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Impact of Control Algorithms on Hybrid Solar Photovoltaic - Battery System Performance

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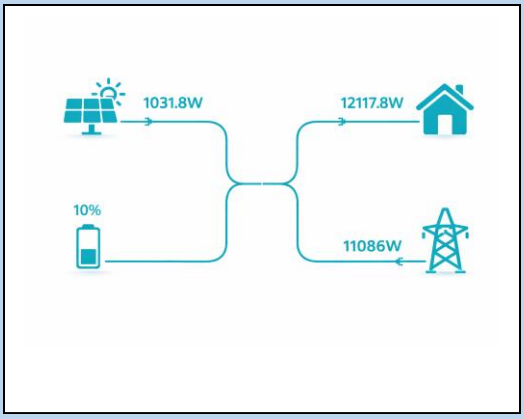
Abstract: Malaysia's National Energy Transition Roadmap (NETR) aims for net-zero carbon emissions by 2050, emphasizing greater adoption of photovoltaic (PV) systems coupled with battery energy storage systems (BESS). However, many existing PV–BESS installations use static, rule-based controls that do not adapt to fluctuating solar input, demand, or tariffs, leading to underutilized storage and reduced overall efficiency. In this study, four control modes – General, Peak Shaving, Economic, and an Adaptive Hybrid strategy – were tested on a 5 kW PV–10.24 kWh battery system under Malaysia's commercial time-of-use tariff. One year of real operational data was utilized to simulate each mode's performance in terms of grid energy usage, electricity cost, and carbon dioxide emissions. All proposed modes improved performance over a grid-only baseline. Notably, the Adaptive Hybrid mode reduced grid energy consumption by ~16.8%, cut electricity costs by ~9.7%, and lowered CO_2 emissions by ~16.8% compared to the baseline. These results demonstrate that adaptive control algorithms can significantly enhance renewable energy utilization and cost savings in PV–BESS systems. The findings support Malaysia's sustainable energy goals by highlighting the impact of intelligent energy management in commercial building applications.



Keywords: Hybrid PV–Battery System; Adaptive Energy Management; Peak Shaving; Time-of-Use Tariff; Carbon Emission Reduction.

Introduction

Energy sustainability has become a central global concern due to the urgent need to address climate change and reduce dependence on fossil fuels. Malaysia is committed to this agenda through the recently launched National Energy Transition Roadmap (NETR), which targets achieving net-zero greenhouse gas emissions by 2050 [1]. This plan calls for a substantial increase in renewable energy generation capacity and the deployment of energy storage to ensure grid reliability. In particular, integrating solar photovoltaic (PV) systems with battery energy storage systems (BESS) is seen as a key strategy for achieving cleaner and more resilient power in commercial and industrial settings. By storing surplus solar energy and releasing it during demand peaks or low-sunlight periods, PV–BESS hybrids can smooth out renewable intermittency and improve energy self-sufficiency, thus aligning with national sustainability goals.

Despite the promise of PV–BESS systems, many existing installations operate under conventional static control schemes that do not adjust to real-time variations in solar output, load demand, or electricity pricing. These fixed rule-based algorithms (e.g., simple charge–discharge schedules) often result in suboptimal performance: solar energy may be wasted when the battery isn't charged opportunely, or the battery might remain unused during times it could offset expensive grid energy [2]. Consequently, the full potential of the battery storage – in terms of reducing grid imports and cutting operational costs – is not realized. For instance, static controls fail to account for daily or seasonal changes, leading to periods of underutilized battery capacity and lower overall energy efficiency. To improve on this, more adaptive control strategies are needed. Recent studies have indicated that adaptive or intelligent algorithms outperform static methods by dynamically adjusting to changing conditions [2,3]. This adaptive approach can significantly enhance the utilization of renewable energy and reduce costs.

However, a clear gap exists in the literature and practice. Many prior works on PV–BESS energy management focus on either simulation with idealized data or single-objective optimization (typically cost), often overlooking real-world complexities such as actual load profiles or environmental benefits. In Malaysia and similar contexts, there is insufficient

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work demonstrating practical control algorithms using real operational data under actual tariff structures. The significance of our study lies in addressing this gap. We directly tackle the drawbacks of conventional static approaches (e.g., wasted solar potential and lack of responsiveness) by proposing an Adaptive Hybrid control mode and evaluating it against other strategies using real data. We connect the challenges (intermittent solar production, variable demand, peak tariff charges) with a practical solution: a tailored control algorithm that switches battery operation based on both time-of-use tariffs and weekday/weekend load patterns.

In this work, we present a comparative analysis of four control algorithms applied to a hybrid solar PV–battery system at a commercial laboratory. The system's performance is evaluated under each strategy in terms of grid dependence, cost, and emissions. By using one year of measured load and generation data for simulation, we ensure the outcomes are grounded in real operating conditions. The results show clear improvements with adaptive control. In summary, the Adaptive Hybrid mode introduced in this study achieved the highest reduction in grid energy usage and CO_2 emissions (~16.8% lower) and substantially reduced electricity bills (~9.7% savings) compared to a grid-only scenario. These findings demonstrate the practical value of advanced control algorithms for PV–BESS, providing important insights for both the research community and industry practitioners on how smarter energy management can contribute to sustainability and cost efficiency.

Literature Review

To provide context for the proposed control approach, we review recent research on energy management strategies for PV–BESS and related hybrid systems. The literature is organized into thematic categories highlighting the evolution from traditional methods to more advanced techniques, as well as the remaining gaps.

Adaptive vs. Static Energy Management

Early PV–BESS installations often relied on simple rule-based or static schedules for battery charging and discharging. Such static methods (e.g. charging the battery at fixed times or using it only when the SOC is above a set threshold) struggle to accommodate the variability of solar generation and load demand. Adaptive strategies, in contrast, adjust control actions based on real-time data or predictions, offering improved performance. A comprehensive review by Khan et al. [2] reported that adaptive control algorithms consistently outperformed static schedules under fluctuating renewable conditions. Similarly, Onsomu et al. [3] integrated real-time monitoring with tariff signals and noted significant gains in cost savings and emission reductions using adaptive management. These studies underscore the need for flexibility: unlike static control, an adaptive mechanism can dynamically respond to changing irradiance or load, thereby enhancing energy utilization and efficiency

Optimization-Based Control Approaches

Optimization techniques have become central in microgrid energy management, enabling systematic decision-making under multiple constraints. Model Predictive Control (MPC) is one widely adopted approach in both residential and commercial PV–battery systems. For example, Gaikwad et al. [4] implemented MPC in smart homes and achieved a marked reduction in grid reliance compared to basic rule-based control. Similarly, Toure et al. [5] developed a hierarchical MPC framework coordinating multiple storage devices, meeting both economic and operational objectives. Although MPC can optimize battery dispatch using forecasts (load, PV, prices), it may incur high computational load. To address this, Lim et al. [6] introduced an event-triggered MPC that reduces computation while maintaining accuracy. Beyond MPC, other optimization methods have been explored: Vaičys et al. [7] incorporated battery degradation costs into a convex optimization model, improving the economic performance of a PV–BESS system. These optimization-based strategies demonstrate improved outcomes, but they typically require accurate models and forecasts. In practice, their effectiveness can be limited by model uncertainties or abrupt changes in conditions.

