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Rule-Based Energy Management for Residential PV-Battery Systems Under Time-of-Use Tariffs: A Data-Driven Scenario Analysis for Sri Lanka

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ABSTRACT

This study develops a deterministic, forecast-free rule-based dispatch algorithm for grid-connected residential photovoltaic battery systems under Sri Lanka's 2026 time-of-use tariff structure. Using empirical residential load patterns from the RECON-SL smart meter dataset, the model evaluates a 5 kW rooftop photovoltaic system with two lithium iron phosphate battery configurations at 15-minute resolution. All possible three-day combinations of sunny, cloudy, and rainy conditions are simulated, generating 81 scenario-days to capture short-term weather variability. Results demonstrate that rule-based control can achieve economically viable performance without forecasting or optimisation, while investment outcomes remain strongly influenced by battery state-of-charge constraints and export tariff design. The findings provide practical insights for residential energy management in emerging renewable-rich power systems.

KEYWORDS

Photovoltaic-battery systems; Rule-based energy management; Time-of-use tariff; Battery energy storage; Residential prosumers; Distributed energy resources; Sri Lanka; Techno-economic analysis

INTRODUCTION

The rapid expansion of rooftop photovoltaic (PV) installations among residential consumers is fundamentally reshaping the economics of household electricity supply in both developed and emerging power systems [1]. As PV penetration increases, the temporal mismatch between solar generation and household demand creates a structural challenge for both consumers and grid operators. Without storage, a substantial portion of midday solar surplus is exported to the grid at relatively low remuneration rates, while households continue to purchase higher-priced electricity during peak periods [2]. This misalignment reduces the effective value of distributed solar and limits its contribution to peak demand reduction.

Residential battery energy storage systems (BESS) provide a direct solution to this mismatch by shifting energy from periods of PV surplus to periods of high-price demand, thereby increasing self-consumption and reducing electricity bill [3]. In addition to cost

savings, PV-battery systems can enhance household resilience to grid outages and contribute to system-level flexibility[4]. While the technical feasibility of such systems is well established, their economic viability remains highly sensitive to electricity tariff design, battery cost trajectories, and the operational strategy used to control battery dispatch[5].

Time-of-use (TOU) electricity tariffs have gained increasing policy attention as a mechanism for aligning residential demand with underlying system cost structures and incentivising demand-side flexibility[6]. By differentiating electricity prices across time periods, TOU tariffs create explicit financial signals for peak load reduction and off-peak consumption, thereby improving the economic attractiveness of storage technologies[7]. A growing body of literature has examined PV-battery systems under TOU pricing in developed markets, consistently finding that economic performance improves with wider peak-off-peak price differentials and declining battery costs [8] and the environemtnal benefits attached [9]. Moreover, when export remuneration for stored energy exceeds the cost of off-peak grid charging, an additional arbitrage channel emerges that is structurally independent of solar availability, though this mechanism remains relatively underexplored in residential contexts [10].

Despite these advances, empirical evidence from emerging power systems remains limited [11]. Tariff structures, consumption patterns, and grid conditions in such systems often differ substantially from those in developed markets, limiting the external validity of existing findings [12]. In particular, the interaction between TOU pricing, distributed PV adoption, and battery operation has not been systematically analysed under the institutional and climatic conditions characteristic of South Asian electricity systems [13].

Sri Lanka provides an instructive and under-examined case study in this regard. The country has experienced rapid growth in distributed solar PV under net metering and net accounting schemes, alongside recent tariff reforms introducing a three-tier domestic TOU pricing structure with a pronounced evening peak period [14]. In parallel, a battery-support mechanism has been introduced that remunerates off-peak battery exports at rates exceeding standard off-peak import prices, thereby creating strong incentives for arbitrage-based battery operation[15]. While these features suggest favourable conditions for residential storage deployment, existing assessments have largely focused on programme-level feasibility and have not explicitly modelled household-level dispatch behaviour or evaluated performance under realistic weather variability [16] and climatic resilience [17].

A key challenge in evaluating residential PV-battery systems in tropical and subtropical regions is the variability of solar generation at daily and sub-daily scales[18]. Sri Lanka's monsoon-driven climate and frequent cloud cover events can lead to multi-day reductions in photovoltaic output [19], constraining the ability of batteries to recover sufficient charge for subsequent peak periods [20] . Many existing studies rely on representative-day approaches or annual average profiles, which may understate the operational and economic impacts of sustained low-irradiance conditions [21]. This limitation is particularly relevant for rule-based dispatch strategies, whose effectiveness depends on managing inter-day energy balances under uncertain generation patterns [22]. It is an important aspect to be considered in Sustiable Energy planning perspective [23].

This paper addresses these gaps by developing a deterministic, rule-based dispatch simulation for a grid-connected residential PV-BESS system operating under Sri Lanka's 2026 TOU tariff structure [24]. The model is implemented at 15-minute temporal resolution and incorporates a structured weather-scenario framework based on 81 three-day sequences constructed from combinations of sunny, cloudy, and rainy conditions. The dispatch strategy is designed for practical implementation on commercial inverters and integrates PV self-consumption, off-peak grid charging, and controlled off-peak battery export through a state-of-charge–based rule set. Two commercially relevant battery sizes are evaluated alongside a PV-only counterfactual scenario. Economic performance is assessed using net present value,

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internal rate of return, and payback period over a 15-year horizon, with sensitivity analysis conducted on key financial and tariff parameters[25] .

The contributions of this work are threefold. First, it provides a detailed household-level assessment of PV–battery economics under Sri Lanka's 2026 TOU and battery-support tariff structure, addressing a significant empirical gap in the energy storage literature for emerging economies. Second, it introduces a structured short-term weather scenario framework that captures inter-day dependencies in battery operation, complementing conventional approaches based on typical days or annual averages. Third, it demonstrates that a simple, forecast-free, rule-based dispatch strategy can achieve stable and economically robust performance across diverse weather conditions, with implications for deployment in data-constrained environments where advanced optimisation methods may not be feasible [26]. The findings are relevant for tariff design, residential storage policy, and demand-side management strategies in Sri Lanka and other emerging power systems with similar structural characteristics [27]. In addition, motivated by provisions in the draft Sri Lankan electricity policy that restrict battery charging from the grid, an alternative no-grid-charging scenario is also evaluated to assess the robustness of economic outcomes under more constrained regulatory conditions.

METHODS

This section describes the methodological framework developed to evaluate the operational and economic performance of residential PV and battery energy storage systems operating under Sri Lanka's 2026 time-of-use tariff structure. The analysis combines a deterministic rule-based dispatch algorithm with high-resolution 15-minute simulations, representative residential load modelling, synthetic photovoltaic generation, structured multi-day weather scenarios, and long-term financial evaluation. Together, these components provide an integrated framework for assessing household energy flows, battery operation, electricity costs, and investment performance under realistic climatic and tariff conditions. The methodology adopted in each stage of the analysis is described in the following subsections.

Modelling assumptions and framework

The simulation framework is developed based on explicit assumptions regarding system configuration, dispatch behaviour, tariff treatment, and financial evaluation. These assumptions define the scope of the analysis and the conditions under which the reported results are applicable.

The first assumption is that the battery dispatch controller operates using a deterministic, forecast-free rule-based strategy. The controller uses only the instantaneous tariff period, PV generation, household demand, and battery SOC to determine charging, discharging, and export decisions. This approach reflects the practical operation of residential inverter-based energy management systems, where real-time optimisation requiring accurate forecasts may not always be feasible due to data and computational limitations [28]. Therefore, the results represent the achievable performance of a practical controller rather than the theoretical optimum under perfect forecasting conditions.

Second, the analysis considers a representative three-phase residential prosumer household rather than a population-level residential portfolio with a lithium iron phosphate (LFP) battery considering State of Charge (SOC) conditions. The demand profile is calibrated using the RECON-SL dataset [29] and national electricity statistics, representing a higher-consumption household segment likely to adopt rooftop PV and battery storage. Variations arising from household behaviour, appliance ownership, and network-level effects are outside the model boundary.

