PERFORMANCE ANALYSIS OF MPPT-QHBM ON SOLAR PANEL SYSTEMS UNDER UNCERTAIN IRRADIATION CONDITIONS

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Abstract
The utilization of solar energy is an important solution in meeting renewable energy needs, especially in Indonesia which has high irradiation potential. However, photovoltaic (PV) systems face challenges in the form of irradiation fluctuations and partial shading effects that reduce efficiency. To overcome this, a reliable Maximum Power Point Tracking (MPPT) algorithm is needed. This study analyzes the performance of the Queen Honeybee Migration (QHBM) algorithm in tracking the maximum power point (MPP) under uncertain irradiation conditions in the Tulungagung region, using a Monte Carlo simulation approach. Simulations were conducted using MATLAB in two scenarios: standard conditions (1000 W/m^2) and fluctuating conditions based on historical data. Results show that the QHBM achieves 99.98% efficiency with the fastest convergence time (5 iterations) under STC conditions, as well as an average efficiency of 98.99% (normal) and 97.86% (abnormal) under fluctuating conditions. In addition, the system successfully charged the battery with an increase in SOC of 0.038% (optimal) and 0.026% (volatile). The QHBM algorithm is proven to be adaptive to irradiation dynamics and superior to GWO, PSO, and P&O, making it a potentially effective solution for PV systems operating under changing irradiation conditions throughout the day.

1. Introduction

Solar power plants have become one of the main solutions to meet the growing global energy demand (Enciso Contreras et al., 2023; Iakovleva et al., 2022). As a renewable energy source, solar energy has the potential to replace depleting fossil fuels and reduce their environmental impact. With its equatorial location, Indonesia has significant potential for solar energy development, with an average irradiance of 4.8 kWh/m^2 per day, equivalent to an energy capacity of approximately 112,000 GW (Asian Development Bank, 2020). This makes Indonesia one of the ideal locations for solar power development (Kementerian Energi dan Sumber Daya Mineral, 2012). Through the Comprehensive Investment and Policy Plan (CIPP) strategic policy, the Indonesian government targets 44% renewable energy mix by 2030 (Simanjuntak, 2023). One of the areas with great potential for solar energy is Tulungagung, where average irradiance reaches 4,103 kWh/m^2 per day (Solargis Prospect, 2025). With its tropical climate and abundant sunlight year-round, a solar power plant is an ideal solution for meeting the region's electricity demand. The Tulungagung local government has installed PLTS at various locations, including schools, hospitals, and other public facilities, to support sustainable energy independence (Tiger, 2024; Bappeda Tulungagung, 2025).

However, despite its great potential, the photovoltaic (PV) system, which is the main component of PLTS, faces several obstacles. These include limited solar irradiation hours, optimized at 4–6 hours per day, variations in irradiation intensity, and module temperature effects, which can significantly impact overall system performance and efficiency (Alghamdi et al., 2023). The unpredictable nature of irradiation variations, especially under dynamic environmental conditions, presents challenges in maintaining PV system efficiency. This stochastic nature of irradiation reflects fluctuations in light intensity influenced by weather conditions, sun position, and partial shading, making PV system operation non-linear.

To address these challenges, Maximum Power Point Tracking (MPPT) technology becomes crucial to ensure the PV system operates at the maximum power point (MPP). Conventional MPPT techniques, such as Perturb and Observe (P&O) and Incremental Conductance (IC), are commonly used due to their simplicity. However, these methods often struggle under shadow conditions, where they cannot differentiate between the local maximum power point (LMPP) and the global maximum power point (GMPP) (Amal, 2024; Almutairi, Abo-Khalil, Sayed, & Albagami, 2020). As a result, various intelligent algorithms have been developed to overcome this limitation, including Particle Swarm Optimization (PSO) (Mukti, Risdiyanto, Kristi, & Darussalam, 2023), Grey Wolf Optimization (GWO) (Sekar, Arasan, & Chandrasekaran, 2023), Chaotic Optimization Algorithm (ChOA) (Elahi, Ashraf, & Kim, 2022), and other hybrid approaches methods.

Queen Honey Bee Migration (QHBM) is a promising algorithm proven to be superior in power tracking efficiency, stability, and convergence time compared to methods like P&O, PSO, Fuzzy Logic, and INC (Aripriharta, Wibowo, Fadlika, Horng, Wibawanto, & Saputra, 2019; Aripriharta, Asnarindra, Nibrosoma, Gumilar, & Habibi, 2023; Aripriharta et al., 2023). QHBM is also effective in handling shadow transitions and maintaining stable power output during peak irradiation conditions. This research aims to analyze the performance of QHBM-based MPPT in tracking the maximum power point of solar panel systems experiencing fluctuating irradiation in the Tulungagung region. The uniqueness of this study lies in applying the QHBM algorithm under both normal and abnormal irradiation conditions simulated with the Monte Carlo method using historical irradiation data from 2023 (Salazar-Peña, Tabares, & González-Mancera, 2023; Chen & Chen, 2017; Pokorádi, 2022). Unlike previous studies that typically use fixed conditions or shadow transitions, this approach offers a more realistic test of PV system behavior in a dynamic tropical environment. This contributes to the development of more adaptive and efficient MPPT methods for managing changing irradiation conditions.

1.1. Photovoltaic

Solar panels, or more commonly called Photovoltaic (PV) systems, convert sunlight into electricity using semiconductor-based cells. This process produces DC electricity through the photovoltaic effect, which can be used directly, stored in batteries, or converted to AC electricity using an inverter for grid needs. Silicon is often used as the main material due to its efficiency and availability (Touti, Rafikiran, Aoudia, Alrougy, Khan, & Ali, 2024).. PV characteristics can be modeled using a simple equivalent circuit consisting of a current source I_{pv} in parallel with a diode, with series resistance R_s and parallel resistance R_p.

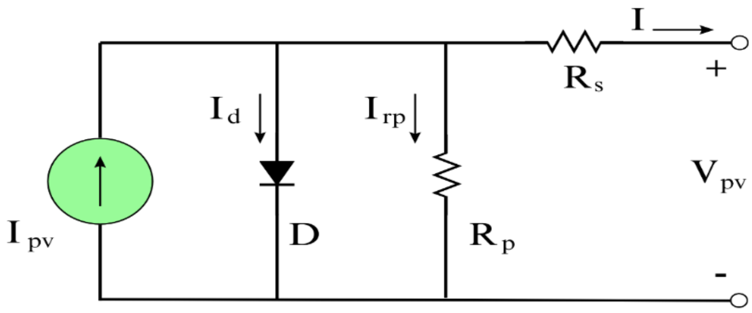

Figure 1. Solar Panel Equivalent Circuit

The mathematical modeling of the PV equivalent circuit above can be written using equation (1) as follows (Jamshidi, Salehizadeh, Yazdani, Azzopardi, & Jately, 2023):

