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Shadow-Price Formation and Battery Storage Co-Optimization in a Renewable-Rich National Grid: A KKT-Based Mixed-Integer Programming Approach for Sri Lanka

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Abstract

Battery energy storage systems (BESS) are increasingly recognised as an enabling technology for renewable-rich electricity systems; however, their sustainability value is often assessed using simplified or externally defined price signals rather than the actual economic structure of the power system. This study develops a KKT-consistent mixed-integer optimisation framework that embeds battery storage directly into a national electricity dispatch model, allowing marginal electricity prices, generator dispatch, and storage operation to be determined simultaneously. Building on the marginal-cost pricing principle established by Schweppe et al., the proposed direct-embedding approach reduces computational complexity compared with conventional big-M complementarity reformulations while preserving the optimality conditions of the underlying bi-level formulation. The framework is applied to Sri Lanka's national electricity system using a corrected 18-plant generator fleet calibrated with real 15-minute dispatch data, together with government-reported solar, wind, and curtailment records. A 240 MW battery system is evaluated under single-day, multi-day, and sizing scenarios. Results demonstrate that storage responds economically to system conditions by charging during periods of high renewable availability and discharging during higher marginal-cost periods, generating 7.21 million LKR in arbitrage revenue across four validated reference days and 42.7 million LKR over a 15-day continuous assessment period. Battery integration also reduces renewable energy wastage by recovering a portion of observed curtailment and provides an estimate of avoided thermal generation externalities. However, comparison with reported curtailment volumes indicates that a single 240 MW battery captures only a limited share of renewable oversupply, highlighting the importance of storage planning based on actual system flexibility requirements rather than average operating conditions. The proposed framework provides a data-driven approach for evaluating the role of battery storage in supporting sustainable renewable integration in transitioning electricity systems.

Keywords: Battery energy storage systems; renewable energy integration; electricity market clearing; marginal electricity pricing; shadow pricing; renewable curtailment; sustainable power systems

1. Introduction

The global transition towards sustainable electricity systems is accelerating through the rapid deployment of variable renewable energy resources, particularly solar photovoltaic and wind generation. Driven by climate mitigation objectives, declining renewable technology costs, and the need to reduce dependence on fossil fuels, renewable energy has become a central component of global decarbonisation strategies[1]. However, unlike conventional thermal generation, renewable resources are characterised by temporal variability and uncertainty[2], creating significant challenges associated with grid flexibility, electricity supply reliability, renewable energy utilisation, and efficient system operation . High penetration of variable renewable generation can introduce periods of renewable oversupply, increased curtailment, and greater short-term electricity price variability, requiring additional flexibility resources to maintain reliable and sustainable electricity supply [3].

Battery energy storage systems (BESS) have emerged as a critical enabling technology for supporting renewable energy transitions [4]. By allowing electricity to be shifted across time, storage can absorb renewable generation during periods of high availability and low demand and discharge during periods of increased demand or reduced renewable output[5], [6]. However, the sustainability benefits and economic value of storage depend strongly on the characteristics of the underlying electricity system, including generation composition, renewable availability, electricity pricing mechanisms, and operational constraints . Therefore, evaluating storage performance requires integration within the actual operational and economic structure of electricity systems rather than relying on simplified assumptions or externally defined price signals[7]

Electricity prices in economically efficient power systems are fundamentally determined by the marginal cost of electricity production[8]. Schweppe et al., established the theoretical foundation of electricity spot pricing by demonstrating that the market-clearing price corresponds to the shadow price of the system power-balance constraint, representing the marginal cost of supplying an additional unit of electricity. This marginal-cost pricing framework was further extended to incorporate spatial and temporal characteristics of electricity networks [9]. Under this framework, electricity prices reflect the cost of the marginal generating unit required to satisfy demand rather than the average cost of all dispatched generators. Consequently, accurate evaluation of battery storage value requires storage operation to be assessed within a marginal-cost dispatch framework where electricity prices emerge endogenously from system operation [10].

Recent research has extended conventional economic dispatch models to incorporate renewable uncertainty and energy storage participation. An adjustable robust optimisation framework incorporating dispatchable generators, storage batteries, and uncertain renewable resources, has been developed demonstrating the importance of representing storage as an active system resource rather than a passive modification to electricity demand [11].However, storage integration introduces additional modelling complexity because storage decisions are

intertemporally coupled through the state of charge and involve operational decisions that extend across multiple dispatch intervals [12], [13].

To represent this interaction, several studies have developed bi-level optimisation approaches where the upper-level problem represents system operation and the lower-level problem represents storage participation and profit optimisation. Fortuny-Amat and McCarl [14] established the mathematical basis for transforming bi-level optimisation problems into single-level formulations through Karush-Kuhn-Tucker (KKT) [15], [16] conditions and complementarity linearisation. Building upon this approach, battery degradation costs have been incorporated into price-maker storage participation models, while a bi-level electricity spot-market formulation has been developed incorporating storage trading preferences using KKT-based mixed-integer reformulation [17]. Furthermore, many existing storage valuation studies assess battery benefits using predefined electricity prices or simplified market representations. While these approaches provide valuable insights into storage arbitrage potential, they may not capture the feedback between storage operation, generator dispatch, and market-clearing price formation [18]. Similarly, renewable curtailment studies have demonstrated the potential of storage to improve renewable utilisation; however, the magnitude of achievable benefits depends strongly on system-specific characteristics, including demand patterns, renewable availability, generation constraints, and market structure[19]. Therefore, sustainability assessments of battery integration require an integrated framework that simultaneously considers electricity price formation, generation dispatch, storage optimisation, and renewable utilisation [20].

These challenges are particularly relevant for developing and transitioning economies, where renewable deployment is expanding within existing electricity systems with limited flexibility infrastructure [20], [21].Unlike mature electricity markets with established storage participation mechanisms, emerging power systems often contain significant thermal generation dependence, constrained operational flexibility, and rapidly changing renewable penetration levels. Consequently, real-data assessments based on national electricity systems are required to understand the practical contribution of storage towards sustainable, reliable, and economically efficient energy transitions.

Sri Lanka provides a relevant case study of such a transition. The country's electricity system combines substantial reservoir hydro resources, increasing solar and wind penetration, and a thermal generation fleet required to maintain system adequacy during periods of renewable variability [22], [23]. While renewable expansion supports national decarbonisation objectives, increasing renewable penetration introduces challenges associated with renewable curtailment, system flexibility, and efficient utilisation of available generation resources [24]. In addition, hydro-dominated electricity systems require consideration of the opportunity cost associated with reservoir operation, where water released for current electricity production has an alternative future value [25].

Beyond operational economics, sustainable electricity transitions require consideration of broader environmental and societal outcomes. While battery storage can support renewable integration and reduce dependence on fossil-

fuel generation, the overall sustainability impact depends on whether storage enables greater utilisation of renewable resources, reduces avoidable curtailment, lowers emissions-intensive generation requirements, and improves long-term system resilience [26]. However, comprehensive assessments combining marginal electricity pricing, storage optimisation, renewable curtailment reduction, and environmental considerations remain limited, particularly for developing-country electricity systems.

This study addresses this research gap by developing a storage-integrated electricity dispatch optimisation framework for the Sri Lankan national electricity system. Unlike previous benchmark-based studies, the proposed approach applies generator-level characteristics derived from real operational datasets and integrates battery storage decisions within a marginal-cost electricity dispatch framework. The study establishes a KKT-consistent storage formulation, demonstrates a price-taking equivalence that simplifies the conventional bi-level representation under verified conditions, and evaluates battery contributions to renewable integration through curtailment reduction and externality assessment.

Through the integration of electricity market economics, battery optimisation, renewable utilisation analysis, and sustainability evaluation, this study provides insights into the role of battery energy storage in supporting sustainable electricity transitions in developing economies with increasing renewable penetration.

2. Methodology

To evaluate the contribution of battery energy storage towards sustainable electricity system operation, this study develops an optimisation framework that links generation dispatch, electricity price formation, and storage decision-making within a unified model. This enables the economic and operational impacts of storage integration to be evaluated under realistic system conditions, including renewable variability, thermal generation dependence, and resource limitations.

The methodology is developed progressively. First, the conventional marginal-cost pricing framework is established to represent electricity price formation without storage. Subsequently, battery energy storage is incorporated as a temporally coupled resource, and its optimal operating behaviour is derived through a storage-integrated optimisation formulation. The resulting framework provides a basis for assessing how storage can improve renewable utilisation, reduce reliance on higher-cost generation, and support a more sustainable electricity transition.

2.1 Baseline: Schweppe's Marginal-Cost Spot Price

Schweppe et al. [8] established the theoretical foundation of electricity spot pricing by demonstrating that market-clearing prices emerge from a constrained economic dispatch optimisation problem. Under this framework, generating units are dispatched in ascending order of operating cost while satisfying demand and technical constraints, with the electricity price represented by the shadow price of the system power-balance constraint. Therefore, the marginal generating unit required to meet demand determines the spot price for each dispatch interval.

The original formulation considers electricity generation and consumption within the same interval and does not include energy storage or intertemporal energy shifting. This conventional marginal-cost pricing framework therefore provides the theoretical baseline for the storage-integrated optimisation model.

For a single dispatch interval t, consider a system consisting of N generating units, where generator i produces electrical output $P_{i,t}$ at a convex operating cost $C_i(P_{i,t})$. The conventional economic dispatch problem can be formulated as:

$$\min_{P_{i,t}} \sum_{i=1}^{N} C_i\left(P_{i,t}\right) \qquad (1)$$

subject to the system power-balance and generator operating constraints:

$$\sum_{i=1}^{N} P_{i,t} = D_t \qquad (2)$$

$$P_i^{min} \le P_{i,t} \le P_i^{max} \qquad (3)$$

where D_t denotes the system demand during interval t. The associated Lagrange multiplier λ_t represents the shadow price of the power-balance constraint in Equation (2), while the multipliers $\psi_{i,t}^{min}$ and $\psi_{i,t}^{max}$ represent the lower and upper generation-limit constraints defined in Equation (3), respectively.