Third, the economic assessment assumes that all monetary parameters are evaluated consistently using nominal values. The 2026 Sri Lankan time-of-use tariff and export compensation rates are applied as the base-case tariff structure. Future tariff changes are

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examined through sensitivity analysis rather than incorporated into the baseline scenario. The principal modelling assumptions adopted in this study are summarised in Table 1. Modelling Assumption adopted in the study

Table 1. Modelling Assumption adopted in the study

Parameter	Assumption	Justification
PV system	5 kW rooftop PV system; 0.82 performance ratio; 06:00–18:00 generation window	Representative of Sri Lankan residential PV installations [30]; Performance ratio consistent with monitored grid-connected PV systems (78 ± 14%) [31]; Daylight based generation at Sri Lankan latitudes
PV generation uncertainty	Three weather states: Sunny (α = 1.00), Cloudy (α = 0.357), Rainy (α = 0.10)	Irradiance scaling factors (α) representing clear, overcast, and monsoon-affected conditions, calibrated to the observed range of Sri Lankan daily global horizontal irradiation (4.5–6.5 kWh/m²/day)[32]
Battery system	10 kWh/3 kW and 16 kWh/4 kW battery configurations; 0.95 charge/discharge efficiency Cost: LKR 600,000-750,000;	Battery capital costs were obtained from supplier price obtained current in the Sri Lankan market in March 2026.
Battery degradation and lifetime	3,000 cycles; 2% annual degradation; 15-year evaluation period	Representative residential LFP operating characteristics [33]
Tariff and export structure	2026 Sri Lankan TOU tariff; solar export 20.9 LKR/kWh; battery export 45 LKR/kWh during peak period	PUCSL approved tariff structure [24]
Economic assumptions	Discount rate: 10%; Tariff escalation: 5%/year	Long-term residential investment assessment assumptions [34]
SOC management	Base case 0–100% SOC;	Sensitivity cases 10–90% and 20–80%

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Rule based dispatch framework

Residential photovoltaic-battery systems operate through continuous interaction between electricity generation, household demand, battery storage, and grid exchange. The economic performance of such systems depends not only on the installed capacities of the photovoltaic array and battery, but also on the operational logic governing how energy is allocated across competing uses throughout the day. In time-of-use tariff environments, dispatch decisions become particularly important because the value of electricity varies substantially across tariff periods. Consequently, the timing of battery charging, discharge, and grid export can materially influence household electricity costs and long-run investment viability.

Figure 1 summarises the rule-based dispatch simulation used to evaluate residential PV–battery arbitrage under the Sri Lankan TOU tariff.

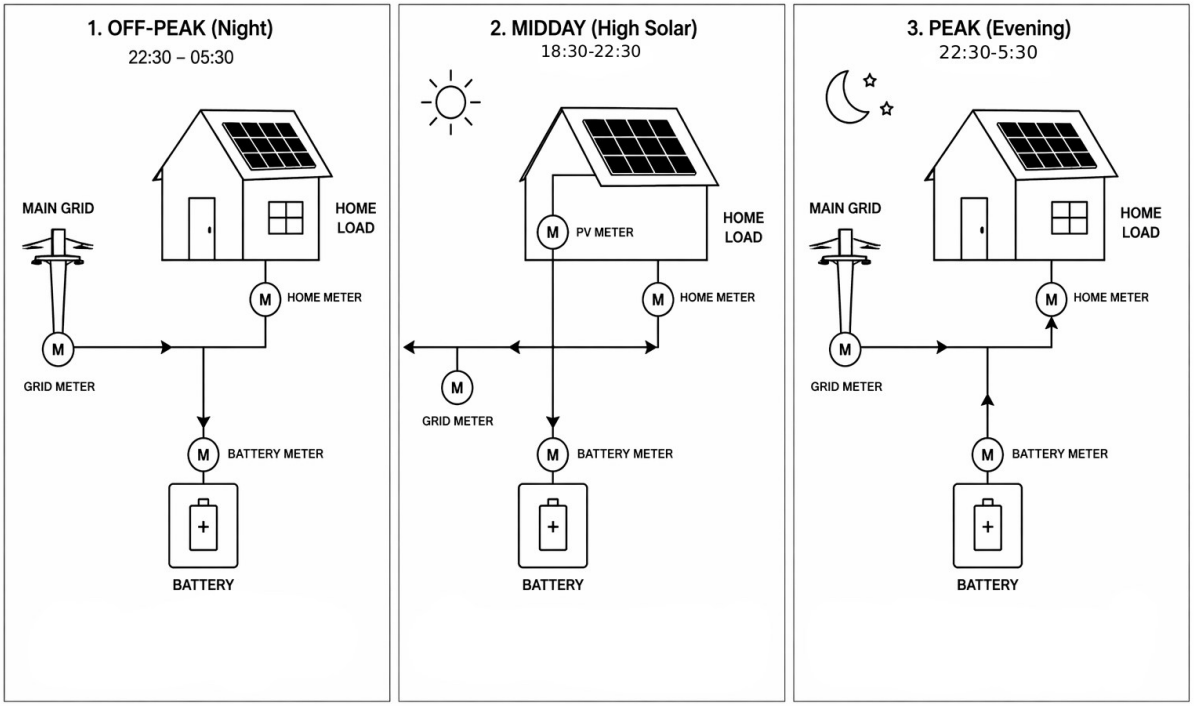


Figure 1. Rule-based Photovoltaic-battery dispatch and energy flow diagram.

The algorithm operates at 15-minute resolution and, at each interval, determines battery charging, discharging and export decisions based on the current tariff period, PV generation, household load and battery SOC. For every step, the model updates SoC, computes energy imports and exports, and reconstructs the customer's bill and savings relative to a no-battery baseline.

The Figure 2 illustrates the rule-based dispatch framework for a residential PV system integrated with battery storage operating under Sri Lanka's TOU tariff structure. The system is evaluated in discrete 15-minute intervals, with decisions taken sequentially based on tariff periods, PV generation, load requirements, and battery SOC