$$I = I_{PV} - I_s \left[\exp\left(\frac{q(V+R_s I)}{akT}\right) - 1\right] - \frac{V+R_s I}{R_p} \quad (1)$$

where I is the PV output current, I_{PV} is the PV short circuit current, I_s is the PV saturation current, a is the diode ideal factor, q is the electron charge (1.602 x 10-19 C), V is the PV voltage, k is the Boltzman constant (1.38 x 10-23 J/^{0}K), T is the cell temperature (Kelvin), R_s is the series resistance, and R_p is the parallel resistance. The output power that can be generated from a PV can be written with the following equations (2) and (3) (Jamshidi, Salehizadeh, Yazdani, Azzopardi, & Jately, 2023):

$$P_{PV}(t) = N_{PV} \,.\, A \,.\, \eta_{PV} \,.\, G(t) \; (2)$$

$$I_{pv} = G(I_{sc} + \alpha\Delta T) \; (3)$$

Where P_{PV} is the solar panel output power (W), G is the irradiation intensity (W/m^2), A is the panel surface area (m^2), η_{PV} is the panel efficiency, and N_{PV} is the number of solar panels. In addition, I_{PV} is the panel output current, I_{SC} is the short-circuit current at standard test conditions (STC), ΔT is the temperature change relative to STC, and α is the temperature coefficient of the solar panel.

1.2. Maximum Power Point Tracker (MPPT)

Solar panels have a relatively low energy conversion efficiency, ranging from 8-45% (Chatterjee, Chattopadhyay, & S. K., 2024; Kamil, Bagaskoro, & Susilo, 2024), and are significantly affected by irradiation intensity and ambient temperature. Fluctuations in irradiance caused by weather conditions or partial shading can reduce the optimal performance of PV systems. To address this, Maximum Power Point Tracking (MPPT) technology is employed (Xu, Cheng, & Yang, 2020). One of the key principles of MPPT is impedance matching between the source and load, ensuring that the voltage (Vmp) and current (Imp) generate maximum power (Pmp). Impedance mismatch leads to power loss, so DC-DC converters are used to balance the impedance (Maniar, 2024).

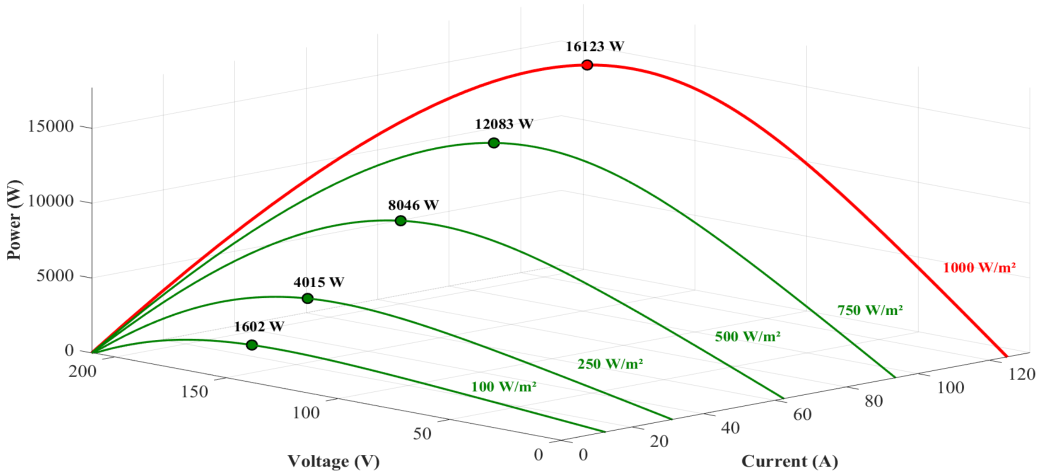

Figure 2. PV Characteristics Against Irradiation Variation

The characteristics of PV output current, voltage, and power fluctuate with changes in environmental conditions (Dey, Khan, Mandal, & Bhattacharjee, 2016; Aripriharta, Surya, Susilo, Mustika, & –, 2023). To compensate, the MPPT algorithm dynamically adjusts the DC-DC converter to maintain impedance matching between the source and load. This approach allows the PV system to produce maximum power under actual conditions, thereby increasing energy efficiency and optimizing system performance (Premkuma et al., 2020).

1.3. Boost Converter

A boost converter is a key component in the MPPT system that increases the PV panel's output voltage to match the load or energy storage requirements. This circuit consists of an inductor to store energy, a capacitor to reduce voltage ripple, and a MOSFET as a switch that regulates the switching process to achieve the desired output voltage. The inductor, capacitor, and output voltage values are calculated using the following equations (Pandey & Pattnaik, 2022; Harmini & Nurhayati, 2020):

$$L \geq \frac{(1-D)^2 . D . R}{2 . fs} \; (4)$$

$$C \geq \frac{Vin . D}{\Delta Vc . fs . R} \; (5)$$

$$D = 1 - \frac{V_{in}}{V_{out}} \quad (6)$$

Where L is the inductor size, fs is the switching frequency, R is the load resistance, D is the duty cycle, and ΔVc is the voltage ripple.

1.4. Uncertain Irradiation

In solar panel systems, solar irradiance is uncertain due to random factors such as weather, clouds, and shading, leading to fluctuations in output power (Pokorádi, 2022). This uncertainty can be modeled using the Monte Carlo method, a probability-based simulation technique with repeated random sampling to estimate the irradiation distribution. This simulation is calculated using the following stochastic model (Salazar-Peña, Tabares, & González-Mancera, 2023; Chen & Chen, 2017):

$$G_{sim}(t) = G_{mean}(t) + \sigma(t) \,.\, Z \quad (7)$$

The simulated irradiation value $G_{sim}(t)$ is calculated from the historical average $G_{mean}(t)$, plus the standard deviation σ(t). A Monte Carlo simulation proceeds by determining the distribution parameters from historical data, generating random numbers, calculating the irradiation value using the equation above, and repeating the process N times.

1.5. Queen Honeybee Migration (QHBM)

The QHBM algorithm mimics the migration behavior of honeybee queens guided by scouts. In this process, new nest locations are selected based on the highest weight assigned by the scouts, considering the colony's internal conditions as well as external factors such as obstacles, weather, and predators. Each iteration involves the queen calculating the migration distance based on several parameters that reflect natural dynamics (Aripriharta et al., 2022).

