International Journal of Engineering Research and Development
e- ISSN: 2278-067X, p-ISSN: 2278-800X, www.ijerd.com
Volume 22, Issue 8 (August 2026), PP 23-29

Adaptive Energy Management for an IoT-Enabled Solar Lighting and Monitoring Station

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ABSTRACT
Solar-powered lighting systems provide a sustainable solution for outdoor and off-grid applications; however, their operating time is strongly affected by variations in solar energy availability and inefficient lighting control. This study presents the design and experimental validation of an Internet of Things-enabled solar lighting and monitoring system incorporating an energy-aware adaptive dimming strategy. The proposed control strategy determines the LED pulse-width modulation level based on ambient illuminance, motion detection, and battery state of charge. A battery-protection mechanism limits the lighting power when the state of charge falls below a predefined threshold, while a hysteresis function prevents frequent switching caused by short-term variations in ambient light. System data are transmitted to a remote dashboard using the MQTT protocol for real-time monitoring and manual control. Outdoor experiments demonstrated reliable sensor operation and stable communication, with data transmission delays of approximately 1.2-2.0 s and a packet loss rate below 0.5%. Compared with constant full-power operation, the proposed strategy increased the operating time from approximately 4.75 h to 6.00-6.25 h, corresponding to an improvement of about 26%. The results indicate that the proposed system can improve energy utilization while maintaining responsive illumination for small-scale outdoor and off-grid applications.
Keywords: *solar lighting; adaptive dimming; energy management; Internet of Things; state of charge.*

Date of Submission: 25-07-2026 Date of acceptance: 06-08-2026

I. INTRODUCTION

Outdoor lighting plays an important role in ensuring visibility, mobility, and public safety. However, conventional grid-connected lighting systems may be costly or impractical in remote and off-grid locations. Solar-powered lighting provides a sustainable alternative, although its reliability depends on balancing photovoltaic generation, battery capacity, and nighttime energy demand. Recent developments in sensing, embedded control, and Internet of Things (IoT) technologies have enabled lighting systems to adjust their output according to real-time operating conditions. Agramelal et al. reviewed a wide range of smart street-lighting methods and showed that current control strategies extend from simple scheduled and threshold-based operation to traffic-responsive, computer-vision, and AI-based approaches [1]. These systems commonly use environmental and traffic information to reduce unnecessary illumination and energy consumption.

Adaptive lighting has also been investigated through practical implementations. Gagliardi et al. developed an adaptive street-lighting architecture capable of regulating lamp brightness according to the presence of different types of road users [2]. Pasolini et al. further assessed context-adaptive lighting through large-scale and long-term field implementations, demonstrating that real-time traffic and environmental information can provide greater energy savings than conventional static schedules or simple motion-based strategies [3]. These studies confirm the energy-saving potential of dynamic lighting control; however, they mainly focus on grid-connected urban infrastructure rather than small autonomous solar-powered stations. For off-grid lighting, energy availability becomes a more critical constraint. Tomczuk et al. evaluated photovoltaic-powered autonomous lighting systems and emphasized that their performance depends on solar irradiance, battery capacity, luminaire power, and the selected control scenario [4]. Their results showed that insufficient solar generation and battery discharge may prevent reliable operation, particularly during periods of low irradiance. More recently, Vadi presented an off-grid smart street-lighting system integrating renewable generation, battery storage, sensing, and IoT communication [5]. Such systems demonstrate the feasibility of autonomous and remotely monitored lighting, but their continuous operation still requires effective coordination between lighting demand and the energy remaining in the battery.

IoT communication provides an additional layer for remote supervision and control. Kuncicky et al. investigated the use of the MQTT protocol for street-lighting control, illustrating the suitability of the publish-subscribe model for exchanging operational data and control commands [6]. However, essential lighting functions should not depend entirely on network availability, particularly in remote installations. Executing the primary control algorithm locally at the edge can maintain system operation during temporary communication interruptions. Battery state of charge is therefore an important variable for energy-aware lighting control. Coulomb counting is widely used for real-time SOC estimation because it tracks the charge entering and leaving the battery. However, its accuracy depends on the initial SOC, battery capacity, current-sensor accuracy, and accumulated integration errors [7], [8]. Despite this limitation, SOC estimation provides useful information for reducing lamp power before the available energy becomes insufficient.