The corresponding Lagrangian function for the optimisation problem defined in Equations (1)-(3) is expressed as:

$$L = \sum_{i=1}^{N} C_i\left(P_{i,t}\right) - \lambda_t\left(\sum_{i=1}^{N} P_{i,t} - D_t\right) - \sum_{i=1}^{N} \psi_{i,t}^{min}\left(P_{i,t} - P_i^{min}\right) + \sum_{i=1}^{N} \psi_{i,t}^{max}\left(P_{i,t} - P_i^{max}\right) \qquad (4)$$

Taking the derivative of the Lagrangian in Equation (4) with respect to the output of generator i gives the first-order stationarity condition:

$$\frac{\partial C_i}{\partial P_{i,t}} - \lambda_t - \psi_{i,t}^{min} + \psi_{i,t}^{max} = 0 \qquad (5)$$

For a generator operating strictly within its feasible operating range defined in Equation (3), the generation-limit constraints are inactive, resulting in:

$$\psi_{i,t}^{min} = \psi_{i,t}^{max} = 0$$

Therefore, Equation (5) simplifies to:

$$\frac{\partial C_i}{\partial P_{i,t}} = \lambda_t \qquad (6)$$

or equivalently:

$$\lambda_t = MC_i\left(P_{i,t}\right)$$

where $MC_i\left(P_{i,t}\right)$ denotes the marginal operating cost of generator i.

Equation (6) represents Schweppe's key contribution: under least-cost economic dispatch, the shadow price of the power-balance constraint equals the marginal cost of the price-setting generator. Thus, λ_t reflects the additional system cost of supplying one more unit of electricity, and the market-clearing price is determined by the marginal generator rather than the average generation cost. However, the formulation in Equations (1)-(6) assumes no energy transfer between dispatch intervals. Battery storage introduces intertemporal coupling through the state of charge, requiring an extension of the conventional marginal-cost framework developed in the following section.

2.2 Introducing Battery Storage as a Nested (Bi-Level) Resource

Unlike conventional generators, storage decisions are coupled across time through the battery state of charge (SOC), meaning that charging and discharging cannot be optimised independently for each dispatch interval. Therefore, storage integration introduces an intertemporal decision problem in which the storage operator optimises its charging, discharging, and SOC trajectory based on the electricity price signal generated by system operation.

This interaction can be formulated as a bi-level optimisation problem, where the upper level represents system cost minimisation and the lower level represents storage profit maximisation. Following the approach established in, the lower-level problem is represented through its KKT conditions to obtain an equivalent single-level formulation.

2.2.1 Lower-Level Problem: Storage Operator's Profit Maximisation

Given the electricity price trajectory $\{\lambda_t\}$ obtained from the system dispatch model in Section 2.1, the storage operator seeks to maximise arbitrage profit over the scheduling horizon $t = 1, \dots, T$. The lower-level optimisation problem is formulated as:

$$\max_{P_{ch,t}, P_{dis,t}, E_t} \sum_{t=1}^{T} \left[\lambda_t \left(P_{dis,t} - P_{ch,t}\right) - \delta \left(P_{ch,t} + P_{dis,t}\right)\right] \qquad (7)$$

subject to the battery energy balance equation:

$$E_t = E_{t-1} + \eta_{ch} P_{ch,t} - \frac{P_{dis,t}}{\eta_{dis}} \qquad (8)$$

and the operational constraints:

$$E^{min} \le E_t \le E^{max} \qquad (9)$$

$$0 \le P_{ch,t} \le P_{ch}^{max} \qquad (10)$$

$$0 \le P_{dis,t} \le P_{dis}^{max} \qquad (11)$$

where E_t denotes the stored energy level at interval t, $P_{ch,t}$ and $P_{dis,t}$ represent charging and discharging power, respectively. The parameters η_{ch} and $\eta_{dis} \in (0, 1]$ denote charging and discharging efficiencies, while δ represents the degradation cost associated with battery cycling.

The simultaneous charging and discharging condition is prevented through the complementary operational constraint:

$$P_{ch,t} P_{dis,t} = 0 \qquad (12)$$

which is implemented through a binary formulation in Section 2.4, following the approach adopted in Ma, Liu, and Li [8].

2.2.2 KKT Conditions of the Lower-Level Problem

To integrate the storage operator's optimisation problem into the upper-level system dispatch model, the lower-level maximisation problem in Equation (7) is transformed into its equivalent minimisation form by minimising the negative storage profit. The corresponding Lagrangian formulation is:

$$\begin{aligned} L_{batt} = & \sum_t \left[-\lambda_t \left(P_{dis,t} - P_{ch,t}\right) + \delta \left(P_{ch,t} + P_{dis,t}\right)\right] \\ & + \sum_t \mu_t \left[E_t - E_{t-1} - \eta_{ch} P_{ch,t} + \frac{P_{dis,t}}{\eta_{dis}}\right] \\ & + \sum_t \nu_t^{max} \left(E_t - E^{max}\right) + \sum_t \nu_t^{min} \left(E^{min} - E_t\right) \\ & - \sum_t \psi_t^{ch,0} P_{ch,t} + \sum_t \psi_t^{ch,max} \left(P_{ch,t} - P_{ch}^{max}\right) \\ & - \sum_t \psi_t^{dis,0} P_{dis,t} + \sum_t \psi_t^{dis,max} \left(P_{dis,t} - P_{dis}^{max}\right) \end{aligned} \quad (13)$$

where μ_t, ν_t^{min}, ν_t^{max}, $\psi_t^{ch,0}$, $\psi_t^{ch,max}$, $\psi_t^{dis,0}$, and $\psi_t^{dis,max}$ denote the dual variables associated with the constraints defined in Equations (8)-(11).

The stationarity conditions obtained by differentiating Equation (13) with respect to the storage decision variables are:

$$\frac{\partial L_{batt}}{\partial P_{ch,t}} = 0: \ \lambda_t = \mu_t \eta_{ch} - \delta + \psi_t^{ch,0} - \psi_t^{ch,max} \quad (14)$$

$$\frac{\partial L_{batt}}{\partial P_{dis,t}} = 0: \ \lambda_t = \frac{\mu_t}{\eta_{dis}} + \delta - \psi_t^{dis,0} + \psi_t^{dis,max} \quad (15)$$

$$\frac{\partial L_{batt}}{\partial E_t} = 0: \ \mu_t = \mu_{t+1} - \nu_t^{max} + \nu_t^{min} \quad (16)$$

The complementary slackness conditions associated with Equations (9)-(11) are expressed as:

$$\psi_t^{ch,0} P_{ch,t} = 0 \quad (17)$$

$$\psi_t^{ch,max} \left(P_{ch,t} - P_{ch}^{max}\right) = 0 \quad (18)$$

$$\psi_t^{dis,0} P_{dis,t} = 0 \quad (19)$$

$$\psi_t^{dis,max} \left(P_{dis,t} - P_{dis}^{max}\right) = 0 \quad (20)$$

$$\nu_t^{max} (E_t - E^{max}) = 0 \quad (21)$$

$$\nu_t^{min} \left(E^{min} - E_t\right) = 0 \quad (22)$$

where all dual variables satisfy the non-negativity conditions:

$$\psi_t^{ch,0}, \psi_t^{ch,max}, \psi_t^{dis,0}, \psi_t^{dis,max}, \nu_t^{min}, \nu_t^{max} \geq 0 \qquad (23)$$

For an interior charging solution, where the charging power remains within its operational limits ($0 < P_{ch,t} < P_{ch}^{max}$), the complementary slackness conditions in Equations (17)-(18) imply:

$$\lambda_t = \mu_t \eta_{ch} - \delta \qquad (24)$$

Equation (24) indicates that the storage operator charges until the current electricity price equals the discounted future marginal value of stored energy, adjusted for charging efficiency and degradation cost.

Similarly, for an interior discharge solution ($0 < P_{dis,t} < P_{dis}^{max}$), Equations (19)-(20) reduce Equation (15) to:

$$\lambda_t = \frac{\mu_t}{\eta_{dis}} + \delta \qquad (25)$$

Equation (25) demonstrates that discharge occurs when the electricity price exceeds the opportunity cost of stored energy, including efficiency losses and battery degradation cost.

Together, Equations (24) and (25) provide the mathematical expression of the classical storage arbitrage principle: the battery charges during low-price periods and discharges during high-price periods while accounting for round-trip efficiency losses and degradation costs. These KKT-derived conditions establish the economic behaviour of the storage operator and provide the equilibrium relationship required to integrate storage decisions into the system-level dispatch framework developed from Schweppe's marginal-cost pricing formulation.

2.2.3 Standard Linearisation

The complementary-slackness conditions derived in Section 2.2.2 introduce bilinear relationships between primal and dual variables. For example, the charging lower-bound condition is expressed as:

$$\psi_t^{ch,0} P_{ch,t} = 0 \qquad (26)$$

where both variables are non-negative. Such complementarity constraints are non-convex and cannot be directly incorporated into a mixed-integer linear programming (MILP) formulation. Therefore, the standard approach is to replace each complementarity condition using a big-M linearisation.

Following the formulation proposed by Fortuny-Amat and McCarl [14] and applied in electricity storage optimisation by Ma, Liu, and Li [17] in Equation (26) can be reformulated by introducing a binary variable b_t:

$$P_{ch,t} \leq M b_t \qquad (27)$$

$$\psi_t^{ch,0} \leq M(1 - b_t) \qquad (28)$$

$$b_t \in \{0, 1\} \qquad (29)$$

where M represents a sufficiently large positive constant. When $b_t = 0$, the primal variable is forced to zero, whereas when $b_t = 1$, the associated dual variable is restricted to zero, thereby maintaining the original complementarity relationship.

The big-M transformation is applied to all complementarity conditions in Equations (17)–(22), converting the original bi-level formulation into a single-level MILP. The lower-level KKT conditions are incorporated explicitly as linear constraints linked to the upper-level dispatch through the shared price variable λ_t. However, this exact reformulation increases computational burden, as each complementarity condition requires additional binary variables and constraints for every dispatch interval. For the six complementarity pairs in this formulation, the problem size grows significantly with increasing temporal resolution and scheduling horizon.

2.3 The Present Approach: KKT-Consistent Direct Embedding

This study adopts a simplified formulation assuming the storage fleet behaves as a price-taking participant, meaning its dispatch decisions do not materially affect the market-clearing price λ_t. This assumption is verified in Section 3. Under this condition, the storage variables can be directly embedded into the system dispatch problem, eliminating the need for explicit MPEC reformulation and big-M linearisation while preserving storage optimality conditions.

The equivalence between the conventional bi-level formulation and the proposed direct embedding approach is demonstrated below.