AI and Machine Learning Techniques

In recent years, artificial intelligence (AI) and machine learning techniques have been increasingly applied to energy management problems, owing to their ability to handle nonlinear behavior and uncertainty. Reinforcement learning (RL) is particularly promising for PV–BESS control. Liu et al. [8] implemented a deep RL controller that learned an optimal battery dispatch policy through trial-and-error, resulting in improved cost efficiency and stable battery cycling. Other works, Ji et al. [9] have used deep Q-learning and multi-agent RL to coordinate multiple homes or to respond to demand response signals, demonstrating better performance than fixed heuristics under time-varying electricity prices. Apart from RL, fuzzy logic and metaheuristic algorithms have provided flexible control solutions when precise models are unavailable. Khallouf et al. [10] applied fuzzy logic in a hybrid PV–wind–battery microgrid, effectively smoothing power flows and maintaining power quality. Additional algorithms like grey wolf optimizers [11], ant lion optimizers [12], and genetic algorithms [13], have also been tested for scheduling and sizing of storage, with positive outcomes.

Robust and Integrated Hybrid Systems

To handle the uncertainty in renewable output and load, robust optimization techniques have been introduced. Wang et al. [14] formulated a robust energy management strategy that maintained operational feasibility despite fluctuations in PV generation and battery degradation. Similarly, Fang et al. [15] employed chance-constrained and adjustable robust optimization to ensure reliable microgrid operation under stochastic conditions. Beyond single microgrids, research has expanded to hybrid energy systems combining multiple energy vectors or storage types. Sasikumar et al. [16] coordinated hydrogen storage with batteries in a two-layer management system, enabling flexible scheduling of hydrogen production and battery charging. Jokar et al [17] integrated thermal loads with PV–battery storage in smart homes to evaluate multi-energy management, finding improved efficiency when accounting for heating/cooling alongside electricity. Khan et al. [18] demonstrated a hierarchical control for remote microgrids that utilized both battery and supercapacitors to maintain stability under renewable intermittency. Additionally, recent contributions have linked energy management with hardware-level considerations. These integrated perspectives broaden the scope of energy management but also introduce complexity in system design and control. Previous experimental work conducted by Kadir et al. [19] evaluated General, Peak Shaving, and Economic inverter modes over short-term operational periods, confirming measurable cost and energy savings under Malaysian tariff structures. However, that study did not incorporate adaptive weekday–weekend switching or full-year simulation using continuous operational data, which motivates the present investigation.

Summary of Gaps: Overall, extensive research exists on algorithms for PV–BESS control – from predictive optimization to AI-driven methods. Yet, relatively few studies validate these strategies using real-world data or under actual tariff regimes, especially in commercial building scenarios. Many implementations optimize a single objective (often cost) and may overlook environmental impacts or practical constraints. Moreover, static and simplistic controls are still prevalent in deployments, indicating a lag in translating advanced algorithms to practice. This study addresses the identified gaps by evaluating multiple control approaches (including a novel adaptive strategy) on a real PV–battery system with actual load/PV profiles. Importantly, we assess multiple performance criteria (economic and environmental) to provide a more holistic view. By doing so, we aim to demonstrate the tangible benefits of adaptive energy management and inform how such strategies can be implemented to support sustainability targets in Malaysia and similar contexts.

System Description and Modeling

System Components and Specifications

The experimental system is a hybrid solar PV and battery storage setup located at the FTKE Solar Laboratory, UTeM. The hardware configuration and key specifications are summarized in Table 1. The PV array consists of 12 × 385 W monocrystalline panels (SunPower SPR-P19-385-COM), totaling 4.62 kW capacity under standard test conditions. These panels are connected to a GoodWe GW5K-ET hybrid inverter rated at 5 kW AC output. The battery bank is a Lynx Home S Series LX S10 lithium-ion battery unit with 10.24 kWh usable energy capacity. This battery is managed through the GoodWe inverter's battery interface, allowing bidirectional power flow (charging and discharging) under control of the inverter's energy management logic.

A smart monitoring system is in place to record electrical parameters. The setup includes AC smart meters on the grid import/export connection and DC sensors on the PV and battery lines. Data from these sensors are collected and logged via the GoodWe SEMS Portal – a cloud-based monitoring application. Over the course of 2024, a full year of operational data (including PV generation, battery State of Charge (SOC), and building load demand at 15-minute intervals) was gathered. This rich dataset provides the basis for realistic simulation and analysis in our study.

Each major component of the system and the chosen control parameters are detailed in Table 1, along with justifications. The component sizes were determined by the laboratory's existing infrastructure (for example, the 5 kW inverter and 10 kWh battery were pre-installed, matching typical commercial-scale testbed configurations). The system's scale is representative of a small commercial building or laboratory setting, making the findings relevant for similar applications. The control parameters (e.g. thresholds and time settings) were selected based on empirical observations of the site's demand profile and common practice, as discussed further below.

Table (1): The chosen control parameters and specifications.

Item / Parameter	Specification / Setting	Justification
PV Array	4.62 kW (12 × 385 W panels)	Sized to utilize available roof space; represents typical small commercial PV installation.
Inverter	GoodWe GW5K-ET (5 kW, hybrid)	Matches PV size and lab load; allows battery integration and multiple modes of operation.
Battery Storage	Lynx Home S Series Li-ion, 10.24 kWh	Provides ~2 hours of peak shaving at 5 kW; capacity selected to meaningfully impact grid usage based on lab's daily consumption.
Tariff Scheme	TNB Commercial C1 with Off-Peak Rider (OPTR)	Time-of-Use tariff with ~20% lower rate at off-peak (10:00 pm–8:00 am); chosen as it incentivizes shifting load to off-peak and is applicable to the site.
Peak Power Threshold (Peak Shaving mode)	5 kW	Set equal to the inverter's max output and typical peak load; any demand above 5 kW triggers battery discharge to **shave peaks**.
Discharge Window (Economic mode)	11:00 am – 6:00 pm (peak tariff period)	Corresponds to high-tariff daytime hours; battery discharges during this window to reduce expensive grid imports.
Charge Threshold (Economic mode)	SOC < 90% (outside 11am–6pm)	Allows battery to charge (from PV or grid) when reasonably empty, but avoids frequent full charges to reserve capacity and prolong battery life.
Weekday Discharge Trigger (Adaptive mode)	Load > 4 kW (11am–6pm), SOC ≥ 20%	Slightly lower power threshold (4 kW) than inverter max to pre-emptively discharge on busy weekdays; ensures **SOC > 20%** to avoid over-discharging battery. The 4 kW threshold reflects typical base load on active weekdays, engaging the battery earlier than the 5 kW limit.
Early Morning Charge (Adaptive mode)	12:00 am – 5:00 am if SOC < 40%	Utilizes cheap off-peak hours to charge the battery if it was heavily drawn down (below 40%) the previous day; ensures a minimum charge by dawn to handle morning load or capture solar.
Weekend Strategy (Adaptive mode)	Charge on solar surplus, no set discharge window	On weekends, lower campus activity leads to reduced load; the battery charges whenever PV exceeds load (until full), and discharges opportunistically if needed. This **maximizes solar utilization** when demand is low.
Minimum State of Charge (SOC_floor)	20%	Reserve capacity to avoid deep discharges that could shorten battery life and to ensure some backup energy remains for critical needs or unexpected loads.
Maximum State of Charge (SOC_ceiling)	100% (90% in Economic mode outside peak period)	Allows full use of battery when solar is abundant (100%), but in Economic mode a 90% limit is used outside peak hours to leave room for midday solar charging and to reduce time spent at full charge (which can degrade Li-ion batteries).

