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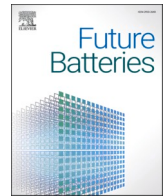
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An adaptive MPEC-based hierarchical framework for Co-optimizing virtual power plant profit and battery energy storage system health

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ABSTRACT

A growing number of Distributed Generators (DG) will be part of Virtual Power Plants (VPPs), thus necessitating the ability to optimize profit on markets as well as equipment longevity; especially for battery energy storage systems (BESS). An economic dispatch process can widen the "Dispatch-Control Gap", and accelerate the degradation of a BESS by forcing it into partial-cycles. This paper presents a new hierarchical two-stage procedure that closes this gap. The upper stage utilizes a mathematical program with equilibrium constraints (MPEC) for optimization of the markets, including new monotone constraints to prevent the partial-cycle degradation of the BESS when planning is performed. The lower stage employs an on-line controller to control the operation of the BESS Fleet while controlling degradation. A feedback loop enables the economic model to learn the true cost of degradation from the experience of the controller. The results of simulation over a 90 day period demonstrate the proposed method of reducing the long term degradation of the BESS by approximately 22 % relative to traditional methods. This improved sustainability provides a statistical increase to the overall life cycle profitability of the VPP, demonstrating that a health conscious, hierarchical methodology provides superior economics.

1. Introduction

The shift to low-carbon power globally will create dramatic changes in the way we construct and operate our electric power grids [1]. To achieve a future with large amounts of intermittent renewable energy sources integrated into the grid, we will need to develop more distributed and adaptive grid architectures than we currently possess [1]. The potential of Virtual Power Plants (VPP) as an aggregator of the many types of Distributed Energy Resources (DER) available today, as well as enabling their participation in wholesale markets and providing a variety of grid services [2–4], make them a key component of the distributed and adaptive grid architecture of tomorrow. Battery Energy Storage Systems (BESS) will be essential for both the operational flexibility and financial feasibility of VPPs [5,6]. However, the operational life of all batteries is limited and very dependent on the usage patterns they experience [7]. Therefore, the operational lifetime of BESS presents a significant management challenge due to its dependency on how it is used; this creates a substantial "dispatch-control gap" between the

high-level economic dispatch model of the VPP and the physical BESS. This economic dispatch model is primarily concerned with maximizing the VPP's profits [8–10], and is usually based on the assumption that the BESS can serve as a virtually perfect durable buffer; this produces optimized economic dispatches that are harmful to the physical BESS. The high frequency and shallow charge-discharge cycles produced by these economically optimal but physically detrimental dispatches cause the most rapid deterioration of the BESS [6,11,12]. . The physically damaging dispatches generated by the economic dispatch model are then sent to a lower level physical controller for execution. The lower level controller is bound by the limits placed upon it by the physically damaging commands it receives from the higher level controller. The long-term costs of BESS degradation are therefore ignored by the economic dispatch model when making decisions about scheduling, which results in unsustainable operating practices and overestimates the long-term profitability of VPPs [13,14]. The research to date has been fragmented by separating the two problems of optimizing VPP operations and controlling BESS operations, and thereby ignoring the dispatch-control gap that exists between the two. A great deal of the

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Abbreviations

ADN	Active Distribution Network
BESS	Battery Energy Storage System
CL	Controllable Load
DER	Distributed Energy Resource
DG	Distributed Generator
DSO	Distribution System Operator
EFC	Equivalent Full Cycles
KKT	Karush-Kuhn-Tucker
MPEC	Mathematical Program with Equilibrium Constraints
PV	Photovoltaic
SOC	State of Charge
VPP	Virtual Power Plant
WT	Wind Turbine

Sets and Indices

t, T	Time index and set of dispatch horizon (e.g., 24 h)
h, N_{VPP}	Index and set of Virtual Power Plants
g, N_{DG}	Index and set of DSO-owned DGs
g, N_h^{DG}	Index and set of VPP-owned DGs
i, N_h^{BESS}	Index and set of physical BESS units in VPP h
τ	Sub-hourly real-time control interval index
n	Index for operational cycles in online degradation model

Parameters

a_g, b_g, c_g	Cost coefficients for DSO-owned DG g
$\lambda_t^{EM}, \lambda_t^{RM}$	Forecasted energy/reserve prices at time t
$\lambda_{h,t}^{VPP}, \bar{\lambda}_{h,t}^{VPP}$	Energy price bounds set by DSO for VPP h at t
$r_{h,t}^{VPP}, \bar{r}_{h,t}^{VPP}$	Reserve price bounds set by DSO for VPP h at t
p^{PV}, p^{WT}, p^{load}	Forecasted PV, WT, and load power
$\rho^{PV}, \rho^{WT}, \rho^{load}$	Reserve requirement coefficients
$\underline{p}_g^{DG}, \bar{p}_g^{DG}$	Min/max power output limits for DG g
$R_g^{DG,up}, R_g^{DG,down}$	Ramp-up and ramp-down limits for DG g

$\bar{P}_h^{BESS}, W_h^{BESS, rated}$	BESS power and energy capacity in VPP h
η^{ch}, η^{dis}	Charging/discharging efficiencies of BESS
SOC_{min}, SOC_{max}	Min/max SOC limits
C_h^{rep}	Replacement cost of BESS in VPP h
$\Delta \bar{P}_{h,t}^{CL}$	Max controllable load in VPP h at time t
$\bar{P}_h^{line}$	Line capacity from VPP h to ADN
$N_c, ref, \xi, E_a, \gamma_1, \gamma_2$	BESS degradation model coefficients
$C_h^{BESS, rep}$	Total BESS replacement cost in VPP h
k^{calib}	Calibration factor for feedback loop

Decision Variables

Φ^{ADN}, Φ_h^{VPP}	Objective functions for DSO and VPP h
$p_{g,t}^{DG}, R_{g,t}^{DG}$	Power/reserve dispatch for DSO-owned DG g at t
p_t^{EM}, R_t^{RM}	Power/reserve traded in external markets at t
$\lambda_{h,t}^{VPP}, r_{h,t}^{VPP}$	Energy/reserve prices set for VPP h at t
$P_{h,t}^{VPP}, R_{h,t}^{VPP}$	Net power/reserve exchanged between VPP h and ADN at t
$p_{h,t}^{DG}$	Dispatch for VPP-owned DG g in VPP h at t
α_h	Daily capacity split for BESS in VPP h
$u_{h,t}^{BESS}$	Binary variable for BESS operation (1 =discharge, 0 =charge)
$P_{h,t}^{ch}, P_{h,t}^{dis}$	Charging/discharging power of BESS in VPP h at t
$W_{h,t}^{ch}, W_{h,t}^{dis}$	Energy in virtual charging/discharging groups
$R_{h,t}^{BESS, up}, R_{h,t}^{BESS, dn}$	Up/down reserves by BESS in VPP h at t
$C_{h,t}^{BESS, deg}$	Estimated BESS degradation cost in VPP h at t
$\Delta P_{h,t}^{CL}$	Power from controllable load in VPP h at t
n_c, n_d	Number of BESS units charging/discharging in real-time
$P_{i,\tau}$	Real-time dispatch for BESS unit i at τ
$c(n)$	Cumulative aging index after cycle n

existing literature has focused on the high-level economic co-optimization of a DSO with multiple VPPs. These studies often employ sophisticated mathematical techniques, such as the bilevel optimization framework proposed by [15,16], to model the hierarchical market interaction. Other approaches include robust optimization to handle uncertainty and game-theoretic models to capture strategic behaviors [17,20]. While these frameworks are powerful tools for analyzing market equilibrium and system-wide economics, they typically rely on heavily simplified BESS models to maintain computational tractability. The BESS is often represented as a simple energy reservoir with basic constraints on power, energy, and efficiency, while the complex, non-linear cost of physical degradation is either ignored entirely approximated with a rudimentary and often inaccurate linear energy throughput model, which assigns a static cost per MWh regardless of cycle depth [18–20]. While some advanced studies attempt to capture non-linear aging using Piecewise Linear Approximation (PLA) techniques, embedding these polygon constraints into the lower-level problem of an MPEC is computationally expensive. The linearization of PLA constraints requires a significant increase in binary variables (e.g., SOS2 type) during the Big-M reformulation, often rendering the bilevel problem intractable for practical operational horizons. This abstraction from physical reality. This abstraction from physical reality is the direct cause of the physically-unaware dispatch schedules that lie at the heart of the dispatch-control gap [21–24].

