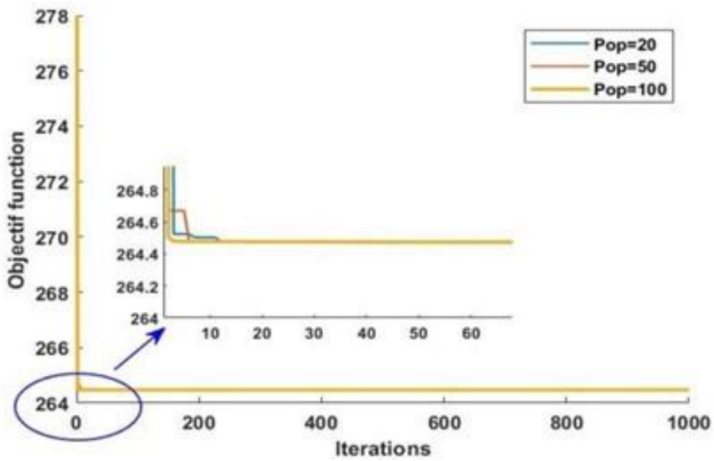

Figure 6. Optimization results.

Table 3. PV Panel characteristics.

Peak Output Power (Pmax)	264 watts
Voltage at Maximum Power	17.1 Volts
Current at Maximum Power	3.5 Amps
Short-Circuit Current, Isc	3.8 Amps
Open–Circuit Voltage, Vco	21.1Volts
Open-Circuit Voltage (Temperature Influence) (Voc)	-80mV/°C
Short-Circuit Current(Temperature Influence) (Isc)	2.4mA/°C

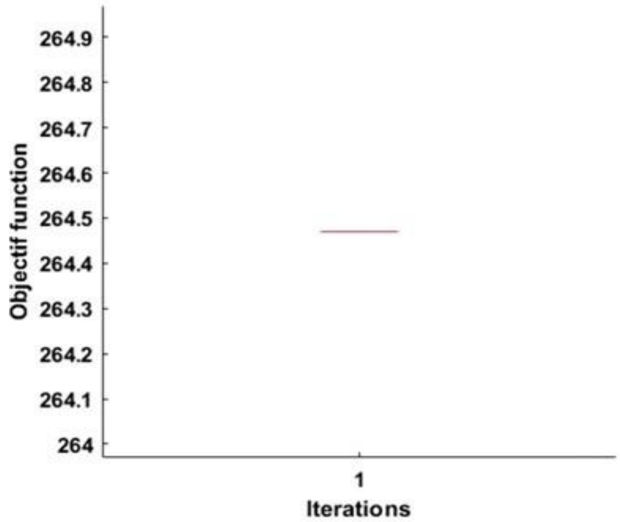

Figure 7. Boxplot of objective function.

3.2. Simulation results

A control frequency of 6.66 kHz was chosen, meaning the program runs 1000 times per period T=1/f. This results in an average power value based on 1000 measurements per period, allowing for the determination of the range within which the power oscillates. The alpha value is adjusted every 5 periods to avoid power peaks that could occur if alpha were modified after each period. The results obtained are shown in Figures 8, 9, and 10. The offset used to modify the alpha value is a critical factor in the system's precision. A large offset may cause the system to oscillate between two distant values, while a small offset can significantly slow down the system's response; Table 4 compares the simulation and optimization results.

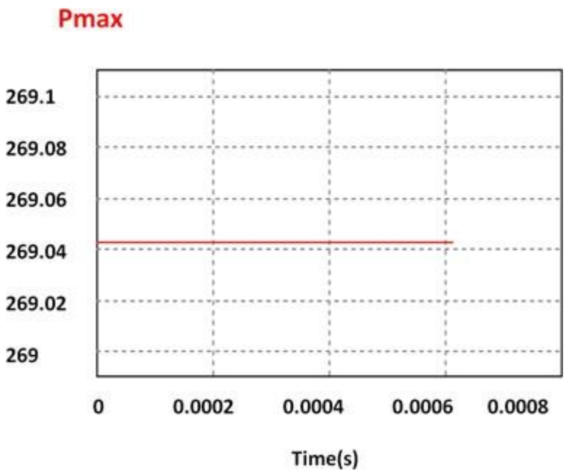

Figure 8. Simulation result of Power max.