Note: USD currency is used for cost calculations (1 USD ≈ 4.57 MYR, 2024 average). Tariff C1 (OPTR) imposes a higher rate during peak hours (roughly 36.5 sen/kWh base rate) and ~20% discounted rate off-peak. This study assumes an off-peak rate applied from 10:00 pm to 8:00 am daily, in line with TNB's OPTR scheme.

Operational Strategies and Control

1. Four distinct control strategies were evaluated in this work: General, Peak Shaving, Economic, and Adaptive Hybrid. Additionally, a Grid-Only scenario (no PV or battery usage) was considered as a baseline for comparison. The logic of each strategy is outlined below. All modes were implemented through a Python-based simulation that emulates the battery and inverter behavior given the control

rules. The flowcharts in Figures 1–4 illustrate the decision process for each mode.

2. General Mode: This basic strategy prioritizes using solar energy whenever available. As shown in Figure 1, during daylight hours the PV output first supplies the load. If PV generation exceeds the load, the surplus charges the battery until it reaches its upper SOC limit. Conversely, if the load exceeds PV output, the battery discharges to supply the deficit, but only down to a safe SOC limit (20%). If the battery is depleted (SOC at floor) or PV is insufficient, the remaining demand is drawn from the grid. This mode effectively maximizes solar self-consumption but does not incorporate any tariff timing or peak shaving considerations. It is a straightforward rule set often found in default inverter configurations, ensuring no solar energy is wasted while maintaining battery protection limits.
3. Peak Shaving Mode: This mode is designed to reduce peak demand drawn from the grid. A power threshold of 5 kW was defined (matching the inverter capacity and typical peak load at the site). Figure 2 illustrates the control logic: whenever the total load would exceed 5 kW, the battery immediately discharges to cap the net grid import at approximately 5 kW. In practice, this means the battery steps in to supply any load above the threshold, thereby "shaving" the peaks. During times of lower demand, the battery can recharge if there is surplus PV power or even from the grid during off-peak tariff hours (since no specific time window is enforced except by the threshold rule). By maintaining the grid draw below the threshold, this mode aims to minimize demand charges or strain on the grid. It is particularly useful for facilities with tariff structures that penalize high peak usage. In our setup, while there is no explicit demand charge, this mode still helps by shifting some energy use from peak periods to times when the battery can later recharge more cheaply.
4. Economic Mode: The Economic mode uses a time-of-use (TOU) schedule aligned with tariff periods to minimize electricity cost. As depicted in Figure 3, the battery is discharged primarily during the expensive tariff window of 11:00 am – 6:00 pm (weekday peak period under Tariff C1). During these hours, if the battery has sufficient charge (SOC ≥ 20%), it supplies the load to reduce grid purchases when each kWh is costliest. Outside the peak window (evenings, overnight, and early morning), the controller charges the battery whenever possible – giving priority to PV generation but also allowing grid charging if the battery is below about 90% SOC. This strategy ensures the battery is full or nearly full before the next day's peak period begins, so that maximum grid offset can occur during 11 am–6 pm. Compared to General mode, the Economic strategy might draw more from the grid at night (when rates are lower) in order to avoid grid use in midday (when rates are higher). It essentially arbitrages the tariff differential to achieve cost savings. We implemented this mode reflecting Tenaga Nasional Berhad's OPTR details, wherein energy drawn during off-peak (night) hours costs ~20% less.
5. Adaptive Hybrid Mode: This is the proposed mode with a dynamic control framework that adapts to both the day type (weekday vs. weekend) and time-of-day. Figure 4 shows an overview of this strategy. On weekdays (when campus load is high), the mode behaves similarly to Economic mode during the daytime peak period (11 am–6 pm) but with an important enhancement: the battery discharge triggers not only by time but also by load level. Specifically, during 11 am–6 pm on weekdays, if the load exceeds ~4 kW and the battery SOC is ≥ 20%, the battery discharges to assist – even if 4 kW is below the inverter's 5 kW capacity. This preemptive discharge threshold (4 kW) was chosen by analyzing typical weekday demand, which often hovered around 4–5 kW; by starting discharging at 4 kW, the battery output can prevent the grid draw from ever hitting the 5 kW peak in the first place. In addition, the Adaptive mode incorporates an early-morning charge routine: between midnight and 5 am (low-demand, off-peak hours), if the battery SOC has fallen below 40%, the system draws cheap grid energy to charge the battery up to ~40%. This ensures the battery isn't empty at sunrise and can both supply morning loads and store new solar energy. On weekends, the pattern shifts because loads are much lower (the campus is largely inactive). The Adaptive strategy in weekend mode does not enforce a midday discharge window; instead, it simply charges the battery whenever PV generation exceeds the load (to capture all possible solar energy) and discharges only as needed to meet any evening or sudden loads. Essentially, on weekends the battery serves as a solar energy buffer, filling up during sunny hours and covering any minor deficits, whereas on weekdays it aggressively targets the costly peak period with a tailored discharge. This mode was developed to combine the benefits of the Economic and Peak Shaving modes while adjusting to actual usage patterns observed at the site.

Finally, a Grid-Only scenario was modeled for reference. In this baseline case, all loads are met by grid electricity with no contribution from PV or battery. Although not an operational mode per se (since the system physically has PV and BESS installed), the grid-only case provides a benchmark to quantify the improvements achieved by the other modes. It represents the consumption and cost if the hybrid system were not utilized at all.

Figures 1 through 4 (flowcharts) were redrawn with improved clarity to visualize each control algorithm's decision flow. In the simulation, these rules are applied step-by-step on the 15-minute interval data over the year. At each time step, the control logic decides whether to draw from PV, battery, or grid, and whether to charge the battery, based on the mode's rules and the available PV power and load demand.

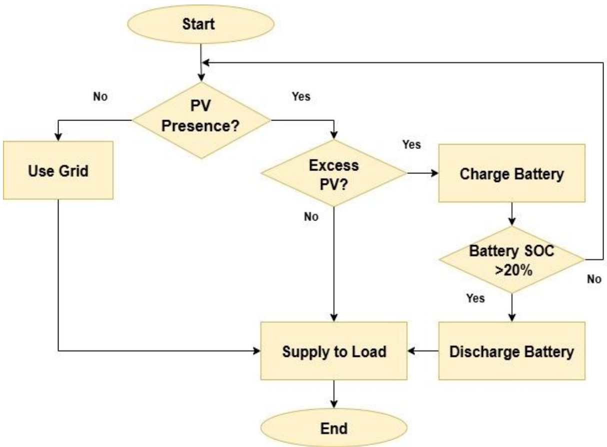

Figure (1): Flowchart of control logic for General Mode (PV priority strategy).