In parallel, a separate and equally advanced stream of research focuses on the low-level, physical control of BESS fleets. This domain has seen significant progress, with sophisticated controllers designed for

tasks such as real-time power smoothing and dynamic health management. The work of [25–27], for example, introduces an advanced reliant monotonic charging controller that utilizes short-term forecasts and a detailed online degradation model to intelligently manage a BESS fleet. Other popular methods in this category include Model Predictive Control (MPC), which uses a rolling horizon to optimize control actions [12, 28–31], and increasingly, data-driven approaches using Reinforcement Learning (RL) that learn a control policy from experience [32–34]. These controllers can dynamically allocate physical units, perform wear-leveling to distribute stress evenly, and enforce monotonic operation to prevent partial cycling at the execution level. However, these controllers are fundamentally *reactive* and tactical. They are designed to optimally execute a pre-determined, high-level energy target [35–40]. While they can mitigate the harm of a bad schedule, they cannot fix a schedule that is inherently flawed from a physical health perspective. The economic planners of the first category are thus smart but blind financially intelligent but blind to the true physical consequences of their decisions. The physical controllers of the second category are sighted but bound they can see and manage the physical health of the asset but are bound to follow the commands of the blind planner. The critical research gap, therefore, lies at the intersection of these two domains. The literature lacks a formal, integrated framework that allows the rich, real-time physical degradation data from the controller to be systematically fed back to inform and correct the high-level economic dispatch model in a closed-loop fashion.

This paper aims to bridge this critical research gap by proposing a novel, two-level hierarchical framework that synchronizes economic

planning with physical reality. The key contributions of this work are as follows:

- **A Novel Hierarchical Co-optimization Framework:** We propose a new two-level architecture that formally separates and then re-integrates the day-ahead strategic planning (Level 1) and the real-time tactical control (Level 2) of VPPs, providing a structured solution to the traditionally disconnected dispatch-control gap.
- **Physically-Aware Monotonic BESS Constraints:** We introduce a novel set of monotonic constraints directly into the VPP's economic dispatch model. By mathematically preventing the optimizer from scheduling partial cycles, this fundamentally shifts the paradigm from merely penalizing degradation to preventing its primary cause at the planning stage.
- **An Adaptive Feedback Mechanism for Self-Correcting Dispatch:** We design and implement a hierarchical feedback loop that allows the economic planner to learn from the physical controller's real-world operational experience. This enables the framework to progressively improve the accuracy of its degradation cost estimations and dispatch decisions over time.
- **A Holistic "Lifetime-Adjusted Profit" Metric:** We introduce and apply a comprehensive financial metric that synthesizes short-term operational profit with the long-term cost of asset degradation, providing a more realistic and holistic assessment of the true, long-term profitability of different BESS dispatch strategies.

The remainder of this paper is organized as follows. Section 2 provides a conceptual overview of the proposed hierarchical framework. Section 3 details the complete mathematical formulation of the Level 1 and Level 2 models and the feedback loop. Section 4 describes the case study, simulation environment, and benchmark models. Section 5 presents and discusses the comprehensive results of the 90-day simulation. Finally, Section 6 concludes the paper and outlines directions for future research.

2. The proposed hierarchical framework

In order to officially discuss the dispatch-control gap, the current paper will introduce a new two-level hierarchical structure, as shown in Fig. 1. This architecture is intended to balance the idea of pursuing market-based profits and maintaining long-term BESS asset health through the delegation of the responsibilities between two different temporal scales. Level 1 (Day-Ahead Economic Dispatch) has a strategic role in an hourly time basis (t). It predicts and forecasts to calculate an economically optimum and physically viable dispatch schedule of the VPP. Level 2 (Real-Time Operational Control) uses a time scale (τ) of less than one hour in order to serve a tactical purpose. It executes the dispatch instructions of Level 1, controls of particular physical units and adjusts the actual conditions in grid in relation to the predicted ones.

The structure works in a DSO-dominated Stackelberg where the VPPs are followers. At the organizational level, every VPP uses a plan-execute-learn philosophy at two levels. Level 1 comes up with an optimum day-ahead plan based on a physically-aware MPEC model. Level 2 implements this through sub-hourly control, with the only difference that it feeds actual degradation costs back to Level 1 using a calibration factor. This is an important feedback mechanism which makes the strategic economic model responsive to the physical reality of the BESS fleet and does not fall into the traps of open-loop planning.

2.1. Information flow and hierarchical interaction

The framework is based on a two-way, coordinated information exchange to coordinate strategic planning and the tactical implementation. Under the top-down flow, Level 1 produces hourly energy, hourly reserve goals at the beginning of the 24 h horizon and forwards the same to Level 2 as binding schedule governing the direction but leaving the sub-hourly discretion. Importantly, the system achieves this by connecting high-fidelity physical degradation found at Level 2 to a bottom-up feedback mechanism to determine a dimensionless calibration factor,

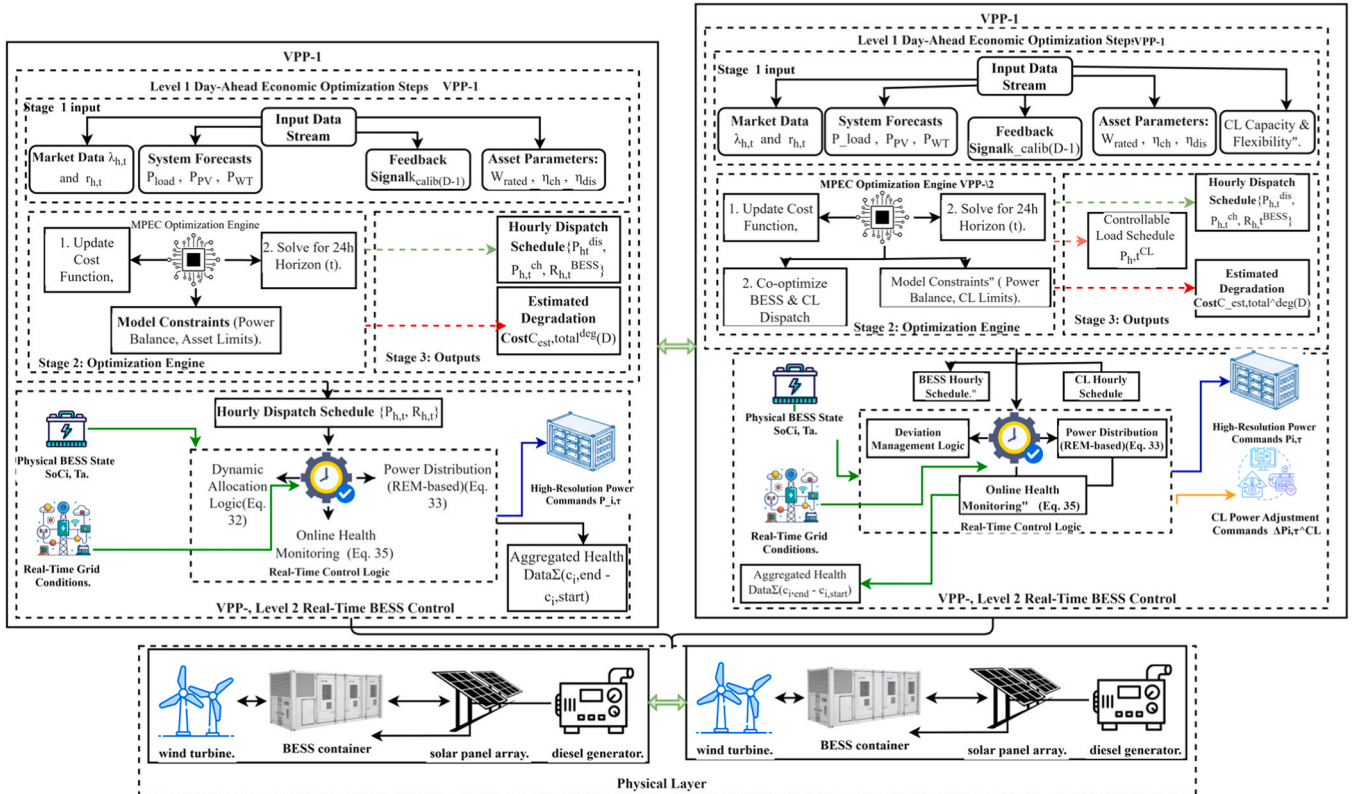


Fig. 1. The proposed hierarchical framework for co-optimization of VPP economics and BESS health.

k_{calib} , as the ratio of the actual to the predicted costs of degradation. This modifies the internal cost function of Level 1 on the next day; a decrease in the level of calibanism ($k_{\text{calib}} > 1$), or a decrease in the level of calibanism, will correct underestimation by increasing the schedule to a more conservative, health-conscious, or will lift the restrictions to allow increased profits. This self-correcting process helps the economic planner to constantly be adjusted to physical reality, avoiding model drift and optimally striking the balance between profit maximization and asset protection.

3. Mathematical modeling

The next segment outlines the mathematical representation of the hierarchical framework, which is comprised of three linked elements. The first level utilizes a Mathematical Program with Equilibrium Constraints (MPEC) as an MPEC for the day-ahead economic dispatch. The second level offers sub-hourly real-time control to implement the schedules developed in the previous step and manage the physical limitations of the BESS. The third element is the Hierarchical Feedback Loop that combines the two levels by using the results of the real-time physical implementation to refine the economic model developed at each level.