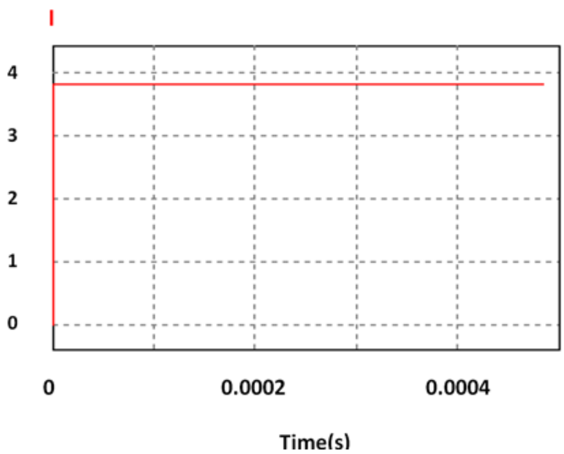

Figure 9. Simulation of the output current.

An analysis compared the Perturb and Observe method with PSO-based MPPT control. While P&O showed quicker response times, PSO provided more accurate tracking of the MPP, resulting in better overall performance metrics.

Pmax (W): Our systems error of 1.8% indicates precise power tracking, aligning with the high efficiency observed in PSO-based MPPT systems [23] [24].

I(A): An error of 2.6% in current is acceptable; however, PSO-based systems have demonstrated identical errors, indicating room for improvement [24] [25].

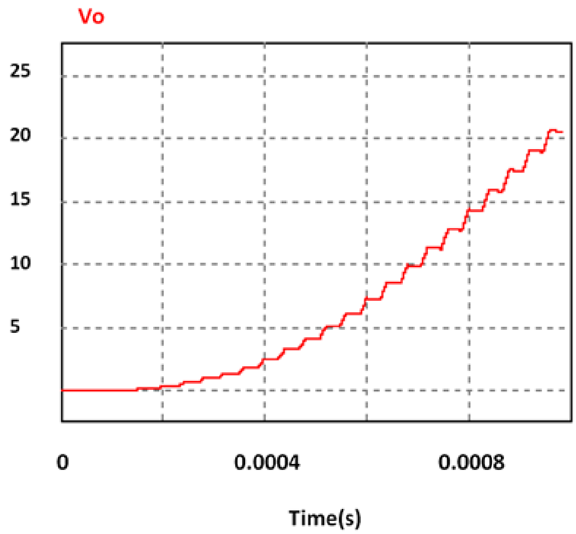

Figure 10. Simulation of output voltage.

Table 4. Comparison of different results.

Parameters	Optimization result	Simulation result	Error (%)
Pmax (w)	264	269	1.8
V (v)	17.1	20.09	14.8
I (A)	3.8	3.7	2.6

4. CONCLUSIONS

This paper presents the development of a PSIM model and a PSO-MPPT algorithm for a photovoltaic module using MATLAB/SIMULINK. The model is grounded in the fundamental circuit and equations of a photovoltaic cell, incorporating key factors such as radiation, temperature, and the cell's internal parameters, including series and shunt resistances and diode saturation current. Based on this framework, the photovoltaic generator was successfully implemented and simulated within the PSIM environment.

And as a recommendation to resolve the discrepancies in voltage accuracy. Implementing advanced PSO-based MPPT algorithms, such as IPSO or PSOMA, to enhance voltage tracking, leading to overall improved system efficiency.

Authors' Contributions: All authors contributed equally to the design, simulation, analysis, and writing of this manuscript. Yassine Elyaakouby led the MATLAB/Simulink and PSIM modeling, Amine Tilioua supervised the optimization and theoretical framework, and Issa Sabiri contributed to the literature review and validation. All authors reviewed and approved the final version of the paper.

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