2.3.1 Embedded Single-Level Problem

The system operator's optimisation problem is extended by incorporating storage charging, discharging, and energy-state variables directly into the economic dispatch formulation:

$$\min_{P_{i,t}, P_{ch,t}, P_{dis,t}, E_t} \sum_{t=1}^{T} \sum_{i=1}^{N} C_i\left(P_{i,t}\right) + \sum_{t=1}^{T} \delta\left(P_{ch,t} + P_{dis,t}\right) \qquad (30)$$

subject to the generator constraints defined in Equations (2) and (3), together with the battery state-of-charge dynamics and operational limits defined in Equations (8)-(11).

The system power-balance constraint is modified to include the contribution of storage:

$$\sum_{i=1}^{N} P_{i,t} + P_{dis,t} - P_{ch,t} = D_t\ (\lambda_t) \qquad (31)$$

where λ_t represents the dual variable associated with the system power-balance constraint.

For an interior charging solution, where charging limits are inactive, the stationarity condition with respect to $P_{ch,t}$is:

$$\frac{\partial L}{\partial P_{ch,t}} = \delta + \lambda_t - \mu_t \eta_{ch} = 0 \qquad (32)$$

which gives:

$$\lambda_t = \mu_t \eta_{ch} - \delta \qquad (33)$$

Similarly, for an interior discharging solution:

$$\frac{\partial L}{\partial P_{dis,t}} = \delta - \lambda_t + \frac{\mu_t}{\eta_{dis}} = 0 \qquad (34)$$

resulting in:

$$\lambda_t = \frac{\mu_t}{\eta_{dis}} + \delta \qquad (35)$$

2.3.2 Equivalence Proof

The optimality conditions from the embedded formulation (Equations (33) and (35)) are identical to those of the storage operator's lower-level problem (Equations (24) and (25)). This equivalence results from the price-taking assumption: since storage does not influence λ_t, the price acts as an external parameter for the storage operator and as the dual variable of the system balance constraint in the embedded formulation. Therefore, storage optimality is preserved without explicitly modelling the lower-level KKT constraints and big-M linearisation.

This equivalence remains valid only while storage does not materially affect price formation. If the storage fleet becomes large enough to become price-making, the full bi-level reformulation becomes necessary. The validity of the price-taking assumption is evaluated in Section 3.

2.4 Mixed-Integer Reformulation and Two-Stage Solution

Although the embedded formulation developed in Section 2.3.1 preserves the economic optimality conditions of the storage operator, it remains subject to the operational requirement that a storage unit cannot simultaneously charge and discharge within the same dispatch interval. This mutual-exclusion constraint is introduced through a binary decision variable u_t, defined for each interval t:

$$P_{ch,t} \leq P_{ch}^{max} u_t \qquad (36)$$

$$P_{dis,t} \leq P_{dis}^{max} (1 - u_t) \qquad (37)$$

$$u_t \in \{0, 1\} \qquad (38)$$

where $u_t = 1$ represents a charging state and $u_t = 0$ represents a discharging state. Equations (36)-(38) ensure that only one operating mode is active during each dispatch interval.

The quadratic generation cost functions are approximated using convex piecewise-linear segments to maintain MILP compatibility, resulting in a mixed-integer formulation with both continuous dispatch variables and binary operating decisions. Since MILP solvers do not provide meaningful dual values for constraints containing integer variables, the marginal electricity price λ_t is obtained through a two-stage solution procedure. First, the MILP is solved to determine the optimal binary decisions u_t. These decisions are then fixed, and the resulting LP is re-solved to extract the dual value of the power-balance constraint as the market-clearing price.

$$\lambda_t = \frac{\partial C_{system}}{\partial D_t} \qquad (39)$$

where λ_t represents the marginal increase in total system operating cost associated with supplying one additional unit of electricity during interval t.

This two-stage approach preserves the operational decisions obtained from the full MILP while enabling the extraction of economically interpretable marginal prices. The resulting λ_t values are therefore consistent with the marginal-cost pricing framework established in Section 2.1 and are used as the market-clearing prices throughout this study.

2.5 Generator Cost Function Specification

Each thermal generating unit i is represented by a convex quadratic operating cost function:

$$C_i(P_{i,t}) = a_i + b_i P_{i,t} + c_i P_{i,t}^2 \qquad (40)$$

where a_i, b_i, and c_i represent the fixed, linear, and quadratic cost coefficients, respectively. The corresponding marginal cost function is obtained by differentiating Equation (40):

$$MC_i(P_{i,t}) = \frac{\partial C_i}{\partial P_{i,t}} = b_i + 2c_i P_{i,t} \qquad (41)$$

In accordance with the convex economic dispatch formulation presented in Section 2.1, the quadratic coefficient must satisfy $c_i \geq 0$ to ensure increasing marginal costs and maintain convexity of the optimisation problem.

To achieve compatibility with the MILP formulation developed in Sections 2.3 and 2.4, each quadratic cost function is approximated using convex piecewise-linear segments over the feasible operating range:

$$P_i^{min} \leq P_{i,t} \leq P_i^{max} \qquad (42)$$

The cost coefficients were estimated using least-squares regression against historical operating-point data obtained from PUCSL generation licensing records and CEB generation logs, as described in Section 2.7.

During the calibration process, certain fitted quadratic coefficients were identified as negative ($c_i < 0$). Such values imply decreasing marginal costs, which are physically inconsistent with conventional thermal generator behaviour and violate the convexity assumption required by the optimisation framework described in Sections 2.3-2.4. Therefore, where negative curvature was identified, the sign of the quadratic coefficient was inverted while preserving the fitted magnitude:

$$c_i^* = | c_i | \qquad (43)$$

This adjustment restores convexity while maintaining the observed cost sensitivity derived from historical operating data. The resulting cost functions were subsequently verified through the audit procedure described in Section 4.

2.6 Curtailment and Hydro Water Value

Renewable generation resources such as solar and wind are characterised by variable availability and limited controllability. Therefore, a renewable curtailment variable is introduced to accommodate intervals where available

renewable generation exceeds the amount that can be absorbed by demand, storage operation, and the minimum operating requirements of conventional generators.

The system balance constraint in Equation (31) is therefore extended as:

$$\sum_{i=1}^{N} P_{i,t} + P_{dis,t} - P_{ch,t} + R_t^{use} = D_t + R_t^{curt} \qquad (44)$$

where R_t^{use} represents utilised renewable generation and R_t^{curt} denotes curtailed renewable energy during interval t. The curtailment variable is bounded by the available renewable resource:

$$0 \leq R_t^{curt} \leq R_t^{avail} \qquad (45)$$

This formulation enables the optimisation framework to accommodate renewable generation uncertainty while maintaining feasibility under high renewable availability conditions.

Unlike variable renewable resources, reservoir hydro generation involves an intertemporal optimisation decision because water released for electricity generation during the current period cannot be simultaneously stored for future use. Therefore, hydro dispatch is governed by the opportunity cost of water, commonly referred to as the water value.

2.7 Real Curtailment Identification and Renewable Energy Recovery

In addition to the model-endogenous curtailment defined in Section 2.5, this study separately quantifies historically observed renewable energy curtailment from measured solar and wind generation data. At each 15-minute interval, curtailment is calculated as the difference between available renewable potential and actual grid-dispatched generation. The calculation is performed independently for solar and wind resources and aggregated to represent renewable energy that was available but not utilised due to practical system constraints. This empirical curtailment measure captures real operational limitations beyond those represented in the single-node optimisation framework.

To assess the contribution of battery storage towards improving renewable utilisation, a separate battery absorption simulation is performed. The battery charges using available curtailed energy, subject to power and state-of-charge limitations, while maintaining sufficient capacity for subsequent curtailment events.This provides an estimate of the economic value of renewable energy recovered through storage and quantifies the role of battery systems in reducing renewable energy wastage and supporting sustainable electricity system operation.

2.8 Externality-Adjusted Cost Assessment

The marginal-cost framework developed above represents the private operating cost of electricity generation and does not account for environmental and social externalities associated with thermal generation. To provide a broader sustainability perspective, the private marginal costs of representative thermal units were supplemented with externality cost estimates from the SLEMA/PUCSL (2017) assessment of Sri Lankan power generation impacts.

The externality estimates were mapped to the corresponding modelled generating units based on fuel type and installed capacity. Lakvijaya was directly matched, while Kelanitissa CCY, Sapugaskanda units, and West Coast were considered approximate technology-based equivalents for the remaining assessed plants.

The adjustment demonstrates that incorporating environmental costs substantially increases the effective cost of generation, particularly for coal and heavy-fuel-oil-based units. For example, Lakvijaya's marginal cost increases from approximately 17.3 LKR/kWh to around 27.5–27.7 LKR/kWh after accounting for greenhouse gas and local environmental damages. These results highlight that conventional merit-order dispatch based solely on private operating costs does not fully represent the societal cost of fossil-based generation.

The externality-adjusted costs are used only for sustainability interpretation and are not incorporated into the optimisation model, as current electricity market prices are based on private marginal costs rather than internalised environmental costs. This assessment therefore provides additional context for evaluating the potential sustainability benefits of renewable integration and battery storage in reducing dependence on high-impact thermal generation.

2.9 Data Sources

The proposed framework integrates operational, technical, renewable resource, and environmental datasets to evaluate the role of battery energy storage in supporting sustainable electricity system operation. The optimisation model requires accurate representation of the existing generation fleet, historical dispatch behaviour, renewable resource availability, hydro resource characteristics, and battery storage constraints. The primary data sources and corresponding parameter classes are summarised in Table 1.

Table 1. Data sources and parameter classes used in the optimisation framework

Parameter class	Source
Generator installed capacity and generation fleet inventory	Public Utilities Commission of Sri Lanka (PUCSL) generation licensing records [27]
Historical electricity generation by fuel type at 15-minute resolution	Public Utilities Commission of Sri Lanka (PUCSL) generation licensing records (2024)
Solar and wind resource availability	Sri Lanka Sustainable Energy Authority (SLSEA)

Battery technical parameters	Manufacturer-typical operational specifications; battery degradation cost represented as an uncertain parameter and evaluated through sensitivity analysis
Generator externality costs (GHG and local environmental damage)	SLEMA/PUCSL externality cost assessment (2017) [28]

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3. Results

3.1 Fitted Generator Cost Functions

The generator cost functions obtained from the fitting and correction procedure described in Sections 2.5 and 4.1 are presented in this section. These functions represent the final operating-cost representation used in the optimisation framework to determine generator dispatch, storage operation, and marginal electricity prices. The explicit reporting of fitted coefficients enables independent reproduction of the dispatch outcomes and price signals presented in the subsequent sections.