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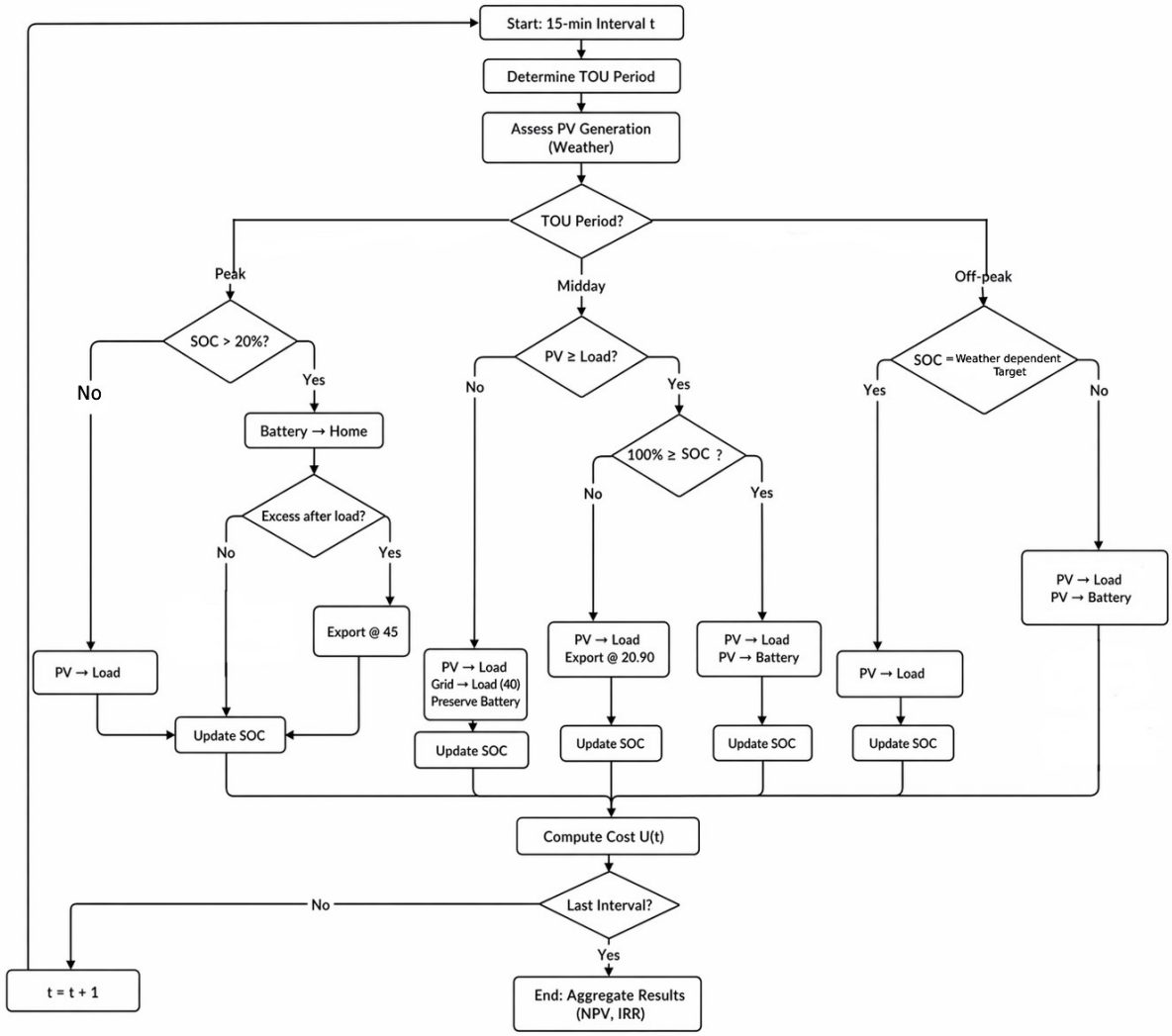


Figure 2. Rule-based dispatch framework

At the beginning of each interval, the applicable TOU period is identified, which determines the prevailing electricity price and guides subsequent dispatch decisions. During the off-peak period, when grid electricity is cheapest, the system imports from the grid to serve household load directly. The battery remains idle during this window, conserving stored energy for the peak period ahead.

During the midday period, dispatch is driven primarily by PV availability. If PV generation exceeds load, the surplus is first used to charge the battery, provided that SOC remains below its upper limit. Any additional surplus beyond battery capacity is exported to the grid at the daytime export rate. If PV generation is insufficient to meet load, the system supplies demand using available PV and imports the remainder from the grid, while preserving battery charge for the peak period. The operational objective in this period is to maximise solar self-consumption and achieve the highest possible SOC prior to peak pricing.

During the peak period, when electricity prices are highest, the battery is discharged first to meet household demand, thereby avoiding expensive grid imports. If, after serving the full peak load, residual stored energy remains above the minimum SOC floor, the surplus is exported to the grid at the peak battery export rate of 45 LKR/kWh. Discharge and export continue until the SOC reaches its minimum allowable level, at which point the system switches to grid-only

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supply. This ensures that battery operation remains within technical constraints while maximising both cost savings and export revenue.

At the end of each interval, the SOC is updated to reflect charging and discharging actions, accounting for efficiency losses and capacity limits. The net cost or revenue for the interval is then calculated based on grid imports, exports, and applicable tariffs. This process repeats iteratively for all 96 intervals in the day, after which total costs and savings are aggregated.

Study context and tariff design

This study examines a grid-connected residential customer in Sri Lanka with a three-phase supply, rooftop PV and behind-the-meter battery operating under the domestic TOU tariff revised as effective from 1st April 2026. The tariff differentiates three import periods which are off-peak, midday and peak with strongly tiered prices that reflect underlying system supply costs and therefore strongly influence the value of residential storage as depicted in Table 2.

Table 2. Time-of-use import charges and export tariffs considered in the analysis

Tariff Component	Time Period	Charge (LKR/KWh)
Off-peak import	22:30-05:30	28
Midday/daytime import	05:30-18:30	40
Peak import	18:30-22:30	90
Export to grid (daytime)	05:30-18:30	20.9
Export to grid (Peak)	18:30-22:30	45

The case study focuses on a "prosumer" household that has both the technical capability and financial incentive to invest in rooftop PV and a residential battery, broadly aligned with higher-consumption domestic customers considered in recent PV-battery feasibility studies in Sri Lanka. All monetary values are expressed in real terms, and the base case assumes that nominal tariff and export rates remain constant in real terms over the project lifetime. Potential future tariff changes are treated explicitly in the sensitivity analysis.

Load Modelling

Residential electricity demand is represented by an hourly profile for a grid-connected three-phase household. The aim is not to reproduce the load of a specific dwelling, but to construct a "typical" higher-consumption urban or peri-urban household that is representative of early adopters of PV and batteries in Sri Lanka. The load profile is derived from the RECON-SL dataset, which provides high-resolution residential consumption data across multiple households [29]. Formally, household electricity demand at time interval t is represented as a time-dependent function of the hour of the day, as given in Equation (1) where L_t denotes electricity demand and t_h represents the hour of the day. The function $f(\cdot)$ captures the diurnal variation in demand as Equation 1

$$L_t = f(t_h) \quad (1)$$

First, a base 24-hour shape is selected to reproduce key patterns observed in Sri Lankan residential load, including a pronounced evening peak after about 18:30, moderate daytime appliance use and a modest night-time baseload. This shape is derived from load curves and planning profiles presented in regulatory and consultancy studies and smoothed to remove artefacts while preserving the diurnal structure [35].The base shape is then normalised and scaled to match a target annual consumption that is consistent with three-phase domestic

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customers in the upper part of the consumption distribution, using national statistics and tariff documentation as benchmarks [36]. Seasonal variation is represented by applying monthly scaling factors, calibrated so that monthly totals fall within plausible ranges inferred from billing data and national statistics.

Photovoltaic Solar Modelling

The rooftop PV array is represented by a synthetic generation profile calibrated to the general characteristics of residential installations in Sri Lanka. Rather than using measured site-specific irradiance, output is modelled using a Gaussian bell-curve approximation of the diurnal profilecentred at solar noon, as given in Equation 2

$$G_t = min\left(P_{PV} \cdot exp\left(\frac{(t_{noon})^2}{2\sigma^2}\right) \cdot \alpha_t \cdot \theta,\ P_{PV}\right) \cdot \Delta t \quad (2)$$

where P_{PV}= 5 kW is the installed capacity, θ = 0.82 is the overall performance ratio (incorporating temperature losses, wiring losses, and inverter efficiency), t_{noon} = 12.5 h is the time of peak production, σ = 3.5 h controls the spread of the generation curve, Δt = 0.25 h is the 15-minute interval duration, and α is the weather scaling factor taking values of 1.00 (Sunny), 0.357 (Cloudy), and 0.10 (Rainy). Generation is set to zero outside 06:00-18:00. System degradation and tariff escalation are incorporated jointly in the financial model and are not applied to the per-interval PV profile directly.

The residential battery energy storage system is modelled as a single aggregated storage unit whose SOC evolves through sequential 15-minute intervals. Two configurations are analysed to reflect commercially relevant residential systems in Sri Lanka. The first is a 10 kWh LFP unit with a rated inverter power of 3 kW, priced at LKR 600,000; the second is a 16 kWh LFP unit with a rated inverter power of 4 kW, priced at LKR 750,000. LFP chemistry is specified rather than the generic lithium-ion classification because its cycle-life characteristics, flat discharge voltage profile, and thermal stability under partial cycling make it the dominant technology choice for residential storage.