Taken together, previous studies have mainly addressed adaptive lighting, off-grid energy-system design, IoT communication, or battery estimation as separate issues. The coordinated use of ambient illuminance, motion detection, and battery SOC within a low-cost edge controller has received comparatively limited attention. In particular, a lighting system should not only increase brightness in response to user presence but also reduce its power demand when the stored energy becomes limited.

To address this gap, this study develops an IoT-enabled solar lighting and monitoring system with an energy-aware adaptive dimming strategy. An ESP32-S3 controller regulates the LED brightness through pulse-width modulation according to ambient illuminance, motion status, and battery SOC. The system maintains a lower base brightness when no motion is detected, increases illumination when required, and limits the lamp output under low-battery conditions. Illuminance hysteresis is included to prevent unstable switching, while local execution of the control algorithm allows the lighting function to continue during temporary network interruptions. MQTT communication is used for real-time monitoring and manual control.

The remainder of this paper is organized as follows. Section 2 presents the system architecture, energy-demand calculation, SOC estimation, and the proposed adaptive dimming strategy. Section 3 describes the experimental setup and discusses the system performance and energy-saving results. Finally, Section 4 concludes the study and outlines future research directions.

II. METHODOLOGY

A. System Architecture

The proposed system integrates photovoltaic energy generation, battery storage, environmental sensing, LED dimming, and IoT-based monitoring. As shown in Fig. 1, it consists of three main subsystems: the energy subsystem, the control and lighting subsystem, and the IoT monitoring subsystem.

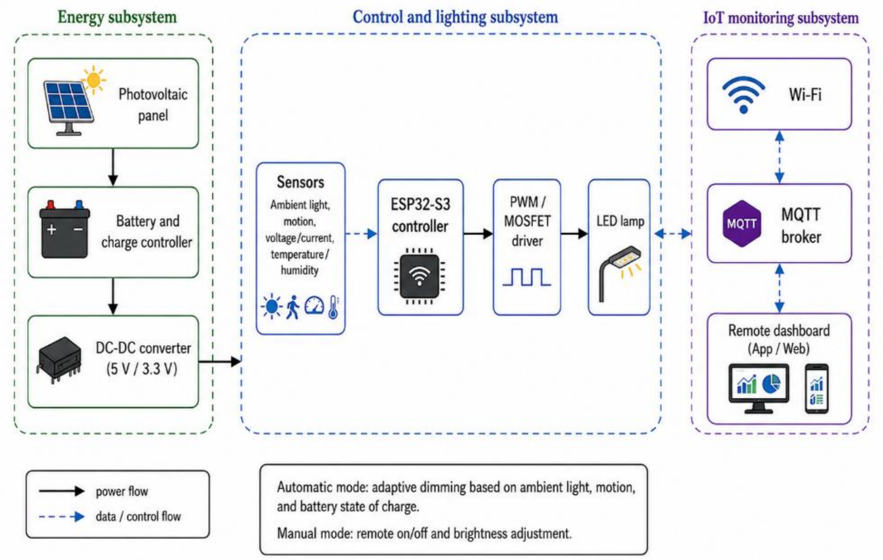

Fig. 1. Overall system architecture of the proposed IoT-enabled solar lighting and monitoring system.

The energy subsystem comprises a 50 W photovoltaic panel, a charge controller, a 12 V-7.5 Ah valve-regulated lead-acid battery, and DC-DC converters that provide regulated 5 V and 3.3 V outputs. The photovoltaic panel supplies the system and charges the battery during daytime, whereas the battery powers the system under low-irradiance and nighttime conditions.