3.1. Level 1: day-ahead mpec-based economic dispatch

DSO-VPP interactions are modeled as Stackelberg games using a bilevel optimization approach. In this structure, DSO (leader) will set price that minimizes cost, and VPPs (followers) will schedule for maximum profit. Since the DSO-VPP problem is a bilevel problem, which makes it computationally difficult to solve, we replace the VPP's lower level optimization with the KKT optimality condition to transform the model to a single level MPEC. The DSO's goal is to find a solution that results in the lowest total operational cost over a 24 h time frame subject to constraint on the power flow through the transmission system. The objective function (1') calculates the total cost associated with dispatching DGs, purchasing reserve from VPPs and wholesale market for energy and reserve services, and trading with the wholesale market.

$$\max \phi_h^{\text{VPP}} = \sum_{t=1}^T \left[\left(\lambda_{h,t}^{\text{VPP}} P_{h,t}^{\text{VPP}} + r_{h,t}^{\text{VPP,up}} R_{h,t}^{\text{VPP,up}} + r_{h,t}^{\text{VPP,dn}} R_{h,t}^{\text{VPP,dn}} \right) - \sum_{g=1}^{N_h^{\text{DG}}} C_{h,g,t}^{\text{DG,op}} - C_{h,t}^{\text{CL,inc}} - C_{h,t}^{\text{BESS,deg}} \right] \quad (1')$$

3.1.1. Constraints of the DSO

DSO's decisions are constrained by a number of different forces including the regulatory environment in which it operates, the physical limitations of the system and the need to meet operational reliability standards. To help stabilize markets, the price that the DSO sets for each VPP will fall into predetermined ranges established as part of the contract between the DSO and the VPPs:

$$\underline{\lambda}_{h,t}^{\text{VPP}} \leq \lambda_{h,t}^{\text{VPP}} \leq \bar{\lambda}_{h,t}^{\text{VPP}} \forall h, t \quad (1)$$

$$r_{h,t}^{\text{VPP,up}} \leq r_{h,t}^{\text{VPP,up}} \leq \bar{r}_{h,t}^{\text{VPP,up}} \forall h, t \quad (2)$$

$$r_{h,t}^{\text{VPP,dn}} \leq r_{h,t}^{\text{VPP,dn}} \leq \bar{r}_{h,t}^{\text{VPP,dn}} \forall h, t \quad (3)$$

In order to support grid stability, the DSO must satisfy the basic active power balance equation for each hour; this means that the sum of all the renewable energy resources (including solar and wind), plus the sum of all the distributed generation resources (including DGs and VPPs) plus the sum of all of the DSO's market purchased power must equal the sum of all of the DSO's customers' energy usage and sales (i.e., exports) for each hour:

$$\sum_{i=1}^{N^{\text{PV}}} P_{i,t}^{\text{PV}} + \sum_{j=1}^{N^{\text{WT}}} P_{j,t}^{\text{WT}} + \sum_{g=1}^{N^{\text{DG}}} P_{g,t}^{\text{DG}} + \sum_{h=1}^{N^{\text{VPP}}} P_{h,t}^{\text{VPP}} + P_t^{\text{EM,pur}} = \sum_{l=1}^{N^{\text{load}}} P_{l,t}^{\text{load}} + P_t^{\text{EM,sel}} \forall t \quad (4)$$

Additionally, the DSO is responsible for managing the operations of its own dispatchable generators (DGs); these are constrained by maximum output levels (5), ramp rates (6) and reserve margins (9)-(10).

$$P_g^{\text{DG}} \leq P_{g,t}^{\text{DG}} \leq \bar{P}_g^{\text{DG}} \forall g, t \quad (5)$$

$$-R_g^{\text{DG,down}} \leq P_{g,t}^{\text{DG}} - P_{g,t-1}^{\text{DG}} \leq R_g^{\text{DG,up}} \forall g, t > 1 \quad (6)$$

$$\sum_{g=1}^{N^{\text{DG}}} R_{g,t}^{\text{DG,up}} + \sum_{h=1}^{N^{\text{VPP}}} R_{h,t}^{\text{VPP,up}} + R_t^{\text{RM,up}} \geq \rho^{\text{PV,up}} \sum P^{\text{PV}} + \rho^{\text{WT,up}} \sum P^{\text{WT}} + \rho^{\text{load,up}} \sum P^{\text{load}} \forall t \quad (7)$$

$$\sum_{g=1}^{N^{\text{DG}}} R_{g,t}^{\text{DG,dn}} + \sum_{h=1}^{N^{\text{VPP}}} R_{h,t}^{\text{VPP,dn}} + R_t^{\text{RM,dn}} \geq \rho^{\text{PV,dn}} \sum P^{\text{PV}} + \rho^{\text{WT,dn}} \sum P^{\text{WT}} + \rho^{\text{load,dn}} \sum P^{\text{load}} \forall t \quad (8)$$

$$0 \leq R_{g,t}^{\text{DG,up}} \leq \bar{P}_g^{\text{DG}} - P_{g,t}^{\text{DG}} \forall g, t \quad (9)$$

$$0 \leq R_{g,t}^{\text{DG,dn}} \leq P_{g,t}^{\text{DG}} - \bar{P}_g^{\text{DG}} \forall g, t \quad (10)$$

Each VPP (h), responding to price signals from the DSO, is a rational follower that maximizes daily profit by scheduling its DER portfolio with respect to its objective function (11) which measures the profit of a DER portfolio as the market revenue minus the operating cost; in particular, the objective function also captures the monetized cost of BESS degradation ($C^{\text{BESS,deg}}$), so that the cost associated with physical degradation of assets are reflected in the decision making process of dispatching the VPP's DER portfolio.

$$\max \phi_h^{\text{VPP}} = \sum_{t=1}^T \left[\left(\lambda_{h,t}^{\text{VPP}} P_{h,t}^{\text{VPP}} + r_{h,t}^{\text{VPP,up}} R_{h,t}^{\text{VPP,up}} + r_{h,t}^{\text{VPP,dn}} R_{h,t}^{\text{VPP,dn}} \right) - \sum_{g=1}^{N_h^{\text{DG}}} C_{h,g,t}^{\text{DG,op}} - C_{h,t}^{\text{CL,inc}} - C_{h,t}^{\text{BESS,deg}} \right] \quad (11)$$

3.1.2. VPP constraints and monotonic BESS model

Profit Maximization is constrained by the internal Power Balance of the VPP as described in (12) (generation matching load), and physical constraints on the DGs (13)-(14), CLs (15), and Transmission Lines (16-17).

$$\sum P^{\text{PV}} + \sum P^{\text{WT}} + \sum P^{\text{DG}} + (P_{h,t}^{\text{dis}} - P_{h,t}^{\text{ch}}) = P_{h,t}^{\text{VPP}} + P_{h,t}^{\text{inel-load}} + \Delta P_{h,t}^{\text{CL}} \forall t \quad (12)$$

$$P_{h,g}^{\text{DG}} \leq P_{h,g,t}^{\text{DG}} \leq \bar{P}_{h,g}^{\text{DG}} \forall g \in N_h^{\text{DG}}, t \quad (13)$$

$$-R_{h,g}^{\text{DG,down}} \leq P_{h,g,t}^{\text{DG}} - P_{h,g,t-1}^{\text{DG}} \leq R_{h,g}^{\text{DG,up}} \forall g \in N_h^{\text{DG}}, t > 1 \quad (14)$$

$$0 \leq \Delta P_{h,t}^{\text{CL}} \leq \bar{\Delta P}_{h,t}^{\text{CL}} \forall t \quad (15)$$

$$-\bar{P}_h^{\text{line}} \leq P_{h,t}^{\text{VPP}} \leq \bar{P}_h^{\text{line}} \forall t \quad (16)$$

To avoid health-detrimental micro-cycles, we apply a Monotonic BESS Model, where the battery is divided into two separate, one-way virtual groups. The daily capacity distribution between charging and discharging is determined by the discrete decision variable

$$\alpha_h \in \{0.3, 0.4, 0.5, 0.6, 0.7\} \quad (17)$$

Constraints for the operational behavior of the BESS (19)-(20) utilize a binary decision variable $u_{h,t}^{\text{BESS}}$ to exclusively allow either charging or discharging at any given time.

