Acta Informatica Pragensia
2025, Volume 14, Issue 3, 422–444
https://doi.org/10.18267/j.aip.267

Article Open Access

Optimizing Battery Charging in Wireless Sensor Networks: Performance Assessment of MPPT Algorithms in Different Environmental Settings

Abdullah Fadhil Noor Shubbar [1], Serkan Savaş [2], Osman Güler [3]

[1] Department of Electrical and Electronics Engineering, Faculty of Engineering, Çankırı Karatekin University, Çankırı, Turkey
[2] Department of Computer Engineering, Faculty of Engineering and Natural Sciences, Kırıkkale University, Kırıkkale, Turkey
[3] Department of Computer Engineering, Faculty of Engineering, Çankırı Karatekin University, Çankırı, Turkey

Corresponding author: Serkan Savaş (serkansavas@kku.edu.tr)

Abstract

Background: Photovoltaic (PV)-based energy harvesting systems are crucial for ensuring the sustainability and long-term operation of wireless sensor networks (WSNs), especially in remote or infrastructure-less environments. Given the critical role of battery performance in WSN reliability, efficient energy management through Maximum Power Point Tracking (MPPT) algorithms is essential to adapt to variable environmental conditions such as solar irradiance and ambient temperature.

Objective: This study aims to comparatively assess the performance of four widely adopted MPPT algorithms—Perturb and Observe (P&O), Incremental Conductance (IC), Fuzzy Logic (FL), and Particle Swarm Optimization (PSO)—in enhancing battery charging efficiency in PV-powered WSNs under dynamic environmental conditions.

Methods: A simulation-based evaluation framework was developed using MATLAB/Simulink to model a PV-powered WSN system. Each MPPT algorithm was implemented and tested using the same simulation conditions, with key performance metrics including voltage and current overshoot, response time, energy transfer efficiency, and adaptability to fluctuating irradiance and temperature profiles. A Proportional-Integral (PI) controller was also used to manage the battery charging process, and environmental profiles were varied across simulation periods to assess algorithm robustness.

Results: The PSO algorithm achieved superior performance across all metrics, demonstrating the fastest response time (0.1 s), lowest overshoot (14.8 V, 25 mA), and highest energy transfer efficiency. IC and FL methods showed balanced adaptability and performance, while P&O lagged in both responsiveness and efficiency. The simulation results also confirmed that environmental conditions significantly affect PV panel output and battery State of Charge (SoC), highlighting the necessity for adaptive MPPT solutions.

Conclusion: This study provides a unified and realistic comparative analysis of major MPPT algorithms for PV-powered WSNs. The PSO algorithm emerges as the most effective, though its computational complexity may limit its application in low-power systems. IC and FL serve as promising alternatives for scenarios with resource constraints. The findings contribute to the design of environmentally adaptive and energy-efficient WSNs, paving the way for their robust deployment in real-world settings.

Index Terms

Photovoltaic; MPPT Algorithms; Wireless sensor networks; Battery charging; PSO; Maximum power point tracking.

Editorial Record

First submission received:
February 13, 2025

Revisions received:
April 11, 2025
May 7, 2025

Accepted for publication:
May 9, 2025

Academic Editor:
Zdenek Smutny
Prague University of Economics and Business, Czech Republic

This article was accepted for publication by the Academic Editor upon evaluation of the reviewers' comments.

How to cite this article:
Shubbar, A. F. N., Savaş, S., & Güler, O. (2025). Optimizing Battery Charging in Wireless Sensor Networks: Performance Assessment of MPPT Algorithms in Different Environmental Settings. *Acta Informatica Pragensia*, 14(3), 422–444. https://doi.org/10.18267/j.aip.267

1 INTRODUCTION

Wireless sensors are vital for Internet of Things (IoT) applications and often operate within wireless sensor networks (WSNs). These networks can be based on an existing infrastructure led by a base station or can be infrastructure-less with decentralized coordination. WSNs have significantly impacted multi-hop wireless networks, finding applications in environmental monitoring, structural monitoring, border protection, and healthcare, among others (Ammari, 2014). A significant challenge for WSNs is energy efficiency. Since they are primarily battery-powered, once the battery is depleted, a node is considered dead. Replacing or recharging these batteries can be costly and logistically challenging, thereby affecting network performance. As a result, measures such as power control and duty cycle-based operations have been introduced to optimize battery usage (Colesanti et al., 2011; Melikov & Rustamov, 2012; You et al., 2021). However, these approaches might not fulfil the longevity requirements of certain applications. Recent research suggests the use of energy harvesters, rechargeable batteries, and super capacitors to achieve perpetual WSN operations (Alsharif et al., 2019). Given that WSNs play a critical role in various sensitive applications, it's essential to ensure energy-aware solutions (Alsharif et al., 2015).

Energy Harvesting-based WSNs (EHWSNs) have the potential to provide endless power to nodes by harvesting energy from environmental sources. The design of EHWSNs demands adaptability to environmental changes and the development of efficient energy storage and usage protocols (Getahun et al., 2022). The energy harvester gathers ambient or human-generated energy and converts it into electrical energy, while the power management module either stores or delivers this energy to other system components (Sharma et al., 2018). The energy storage component preserves the harvested energy. Meanwhile, the microcontroller and radio transceiver facilitate the node's ability to transmit and receive information. The sensory equipment, combined with the A/D converter and memory, allows the node to digitize analog signals, store the sensed information, and process data. Together, all these components form a comprehensive system architecture for a wireless sensor node.

Energy harvesting (EH) refers to the process of generating electricity from non-traditional sources, such as solar radiation, wind, thermal energy, and vibration, to power WSN. Solar-powered systems are among the most promising EH approaches for WSNs. They provide a sustainable, affordable, and dependable energy option. Solar-powered EH solutions provide many benefits over conventional power systems. They're eco-friendly, cost-effective, and simple to keep up. Because they are not influenced by blackouts or other external interruptions, solar-powered WSNs are noticeably more dependable. The energy captured by such WSNs is also more efficient than that captured by more traditional means.

Wi-Fi networks are the backbone of the technology that makes smart homes, garages, and communities possible. Due to high duty cycles, these WSN nodes can only function for a limited amount of time on their batteries. The importance of this research rests in its solution to the power problem inherent in the design of nodes for WSNs. The Photovoltaic (PV) energy generated by the sun is used by the suggested system to keep the WSN nodes running for longer and improve their performance. Improvements to the efficiency of the solar panels, the regulated DC-DC converter, and the rechargeable batteries are another focus of the study. The expanding IoT infrastructures of smart buildings, smart parking, and smart cities rely heavily on such developments. In this study, the research focus is on enhancing the efficiency of the harvesting system, which depends on the efficiency of the solar panels, the controlled DC-DC converter, and the rechargeable batteries. The aim is to develop WSNs with improved power charging efficiency, reliability, and scalability. The study will also explore the potential of using emerging technologies to enhance the monitoring and optimization of these systems.

Recent studies emphasize the importance of renewable energy sources due to concerns about climate change and pollution. Among these, EH devices are drawing attention as they transform environmental sources like solar, thermal, and wind energy into electricity, with a particular focus on WSNs. Sucupira and Castro-Gomes (2021) highlighted the benefits of materials added to energy capture parts for solar and thermal energy conversion, suggesting further research is needed in this domain. Cao et al. (2022) explored the foundational technologies of WSN and the omnipresent power IoT, emphasizing the data-gathering potential and future cross-professional integration opportunities. However, there's a gap in discussions on utilizing the data efficiently. Singh et al. (2021) presented a survey on the latest EH techniques and emphasized hybrid EH systems. They recognized the need for further studies on challenges and research gaps linked to these systems. Mazunga and Nechibvute (2021) reviewed advances in EHWSNs, stressing the importance of ultra-low power techniques. Akyildiz et al. (2002) provided insights into Solar EHWSNs, touching on efficiency, challenges, and future trends. Rokonuzzaman et al. (2021)

introduced an EH system for smart home-building applications but lacked details on its real-world applications and effectiveness. Antony et al. (2020) proposed a solar harvester for WSN nodes with hybrid energy storage. Yet, the study fell short on discussing its practical applications and challenges. Sharma et al. (2018) evaluated two solar energy harvester control techniques, proving MPPT to be superior to PWM. They proposed the exploration of advanced MPPT algorithms for better efficiency. Anand et al. (2021) demonstrated the effectiveness of a solar EH system with MPPT for WSN nodes but suggested room for further optimization.

The integration of EH mechanisms in WSNs has attracted growing attention due to the increasing demands for sustainability, long-term deployment, and reduced maintenance costs in IoT ecosystems. Within EHWSNs, solar energy stands out as a prevalent and viable energy source. However, harvesting and managing this energy efficiently presents numerous technical challenges. Despite the potential of MPPT algorithms to maximize energy efficiency, practical implementation in WSNs poses several challenges. Sharma et al. (2018) emphasized the difficulty of adapting MPPT controllers to fluctuating environmental conditions, which may lead to delayed responses or mismatched power regulation. Similarly, Sucupira and Castro-Gomes (2021) noted that material characteristics and energy storage limitations hinder the scalability of EHWSNs, particularly under non-ideal solar irradiance conditions. The computational constraints of low-power sensor nodes also limit the applicability of more advanced MPPT algorithms. Various MPPT techniques have been proposed and analysed in the literature, but comparative insights, especially under dynamic environmental conditions, remain limited.

Perturb and Observe (P&O) has been widely studied for its simplicity and ease of implementation. However, it is prone to oscillations near the maximum power point and may not adapt well to rapid environmental changes (Salman et al., 2018). Incremental Conductance (IC) was proposed to address the limitations of P&O by using slope comparisons of the PV curve (Başoğlu & Çakır, 2015). It is more accurate but slightly slower and computationally demanding. Fuzzy Logic (FL) controllers have gained attention for their ability to handle nonlinearities and uncertainties in solar power systems. Narwat and Dhillon (2021) demonstrated that fuzzy-based MPPT techniques can enhance energy conversion, though they require careful tuning of rule bases. Particle Swarm Optimization (PSO) has been proposed in recent years as a global optimization solution. Gad (2022) showed that PSO-based MPPT systems significantly outperformed classical techniques in terms of convergence speed and stability under diverse conditions, albeit with increased computational complexity.

While individual studies have explored these algorithms, few works have systematically compared them in the context of battery charging efficiency for WSNs under variable temperature and irradiance levels. This gap motivates the present study.

Environmental conditions, especially solar irradiance and ambient temperature, have a profound impact on the performance of MPPT algorithms. Reza Reisi et al. (2013) and Vinod et al. (2018) highlighted that both open-circuit voltage and short-circuit current are highly sensitive to irradiance and temperature, affecting the position of the maximum power point. Reza Reisi et al. (2013) categorized MPPT techniques and emphasized the need for robustness against environmental fluctuations. Furthermore, Anand et al. (2021) conducted a performance analysis of MPPT methods but focused on constant conditions without accounting for real-time environmental variability. This underscores the importance of evaluating MPPT performance across fluctuating operating conditions, which is a key contribution of the current study. Despite the variety of MPPT strategies available, the literature lacks:

- A unified comparative evaluation of P&O, IC, FL, and PSO in a realistic EHWSN simulation setting.
- A performance-based assessment with metrics such as overshoot, settling time, and SoC under dynamic environmental inputs.
- An integration of environmental modelling (temperature, irradiance) with MPPT efficiency analysis in battery charging.

This study addresses these gaps by designing a simulation framework that evaluates the performance of four major MPPT algorithms under varying environmental conditions in terms of charging speed, overshoot minimization, and energy harvesting efficiency.

The primary objective of this study is to evaluate and compare the performance of four distinct MPPT algorithms (P&O, IC, FL, PSO) under different environmental conditions with respect to battery charging efficiency in WSNs. The secondary objective is to identify the most optimal algorithm for real-time applications in EH-based WSNs in terms of response time, overshoot, and scalability, supported by simulation-based performance metrics.

The structure of the study is as follows. The second section is organized to explain the materials and methods used in this study. In the third section, the results obtained in the study are explained and discussed. Finally, the fourth section concludes the study.

2 RESEARCH METHODS

Solar harvesting refers to the act of capturing and storing energy from the sun. Solar energy production is a renewable energy technique that converts the sun's rays into usable forms like electricity, hot water, and heat using various solar energy collectors like PV panels and solar thermal energy collectors (İ. Ay et al., 2023; I. Ay et al., 2022). This method's rising popularity may be traced to its ability to lessen our reliance on fossil fuels and lower our energy bills in comparison to other renewable power options. Solar energy collection has various potential uses, including providing electricity to homes, offices, and manufacturing facilities. Figure 1 shows the solar EH in WSNs (Ponnimbaduge Perera et al., 2018).