The ESP32-S3 serves as the central controller. A BH1750 sensor measures ambient illuminance, a PIR SR505 sensor detects motion, and an ACS712 sensor and voltage-divider circuits monitor battery current and voltage. A DHT11 sensor provides supplementary temperature and humidity measurements. The LED lamp is driven through a power MOSFET using a PWM signal generated by the controller.

Remote monitoring is implemented using the MQTT publish-subscribe protocol. Through Wi-Fi, the controller transmits sensor data, battery status, and LED brightness to a remote dashboard, which also allows operating-mode selection and manual brightness adjustment. Since the lighting algorithm is executed locally, automatic operation continues during temporary network interruptions.

B. Energy Demand and Battery State Estimation

The daily energy demand is calculated from the power and operating time of the system loads:

$$E_{\text{day}} = \sum_{i=1}^{n} P_i\, t_i \tag{1}$$

where P_i and t_i are the power and daily operating time of the i-th load, respectively.

The continuously operating electronic devices were approximated as a 1 W load, while the 6 W LED lamp was assumed to operate for 5 h per night. Therefore,

$$E_{\text{day}} = (1 \times 24) + (6 \times 5) = 54\ \text{Wh}. \tag{2}$$

Including a safety factor of 1.1, the required daily energy is:

$$E_{\text{req}} = 1.1E_{\text{day}} = 59.4\ \text{Wh}. \tag{3}$$

The minimum battery capacity is estimated as:

$$C_{\text{bat,min}} = \frac{E_{\text{req}}}{V_{\text{bat}}\eta_{\text{bat}}D_u} \tag{4}$$

where V_{bat} is the nominal battery voltage, η_{bat} is the overall battery and conversion efficiency, and D_u is the usable fraction of the nominal battery capacity. Since the proposed control strategy identifies $SOC \leq 20\%$ as a low-energy condition, the usable battery fraction was set to $D_u = 0.80$. Using $V_{\text{bat}} = 12$ V and $\eta_{\text{bat}} = 0.80$,

$$C_{\text{bat,min}} = \frac{59.4}{12 \times 0.80 \times 0.80} = 7.73\ \text{Ah}. \tag{5}$$

A 12 V–7.5 Ah battery was used for prototype validation. Although this value is slightly lower than the conservative calculation, it is sufficient for evaluating the proposed control strategy. For practical long-term deployment, a battery capacity of at least 8 Ah is recommended.

The minimum photovoltaic-panel power is determined from:

$$P_{\text{PV,min}} = \frac{E_{\text{req}}}{\eta_{\text{sys}}t_{\text{sun}}} \tag{6}$$

where η_{sys} is the overall photovoltaic charging and conversion efficiency, and t_{sun} is the equivalent daily peak-sun duration. Using $\eta_{\text{sys}} = 0.80$ and $t_{\text{sun}} = 5$ h,

$$P_{\text{PV,min}} = \frac{59.4}{0.80 \times 5} = 14.85\ \text{W}. \tag{7}$$

A 50 W panel was selected to provide additional charging capacity under reduced irradiance and practical conversion losses. The battery SOC is initialized from the measured battery voltage and updated using Coulomb counting:

$$SOC[k] = SOC[k-1] + \frac{100\,\eta_I[k]I_{\text{eff}}[k]\Delta t}{3600Q_n} \tag{8}$$

where $SOC[k]$ is the estimated state of charge at the k-th sampling instant, Q_n is the nominal battery capacity in ampere-hours, $I_{\text{eff}}[k]$ is the effective battery current after noise suppression, and Δt is the sampling interval in seconds.

Charging current is defined as positive, while discharging current is negative. A charging efficiency of 0.85 is applied, and current values below 0.08 A are ignored to reduce accumulated sensor error. The estimated SOC is limited to the range of 0-100% and is used as an input to the dimming algorithm.