For each thermal generating unit, the fitted cost function was represented either as a convex quadratic function:

$$C_i(P) = a_i + b_i P + c_i P^2 \qquad (46)$$

where $C_i(P)$ represents the hourly operating cost (LKR/hr) and P represents generator output in MW, or as a linear cost function where insufficient operating data were available to reliably estimate quadratic curvature.

The fitted quadratic coefficients for the major generating units are presented in Table 2.

Table 2. Fitted quadratic generator cost functions used in the optimisation model

Plant	a (LKR/hr)	b (LKR/MWh)	c (LKR/MWh²)	Operating range (MW)
Lakvijaya (Coal)	187,076.9	16,760.43	+0.5359	243–810
West Coast	3,198,460.8	20,888.70	29.72	81–270
Kelanitissa CCY	4,221,685.0	−14,014.81	151.58	48.3–161
Sapugaskanda G08	94,155.9	14,029.53	1,699.51	8.4–28
Sapugaskanda G11	146,739.3	−1,358.58	2,833.07	8.4–28
Sapugaskanda G12	147,082.2	−7,479.77	3,748.62	8.4–28

The fitted quadratic functions demonstrate significant variation in both fixed and incremental operating costs among thermal generators. Large-scale units such as Lakvijaya coal power station exhibit relatively low quadratic curvature, reflecting the operational characteristics of high-capacity baseload generation [29]. In contrast, smaller oil-based thermal units display substantially higher quadratic coefficients, indicating rapidly increasing marginal costs as generation approaches technical operating limits.

The negative values initially obtained for some linear coefficients (b_i) do not imply negative generation costs. Rather, they arise from the statistical fitting of quadratic functions over limited historical operating ranges, where

the fixed-cost component and curvature term compensate during regression. As described in Section 2.5, convexity was preserved by enforcing physically consistent cost characteristics before integration into the optimisation model.

For generating units where historical operating data were insufficient to estimate reliable quadratic curvature, a linear cost representation was adopted:

$$C_i(P) = b_i P \times 1000 \qquad (47)$$

where b_i represents the marginal energy cost in LKR/kWh. The resulting linear cost coefficients are presented in Figure1. Figure 1 presents the merit-order ranking of the 18 thermal generating units included in the dispatch model, ordered by marginal cost from lowest to highest. Each bar represents the operating range of the corresponding plant between its minimum stable output and maximum capacity, with the associated marginal cost indicated alongside.

The ranking highlights significant cost variation across the fleet. Lakvijaya coal power plant provides the lowest-cost generation at approximately 17.3 LKR/kWh with the largest operating range (243–810 MW), while Sapugaskanda G12 represents the highest-cost unit at approximately 129.0 LKR/kWh. Several units form cost clusters, including Uthuru Janani, Barge, Hambantota, Mathugama, and Oil (CEB) at 45.4 LKR/kWh, with Oil (CEB) contributing the largest capacity within this group. Similarly, KPS GT7, KCCPS-2, and Sobadhanavi form a higher-cost peaking group at 89.0 LKR/kWh.

This merit-order structure explains the price variations observed in Section 3, as the market-clearing price increases when progressively higher-cost generators become marginal units during periods of increased net demand.

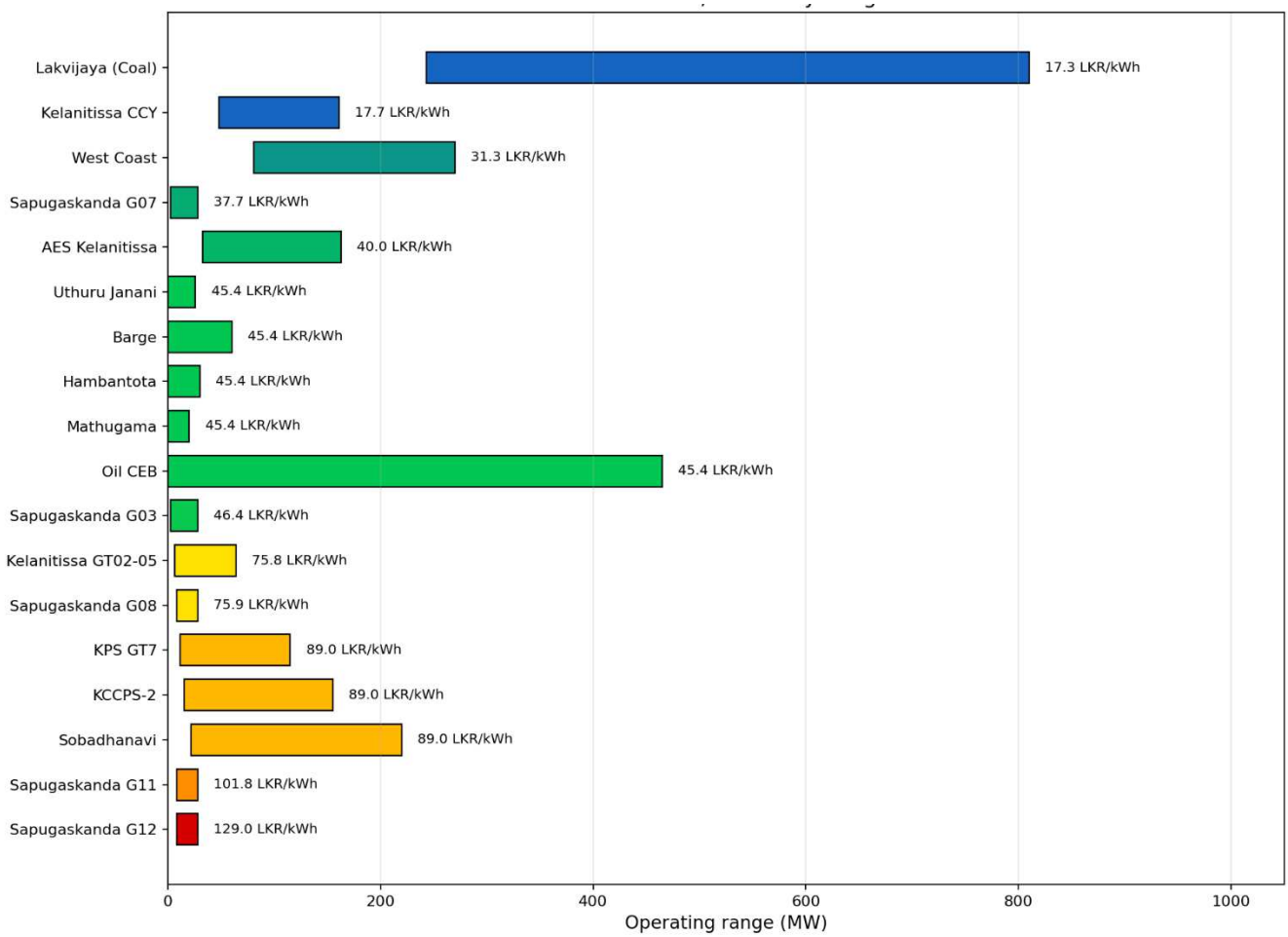


Figure 1: Merit-order ranking of the 18 thermal generating units based on marginal cost and operating range.

3.2 Full Generation Mix, Demand, Price, and Battery Response

Figure 2 presents the complete dispatch solution for a high-solar reference day, showing the generation mix, system demand, market-clearing price, and 240 MW battery operation (SOC and net charging/discharging power) on a common time axis. The results were obtained using the fitted generator cost functions in Section 3.1 and the storage-integrated optimisation framework developed in Sections 2.3–2.4.

The selected day, 13 March 2024**,** represents the highest verified solar generation day within the study period, with a peak solar contribution of 691 MW, validated against the reference solar dataset described in Section 2.7. The case illustrates the interaction between renewable generation, thermal displacement, price formation, and battery arbitrage behaviour. During high solar availability, lower-cost renewable generation reduces reliance on higher-cost thermal units, resulting in lower marginal prices and battery charging opportunities. As renewable output declines, the battery discharges in response to increasing marginal prices. The figure incorporates the corrected 18-plant generation fleet used throughout the optimisation analysis.