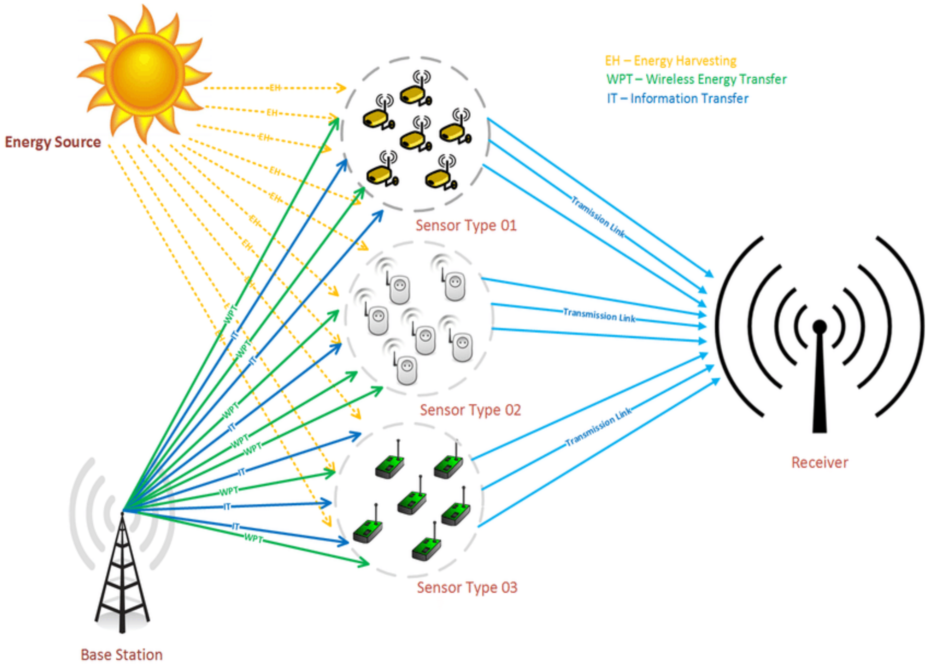


Figure 1. *Energy harvesting in wireless sensor networks. Source: (Ponnimbaduge Perera et al., 2018).*

EH has the potential to revolutionize WSNs by enabling them to be self-sustaining and operate in remote locations without traditional power sources. This capability could diminish the need for costly and labor-intensive maintenance of sensor nodes, making WSN operations more cost-effective and efficient. Moreover, solar EH might allow WSNs to function autonomously, expanding their application range and benefits. Therefore, solar powered EH for WSNs could be a transformative technology for the industry. In this study, the proposed system design for solar powered EH comprises: PV panel system, MPPT DC-DC buck converter, battery, and wireless sensor node. The PV system for low power applications shown in Figure 2 (Hidalgo-Leon et al., 2022).

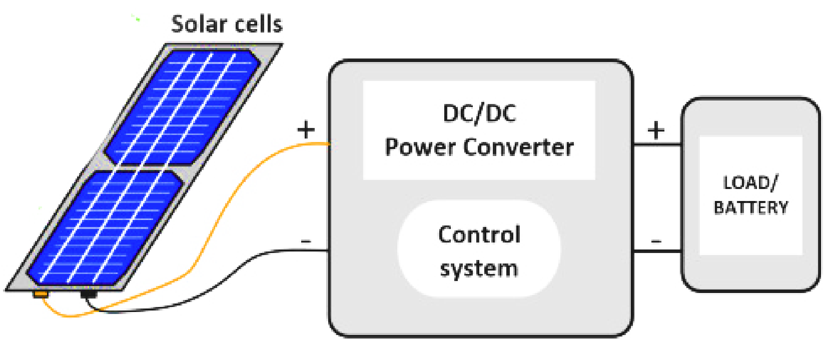


Figure 2. *Solar powered EH for WSN. Source: (Hidalgo-Leon et al., 2022).*

2.1 Photovoltaic panel system

The adoption of PV panels in low-power DC WSNs is on the rise. The merits of using PV panels are evident, they offer a dependable and cost-effective energy source, capable of harvesting energy from the environment even during overcast conditions. However, several challenges might arise, including fluctuating power output due to changing environmental factors, reduced longevity from wear and tear, and occasional inadequate power production for the nodes. Yet, even with these potential drawbacks, the advantages of integrating PV panels in DC low-power WSNs underscore their significance in numerous applications (Hidalgo-Leon et al., 2022).

The current (I) circulates through the circuit, with the voltage (V) being measured across the resistor. The resistance value of the resistor (Rs) is based on the electrical properties of the solar cell. Additionally, the diode (D) serves to prevent current from flowing backward and to regulate the voltage.

Equations (1), (2) and (3) describe the operation of solar panels, which are made by connecting solar cells in parallel and series.

$$I_L = \left[I_{L,n} + K_i(T - T_r)\right] * \frac{G}{G_n} \tag{1}$$

The amount of current (IL) generated by a solar cell array is directly influenced by the light it receives. However, other factors like the temperature (T) of the solar cell array and the solar radiation intensity (G) also play a crucial role. If we consider a reference current (IL,n) produced at specific reference conditions of temperature (Tr) and solar radiation (Gn), we can modify this current based on deviations from these reference conditions. A key parameter in this adjustment is Ki, which represents how short-circuit current changes with a temperature variation. By tweaking the reference values of temperature and solar radiation, one can effectively modulate the current output of the solar cell array (Vinod et al., 2018).

$$I_o = \frac{I_{Sc,n} + K_i(T - T_r)}{\exp\left(q * \dfrac{V_{Oc,n} + K_v(T - T_r)}{a.N_S \cdot K.T}\right) - 1} \tag{2}$$

Voc,n is the working voltage in a vacuum at the reference temperature and solar radiation. Io is the saturation current that varies according to the temperature. Isc,n is the nominal short current. Q is the electron charge which is equal to 1.6x10−19 c. Ns is the number of serially connected solar cells. K is the Boltzmann constant which is equal to 1.38x10−23 J/K. Kv is the coefficient of change of the work effort over a vacuum due to the change in temperature. Ego is the excitation energy for the semiconductor, and for silicon, it is Ego = 1.1. Lastly, a is the ideal condition parameter. All these parameters are important for the proper functioning of solar cells (Vinod et al., 2018).

$$I = I_L - I_0\left[\exp\left(\frac{q*(V+IR_S)}{a.N_S \cdot K \cdot T}\right)\right] - \frac{V+IR_S}{R_p} \tag{3}$$

The power that a solar cell array produces hinges on a few factors: current, voltage, and how the cells are connected. By linking cells side by side, or in parallel, it boosts the current. On the other hand, lining them in series ramps up the voltage. So, depending on the setup and number, the array's output can be adjusted for different needs (Cubas et al., 2014).

2.2 DC-DC buck converters

Figure 3 showcases the buck converter, a type of DC/DC transformer made to reduce voltage levels. It works by transforming a stronger voltage source, perhaps from a battery, into a diminished voltage ideal for running gadgets or other equipment. Owing to its cost-effectiveness and superior performance, it's often preferred in various uses, as pointed out in (Lakshmi & Raja, 2014).

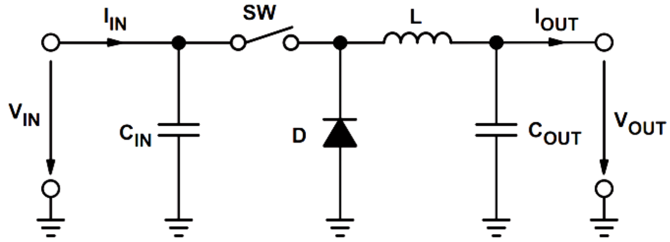


***Figure 3**. DC-DC buck converter.*

The input voltage range VIN (min) and VIN (max), the nominal output voltage (VOUT), the maximum output current IOUT (max), and the integrated circuit used to build the buck converter. All this information is necessary to get the right parameters for the calculations.

Switch current is calculated by first finding the duty cycle, D, for the highest input voltage. As the highest input voltage produces the highest switch current (Equation (4)) (Hauke, 2015).

$$\text{Maximum Duty Cycle: D} = \frac{V_{OUT}}{V_{IN(max)} \times \eta} \tag{4}$$

where V_{OUT} represented to output voltage and VIN (max) refer to maximum input voltage and η the efficiency of converter.

Once an appropriate inductor has been chosen, the ripple current must be calculated to determine the maximum switch current. The inductor value given in the converter's data sheet should be used as a starting point. Once the ripple current has been calculated, the maximum switch current can be determined as in Equation (5) (Hauke, 2015).

$$\text{Inductor Ripple Current: } \Delta L_L = \frac{\left(V_{IN(max)} - V_{OUT}\right) \times D}{f_S \times L} \tag{5}$$

When no inductor range is specified, the Equation (6) may be used to provide a decent approximation of the required inductor value (Hauke, 2015).

$$L = \frac{V_{OUT} \times (V_{IN} - V_{OUT})}{\Delta I_L \times f_S \times V_{IN}} \tag{6}$$

Schottky diodes are useful for lowering losses. The maximum output current is equivalent to the required forward current rating (Equation (7) (Hauke, 2015). Where IF the average receiver diode forward current.

$$I_F = I_{OUT(max)} \times (1 - D) \tag{7}$$

To minimize output voltage fluctuations, capacitors with lower capacitance have been used. Ceramic capacitors rated X5R are perfectly suited for this. Equation (8) is used to work out the capacitance (Hauke, 2015).

$$C_{OUT(min)} = \frac{\Delta L_L}{8 \times f_S \times \Delta V_{OUT}} \tag{8}$$

Where C_{OUT} (min) = minimum output capacitance, ΔL_L = estimated inductor ripple current, f_S=minimum switching frequency of the converter and ΔV_{OUT} = desired output voltage ripple.

2.3 Maximum power point tracking

MPPT is a technique used in PV systems, wind turbines, and other renewable energy systems to optimize power output by tracking the Maximum Power Point (MPP) and adjusting input voltage to maintain consistent output. Factors like load operating voltage, cell temperature, and solar radiation can influence output power. To determine the operational point, a variable load resistance is connected to the module's terminals. The peak power point is located at the knee of the power curve. The module's internal impedance in Zone I is high, while in Zone II it is low. As temperature rises due to solar radiation, internal impedance decreases, leading to increased short-circuit current and decreased open-circuit voltage. The maximum power transfer theorem requires matching source and load impedances. Figure 4 shows the MPPT I-P/V characteristics.

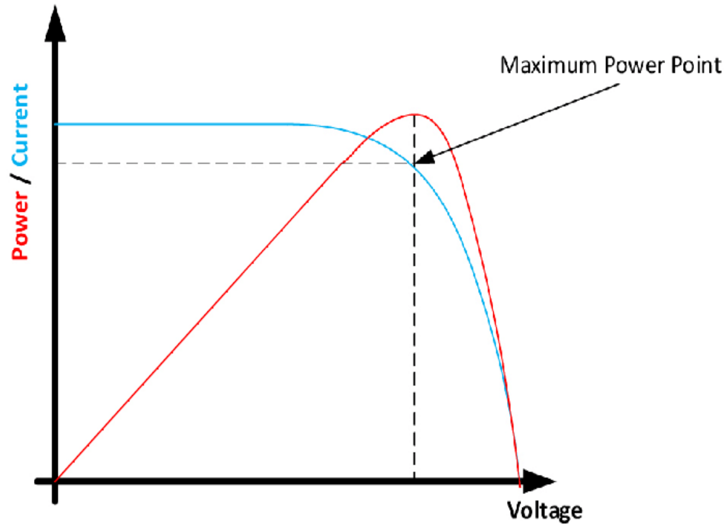


***Figure 4**. Maximum power point tracking. Source: (Reza Reisi et al., 2013).*

MPPT algorithms such as Perturb and Observe (P&O), Incremental Conductance (IC), Fuzzy Logic (FL) Control, and Particle Swarm Optimization (PSO) track the MPP by adjusting the WSN loads on PV panels to maintain the voltage and current at the MPP.

For Multi-Phase Photovoltaic systems, the P&O method is commonly used. In this approach, a small change is applied to the connected load of the solar panel, and the power output is measured. Once the MPP is identified, the load is adjusted in the direction that yields higher power output. The P&O system continuously monitors the solar panel's voltage and current output, making instantaneous adjustments to the load through a microcontroller or control circuit. This control circuit can be programmed to intermittently perturb the load by a slight amount, measuring the consequent variation in power output. While the P&O method is versatile and can easily be applied to various solar panels, it can sometimes be inefficient. This is because it might be slow to respond to changes in the solar panel output and can oscillate around the MPP (Salman et al., 2018).

To maximize the efficiency of PV systems, the IC MPPT technique is commonly employed. The primary goal of MPPT algorithms is to ensure the PV system operates at the MPP on the power-voltage (P-V) curve generated by the PV array. This is done to ensure the PV system harnesses the maximum energy from its resources, regardless of the weather or the intensity of sunlight on the panels. The IC technique determines the maximum power point based on the location where the P-V curve has a zero slope. In the IC approach, the instantaneous conductance (I/V) and IC (dI/dV) are compared to determine the direction of the operating point shift (Başoğlu & Çakır, 2015).

Optimizing the power output of solar panels in PV systems is achievable using the FL MPPT. This technology continually adjusts the operating point to track the MPP amidst varying environmental conditions. FL is a mathematical approach designed to manage vagueness and approximation. In MPPT applications, it facilitates reasoning and decision-making in situations where variables might assume non-binary values. By dynamically adjusting the operating point, the FL MPPT optimizes energy extraction from solar panels, thus maximizing energy efficiency and power output in PV systems (Narwat & Dhillon, 2021). The functional block diagram of the FL MPPT can be found in Figure 5. Also, FL implemented as shown in Figure 6.