C. Energy-Aware Adaptive Dimming Strategy

The proposed energy-aware adaptive dimming strategy regulates the LED brightness according to ambient illuminance, motion status, battery state of charge (SOC), and the selected operating mode. The reference PWM duty cycle is expressed as:

$$D_{\text{ref}}[k] = f(L[k], M[k], SOC[k]) \tag{9}$$

where $D_{\text{ref}}[k]$ is the reference PWM duty cycle at the k-th sampling instant, $L[k]$ is the ambient illuminance measured by the BH1750 sensor, $M[k]$represents the motion-detection state, and $SOC[k]$ is the estimated battery state of charge.

The system operates in automatic or manual mode. In automatic mode, the controller determines the LED brightness from ambient illuminance, motion status, and battery SOC, while temperature and humidity are used only for monitoring. In manual mode, the lamp can be switched on or off and adjusted from 0% to 100% through the MQTT dashboard or local buttons.

Ambient illuminance is classified as daylight ($L \geq 900$ lux), twilight ($300 < L < 900$ lux), or nighttime ($L \leq 300$ lux), with a 30 lux hysteresis margin to prevent frequent switching. The lamp remains off during daylight. Under twilight and nighttime conditions, the PWM duty cycle is selected according to motion and SOC, with reduced brightness applied when $SOC \leq 20\%$. The complete control process is shown in Fig. 2.