Figure 1 shows the General Mode operation. The battery charges on excess PV and discharges when load exceeds PV output (down to a minimum SOC of 20%). Grid power is used only when PV and battery cannot fully supply the load.

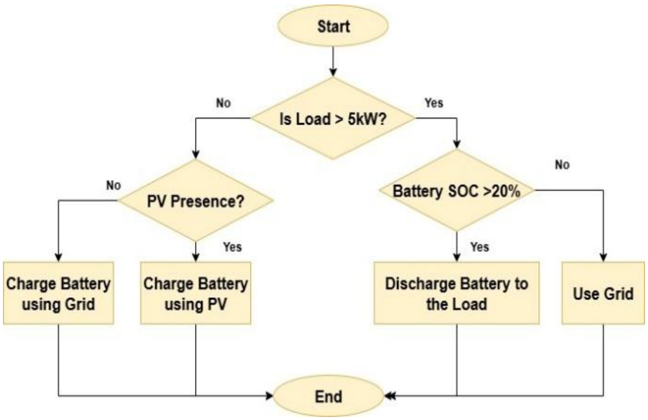

Figure (2): Flowchart of control logic for Peak Shaving Mode.

Figure 2 shows the battery maintains grid import at or below 5 kW. When load > 5 kW, battery discharges; if PV + grid supply exceeds load (meaning some capacity is free), the battery can charge. This ensures peak demand from the grid is capped.

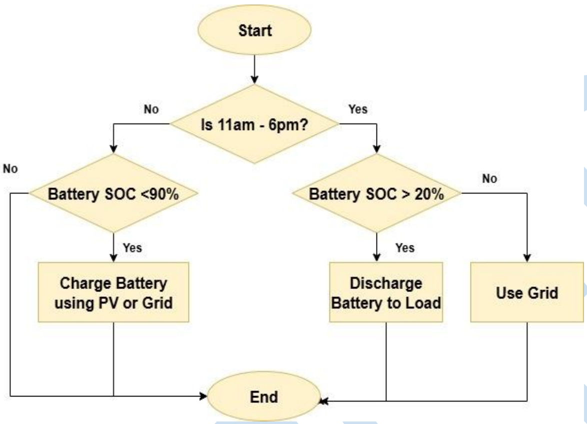

Figure (3): Flowchart of control logic for Economic Mode (TOU cost optimization).

Figure 3 shows the Economic Mode: The battery discharges during high-cost hours (11:00–18:00) if SOC ≥ 20% to minimize expensive grid usage. During off-peak times, if battery SOC < 90%, it charges using surplus PV or cheaper off-peak grid power, preparing for the next peak period.

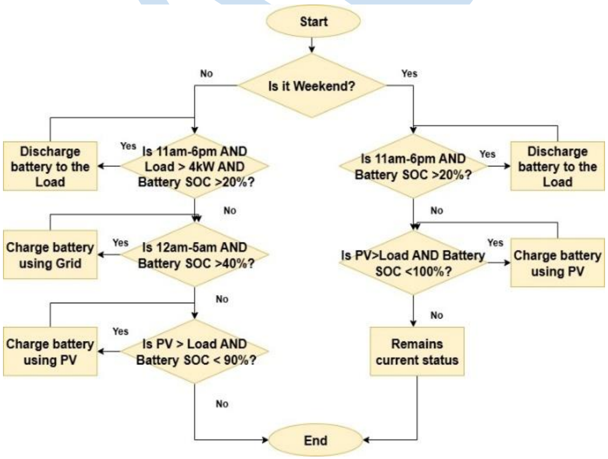

Figure (4): Flowchart of control logic for Adaptive Hybrid Mode (proposed strategy).

Figure 4 shows the Adaptive Hybrid Mode: On weekdays, battery discharges during 11:00–18:00 when load > 4 kW (if SOC ≥ 20%) and charges from grid during 00:00–05:00 if SOC < 40% (off-peak). On weekends, battery charging is driven by PV surplus and discharging occurs only to meet loads, reflecting lower weekend demand.

Simulation Model and Data Analysis

The above operational strategies were modeled and analyzed using Python (in a Jupyter/Colab environment) to ensure a consistent and controlled comparison. The real measured data (12 months of 2024) for solar production and building load was used as input to the simulation script. The simulation progressed in discrete time steps of 15 minutes, aligning with the data resolution. At each step, the algorithm computed the power flows according to the rules of the selected mode. The battery's state of charge was updated based on charging/discharging (with an assumed round-trip efficiency of approximately 95%, typical for lithium-ion BESS). If a control rule required charging from or discharging to the grid, the model accounted for it with the appropriate sign convention (charging from grid adds to cost, discharging reduces grid draw).

To quantify performance, we evaluated several metrics for each mode:

1. Grid Energy Consumption: The total electrical energy drawn from the utility grid over the year (kWh). Lower values indicate better utilization of on-site PV and battery. This metric directly affects both cost and emissions.
2. Total Electricity Cost: The annual electricity bill in USD, calculated by applying the time-of-use tariff rates to the grid energy profile. Peak period consumption (weekday daytime) was billed at the higher rate and off-peak consumption at the discounted rate, per TNB's C1 OPTR tariff structure. The simulation computed cost incrementally: for each interval, Cost += E_grid_interval * Tariff_rate_interval. We used an average exchange rate of 1 MYR = 0.22 USD for conversion.
3. CO_2 Emissions: The annual carbon emissions associated with the grid electricity used (in kg CO_2). We applied an emissions factor of 0.694 kg CO_2 per kWh of grid electricity, which is the reported average carbon intensity of Malaysia's grid mix. Thus, emissions were calculated as Emissions = 0.694 * (total grid kWh). (The PV energy is treated as carbon-free and battery energy inherits the source – PV or grid – used to charge it. We assume any incremental grid charging occurs at the same emission factor, since it is drawn from the grid.)

By comparing these metrics across modes, we can assess trade-offs in economic and environmental performance. It should be noted that the simulation assumes ideal battery behavior without degradation and perfect data foresight within each day (for scheduled modes). In reality, battery ageing could slightly reduce capacity over time, and forecasting errors might affect optimal dispatch; those aspects are beyond our current scope. However, because we used actual historical data, the simulation results closely reflect real outcomes if the same year's conditions repeat.

We also cross-verified the simulation outcomes against the actual monitored data in periods where the system was manually operated in a certain mode. For example, a brief test of the Peak Shaving mode was conducted in the lab to ensure the battery responded at the 5 kW threshold as expected. The measured response matched the simulation's logic, adding confidence that the model accurately represents the system. In general, because our model uses the actual load and PV profiles and the manufacturer's specifications for battery/inverter, it effectively emulates how the system would behave under each strategy. This approach provides a realistic comparison without having to physically switch modes over the entire year (which would have been impractical).

