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Research Article

Comparison of PSO, AG and Krill Herd algorithms for the optimization of a PI regulator applied to photovoltaic MPPT

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ABSTRACT

Optimizing PI controller parameters is crucial for improving the performance of photovoltaic systems, especially in the context of maximum power point tracking (MPPT). Meta-heuristic algorithms such as Particle Swarm Optimization (PSO), Genetic Algorithm (GA), and Krill Herd Algorithm (KHA) are widely used for this type of optimization. PSO is valued for its fast convergence and ease of implementation, but it can sometimes get trapped in local optima. GA, while efficient in global search, has higher algorithmic complexity and longer computation time. In contrast, KHA, inspired by the behavior of krill schools, offers a good balance between exploration and exploitation, allowing for more stable convergence and better accuracy in finding the maximum power point. Comparative studies show that KHA provides better dynamic control, with faster transient response, reduced overshoot, and effective error minimization (ITAE), surpassing in several cases the performance achieved with PSO and GA. The choice of algorithm, therefore, depends on the desired compromise between speed, accuracy, and robustness.

Keywords: Classical PI Genetic algorithm, Particle Swarm Optimization, Krill Herd Algorithm, photovoltaic system

INTRODUCTION

Since the widespread use of electricity, energy consumption has continued to increase. This trend has underscored the urgent need for innovative solutions in energy conversion and storage. The inevitable depletion of fossil fuels, their significant environmental impact, and the challenges associated with waste management have intensified global interest, prompting many countries to decisively shift toward solar energy [1,2].

The optimization of photovoltaic (PV) systems extends far beyond the mere installation of solar panels. It involves a comprehensive set of strategies and technologies aimed at maximizing electricity production, enhancing energy conversion efficiency, and minimizing losses, all while reducing long-term costs. This holistic approach is essential, as the performance of a PV system is influenced by numerous factors: climatic conditions (temperature, solar irradiance, shading), component characteristics (panels, inverters) and overall energy management.

We will explore both hardware and software optimization strategies, highlighting the importance of key technologies such as MPPT (Maximum Power Point Tracking), intelligent energy management, and the integration of emerging technologies, particularly artificial intelligence [3,4]. The objective is to demonstrate how an optimized approach can transform a basic solar panels array into a highly efficient and economically viable energy source [5].

Traditionally, PI (Proportional-Integral) controllers are employed to regulate the operation of photovoltaic systems. Although these control techniques are linear and relatively simple to implement, they face growing limitations. Their effectiveness decreases significantly when dealing with complex and nonlinear processes. As noted in reference [6], classical PI regulators struggle with nonlinear systems and time-varying parameters. The lack of robustness in conventional control laws renders them inadequate, especially when high precision and dynamic responsiveness are required [7,8]. It is therefore imperative to develop control strategies that are resilient to disturbances and

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nonlinearities to ensure optimal performance.

To overcome these challenges, we propose an innovative approach: the optimal tuning of the PI regulator parameters is achieved using three metaheuristic optimization algorithms inspired by natural phenomena: Particle Swarm Optimization (PSO), Genetic Algorithm (GA), and Krill Herd (KH). The application of these methods aims to significantly enhance the speed, accuracy, and stability of MPPT algorithm.

A comparative analysis will be conducted to evaluate the performance of each method in terms of convergence speed, energy efficiency, and robustness to solar irradiance variations. The obtained results will demonstrate the effectiveness of the proposed approach and highlight the specific advantages of each algorithm in the context of optimal control for photovoltaic systems.

MODELING OF A PHOTOVOLTAIC SYSTEM

The overall scheme of the grid-connected photovoltaic system is illustrated in Figure 1. The photovoltaic system captures solar energy and converts it into electrical energy. Three factors determine the relationship between the solar energy received and the electrical energy produced: the intensity of solar radiation, the surface area of the photovoltaic panels, and the efficiency of the cells. Solar radiation intensity is a climatological parameter that depends on the geographical location.