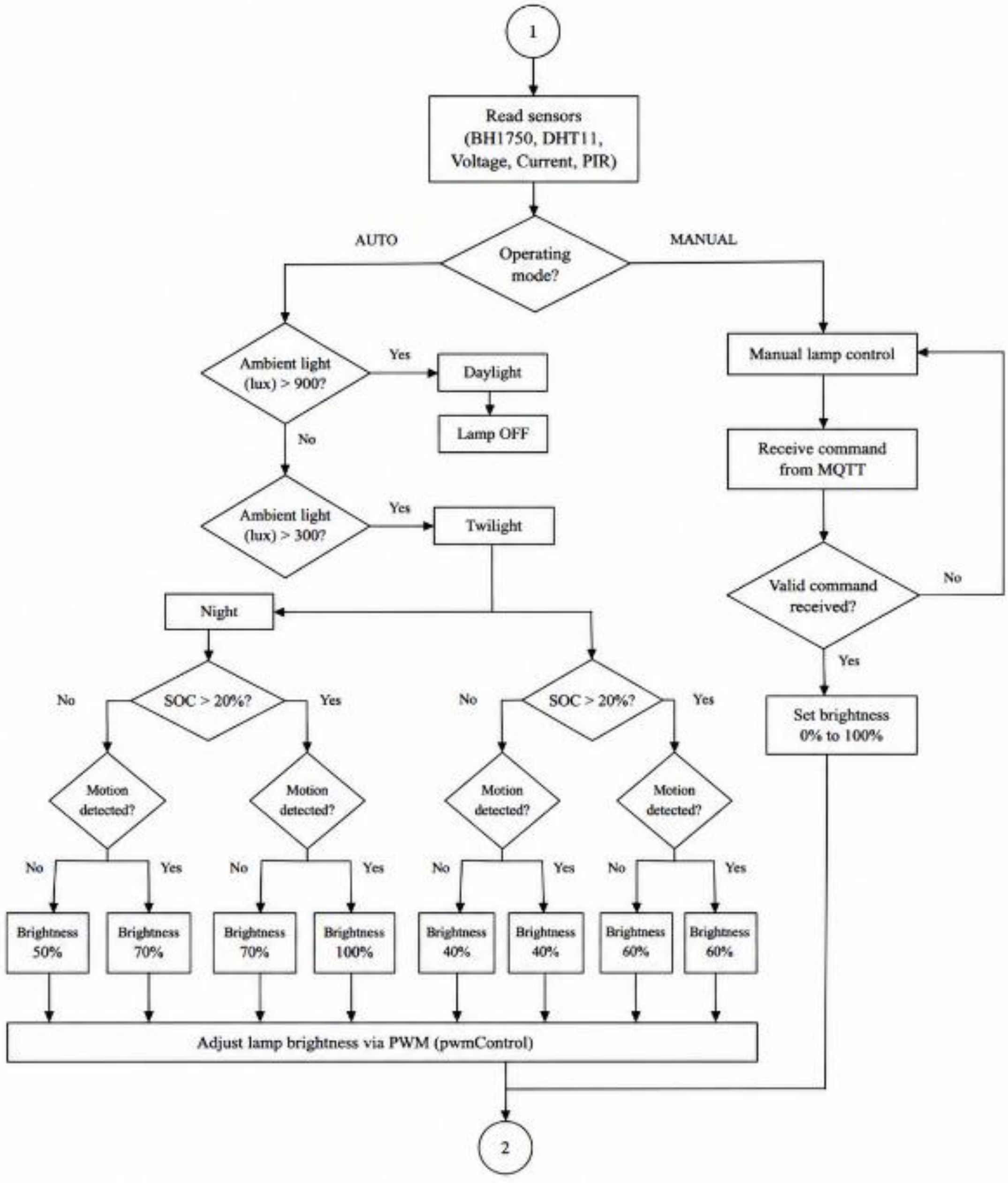

Fig. 2. Flowchart of the proposed energy-aware adaptive dimming algorithm.

The PWM duty-cycle values corresponding to the control decisions are summarized in Table 1. The PWM levels were selected empirically to balance minimum background illumination, motion-responsive visibility, and battery protection.

Table 1. PWM duty-cycle rules of the proposed adaptive dimming strategy.

Ambient condition	Battery condition	Motion status	PWM duty cycle	Operating purpose
Daylight	Any SOC	Any state	0%	Save energy during daytime
Twilight	SOC > 20%	No motion	40%	Orientation lighting

Ambient condition	Battery condition	Motion status	PWM duty cycle	Operating purpose
Twilight	SOC > 20%	Motion detected	60%	Visibility lighting
Twilight	SOC ≤ 20%	No motion	25%	Battery protection priority
Twilight	SOC ≤ 20%	Motion detected	40%	Battery protection priority
Night	SOC > 20%	No motion	70%	Area security lighting
Night	SOC > 20%	Motion detected	100%	Maximum lighting demand
Night	SOC ≤ 20%	No motion	50%	Battery protection priority
Night	SOC ≤ 20%	Motion detected	70%	Battery protection priority

The motion-activated brightness is maintained for approximately 8 s after the last detected event. The controller then gradually returns the lamp to its base level using a fade-in/fade-out process. The complete algorithm is executed locally on the ESP32-S3, while MQTT dashboard is used for remote monitoring and manual control.

III. EXPERIMENTAL RESULTS AND DISCUSSION

A. Experimental Setup

The developed prototype was installed outdoors to evaluate its energy-generation, sensing, lighting-control, communication, and operating-time performance. As shown in Fig. 3, the 50 W photovoltaic panel was mounted at an inclination angle of approximately 15° toward the south. The 12 V-7.5 Ah battery and ESP32-S3 controller were placed inside a protective enclosure, while the ambient-light, motion, temperature, and humidity sensors were mounted externally. The system communicated with a remote dashboard through Wi-Fi and MQTT.