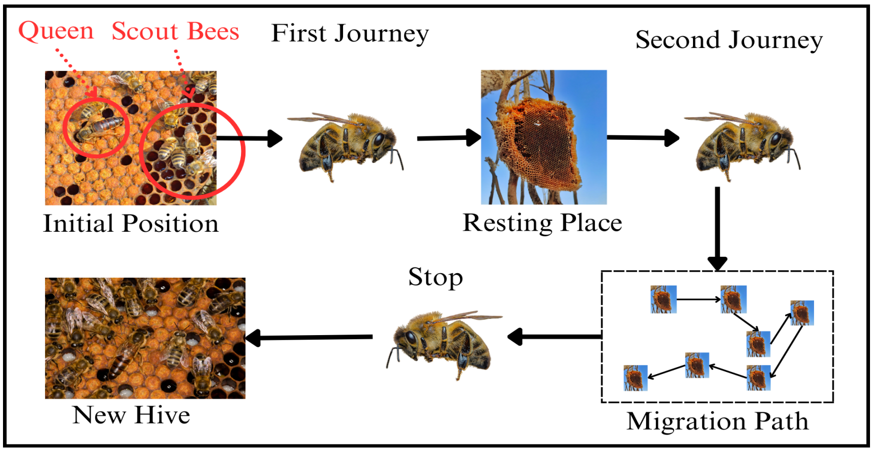

Figure 3. QHBM Searching

In the initialization phase of the QHBM algorithm, the queen bee starts from a certain starting point, while the scouts ([n]) are scattered with random [V] and [P] values. In the second phase, the decision-making phase, the queen evaluates the probability of each sector in her neighbourhood. Sector weights are calculated using the following equation (Aripriharta, Hao, Muladi, Horng, & Jong, 2020).

$$C_j = \frac{1}{n}\sum_{j=1}^{n} e_{r(j)} \quad (8)$$

$$S_j = \frac{C_j}{\sum_{j=1}^{8} C_j} \quad (9)$$

Where C_j is the weight of scouts, $e_{r(j)}$ is information from scout bees, S_j is the probability of sectors, and j=1,2, ...,8 is the sector of the cardinal directions (north, south, etc.). In the final stage, the queen bee moves towards the sector with the greater chance, based on the radius value and the Queen Honeybee resistance update.

$$r_m^{(ith+1)} = (1 - G_s^{(ith)}) \ (10)$$

$$V_{pv}^{(ith+1)} = \mathrm{V}_{pv} + r_m^{(ith+1)} \times cos\ cos\ \theta^{\ (ith+1)} \ (11)$$

$$P_{pv}^{(ith+1)} = \mathrm{P}_{pv} + r_m^{(ith+1)} \times sin\ sin\ \theta^{\ (ith+1)} \ (12)$$

Equation (13) is used to update the Queen Honeybee resistance. ith is the iteration value, ith = 1, 2, 3, ..., n.

$$G_s^{(ith+1)} = G_m^{(ith+1)} \times rand(1) \ (13)$$

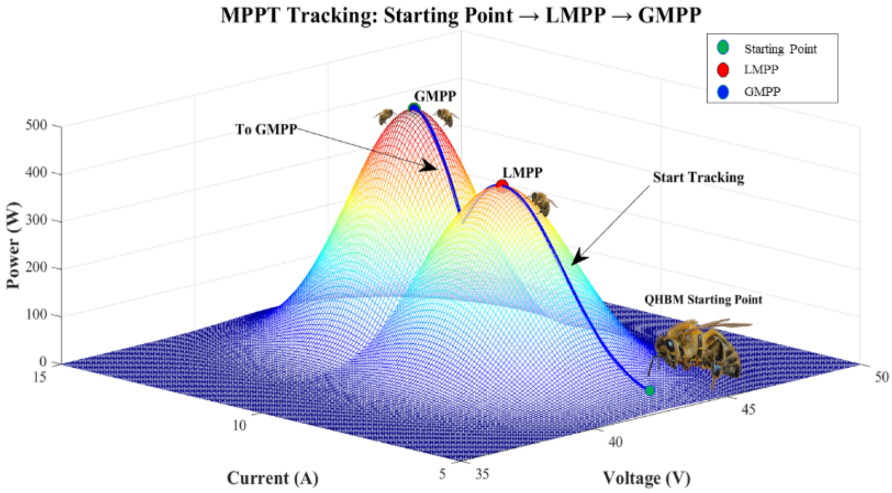

Figure 4. Queen Honeybee Migration MPPT

2. Method

2.1. System Description

MPPT is a control method that optimizes the power output of solar panels by continuously adjusting their operating point to extract maximum energy under varying environmental conditions. In this research, an autonomous solar panel system is developed, incorporating the QHBM algorithm as the core of the MPPT strategy. The use of QHBM aims to enhance the speed and accuracy in locating the maximum power point, thereby increasing the overall efficiency of the system. The captured energy is then stored in a battery unit, which serves as a buffer to maintain power availability during low irradiance or nighttime conditions. To replicate real-world operating scenarios, the Monte Carlo method is employed to generate stochastic variations in solar irradiation and ambient temperature based on historical weather data from the Tulungagung region in 2023. This probabilistic approach introduces realistic fluctuations, providing a closer approximation of actual field conditions than static or uniform input data. The solar energy system under study utilizes TSM-DE18M Trinasolar photovoltaic modules with a peak capacity of 500 Wp, selected for their reliability and suitability for residential-scale renewable energy applications. Figure 5 illustrates the overall structure and configuration of the system under study.

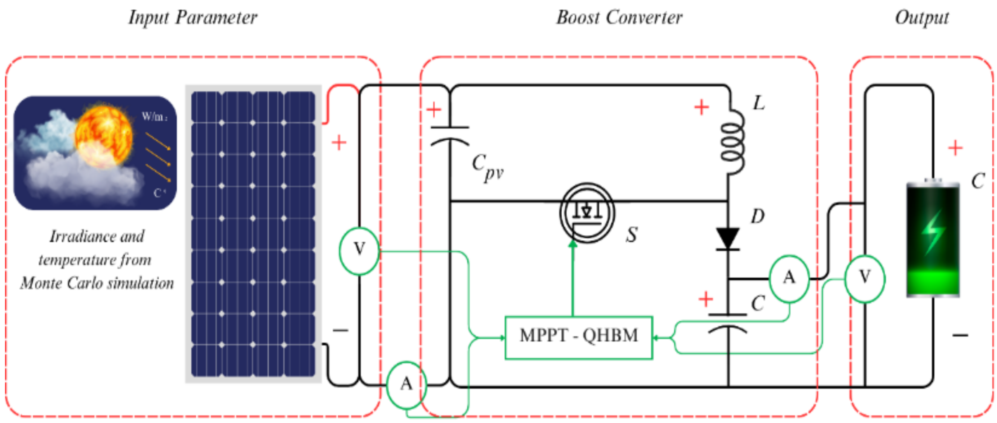

Figure 5. Researched System

The designed system will be tested through several simulation scenarios using MATLAB, the scenarios include:

1) Simulation of the solar panel system under normal conditions with an irradiation of 1000 W/m^2 and a temperature of 25°C, which represents the standard testing condition (STC).
2) Simulation of a solar panel system with the most volatile irradiation modeled using the Monte Carlo method.

Furthermore, simulation results are collected and analyzed across multiple simulation runs to ensure the reliability and accuracy of MPPT-QHBM performance under uncertain irradiation conditions.