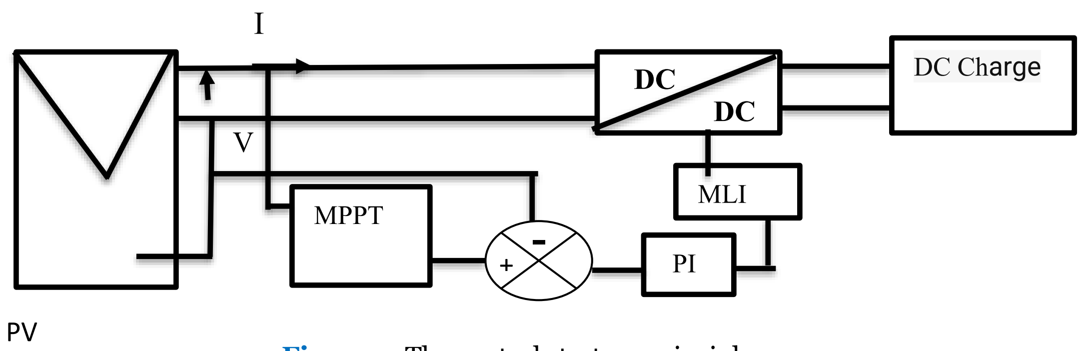

Figure 1. The control strategy principle.

The modeling of a photovoltaic panel is based on the electrical representation of the solar cells that constitute it. The incident solar power captured by a surface S is expressed by the following relationship:

$$P_{solar} = G \times S \tag{1}$$

Where G represents the solar irradiance (in W/m²) and S the exposed surface area. A photovoltaic panel consists of many cells connected in series and/or parallel. Each cell can be modeled using an equivalent circuit comprising two diodes, a series resistor Rs and a parallel resistor Rsh. The output current of the two-diode model is given by [9,10,11]

$$I = I_{ph} - I_{d1}\left[e^{\frac{q(V+I.R_S)}{n_1 kT}} - 1\right] - I_{d2}\left[e^{\frac{q\left(V+I.R_S\right)}{n_2 kT}} - 1\right] - \frac{V+IR_S}{R_p} \tag{2}$$

To maximize the extracted energy, an MPPT (Maximum Power Point Tracking) algorithm adjusts the electrical load so that the system operates at the point where the power P=V×I is maximum.

OPTIMIZATION OF A PHOTOVOLTAIC SYSTEM

The PSO, AG, and KH algorithms were implemented to ensure maximum power point tracking (MPPT) in a photovoltaic system subjected to variable solar conditions. The evaluation was based on several performance criteria: convergence speed, tracking accuracy, stability, and the ability to avoid local minima.

optimization by genetic algorithms

The Optimization is the search for the best solution to a problem in the sense of one or more selected criteria, respecting the characteristics of the system and the imposed constraints on it. The optimal solution is sought from a population of solutions by using random processes. The search for the best solution is carried out based on the

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creation of a new solutions generation, by the application of three operators successively; to the current population: the selection, the crossing, and the mutation. These operations are repeated until a stop criterion is reached [12]. A simple Genetic Algorithm principle is shown in Figure 2.

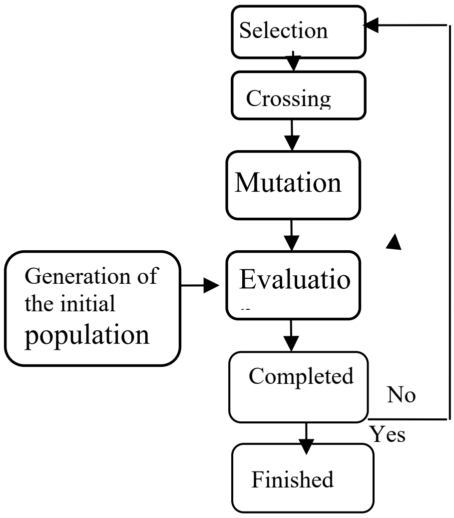

Figure 2. The general principle of genetic algorithm.

Application of genetic algorithm for PI regulator optimization in a photovoltaic system

In this section, we detail the implementation aspects of PI controller parameter optimization using the Genetic Algorithm (GA). The objective is to find the optimized parameters P= [K*Popt*, KIopt] so that the speed (or output) response of the closed-loop system is stable and as robust as possible to variations in system conditions, such as solar irradiation and photovoltaic cell temperature. Using the genetic algorithm, it is possible to search for the optimal solution in a three-dimensional space, unlike the quasi-one-dimensional search implemented by the iterative approach. Each of the three dimensions of the search space corresponds to an individual variable x that we seek to optimize. The principle of PI corrector optimization by genetic algorithm is illustrated in Figure 3.