Battery dynamics follow an energy-balance formulation in which the SOC [30] is updated recursively at each interval t based on net charging and discharging flows as Equation 3

$$SOC_t = SOC_{t-1} + \eta_{ch}(N_t + P_t) - \frac{Q_t + T_t}{\eta_{dis}} \quad (3)$$

where SOC(t) is the of charge at interval t; N(t) is grid-to-battery charging energy; P(t) is solar-to-battery charging energy; Q(t) is battery discharge energy serving on-site load; T(t) is battery energy exported to the grid during peak arbitrage intervals at 45 LKR/kWh; and ηch and ηdis are the one-way charging and discharging efficiencies. Both efficiencies are set to 0.95, giving a round-trip efficiency of 0.9025 as Equation 4.

$$\eta_{rt} = \eta_{ch} \cdot \eta_{dis} \quad (4)$$

To ensure physically feasible operation, the SOC update in Equation (4) is implemented with bounds, resulting in the constrained SOC formulation of]Equation 5

$$SOC_t = max\left(SOC_{min},\ \min\left(SOC_{t-1} + \eta_{ch}(N_t + P_t) - \frac{Q_t + T_t}{\eta_{dis}},\ SOC_{max}\right)\right) \quad (5)$$

where SOC_{max} is the rated usable capacity (10 kWh or 16 kWh). In addition to this algebraic constraint, the dispatch rules impose a soft operational floor of 20 % × SOC_{max} where the controller does not dispatch the battery below this threshold in any tariff period.. An upper charging threshold of 80 % ×SOC_{max} is similarly applied during midday solar charging to preserve headroom for the afternoon solar-fill required to bring the battery to full capacity before the 17:00 peak onset. Both soft limits are therefore dispatch-level constraints, distinct from the hard algebraic bounds above.

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However, charging and discharging rates are limited by the rated inverter power Pinv, so the maximum energy transferable in any single 15-minute interval is Pinv × Δt: equal to 0.75 kWh per interval for the 10 kWh system (Pinv = 3 kW) and 1.00 kWh per interval for the 16 kWh system. This constraint applies identically to grid charging N(t), solar charging P(t), load discharge Q(t), and export discharge T(t), each of which is additionally bounded by the available SOC headroom and the remaining capacity at every interval.

Detailed electrochemical behaviour, rate-dependent efficiency losses, and temperature effects are not modelled explicitly, as the focus of the study is on long-run techno-economic performance rather than battery physics. Their aggregate influence is captured through the constant one-way efficiency of 0.95, consistent with reported values for LFP cells under partial-cycling residential duty cycles. Capacity degradation is incorporated in the financial evaluation through a 2 % per annum derating of the annual bill saving in each project year, applied jointly with a 5 %/yr nominal tariff escalation factor. Degradation is therefore not modelled as a physical reduction in usable battery capacity or as a discrete mid-project replacement event. The implications of this simplification, including the omission of an explicit battery replacement cost within the 15-year project horizon, are further discussed as limitations.

Power-Flow Hierarchy within the Household

Within each 15-minute interval, energy flows between PV generation, household load, battery, and the grid follow a fixed priority order. The hierarchy is applied in three sequential steps: (i) PV generation serves load directly; (ii) any PV surplus charges the battery or is exported to the grid; and (iii) any residual load is met by battery discharge and, finally, grid imports. This priority mirrors the operational structure of commercial behind-the-meter inverters and is consistent with Sri Lanka's net-accounting and net-billing frameworks, under which battery exports are separately regulated from solar exports. Direct PV self-consumption is computed as Equation 6 below, where O(t) is the energy drawn directly from PV to serve load.

$$O_t = min(G_t, L_t) \tag{6}$$

Any remaining PV surplus after serving demand is allocated to battery charging, subject to SOC and power constraints. This surplus is first directed to the battery as P_t, and any remaining excess is exported to the grid. Solar exports are therefore defined as Equation 7:

$$S_t = max(0, G_t - O_t - P_t) \tag{7}$$

When PV generation is insufficient to meet demand, the battery may discharge to supply the remaining load, provided the SOC constraint is satisfied. Any residual demand after battery discharge is met by grid imports, defined as as given in Equation 8 where R_t denotes grid-supplied energy.

$$R_t = \max(0, L_t - O_t - Q_t) \tag{8}$$

During off-peak intervals, $Q(t) = 0$ and the grid serves all household load directly; battery operation in that window is devoted entirely to charging, arbitrage cycling, and conditional export as described in the next section.

Arbitrage-Driven Rule-Based Dispatch Strategy

The dispatch controller is rule-based rather than optimisation-based, reflecting the operational capabilities of commercial residential inverters and the practical constraint that near-real-time load and PV forecasts are unavailable. At each interval the controller observes only the current tariff period, the instantaneous PV output, the household load, and the current SOC. Three mutually exclusive period indicators are defined as Equation 9 where each indicator identifies whether time interval t belongs to the off-peak, midday, or peak period.

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$$I_t^{off},\ I_t^{mid},\ I_t^{peak} \in \{0,1\} \quad with \quad I_t^{off} + I_t^{mid} + I_t^{peak} = 1 \tag{9}$$

Off-Peak Operation

The off-peak window spans 28 intervals of 15 minutes. The controller plans the entire window before the first interval executes, in two sequential phases.

The first phase is the floor reaching phase. There, the controller first drives the SOC to the overnight floor, SOC*floor*(t, tomorrow) = max(*R*(α*today*), *T*(α*today*), *T*(α*tomorrow*)), where *R*(α) is the morning-ramp reserve, the minimum SOC at 05:30 needed to serve the (05:30, 07:00) load with zero grid draw given weather α; and *T*(α) is the minimum SOC at 05:30 such that the morning ramp discharge and subsequent solar generation fill the battery to rated capacity by 18:15. If SOC > SOC*floor*, the surplus is exported at τ*bat* = 28 LKR/kWh. If SOC < SOC*floor*, the deficit is charged from the grid at τ*OP* = 28 LKR/kWh.

Midday Period

Grid charging is disabled throughout the midday window (N(t) = 0). The dispatch sequence at each interval is where first direct PV self-consumption takes place. Then, Solar charging takes place. Finally, the battery discharge to load, subject to a solar-refill constraint. The controller computes the remaining solar energy that can charge the battery between the current interval and 18:15 as equation Equation 10

$$P(t) = \left(G(t) - O(t), \frac{SOC_{max} - SOC(t-1)}{\eta_{ch}}, P_{inv} \cdot \Delta t\right) \tag{10}$$

Battery discharge is limited to SOC headroom above SOC*min*(t) as Equation 11 ensuring, that the battery enters the peak period at rated capacity in every weather scenario. Any remaining load afterbattery discharge is met by grid imports.

$$Q(t) = min((SOC(t-1) - SOCmin(t)) \cdot \eta dis,\ L(t) - O(t),\ Pinv \cdot \Delta t). \tag{11}$$

Peak Period

The battery is at rated capacity at 18:30 by construction of the midday dispatch. Throughout the peak window the controller discharges at the maximum rate permitted by the inverter, subject to the state-of-charge dispatch floor, as given in Equation 12. Discharge first serves on-site load; any discharge in excess of instantaneous net demand is exported to the grid and compensated at the peak battery export tariff τ_bat = 45 LKR/kWh (Table 2. Time-of-use import charges and export tariffs considered in the analysis) Grid imports cover only load that battery discharge and residual PV generation cannot supply. No grid charging occurs during the peak window. Battery export is confined to this window. During off-peak intervals, surplus above the overnight floor is exported at the lower off-peak rate of 28 LKR/kWh no battery export occurs during the midday window.

$$Q(t) = min((SOC(t-1) \cdot \eta dis,\ Pinv \cdot \Delta t) \tag{12}$$

$$E_{bat}(t) = \max\ (0,\ Q(t)\,\eta_{dis} - [L(t) - O(t)])$$

Operational Constraint

Simultaneous charging and discharging are prohibited in every interval. This is satisfied automatically by the period-separated dispatch rules: in any given interval the controller is in

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exactly one of the three modes (off-peak charge/export, midday solar management, or peak discharge), so grid charging and battery discharge cannot co-occur.