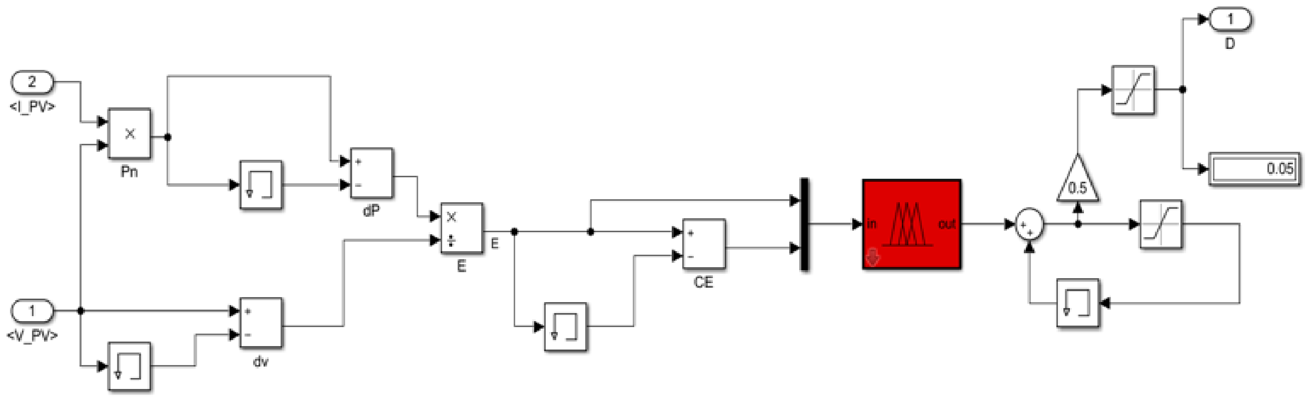


***Figure 5**. Block diagram of FL MPPT.*

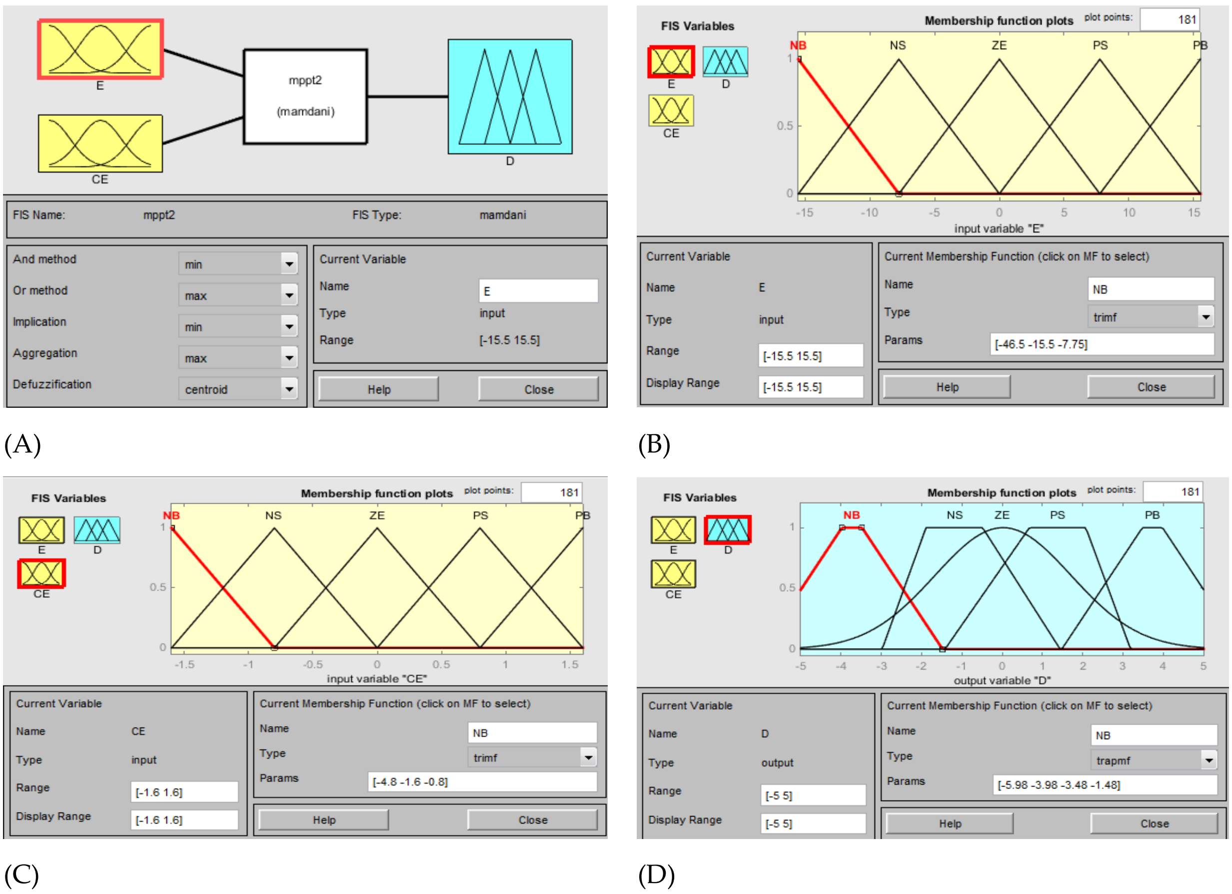


***Figure 6**. FL implementation, (A) MPPT FL setup, (B) Membership function for error section (C) Membership function input variable, and (D) Membership function output variable.*

The PSO algorithm, an example of a population-based optimization method, is inspired by the cooperative behaviors of animals, such as flocks of birds or schools of fish. While the PSO can be employed to address a variety of optimization challenges, one significant application is in the MPPT for PV systems. The MPPT algorithm aims to consistently operate solar panels at their MPPT — the specific voltage and current combination resulting in the highest power output. This ensures optimal energy collection from the sun, allowing the PV system to run efficiently. The adaptability of the PSO algorithm to search for and track the MPP in real-time makes it a strong candidate for MPPT applications (Gad, 2022).

2.4 Battery and PI controller for WSN charging

WSNs often depend on battery power, making efficient battery management vital. A Proportional-Integral (PI) controller can optimize the charging process, enhancing the performance and lifespan of batteries within WSNs. The controller ensures the battery remains within the ideal charging range, guarding against both overcharging, which can cause degradation, and undercharging, which may lead to an insufficient power supply for the sensor nodes. Effective battery management with a PI controller can bolster the performance, longevity, and reliability of WSNs. Figure 7 illustrates the PI management control for WSN charging.

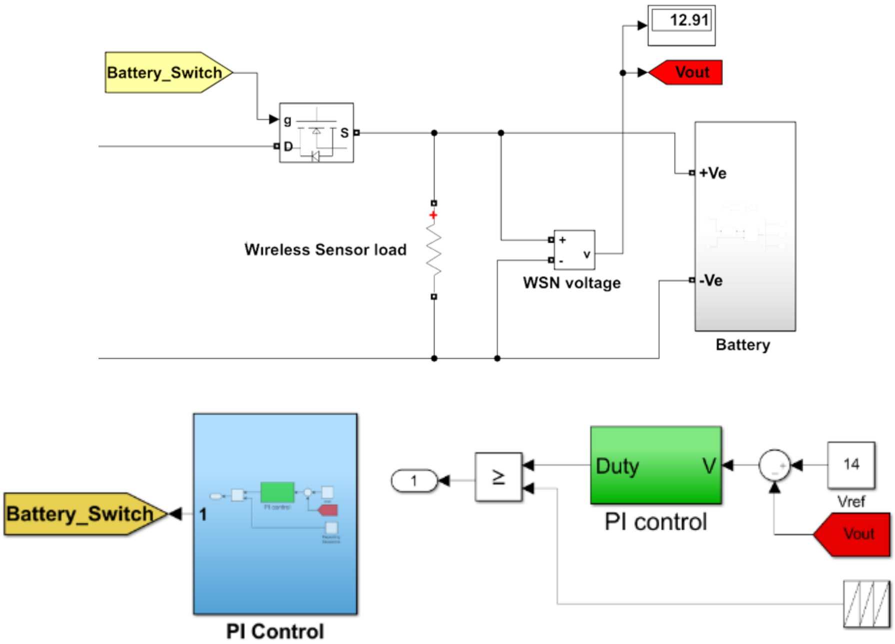


Figure 7. *Maximum power point tracking. Source: (Reza Reisi et al., 2013).*

2.5 Simulation framework and system design

This study employed a simulation-based design research methodology to evaluate the performance of various MPPT algorithms for solar energy harvesting in WSNs. The simulations were conducted using MATLAB/Simulink R2021b. The simulation framework was developed based on a modular system architecture, which integrates four main components: a PV panel, a DC-DC buck converter with MPPT controller, a lithium-ion battery, and a wireless sensor node. Each component is modelled to reflect realistic physical behaviours under dynamic environmental conditions.

2.5.1 Simulation architecture

The proposed energy harvesting system for WSNs consists of the following interconnected modules:

- Photovoltaic (PV) Panel: Modelled as a standard single-diode equivalent circuit using manufacturer-specified parameters. The selected panel has a maximum power output of 200 W with $V_{oc} = 36V$ and $I_{sc} = 7A$, and is designed to operate under variable irradiance and temperature conditions.
- DC-DC Buck Converter: Used to regulate the output voltage and current to ensure efficient power delivery to the battery and load. Converter design is based on standard equations for ripple current, duty cycle, and capacitor sizing, as presented by Hauke (2015) and implemented in Simulink.
- MPPT Controller: Four different MPPT techniques are integrated: P&O, IC, FL, and PSO. Each algorithm is implemented as a control logic block connected to the converter.
- Battery Storage: A rechargeable lithium-ion battery (nominal 12 V) is used to store the harvested energy and supply the WSN node. The charging process is regulated by a Proportional-Integral (PI) controller to ensure optimal state-of-charge (SoC) levels.

The overall system pipeline is shown in Figure 8.

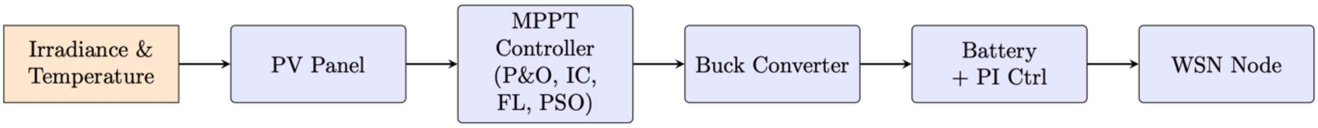


***Figure 8**. Diagram of the system structure.*

2.5.2 Simulation parameters

To simulate real-world performance, the following environmental and system-level parameters were used (Table 1):

***Table 1**. Simulation settings.*

Parameter	Value / Range
Solar Irradiance	200 – 1000 W/m²
Temperature Range	15°C – 50°C
PV Module V_{oc}	36 V
PV Module I_{sc}	7 A
Battery Capacity	12 V, 12 Ah (Li-ion)
Switching Frequency	50 kHz
Simulation Duration	10–60 seconds (extended)

2.5.3 MPPT algorithms implementation

Each MPPT technique was modelled and tested individually under the same environmental conditions to ensure fairness in comparison. The simulation recorded the following performance metrics for each algorithm:

- Tracking Efficiency (%)
- Response Time (s)
- Overshoot and Settling Time
- Energy Delivered to Battery (Wh)
- State of Charge (SoC) Fluctuations

The simulation inputs (irradiance and temperature) were applied as time-varying profiles to test the adaptability of the MPPT algorithms under dynamic environmental conditions. The outputs were analysed to assess algorithmic performance in terms of energy harvesting stability and efficiency.

Efficiency values (92%–98%) for each MPPT algorithm are drawn from representative values reported in previous comparative studies and are used here for performance simulation rather than algorithmic modelling.

In the absence of full algorithmic simulations for each MPPT technique within modelling framework, representative efficiency values were adopted from relevant literature to approximate algorithmic performance in a comparative context. Specifically, the simulation assumed typical efficiency levels for each algorithm based on prior empirical and simulation-based studies: 92% for P&O, 94% for IC, 96% for FL, and 98% for PSO. These values reflect widely reported performance trends across a range of environmental conditions and system setups. Başoğlu and Çakır (2015), Narwat and Dhillon (2021), and Salman et al. (2018) observed P&O efficiency around 92% under steady and variable irradiance. Başoğlu and Çakır (2015) demonstrated improved IC performance in the range of 93–95%. Narwat and Dhillon (2021) reported FL-based MPPT systems achieving up to 96% conversion under uncertain conditions. Gad (2022), in a systematic review, confirmed that PSO-based controllers often yield efficiencies between 97% and 99% due to their adaptive global optimization capabilities. Accordingly, these benchmark values provide a reasonable basis for algorithmic comparison of PV-based energy harvesting and battery charging.

2.5.4 Novelty and design rationale

What differentiates this study from existing works is the unified comparative modelling of four MPPT techniques within a WSN charging scenario that includes realistic irradiance-temperature interplay. Unlike conventional studies that test algorithms in static PV systems, this work emphasizes the end-to-end efficiency from solar energy input to battery SoC under EH-WSN conditions.