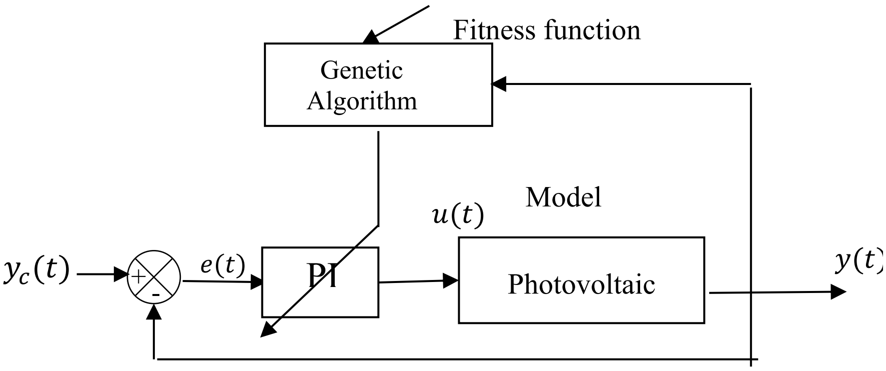

Figure 3. The principle of optimizing the PI controller using a genetic algorithm.

$$\text{We have:} K_{p_{solar}} \in \left[K_{p_{min}}, K_{p_{max}}\right], K_{I_{solar}} \in \left[K_{I_{min}}, K_{I_{max}}\right] \tag{4}$$

• The Objective Function

The objective function measures the sum of the squared differences between the reference voltage V_{ref} and the actual output voltage $V(t)$ over a time interval T.

• Optimization Objective

Find the optimal values of the PI controller parameters PI $(K_{P_{opt}}, K_{I_{opt}})$ that minimize the objective function f_{ad} in

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order to ensure system stability and improve the voltage response.

- Error: $e(t) = V_{ref} - V(t)$
- Control signal: $u(t) = k_p . e(t) + k_I \int_0^t e(\tau)d\tau$

• Role of the Control Signal

The control signal $u(t)$ is used to adjust the load or the energy converter (DC/DC converter) in order to improve the stability and accuracy of the voltage produced by the solar panels.

Particle Swarm Optimization (PSO)

Particle swarm optimization (PSO) is a stochastic optimization method developed in 1995 by Kennedy and Eberhart, and is an adaptive evolutionary optimization technique used to solve optimization problems. It relies on a population of particles, each representing a candidate solution in the search space. Initially, a swarm of particles is randomly generated, with each particle position corresponding to a possible solution point.

Each particle i in the swarm is characterized by its position vector [13]

$$\overrightarrow{X_\iota} = (x_{i1}, x_{i2}, x_{i3}, \dots \dots, x_{iD}) \tag{5}$$

And by its velocity vector

$$\overrightarrow{V_\iota} = (v_{i1}, v_{i2}, v_{i3} \dots \dots, v_{iD}) \tag{6}$$

The fitness function f is evaluated using the particle's position coordinates as input values. Each particle retains in memory the best position it has visited so far, which is denoted by its personal best position:

$$\overrightarrow{P_{\iota best}} = (p_{ibest}, p_{ibest}, p_{ibest} \dots, p_{iDbest}) \tag{7}$$

The best position reached by all the particles of the swarm is noted

$$\overrightarrow{G_{\iota best}} = (g_{1best}, g_{2best}, g_{3best} \dots \dots, g_{Dbest}) \tag{8}$$

At time, the velocity vector is calculated from equation (9), [14] [15] [16].

$$v_{ij}(t) = wv_{ij}(t-1) + c_1 r_1 \left(p_{ijbest}(t-1) - x_{ij}(t-1)\right) + c_2 r_2 \left(p_{ijbest}(t-1) - x_{ij}(t-1)\right) \tag{9}$$