2.2. Irradiation Potential of Tulungagung Region

Tulungagung has high solar energy potential, with solar irradiance varying with weather conditions and seasons. Based on the Global Solar Atlas and the Indonesia Solar Map, Tulungagung has an irradiation potential of 3,588-4,103 kWh/m^2 per day, with an average temperature of 28.4°C [38], [39]. The historical irradiation data used comes from months throughout 2023 to reflect the uncertainty of overall weather conditions. The data collection period is 09:00 to 14:00, when solar irradiation generally peaks, allowing solar panels to optimally harvest electrical energy.

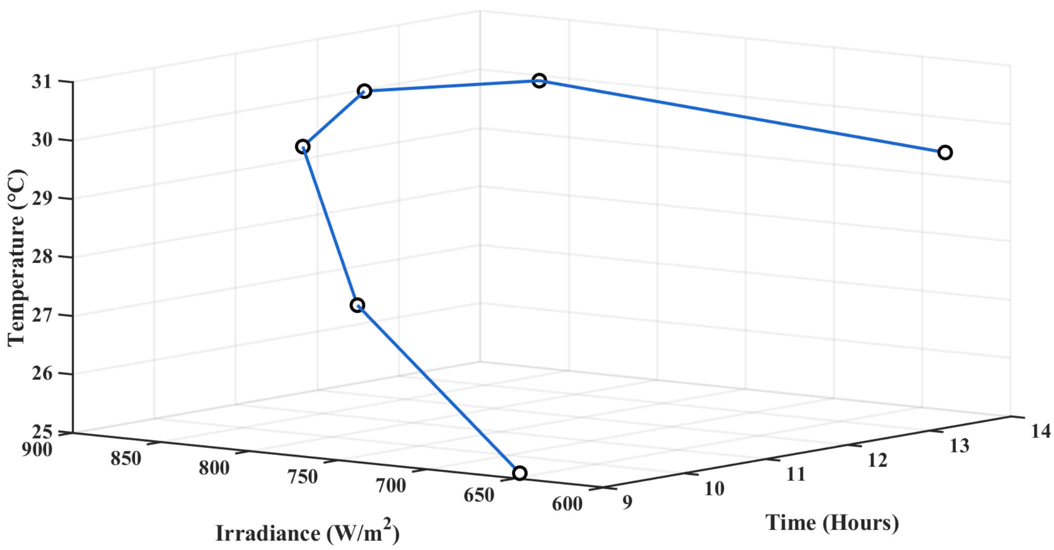

Figure 6. Average solar irradiation in Tulungagung 2023

2.3. Irradiation Generation Using Monte Carlo

Irradiation random sample generation was conducted using the Monte Carlo method with 1000 samples based on historical irradiation and temperature data in the Tulungagung region in 2023

(Figure 6). Figure 7 below shows the results of a Monte Carlo simulation of random sample generation.

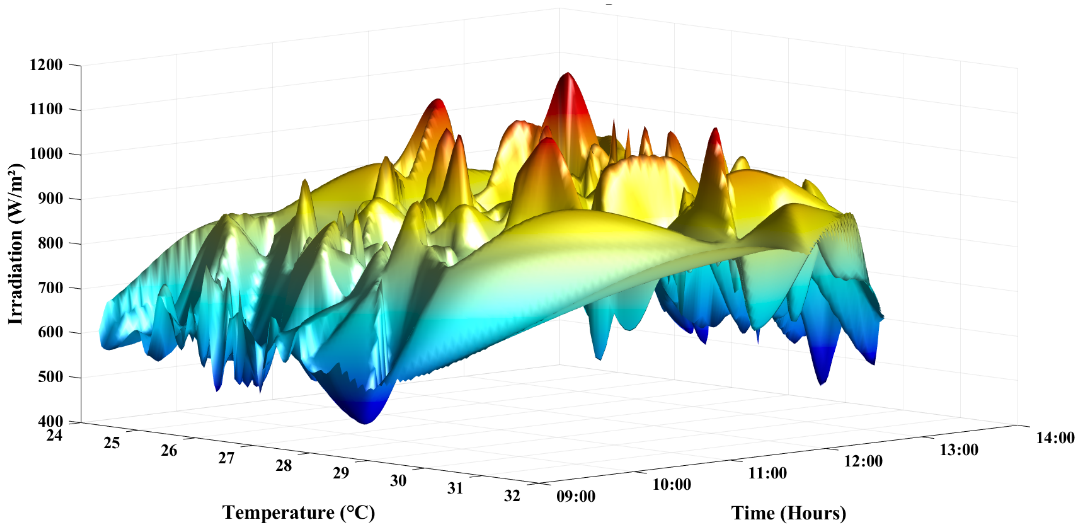

Figure 7. Irradiation and Temperature Using Monte Carlo Simulation

The figure above shows the distribution of irradiation and temperature from 09:00 to 14:00 based on a Monte Carlo simulation using Tulungagung irradiation data from 2023 (Figure 6). It illustrates the dynamic relationship between irradiation, temperature, and time. Irradiation increases with temperature, peaking between 10:00 and 13:00 before declining. The widespread data indicate uncertainties caused by random factors such as sun position and atmospheric conditions. At 09:00, irradiation ranges from 500-800 W/m^2 and temperature from 24-28°C; at 12:00, irradiation reaches 600-1200 W/m^2 and temperature 25-32°C; and at 14:00, it is between 600-1150 W/m^2 24-31°C.

From the 1000 iterations, a total of 6000 irradiation and temperature data were obtained, with 3135 samples showing normal irradiation (>800 W/m^2) and 2865 showing low irradiation (≤800 W/m^2). Meanwhile, the temperature parameter ranged from 26°C to 32°C. The variation in irradiation and temperature data reflects the uncertainty inherent in a dynamic real environment.

The data used in this study comes from Monte Carlo simulations, with the highest level of fluctuation occurring at the 672nd iteration, which is used as research input in analyzing MPPT-QHBM performance under uncertain conditions. The data are shown in the table below.

Table 1. Monte Carlo Data Used

Time	Irradiation (W/m2)	Temperature (0C)
09:00	462,1	27,1
10:00	608,4	26,9
11:00	794,6	28,3
12:00	981,9	29,2
13:00	892,3	30,8
14:00	674,6	28,5

2.4. System Parameters

In this study, the solar panel module used is a TSM-DE18M Trinasolar type solar panel with a capacity of 500 Wp, which is used in this system and has the specifications shown in Table 2 below.