2.6 Proposed solution

To address the challenge of optimizing battery charging in EHWSNs, this study proposes a simulation-based comparative evaluation framework for MPPT algorithms under variable environmental conditions. The solution framework consists of a photovoltaic energy harvesting system modelled in MATLAB/Simulink and, in parallel, a simplified numerical model implemented in Python to validate algorithmic efficiency over extended operational time.

The core simulation model is structured around a modular PV system architecture comprising the following components:

- PV Panel: Modelled as a single-diode equivalent circuit with temperature- and irradiance-dependent characteristics (I_{sc}, V_{oc}).
- DC-DC Buck Converter: A power converter controlled via MPPT logic.
- MPPT Controller Block: Implemented with four distinct algorithms—P&O, IC, FL, and PSO.
- Battery Module: A 12 V lithium-ion battery controlled by a PI-based charge controller.

The system operates with variable irradiance and temperature inputs to reflect real-world outdoor conditions.

To compare the performance of the MPPT algorithms, the following quantitative metrics are employed:

- Tracking Efficiency (%): Ratio of power harvested to available PV power.
- Battery State of Charge (SoC): Monitored over time to measure energy transfer effectiveness.
- Charging Time (s): Time taken to reach full battery capacity from a predefined SoC.
- Response Time and Stability: Observed through overshoot and settling behaviour.

MATLAB/Simulink is used to implement block-based simulations for control design, converter response, and dynamic interactions between PV modules, converters, and batteries. Python is used for simplified simulations over extended durations using empirical MPPT efficiency values derived from the literature, enabling full-day performance visualization and analysis. This dual-environment approach enables both detailed system modelling and longer-term behavioural trends to be assessed with minimal computational overhead.

There are some assumptions and limitations in the study also. MPPT efficiencies (92%–98%) used in Python simulations are derived from literature-based approximations ((Başoğlu & Çakır, 2015; Gad, 2022; Narwat & Dhillon, 2021; Salman et al., 2018)) and do not represent full algorithmic dynamics. Battery discharge (load consumption) is not modelled in this study and is assumed negligible or externally regulated. PV output is assumed to be delivered entirely to the battery, without system losses beyond converter efficiency. Environmental conditions are idealized.

Despite these simplifications, the proposed model effectively demonstrates the comparative strengths and weaknesses of MPPT techniques in EH-WSNs under fluctuating conditions.

2.7 Environmental effects on PV panel performance

The performance of PV panels is highly sensitive to two environmental parameters: solar irradiance (G) and ambient temperature (T). Accurate modeling of these dependencies is essential for realistic simulation and performance evaluation of energy harvesting systems. The output characteristics of a PV module—most notably the short-circuit current (I_{sc})and open-circuit voltage (V_{oc})—are directly influenced by G and T, and can be approximated using the following standard equations (Equations (9) and (10)):

$$I_{sc}(G,T) = I_{sc,ref} \cdot \left(\frac{G}{G_{ref}}\right) + \alpha_{I_{sc}} \cdot (T - T_{ref}) \tag{9}$$

$$V_{oc}(T) = V_{oc,ref} + \beta_{V_{oc}} \cdot (T - T_{ref}) \tag{10}$$

where:

- $I_{sc,ref}$ and $V_{oc,ref}$ are reference values at standard test conditions (STC),
- $G_{ref} = 1000W/m^2$, $T_{ref} = 25°C$,
- $\alpha_{I_{sc}}$ is the temperature coefficient of current (A/°C),
- $\beta_{V_{oc}}$ is the temperature coefficient of voltage (V/°C).

In this study, the following typical values are used for simulation purposes:

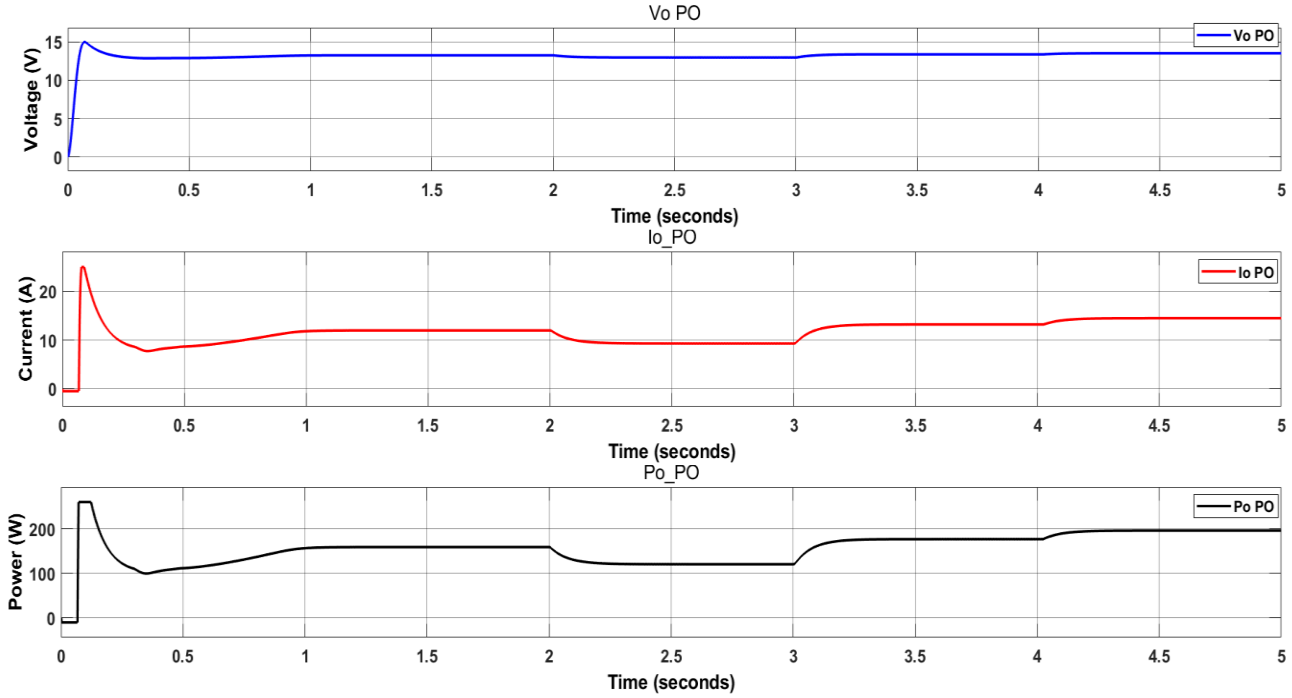
- $I_{sc,ref} = 7A$,
- $V_{oc,ref} = 36V$,
- $\alpha_{I_{sc}} = 0.0006$A/°C,
- $\beta_{V_{oc}} = -0.123V$/°C.

To illustrate the impact of environmental changes the conditions are divided into three periods:

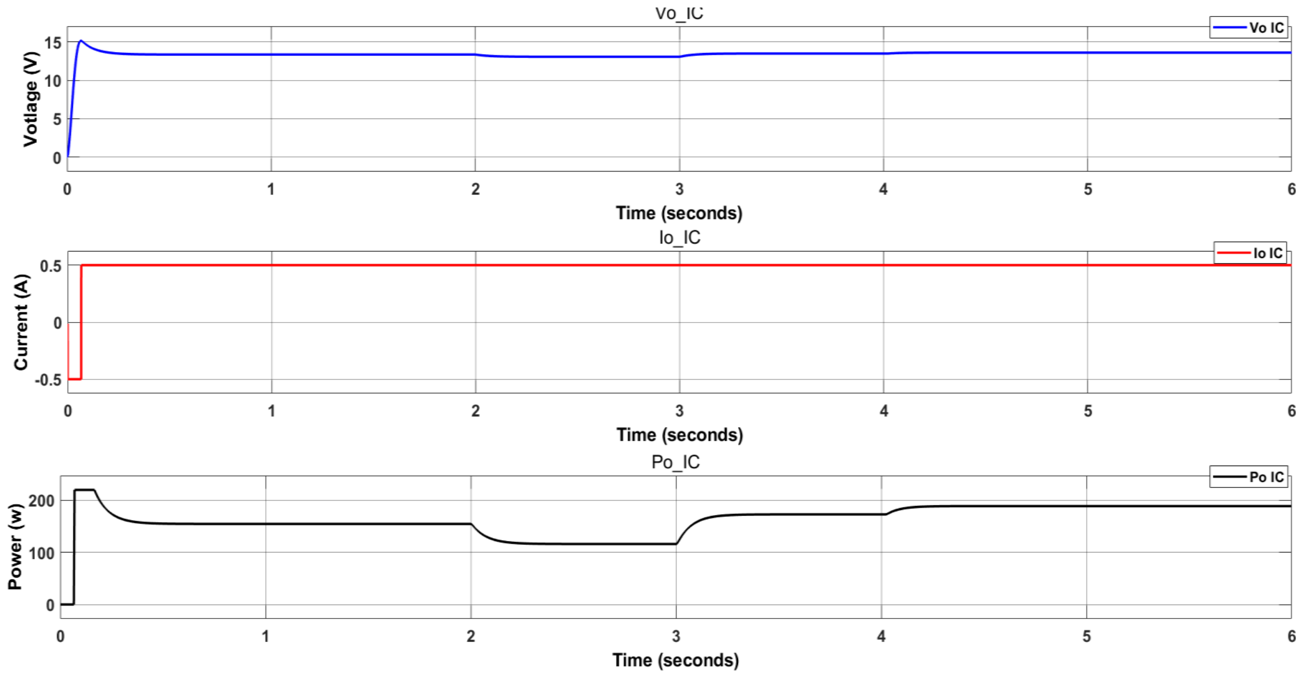
- 0–20s: Moderate irradiance (800 W/m²), baseline temperature (25°C),
- 20–40s: Low irradiance (400 W/m²), high temperature (35°C),
- 40–60s: High irradiance (1000 W/m²), low temperature (20°C).

3 RESULTS AND DISCUSSION

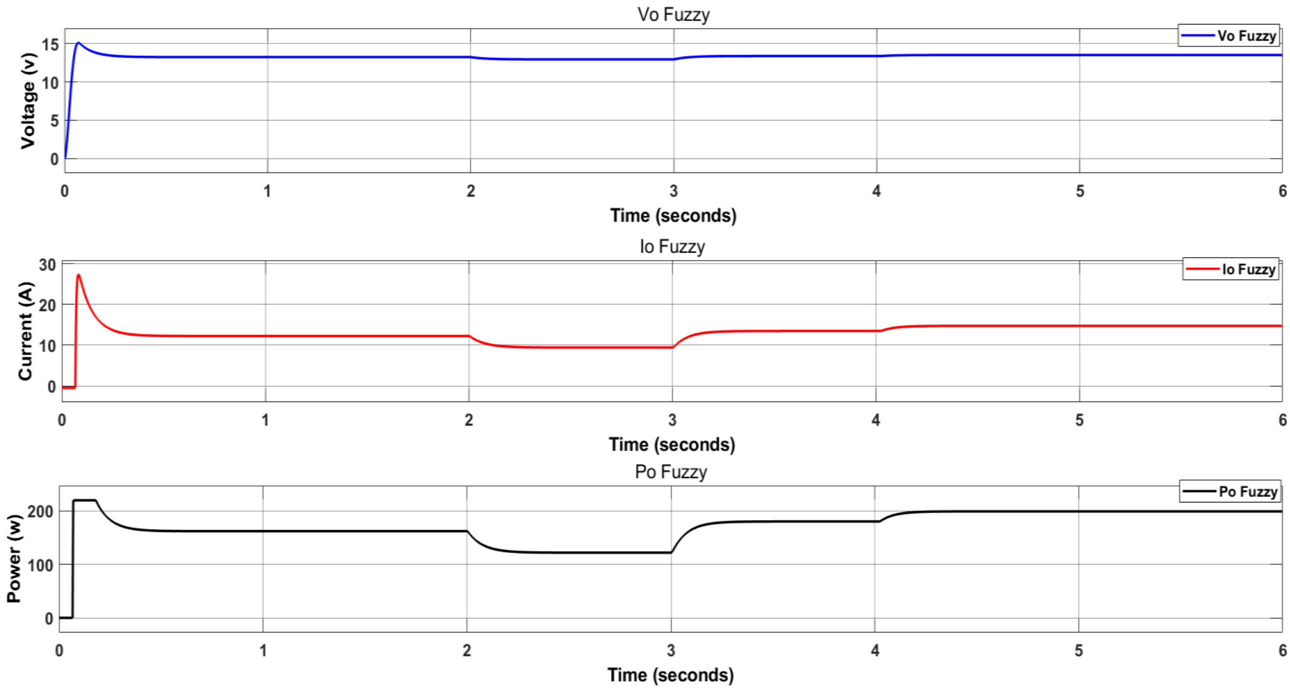
This section presents the results obtained from simulating the algorithms. Figure 9 displays the outputs of these four MPPT algorithms (P&O, IC, FL, and PSO) respectively, implemented in this study.