The position at time t of particle i is then defined by equation (10):

$$x_{ij}(t) = x_{ij}(t-1) + v_{ij}(t)\,, j \in \{1, \dots . D) \tag{10}$$

The coefficient of inertia is given by

$$\mathrm{w} = \mathrm{w_{max}} \left(\frac{\mathrm{w_{max}} - \mathrm{w_{min}}}{\mathrm{k_{max}}}\right) * \mathrm{k} \tag{11}$$

Figure 4 shows the general flowchart of the PSO method [13]:

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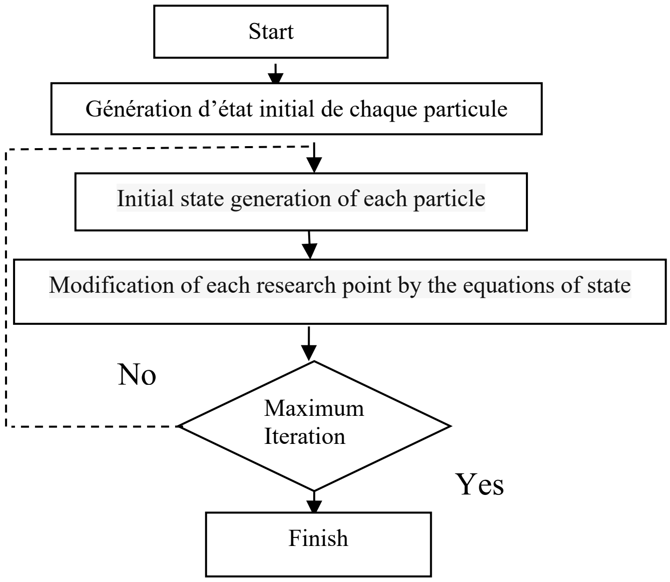

Figure 4. General flowchart of the PSO method.

Optimization by KH

Krill Herd is a historical meta-heuristic optimization method used to solve complex optimization problems. This method is inspired by the simulation of krill swarm behavior in response to specific biological and environmental processes [17]. In nature, the fitness of an individual is determined by its distance from food sources and the density of the surrounding krill population. Accordingly, based on the concept of an imaginary distance, the fitness is the evaluated as the value of the objective function. In a two-dimensional space, the position of an individual krill varies over time according to three main actions [18], [19], [20].

• **Induced movement:** This refers to the interaction among individuals, where each krill adjusts its movement in response to the positions of other krill.

For an individual krill, the induced movement is mathematically formulated as follows [21]:

$$N_i^{new} = N^{max}\alpha_i + \omega_n N_i^{old} \tag{12}$$

$$\text{With:} \quad \alpha_i = \alpha_i^{local} + \alpha_i^{target} \tag{13}$$

- **Foraging movement:** The foraging movement is determined by two main factors: The location of the food source and the individual's previous experience with food locations. For the i^{th} krill, this movement can be mathematically expressed as follows [22]:

$$F_i = v_f \beta_i + \omega_f F_i^{old} \tag{14}$$

With:

$$\beta_i = \beta_i^{food} + \beta_i^{best} \tag{15}$$

- **Random diffusion:** Random diffusion represents a physical and stochastic movement and it is formulated as follows [18]:

$$D_i = D^{max}\delta \tag{16}$$

Additionally, an extra term is introduced into the physical diffusion formula to account for this effect. This term linearly decreases the random velocity with time (iterations):

$$D_i = D^{max}(1 - \frac{1}{I_{max}})\delta \tag{17}$$

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Using three formulated motions, the position vector of an individual krill during the interval Δt is formulated as follows:

$$X_i(t + \Delta t) = X_i(t) + \Delta t \frac{dX_i}{dt} \tag{18}$$

With: $$\Delta t = C_t \sum_{j=1}^{NV} (UB_j - LB_j) \tag{19}$$

Simplified flowchart of the Krill Heard algorithm shown in Figure (5) [18], [23], [24],

