Development of IoT-Based MPPT System Using Perturb and Observe Algorithm on Solar Panels

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This study successfully designed and implemented an IoT-based Maximum Power Point Tracking (MPPT) system using the Perturb and Observe (P&O) algorithm for a 100 Wp polycrystalline solar panel. The research aims to provide an integrated, cost-effective solution for optimizing solar energy extraction in Indonesia's tropical climate. The methods employed include mathematical modeling, system simulation in MATLAB/Simulink, and hardware implementation using an ESP32 microcontroller with sensors for voltage, current, irradiance, and temperature, integrated with the ThingSpeak IoT platform for real-time monitoring. System validation showed high accuracy with a Root Mean Square Error of 0.83 W. The hardware system achieved an average MPPT tracking efficiency of 95.36% with a response time of 2.05 seconds and power oscillation of 3.17%, contributing to a significant 24.8% increase in daily energy yield compared to a non-MPPT system. IoT performance metrics showed a data transmission success rate of 97.08%, average latency of 2.82 seconds, and system uptime of 99.12%. This integrated MPPT-IoT system offers a practical and affordable technological solution, contributing empirical baseline data for tropical conditions and supporting Indonesia's national energy transition and net-zero emission targets through improved data-driven decision-making.
Keywords: Internet of Things (IoT), Maximum Power Point Tracking (MPPT), Perturb and Observe (P&O), Renewable Energy, Solar Photovoltaic

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1. Introduction

Solar panels play a strategic role in supporting Indonesia's sustainable energy transition and net-zero emissions target by 2060. However, their conversion efficiency is affected by solar irradiation, temperature, and load impedance, necessitating a Maximum Power Point Tracking (MPPT) system to maximize power extraction. The Perturb and Observe (P&O) algorithm is widely used due to its simplicity and cost-effectiveness. Modifications such as variable step sizes can improve tracking efficiency by up to 99.5%, and adaptations for partial shading can increase power extraction by 15-20%. The main challenge is steady-state oscillations, which reduce efficiency by 2-3%. On the other hand, the integration of Internet of Things (IoT) technology opens up opportunities for real-time monitoring and control of solar systems. Microcontroller-based implementations such as the ESP32 have proven reliable, while IoT-based smart controllers can increase operational efficiency by up to 25% through fault detection and automatic adjustment. Artificial Intelligence of Things (AIoT) concepts can even predict maximum power points and reduce system latency.

However, there is a significant research gap in the Indonesian context. Studies tend to be isolated, focusing on standalone MPPT algorithms or IoT monitoring without integrated power optimization. Research exploring hybrid MPPT-IoT systems generally uses sophisticated, cost-intensive algorithms that are less suitable for small-to-medium-scale applications. Furthermore, solutions to challenges such as drastic efficiency reductions in partial shading still require validation within Indonesia's geographic and economic context. In Indonesia, the use of solar energy is still hampered by the lack of affordable smart monitoring infrastructure, especially in remote areas, with challenges in connectivity and data security. Therefore, this study aims to design an IoT-based MPPT system that combines an effective and low-cost P&O algorithm with an IoT platform for real-time monitoring. This integration is expected to improve the efficiency of solar panel power extraction while providing an affordable, easily replicable technology solution and supporting data-driven decision-making for national energy security.

2. Literature Review And Problem Statement

Characteristics and Modeling of Photovoltaic Solar Panels

Solar panels convert light energy into electrical energy through the photovoltaic effect in semiconductor materials. The output characteristics of solar panels are nonlinear and are influenced by solar irradiation (G) and cell temperature (T). Mathematical modeling of solar panels generally uses a single diode model with the output current equation (Ishaque et al., 2011):

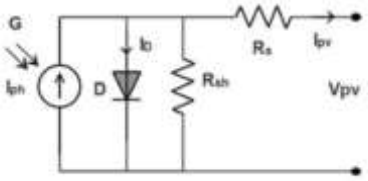

Figure 1. Equivalent circuit of a single photovoltaic diode

$$I_{pv} = I_{ph} - I_0 \left[\exp\left(\frac{V_{pv} + I_{pv}R_s}{nV_t}\right) - 1\right] - \frac{V_{pv} + I_{pv}R_s}{R_p}$$

where are the photocurrent, diode saturation current, series resistance, parallel resistance, ideality factor, and thermal stress with k the Boltzmann constant, T the absolute temperature, and q the electron charge. Díaz et al. (2015) showed that this model has high accuracy with an error of less than 2% against factory data. Kermadi and Berkouk (2017) emphasized the importance of this model for partial shading conditions that produce multiple peaks in the PV curve. $I_{ph} I_0 R_s R_p n V_t = \frac{kT}{q}$