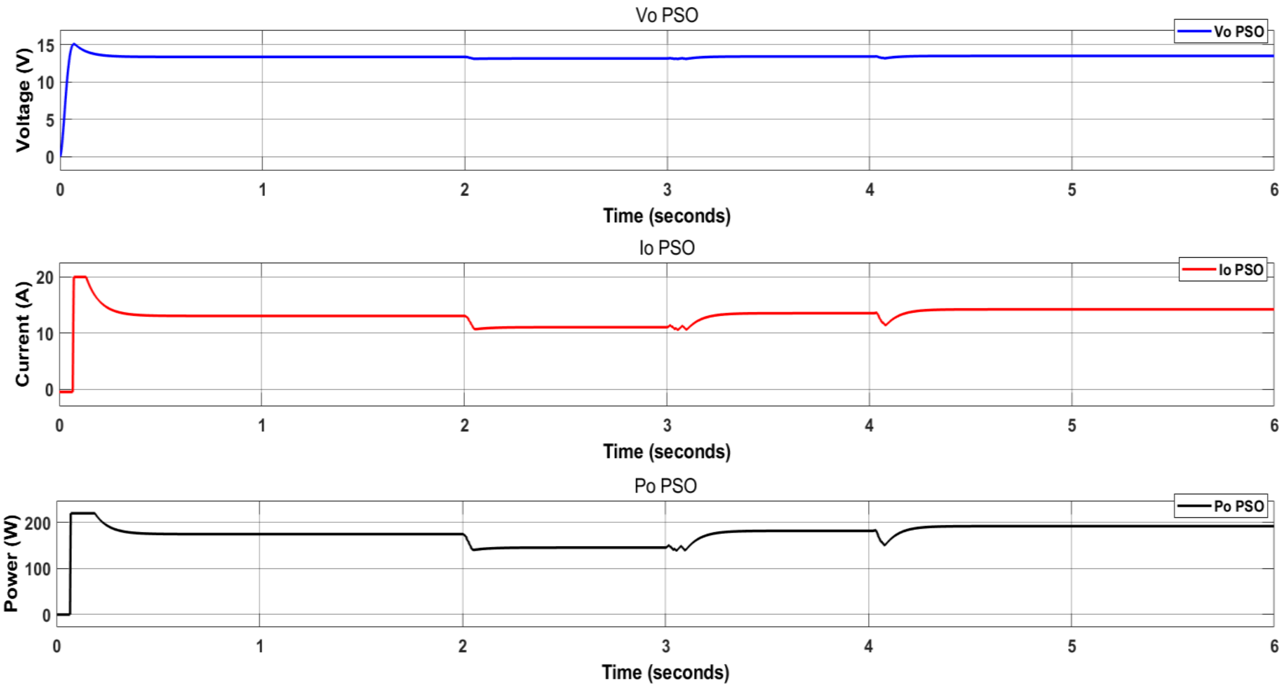
(A)


Vo_IC
Vo IC
Voltage (V)
15
10
5
0
0
1
2
3
4
5
6
Time (seconds)
Io_IC
Io IC
Current (A)
0.5
0
-0.5
0
1
2
3
4
5
6
Time (seconds)
Po_IC
Po IC
Power (w)
200
100
0
0
1
2
3
4
5
6
Time (seconds)

(B)


Vo Fuzzy
Vo Fuzzy
Voltage (v)
15
10
5
0
0
1
2
3
4
5
6
Time (seconds)
Io Fuzzy
Io Fuzzy
Current (A)
30
20
10
0
0
1
2
3
4
5
6
Time (seconds)
Po Fuzzy
Po Fuzzy
Power (w)
200
100
0
0
1
2
3
4
5
6
Time (seconds)

(C)



(D)

***Figure 9**. Outputs of the MPPT algorithms implemented in the study: (A) P&O, (B) IC, (C) FL, and (D) PSO.*

Figure 10 shows the short-term responses to measure the response of the outputs of the algorithms at initial startup.

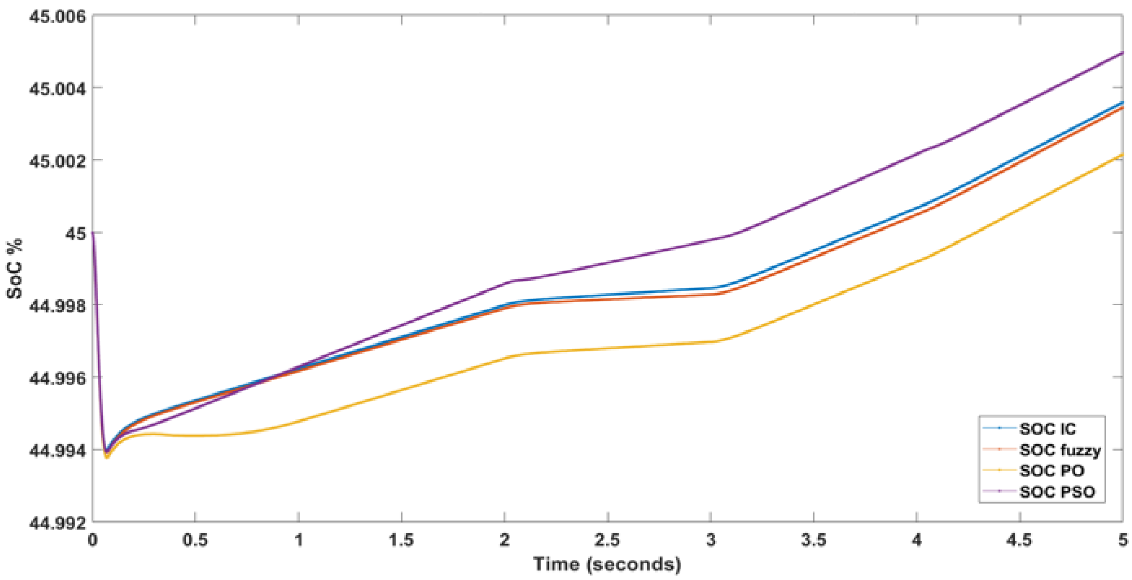


***Figure 10**. State of charge of WSN battery comparing with proposed MPPT methods.*

A longer (60seconds) power output comparison is presented in Figure 11. In Figure 11, Simulated PV power output over a 60-second period under dynamic environmental conditions and four different MPPT algorithms. The irradiance profile changes from 800 W/m² (0–20 s), to 400 W/m² (20–40 s), and finally to 1000 W/m² (40–60 s). Correspondingly, the temperature varies from 25°C, to 35°C, and then drops to 20°C. The PV panel is characterized by a reference short-circuit current $I_{sc,ref} = 7A$ and $V_{oc,ref} = 36V$, with appropriate temperature coefficients applied. MPPT efficiencies are assumed to be 92% (P&O), 94% (IC), 96% (FL), and 98% (PSO).

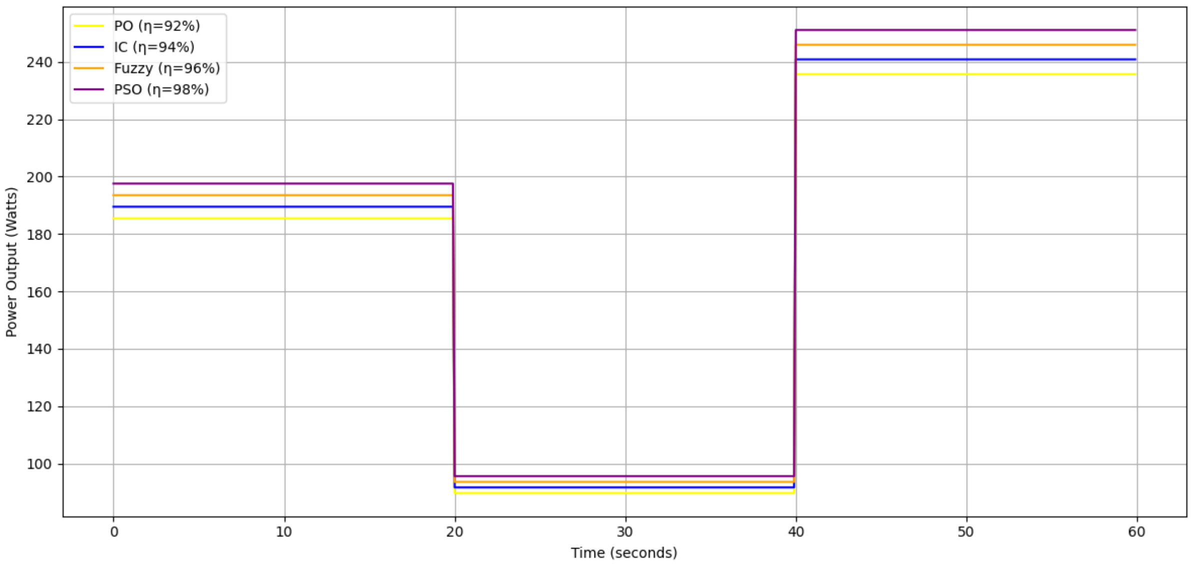


***Figure 11**. Outputs of the MPPT algorithms for extended time.*

As seen in Figure 11, all algorithms respond to environmental fluctuations in real-time, with PSO consistently achieving the highest power extraction. A noticeable drop in output is observed during the low irradiance phase (20–40 s), though efficiency-based differences between the algorithms remain distinguishable throughout the simulation.

Based on our comparison of the four algorithms: PSO, P&O, IC, and FL - with respect to the state of charge (SoC), PSO appears to be the most effective approach for optimizing battery charging in WSNs, as shown in Figure 12.

When evaluating the SoC of a WSN battery under different MPPT methods, PSO yields a high state of charge in a shorter time to reach full capacity. In contrast, IC, and fuzzy logic result in a normal state of charge, while the PO technique appears to be less effective, needing more time to charge the WSN battery and delivering a suboptimal state of charge. The choice of MPPT technique can significantly influence the efficiency of energy harvesting, thereby affecting the WSN battery's SoC. Graph representing the 24-hour simulation for PSO algorithm is presented in Figure 12.

Results of a 24-hour simulation illustrating the photovoltaic (PV) system’s performance and battery charging behavior under varying solar irradiance and ambient temperature conditions. The top panel shows the irradiance profile, which follows a clear-sky sinusoidal pattern from sunrise (06:00) to sunset (18:00), peaking at noon. The middle panel presents the resulting PV power output (W), calculated using irradiance- and temperature-dependent I_{sc} and V_{oc} values, with a fixed MPPT efficiency of 98% (PSO algorithm). The bottom panel displays the battery’s state of charge (SoC), which starts at 20% and steadily increases throughout the day, reaching full capacity by mid-afternoon. The results emphasize the effectiveness of PSO-based MPPT in maximizing energy harvesting and ensuring efficient battery charging in realistic environmental conditions. This 24-hour simulation demonstrates the significant impact of diurnal irradiance and temperature cycles on the performance of a PV-based energy harvesting system and its associated battery charging process. As solar irradiance increases from sunrise and peaks at midday, the PV power output correspondingly rises, reflecting the panel’s sensitivity to environmental input. The power curve also integrates temperature effects, which slightly reduce voltage output during warmer hours. The battery’s state of charge (SoC), starting from 20%, exhibits a continuous upward trend during daylight, achieving full charge in the early afternoon. This result confirms the PSO algorithm’s ability to extract and utilize solar energy efficiently throughout the day, ensuring optimal battery performance even under fluctuating atmospheric conditions. The simulation highlights how system design and MPPT selection must account for environmental dynamics to sustain reliable energy supply in real-world wireless sensor network deployments.

While all four algorithms aim to track the MPP of PV systems, their efficacy can vary. Based on the presented data in Figure 13 and Figure 14, PSO stands out as the most efficient algorithm in this study, showing superior performance in various conditions. However, the choice of algorithm can often depend on the specific application and requirements of the PV system.