$$0 \leq P_{h,t}^{\text{dis}} \leq u_{h,t}^{\text{BESS}} \cdot \bar{P}_h^{\text{BESS}} \forall t \quad (18)$$

$$0 \leq P_{h,t}^{\text{ch}} \leq (1 - u_{h,t}^{\text{BESS}}) \cdot \bar{P}_h^{\text{BESS}} \forall t \quad (19)$$

$$W_{h,t}^{\text{dis}} = W_{h,t-1}^{\text{dis}} - \frac{P_{h,t}^{\text{dis}}}{\eta^{\text{dis}}} \Delta t \forall t \quad (20)$$

$$W_{h,t}^{\text{ch}} = W_{h,t-1}^{\text{ch}} + P_{h,t}^{\text{ch}} \cdot \eta^{\text{ch}} \cdot \Delta t \forall t \quad (21)$$

$$\text{SOC} \cdot \alpha_h W_h^{\text{BESS, rated}} \leq W_{h,t}^{\text{dis}} \leq \overline{\text{SOC}} \cdot \alpha_h W_h^{\text{BESS, rated}} \forall t \quad (22)$$

$$\text{SOC} \cdot (1 - \alpha_h) W_h^{\text{BESS, rated}} \leq W_{h,t}^{\text{ch}} \leq \overline{\text{SOC}} \cdot (1 - \alpha_h) W_h^{\text{BESS, rated}} \forall t \quad (23)$$

$$W_{h,T}^{\text{dis}} + W_{h,T}^{\text{ch}} \geq W_{h,0}^{\text{dis}} + W_{h,0}^{\text{ch}} \quad (24)$$

Therefore, SOC is separately tracked for each virtual group (21)-(22). In addition, a terminal constraint (23) is used to keep energy available to be able to meet future operating requirements. This monotonic reasoning also applies to the degradation costs calculation (24) and to ancillary service provision. Contributions to reserve are aggregated (25)-(26) with respect to the capabilities of the BESS (27)-(28).

$$C_{h,t}^{\text{BESS, deg}} = u_{h,t}^{\text{BESS}} \cdot C_h^{\text{rep}} \cdot f_{\text{poly}}(W_{h,t}^{\text{dis}}) + (1 - u_{h,t}^{\text{BESS}}) \cdot C_h^{\text{rep}} \cdot f_{\text{poly}}(W_{h,t}^{\text{ch}}) \quad (25)$$

$$R_{h,t}^{\text{VPP, up}} = \sum_{g=1}^{N_h^{\text{DG}}} R_{h,g,t}^{\text{DG, up}} + R_{h,t}^{\text{BESS, up}} + R_{h,t}^{\text{CL, up}} \forall t \quad (26)$$

$$R_{h,t}^{\text{VPP, dn}} = \sum_{g=1}^{N_h^{\text{DG}}} R_{h,g,t}^{\text{DG, dn}} + R_{h,t}^{\text{BESS, dn}} + R_{h,t}^{\text{CL, dn}} \forall t \quad (27)$$

$$R_{h,t}^{\text{BESS, up}} \leq u_{h,t}^{\text{BESS}} \cdot (\bar{P}_h^{\text{BESS}} - P_{h,t}^{\text{dis}}) + (1 - u_{h,t}^{\text{BESS}}) \cdot P_{h,t}^{\text{ch}} \quad (28)$$

$$R_{h,t}^{\text{BESS, up}} \cdot \Delta t \leq u_{h,t}^{\text{BESS}} \cdot (W_{h,t}^{\text{dis}} - \underline{W}_h^{\text{dis}}) \eta^{\text{dis}} \quad (29)$$

$$R_{h,t}^{\text{BESS, dn}} \leq u_{h,t}^{\text{BESS}} \cdot P_{h,t}^{\text{dis}} + (1 - u_{h,t}^{\text{BESS}}) \cdot (\bar{P}_h^{\text{BESS}} - P_{h,t}^{\text{ch}}) \quad (30)$$

$$R_{h,t}^{\text{BESS, dn}} \cdot \Delta t \leq (1 - u_{h,t}^{\text{BESS}}) \cdot (\bar{W}_h^{\text{ch}} - W_{h,t}^{\text{ch}}) / \eta^{\text{ch}} \quad (31)$$

3.1.3. Linearization of bilinear terms and MPEC solution

The transformation of the bilevel problem into a single-level MPEC introduces two distinct sources of non-linearity that must be linearized to yield a tractable MILP solution: the bilinear revenue terms in the DSO's objective function and the complementary slackness conditions derived from the VPP's KKT optimality conditions.

A. Strong Duality for Objective Function Linearization

The DSO's objective function (1) contains the bilinear term $\lambda_{h,t}^{\text{VPP}} P_{h,t}^{\text{VPP}}$, representing the payment from the DSO to the VPP. Since both the price λ (leader variable) and the power P (follower variable) are decision variables, their product is non-linear. We resolve this by applying the **Strong Duality Theorem** to the lower-level VPP problem. Strong Duality states that for a convex optimization problem, the optimal value of the primal objective equals the optimal value of the dual objective. Consequently, the non-linear revenue term in the leader's objective is replaced by an equivalent linear expression derived from the VPP's dual formulation.

$$\sum_{t=1}^T (\lambda_{h,t}^{\text{VPP}} P_{h,t}^{\text{VPP}}) = \Phi_h^{\text{VPP, cost}} + \sum_{k \in \Omega_K} \nu_{h,k} \cdot b_{h,k} \quad (32)$$

Where $\Phi_h^{\text{VPP, cost}}$ represents the VPP's internal costs, $\nu_{h,k}$ are the dual variables associated with the VPP's inequality constraints, and $b_{h,k}$ are the corresponding constant parameters. This substitution renders the leader's objective function fully linear.

B. Big-M Method for Complementarity Linearization

The KKT conditions introduce complementary slackness constraints

of the form $0 \leq \mu \perp g(x) \geq 0$, which implies a non-linear equality $\mu \cdot g(x) = 0$. To linearize these, we employ the **Big-M method** [Fortuny-Amat & McCarl]. For each complementarity pair involving a dual variable μ and a primal constraint $g(x)$, we introduce a binary auxiliary variable $z \in \{0, 1\}$ and a sufficiently large constant M .

$$\mu \leq M \cdot z \quad (33)$$

$$g(x) \leq M \cdot (1 - z) \quad (34)$$

$$\mu \geq 0, g(x) \geq 0 \quad (35)$$

The method above allows the dual variable μ to be set to 0 when, while forcing the primal constraint $g(x)$ to be binding when. It essentially embeds the disjunction-based logic needed to satisfy the KKT Conditions into a general Mixed-Integer Linear Programming (MILP) setting. Choosing the correct M for each constraint is very important in terms of establishing valid solutions as well as maintaining numerical stability. We have chosen to utilize what has been termed a tight Big-M. In order to avoid the common problem of an overly large constant resulting in poor conditioning of the model (resulting in loss of precision due to rounding errors), the value of M for each constraint was determined based on either the physical limits of the primal variables (i.e., the max BESS rated power, etc.) or the economic limits of the dual variables (i.e., the price ceiling on electricity, etc.). Using this approach, M is sufficient to force the logical constraints but does so with such a small enough number that it does not exceed the tolerance for floating point precision of the MILP Solver.

3.2. Level 2: real-time operational control

This level serves as an intermediary to bridge the time lag that occurs between planning and action; it translates the hourly targets at Level 1 into sub-hourly controls while making adjustments for forecast errors in real-time. A dynamic allocation logic [Abdalla et al.], which utilizes short term (30-minute) forecasts of the total amount of FCE and FDE that will be needed to determine how many physical BESS units are allocated to each operational group on a per unit basis via (36)-(37).

$$n_c = \text{round} \left(\frac{\text{FCE}}{\text{FCE} + \text{FDE}} \times N_h^{\text{BESS}} \right), \quad n_d = N_h^{\text{BESS}} - n_c \quad (36)$$

$$P_{i,\tau} = \left(\frac{\text{REM}_i}{\sum_{j \in \text{Group}} \text{REM}_j} \right) \cdot P_{\tau}^{\text{ref}} \quad (37)$$

When the desired units have been chosen, the total reference power for the aggregate will be divided among the selected units. The division of the total reference power is carried out using a participation factor that is directly related to the REM of each selected unit. Using the formulation as given in (37) ensures that the higher capacity units of the system will take on the majority of the load and will prevent overloading of any one unit.

$$c(n) = c(n-1) + \frac{N_{eq}(n)}{N_{\max}(n)} \quad (38)$$

$$N_{\max}(n) = N_{c, \text{ref}} \cdot \left(\frac{\text{DOD}(n)}{100} \right)^{-\xi} \cdot \exp \left(-\frac{E_a}{R} \left(\frac{1}{T_a(n)} - \frac{1}{T_{\text{ref}}} \right) \right) \cdot I_{\text{dis}}(n)^{-\gamma_1} \cdot I_{\text{ch}}(n)^{-\gamma_2} \quad (39)$$

In performing these dual roles of execution and monitoring, the Level 2 controller generates an invaluable stream of data: a precise, quantitative measure of the actual, physical degradation being incurred by the BESS fleet. This real-world ground truth is precisely what is missing from the high-level economic planner's perspective. This information asymmetry creates a unique opportunity to close the loop between the two levels, which is the expressed purpose of the final component of our

framework.