Weather-Sequence Scenarios

Weather variability is the primary source of uncertainty in residential battery economics because it determines both PV output and, through the overnight floor constraint, the availability of off-peak arbitrage headroom. Rather than relying on a single representative day or an annual average, this study enumerates all possible three-day sequences of three discrete weather states, providing complete coverage of short-run irradiance variability.

Each day is assigned one of three weather states characterised by a fixed irradiance scaling factor α as Equation 13

$$\alpha \in \{1.00\,(\text{Sunny}),\ 0.357\,(\text{Cloudy}),\ 0.10\,(\text{Rainy})\} \tag{13}$$

The scaling factor α enters the PV generation model directly. These three states are calibrated to represent the characteristic irradiance levels of clear, overcast, and monsoon-affected days in Sri Lanka, consistent with the diurnal solar profiles used in recent techno-economic assessments for the region. Since each of the three days in a sequence can take any of the three states, the number of distinct three-day combinations is as Equation 14

$$N_{se}\mathbb{C} = 3^3 = 27 \tag{14}$$

Each combination is simulated for all three of its constituent days, yielding 81 scenario days as mentioned in Equation 15.

$$N_{saen} = 27 \times 3 = 81 \text{ scenario-days} \tag{15}$$

In this study, a “scenario-day” represents one simulated operating day extracted from a three-day weather sequence. Since each three-day sequence consists of three individual operating days, the 27 possible weather sequences generate a total of 81 scenario-days. Each scenario-day is evaluated independently for both battery configurations considered in this study. Therefore, the complete simulation dataset comprises 162 battery-scenario evaluations (81 scenario-days × 2 battery configurations).

The 81 figure therefore represents 27 three-day weather combinations, each evaluated across its three days. The fourth day is defined as the same as the first, so the overnight floor constraint on Day 3 looks forward to Day 1, creating a self-consistent repeating cycle without requiring a boundary assumption.

The initial SOC at the start of each sequence is set to the overnight floor appropriate for the first day’s weather and the second day’s forecast. This initialisation is weather-sequence dependent and ensures the battery is in a physically consistent state at the start of each simulation rather than an arbitrary fraction of capacity. All 81 scenario-days are weighted equally when computing the grand-mean daily saving, reflecting the treatment of the three weather states as equally representative of the operating conditions experienced by a residential prosumer over a typical annual cycle.

Bill Reconstruction

The household electricity bill is reconstructed at the interval level to accurately capture the interaction between consumption, solar generation, and battery dispatch under time-of-use pricing. Each day is divided into 96 intervals (15-minute resolution), and the gross bill for a given interval *t* is computed as Equation 16.

$$V_t = R_t \cdot \tau(t) + N_t \cdot \tau_{OP} - S_t \cdot \tau_{SOL} - T_t \cdot \tau_{bat}(t) \tag{16}$$

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where R_t denotes grid imports, N_t represents non-shiftable consumption billed at the off-peak tariff τ_{OP} , S_t is solar energy exported at the regulated export tariff $\tau_{SOL} =$ 20.9 LKR/kWh, and T_t captures battery exports compensated at $\tau_{bat}(t)$, which varies by time-of-use (45 LKR/kWh during peak and 28 LKR/kWh during off-peak periods). The applicable import tariff $\tau(t)$ reflects the prevailing time-of-use structure.

The daily bill is obtained as the sum of V_t across all 96 intervals. Savings are then defined as the difference between the bill under the battery-enabled scenario and the corresponding no-battery counterfactual, ensuring that all comparisons are made on a consistent operational and tariff basis. This formulation allows the model to fully internalize arbitrage opportunities arising from both intra-day price differentials and export compensation mechanisms, while preserving physical energy balance constraints.

State-of-Charge Constraint Sensitivity

To evaluate the impact of operational constraints on battery performance, three distinct SOC regimes are considered: (i) an unconstrained range of 0–100%, (ii) a conservative range of 20–80%, and (iii) a moderate range of 10–90%. These regimes are designed to capture the trade-off between maximizing arbitrage potential and preserving battery longevity, particularly in the context of LFP systems commonly used in residential applications.

The unconstrained case (0–100%) represents a theoretical upper bound on economic performance, as it allows the battery to fully exploit all available charging and discharging opportunities without regard to degradation concerns. In contrast, the 20–80% regime reflects typical manufacturer-recommended operating limits, which restrict deep discharge and full charge cycles in order to extend cycle life. The 10–90% regime serves as an intermediate case, balancing increased usable capacity with moderate protection against accelerated wear.

Importantly, all three regimes employ identical dispatch logic, ensuring that differences in outcomes are attributable solely to the imposed SOC bounds. The results indicate that tighter SOC constraints reduce the effective arbitrage window, particularly in sequences with high solar availability, where excess generation cannot be fully stored. Conversely, under low-generation conditions, the marginal impact of SOC limits is less pronounced, as the battery is rarely driven to its operational extremes. This highlights the role of SOC policy as a key determinant of realized economic value, particularly in environments with high variability in solar output.

Economic Evaluation

The economic viability of the battery investment is assessed using a standard net present value (NPV) framework. The analysis adopts a discount rate of $r = 10\%$, a tariff escalation rate of $\epsilon = 5\%$ per annum, and a capacity degradation rate of $\delta = 2\%$ per annum. The initial investment cost of the battery system is treated as a capital expenditure incurred at year zero. Since capital expenditure is not an annual value, it is converted into an equivalent annualised capital cost (ACC) to enable consistent comparison between annual economic benefits and investment requirements as Equation 17:

$$ACC = C_0 \frac{r(1+r)^n}{(1+r)^n - 1} \tag{17}$$

where ACC is the annualised capital cost, C_0 is the initial battery investment, r is the discount rate, and n is the project evaluation period. The annual net economic benefit is subsequently calculated as Equation 18:

$$B_y = C_y - ACC \tag{18}$$

where B_y represents the annual net benefit and C_y represents the annual electricity cost saving in year y, including the effects of tariff escalation and battery performance degradation. The investment-level economic performance is evaluated using the net present value formulation as Equation 19:

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$$NPV = -C_0 + \sum_{y=1}^{n} \frac{C_y}{(1+r)^y} \quad (19)$$

where C_y represents the degradation-adjusted annual saving during year y. The NPV formulation therefore captures the discounted value of future electricity cost savings relative to the initial investment.

A distinction is made between capital recovery and battery degradation, as these represent different economic and technical processes. Capital recovery reflects the allocation of the initial investment over the project lifetime and is represented through the annualised capital cost formulation. In contrast, degradation represents the physical reduction in battery performance over time and is incorporated through a 2% annual reduction in achievable savings. This separation avoids treating financial depreciation and technical degradation as equivalent processes.

The analysis further derives a break-even export tariff for battery discharge, defined as the minimum peak export compensation rate required for the battery investment to achieve an NPV of zero. This threshold is obtained by expressing annual savings as a function of the battery export tariff and solving the NPV equation for the export price at which discounted future benefits offset the initial investment. The daily saving function is represented as a linear relationship with respect to the peak battery export rate, where the baseline saving at the prevailing export tariff of 45 LKR/kWh is adjusted according to the difference between the actual and reference export prices. The sensitivity of investment viability to export compensation is therefore quantified through the resulting break-even tariff, providing insight into the role of tariff design in supporting residential battery adoption.

Despite providing a detailed operational and economic assessment, several limitations should be acknowledged. The PV generation model uses synthetic irradiance profiles rather than measured site-specific solar data, and therefore represents typical climatic conditions rather than individual rooftop variability. Battery degradation is represented through annual saving derating rather than a detailed electrochemical capacity-fade model, and replacement costs are not explicitly included within the evaluation horizon. Furthermore, the analysis considers a single representative residential prosumer and does not capture feeder-level impacts, network constraints, or population-level heterogeneity. The rule-based controller is also evaluated in isolation, without comparison to an optimisation-based benchmark, so the results represent achievable rather than theoretically optimal performance. In addition, the household load profile is held fixed and does not incorporate demand-side behavioural responses to time-of-use price signals, and the analysis assumes stability of the real-terms tariff structure beyond the scenarios explicitly tested in the sensitivity analysis. These assumptions define the boundary of the present study and provide opportunities for future research using measured operational data, detailed battery ageing models, demand-response modelling, and grid-scale simulations.