Table 2. PV Specifications

Parameters	Value
Brand	Trina Solar
Type	TSM-DE18M
Peak Power (Pmax)	500 Wp
Max Power Volt (Vmp)	42,8 V

Parameters	Value
Max Power Current (Imp)	11,69 A
Open Circuit Volt (Voc)	51,7 V
Short Circuit Current (Isc)	12,28 A
Temperature Operation	-40°C until +85°C
Efficiency Cell	21%

The MPPT system designed in this study targets a 100 V output and a corresponding 500 W of power, serving as the input to the battery charging process. The initial duty cycle is determined by the QHBM algorithm, which represents the queen bee colony's initial position during its migration to locate the optimal power source. This starting point is crucial, as it influences the MPPT algorithm's convergence speed and tracking accuracy at the Maximum Power Point (MPP). Based on these design parameters and algorithmic considerations, the MPPT system parameters used in this simulation are as follows:

Table 3. Boost Converter Parameters

Parameters	Value
Current Output	5 A
Battery	100V 50 Ah
Duty Cycle	0 – 1 (QHBM)
Inductor	100,8 μH
Capacitor	42,5 μF

3. Results and Discussions

This chapter analyzes MPPT simulation results for autonomous solar panel systems using the Queen Honeybee Migration (QHBM) method, focusing on the QHBM algorithm's response to changes in irradiance to optimize solar panel output power.

3.1. Algorithm Response of Solar Panel System

The QHBM algorithm is implemented to optimize the search for the maximum power point (MPP) in photovoltaic (PV) systems, and its performance is compared with other optimization algorithms, including the Grey Wolf Optimizer (GWO), Particle Swarm Optimization (PSO), and Perturb and Observe (P&O). The simulations were carried out on a single PV module with specifications detailed in Table 2. For the QHBM algorithm, the main parameters are set at 250 scout bees and 50 iterations, balancing exploration and convergence speed to effectively track the MPP under various conditions. The other optimizations also use the same with 250 agents and 50 iterations to present a balanced and fair performance comparison.

3.1.1. Algorithm Response of Solar Panel System

The search process for determining the optimal operating point of the PV system is shown in Figure 8, which presents a three-dimensional relationship between voltage (X-axis), current (Y-axis), and power (Z-axis). This graphical representation illustrates how the MPPT algorithm navigates the power surface to reach the Maximum Power Point (MPP). Based on the results shown in Figure 9, the QHBM algorithm successfully identifies the MPP at the 5th iteration, demonstrating rapid convergence and effective optimization of the PV system's output. To evaluate the performance of QHBM, a comparative analysis was conducted using three other well-known algorithms: GWO (Grey Wolf Optimizer), PSO (Particle Swarm Optimization), and P&O (Perturb and Observe). Figure 9 highlights that QHBM outperforms the others in terms of response time and convergence speed, reaching MPP faster than all compared methods. Specifically, QHBM achieves a power output of 499.903 W with an efficiency of 99.98% by the 5th iteration. The GWO algorithm converges at the 8th iteration and achieves 99.79% efficiency, while PSO reaches a similar efficiency (99.98%) but requires 10 iterations to converge. In contrast, the P&O method shows the slowest convergence, reaching MPP only after 19 iterations, with an efficiency of 97.15%. These findings are further detailed in Table 4, which summarizes the performance metrics of each algorithm and emphasizes the superior speed and consistency of QHBM in MPPT applications.

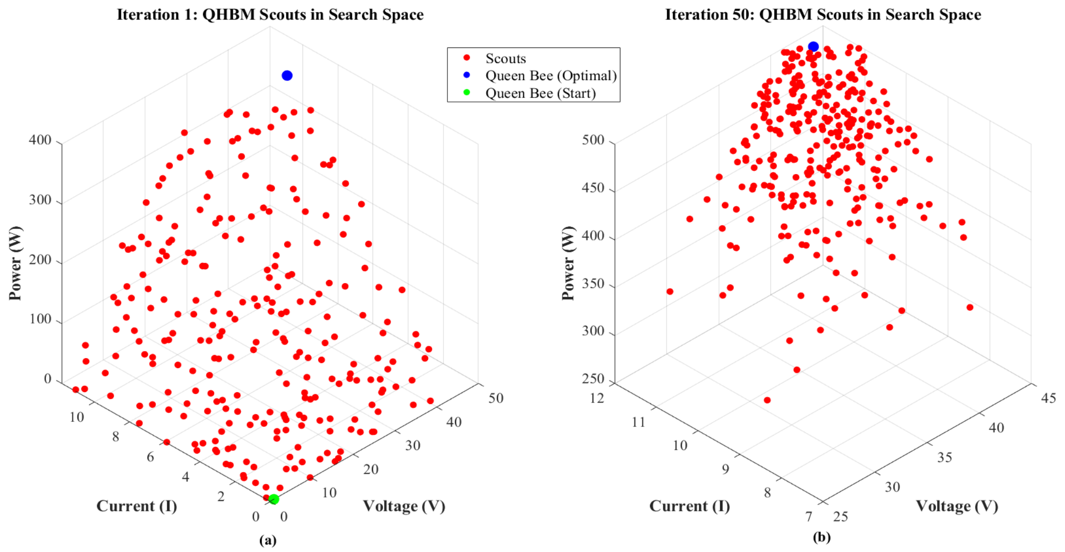

Figure 8. QHBM Scouts in The Search Space; (a) Iteration 1 (b) Iteration 50

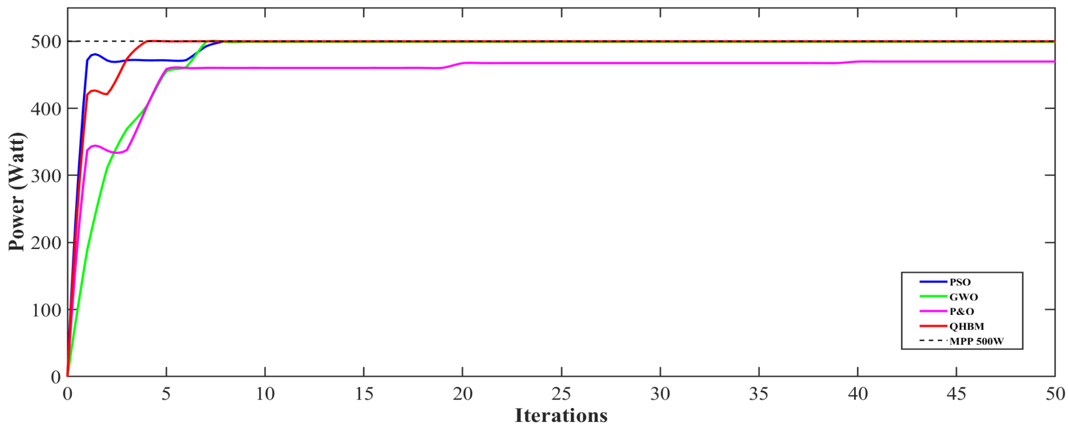

Figure 9. Performance of Each Optimization

Table 4. MPPT Algorithm Performance Comparison

Algorithm	Response Time	Starting Point	Optimum Point	Efficiency
QHBM	5 ith	391,1 W	499,903 W	99,98%
GWO	8 ith	361,9 W	498,952 W	99,79%
PSO	10 ith	487,4 W	499,903 W	99,98%
P&O	19 ith	343,6 W	485,784 W	97,15%

Response time is the time it takes each algorithm to reach the optimal operating point, or Maximum Power Point (MPP), of the PV system. In this study, the QHBM and GWO algorithms demonstrated superior convergence speed compared to PSO and P&O. QHBM reached the MPP at the 5th iteration, followed by GWO at the 8th iteration, indicating that both algorithms possess strong adaptability under stable test conditions. QHBM recorded the best overall response time, with a maximum power output of 499.903 Watts and an efficiency of 99.98%. Although the initial power output of QHBM was slightly lower than that of PSO, it was still higher than the initial values of GWO and P&O, highlighting QHBM's good initial stability. This also reflects its strong global search capability and consistent convergence behavior, which are critical for maintaining performance under fluctuating environmental conditions.