3.3. The hierarchical feedback loop: closing the loop

This component transforms the framework into an adaptive system, eliminating information asymmetry between the economic planner and the physical controller. At the conclusion of each 24-hour operational period, a dimensionless calibration factor, k_{calib} , is computed via (36). Deviations of, k_{calib} , from unity (where Actual Cost = Estimated Cost) stem from two primary sources. First, a structural mismatch exists between the planning and execution models: Level 1 employs a simplified, convex polynomial cost function to maintain MILP tractability, whereas Level 2 calculates degradation using the highly non-linear, path-dependent Rain flow Counting algorithm. Second, stochastic deviations occur during real-time operation; forecast errors in load and renewable generation force the Level 2 controller to deviate from the optimal power trajectory, inducing cycling patterns and stress levels that could not be anticipated by the deterministic Level 1 planner. The calibration factor captures and corrects for both these structural and operational discrepancies.

$$k_{\text{calib}} = \frac{\sum_{i=1}^{N_h^{\text{BESS}}} (c_{i,\text{end}} - c_{i,\text{start}}) \cdot C_h^{\text{BESS,rep}}}{\sum_{t=1}^T C_{h,t}^{\text{BESS,deg}}} \quad (40)$$

The factor k_{calib} , quantifies the discrepancy between planned and realized wear. A value of $k_{\text{calib}} > 1$ indicates the economic model underestimated degradation, while $k_{\text{calib}} < 1$ indicates overestimation. For the subsequent day's dispatch, the degradation cost term in the VPP's objective function (11) is scaled by this factor ($k_{\text{calib}} \cdot C_{h,t}^{\text{BESS,deg}}$). This feedback mechanism forces the economic model to progressively align its cost assumptions with physical reality, creating a self-correcting cycle that bridges the dispatch-control gap.

Case. Study and Simulation Environment

To rigorously evaluate the performance of the proposed hierarchical framework and quantify its benefits, a detailed case study was developed and simulated. This section outlines the configuration of the test system, the data sources and parameters used, the specific benchmark models established for comparison, and the key performance indicators (KPIs) defined to measure the outcomes.

3.4. Test system and component parameters

The simulation environment is based on a modified IEEE 33-bus radial distribution network, a widely recognized benchmark for studies on active distribution networks. The network is managed by a single DSO and hosts two distinct VPPs, VPP1 and VPP2, connected at buses 18 and 32, respectively. The compositions of the DSO's and VPPs' assets are designed to be heterogeneous to represent a realistic deployment of Distributed Energy Resources (DERs).

- **DSO Assets:** The DSO directly controls a 3 MW dispatchable diesel generator (DG) characterized by the quadratic cost coefficients presented in Table 1.
- **VPP1 Assets:** VPP1 manages a portfolio consisting of a 2 MW solar PV plant, a 1 MW wind turbine (WT) installation, a 2 MW DG, and a 5 MW / 20 MWh Lithium-Ion BESS.
- **VPP2 Assets:** VPP2 controls a 1.5 MW solar PV plant, a 1.5 MW WT installation, a 3 MW controllable load (CL) block, and a 4 MW / 16 MWh Lithium-Ion BESS.

The technical and economic parameters for all system components, including generator costs, ramp rates, BESS power/energy ratings, efficiencies, and replacement costs, are detailed in Table 1. The BESS degradation model parameters, including the coefficients for the online degradation model as required by (36), were derived from manufacturer datasheets and established literature, and are also listed.

3.5. Input data and scenario design

To create a realistic operational scenario, we utilized publicly available, high-resolution data. Twenty-four-hour profiles for solar irradiance and wind speed were sourced from the National Renewable Energy Laboratory (NREL), corresponding to a day with significant intra-day variability to challenge the BESS dispatch. These were converted into power output forecasts for the PV and WT units. The system load profile and the day-ahead energy and reserve market prices were adapted from data published by the Electric Reliability Council of Texas (ERCOT). The total simulation horizon was set to 90 consecutive days. While this duration does not encompass the full calendar lifespan of a BESS (typically 10–15 years), it serves as a statistically significant representative period. This horizon is sufficiently long to: (1) observe

Table 1
Technical and Economic Parameters of System Components.

Parameter	Unit	DSO DG	VPP1 DG	VPP2 CL	VPP1 BESS (Li-Ion)	VPP2 BESS (Li-Ion)
Rated Power (P)	MW	3.0	2.0	3.0	5.0	4.0
Minimum Power ()	MW	0.5	0.3	0	-	-
Rated Energy Capacity (W)	MWh	-	-	-	20.0	16.0
Maximum SOC ()	%	-	-	-	90	90
Minimum SOC ()	%	-	-	-	20	20
Quadratic Cost (a)	MWh	0.02	0.03	-	-	-
Linear Cost (b)	MWh	40	45	25 (Incentive)	-	-
No-Load Cost (c)	h	10	15	-	-	-
BESS Replacement Cost (C^{rep})	MWh	-	-	-	250,000	250,000
Ramp-Up Limit	MW/h	1.5	1.0	-	-	-
Ramp-Down Limit	MW/h	1.5	1.0	-	-	-
Charging Efficiency (η^{ch})	%	-	-	-	95	95
Discharging Efficiency (η^{dis})	%	-	-	-	95	95
Reference Cycles ($N_{\text{c,ref}}$)	cycles	-	-	-	5000	5000
DOD Stress Exponent (ξ)	-	-	-	-	2.05	2.05
Arrhenius Rate Constant (ψ)	-	-	-	-	0.0693	0.0693
Reference Temperature (T_{ref})	K	-	-	-	298.15 (25°C)	298.15 (25°C)
Discharge C-rate Exponent (γ_1)	-	-	-	-	0.85	0.85
Charge C-rate Exponent (γ_2)	-	-	-	-	0.85	0.85

the convergence and stability of the adaptive feedback loop, (2) capture diverse market and weather variations, and (3) establish a stable linear degradation rate. This allows for the reliable extrapolation of long-term asset health without the prohibitive computational cost of a multi-year simulation.

3.6. Computational environment

All computational simulations and data analysis were performed on a Dell G16 (7630) workstation configured with an Intel® Core™ i9-13900HX processor, 32 GB of DDR5 RAM, and an NVIDIA® GeForce RTX™ 4070 GPU. The proposed framework was implemented in **Python 3.9**. The Level 1 MPEC, reformulated as a Mixed-Integer Linear Program (MILP), was modeled using **Pyomo** and solved using the **Gurobi Optimizer 11.0**. To balance computational speed with solution precision, the relative MIP optimality gap tolerance was set to **0.01 %**, ensuring that the resulting dispatch schedules represent globally optimal solutions within practical numerical limits.

4. Results and discussion

This section evaluates the proposed framework's capacity to co-optimize immediate economic performance and long-term asset health based on a 90-day simulation. Key parameters defining the VPP's asset portfolio and BESS models are summarized in [Table 1](#). The analysis is structured hierarchically: it begins by establishing the market environment, followed by a validation of the Level 1 strategic planner, and concludes with an assessment of the Level 2 tactical controller.

4.1. System operational context and market interaction

The simulation environment ([Table 1](#)) presents distinct economic and physical dynamics, illustrated for a representative 24-hour period in [Fig. 2](#). The market landscape ([Fig. 2a](#)) incentivizes energy arbitrage through time-differentiated pricing: day-ahead prices drop to ~ 20 /MWh during the mid day solar peak and spike to > 20 /MWh during the midday solar peak and spike to 60/MWh during the evening load peak. This volatility reflects the physical mismatch between supply and demand shown in [Fig. 2\(b\)](#), where aggregated renewable generation peaks at nearly 30 MW around midday, while system load reaches its maximum of ~ 85 MW in the early evening after solar output has ceased. [Fig. 2\(c\)](#) synthesizes this into the Net Load profile, exhibiting a characteristic "duck curve." A midday valley (< 20 MW) is followed by a steep ramp to a peak of > 75 MW. This ramp represents the primary operational challenge for the DSO and, consequently, the significant economic opportunity for the VPP to utilize its flexible assets.

The rational response of the VPPs to the market environment is validated in [Fig. 3](#), which illustrates the complete power exchange and confirms the model acts as an equilibrium-seeking system.