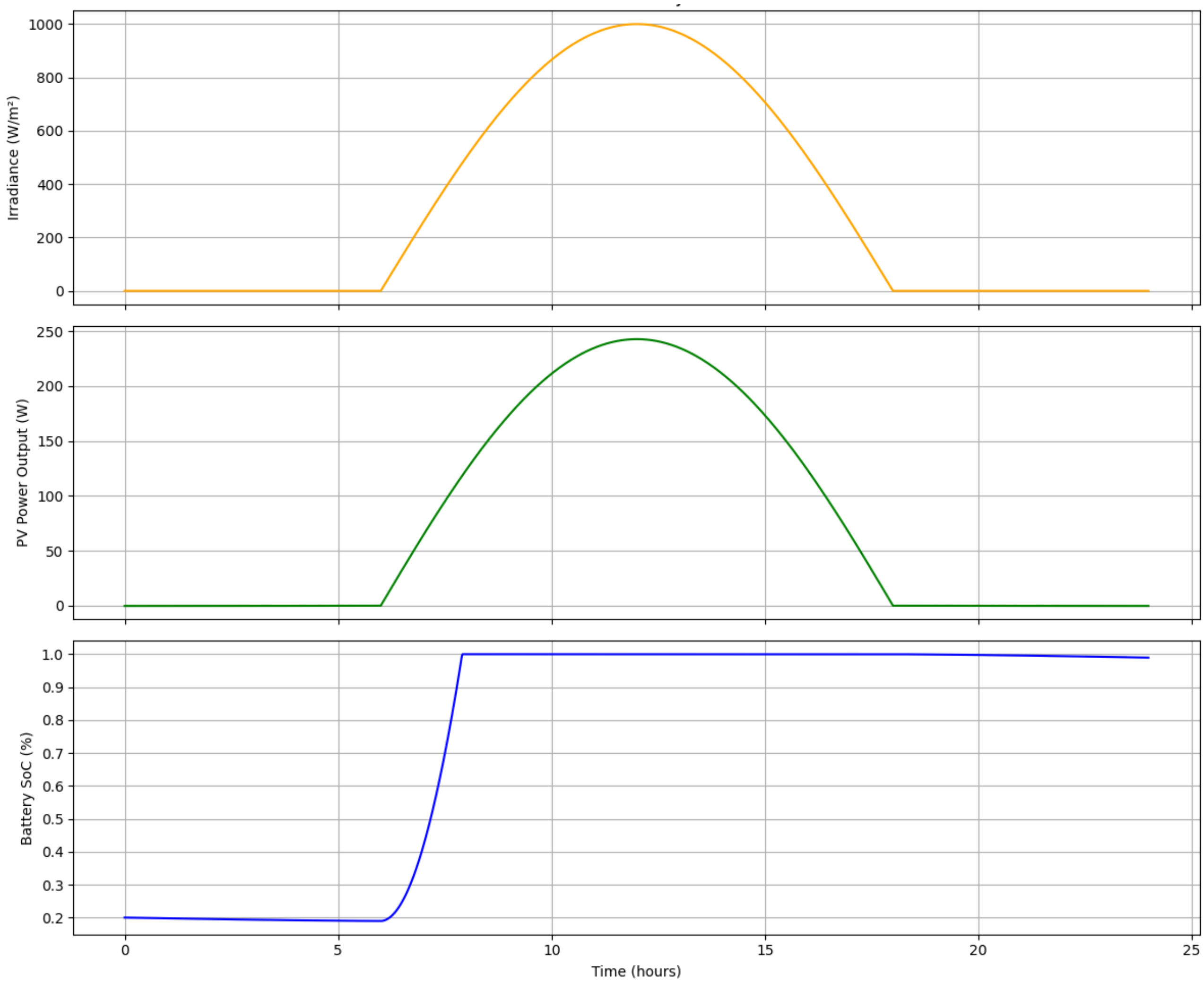


***Figure 12**. 24-Hour PV Irradiance and Battery SoC (MPPT-Controlled).*

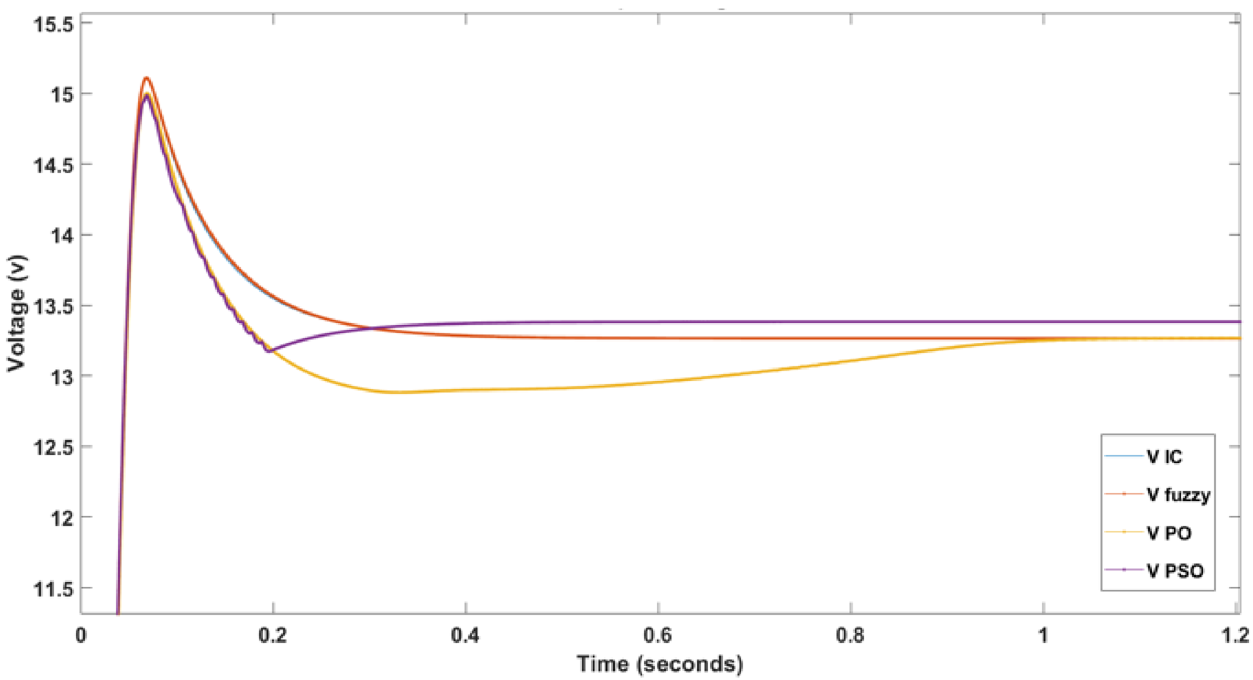


***Figure 13**. Wireless sensor output voltage in different algorithms.*

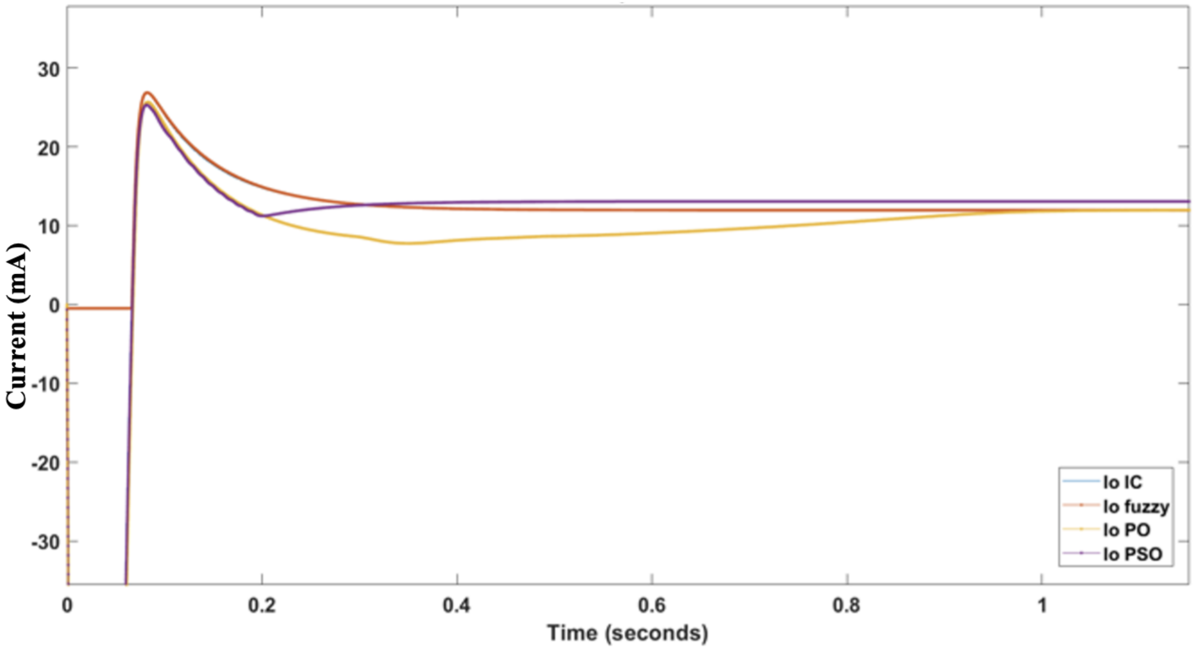


Figure 14*. Wireless sensor output current in different algorithms.*

The PSO algorithm exhibits a low overshoot of 14.8v and 25 mA at 0.1 seconds, followed by the P&O algorithm with an overshoot of 15v and 25.5 mA. Both the IC and FL algorithms displayed a higher overshoot, registering at 15.3v and 27 mA at 0.1 seconds. In terms of settling time, the PSO, IC, and FL algorithms all took a settling time of 0.3 seconds; however, PSO displayed superior tracking when compared to the other methods. Conversely, the P&O algorithm required a longer 1-second settling time, indicating its inferior performance. As depicted in Figure 15 concerning output power, the PSO algorithm outperformed the others, delivering the highest power. This was followed by the IC and FL algorithms, while the P&O algorithm lagged, showcasing the weakest power performance.

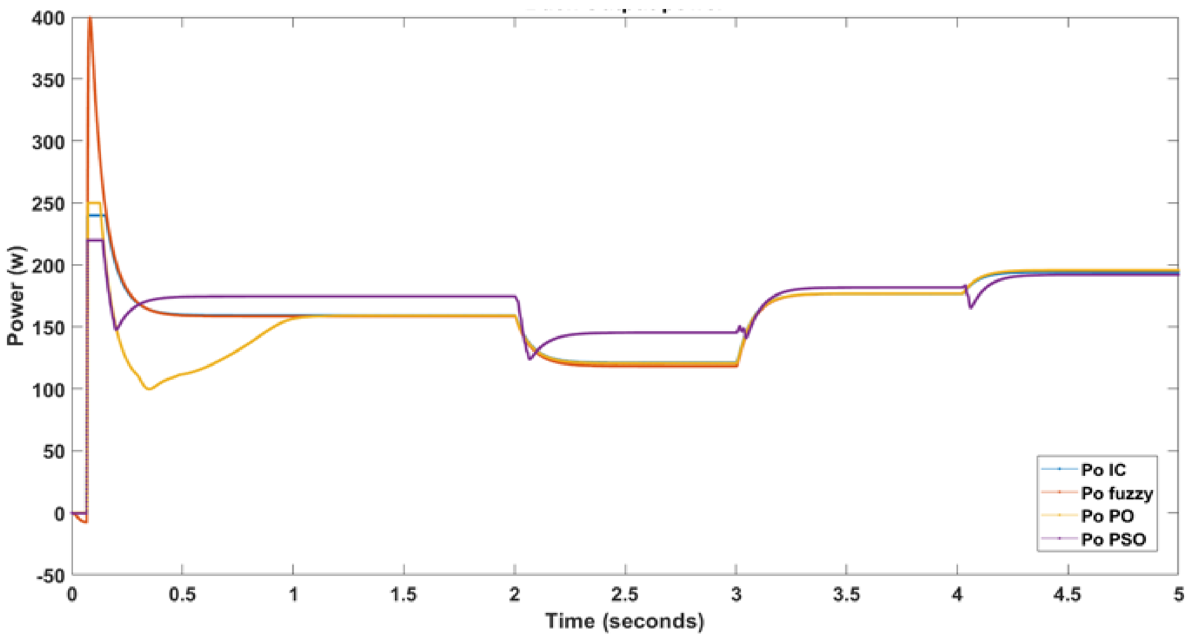


Figure 15*. Wireless sensor output power in different algorithms.*

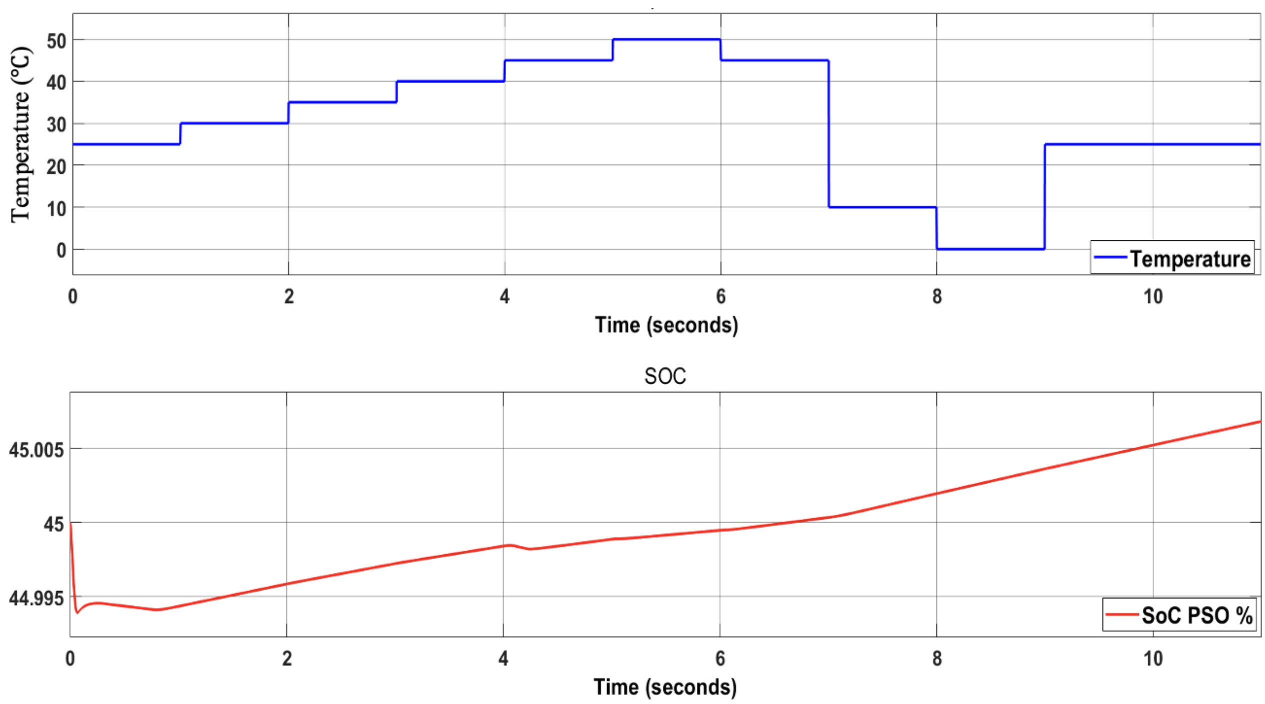
P&O method demonstrates poor performance compared to the other algorithms. It's known for being simple to implement, but its effectiveness is limited due to oscillations around the MPP and poor adaptability to rapidly changing environmental conditions. IC algorithm shows good results. IC is more accurate in tracking the MPP, and it can adapt better to varying environmental conditions compared to the P&O method. However, it is slightly more complex to implement and has a slower response time. FL method also yields good results. It is a more intelligent approach, with a flexible rule-based control strategy that can adapt to different environmental conditions. The main advantages are its robustness and ability to deal with nonlinear and complex systems. Nevertheless, it requires more computational power and tuning of the fuzzy rule base, which can be time-consuming. PSO algorithm has the best performance among the four in terms of voltage, current, and power. PSO is a metaheuristic optimization technique inspired by the social behaviour of bird flocking or fish schooling. It can find the global MPP more efficiently than other methods and adapts well to changing conditions. Despite its effectiveness, the PSO algorithm demands more computational resources compared to other methods, and its implementation can be more complex. So, from results PSO is the most suitable algorithm for optimizing the charging of WSN batteries, with IC and FL being good alternatives. Table 2 shows the comparison of algorithms with each other.