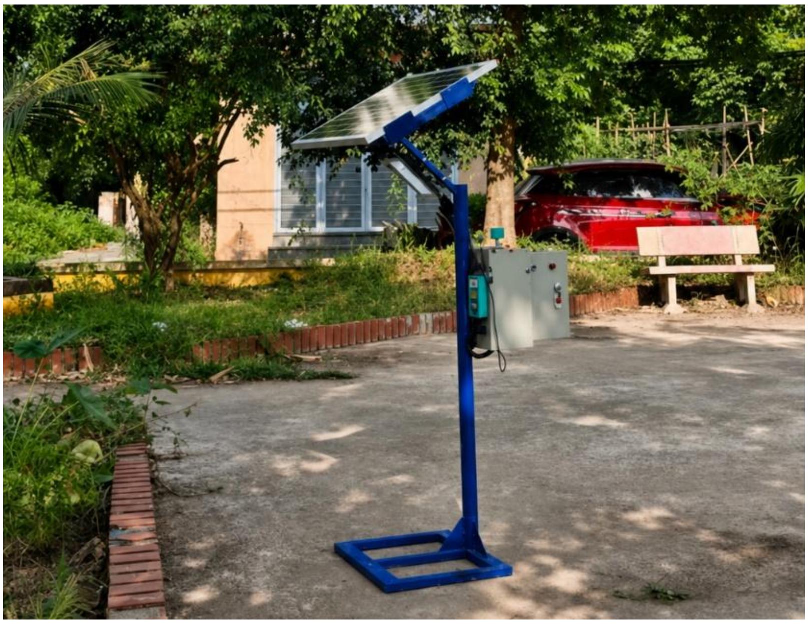

Fig. 3. Outdoor installation of the developed solar lighting and monitoring prototype.

For the runtime comparison, the battery was initially fully charged. The lamp was first operated continuously at 100% PWM and then tested using the proposed adaptive dimming strategy until the battery required recharging.

B. System Performance

The photovoltaic-panel output voltage ranged from 15.8 to 18.0 V, with an average value of approximately 16.9V. The battery charging time was 5 h 10 min under clear-sky conditions and approximately 6 h under partially cloudy conditions, resulting in an average charging time of 5 h 35 min. These results indicate that the 50 W panel could recharge the prototype battery within a sufficiently sunny day.

The PIR sensor achieved a detection rate of 100% at distances of 1-3 m and 90% at 5 m. Its performance decreased to 60% at 7 m and also declined at large angular offsets. Therefore, the sensor was considered reliable mainly within a distance of 5 m and within its effective field of view.

The BH1750 sensor responded to illuminance changes in less than 1 s and successfully classified daylight, twilight, and nighttime conditions. The 30 lux hysteresis margin prevented repeated state transitions caused by short-duration disturbances. The DHT11 sensor showed deviations of approximately ±0.6°C and ±2.5% RH, which were acceptable for supplementary environmental monitoring.

The proposed controller generated the expected PWM levels for all tested operating conditions. During daylight, the lamp remained off. Under twilight and nighttime conditions, the brightness increased when motion was detected. When the SOC decreased to 20% or below, the PWM level was reduced to preserve the remaining battery energy. The transition to a higher brightness level occurred within approximately 0.5 s, while the fade-in/fade-out mechanism prevented abrupt illumination changes.

The MQTT system achieved a data-update delay of approximately 1.2-2.0 s, a packet-loss rate below 0.5%, and a dashboard command-response time below 1 s. After a temporary Wi-Fi interruption, the controller reconnected within approximately 5-10 s. Automatic lighting was not interrupted because the control algorithm was executed locally on the ESP32-S3.

C. Energy-Saving Performance and Discussion

Under constant 100% PWM operation, the system operated for approximately 4 h 45 min before the battery required recharging. With the proposed adaptive dimming strategy, the operating time increased to approximately 6 h-6 h 15 min. To evaluate the energy-saving effectiveness of the proposed strategy, Fig. 4 compares the battery SOC profiles under constant full-output operation and adaptive dimming control.