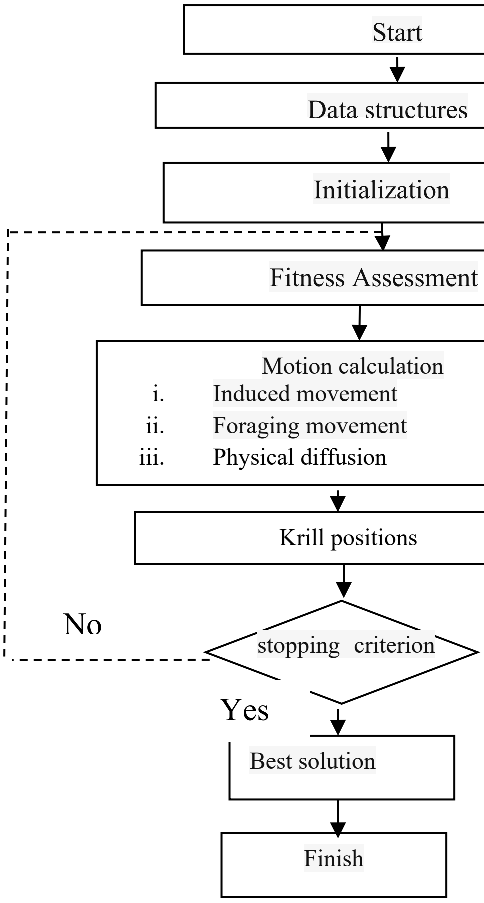

Figure 5. Flowchart of the Krill Herd (KH) algorithm.

PHOTOVOLTAIC SIMULATION

All simulations were carried out using the MATLAB / SIMULINK software environment on a photovoltaic system, as illustrated in Figure 1.

The results in Figure (a), corresponding to the Genetic Algorithm (GA), show that the objective function initially undergoes some fluctuations, followed by a phase of relative stability. A sudden and significant improvement is observed around the 17th iteration, reflecting the GA's ability to make rapid progress after an initial exploration phase.

Figure (b), associated with the Particle Swarm Optimization (PSO) method, illustrates the system's response to a sudden change such as a variation in solar irradiation by initially maintaining a stable value, followed by a rapid drop and then stabilization. This behavior demonstrates PSO's capability to quickly adapt to changing conditions.

Finally, Figure (c), which corresponds to the Krill Herd Algorithm (KHA), shows a rapid improvement in the best solution from the early iterations, while the average value increases more gradually. This indicates the algorithm's strong ability to exploit optimal solutions while maintaining a balanced search process.

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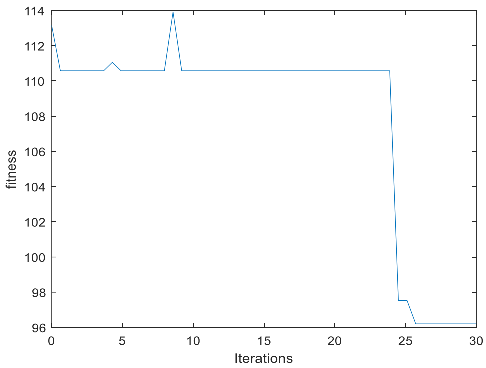
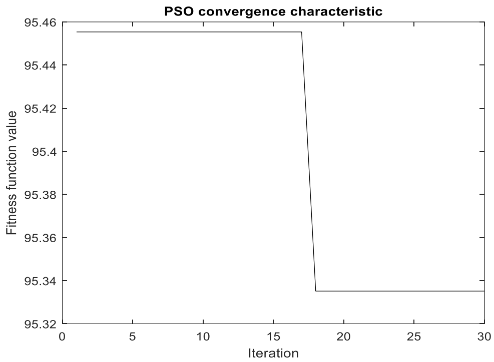
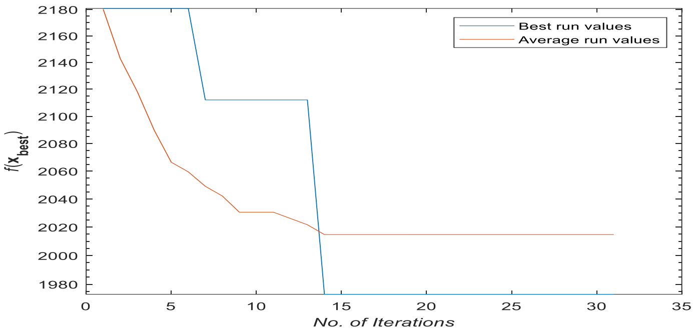