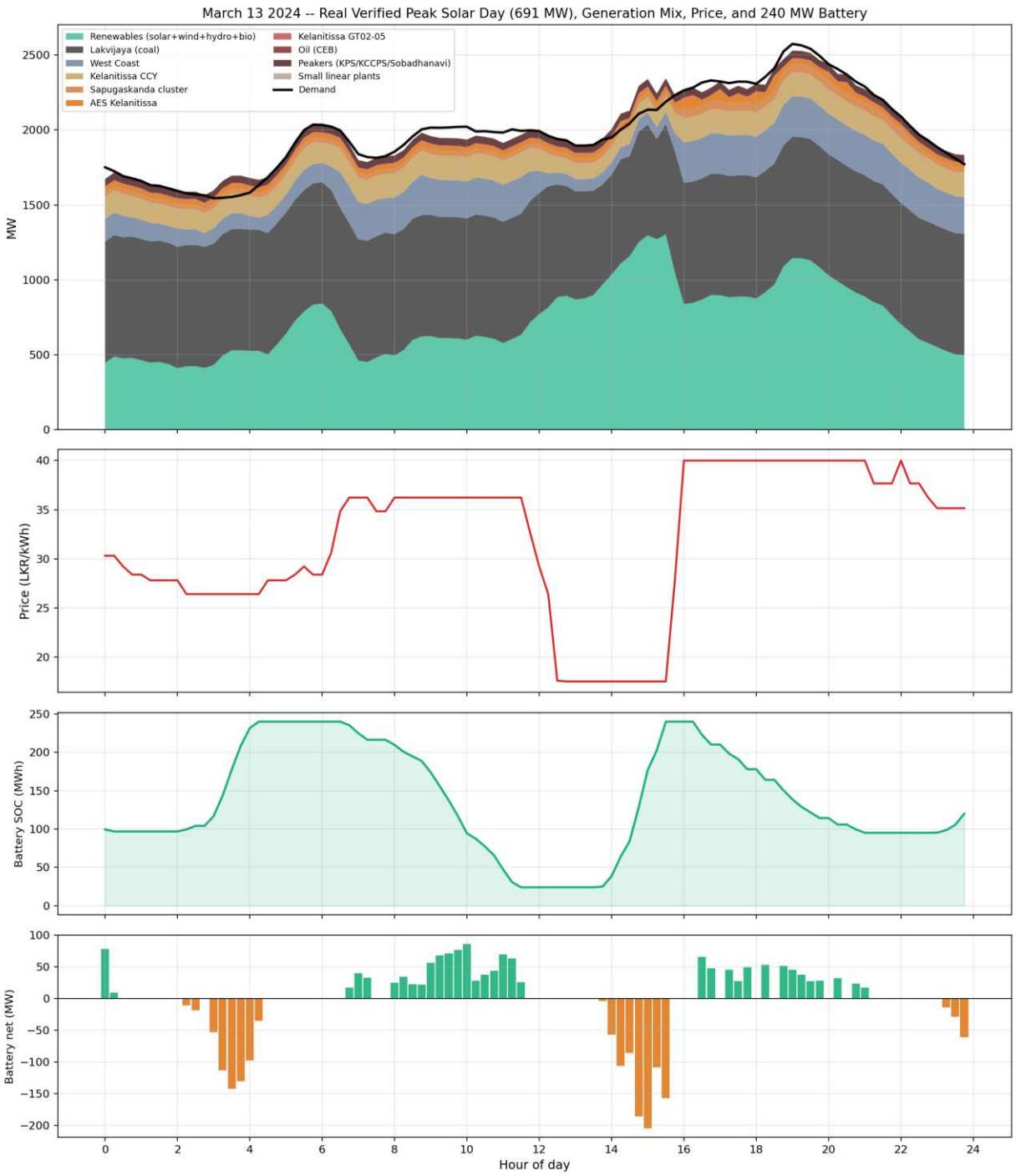


Figure 2:. Full generation mix by plant group, demand, price, and 240 MW battery SOC/dispatch

3.3 Single-Day Reference Case (January 22, 2024)

single-day reference case, represented in Figure 3, was constructed to examine how generation dispatch, renewable availability, market price, and battery operation interact under a representative, moderate-demand day. 22 January 2024 was selected following a data-plausibility screen (solar peak of 489 MW, consistent with neighbouring days, and renewable generation contributing approximately 63% of total demand), ensuring the case reflects typical rather

than extreme system conditions. This examines dispatch behaviour when net thermal demand approaches the system's marginal-cost ceiling. Together, the two cases demonstrate that the model produces internally consistent, economically sensible price and dispatch outcomes across the full range of demand conditions observed in the data from a typical day with moderate renewable penetration to the year's most demand-constrained day rather than being tuned to perform correctly only under one specific scenario.

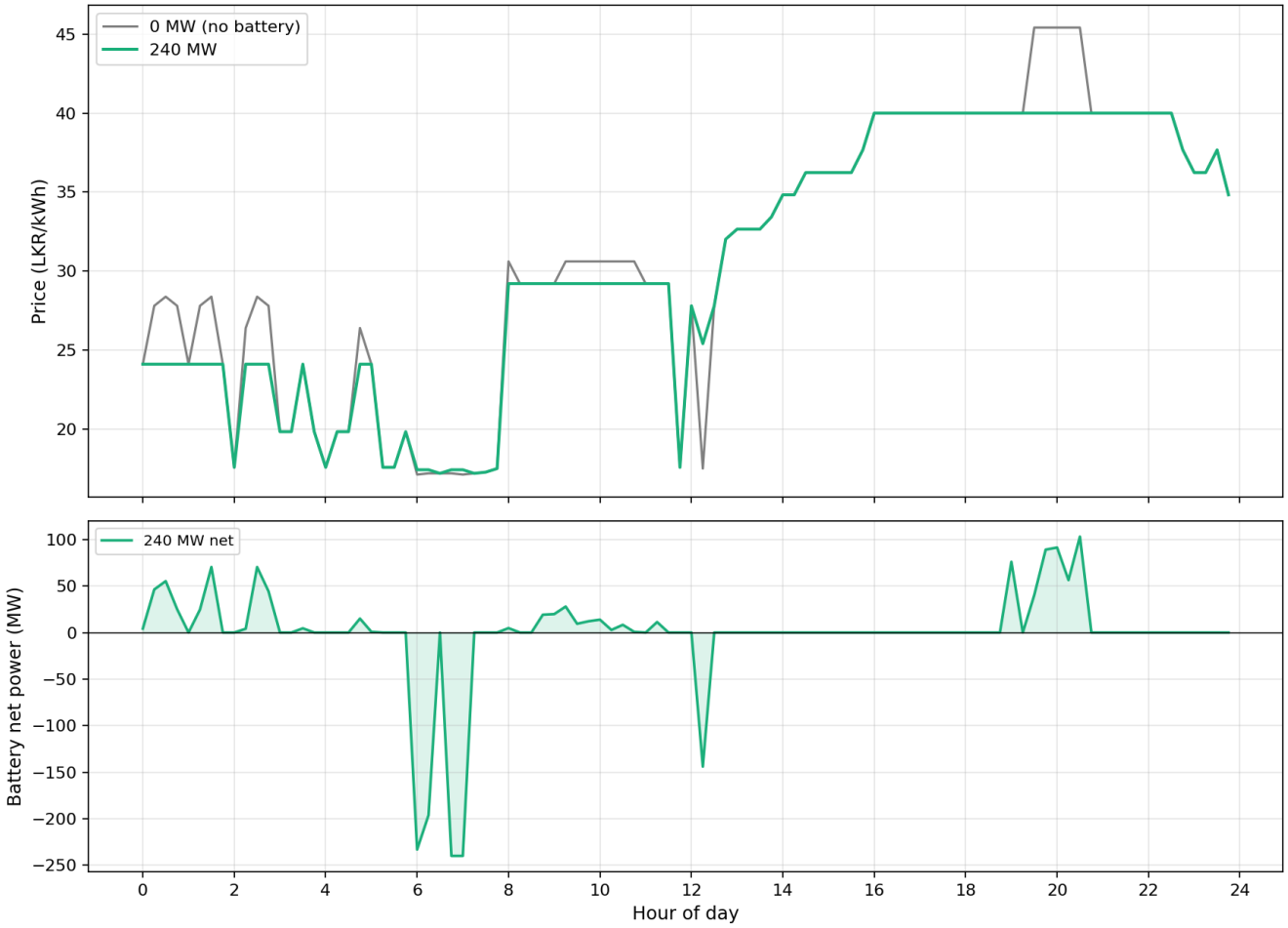


Figure 3. Price signal and battery net dispatch, Jan 22 2024 with and without battery

Figure 4 presents the state of charge (SOC) and net power profile of the 240 MW battery during the reference day. The charging and discharging schedule is obtained from the optimisation framework described in Sections 2.2–2.4, responding to the marginal electricity price signal while satisfying the battery operating constraints. The battery charges during lower-price periods, typically associated with higher renewable availability, and discharges during higher-price periods, demonstrating the expected arbitrage behaviour. The SOC trajectory confirms the intertemporal nature of storage operation, where current decisions are influenced by future energy-shifting opportunities.

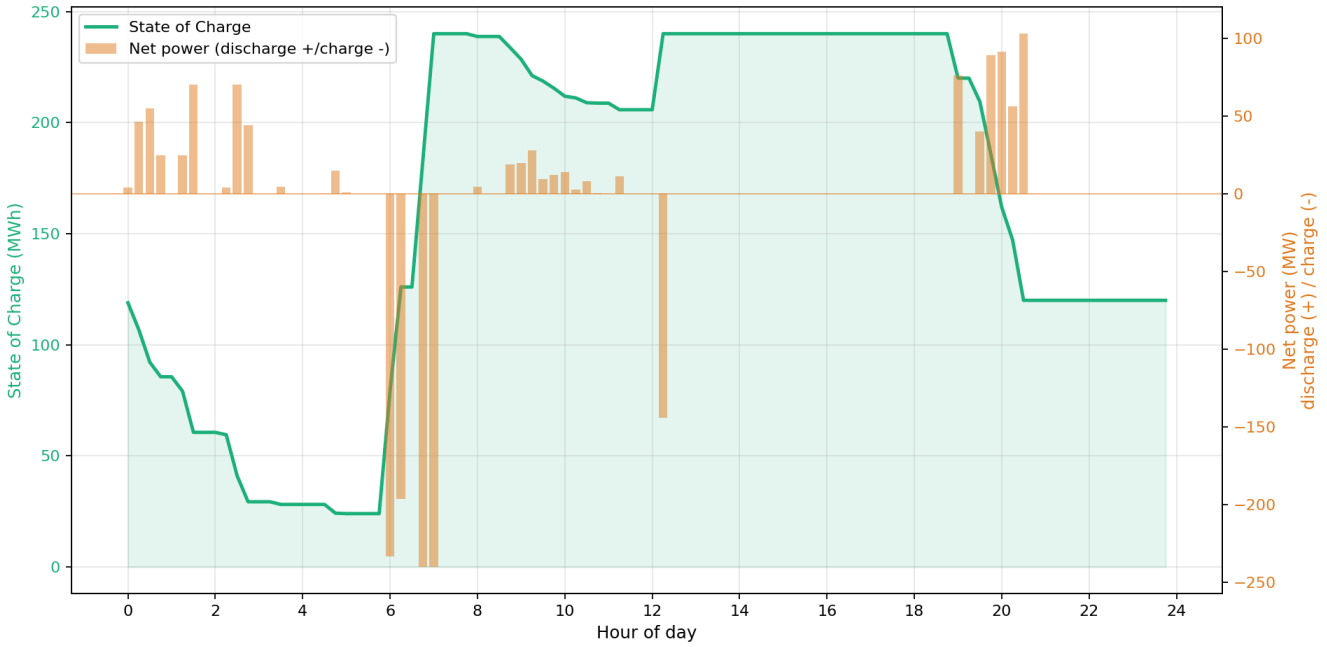


Figure 4. Battery state of charge and net power across the day.

3.4 Battery Size Sensitivity

Figure 5 presents the sensitivity of battery economic performance to increasing battery power rating, evaluated by varying the battery size from 0 to 480 MW for the reference day. The analysis examines the relationship between installed battery capacity, arbitrage revenue, and discharge response under the same system conditions [30]. As battery power rating increases, the ability to shift electricity between low-price and high-price periods improves, resulting in increased revenue up to the point where additional storage capacity provides diminishing economic benefits . This analysis demonstrates the impact of battery sizing on the value obtained from energy arbitrage and identifies the range where additional capacity contributes limited incremental benefit.