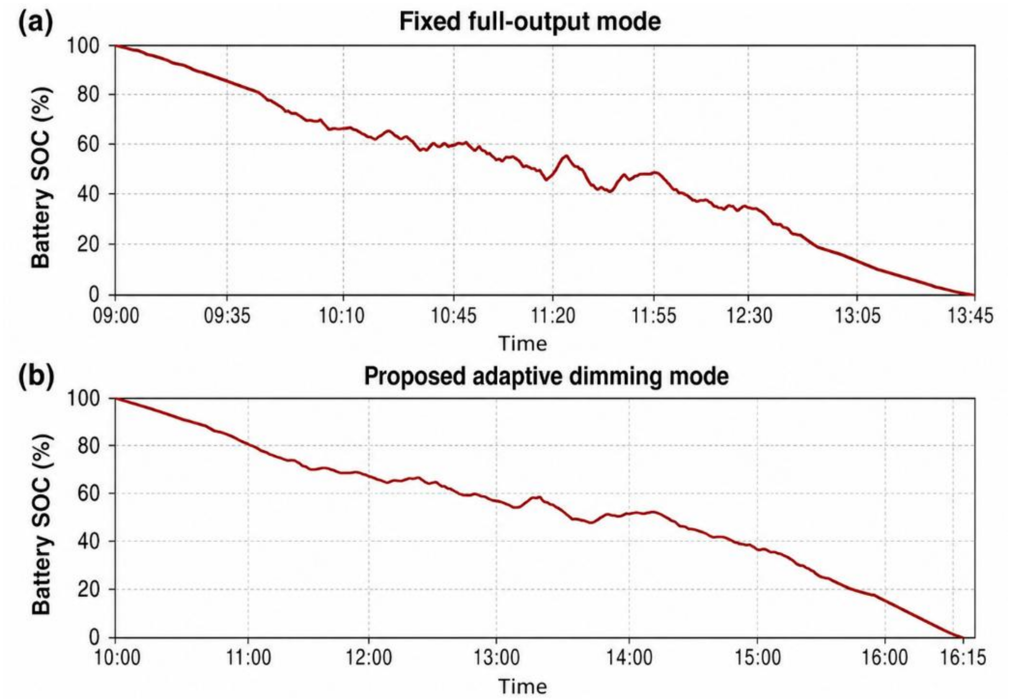

Fig. 4. Comparison of battery state-of-charge profiles under (a) fixed full-output operation and (b) the proposed adaptive dimming strategy.

The improvement in operating time is calculated as:

$$\text{Improvement} = \frac{T_{\text{adaptive}} - T_{\text{fixed}}}{T_{\text{fixed}}} \times 100\%. \quad (10)$$

Using $T_{\text{adaptive}} = 6.00$ h and $T_{\text{fixed}} = 4.75$ h,

$$\text{Improvement} = \frac{6.00 - 4.75}{4.75} \times 100 \approx 26.3\%. \quad (11)$$

Thus, the proposed strategy increased the operating time by at least approximately 26%. This improvement was mainly achieved by maintaining a lower base brightness when no motion was detected and increasing the output only when additional illumination was required. The low-SOC control rule further reduced the battery-discharge rate near the end of the operating period.

However, the achieved improvement depends on pedestrian activity, ambient-light conditions, battery condition, and the actual power consumed at each PWM level. Frequent motion events would increase the time spent at high brightness and reduce the energy-saving benefit. In addition, PWM duty cycle may not vary linearly with actual lamp power or illuminance. Future experiments should therefore directly measure lamp voltage, current, and energy consumption at each brightness level. The accuracy of Coulomb-counting-based SOC estimation may also be affected by current-sensor offset, charging-efficiency assumptions, and battery aging. Combining Coulomb counting with periodic voltage-based correction would improve long-term estimation accuracy.

IV. CONCLUSION

This study developed and experimentally evaluated an IoT-enabled solar lighting system with an energy-aware adaptive dimming strategy. The prototype integrates photovoltaic generation, battery storage, environmental and motion sensing, PWM-based LED control, and MQTT communication. The lighting level is adjusted according to ambient illuminance, motion detection, and battery state of charge, while the low-battery mechanism limits lamp power to prevent excessive discharge.

Outdoor experiments confirmed the reliable operation of the sensing, control, and communication functions. Compared with constant full-output operation, the proposed strategy increased the operating time from approximately 4 h 45 min to 6 h - 6 h 15 min, corresponding to an improvement of at least 26%. The results demonstrate that motion- and battery-aware dimming can improve energy utilization while maintaining adequate illumination when required.

The prototype remains limited by its dependence on solar irradiance, basic nighttime camera performance, and the accuracy of Coulomb-counting-based SOC estimation. Future work will focus on longer field tests, improved SOC estimation, increased energy-storage capacity, fault notifications, and data-driven energy-management methods for practical outdoor deployment.

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