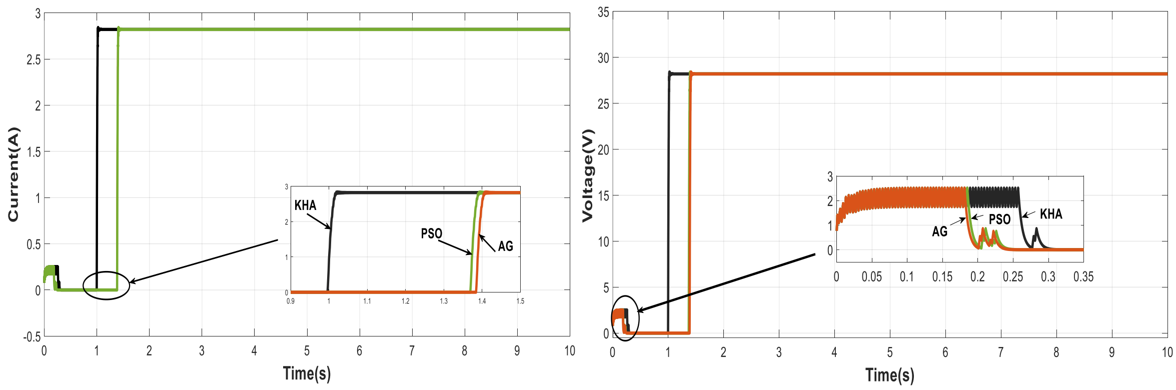
a. Convergence characteristics of AG. **b. Convergence characteristics of PSO.**



c. Convergence characteristics of KHA.

Figure 6. Comparative analysis of the convergence behavior of the AG, PSO, and Krill Herd algorithms in photovoltaic optimization.

In Figure 7, the MPPT performance of the algorithms is compared using the V-I-P curves. The Krill Herd (KH) algorithm demonstrates the fastest response, reaching the maximum power point (MPP) in a very short time with minimal oscillations around the optimal value. The Particle Swarm Optimization (PSO) algorithm also shows good performance with fast convergence, though slightly slower than KH. In contrast, the Genetic Algorithm (GA) reaches the MPP with reasonable accuracy but exhibits slower convergence and more pronounced fluctuations around the operating point.



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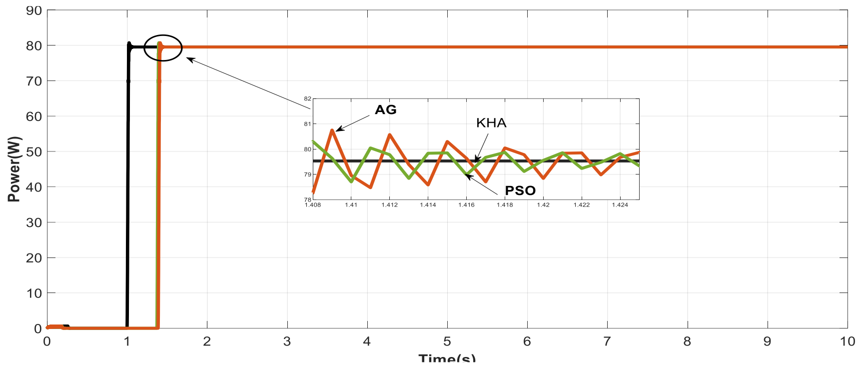

Figure 7. V-I-P characteristics of the PV system in steady-state conditions.

Figure 8 illustrates the effect of variable irradiance on the electrical parameters of the photovoltaic system: power, voltage, and current. It is evident that the Krill Herd Algorithm (KHA) ensures fast and accurate tracking of the maximum power point (MPP), even under sudden changes in solar irradiance. The power output using KHA is more stable and rapidly adapts to the new optimal values. In comparison, both PSO and GA exhibit slower dynamic responses and more noticeable oscillations. The current and voltage follow similar trends, with KHA demonstrating superior performance in terms of response speed and overall stability.