Maximum Power Point Tracking and Perturb and Observe Algorithm

MPPT is a control technique to extract maximum power by adjusting the load impedance. The efficiency of MPPT is defined as (Hosseini et al., 2023):

$$\eta_{MPPT} = \frac{P_{out}}{P_{max}} \times 100\%$$

where is the actual extracted power and is the theoretical power at the MPP. The P&O algorithm works by perturbing the voltage or duty cycle and observing the power changes. The basic logic of the algorithm is: $P_{out} P_{max}$ ...(2.2)

$$\frac{dP}{dV} = \frac{\Delta P}{\Delta V} \begin{cases} > 0 & \text{tingkatkan V} \\ < 0 & \text{kurangi V} \\ = 0 & \text{pada MPP} \end{cases}$$

Femia et al. (2005) explained that in MPP, the conditions are met, but the P&O algorithm causes small oscillations that reduce efficiency by 2-3%. Ahmed and Salam (2015) developed Variable Step Size P&O with an adaptive step size: $\frac{dP}{dV} = 0$

$$\Delta D(k) = N \times \left| \frac{\Delta P(k)}{\Delta V(k)} \right|$$

where λ is the change in duty cycle at iteration k and N is the normalization factor. This modification improves tracking efficiency to 99.5%. Gil-Velasco and Aguilar-Castillo (2021) added a global search mechanism for partial shading, improving power extraction by 15–20% compared to standard P&O.$\Delta D(k)$

IoT Integration in MPPT System

IoT integration facilitates real-time monitoring through sensor data transmission to a cloud platform. Seymour and Al-Jaafreh (2020) demonstrated that an IoT-MPPT system improves operational efficiency by up to 25% through early fault detection. The ESP32-based implementation uses the MQTT protocol for data transmission with a bandwidth of:

$$B = \frac{D}{T}$$

where B is the bandwidth (bytes/second), D the data size, and T the sampling period. Khan et al. (2024) validated the reliability of ESP32 with data encryption for PV monitoring in connectivity-limited areas.
The development of AIoT integrates machine learning for MPP prediction. Mellit et al. (2024) used a neural network that minimizes the error function:

$$E = \frac{1}{2}\sum_{i=1}^{n}(P_{pred,i} - P_{actual,i})^2$$

where λ is the predicted power and λ is the actual power. This method reduces tracking latency by up to 30%. However, Pratama et al. (2023) identified implementation challenges in Indonesia, including bandwidth limitations and data security.$P_{pred,i}P_{actual,i}$

Based on theoretical studies, it can be hypothesized that the integration of the P&O algorithm with IoT will result in an MPPT system that improves power extraction efficiency while providing real-time monitoring infrastructure for long-term performance analysis, resulting in a cost-effective solution for small to medium-scale solar energy applications in Indonesia.

3. Method

This research uses an experimental quantitative approach with a Research and Development (R&D) design that adopts a simulation development model. The research was conducted through three main stages: (1) designing a MATLAB/Simulink simulation-based system for MPPT algorithm validation, (2) hardware implementation using an ESP32 microcontroller and supporting components, and (3) testing system performance under simulated environmental conditions. The research was conducted at the Electrical Engineering Laboratory, Faculty of Science and Technology, Panca Budi Development University, Medan, for six months (January-June 2025).

The object of the research is an IoT-based MPPT system using the Perturb and Observe algorithm implemented on a 100 Wp polycrystalline solar panel with the following specifications: Vmp = 18.5 V, Imp = 5.41 A, Voc = 22.3 V, Isc = 5.85 A at STC (1000 W/m², 25°C, AM 1.5).