***Table 2**. Comparison of algorithms with each other.*

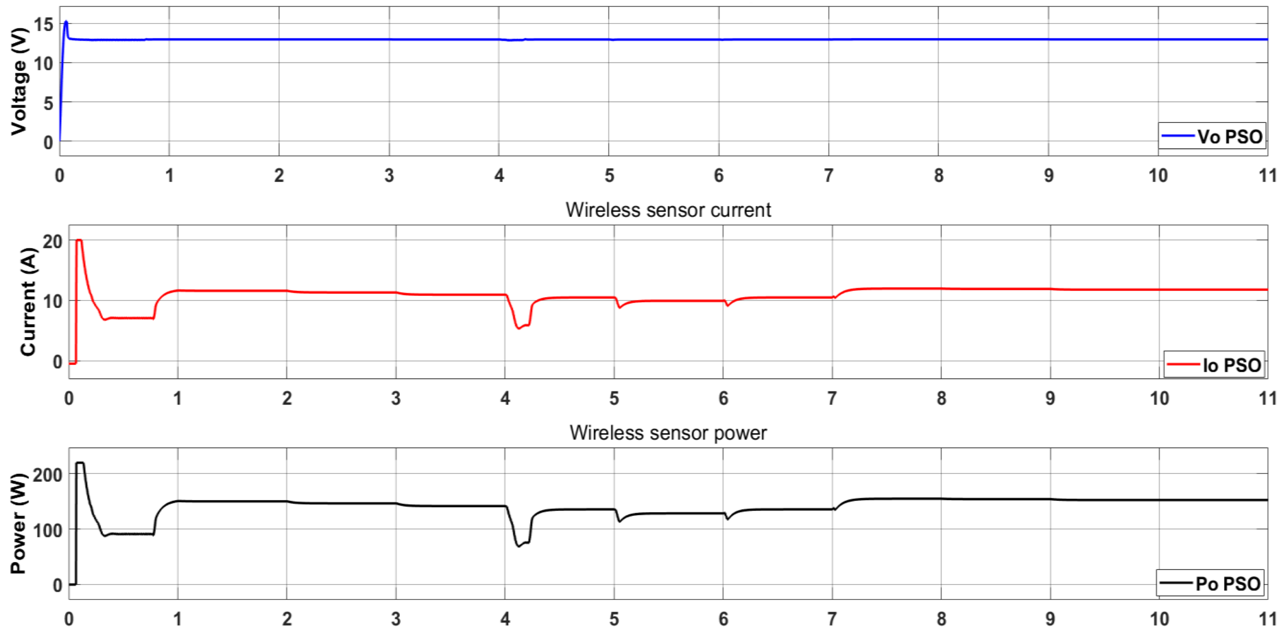
MPPT Algorithm	Performance	WSN-SOC %	Implementation
PO	Poor	low	Simple to implement
IC	Good	Medium	More accurate MPP tracking; Better adaptability than P&O
Fuzzy	Good	Medium	Time-consuming rule base tuning
PSO	Best	High	More complex implementation

WS are powered by batteries, these batteries can be recharged using renewable energy sources such as solar panels. The efficiency of this charging process can be significantly affected by weather conditions. In this study, we also studied the effect of Temperature and Solar Irradiance effected on WS charging with the best resulted algorithm -PSO-.

Figure 16 demonstrates the impact of temperature on battery charging while keeping the solar irradiance constant at 1000 W/m². The graph depicts the relationship between temperature and the charging efficiency or rate of the battery. It indicates how higher or lower temperatures affect the charging process. So, the difference of temperature will not affect in battery charging because the high performance of PSO MPPT algorithm.



(A)



(B)

***Figure 16**. (A) WSN battery under variable temperature condition, (B) Wireless sensor load voltage, current, and power under different temperature with constant irradiance 1000 W/m^2.*

Figure 17 represents the real-time influence of irradiance and temperature on PV power output when operating under a high-efficiency MPPT algorithm (PSO, η = 98%).

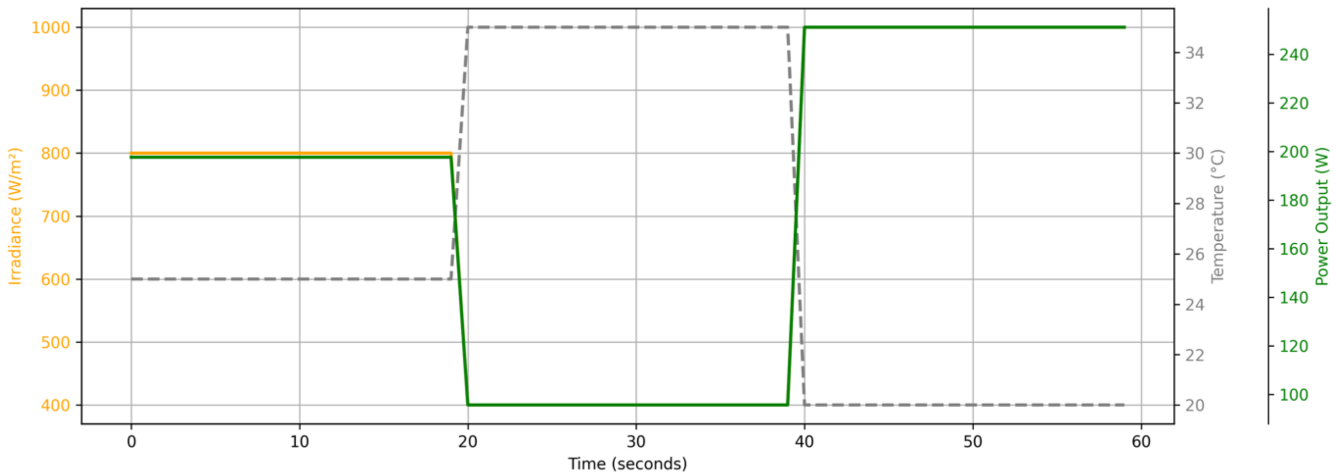
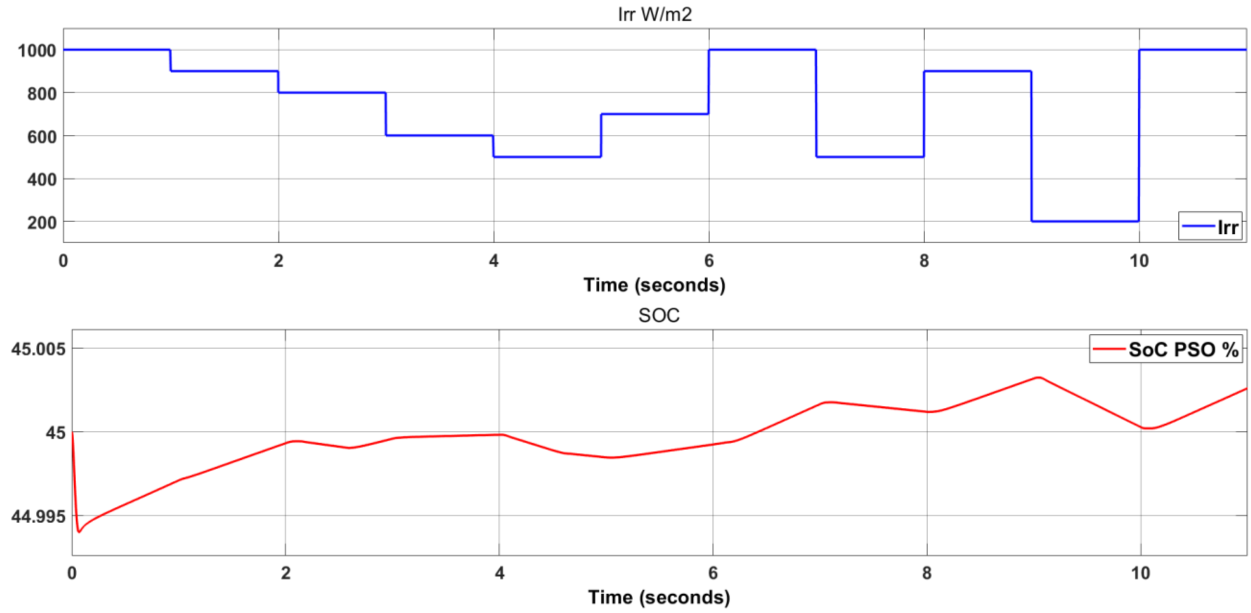


***Figure 17**. Environmental Influence on PV Output (60-Second Simulation, PSO Algorithm).*

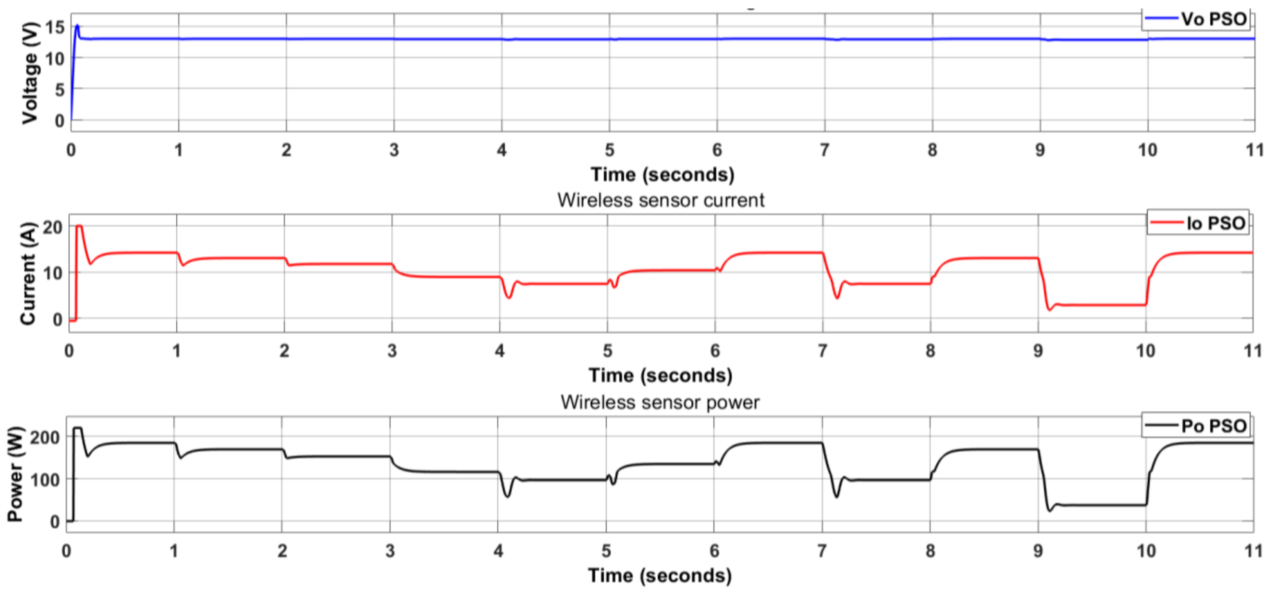
Influence of environmental conditions on PV power output under PSO-based MPPT control during a 60-second simulation. The orange line (left axis) represents solar irradiance (W/m²), reflecting varying sunlight intensity over time. The gray dashed line (right axis) shows ambient temperature (°C), which affects the panel's open-circuit voltage. The green line (far right axis) indicates the resulting PV power output (W), calculated based on real-time irradiance and temperature using temperature- and irradiance-dependent equations for I_{sc} and V_{oc}. The simulation demonstrates the critical impact of environmental dynamics on energy harvesting performance.