3.1.2. Performance Under Uncertain Irradiation Conditions

Based on the analysis in Figure 10, both QHBM- and PSO-based MPPT algorithms demonstrate consistent performance in accumulating high power output, with QHBM showing superior results under high irradiance conditions. However, under low irradiance or partial shading conditions, PSO tends to maintain greater stability than QHBM. The GWO algorithm also delivers relatively high and steady power output, although it does not surpass the peak performance of QHBM or PSO. In contrast, the P&O algorithm exhibits scattered power distribution and is more susceptible to fluctuations, particularly under varying environmental conditions. Figure 11 further supports these observations, showing that QHBM can sustain a peak power output of 499.9 Watts over a longer period from 10:00 to 13:00, compared to PSO, which maintains the same output only between 11:00 and 13:00. This pattern highlights QHBM's better adaptability to the gradual increase in irradiance. From these results, it can also be concluded that the optimal window for solar energy harvesting in Tulungagung district lies between 10:00 and 13:00, as indicated by the consistently high-power outputs recorded by all four algorithms during this period.

Table 5. Average MPPT Performance Under Dynamic Irradiation Conditions

Algorithm	Normal Irradiation (3135 sample)				Abnormal Irradiation (2865 sample)			
	Response Time	Start Point	Optimum Point	Efficiency	Response Time	Start Point	Optimum Point	Efficiency
QHBM	5 ith	389.3 W	483.38 W	98.99%	7 ith	254.7 W	325.61 W	97.86%
GWO	8 ith	358.0 W	479.57 W	98.22%	9 ith	254.7 W	318.55 W	95.77%
PSO	10 ith	398.9 W	483.33 W	98.98%	12 ith	314.5 W	324.17 W	97.47%
P&O	19 ith	323.7 W	471.09 W	96.44%	22 ith	233.4 W	314.45 W	94.51%

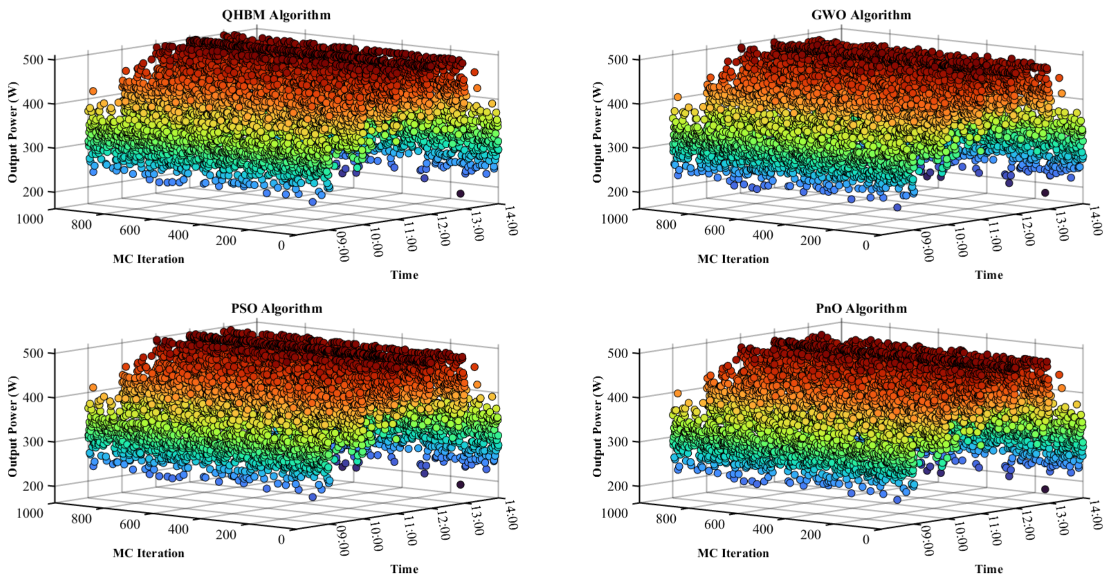

Figure 10. Comparison of PV Power Results of Each Algorithm

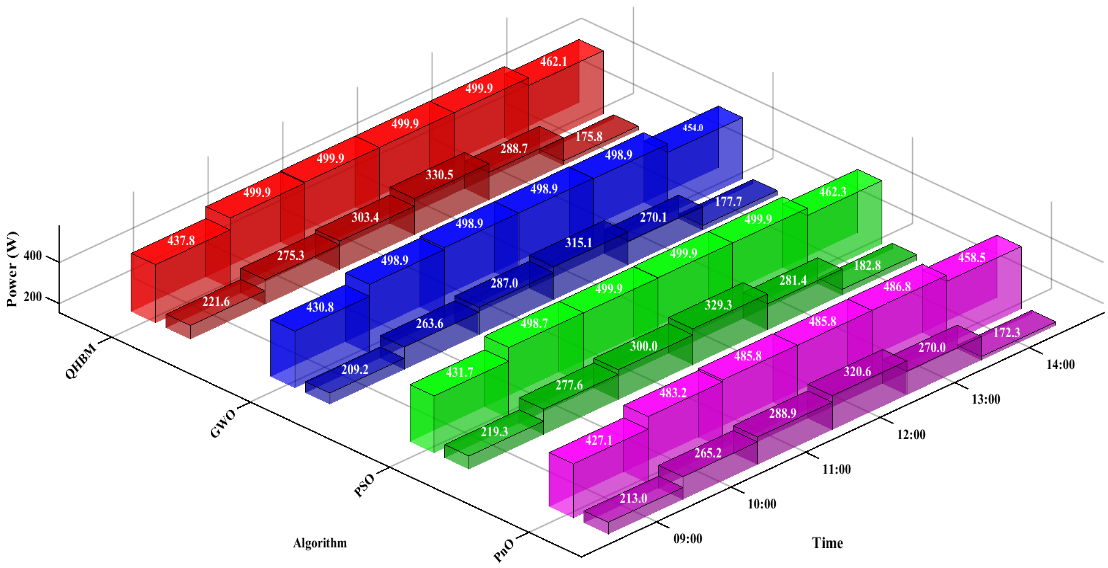

Figure 11. Maximum and Minimum PV Power Per Hour

Based on the test results in two conditions, namely normal irradiation and abnormal irradiation, it can be concluded that the QHBM algorithm shows the most consistent performance compared to the other three algorithms, namely GWO, PSO, and P&O. The average MPP value of 6000 irradiation data should be 488.5 W in normal irradiation conditions and 332.7 W in abnormal irradiation conditions.