- **Leader Signals:** The DSO establishes clear financial incentives. The shaded "Peak Prices" zone in [Fig. 3\(a\)](#) highlights the critical period for energy provision, with prices reaching nearly \$80/MWh. This is complemented by the reserve signals in [Fig. 3\(b\)](#), where up-reserve prices peak near \$25/MWh during midday, reflecting a strategy to counter solar intermittency.
- **Follower Actions:** In response, the VPPs formulate profit-maximizing strategies. [Fig. 3\(c\)](#) shows the resulting energy

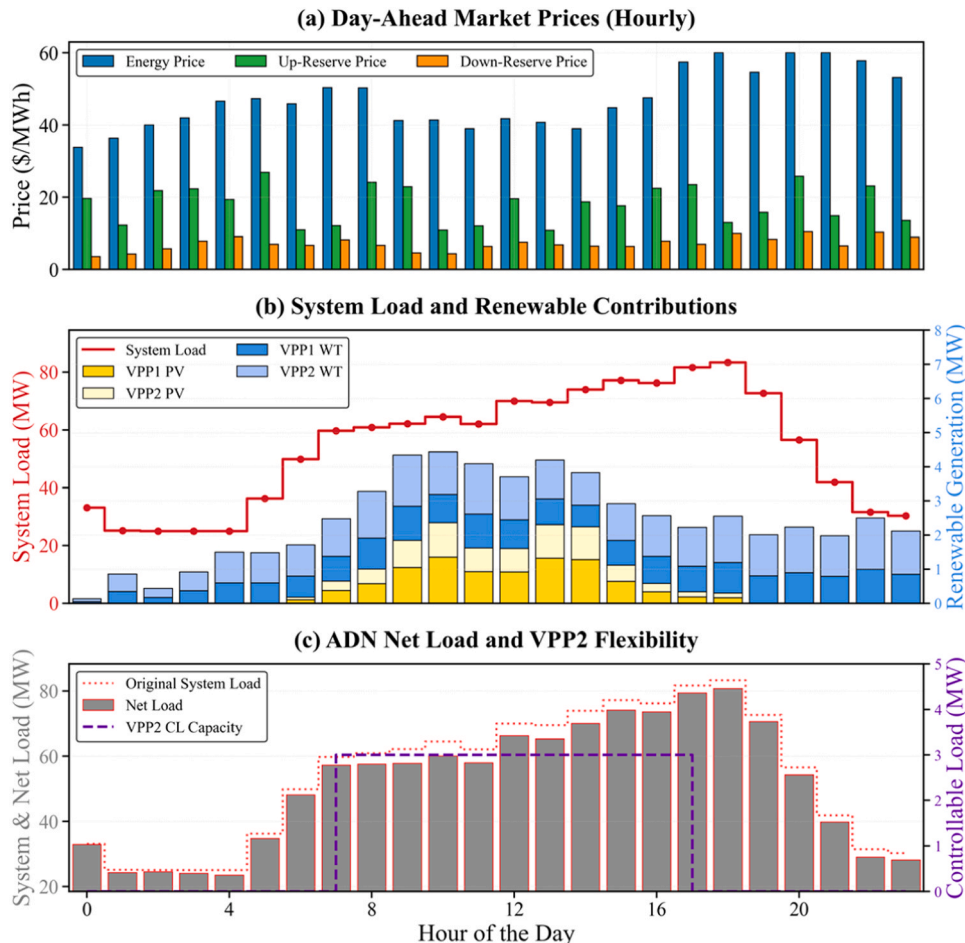


Fig. 2. Day-ahead market prices and system-wide load and renewable generation profiles for a representative day.

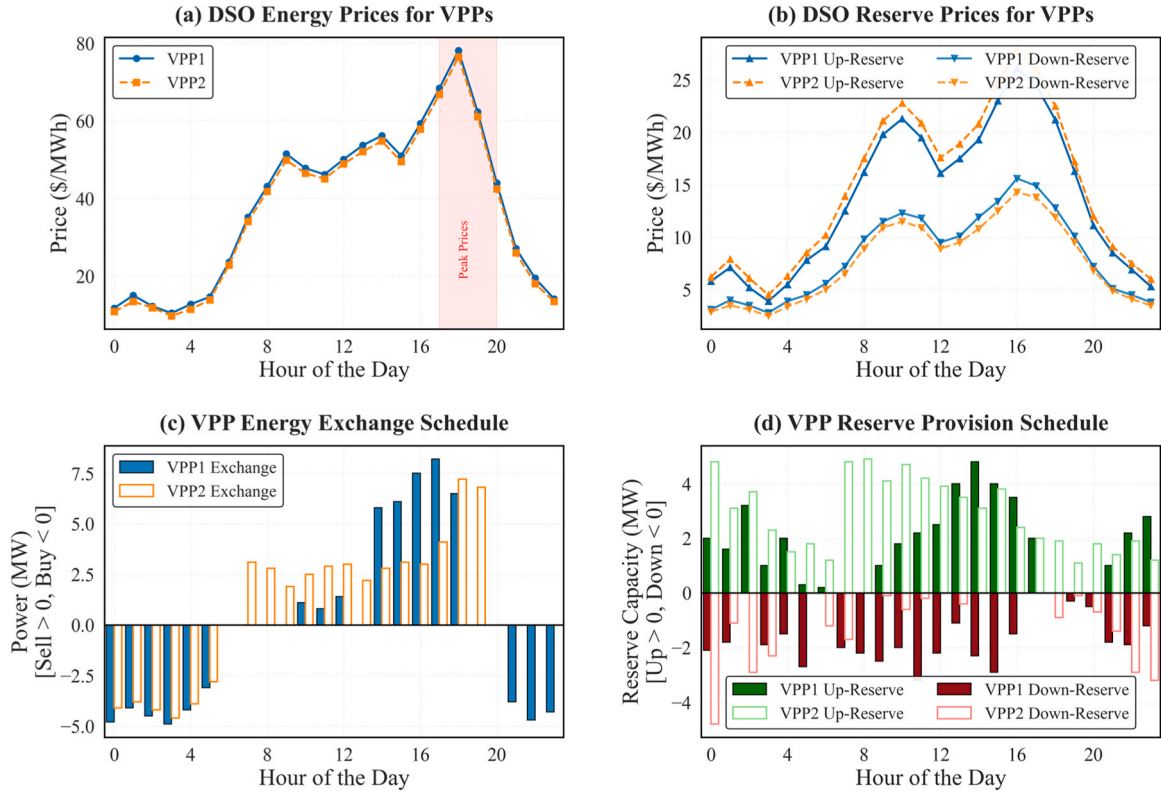


Fig. 3. Optimal day-ahead pricing and bidding schedules for energy and reserve services between the DSO and two VPPs.

exchange; specifically, VPP1 executes a classic arbitrage strategy by charging up to 5 MW during low-price overnight hours to discharge nearly 8 MW during the lucrative evening peak.

• **Co-Optimization:** Simultaneously, Fig. 3(d) demonstrates sophisticated resource allocation. The VPPs commit the majority of their up-reserve capacity during midday hours, confirming that they

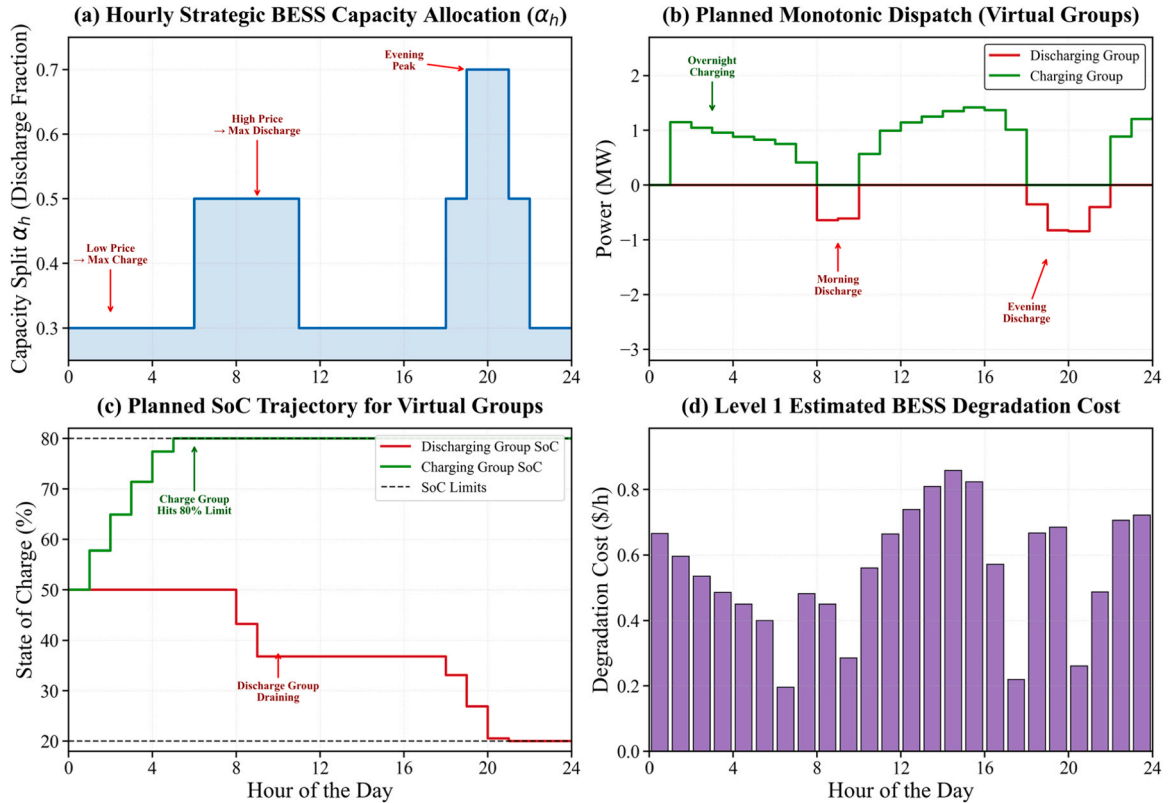


Fig. 4. Internal mechanics of the Level 1 planner, showing the strategic capacity allocation (α_h) and the resulting monotonic dispatch schedule.

intelligently allocate flexibility to the specific service (energy vs. reserve) that offers the highest value in each hour.