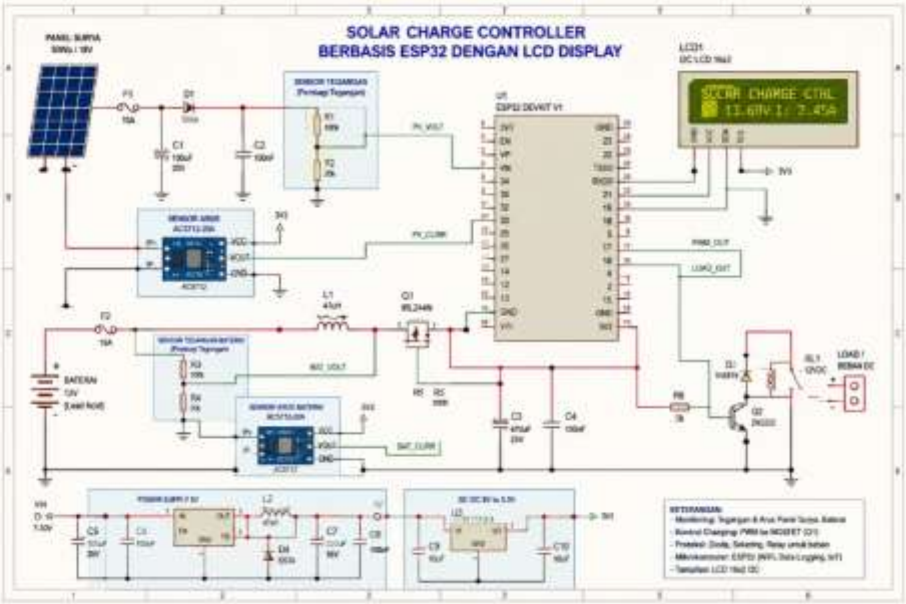

Figure 1. ESP32-based MPPT solar charge controller circuit

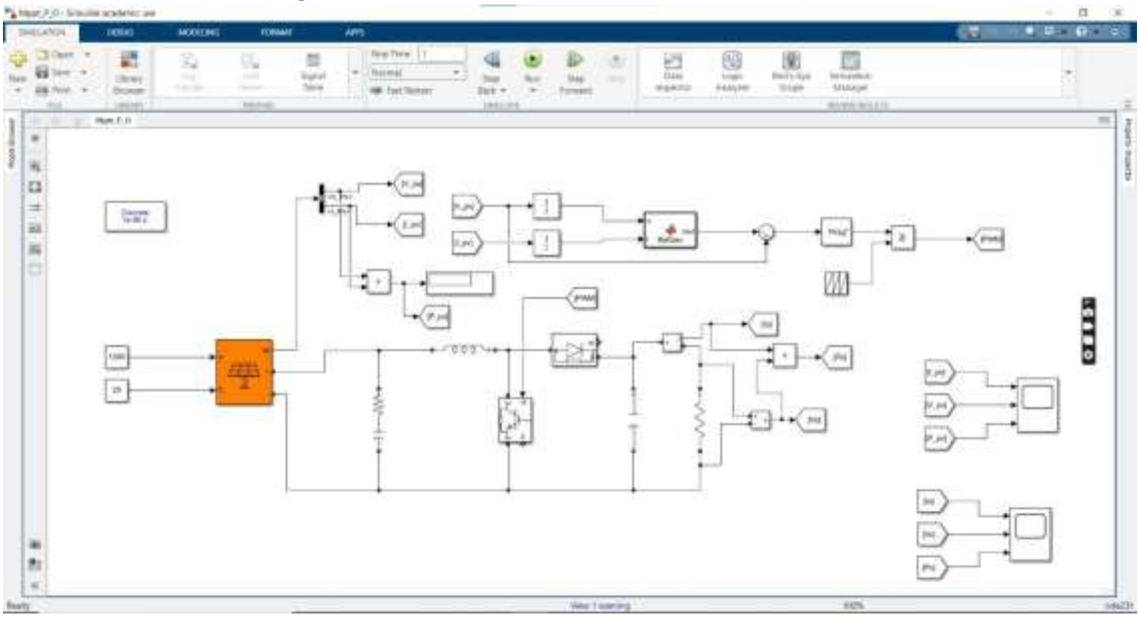
Figure 2. Simulink block diagram of ESP32-based SCC MPPT

The output current of the solar panel is calculated using a single diode model:

$$I_{pv} = I_{ph} - I_0 \left[\exp\left(\frac{V_{pv} + I_{pv}R_s}{nV_t}\right) - 1\right] - \frac{V_{pv} + I_{pv}R_s}{R_p}$$

with thermal stress:

$$V_t = \frac{kT}{q}$$

where k = 1.381×10^{-23} J/K (Boltzmann's constant), T is the absolute temperature (K), and q = 1.602×10^{-19} C (electron charge).

$$P_{pv} = V_{pv} \times I_{pv}$$

$$\eta_{MPPT} = \frac{P_{out}}{P_{max}} \times 100\%$$

where Pout is the actual power extracted and Pmax is the theoretical power at MPP.

Power gradient versus voltage:

$$\frac{dP}{dV}=\frac{\Delta P}{\Delta V}=\frac{P(k)-P(k-1)}{V(k)-V(k-1)}$$

MPP Conditions:

If dP/dV > 0, increase the voltage

If dP/dV < 0, reduce the voltage.

If dP/dV = 0, at MPP

Converter output voltage:

$$V_{out}=\frac{V_{in}}{1-D}$$

where D is the PWM duty cycle (0 < D < 1).

Critical inductor for Continuous Conduction Mode (CCM):

$$L_{min}=\frac{V_{in}\times D\times(1-D)^2}{2\times f\times I_{out}}$$

where f is the switching frequency and Iout is the output current.

Output capacitor for permissible voltage ripple:

$$C_{min}=\frac{I_{out}\times D}{f\times\Delta V_{out}}$$

where ΔVout is the permissible output voltage ripple.