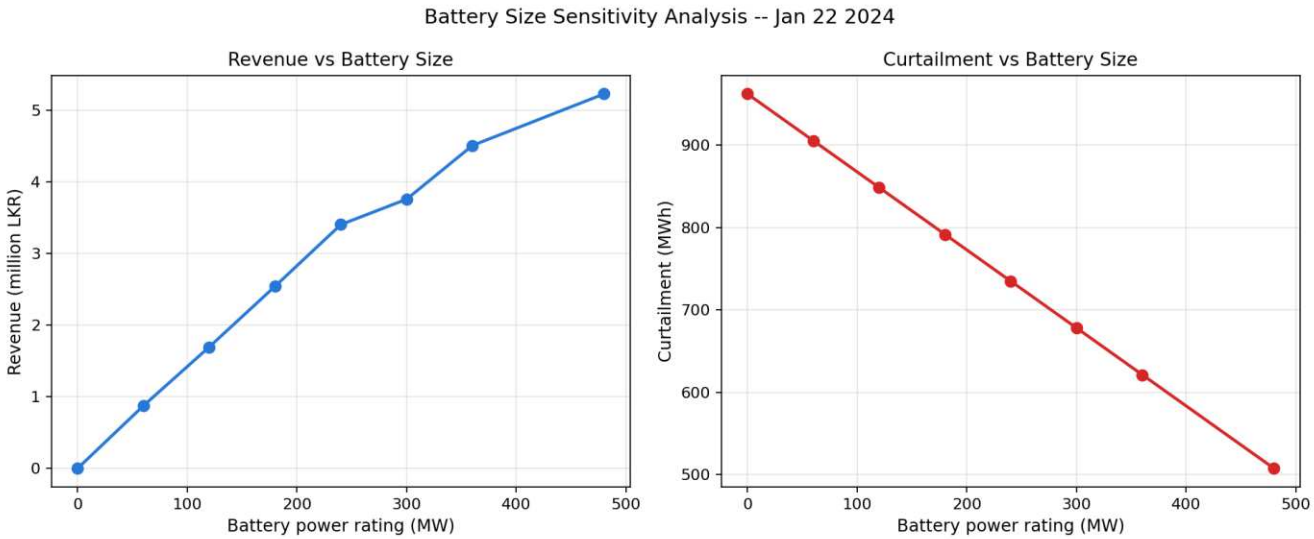


Figure 5. Revenue and discharge response vs. battery size.

Figure 6 presents the marginal revenue obtained from each additional MW of battery capacity. The declining marginal revenue curve demonstrates that initial increases in battery size provide the greatest economic benefit by enabling additional energy shifting opportunities, while further capacity additions yield progressively smaller gains due to limited availability of high-value arbitrage opportunities. This relationship highlights the importance of optimal battery sizing, where capacity expansion should be evaluated based on incremental economic value rather than total revenue alone.

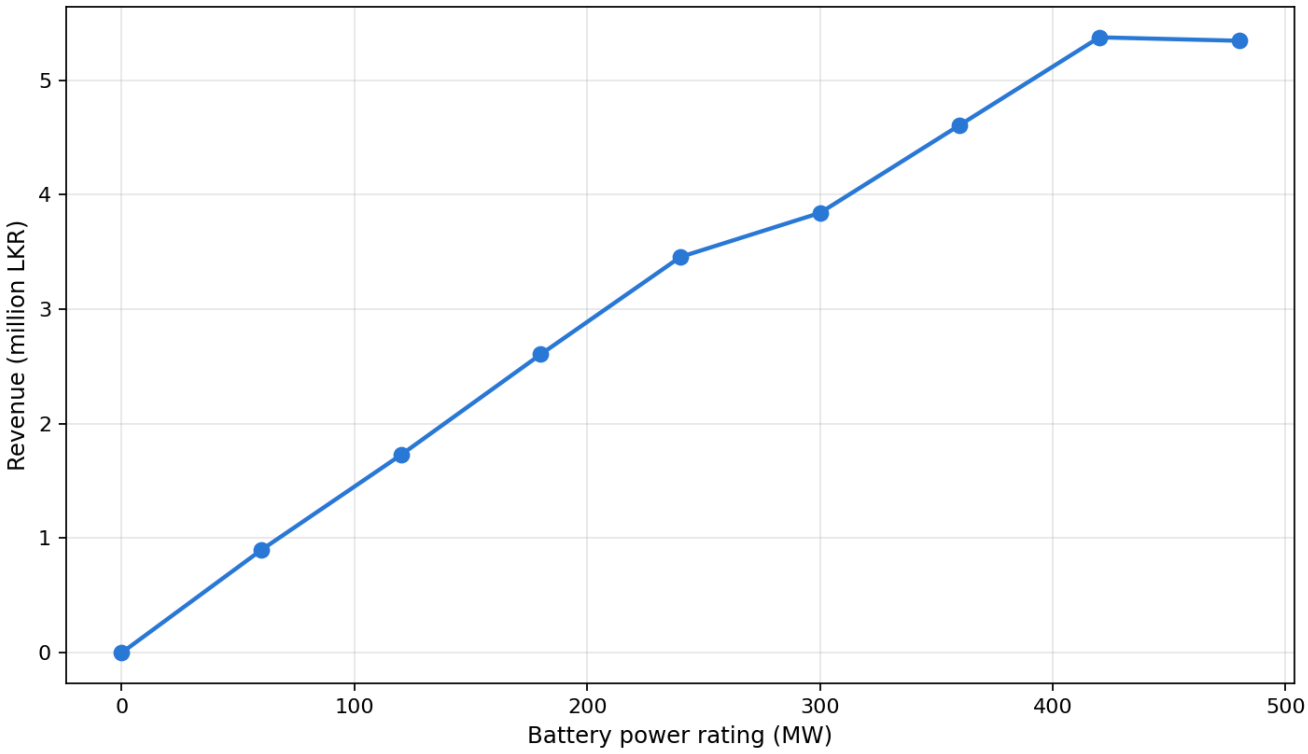


Figure 6. Marginal revenue per additional MW of battery capacity.

The revenue response remains smooth and monotonic as battery power rating increases up to 240 MW, indicating that additional storage capacity continues to capture available arbitrage opportunities within this range. Beyond 240 MW, the marginal revenue per additional MW becomes non-monotonic. This behaviour is attributed to linear programming degeneracy, where multiple battery schedules achieve the same optimal system cost when storage capacity becomes large relative to the available price differential. Therefore, the observed variation in marginal revenue reflects the presence of alternative optimal solutions rather than a numerical instability or modelling error.

3.5 Multi-Day Sample

Figure 7 presents the cumulative battery revenue over the 15-day March 2024 sample for the 240 MW battery system. Unlike the January sample, where revenue was concentrated in a small number of high-value days, the March profile shows a more continuous increase, reaching approximately 42.7 million LKR by March 15.

The steadily rising curve reflects the higher and more consistent demand conditions during March, with each day contributing meaningfully to cumulative revenue. This behaviour is consistent with the lower revenue variability observed in the March sample and indicates that battery arbitrage value is generated more consistently under higher-demand operating conditions rather than being dependent on isolated high-volatility events.

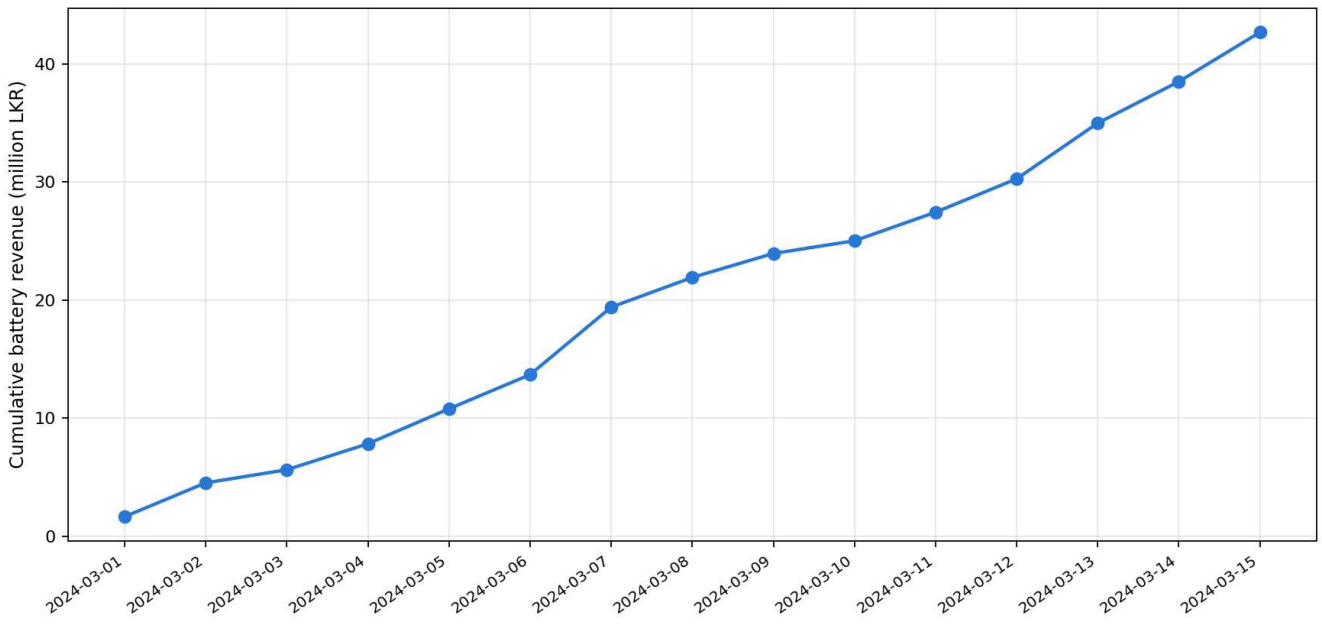


Figure 7. Cumulative battery revenue across the sample.

To examine how consistent this pattern is across an extended period, the solved market-clearing price was computed independently for every 15-minute interval across 15 consecutive real days (March 1–15, 2024) and assembled into a single price surface, with hour of day, day of month, and price as the three axes. Because each day was solved as

an independent optimization, this surface contains no interpolated or estimated values every point is a directly computed shadow price as depicted in figure 8.