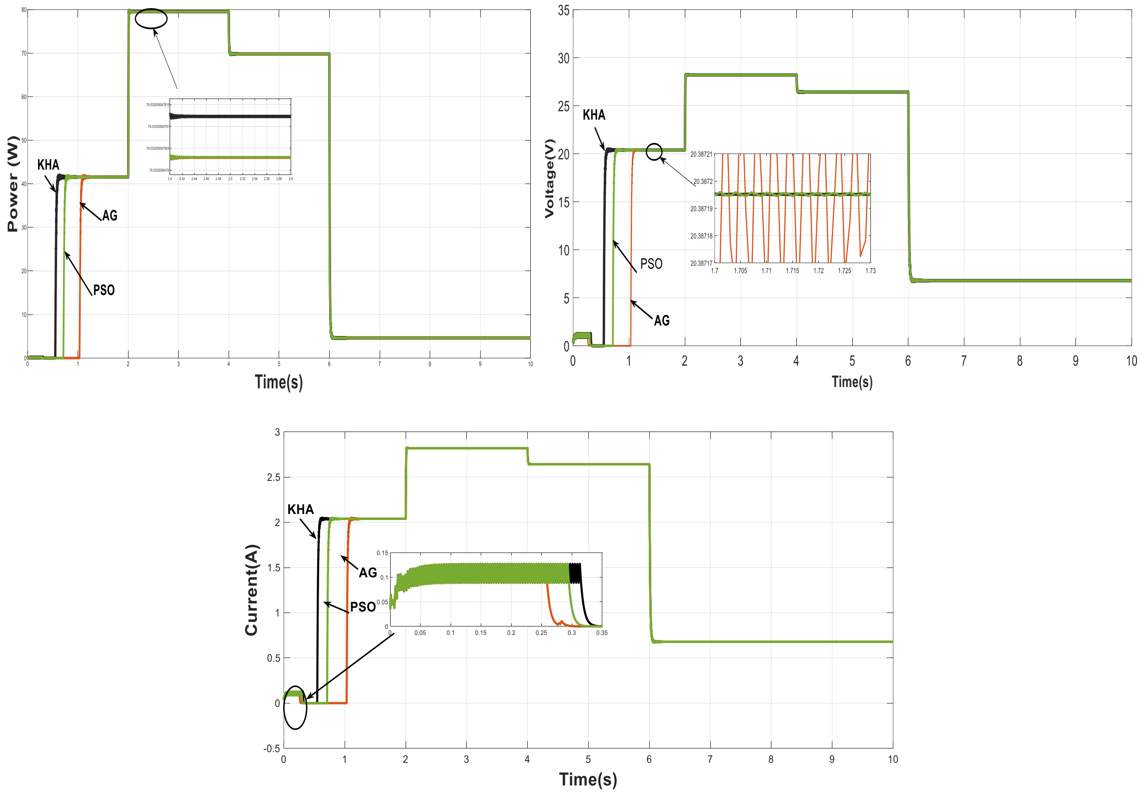

Figure 8. Effect of variable irradiance on the voltage, current, and power of the PV system.

CONCLUSION

The curve analysis clearly highlights the superiority of the KHA algorithm over PSO and AG, whether in constant or variable irradiance conditions. In the stable case, KHA quickly reaches the maximum power point with high stability and almost no oscillation. In variable irradiance, KHA quickly adapts to changes and maintains the system power at its optimal level, unlike PSO and AG which show delay and instability. Thus, KHA is considered the most efficient and reliable for tracking the maximum power point in photovoltaic systems.

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Table 1. Photovoltaic Energy Conversion System Parameters Used

Parameter	Nominal value
Courant photonique.	3.25
La résistance série.	15e-3
La résistance parallèle.	Rp=30
La charge élémentaire constante.	1.76e-19
La constante de Boltzmann.	1.38e-23

Table 2. PARAMETRES DE SIMULATION ADOPTES POUR LES trois METHODES.

AG	PSO	Krill Herd
Population size 30	Population size 30	Population size 30
Number of variables 2	Number of variables 2	Number of variables 2
Probability of mutation 5%	Inertia weight (wmax=0.9, wmin=0.4)	Crossover flag (C_{flag} = 0.4)
Number of generation 50	acceleration factor (c1= c2=2)	Number of generation 50