Interval-Level Cost Analysis

To complement the aggregate daily savings metric, the analysis constructs cumulative intra-day cost trajectories at the interval level for each weather scenario. The cumulative bill at interval t is defined as the running sum of interval costs from midnight to t, thereby providing a dynamic representation of how costs and savings evolve over the course of the day.

This approach reveals that the economic value of the battery is highly time-concentrated, with the majority of savings realized during the evening peak window (18:30–22:30). During this period, battery discharge offsets grid imports priced at approximately 90 LKR/kWh, generating substantial cost avoidance. When the battery has surplus capacity, additional value is created through export of stored energy at the peak export tariff (45 LKR/kWh), further enhancing economic returns.

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On sunny days, the cumulative trajectory often crosses into negative territory before the end of the day, indicating that total export revenues and avoided costs exceed total consumption charges. In such cases, the household effectively becomes a net energy earner within the billing period. In contrast, on rainy days, limited solar generation restricts both charging opportunities and subsequent discharge, resulting in a relatively flat cumulative cost profile with minimal deviation from the no-battery baseline.

RESULTS

The following results are derived from the rule-based dispatch framework described in Section 2 and evaluated across 81 scenario-days generated from 27 three-day weather-sequence combinations. Two residential battery configurations a 10 kWh/3 kW system and a 16 kWh/4 kW system are assessed in conjunction with a 5 kW rooftop photovoltaic installation under the CEB time-of-use tariff structure introduced in 2026.

Intra-Day Dispatch, Cost Dynamics, and Capital Cost Recovery

Figure 3 and Figure 4 present the simulated intra-day operational behaviour of the 16 kWh and 10 kWh LFP battery systems, respectively, under sunny, cloudy, and rainy weather conditions. Each figure is organised as a 3×3 panel structure. Columns correspond to the three representative weather states, while rows represent (i) 15-minute resolution energy dispatch, (ii) interval-level electricity cost, and (iii) cumulative daily bill trajectories incorporating depreciation and xrun degradation effects. This structure enables simultaneous comparison of operational, economic, and lifecycle performance across both weather variability and battery size.

In the dispatch panels, positive values represent energy supplied to the household system, including photovoltaic generation, battery discharge to load, battery export to grid, and grid imports. Negative values represent energy consumption and storage pathways, including household demand, solar-to-battery charging, and solar export. Battery SOC is superimposed on a secondary axis to illustrate charging and discharge dynamics across the three CEB tariff windows.

The middle-row panels report the net electricity cost incurred during each 15-minute interval relative to the no-battery counterfactual. Positive values indicate periods in which the household remains a net electricity purchaser, whereas negative values correspond to intervals in which export earnings exceed import costs. The bottom-row panels extend the analysis to cumulative day-bill trajectories beginning at midnight and additionally incorporate battery depreciation and projected degradation effects in Years 1, 5, 10, and 15 of the project horizon.

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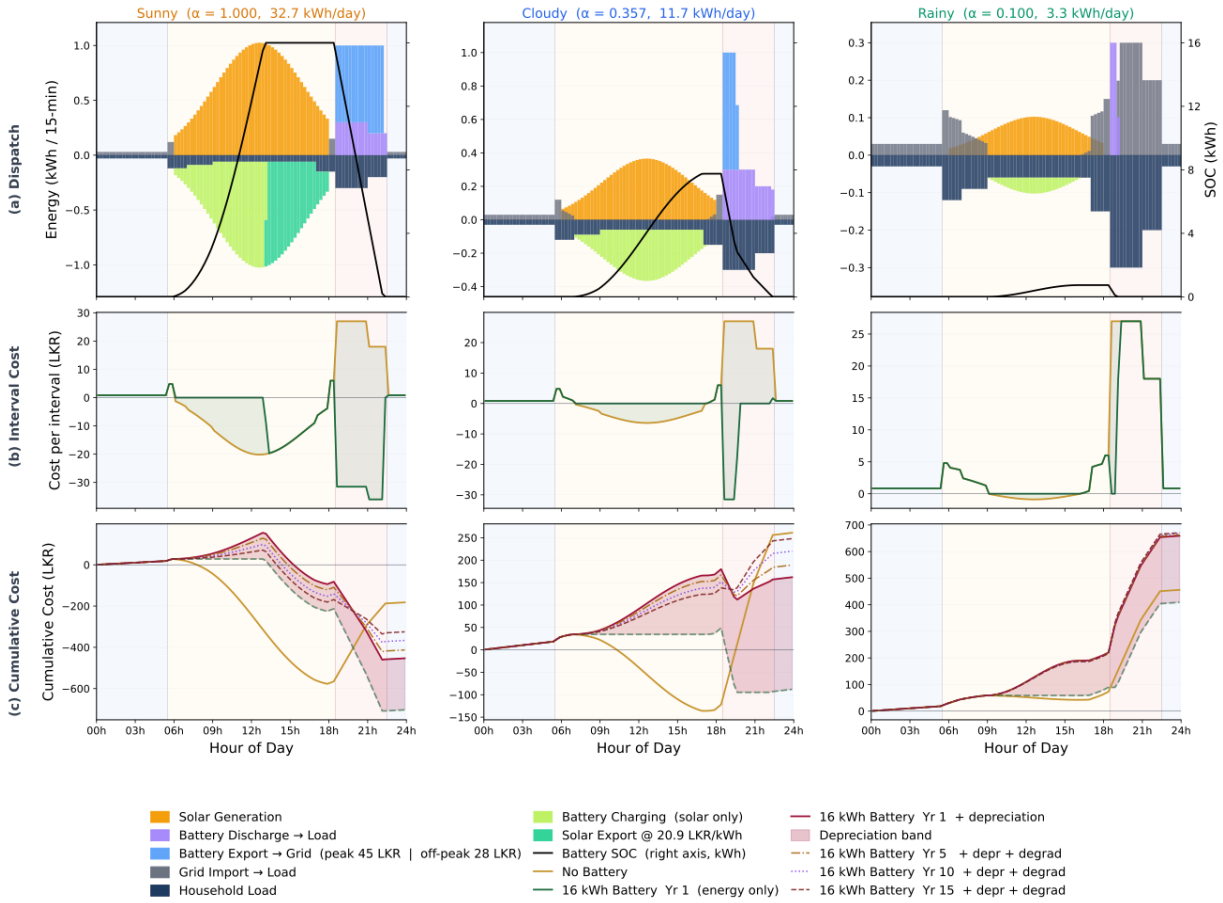


Figure 3. Intra-day dispatch behaviour, interval-level electricity cost, and cumulative daily bill trajectories for the 16 kWh

Figure 3 demonstrates that the economic value of the 16 kWh configuration is strongly dependent on the interaction between solar availability and the peak tariff window. Under sunny conditions, daily photovoltaic generation reaches 32.7 kWh, substantially exceeding household demand and enabling the battery to reach full rated capacity by approximately 17:30 exclusively through PV surplus charging. During the peak tariff period (18:30–22:30), the battery first supplies the entire household peak demand, thereby avoiding imports at 90 LKR/kWh, before exporting the remaining stored energy to the grid at the approved export tariff of 45 LKR/kWh. Consequently, the interval-cost panel exhibits a pronounced negative excursion during the evening peak period, and the cumulative bill trajectory crosses below zero before midnight, indicating that the household becomes a net electricity revenue earner on that day. The resulting daily saving reaches LKR 521 relative to the no-battery case.

Under cloudy conditions, photovoltaic output declines to 11.7 kWh/day, limiting the extent of solar-to-battery charging. Although the battery retains sufficient stored energy to offset most peak-period imports, residual export capacity becomes negligible. As a result, economic benefits arise primarily through peak-load displacement rather than export arbitrage. The cumulative bill remains lower than the no-battery baseline throughout the evening period, producing a daily saving of approximately LKR 349. However, the degradation-inclusive trajectories indicate that the economic margin narrows considerably in later project years under intermittent irradiance conditions.