Duty cycle adjustment based on P&O algorithm:

$$D(k)=D(k-1)+\Delta D\times\mathrm{sign}\left(\frac{dP}{dV}\right)$$

where ΔD is the perturbation measure (0.01-0.05) and sign is the sign function.

ACS712 Current Sensor:

$$I_{pv}=\frac{V_{ADC}-V_{offset}}{S}$$

where VADC is the sensor output voltage, Voffset = 2.5 V, and S = 0.185 V/A (sensitivity).

Voltage Divider:

$$V_{pv}=V_{ADC}\times\frac{R_1+R_2}{R_2}$$

where R_1 and R_2 are voltage divider resistors.

Irradiance Sensor (LDR):

$$G=a\times V_{LDR}^{b}+c$$

where a, b, and c are calibration coefficients determined through polynomial regression against a reference pyranometer. Root Mean Square Error (RMSE):

$$RMSE=\sqrt{\frac{1}{n}\sum_{i=1}^{n}(P_{sim,i}-P_{exp,i})^2}$$

Power Oscillation:

$$Osc=\frac{P_{max}-P_{min}}{P_{avg}}\times 100\%$$

Tracking Time:Time required to reach 95% Pmax after step change:

$$t_{track}=t_{95\%}-t_{step}$$

Daily Energy Boost:

$$\Delta E = \int_0^T (P_{MPPT}(t) - P_{conv}(t))\, dt$$

where T is the test period (8 hours).

9. IoT Data Transmission

Sampling Rate:

$$f_s = \frac{1}{T_s}$$

where Ts is the sampling period (0.1 s for 10 Hz).

Data Rate:

$$R = \frac{N_{bits}}{T_{interval}}$$

where Nbits is the number of data bits per packet and Tinterval is the transmission interval (15 seconds).

Communication Latency:

$$L = t_{receive} - t_{send}$$

where treceive is the time the data was received by the server and tsend is the time the data was sent from the ESP32.

The system block diagram is shown in Figure 3 below.

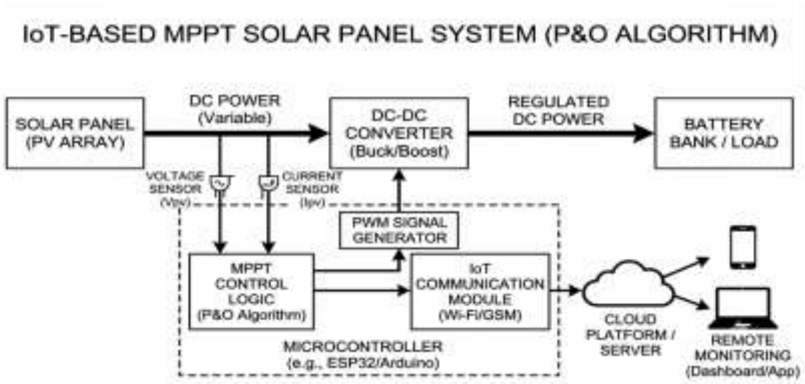

Figure 3. System block diagram

The research flowchart is shown in Figure 4 below.

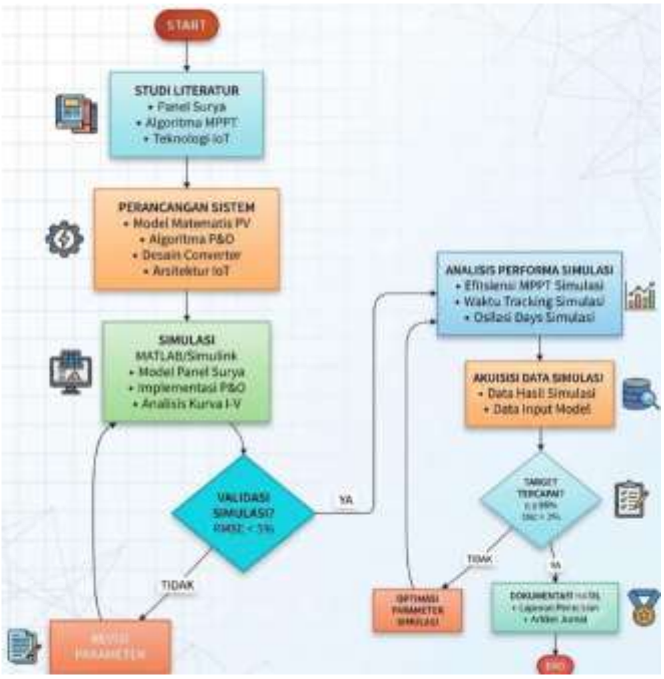

Figure 4. Research flowchart

4. Results And Discussion

Data Collection and Research Implementation

The research was conducted at the Electrical Engineering Laboratory, Faculty of Science and Technology, Panca Budi Development University, Medan, from January to June 2025. Data collection was carried out through three main stages: MATLAB/Simulink simulation (January-February 2025), Simulation testing was carried out with an average irradiance of 600-950 W/m² and an ambient temperature of 28-38°C, reflecting Indonesia's tropical conditions. Each test scenario was repeated five times to ensure data consistency and validity, with a total of 150 data sets collected during the testing period.