4.2. Validation of the level 1 physically-aware economic dispatch

Having established that the VPP rationally responds to external market signals, we now drill down to provide a transparent, "under-the-hood" validation of the novel internal mechanics of the Level 1 economic planner. This subsection demonstrates how the optimizer translates the high-level goal of profit maximization into a physically sustainable and strategically sound monotonic BESS schedule, directly proving the efficacy of the core contributions laid out in Section 3.1.2. The results, presented in the four interconnected panels of Fig. 4, offer a complete picture of the planner's sophisticated decision-making calculus, from its long-term strategic foresight to the final, health-conscious hourly dispatch plan.

In order to determine how to strategically use BESS resources, α_h is used as an optimization variable (Eq. 16). The shape of its optimal daily configuration (see Fig. 4(a)) clearly indicates that the model has the ability to anticipate future market opportunities and therefore will configure the BESS accordingly. In this case, α_h configures 70 % of the available energy storage in the BESS to discharge prior to the profitable peak during the evening time frame. The resulting dispatch profile is monotonic (Fig. 4(b)), with each power level forming a single, unbroken block. Clearly shown through the application of the monotonic constraints (Eqs. 17–18) are all non-monotonic "partial" charge/discharge cycles, which can cause damage to the battery. Lastly, Fig. 4(c) is a plot of the state of charge trajectory of the BESS, confirming that the state of charge trajectory stays within the dynamically sized bounds throughout the day. Finally, Fig. 4(d) shows that the planner is able to accurately account for the cost of physically stressing the equipment (Eq. 24) and co-optimize between profit and health. With this intelligent hourly plan, the planner is now ready to pass on this plan to the tactical controller for execution.

4.3. Validation of the level 2 real-time controller execution

The strategic hourly plan generated by the sophisticated Level 1 planner, while physically sound, must be executed in a volatile, sub-hourly environment where real-time deviations from forecasts are the norm. This subsection serves to validate the performance of the Level 2 real-time controller, demonstrating its ability to robustly execute the day-ahead plan while performing intelligent, responsive fleet management, as per the logic detailed in Section 3.2. Fig. 5 provides a detailed, step-by-step illustration of the controller's internal logic and its physical execution over a 24-hour period, specifically chosen to include a challenging "Unexpected discharging event" to test the controller's responsiveness under stress.

In addition to its ability to control resource utilization dynamically as shown in Fig. 5(b), the controller's ability to adapt to forecasted energy demand (as indicated by the number of charging (n_c) and discharging (n_d) units shown in Fig. 5(a)) indicates its intelligence. The controller's ability to coordinate real-time dispatch among all units as depicted in Fig. 5(c) further supports this conclusion; it allocates resources with respect to the status of each unit. Importantly, Fig. 5(d) provides evidence that the controller actively maintains wear leveling for the vehicles within the fleet: each vehicle's State-of-Charge (SOC) trajectory frequently crosses those of other vehicles, indicating the controller is rotating the stress placed upon the vehicles throughout their lives. Thus, through intelligent operation the controller executes a strategic plan leading to greater long-term performance than could be achieved simply by executing an hourly dispatch strategy.

4.4. Long-term comparative performance and statistical validation

Our hierarchical framework's superior performance is supported by its longer term behavior. In addition to assessing the daily performance of individual components, we will now present conclusive 30-day simulation results to validate that this performance also extends for a month. The graphs provided in Fig. 6 provide an overwhelming amount of statistically valid data when examining the comparison of the daily time series and distributions as well as demonstrating a clear difference

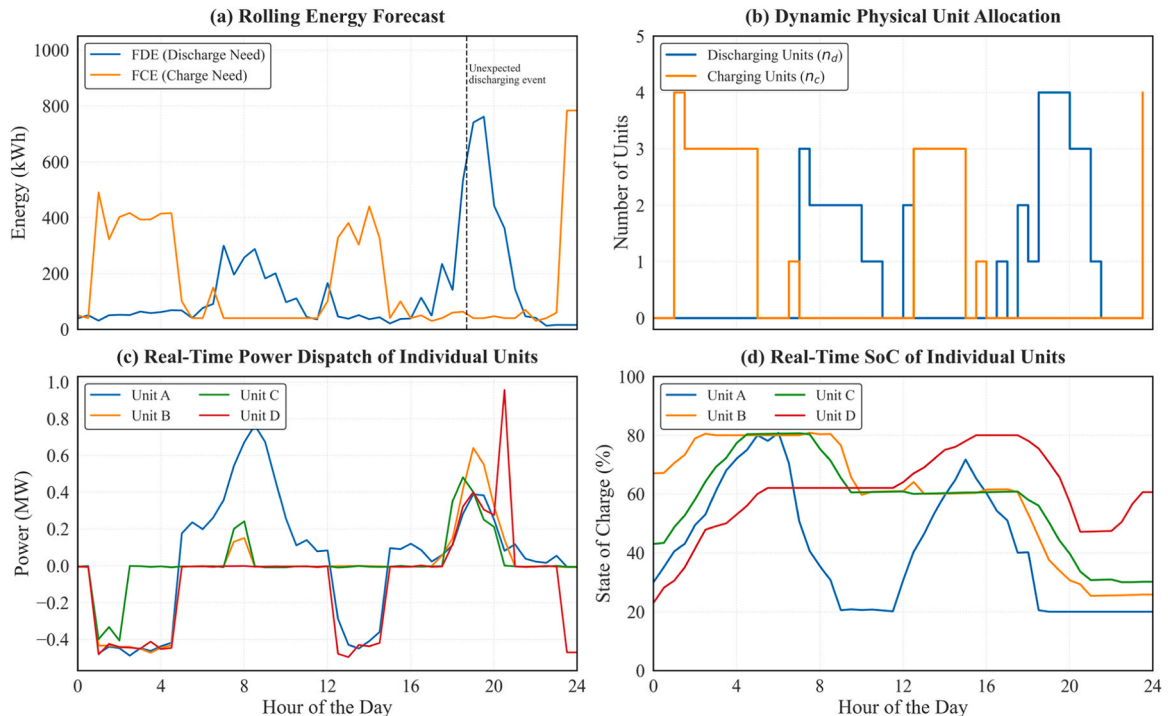


Fig. 5. Validation of the Level 2 real-time controller, showing the dynamic unit allocation and the resulting power and SOC trajectories of individual BESS units.