All costs and savings are reported in USD for broader relevance. At the 2024 average exchange rate (~RM4.57 to 1 USD), this means that a reduction of, say, RM100 in the electricity bill is presented as about $21.9. The outcomes of each mode are compiled in the next section, and key differences are illustrated with both tables and graphs for clarity.

Results and Discussion

This section compares the performance of the hybrid PV–BESS under each control mode. Table 2 summarizes the annual grid energy usage, electricity costs, and CO_2 emissions for the baseline (Grid-Only) and the four modes. To highlight the benefits of the PV and battery, we also discuss the relative savings of each mode compared to the grid-only case.

Table (2): Annual Energy Consumption, Cost, and CO_2 Emissions by Mode.

Mode	Grid Energy (kWh/year)	Electricity Cost (USD/year)	CO_2 Emission ($kgCO_2$/year)
Grid-Only (no PV, no battery)	32,454.98	4,507.89	22,523.76
General	28,121.67	4,159.05	19,516.44
Peak Shaving	27,997.77	4,147.16	19,430.45
Economic	27,961.69	4,147.48	19,405.42
Adaptive Hybrid	27,004.80	4,070.38	18,741.33

From Table 2, it is evident that all four control modes outperform the Grid-Only baseline in reducing grid consumption, cost, and emissions. The baseline scenario, which relied solely on the grid for 32,455 kWh, incurred an annual cost of about $4,507 and associated emissions of ~22.52 metric tons CO_2. In contrast, any use of the PV–battery system dramatically improved these figures. The PV generation (4.62 kW array) contributed significantly to offsetting grid energy, and the battery enabled strategic timing of grid use.

Among the modes, the Adaptive Hybrid mode delivered the best overall performance. It drew approximately 27,004.8 kWh from the grid over the year, which is a 16.8% reduction in grid energy compared to the baseline (saving about 5,450 kWh annually). This translated to an annual cost of $4,070, yielding savings of $437.5 (≈9.7%) on the electricity bill. Likewise, CO_2 emissions dropped to about 18,741 kg, which is 3,782 kg (16.8%) lower than the grid-only case. The Adaptive mode's superior results can be attributed to its combined approach of peak period optimization and load-adaptive response – it takes advantage of both time-of-use price differences and the load-following discharge to minimize high-cost, high-carbon grid consumption.

The Economic mode also performed strongly, ending the year with roughly 27,961.7 kWh of grid usage (about 13.8% less than baseline). This mode's cost savings was around $360.4 (8.0%) annually, with a final cost of ~$4,147. The annual emissions (19,405 kg) were lower by about 3,118 kg (13.8%) relative to baseline. Notably, the Economic mode's outcomes are very close to those of Peak Shaving – both saved roughly 13–14% in energy and emissions and ~8% in cost. This is expected, since both strategies make use of the battery daily, albeit in different ways (time-scheduled vs. threshold-triggered). The Economic strategy maximized use of the battery during expensive periods, which effectively also meant it was utilized on most sunny days when loads were moderate to high.

The Peak Shaving mode achieved an annual grid import of 27,997.8 kWh (about 13.7% saving). The cost came to $4,147, almost identical to Economic mode, yielding a savings of ~$360 (8.0%). CO_2 emissions at 19,430 kg were cut by 3,093 kg (13.7%) from baseline. Peak Shaving's performance indicates that by capping the grid draw at 5 kW, the battery was frequently used during high-demand moments. Many of those high-demand times coincided with midday or early afternoon (when PV was available) and/or peak tariff periods, so this mode indirectly also provided some TOU benefit. However, because it didn't intentionally charge up during cheap hours, it occasionally had less energy available to offset some mid-day usage if the battery hadn't been charged from solar. This resulted in slightly less energy offset than Economic mode in some months, though over the year the difference was marginal.

The General mode, which purely maximizes PV self-consumption, resulted in 28,121.7 kWh grid use annually, about 13.3% lower than baseline. The annual cost was $4,159, saving roughly $348 (7.7%). CO_2 emissions were 19,516 kg, reduced by 3,007 kg (13.35%) versus grid-only. General mode's performance was only modestly behind Peak Shaving and Economic modes in terms of percentage savings. This outcome highlights that even a simple PV-priority strategy yields substantial benefits as long as a battery is available to store excess solar. The differences among General, Peak, and Economic modes were on the order of 1–3 percentage points in these metrics. The slightly smaller savings for General mode can be explained by the fact that it does not specifically target the timing of grid usage—some battery energy might be used at night even when grid power is cheap, and it might leave the battery partially charged at times when it could have offset more expensive energy. Nonetheless, General mode still considerably improved on the baseline by ensuring most solar production was utilized, either instantly or via storage.

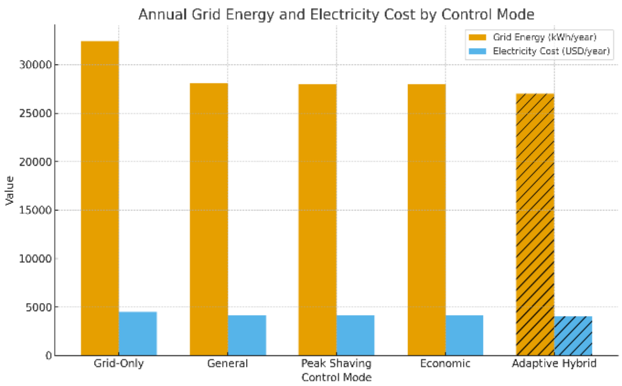

Figure (5): Annual performance comparison of each mode.

The top chart shows grid electricity consumed (kWh) per year, and the bottom chart shows the corresponding annual electricity cost (USD). The Adaptive Hybrid mode draws the least from the grid and incurs the lowest cost, followed by the Economic and Peak Shaving modes. All modes use significantly less grid energy than the Grid-Only case, reflecting the contributions of PV and battery under each strategy.

Figure 5 provides a visual comparison of the annual grid usage and cost for each mode. The Grid-Only bar is the highest in both plots, reinforcing the magnitude of reduction achieved by deploying the PV–BESS system. Adaptive Hybrid stands out with the shortest bars, indicating the lowest grid consumption and cost. Economic and Peak Shaving modes are nearly tied, and both are only slightly above Adaptive. General mode also shows substantial reductions relative to baseline, though not as pronounced as the others in cost terms. These graphical results make it clear that incorporating an intelligent control strategy is pivotal – even the basic General control yielded notable savings, and more sophisticated controls yielded even greater ones.