Under rainy conditions, daily solar generation falls to only 3.3 kWh/day, leaving the battery severely undercharged prior to the evening peak window. Grid imports therefore dominate household supply during peak hours, and the operational behaviour of the battery system converges closely toward the no-battery counterfactual. The resulting daily saving declines sharply to LKR 47, reflecting only marginal gains from limited direct solar self-consumption.

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Once depreciation and long-run degradation are incorporated, the cumulative cost trajectories exceed the no-battery baseline from the early project years onward, illustrating that prolonged low-irradiance conditions materially weaken the financial contribution of storage.

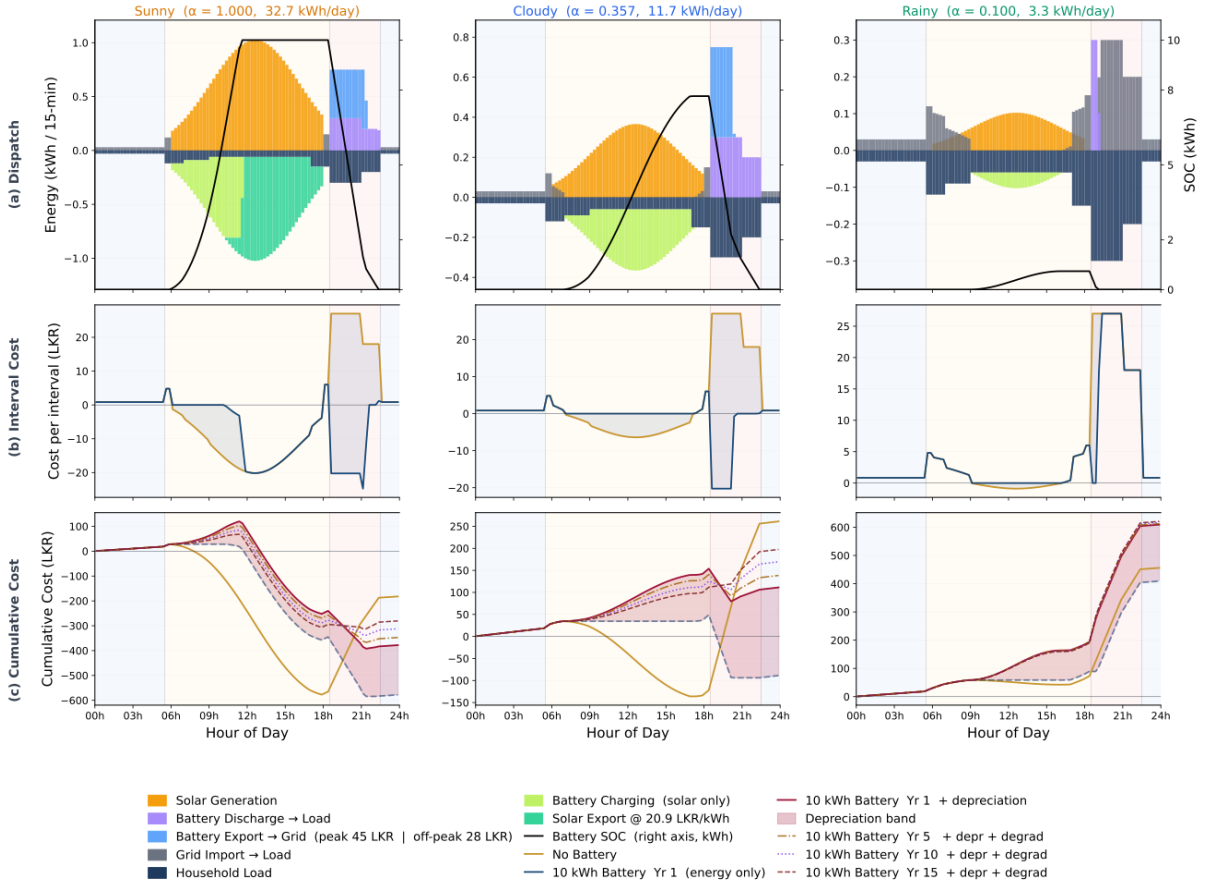


Figure 4. Intra-day dispatch behaviour, interval-level electricity cost, and cumulative daily bill trajectories for the 10 kWh

The operational behaviour of the 10 kWh configuration shown in Figure 4 broadly mirrors that of the larger battery system, although important differences emerge under high-irradiance conditions. On sunny days, the smaller battery reaches full capacity earlier in the afternoon, causing excess photovoltaic generation to be exported directly to the grid at the lower solar export tariff before the onset of the peak period. Although the battery fully offsets household peak demand, the remaining exportable stored energy is substantially lower than in the 16 kWh configuration. Consequently, evening export revenue is reduced, and the daily saving falls to LKR 396, compared with LKR 521 for the larger system. The differential therefore arises almost entirely from the larger battery's superior capacity for peak-period energy export.

By contrast, under cloudy and rainy conditions, the performance gap between the two configurations narrows substantially. On cloudy days, both systems are constrained primarily by limited solar availability rather than rated battery capacity, resulting in near-identical daily savings. This convergence suggests that the additional capital expenditure associated with the 16 kWh system yields minimal incremental value under moderate irradiance conditions. Similarly, under rainy conditions, both systems exhibit negligible operational contribution beyond limited direct self-consumption of photovoltaic generation, and depreciation-adjusted cumulative costs exceed the no-battery baseline over much of the project horizon.

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Weather-Dependent Savings different Scenario-Days

This section examines how battery storage benefits vary under different weather conditions using 81 scenario-days representing sunny, cloudy, and rainy states. The analysis focuses on mean daily electricity bill savings for two residential battery configurations (10 kWh and 16 kWh) under the unconstrained SOC case, highlighting how solar resource variability influences the economic value of distributed storage in a Sri Lankan household context. The results are interpreted in terms of both operational savings and their implications for the viability of behind-the-meter storage under time-of-use tariff structures. Table 3 summarises the mean daily savings for both battery configurations across the three weather states and as a grand mean over all 81 scenario-days under the unconstrained SOC baseline.

Table 3. Mean daily bill saving (LKR/day) by weather state and battery configuration, unconstrained State of Charge (0–100%).

Weather	10 kWh saving	16 kWh saving	16k advantage
Sunny	396	521	+125
Cloudy	350	349	−1
Rainy	47	47	0
Mean	264	306	+42

The results indicate a clear state-dependent divergence in performance between the two configurations. The 16 kWh battery outperforms the 10 kWh system only under sunny conditions, where higher levels of solar generation enable the larger system to store sufficient surplus energy to both satisfy peak household demand and export additional energy during the peak tariff window. This export capability constitutes the primary source of the observed advantage of LKR 125/day.

In contrast, under cloudy and rainy conditions, the savings of the two configurations are nearly identical. Reduced solar availability constrains battery charging to levels that are just sufficient, or in some cases insufficient, to meet peak demand. As a result, neither system is able to generate meaningful exportable surplus, and the marginal value of additional storage capacity is effectively negligible. The convergence of savings under these conditions implies that the economic benefit of increased capacity is contingent on the availability of excess generation rather than storage capability per se.

This asymmetry has important implications for system design. The incremental capital cost associated with the 16 kWh battery approximately LKR 150,000 relative to the 10 kWh configuration is recovered only through the additional revenue generated on high-generation (sunny) days. Consequently, the economic justification for the larger system depends critically on the frequency and persistence of such conditions within the relevant climatic context. This consideration is examined further in the sensitivity analysis.