The surface confirms the expected daily cycle repeating across all 15 days, with price rising from a low overnight/midday range (approximately 17–20 LKR/kWh) to an evening peak (approximately 30–40 LKR/kWh) as demand increases and progressively more expensive generators become marginal. The surface also reveals genuine day-to-day variation in the timing of this evening rise: on most days the price increase begins by hour 16, but on Day 10 specifically it is delayed until hour 17:15, creating a visible discontinuity in the surface relative to neighbouring days. This delay corresponds to the battery reaching full state of charge in the early afternoon and holding that position declining to discharge until price crosses its KKT-derived discharge threshold providing a direct, empirically observed instance of the theoretical discharge condition established in the Methodology.

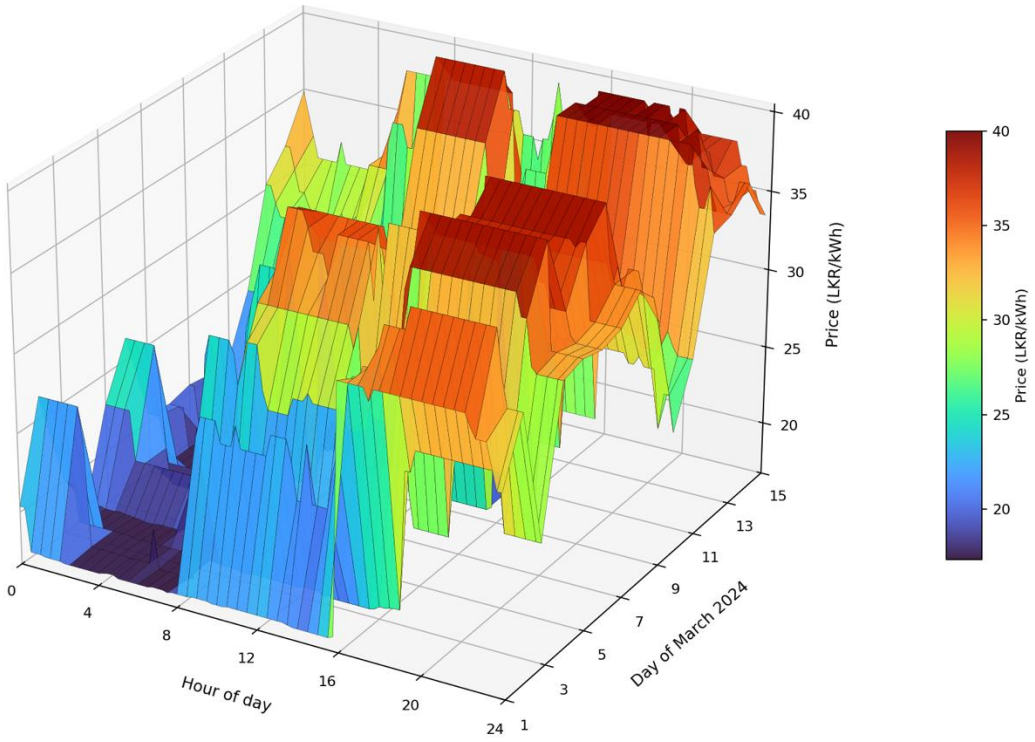


Figure 8. Market-clearing price surface,

3.6 Degradation-Cost Sensitivity

Figure 9 presents the battery arbitrage performance across the four validated reference days. Over this sample, the 240 MW battery generated a combined revenue of 7,210,791 LKR by discharging during high-price periods and charging during lower-price periods, consistent with the KKT-derived storage operating conditions established in the methodology. The average cycling activity was 0.60 cycles/day, reflecting the moderate price spreads observed

and the degradation-cost assumption applied. The underlying no-battery price volatility across the sample was moderate, with a mean price standard deviation of 4.32 LKR/kWh. Days with greater price variation provided stronger arbitrage opportunities and higher battery revenue, while lower-volatility days resulted in reduced cycling and revenue. Given the limited four-day sample size, these results are complemented by the broader 15-day March analysis presented later in this section.

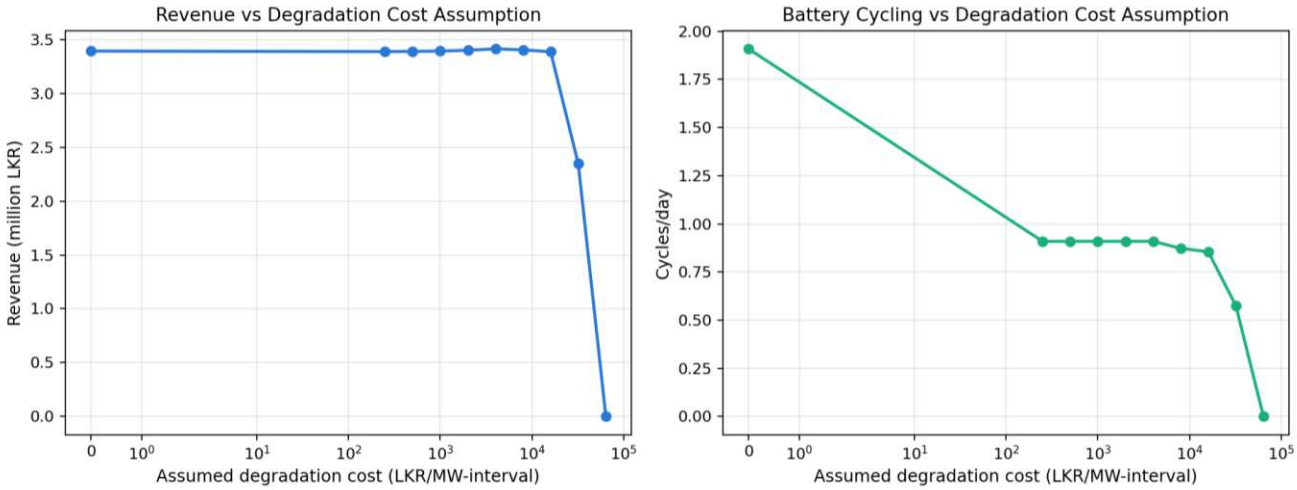


Figure 9. Revenue and cycling response to assumed degradation cost.

3.7. Contribution of Battery Storage to Renewable Utilisation and Externality Reduction

This figure 10 illustrates reported curtailment for each day from January 1 to June 30, 2024, decomposed into the portion a 240 MW battery could capture (green, stacked at the base) and the remaining uncaptured portion (red, stacked on top). Daily curtailment volumes are substantial and highly variable, ranging from roughly 1,000 to over 6,000 MWh, with a pronounced increase visible from mid-April through June. The lower panel reports the same result as a daily percentage of curtailment avoided, which fluctuates between approximately 3% and 65% depending on the day, with the highest avoidance rates occurring on days of comparatively lower total curtailment. Across the full period, the battery captures only a small fraction of total real curtailment on most days, reflecting a substantial mismatch between the scale of real curtailment and the capacity of a single 240 MW storage unit.

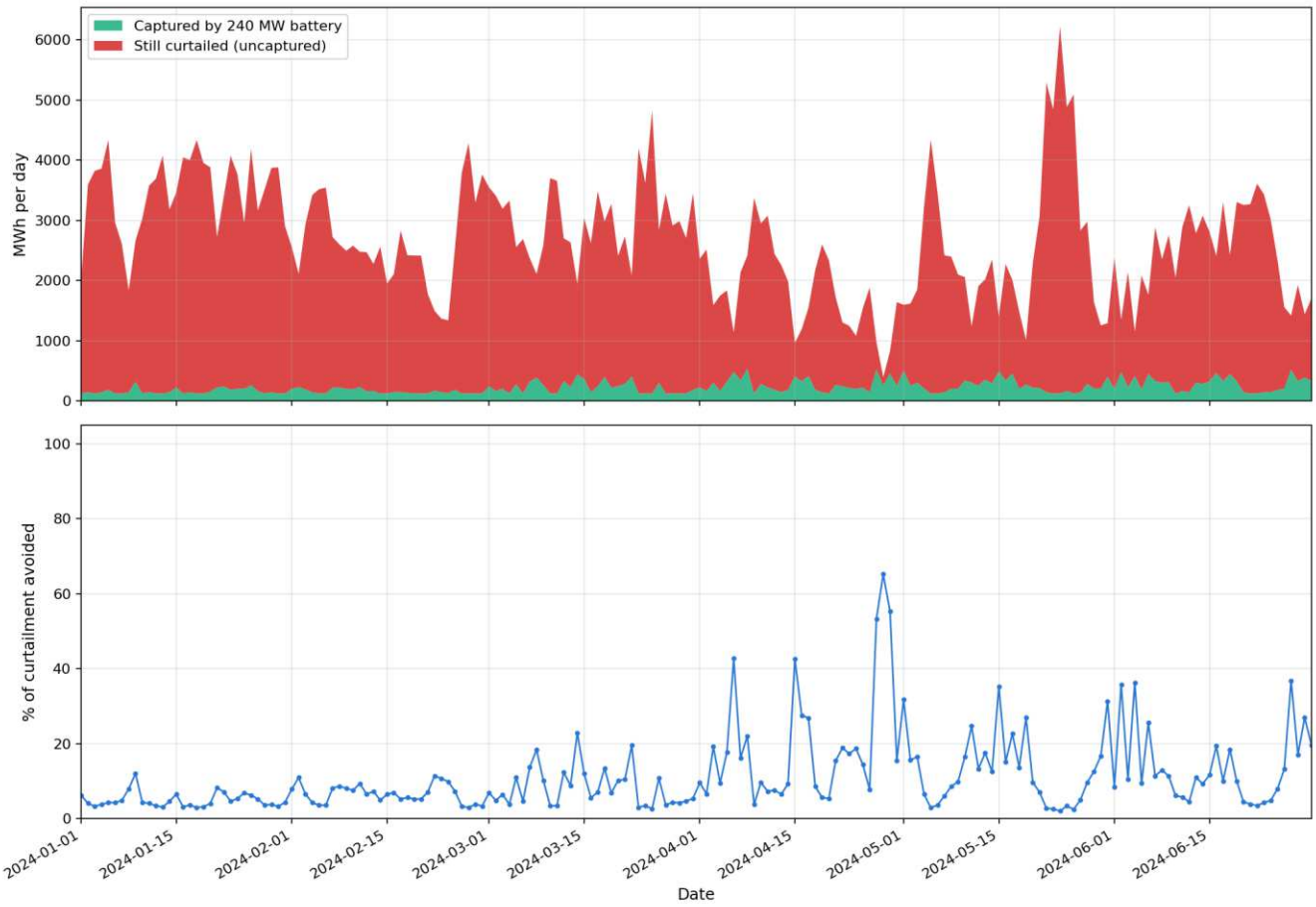


Figure 10. Solar and wind curtailment allocation under 240 MW battery absorption capacity

Also, figure 11 translates the curtailment captured by the battery (from the preceding figure) into an avoided externality cost, valued under five scenarios corresponding to different assumptions about which thermal generator's output was displaced. Each scenario applies a fixed externality rate (LKR/kWh) drawn from the SLEMA (2020) externality cost assessment: four scenarios apply greenhouse gas costs only, while a fifth (Lakvijaya, GHG plus local) additionally includes the local environmental damage costs estimated for that specific plant. Daily avoided cost tracks the same volatility pattern as captured curtailment, peaking above 5 million LKR/day on several occasions in April, May, and June. The consistent vertical separation between the Lakvijaya GHG-only and GHG-plus-local lines illustrates the material contribution of local environmental damages where they have been estimated, while the remaining three plants' lines represent lower-bound valuations only, since their local damage costs were not assessed in the source study.