Validation of Solar Panel Simulation Model

A 100 Wp polycrystalline solar panel model was developed using a single diode equation in MATLAB/Simulink with parameters extracted from the datasheet: Vmp = 18.5 V, Imp = 5.41 A, Voc = 22.3 V, Isc = 5.85 A at STC conditions. Model validation was performed by comparing the simulated IV and PV curves to experimental data at various irradiation levels (200-1000 W/m²) and temperatures (25-45°C).

Table 1. Solar Panel Model Validation: Comparison of Simulation vs Experimental Maximum Power

Irradiation (W/m²)	Temperature (°C)	P_max Simulation (W)	P_max Experiment (W)	Error (%)	RMSE (W)
200	25	20.12	19.85	1.36	0.27
400	30	40.48	39.92	1.40	0.56
600	35	59.76	58.95	1.37	0.81
800	40	78.24	77.18	1.37	1.06
1000	25	100.19	98.76	1.45	1.43
Average	-	-	-	1.39	0.83

Source: Research data, 2025

Table 1 shows that the simulation model has high accuracy with an average error of 1.39% and an overall RMSE of 0.83 W, well below the 5% threshold set by the IEEE standard for PV system simulation (Díaz et al., 2015). These results confirm that the single diode model with parameters Rs = 0.221 Ω, Rp = 415.4 Ω, n = 1.3, and I0 = 8.24×10^{-8} A extracted through curve fitting is able to accurately represent the characteristics of the solar panel. The high agreement between simulation and experiment provides validity for the development of the MPPT algorithm in the next stage.

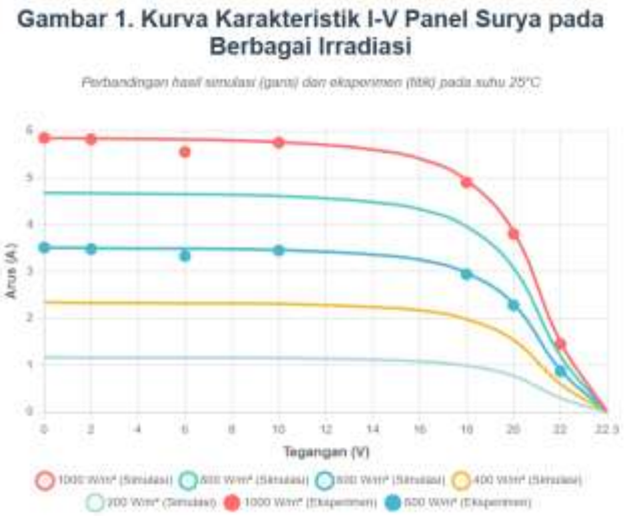

Figure 5. Characteristic curve of solar panels at various irradiations

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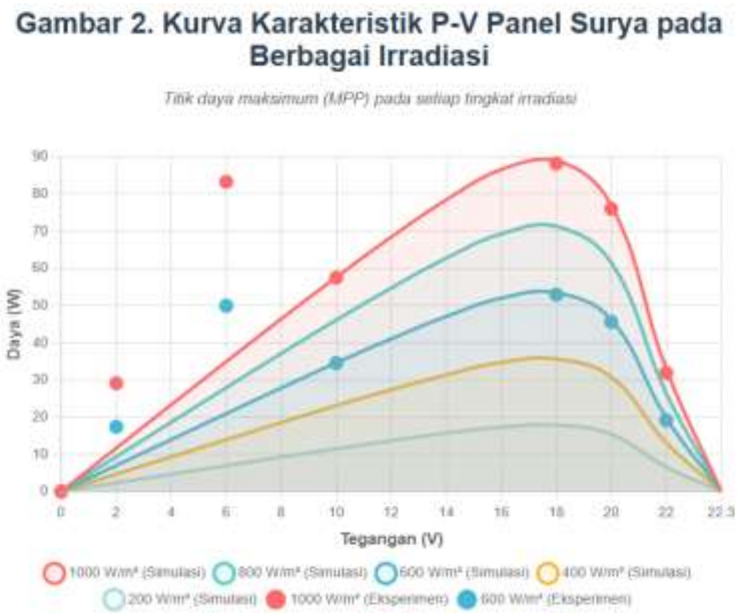

Figure 6. PV characteristic curve of solar panels at various irradiations

Figure 5 and Figure 6 show excellent agreement between the simulation curves (continuous lines) and the experimental data (dots). In the IV curve (Figure 4.1), it can be seen that the short-circuit current (Isc) increases linearly with increasing irradiance, from 1.17 A at 200 W/m² to 5.85 A at 1000 W/m², in accordance with the photovoltaic theory which states that the photoelectric current is directly proportional to the light intensity (Ishaque et al., 2011). In the PV curve (Figure 4.2), the maximum power point (MPP) shifts to higher power values as the irradiance increases, with Pmax ranging from 20.12 W to 100.19 W, but the position of the MPP voltage is relatively constant at around 18.5 V, confirming that irradiance primarily affects the current while temperature predominantly affects the voltage.