Turning to mode-specific observations:

1. Adaptive Hybrid Mode: This mode's dynamic approach resulted in the largest decrease in grid dependence (about 5.45 MWh less than baseline annually). On average, that's roughly 454 kWh saved per month (≈16.8%). Monthly analysis (not fully shown here) indicated that Adaptive mode particularly excelled during workdays: it consistently kept the midday grid draw low and took full advantage of weekend solar surplus. The financial savings (~$437/year) may seem moderate in percentage terms due to Malaysia's relatively low commercial tariff (around $0.14/kWh on average), but they are significant considering they require no extra energy input beyond what PV provides. Importantly, the Adaptive mode also had the steepest reduction in CO_2 emissions (~3.78 tons less CO_2 annually), directly supporting environmental goals. The strong performance of Adaptive mode validates the premise that combining load-based control with tariff-based scheduling yields compounded benefits. Essentially, this mode captured the upside of the Economic strategy (TOU optimization) and the Peak Shaving strategy (limiting high draws) simultaneously. One minor trade-off is the complexity of implementation: the inverter's control had to be customized to handle dual regimes (weekday vs weekend) and multi-threshold logic, which might not be readily available in all off-the-shelf controllers. Nonetheless, modern energy management systems could be programmed for such rules, and the payoff is evident.
2. Economic Mode: By focusing on tariff times, the Economic mode ensured that nearly all solar generation was used to offset expensive electricity, and the battery was kept for those peak-rate periods. It saved about 4.49 MWh of grid energy over the year (13.8%). Interestingly, the Economic mode's cost savings (8.0%) were only slightly lower than Adaptive's 9.7% despite using about 2.96% more grid energy than Adaptive. This is because the remaining grid energy in Economic mode was often taken during cheaper periods (nighttime), softening the cost impact. In fact, the Economic algorithm successfully shifted some consumption from peak to off-peak—evidenced by the battery charging at night—which is why its cost performance is proportionally a bit better than its raw energy reduction. The limitation of Economic mode is that it does not consider actual load magnitude; on a very high-load day, the battery might become depleted by mid-afternoon, after which the grid still must supply the remaining peak hours. Likewise, if a peak demand spike occurred outside 11 am–6 pm (which is rare in our case, but could happen in early morning), Economic mode wouldn't react. This rigidity is where Adaptive has an edge. Nevertheless, the Economic strategy is simpler to implement (just a fixed schedule), and our results show it is highly effective under a TOU tariff structure.
3. Peak Shaving Mode: This mode's primary advantage is reducing instantaneous grid load rather than total energy. In our results, it achieved energy and cost outcomes very close to the Economic mode, indicating that peak demands often coincided with expensive times or that shaving peaks indirectly meant using battery during many daytime hours. One specific benefit of peak shaving is mitigating any demand charges (though our tariff did not have a large demand-charge component, some tariffs do charge based on monthly peak kW). If such charges were present, Peak Shaving could yield additional financial savings not reflected fully in our cost calculation. In terms of grid energy, Peak Shaving saved about 4.46 MWh (13.7%) annually. We observed that on some days, once the battery engaged to shave a peak, it continued to discharge until it hit the SOC minimum, even if load dropped slightly below 5 kW, because the controller doesn't rapidly toggle charging/discharging around the threshold (to avoid oscillations). This meant it sometimes discharged a bit more than necessary, using up stored energy that could have been saved for later in the day. Conversely, if the battery was empty, any subsequent peaks could not be shaved. These nuances make Peak Shaving somewhat less optimal in energy terms than a perfectly scheduled approach. However, it provides a very straightforward rule that is robust to unpredictable load spikes – it will always respond when a threshold is exceeded. This characteristic can be valuable for facilities where occasional spikes (e.g., when large equipment turns on) are a concern.

General Mode: The General mode's performance, while slightly behind the other modes, still underscores the value of having any battery at all with PV. By simply charging whenever there's extra PV and discharging when there's a shortfall, the system managed to cut grid usage by over 4.33 MWh in the year. This mode is essentially maximizing self-consumption and can be thought of as a baseline use-case for the battery. It does not require any forecast or tariff knowledge, making it easy to implement. One observation was that during long stretches of cloudy weather, the General mode battery might remain at a low SOC (since there's little excess PV to charge it), and at night it can't help because it's empty – this is a scenario where Economic mode might have pre-charged the battery from the grid to prepare for such a day. General mode missed that opportunity. On very sunny days with low load (like some weekends), the battery would fill up by midday and the PV would then be curtailed (since nowhere to go), which is a limitation shared by all modes unless one allows export to grid (which we did not assume due to no feed-in tariff at the site). The key takeaway is that General mode provides solid benefits with minimal intelligence; however, by not taking into account time-based pricing or specific load thresholds, it leaves some savings on the table.

Overall, the results demonstrate that integrating a PV–BESS with any of these control strategies brings notable reductions in both cost and emissions. The Adaptive Hybrid mode emerges as the most effective, confirming that a tailored approach which adapts to usage patterns and tariff schedules can outperform more generic strategies. Not far behind, the Economic and Peak Shaving modes each achieve about 8% cost savings and ~13–14% emission reductions, which is impressive given their narrower focus (one on time, one on power level). The General mode, while not optimizing any particular metric, still delivers a broad benefit (7.7% cost, 13.3% emissions saved) simply by utilizing solar energy whenever possible.

It's worth discussing the technical reasoning and potential limitations of each mode's performance. The Adaptive mode's superior performance can be attributed to how it strategically uses the battery: on weekdays it essentially combines time-based dispatch with load-based triggers, ensuring the battery's energy is used when it is most needed (high load and high price) – this double criterion is why it edged out the single-criterion Economic or Peak modes. On weekends, Adaptive conserves battery life by not cycling unnecessarily, but still captures solar overflow; this flexibility means the battery is being used only when beneficial (either economically or to prevent curtailment). One limitation of the Adaptive approach is that it relies on pre-defined thresholds (like 4 kW, 40% SOC) which were tuned to our observed patterns; if the load profile changes significantly (say, new equipment on weekends), those thresholds might need retuning. In a broader sense, Adaptive control introduces more complexity, requiring the system controller to handle different rules on different days and times. The effort is justified by the gains here, but it may require more sophisticated programming or control hardware.

For the Economic mode, the main limitation is that it does not consider actual load magnitude – it will discharge during 11–6 regardless of whether the load is high or relatively low (as long as battery has charge). If the load is low, that battery discharge might only offset cheap base usage, whereas saving it for a later spike could have been better. Incorporating some load-sensitivity (like Adaptive does) would improve it. The Economic mode also implicitly assumes the tariff schedule is static and known (which it is, in our case). If tariffs were dynamic or included critical peak pricing, a fixed schedule would be suboptimal.

Peak Shaving mode is limited by the fact that it looks only at instantaneous power. It doesn't "plan" for the day or consider tariff timing. For example, it might discharge the battery to shave a relatively small peak in the morning (say 5.2 kW to 4.8 kW), using energy that could have saved more cost if used during the afternoon peak period. In our data, such situations were rare because mornings typically didn't exceed 5 kW much, but it's a conceivable inefficiency. Peak Shaving is excellent for facilities where avoiding high demand peaks is priority (perhaps to reduce transformer stress or demand charges). In our context of cost savings under TOU, it wasn't the very top performer but still nearly matched Economic mode because most peaks aligned with expensive times.