Under normal irradiation conditions with a total of 3135 samples, QHBM recorded the fastest response time of 5 iterations to reach an MPP of 483.38 W, with the highest efficiency reaching 98.99%. PSO achieved almost the same maximum power of 483.33 W but required 10 iterations to converge. GWO was in the middle position, with a response time of 8 iterations and an efficiency of 98.22%, and a power of 479.57 W, while P&O reached an MPP of 471.09 W in 19 iterations and an efficiency of 96.44%.

Under abnormal irradiation conditions with 2865 samples, the performance pattern of the algorithms remained consistent. QHBM recorded the highest maximum power of 325.61 W, or 97.86%, followed by PSO, which achieved 324.17 W and 97.47% efficiency, but with a slower response time of 12 iterations. QHBM remains superior in adaptation speed, with a response time of 7 iterations and an efficiency of 97.36%, demonstrating its ability to respond to stochastic irradiation dynamics. GWO achieved a 95.77% efficiency and a maximum power of 312.58 W, while P&O recorded the lowest efficiency of 94.51% and a response time of 22 iterations. Thus, the QHBM is considered the most suitable for the case under study, as it can maintain high efficiency and adapt well to variations in irradiation conditions, making it feasible for application in MPPT systems in real operational environments.

Table 5. MPPT Performance Results

Criteria	Algorithm			
	QHBM	GWO	PSO	P&O
Response Time	Very fast	Very fast	Fast enough	Not fast enough
Efficiency (Normal)	Highly efficient	Highly efficient	Highly efficient	Efficient enough
Efficiency (Abnormal)	Highly efficient and stable	Efficient enough	Highly efficient	Not efficient enough

3.2. Performance MPPT-QHBM in Solar Panel System

The series of solar panel system tests conducted in this study is illustrated in Figure 12. Two simulation scenarios are employed to validate the performance of the proposed system: the first under optimal irradiation conditions (Standard Testing Conditions, STC), and the second under dynamically fluctuating irradiation conditions generated from Monte Carlo simulation data. These scenarios are specifically designed to capture the impact of natural solar irradiance variability on system behavior and efficiency. By comparing the system's response in both stable and highly variable environments, the study aims to comprehensively assess the robustness, adaptability, and reliability of the solar panel system, particularly the effectiveness of the QHBM-based MPPT in maintaining optimal power extraction across different real-world conditions.

3.2.1. Scenario 1

In the first scenario, the supply is given to the PV side with constant irradiation and temperature of 1000 W/m2 and 25 0C. In this scenario, as shown in Figure 4.5, the converter has an efficiency of 98.6% and a power output of 493 Watts. The battery current, as shown in Figure 4.6, is negative, which indicates that the battery is charging. In this normal state, the QHBM performs well, as indicated by a steady-state response time of less than 0.05 seconds.

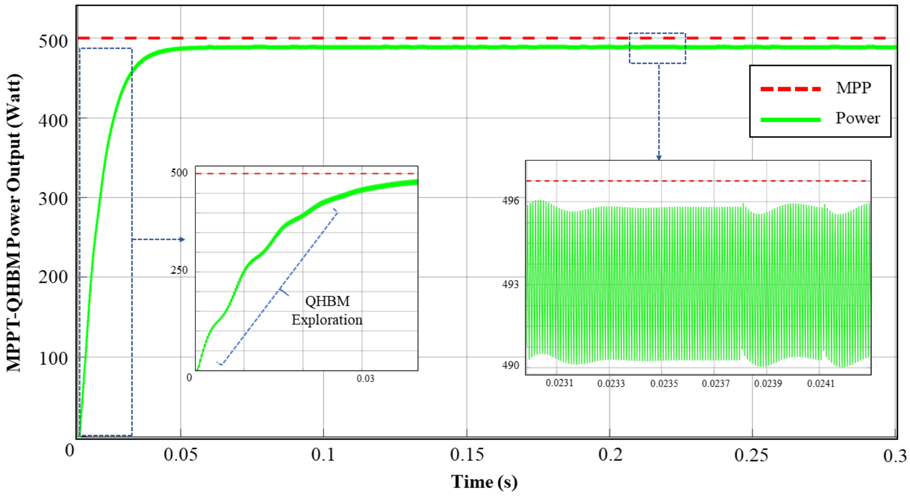

Figure 12. MPPT Power Output

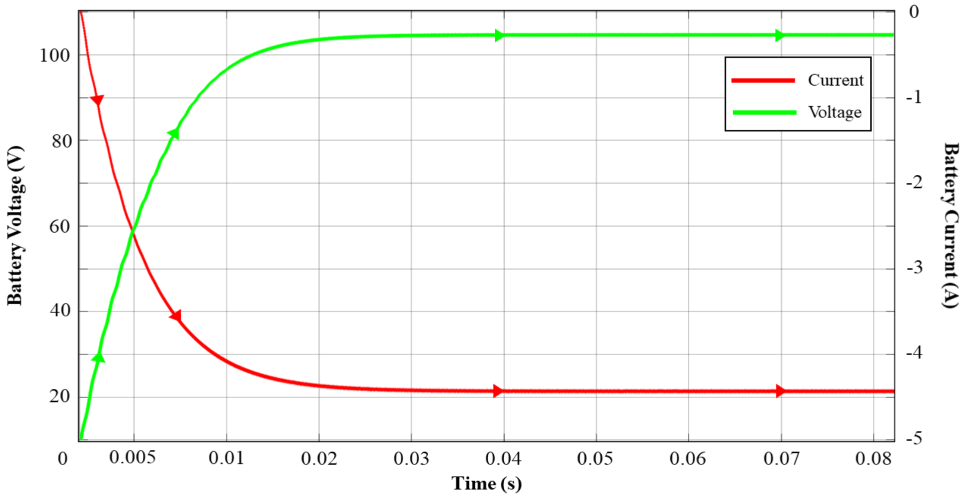

Figure 13. Battery Voltage and Current

3.2.2. Scenario 2

Figure 14 shows the output power response of the QHBM-based MPPT system to fluctuating irradiation changes (data in Table 3.1). An increase in irradiation generally leads to an increase in output power; for example, when irradiation rises from 462 W/m^2 to 982 W/m^2, the power also increases from 230.1 W to 493.8 W. This indicates that the QHBM algorithm can adjust the working point to follow the maximum power point despite rapid changes in lighting conditions. However, the decrease in power after the peak indicates the system's sensitivity to decreasing irradiation. As the irradiation drops from 982 W/m² to 674 W/m², the power also decreases from 493.8 W to 338 W.