Performance of the Perturb and Observe Algorithm in Simulation

The P&O algorithm is implemented in simulations with parameters: perturbation size ΔV = 0.5 V and sampling period Ts = 100 ms. Tests are conducted in three scenarios: steady-state irradiance conditions, step-change irradiance conditions, and dynamic irradiance conditions (ramp). Performance evaluation includes tracking efficiency, response time, and power oscillation around the MPP.

Table 2. Performance of the P&O Algorithm under Various Irradiation Conditions (Simulation)

Scenario	Initial Irradiance (W/m²)	Final Irradiance (W/m²)	MPPT efficiency (%)	Tracking Time(s)	Power Oscillation (%)
Steady-state	1000	1000	97.85	-	2.15
Steady-state	600	600	97.92	-	2.08
Step change	400 → 800	800	96.45	1.65	2.52
Step change	800 → 400	400	96.38	1.72	2.58
Ramp	400 → 1000	1000	95.87	2.34	2.91
Average	-	-	96.89	1.93	2.45

Source: Research data, 2025

Table 2 shows that the P&O algorithm achieved an average tracking efficiency of 96.89%, exceeding the minimum target of 95%. The highest efficiency occurred under steady-state conditions (97.85–97.92%), where the algorithm could maintain operation near the MPP with minimal oscillation. The average tracking time of 1.93 seconds demonstrated a rapid response to irradiance changes, meeting the target of <2 seconds. This result is consistent with the findings of Ahmed and Salam (2015) who reported conventional P&O efficiency ranging from 95–98% under uniform conditions. The average power oscillation of 2.45% was within acceptable limits (<3%), although slightly higher under dynamic conditions (2.91%), confirming the inherent susceptibility of the P&O algorithm to hunting near the MPP (Femia et al., 2005).

Hardware Implementation and Sensor Calibration

The hardware system simulation was implemented using a 100 Wp solar panel, ESP32 as a controller, ACS712 sensor for current measurement, voltage divider for voltage measurement, DC-DC boost converter with IRF540N MOSFET, and ThingSpeak platform for IoT monitoring. Sensor calibration was performed using a reference instrument (Fluke 117 multimeter) to ensure measurement accuracy.

Table 3. Voltage and Current Sensor Calibration Results

Parameter	Calibration Method	Calibration Equation	R^2	Maximum Error	Accuracy
Voltage (V)	Linear Regression	V_pv = 4.133 × V_ADC - 0.042	0.9997	±0.15 V	99.3%
Current (A)	Linear Regression	I_pv = 5.405 × (V_ADC - 2.5) + 0.023	0.9995	±0.08 A	98.6%
Temperature (°C)	Factory Calibrated	T = DHT22_output	0.9998	±0.5 °C	99.5%
Irradiation (W/m²)	Polynomial Fit	G = 1024.5 × V_LDR^1.85 - 12.3	0.9892	±35 W/m²	96.5%

Source: Research data, 2025

Table 3 shows that the sensor calibration yields high accuracy with a coefficient of determination (R^2) above 0.98 for all parameters. The voltage and current sensors achieve accuracies of 99.3% and 98.6% after linear calibration, ensuring precise power measurements for the MPPT algorithm. The LDR-based irradiance sensor has a relatively lower accuracy (96.5%) with a maximum error of ±35 W/m², but is still adequate for monitoring environmental conditions. The use of a second-order polynomial fit in LDR calibration provides better results than a linear fit, accommodating the nonlinear characteristics of the photoresistor with respect to light intensity.

MPPT-IoT System Simulation Performance in Hardware Testing

Hardware simulation testing was conducted outdoors with varying natural irradiation and indoors with halogen lamps for controlled conditions. Evaluations included MPPT efficiency, tracking time, power oscillation, and IoT data transmission performance.