Regarding battery health and constraints: all these modes were simulated without considering degradation or cycle life. In practice, aggressively cycling the battery (especially daily deep discharges) can shorten its lifespan. The General mode often keeps the battery cycling shallowly (because it discharges only until grid needed, and charges only on excess PV), which might be gentle. Economic and Adaptive modes, on the other hand, deliberately cycle the battery deeply every weekday (from full charge to at least 20% by end of peak hours). Over a year, that's about 250 deep cycles. Modern Li-ion batteries can handle a few thousand cycles, so a few hundred per year is acceptable, but it does consume some of the battery's life. The trade-off here is between immediate savings and long-term battery replacement costs. A rough analysis suggests that the cost savings (~$360–$440/year) might not fully pay for battery replacement if the battery's lifespan is significantly shortened. Therefore, one might consider this: if the goal is purely financial, the moderate cycling of General mode might preserve battery life better, whereas Adaptive/Economic maximize savings at the expense of more cycling. Incorporating battery degradation into the strategy (an advanced topic) could further refine optimal use. In our case, we assumed the battery management system would handle things like not letting SOC go to 0% and limiting charge rates, which mitigates stress.

Another discussion point is payback period and economic feasibility. While our control strategies saved up to about $438 per year, the capital cost of the PV and battery system is much higher. For instance, a 4.62 kW PV + 10 kWh battery system might cost on the order of tens of thousands of USD in Malaysia. Even without precise numbers, if we assume (for argument) a $12,000 system cost, the simple payback from electricity savings (around $400/year) exceeds 25 years. Our results reinforce that viewpoint: the hybrid system yields substantial energy and emission benefits, but the financial return is modest given present tariff rates and battery prices. This suggests that the motivation for such systems may need to include intangibles or external incentives (e.g., sustainability goals, backup power value, or future tariff changes). It also highlights that future reductions in battery cost or higher differential between peak and off-peak prices would be needed to improve the economics. In fact, our Adaptive mode's ~9.7% cost saving is the highest scenario; even there, the ROI would be long without subsidies or other value streams (like selling battery services to the grid).

In conclusion of this comparative discussion: each control mode aligns with different operational goals. The Adaptive Hybrid mode provides the best all-around improvements, making it most suitable when both economic and environmental performance are priorities. The Economic and Peak Shaving modes offer targeted advantages (cost and peak management respectively) and perform nearly as well in our TOU context. The General mode, while simpler, still delivers a reasonable chunk of the possible benefits with minimal requirements. For a commercial building like our case study, if one can implement the adaptive strategy, it clearly yields the highest payoff in terms of reduced grid usage and emissions. But even a straightforward strategy is worthwhile if more complex control is not feasible.

Finally, it's worth noting that all these findings were obtained via simulation using actual data, which provides confidence in their real-world applicability. Nevertheless, real-world validation (as mentioned earlier) would be the next step: implementing the Adaptive Hybrid algorithm on the actual system's controller to confirm that the savings materialize as predicted and that there are no unforeseen operational issues (like battery overheating or occupant discomfort if some loads are curtailed, though in our case we did not curtail loads, only changed power sources). The remarkably annual savings (Table 2) also show that the performance of each mode was relatively stable throughout the year – there were no extreme outlier months where one mode failed. This reliability is an encouraging sign for practical deployment.

Environmental Impact of BESS Integration

The deployment of the PV–battery hybrid system and its control strategies has significant environmental implications, particularly in terms of carbon emissions reduction. Using the Malaysian grid emission factor of 0.694 kg CO_2/kWh, our results show that all modes with PV–BESS substantially cut CO_2 emissions relative to a grid-only scenario. The Adaptive Hybrid mode yields the largest reduction, avoiding approximately 3.78 tons of CO_2 emissions per year compared to relying solely on the grid. This is a 16.8% decrease in the building's operational carbon footprint, achieved simply by intelligently shifting and sourcing energy from cleaner PV generation. Such a reduction is meaningful in the context of climate targets – for example, a ~17% cut in emissions for a building is in line with findings from other studies that analyzed PV–battery additions. Our operational results (not a full life-cycle analysis but focusing on use-phase emissions) align closely with those figures.

The Economic and Peak Shaving modes each reduce annual emissions by around 3.1 tons (13.7–13.8%), while the General mode achieves about 3.0 tons (13.3%) reduction. To put this into perspective, a 3-ton CO_2 reduction is roughly equivalent to the carbon sequestered by 50 tree seedlings grown for 10 years, or avoiding the emissions from burning over 1,300 liters of diesel fuel. In a single small facility, these savings may appear modest, but across many commercial sites, the cumulative impact would be significant. Moreover, these reductions contribute directly to Malaysia's broader commitments under the NETR and the Paris Agreement. By cutting demand for grid electricity, especially during peak times, PV–BESS systems help reduce the need for peaking power plants (often fueled by fossil fuels) and improve the overall grid emissions factor over time.

It should be noted that our emission calculations considered only the operational emissions (i.e., those associated with electricity consumption from the grid). We did not account for the embodied emissions of manufacturing and eventually disposing of the battery and PV system. In a full environmental assessment, one must consider that battery production is energy-intensive and involves materials with their own environmental footprints. However, several studies suggest that the operational emission savings of PV–battery systems can outweigh the manufacturing emissions under the right conditions. For instance, Wang et al. [20] reported a life-cycle study indicated up to a 44% reduction in life-cycle carbon emissions when combining PV and storage in a residential building, despite the added manufacturing footprint of the battery. In our scenario, given the sizable yearly CO_2 savings, the PV–BESS is likely to offset its embodied carbon within a few years of operation. Every year after that, it provides net CO_2 avoidance.

Another aspect of environmental impact is how battery usage can enable greater penetration of renewables on the grid. By using the battery to smooth out PV generation and reduce peak grid draw, the system not only cuts its own emissions but also helps the utility manage renewable intermittency. During sunny hours, excess PV charging the battery means less curtailment of solar (if that were an issue) and potentially supply of clean energy later in the day. During peak demand periods (especially in the evening when PV is low), having battery energy available reduces the need for grid peaker plants, which are often the least efficient and most carbon-intensive generators. Therefore, beyond the direct accounting of CO_2 in our facility, there is a broader grid benefit: battery storage mitigates stress on the grid and can reduce reliance on fossil backup generation. This aspect is particularly relevant as Malaysia increases its share of renewables from the current 4% towards the targeted 22% by 2050. BESS will play a pivotal role in addressing the intermittency of solar and wind, ensuring that renewable energy can contribute effectively without compromising grid stability.

Our results specifically underscore the environmental value of the Adaptive Hybrid strategy. By maximizing the use of PV (clean energy) and minimizing the import of grid electricity during high-carbon periods (daytime grid power in Malaysia often comes from gas/coal plants meeting peak demand), the Adaptive mode provides the greatest CO_2 reduction. For organizations with sustainability goals or carbon reduction targets, implementing such an adaptive control can be a relatively low-cost measure (once the PV–BESS system is in place) to cut emissions further. Essentially, the control algorithm is extracting more emissions benefit out of the same hardware, just by operating it smarter. This is an important point: software and control improvements can yield environmental gains without additional hardware.

In terms of environmental policy implications, demonstrating these emission reductions could support incentives for battery storage. Currently, the financial payback for batteries is a challenge, but if valued for their carbon reduction (e.g., through carbon credit markets or sustainability indices), that could tip the scales. For instance, avoiding ~3.8 tons CO_2/year in our system might be monetized if carbon has a price (some markets price carbon at \$10–\$30/ton or more). While Malaysia does not yet have a widespread carbon pricing mechanism, the data we've provided could feed into future considerations of how behind-the-meter storage contributes to emission reductions nationally.