Divergence between configurations begins with the onset of solar generation. During the daylight period, photovoltaic output reduces reliance on grid imports and, in the case of battery configurations, enables charging from surplus generation. However, the most economically significant divergence occurs during the peak tariff window (18:30–22:30), where the value of stored energy is realized. Under sunny conditions, the 16 kWh system not only avoids high-cost imports but also generates substantial export revenue, resulting in a cumulative trajectory that crosses into negative territory before the end of the peak period and reaches approximately −LKR 703 by midnight. In contrast, the no-battery case remains less negative (−LKR 182), reflecting foregone arbitrage opportunities.

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Under cloudy conditions, both battery configurations achieve moderate cost reductions relative to the no-battery baseline, with end-of-day values converging around −LKR 89, compared to a positive bill of approximately LKR 261 in the absence of storage. This indicates that, even without exportable surplus, the battery retains value through peak load displacement. By contrast, under rainy conditions, all configurations exhibit positive cumulative bills throughout the day and converge near midnight, confirming that limited solar availability constrains both charging and discharge, thereby reducing the economic contribution of storage to negligible levels.

To extend the analysis beyond operational savings, capital cost recovery and physical degradation are incorporated into the cumulative framework. Figure 5 presents the adjusted trajectories for the 16 kWh system, distinguishing between energy-only savings, depreciation-inclusive costs, and combined depreciation and degradation effects over the project lifetime. Depreciation is modeled as a fixed daily capital recovery cost (LKR 250/day), allocated proportionally to battery throughput, and represents a financial accounting construct independent of physical performance. In contrast, capacity degradation assumed at 2% per annum represents a physical constraint, reducing the effective usable capacity of the battery and hence the achievable savings over time.

Long-Run Financial Viability and State-of-Charge Constraint Sensitivity

This section evaluates the long-run economic viability of residential BESS under Sri Lanka's time-of-use tariff structure by examining how SOC operating constraints influence investment performance over the project lifetime. While battery arbitrage profitability is generally driven by the ability to shift energy from low-value to high-value tariff periods, operational SOC limits restrict the usable storage window and therefore alter the realised economic value of storage. To assess this effect, a 15-year discounted cash flow framework is applied across three SOC regimes and two battery capacities, incorporating tariff escalation, battery degradation, and intertemporal dispatch behaviour under the 81 scenario-day structure.

The financial analysis is conducted using the NPV framework specified in Equation (18), assuming a real discount rate of 10%, annual tariff escalation of 5%, and annual battery degradation of 2%. These assumptions approximate long-run retail electricity price growth and the gradual decline in usable storage capacity resulting from repeated cycling. Under unconstrained operation (0–100% SOC), both battery systems generate strong positive returns, with discounted payback periods of approximately seven years and internal rates of return exceeding the assumed discount rate. However, progressively tighter SOC limits substantially reduce profitability, with both systems becoming economically unviable under the conservative 20–80% operating regime.

The results indicate that the profitability of residential storage depends not only on installed capacity, but also on the degree of operational flexibility available within the usable SOC window. Restrictive SOC constraints reduce the battery's ability to exploit high-value peak tariff periods, thereby limiting the effectiveness of intertemporal energy arbitrage. Consequently, relatively small reductions in usable capacity generate disproportionately large declines in long-run investment returns. While the 16 kWh configuration achieves the highest returns under unconstrained operation, its relative advantage diminishes sharply as SOC bounds tighten, reflecting the greater dependence of larger systems on sustained arbitrage opportunities to recover higher capital costs.

From a policy perspective, these findings highlight the sensitivity of distributed battery adoption to both technical operating assumptions and retail tariff structures. Since the profitability of storage depends heavily on access to high-value discharge opportunities, regulatory or operational constraints that indirectly limit dispatch flexibility may materially weaken household investment incentives. This is particularly relevant in emerging electricity systems such as Sri Lanka, where distributed storage is increasingly considered a mechanism

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for supporting renewable integration, reducing evening peak demand, and improving household energy resilience.

Figure 5 illustrates the combined effects of SOC operating constraints, long-run degradation, and weather-dependent variability on the economic performance of the residential battery systems. The figure demonstrates a pronounced decline in investment performance as usable SOC flexibility becomes increasingly restricted. Under unconstrained operation, both battery configurations generate strong cumulative savings and positive long-run returns, reflecting the ability of the systems to fully exploit intertemporal arbitrage opportunities between low-cost and peak tariff periods. However, tighter SOC limits substantially reduce the effective dispatchable energy available during high-value periods, leading to a non-linear deterioration in financial viability.

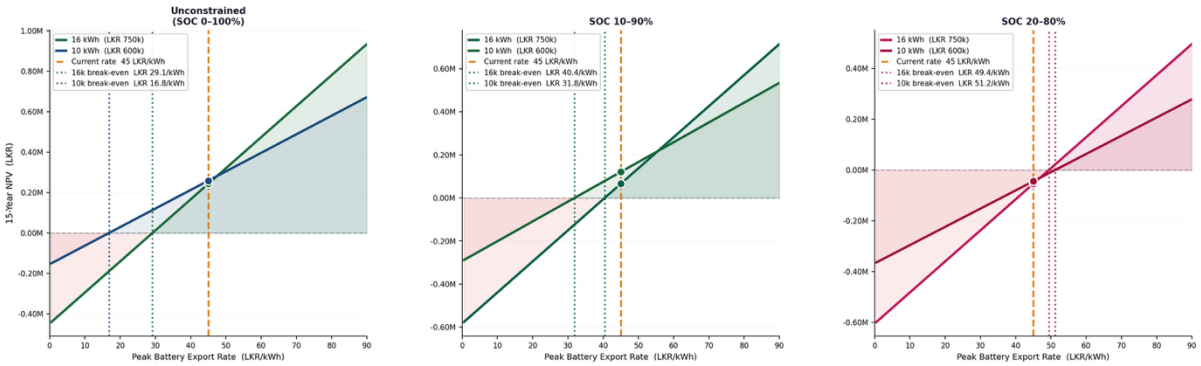


Figure 5. Long-run financial viability and scenario-based savings performance under alternative SOC regimes

The figure further highlights that the larger 16 kWh configuration exhibits greater sensitivity to restrictive operating bounds. Although the additional storage capacity improves resilience during prolonged low-generation sequences, much of this advantage depends on the ability to utilise a wide SOC range. Once operational flexibility is constrained, the incremental economic benefit of the larger system declines considerably, producing diminishing marginal returns relative to its higher capital cost. The degradation-adjusted trajectories additionally show that long-run profitability is progressively moderated by declining usable capacity over time, even under favourable tariff conditions.

Across the scenario-day combinations, the figure also demonstrates that the value of storage depends critically on the persistence and sequencing of weather conditions. Larger storage systems perform relatively better during extended cloudy or rainy sequences, where intertemporal energy shifting becomes more valuable. In contrast, under frequent sunny conditions, the smaller configuration is often sufficient to satisfy peak demand arbitrage opportunities, limiting the additional benefit derived from expanded storage capacity. These findings collectively indicate that the financial viability of residential storage in Sri Lanka is jointly determined by tariff structure, operational flexibility, climatic variability, and long-run degradation dynamics.

CONCLUSIONS

This study developed a deterministic rule-based dispatch framework to evaluate the techno-economic performance of residential PV–battery systems under Sri Lanka's 2026 time-of-use tariff structure. The framework integrates 15-minute energy simulations, empirically derived residential demand profiles, synthetic PV generation modelling, multi-day weather scenarios, and battery operating constraints to assess storage performance under tropical climatic variability.

The results demonstrate that residential batteries can provide meaningful economic value by shifting solar energy availability towards high-cost tariff periods, with performance strongly influenced by

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battery capacity, state-of-charge constraints, weather conditions, and export compensation mechanisms. The analysis further shows that operational simplicity does not necessarily prevent effective battery utilisation, highlighting the potential of rule-based controllers for practical residential deployment in emerging power systems.

The findings provide insights for tariff design, distributed energy policy, and residential storage adoption in Sri Lanka and similar renewable-rich developing electricity markets. Future studies should incorporate measured household operational data, detailed battery degradation models, and network-level impacts to further improve the assessment of distributed storage integration.

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