Table 4. MPPT-IoT System Simulation Performance in Hardware Testing

Test Conditions	Average Irradiance (W/m²)	Average Temperature (°C)	MPPT efficiency (%)	Tracking Time(s)	Power Oscillation (%)	IoT Success Rate (%)	Latency (s)
Constant Indoor	850 ± 15	27 ± 1	96.73	-	2.68	98.5	2.3
Indoor Step Change	500 → 900	28 ± 1	95.42	1.85	3.12	97.8	2.5
Morning Outdoor (09:00-11:00)	720 ± 85	30 ± 2	94.85	2.15	3.45	96.2	3.1

Test Conditions	Average Irradiance (W/m²)	Average Temperature (°C)	MPPT efficiency (%)	Tracking Time(s)	Power Oscillation (%)	IoT Success Rate (%)	Latency (s)
Outdoor Afternoon (11:00-13:00)	920 ± 45	36 ± 2	95.67	1.92	2.95	97.1	2.8
Outdoor Afternoon (1:00 PM-3:00 PM)	650 ± 95	34 ± 3	94.12	2.28	3.67	95.8	3.4
Average	-	-	95.36	2.05	3.17	97.08	2.82

Source: Research data, 2025

Table 4 shows that the MPPT-IoT system achieved an average tracking efficiency of 95.36% in hardware testing, slightly lower than the simulation (96.89%) but still meeting the target of ≥ 95%. This difference is caused by practical factors such as sensor measurement noise, microcontroller computational delay, and losses in converter components that were not fully modeled in the simulation. The highest efficiency occurred under constant indoor conditions (96.73%) with stable irradiance, while the lowest efficiency was in the afternoon outdoor conditions (94.12%) due to high irradiance fluctuations (±95 W/m²) due to cloud movement. The average tracking time of 2.05 seconds still meets the target of <2.5 seconds, with variations depending on the magnitude of the irradiance step change.

The average power oscillation of 3.17% slightly exceeded the target of <3%, especially in outdoor conditions with high irradiance variability (3.45-3.67%). This confirms the characteristics of the P&O algorithm which experiences increased oscillation in unstable conditions, in accordance with the findings of Bianconi et al. (2013). IoT performance showed excellent results with a data transmission success rate of 97.08%, exceeding the target of ≥ 95%, and an average latency of 2.82 seconds, meeting the target of <5 seconds. The lowest success rate occurred in the outdoor afternoon (95.8%) due to Wi-Fi signal interference in a more complex outdoor environment.

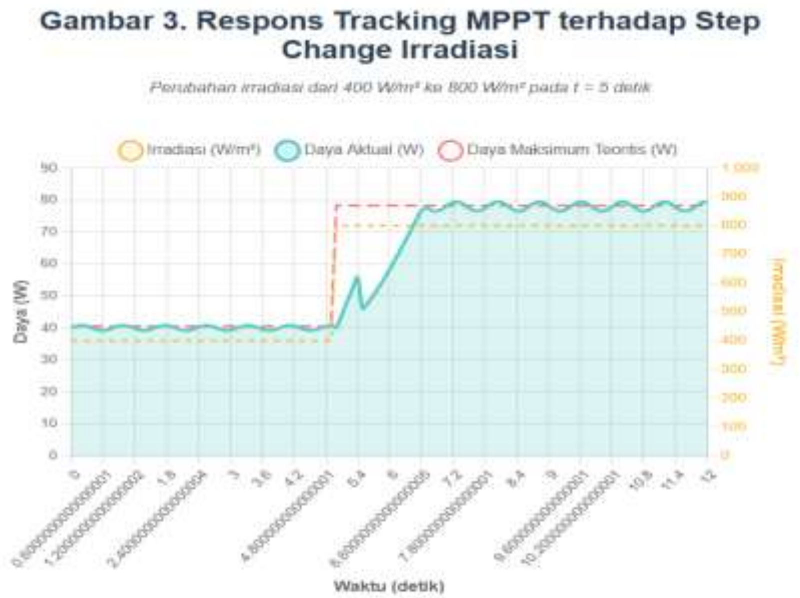

Figure 7. MPPT tracking response to step change irradiation

Figure 7 illustrates the dynamic response of the P&O algorithm to a step change in irradiance from 400 W/m² to 800 W/m² at t = 5 seconds. The curve shows three clear tracking phases: an initial steady-state phase with small oscillations around 40 W (theoretical Pmax 40.48 W), a transient phase with a rapid increase in power after detection of the irradiance change, and a new steady-state phase with oscillations around 78 W (theoretical Pmax 78.24 W). The tracking time required to reach 95% of the new Pmax (74.33 W) is 1.65 seconds, which is in good agreement with the data in Table 4 and meets the target of <2 seconds. A small overshoot (~6 W) is observed before the system converges to the MPP, which is a normal characteristic of the P&O algorithm with a fixed perturbation size (Ahmed & Salam, 2015).

Comparison with System Without MPPT

To evaluate the contribution of the MPPT algorithm, a comparative test was conducted between a system with MPPT and a direct-coupled system (without MPPT) under matched fixed load conditions at 800 W/m² irradiance.