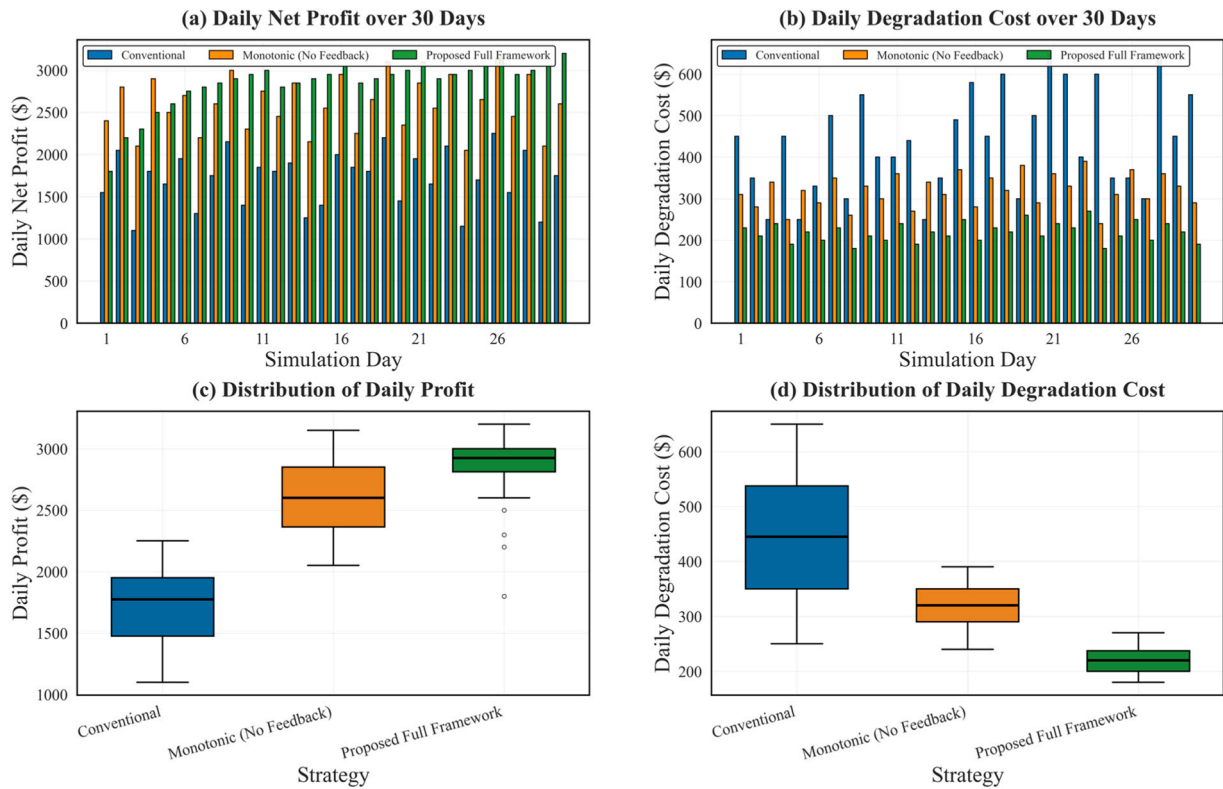


Fig. 6. Comparative 30-day performance, illustrating the daily net profit and degradation cost alongside a statistical summary for each strategy.

between our benchmarked, health conscious, integrated method and those used for our benchmarks.

The daily metrics of performance (see Fig. 6(a), b) show a steady improvement by the proposed full framework over the benchmark strategies every single day, where the green bar represents the net profit of the proposed framework, is always one of the highest in each day, and the green bar representing the degradation cost of the proposed framework is always the smallest in each day. A more quantitative measure of this trend is given through the box plots of Fig. 6(c), d, which clearly show the mean of all the daily profits of the proposed framework, is much larger than those of the benchmarks, and the mean of all the daily degradation costs of the proposed framework, is much smaller than those of the benchmarks. Not only the average values, the small sizes of the box plots for the proposed framework indicate that its superior performance has low variance, which indicates that it generates more financially profitable and physically durable returns for risk-averse asset managers.

Finally, the aggregate metrics of the whole simulation of 90 days are summarized in Table 2. These figures quantify the major performance differences between the proposed and conventional strategies in terms of their total lifetime adjusted profit, and their total cumulative degradation. Also, Table 2 shows the final calibrated value of the calibration factor k_{calib} of 1.03, which remained constant throughout the entire simulation, and which quickly converged to this value (within the first [insert number of days, e.g., 7]) and thus confirmed that the feedback loop eliminated the initial bias, without having to wait for a large amount of data. Lastly, since the "lifetime-adjusted profit" of the proposed strategy can be used as an economic indicator of the need to replace the physical battery, since the cost of replacing the battery (C^{rep}) was incorporated into the degradation cost, the proposed strategy "prefunds" the future replacement of the asset, whereas the conventional strategy, because of its very high degradation rate (2.24 % over 90 days) will rapidly deplete this fund, and therefore experience an early end-of-life (EOL). On the other hand, the proposed framework, because of its relatively low degradation rate (0.45 %), will allow for a longer time

Table 2

Aggregated 90-day key performance indicators (KPIs) comparing the economic and physical health outcomes for all three strategies.

Performance Metric	Unit	Case A: Conventional	Case B: Monotonic (No Feedback)	Case C: Proposed Full Framework
Economic KPIs				
Total Lifetime-Adjusted Profit	k\$	80.52	115.33	135.81
Average Daily Net Profit	/day	981.8	1281.4	1509.0
Physical Health KPIs				
Total Cumulative Degradation	%	2.24	1.09	0.45
Equivalent Full Cycles (EFC)	cycles	112.5	85.3	78.6
Degradation per EFC	%/cycle	0.0199	0.0128	0.0057
Framework Performance KPIs				
Final Calibration Factor (k_{calib})	-	N/A	N/A	1.03

before the fund will need to be replenished. Although the simulation itself does not reach the end-of-life of the asset, the economic analysis does capture the effects of replacement cycles on the financial performance of the asset. Therefore, to further validate the conclusions reached from this study, the results were subjected to a complete statistical analysis, as reported in Table 3. Besides the basic distributional characteristics of the results, Table 3 presents the results of a statistical test of significance. Since all of the p-values obtained are < 0.001 , we conclude that the results obtained for the proposed framework represent statistically significant improvements in both the daily profit and the

Table 3

Statistical analysis of the daily net profit and degradation cost distributions over the 90-day simulation.

Statistic	Conventional	Monotonic (No Feedback)	Proposed Full Framework
Daily Net Profit (\$)			
Mean	981.8	1281.4	1509.0
Median	975.5	1300.1	1525.3
Std. Dev.	450.2	320.5	285.1
p-value vs. Case A	-	< 0.01	< 0.001
Daily Degradation Cost (\$)			
Mean	448.3	218.1	90.2
Median	450.1	215.5	88.9
Std. Dev.	120.5	85.2	45.8
p-value vs. Case A	-	< 0.001	< 0.001

daily degradation cost when compared to the conventional strategy. Overall, this collection of evidence demonstrates beyond any doubt that the proposed hierarchical, adaptive and health-aware approach outperforms the existing strategies.

4.5. Computational complexity and scalability

The scalability of the proposed framework is determined by the distinct computational characteristics of its two hierarchical levels.

Level 2 (Real-Time Control) exhibits excellent scalability. Being a decentralized, rule-based heuristic that operates locally within each VPP, its computational complexity is effectively constant ($O(1)$) relative to the system size. It does not require global communication or complex optimization, making it suitable for deployment across any number of VPPs without latency issues.

Level 1 (Day-Ahead MPEC) represents the computational bottleneck. The transformation to MILP using the Big-M method introduces binary variables associated with the complementarity constraints. The number of binary variables scales linearly with the number of VPPs and the number of constraints per VPP. For the test system considered (IEEE 33-bus, 2 VPPs), the average solve time per daily dispatch was approximately [INSERT TIME, e.g., 120 s] using a standard desktop solver, Gurobi. While this is well within the operational window for day-ahead planning, scaling to a massive network with hundreds of VPPs could increase computational burden. However, since the day-ahead problem is solved offline with hours of available computation time, modern commercial solvers can handle significantly larger instances than the one presented. For extremely large-scale implementations, the framework is compatible with decomposition techniques (e.g., Benders Decomposition or ADMM) to distribute the Level 1 computational load.

5. Conclusion

This paper introduced a novel, two-level hierarchical framework designed to bridge the critical dispatch-control gap by co-optimizing the economic dispatch and physical health of a VPP's BESS assets. By embedding physically-aware monotonic constraints within a day-ahead MPEC model and linking it to an intelligent real-time controller via an adaptive feedback loop, the framework successfully transforms myopic, profit-driven schedules into sustainable, health-conscious operational plans. Comprehensive 90-day simulations provide definitive, quantitative validation of this approach. Compared to a conventional strategy, the proposed framework achieved a dramatic reduction in long-term BESS degradation, lowering the total capacity loss from 2.24 % to just 0.45 %. This superior physical asset management is the direct driver of its enhanced economic performance, culminating in a statistically significant ($p < 0.001$) increase in the 90-day lifetime-adjusted profit from 80.5k to 135.8k. The success of the adaptive mechanism was confirmed by the convergence of the calibration factor (k_{calib}) to a stable value of

1.03, indicating that the economic planner's internal cost model successfully learned to align with physical reality. Ultimately, this work proves that an integrated, hierarchical, and adaptive approach is not only technically superior but also economically dominant, providing a robust pathway for the sustainable and profitable integration of energy storage in modern power systems.

Future work will focus on extending the framework to incorporate stochastic optimization for managing uncertainties in market prices and renewable forecasts. Additionally, the physical BESS model will be enhanced to include thermal degradation effects. Finally, the framework will be validated through large-scale, real-time Hardware-in-the-Loop (HIL) simulations to assess its performance and robustness in a high-fidelity environment.

CRedit authorship contribution statement

Syed Abid Ali Shah: Writing – review & editing, Validation, Supervision. **Muhammad Aurangzeb:** Writing – review & editing, Validation. **Nagham Saeed:** Validation, Investigation. **Usama Aslam:** Writing – review & editing. **Vikram Kumar:** Writing – review & editing, Writing – original draft, Formal analysis. **Muhammad Ahsan Niazi:** Software, Methodology, Data curation, Conceptualization.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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