Figure 17 clearly demonstrates how sensitive the power output of a PV panel is to environmental conditions—particularly solar irradiance and ambient temperature. During the simulation, both irradiance and temperature were varied across three distinct intervals, resulting in noticeable fluctuations in PV output. In the first 20 seconds, moderate irradiance (800 W/m²) and baseline temperature (25°C) produced a medium level of power. In the next 20 seconds, a decrease in irradiance and an increase in temperature led to a significant drop in power output. During the final 20 seconds, irradiance peaked at 1000 W/m² while the temperature dropped to 20°C, creating optimal conditions for maximum power generation. These results highlight the critical role of environmental factors in the performance of PV systems and emphasize the importance of using high-efficiency MPPT techniques like PSO to adapt effectively to changing conditions.

Figure 18 illustrates the influence of solar irradiance on the charging of a wireless sensor battery load, with the temperature held constant at 25 degrees Celsius. The Figure displays the relationship between solar irradiance, measured in units such as watts per square meter (W/m²), and the charging efficiency or rate of the wireless sensor battery. It demonstrates how different levels of solar irradiance impact the charging process, with higher irradiance resulting in faster charging and lower irradiance leading to slower or no charging.



(A)



(B)

Figure 18. *(A) WSN battery under variable solar irradiance condition, (B) Wireless sensor load voltage, current and power under different irradiation condition with constant temperature 25 degree.*

The weather conditions, specifically temperature and solar irradiance, have a significant impact on the battery charging process of WS. Both high and low temperatures can reduce battery capacity and longevity, affecting the overall efficiency of the charging process. Extremely cold temperatures can lead to a loss of capacity in lithium-ion batteries commonly used in WS devices, while high temperatures can accelerate battery degradation.

Moreover, solar irradiance plays a crucial role in the efficiency of solar charging for WS batteries. Cloudy or rainy weather conditions diminish the amount of sunlight reaching the solar panels, resulting in slower charging rates or no charging at all if the sunlight is too weak. Figure 18 demonstrates the impact of solar irradiance on the charging process, showing the relationship between different levels of irradiance and the charging efficiency or rate of the wireless sensor battery.

Understanding these effects is vital for optimizing the performance and reliability of WSNs. By considering the weather conditions and their impact on battery charging, researchers and practitioners can develop strategies to mitigate the negative effects and improve the overall efficiency and longevity of WSN batteries. This knowledge can lead to the development of more robust and sustainable WSN systems, ensuring their reliable operation even in challenging environmental conditions.

4 CONCLUSION

This study presented a comprehensive analysis of four prominent MPPT algorithms—P&O, IC, FL, and PSO—within photovoltaic EHWSNs under dynamically changing environmental conditions. Simulations based on both short-term (60 seconds) and extended (24-hour) scenarios revealed that solar irradiance and ambient temperature significantly influence PV panel performance, battery charging rate, and overall system efficiency. Mathematical modelling of PV behaviour showed that both I_{sc} and V_{oc} are highly sensitive to environmental inputs, and visualization of these effects confirmed that adaptive MPPT algorithms are essential for optimal energy harvesting.

Among the evaluated algorithms, PSO demonstrated the most robust performance, achieving the highest power output, the fastest tracking response (0.1 s), and the lowest overshoot (14.8 V, 25 mA). In comparison, P&O, while simple, exhibited slower response times (1 s settling) and the lowest efficiency. IC and FL offered moderate overshoot (15.3 V, 27 mA) with a settling time of 0.3 seconds and were identified as promising alternatives in scenarios where computational resources are limited.

Additionally, comparative battery charging simulations illustrated that PSO led to the fastest and most complete charging, followed by FL and IC, while P&O consistently lagged. These findings were further validated through Python-based performance simulations using literature-informed efficiency approximations (%92–98), demonstrating how algorithmic differences manifest in both power output and battery state-of-charge evolution.

Despite its superior performance, PSO's computational complexity may pose challenges for real-time, low-power embedded systems, especially in constrained WSN environments. Therefore, IC and FL are recommended as efficient fallback options when system simplicity or power constraints are paramount.

In conclusion, this research emphasizes the importance of integrating environmental awareness into MPPT strategies, selecting MPPT algorithms aligned with system capabilities, and choosing battery technologies resilient to environmental stressors. The findings contribute to designing more adaptive, efficient, and resilient energy harvesting solutions for next-generation WSNs deployed in diverse and variable conditions.

ADDITIONAL INFORMATION AND DECLARATIONS

Conflict of Interests: The authors declare no conflict of interest

Author Contributions: A.F.N.S.: Conceptualization, Formal analysis, Methodology, Software, Validation, Visualization, Writing – original draft. S.S.: Conceptualization, Methodology, Formal analysis, Supervision, Validation, Visualization, Writing – original draft, Writing – review & editing. O.G.: Conceptualization, Methodology, Validation, Writing – original draft, Writing – review & editing.

Statement on the Use of Artificial Intelligence Tools: The authors declare that they didn't use artificial intelligence tools for text or other media generation in this article.

REFERENCES

Akyildiz, I. F., Su, W., Sankarasubramaniam, Y., & Cayirci, E. (2002). Wireless sensor networks: a survey. *Computer Networks*, 38(4), 393–422. https://doi.org/10.1016/S1389-1286(01)00302-4

Alsharif, M. H., Kim, S., & Kuruoğlu, N. (2019). Energy Harvesting Techniques for Wireless Sensor Networks/Radio-Frequency Identification: A Review. *Symmetry*, 11(7). https://doi.org/10.3390/sym11070865

Alsharif, M. H., Nordin, R., & Ismail, M. (2015). Energy optimisation of hybrid off-grid system for remote telecommunication base station deployment in Malaysia. *Eurasip Journal on Wireless Communications and Networking*, 2015(1), Article 64. https://doi.org/10.1186/S13638-015-0284-7

Ammari, H. M. (2014). *The Art of Wireless Sensor Networks*. Springer. https://doi.org/10.1007/978-3-642-40066-7

Anand, M., Anusha, N., Anitha, P., Chaitanyalaksmi, G., & Divyashree, J. K. (2021). An Efficient Solar Energy Harvesting Management with MPPT for WSN. *International Journal of Research in Engineering, Science and Management*, 4(8), 250–253.

Antony, S. M., Indu, S., & Pandey, R. (2020). An efficient solar energy harvesting system for wireless sensor network nodes. *Journal of Information and Optimization Sciences*, 41(1), 39–50. https://doi.org/10.1080/02522667.2020.1714182

Ay, İ., Kademli, M., Savaş, S., Karellas, S., Markopoulos, A., Hatzilau, C.-S., Devlin, P., Duşbudak, H., Arslan, A. S., Koç, M., Duraklar, K., Sunal, K., & Ozer, M. M. (2023). Smart Maintenance with Regression Analysis for Efficiency Improvement in Photovoltaic Energy Systems. *Journal of Solar Energy Research*, 8(4), 1663–1679. https://doi.org/10.22059/JSER.2023.363200.1335

Ay, İ., Kademli, M., Karabulut, S., & Savas, S. (2022). Affecting Factors of Efficiency in Photovoltaic Energy Systems and Productivity-Enhancing Suggestions. In *2022 Innovations in Intelligent Systems and Applications Conference,* (pp. 1–6). IEEE. https://doi.org/10.1109/ASYU56188.2022.9925271

Başoğlu, M. E., & Çakır, B. (2015). An improved incremental conductance based MPPT approach for PV modules. *Turkish Journal of Electrical Engineering and Computer Sciences*, 23(6), 1687–1697. https://doi.org/10.3906/elk-1404-196

Cao, L., Wang, Z., & Yue, Y. (2022). Analysis and Prospect of the Application of Wireless Sensor Networks in Ubiquitous Power Internet of Things. *Computational Intelligence and Neuroscience*, 2022, 9004942. https://doi.org/10.1155/2022/9004942

Colesanti, U. M., Santini, S., & Vitaletti, A. (2011). DISSense: An adaptive ultralow-power communication protocol for wireless sensor networks. In *2011 International Conference on Distributed Computing in Sensor Systems and Workshops, DCOSS'11*. IEEE. https://doi.org/10.1109/DCOSS.2011.5982162

Cubas, J., Pindado, S., & De Manuel, C. (2014). Explicit Expressions for Solar Panel Equivalent Circuit Parameters Based on Analytical Formulation and the Lambert W-Function. *Energies*, 7(7), 4098–4115. https://doi.org/10.3390/en7074098

Gad, A. G. (2022). Particle Swarm Optimization Algorithm and Its Applications: A Systematic Review. *Archives of Computational Methods in Engineering*, 29(5), 2531–2561. https://doi.org/10.1007/S11831-021-09694-4

Getahun, M., Azath, M., Sharma, D. P., Tuni, A., & Adane, A. (2022). Efficient Energy Utilization Algorithm through Energy Harvesting for Heterogeneous Clustered Wireless Sensor Network. *Wireless Communications and Mobile Computing*, 2022, 4154742. https://doi.org/10.1155/2022/4154742

Hauke, B. (2015). Basic Calculation of a Buck Converter's Power Stage. Texas Instruments. https://www.ti.com/lit/an/slva477b/slva477b.pdf

Hidalgo-Leon, R., Urquizo, J., Silva, C. E., Silva-Leon, J., Wu, J., Singh, P., & Soriano, G. (2022). Powering nodes of wireless sensor networks with energy harvesters for intelligent buildings: A review. *Energy Reports*, 8, 3809–3826. https://doi.org/10.1016/J.EGYR.2022.02.280

Lakshmi, S., & Raja, S. R. (2014). Design and implementation of an observer controller for a buck converter. *Turkish Journal of Electrical Engineering and Computer Sciences*, 22(3), 562–572. https://doi.org/10.3906/elk-1208-41

Mazunga, F., & Nechibvute, A. (2021). Ultra-low power techniques in energy harvesting wireless sensor networks: Recent advances and issues. *Scientific African*, 11, e00720. https://doi.org/10.1016/J.SCIAF.2021.E00720

Melikov, A., & Rustamov, A. (2012). Queuing Management in Wireless Sensor Networks for QoS Measurement. *Wireless Sensor Network*, 4(9), 211–218. https://doi.org/10.4236/WSN.2012.49031

Narwat, L. K., & Dhillon, J. (2021). Design and Operation of Fuzzy Logic Based MPPT Controller under Uncertain Condition. *Journal of Physics: Conference Series*, 1854(1), 012035. https://doi.org/10.1088/1742-6596/1854/1/012035

Ponnimbaduge Perera, T. D., Jayakody, D. N. K., Sharma, S. K., Chatzinotas, S., & Li, J. (2018). Simultaneous Wireless Information and Power Transfer (SWIPT): Recent Advances and Future Challenges. *IEEE Communications Surveys & Tutorials*, 20(1), 264–302. https://doi.org/10.1109/COMST.2017.2783901

Reza Reisi, A., Hassan Moradi, M., & Jamasb, S. (2013). Classification and comparison of maximum power point tracking techniques for photovoltaic system: A review. *Renewable and Sustainable Energy Reviews*, 19, 433–443. https://doi.org/10.1016/J.RSER.2012.11.052

Rokonuzzaman, M. D., Mishu, M. K., Amin, N., Nadarajah, M., Roy, R. B., Rahman, K. S., Buhari, A. M., Binzaid, S., Shakeri, M., & Pasupuleti, J. (2021). Self-Sustained Autonomous Wireless Sensor Network with Integrated Solar Photovoltaic System for Internet of Smart Home-Building (IoSHB) Applications. *Micromachines*, 12(6), 653. https://doi.org/10.3390/MI12060653

Salman, S., Ai, X., & Wu, Z. (2018). Design of a P-&-O algorithm based MPPT charge controller for a stand-alone 200W PV system. *Protection and Control of Modern Power Systems*, 3(1), 1–8. https://doi.org/10.1186/S41601-018-0099-8/FIGURES/10

Sharma, H., Haque, A., & Jaffery, Z. A. (2018). Modeling and Optimisation of a Solar Energy Harvesting System for Wireless Sensor Network Nodes. *Journal of Sensor and Actuator Networks*, 7(3), 40. https://doi.org/10.3390/JSAN7030040

Singh, J., Kaur, R., & Singh, D. (2021). Energy harvesting in wireless sensor networks: A taxonomic survey. *International Journal of Energy Research*, 45(1), 118–140. https://doi.org/https://doi.org/10.1002/er.5816

Sucupira, L., & Castro-Gomes, J. (2021). Review of Energy Harvesting for Buildings Based on Solar Energy and Thermal Materials. *CivilEng*, 2(4), 852–873. https://doi.org/10.3390/civileng2040046

Vinod, Kumar, R., & Singh, S. K. (2018). Solar photovoltaic modeling and simulation: As a renewable energy solution. *Energy Reports*, 4, 701–712. https://doi.org/10.1016/J.EGYR.2018.09.008

You, S., Eshraghian, J. K., Iu, H. C., & Cho, K. (2021). Low-Power Wireless Sensor Network Using Fine-Grain Control of Sensor Module Power Mode. *Sensors*, 21(9), 3198. https://doi.org/10.3390/s21093198

Acta Informatica Pragensia is published by the Prague University of Economics and Business, Czech Republic │ eISSN: 1805-4951