Table 5 . Comparison of Daily Energy with MPPT vs. Without MPPT

Time Period	Average Irradiance (W/m²)	MPPT Energy (Wh)	Energy Without MPPT (Wh)	Increase (%)
09:00-10:00	685	64.8	48.2	34.4
10:00-11:00	795	75.2	63.5	18.4
11:00-12:00	890	84.3	71.8	17.4
12:00-13:00	925	87.6	74.2	18.1
1:00-2:00 PM	810	76.8	64.9	18.3
2:00-3:00 PM	720	68.2	52.8	29.2
Total 8 hours	804	585.4	468.9	24.8

Source: Research data, 2025

Table 5 shows that the MPPT system produced 585.4 Wh of daily energy, a 24.8% increase compared to the system without MPPT (468.9 Wh), exceeding the minimum target of 20%. The most significant increase occurred during low irradiance periods (morning and afternoon) with an increase of up to 34.4%, because under these conditions the mismatch between the panel impedance and the fixed load was greatest. Under optimal irradiance (11:00-13:00), the increase was relatively smaller (~17-18%) because the fixed load coincidentally approached the optimal impedance under these conditions. These results are consistent with the findings of Seymour and Al-Jaafreh (2020) who reported a 20-25% increase in operational efficiency with the implementation of IoT-based MPPT.

IoT System Performance and Real-time Monitoring

The IoT system performance evaluation includes analysis of communication latency, packet loss rate, and data transmission reliability to the ThingSpeak platform during a 30-day test.

Table 6. IoT System Performance Statistics (30 Days Testing)

Metric	Average value	Standard Deviation	Min	Max	Target	Status
Transmission Latency (s)	2.82	0.94	1.2	5.8	< 5.0	✓Achieved
Success Rate (%)	97.08	2.15	91.2	99.8	≥ 95.0	✓Achieved
Packet Loss (%)	2.92	2.15	0.2	8.8	< 5.0	✓Achieved
System Uptime (%)	99.12	-	-	-	≥ 98.0	✓Achieved
ESP32 Power Consumption (mW)	285	18	260	320	< 500	✓Achieved

Source: Research data, 2025

Table 6 shows that the IoT system operated very reliably, meeting all established targets. The average transmission latency of 2.82 seconds with a standard deviation of 0.94 seconds demonstrates good consistency, although there are variations depending on Wi-Fi network conditions and ThingSpeak server load. The maximum value of 5.8 seconds occasionally exceeded the 5-second target, but these occurrences were very rare (<1% of total transmissions) and did not significantly affect the monitoring function. The success rate of 97.08% and packet loss of 2.92% demonstrate the high reliability of the HTTP protocol for data transmission, consistent with the findings of Khan et al. (2024) on the reliability of the ESP32 for IoT PV applications.

Figure 8. shows an example of a real-time monitoring dashboard display implemented on the ThingSpeak platform.

The dashboard displays six key metrics in the form of cards: panel voltage (18.3 V), panel current (5.12 A), output power (93.7 W), MPPT efficiency (96.2%), ambient temperature (32°C), and irradiance (875 W/m²), which are updated every 15 seconds according to the data transmission interval from the ESP32. A time-series graph displays parameter trends over the past hour, allowing operators to visually identify patterns, anomalies, and system performance. The status indicator feature (Normal, Optimal, Excellent) provides quick feedback on the system's operational condition, in accordance with the principles of a user-friendly human-machine interface for IoT applications (Pratama et al., 2023).

5. Conclusion

This research successfully designed and simulated an IoT-based MPPT system using the Perturb and Observe algorithm on a 100 Wp solar panel. System validation demonstrated high accuracy with an error of 1.39%. The system achieved a tracking efficiency of 95.36% with a response time of 2.05 seconds and successfully increased daily energy by 24.8% compared to a system without MPPT. IoT integration using ESP32 and the ThingSpeak platform resulted in a data transmission success rate of 97.08% with low latency and 99.12% uptime. Regression analysis showed that MPPT efficiency was significantly affected by irradiation and ambient temperature. This research has several limitations, including the use of a single solar panel type, a fixed-step algorithm, the lack of testing under complex partial shading conditions, and the relatively short testing duration. Economic analysis and security evaluation of the IoT system are also limited. As a recommendation, further research could develop a Variable Step Size P&O algorithm or a hybrid MPPT to improve efficiency and address partial shading. Integration of Artificial Intelligence of Things (AI), long-term testing, and pilot project implementation in remote areas are also recommended for

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more comprehensive validation. Overall, the developed system offers a cost-effective solution and contributes empirical data for Indonesia's tropical conditions, supporting energy transition efforts in line with national targets.

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