It is also worth discussing that the marginal emissions factor of the grid can be higher during peak demand times. If peak hours are met by less efficient generators, then reducing consumption at those times (which our battery does) might avert more than the average 0.694 kg/kWh. Our calculation used the average factor for simplicity. In reality, because the battery discharges during the day (when the grid mix might include oil or gas peakers) and charges at night (when base-load gas or even some coal with possibly slightly different efficiency is on), the net CO_2 benefit could be slightly different. It's possible we under- or over-estimated by using a constant factor. A refined analysis might apply a higher emission factor during 11 am–6 pm and a lower one at night. Regardless, the trend would remain: shifting load from peak to off-peak likely also shifts from higher-emission generation to lower-emission generation, thus improving the carbon outcome beyond just the kWh reduction.

In summary, the PV–BESS system with intelligent control not only saves costs but also delivers tangible environmental benefits. Our study quantifies those benefits for a representative scenario: up to ~17% reduction in building CO_2 emissions. These savings contribute to a more sustainable campus operation and demonstrate how distributed energy resources can support national and global climate objectives. Adopting such systems widely in commercial and industrial sectors would help reduce the overall carbon intensity of the economy. That said, to fully realize the environmental potential, supportive measures (like renewable energy credits for solar exports or grid services) could amplify the impact and encourage more rapid uptake of BESS technology.

Finally, beyond CO_2, one could consider other environmental impacts: reducing peak grid demand can alleviate the need to fire up additional power plants that might cause local air pollution. Increased renewable usage reduces not only CO_2 but also pollutants like SO_2, NO_x, and particulate matter from fossil fuel combustion. Those co-benefits, while not quantified here, are real and align with public health and environmental quality improvements. Battery systems also provide resilience (backup power during outages), which though not an "environmental" benefit per se, ties into sustainability by improving energy security. On the flip side, we must eventually address battery end-of-life recycling to ensure that the environmental gains during operation are not offset by disposal issues. Encouragingly, battery recycling technologies are improving, and the value of recovered materials (like lithium and cobalt) provides economic incentive to recycle.

In conclusion, the integration of a BESS with solar PV under advanced control is a positive step for the environment. It substantially reduces operational emissions and fosters a more flexible and renewable-friendly grid. Our Adaptive Hybrid strategy showcases how maximizing these environmental benefits can go hand-in-hand with operational efficiency. As Malaysia and other countries pursue their net-zero targets, widespread implementation of such smart PV–BESS systems can be one of the key enablers, turning commercial buildings from passive consumers into active participants in carbon reduction.

Conclusion

This study demonstrates that advanced energy management strategies can significantly enhance the performance of a hybrid photovoltaic–battery system in a commercial building context. By evaluating four control modes against a baseline, we found that an intelligently managed PV–BESS can reduce grid consumption, lower electricity bills, and cut carbon emissions, all without any increase in installed generation capacity. Among the strategies tested, the Adaptive Hybrid mode consistently delivered the most favorable outcomes. It achieved the greatest reduction in annual grid electricity use (~16.8%) and CO_2 emissions (~16.8%), as well as the largest cost savings (~9.7%), by aligning battery charging and discharging with both the facility's load patterns and the utility's time-of-use tariff. This mode's superior performance underscores the value of incorporating both load adaptiveness and tariff awareness into the control algorithm.

The more specialized control modes also proved effective in their own right. The Economic mode, which targets high-tariff periods, yielded substantial benefits (about 13–14% reduction in grid energy and emissions) and was the next-best performer in cost savings (~8.0% reduction). This confirms that time-of-use optimization is a viable strategy for sites facing significant peak pricing. The Peak Shaving mode demonstrated its strength in limiting peak demand, achieving similar annual results (~13–14% energy/emissions reduction, ~8% cost savings) and would be particularly valuable if demand charges were a concern. Even the simple General mode – prioritizing solar usage – provided a notable improvement (~13% less grid energy and emissions, ~7.7% cost savings) over not using the PV–BESS at all. Each mode aligned with different operational goals, but all proved the fundamental point that coordinating a battery with solar PV markedly improves energy efficiency and sustainability in a building.

From a broader perspective, our results highlight a few important insights. First, maximizing renewable self-consumption (as all modes did) directly supports net-zero objectives by displacing grid electricity from fossil-fuel sources. Second, the addition of relatively simple control logic (like TOU schedules or demand thresholds) can yield disproportionate gains compared to static operation – essentially, "smarter" use of the same hardware produces better outcomes. Third, there are trade-offs to consider: aggressive use of the battery (as in Adaptive or Economic modes) brings more savings and emission reductions, but also cycles the battery more deeply, which could impact its lifespan. Thus, the choice of strategy may balance short-term gains with long-term asset management, depending on the user's priorities (cost vs. longevity vs. carbon reduction).

In summary, the Adaptive Hybrid strategy emerged as the optimal control approach for our PV–BESS system, delivering the highest overall efficiency and economic performance. Implementing such advanced control algorithms in real-world building energy management systems can substantially advance energy sustainability and cost-effectiveness. The findings of this study are directly relevant to commercial and institutional facilities in Malaysia and similar regions, where solar potential is high and time-varying tariffs are in place. By deploying adaptive, intelligent energy management, these facilities can reduce their reliance on the grid, lower operating costs, and contribute to carbon reduction commitments.

Future work could involve validating these control strategies under real operating conditions and further refining the Adaptive Hybrid logic for different demand patterns. On-site experiments at the UTeM Solar Laboratory (or similar settings) would provide valuable practical insights, including the dynamic response of the battery and any control challenges not evident in simulation. Additionally, tailoring the adaptive algorithm to even more granular patterns (for example, distinguishing individual weekdays or seasonal adjustments) could yield incremental improvements. Investigating the integration of forecast data (solar irradiance predictions or next-day load forecasts) with the control decisions is another promising avenue – this could turn the current rule-based Adaptive mode into an even smarter predictive control. Finally, a detailed economic analysis incorporating battery degradation costs and potential revenue streams (such as grid ancillary services) would complement the operational findings, helping to paint a complete picture of the viability of PV–BESS systems. Such work will further bridge the gap between simulation and deployment, moving us closer to widespread adoption of clean, efficient energy systems in pursuit of sustainable development goals.

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- **Ethics approval and consent to participate:** Not applicable. This study did not involve human participants or animal experiments.
- **Consent for publication:** Not applicable.
- **Availability of data and materials:** The datasets generated and analyzed during the current study are available from the corresponding author upon reasonable request.
- **Author's contribution:** Kamarul Amin Kamarudin: Methodology development, simulation framework, data analysis, and manuscript preparation. Aida Fazliana Abdul Kadir: Conceptualization, system design, and supervision of the experimental setup. Mohamad Firdaus Sukri: Laboratory experiments, data collection, and validation of results. Subiyanto Subiyanto: Technical support for PV–BESS integration, and performance monitoring. Zulkifli Ab Rahman: Critical review, project administration, and alignment with Malaysia's energy transition roadmap.
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