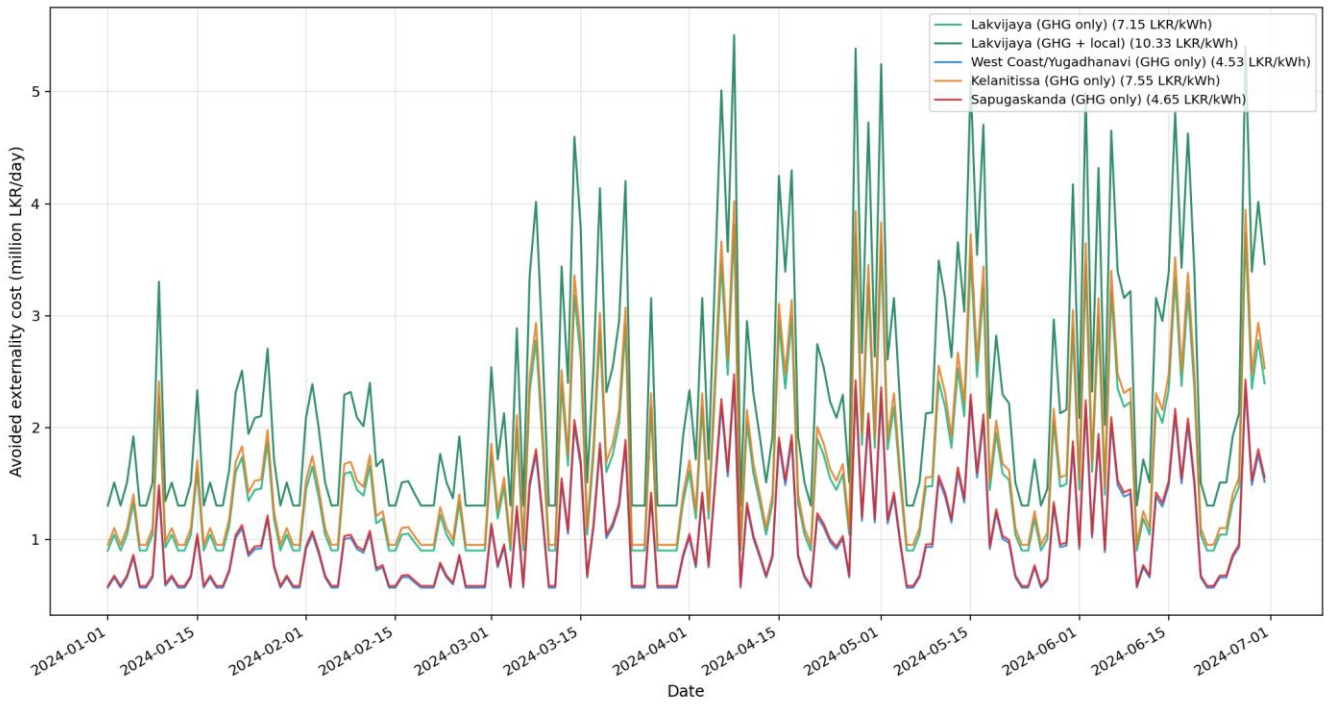


Figure 11. Avoided environmental externality costs through battery-enabled recovery of curtailed renewable energy

3.8. Model Verification

Beyond the results reported in Section 3, three independent checks were carried out to confirm the model was behaving correctly rather than simply producing plausible-looking output. First, an audit of generator marginal costs against real observed dispatch data identified and corrected two genuine errors in the initial fleet specification, a non-convexity in one generator's cost curve and an entire generating unit (0–606 MW observed range) missing from the fleet inventory. Second, the power balance was independently recomputed at every interval of a representative day and confirmed to hold to floating-point precision, with the marginal cost of the actively-dispatched plant matching the reported market price exactly at stable operating points. Third, solver termination was confirmed as a certified global optimum, and battery state-of-charge dynamics were verified to move in the correct direction decreasing during discharge and increasing during charge with no sign errors in the underlying energy balance.

Together, these checks confirm that the reported results reflect a correctly specified and correctly solved model: the generator fleet was validated against real data rather than assumed correct, the fundamental physical and economic constraints hold exactly rather than approximately, and the solver reached genuine optimality rather than a heuristic or partial solution.

4. Discussion

The results presented in this study provide methodological and practical insights into the role of battery energy storage as an enabling technology for sustainable electricity transitions in renewable-rich power systems. By integrating storage operation with endogenous electricity price formation and real system constraints, the proposed framework demonstrates how storage can improve renewable utilisation, enhance system flexibility, and support economically efficient decarbonisation pathways.

The observed difference between marginal electricity prices and output-weighted average generation costs highlights the importance of accurate economic valuation when assessing the sustainability benefits of battery storage. The proposed framework follows the marginal-cost pricing principle of Schweppe et al. [1], where electricity value is determined by the marginal generating unit rather than the average generation cost. This distinction is important for sustainable energy planning because storage provides its greatest system value during periods when renewable variability increases dependence on higher-cost thermal generation. Therefore, marginal pricing provides a more realistic representation of the flexibility value delivered by storage in supporting renewable integration.

The storage dispatch behaviour observed on Day 10 provides empirical confirmation that the proposed formulation enables economically optimal energy shifting. The battery remained charged during periods of lower system value and discharged when electricity scarcity increased the marginal value of stored energy. This behaviour demonstrates the ability of storage to transfer renewable electricity availability across time, reducing dependence on high-cost balancing resources and improving the utilisation of existing low-carbon generation. Furthermore, the successful application of the simplified price-taking formulation to a fully identified national electricity system demonstrates its practical relevance for sustainability assessments in developing power systems.

The comparison between January and March operating conditions demonstrates that the sustainability contribution of battery storage is strongly influenced by seasonal interactions between renewable availability, demand patterns, and system flexibility requirements. While battery value was concentrated in a limited number of high-volatility periods during January, March exhibited more consistent storage benefits due to higher and more sustained system demand. These findings indicate that storage planning should consider seasonal characteristics of renewable generation and electricity consumption rather than relying only on average annual conditions. Such consideration is particularly important for developing economies where renewable deployment is expanding alongside existing thermal infrastructure.

The generator fleet audit further highlights the importance of reliable data representation in evaluating sustainable energy transitions. Corrections to non-convex cost functions and the identification of omitted generation capacity significantly influenced dispatch outcomes, electricity prices, and renewable curtailment estimates. This demonstrates that sustainability assessments based on optimisation models require rigorous validation of underlying

operational data, as inaccurate system representation may lead to misleading conclusions regarding renewable integration potential and storage benefits.

5. Limitations and Future Directions

Despite the contributions of this study, several limitations should be acknowledged.

The proposed framework does not include explicit unit commitment decisions for thermal generators. Thermal units are assumed to remain available between their minimum and maximum operating limits, which may constrain renewable absorption during low-demand periods and potentially overestimate curtailment under certain operating conditions. Future research should incorporate start-up costs, minimum up/down time constraints, and binary commitment decisions to better represent the operational flexibility of thermal generation and improve the assessment of renewable integration pathways.

The electricity system is represented as a single-node network without transmission constraints, losses, or locational pricing effects. While this approach is appropriate for evaluating national-level storage impacts, it does not capture spatial limitations that may influence renewable curtailment and storage deployment decisions. Future studies should extend the framework to multi-node network models to evaluate optimal storage placement and its contribution to improving grid resilience and renewable accessibility.

Battery degradation is represented through an uncertain cost parameter rather than technology-specific ageing data. Although sensitivity analysis indicates that the main conclusions remain robust, long-term sustainability assessments require more accurate representation of battery lifecycle impacts, including technology-specific degradation behaviour, replacement requirements, and environmental impacts associated with battery production and disposal.

Renewable resource profiles were validated against independent reference data over a representative period; however, full-period validation across different seasonal and climatic conditions was not performed. Expanding renewable resource validation would improve confidence in long-term assessments of renewable integration, curtailment reduction, and storage requirements under changing climate conditions.

Further research should also integrate environmental and lifecycle considerations more comprehensively. Incorporating hydro reservoir optimisation directly through endogenous water-value modelling, extending the analysis over a full annual cycle, and coupling operational optimisation with lifecycle emission assessment would provide a more complete evaluation of the sustainability benefits of battery-integrated renewable electricity systems. In addition, comparison with decentralised market-based storage operation could quantify the trade-off between economic efficiency and practical market participation.

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Declarations

Ethics approval and consent to participate

Not applicable.

Consent for publication

Not applicable.

Availability of data and materials

The datasets analysed during the current study are available from the corresponding author on reasonable request.

Competing interests

The authors declare that they have no competing interests.

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Authors' contributions

W.D. Gammanpila (W.D.G.) conceptualised the study, developed the methodology, performed data preprocessing, modelling, formal analysis, and visualisation, and drafted the original manuscript. A.C. Gammanpila (A.C.G.) contributed to methodological refinement, software validation, and critical revision of the manuscript. A.H.T.S. Kularathna (A.H.T.S.K.) supervised the research, contributed to the study design, and critically reviewed the manuscript. N.K. Jayasooriya (N.K.J.) co-supervised the research, contributed to the theoretical framework and analytical interpretation, and reviewed and approved the final manuscript. All authors read and approved the final manuscript.

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