The battery current shown in Figure 15 is negative, indicating that the battery is charging even under less-than-optimal irradiation conditions. These two patterns shown in Figures 14 and 15 confirm that irradiation is the dominant factor affecting PV system performance, and that the QHBM algorithm is responsive in maintaining MPPT performance and reaching the maximum power point during erratic irradiation conditions.

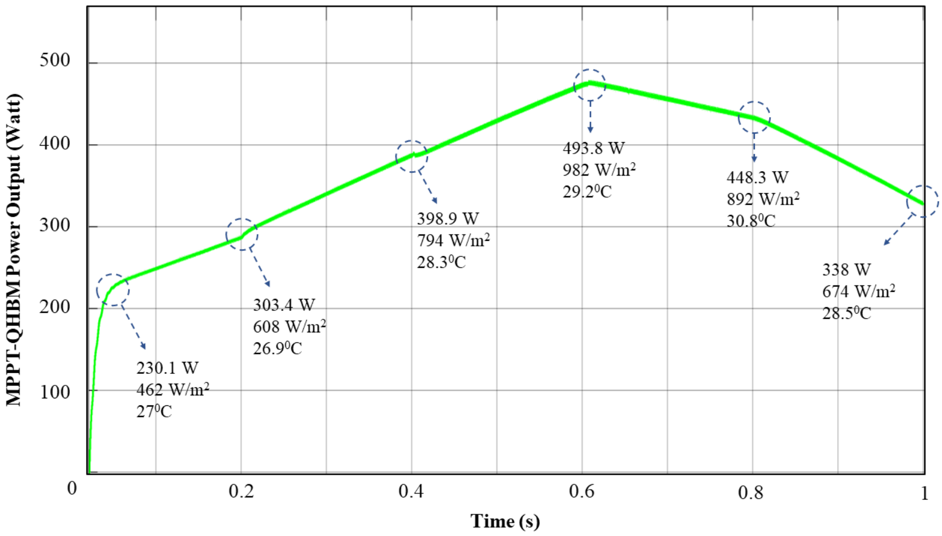

Figure 14. MPPT Power Output Under Uncertain Irradiation Conditions

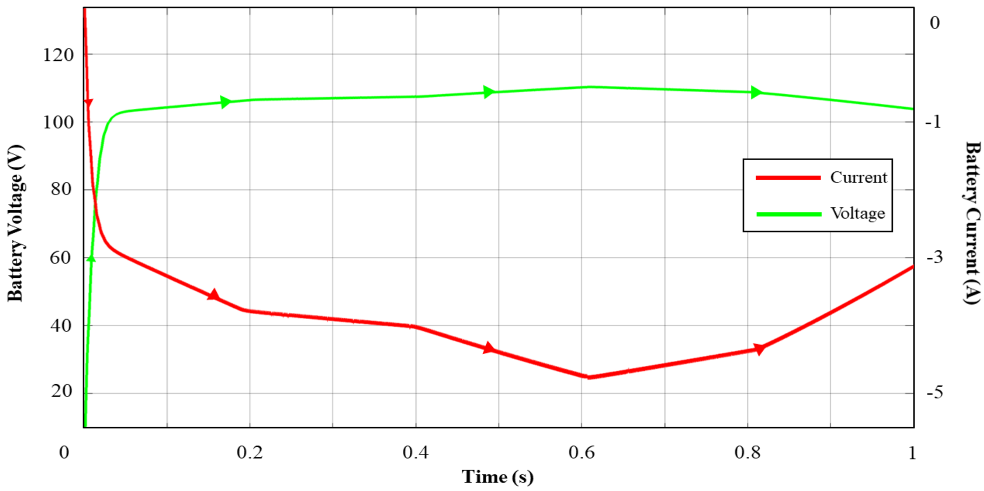

Figure 15. Battery Voltage and Current Under Uncertain Irradiation Conditions

3.3. State of Charge (SOC) of Battery in the System

In this study, the battery was initialized with a State of Charge (SOC) of 30% to monitor the charging condition during the process. SOC is an indicator that shows the percentage of the battery's capacity remaining; 100% means the battery is full, and 0% means it is empty. The results of both scenarios show that the battery undergoes charging, characterized by an increase in the SOC value, as shown in Figure 16. In the first scenario (optimal irradiation conditions), the highest SOC increase occurred at the 1st second by 0.038%. Meanwhile, in the second scenario (with Monte Carlo irradiation fluctuations), the increase in SOC was lower at 0.026%. This difference reflects the influence of irradiation conditions on the battery charge rate.

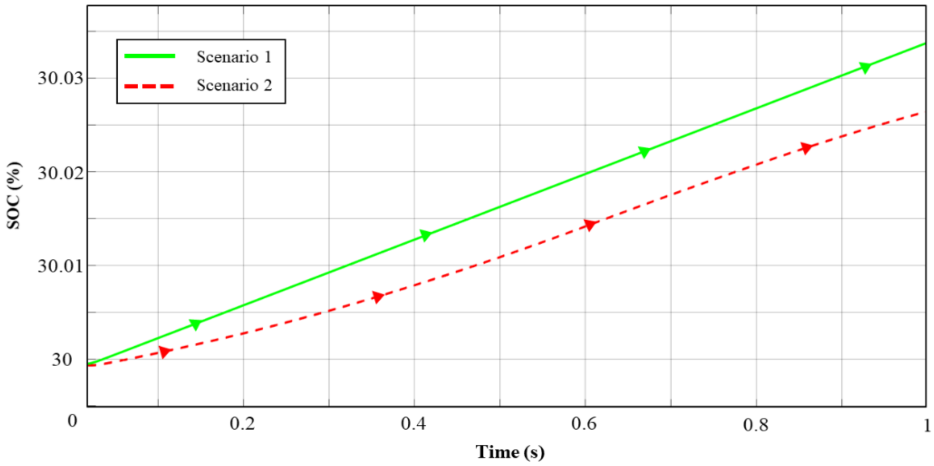

Figure 16. Battery SOC Under Both Scenario Conditions

4. Conclusions

This study assesses the performance of the Queen Honeybee Migration (QHBM) MPPT algorithm for optimizing Maximum Power Point (MPP) tracking in a single solar panel system under uncertain irradiation conditions. Compared to GWO, PSO, and P&O algorithms, QHBM demonstrates superior performance, achieving the fastest convergence at the 5th iteration and a maximum efficiency of 99.98% under Standard Test Conditions (STC). When tested with Monte Carlo simulation-based uncertain irradiation data, QHBM maintained high efficiency, averaging 98.99% under normal conditions and 97.86% under abnormal conditions. In both scenarios, the battery's State of Charge (SOC) increased while the battery current was negative, indicating that charging continued despite non-ideal irradiation. These results show that the QHBM algorithm is highly adaptable and can reliably sustain stable MPPT performance, making it an effective solution for solar energy systems in environments with variable light intensity.

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