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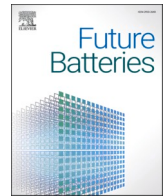
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A holistic optimization framework for virtual power plants with physics-informed battery degradation and probabilistic stability constraints

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ABSTRACT

The operation of Virtual Power Plants (VPPs) is impacted by both the uncertainty of markets and the limitations of physical assets, affecting the financial reliability and asset longevity of VPPs. This paper outlines a new two-stage stochastic optimization method for the co-optimization of the VPP's financial performance, its battery degradation, and its ability to provide primary frequency response. Key aspects of this method include: (1) a real-time, physics based electrochemical model to estimate the marginal cost of battery degradation in real time; (2) a multivariate ARIMA-GARCH model to forecast correlated market price and renewable power production forecasts; and (3) a Conditional Value at Risk (CVaR) probabilistic constraint to insure reliable frequency response. A detailed case study demonstrates that employing a degradation-aware strategy, rather than a traditional profit-maximizing approach, results in a 5.4 % increase in annual net profit alongside a significant extension of battery lifetime. The proposed method will provide utilities with a strategic decision-making tool to balance their short-term revenue requirements, their long-term asset health needs, and their obligation to maintain grid stability.

Introduction

Virtual Power Plants (VPPs), represent an important part of the evolving energy landscape and have become central to the integration of distributed energy resources (such as solar PV, battery storage, and other load management devices) into a singular, schedulable resource. The role of VPPs in providing ancillary services; enhancing grid stability and economic efficiency; and increasing renewable penetration into existing grids has been well documented through their ability to participate in wholesale electricity markets and provide various forms of grid support [1,2].

The key to achieving the full potential of VPPs lies in the development of advanced operational strategies that can integrate the many different forms of uncertainties that exist within today's power systems. These uncertainties include but are not limited to, the variability of renewable generation, market price volatility, and the unpredictability of consumer demand. Examples of such operational strategies include stochastic scheduling in reserve service markets; carbon aware operations; and robust multi-market optimization [3,4].

One of the primary challenges associated with the successful deployment of virtual power plants is the coordination of the day-ahead commitment and the real time dispatch of DERs under conditions of uncertainty [5]. To mitigate this problem, much work has been done using multi-stage stochastic programming to account for the volatility associated with renewable generation and market prices [6,7]. Some examples of these types of approaches include: risk-averse two stage models for managing uncertainty in integrated energy systems [8]; bi-level frameworks used to coordinate the objectives of the VPP and the bulk power system [9,10]; and chance constrained methods for optimizing VPP scheduling across multiple markets [11]. Recent work on the use of blockchain based VPPs [12]; stochastic bidding with peer-to-peer trading [13]; and uncertainty aware frequency regulation scheduling [14] and VPP scheduling under conditions of renewable generation uncertainty [15], further advance the state-of-the-art.

Despite these advances, there still exists a critical gap in the development of a comprehensive framework that addresses all three of the following key areas: the co-optimization of the financial objectives of the VPP; the detailed physical battery degradation associated with repeated charge/discharge cycles; and the provision of the required level of grid

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Nomenclature		ζ	Value-at-Risk (VaR) auxiliary variable, \$
<i>Parameters (Input Data)</i>		u_s	CVaR deficit variable for scenario s , \$
λ_t^{DA}	Day-ahead electricity market price, \$/MWh	<i>Electrochemical Degradation Model Symbols</i>	
$\lambda_{t,s}^{RT}$	Real-time electricity market price in scenario s , \$/MWh	$I(\tau)$	Instantaneous current, A
$P_{t,s}^{PV}$	Available PV generation in scenario s , MW	$T(\tau)$	Internal battery core temperature, K
D_t	Aggregated electrical load demand, MW	Q_{loss}	Total capacity loss, Ah
$r_{t,s}^{reg}$	Real-time regulation signal magnitude ($[-1, 1]$), p.u.	k_{SEI}	Rate constant for SEI growth, –
π_s	Probability of scenario s , –	k_{plate}	Rate constant for Lithium Plating, –
$CapEx$	Capital expenditure of the BESS, \$	k_{mech}	Rate constant for Mechanical Stress, –
$E_{throughput}$	Warrantied lifetime energy throughput of the BESS, MWh	E_a	Activation energy (Arrhenius equation), J/mol
Q_{nom}	Nominal capacity of the battery cell, Ah	η_{crit}	Critical overpotential threshold for plating, V
R_{max}	Maximum ramp rate / reserve capacity, MW	σ	Mechanical stress in electrode particles, MPa
$SOC^{min/max}$	Minimum/Maximum State of Charge limits, %	<i>Abbreviations</i>	
$\eta^{ch/dis}$	Charging/Discharging efficiency, %	ARIMA	Auto-Regressive Integrated Moving Average, –
α	Confidence level for CVaR (e.g., 0.95), –	BESS	Battery Energy Storage System, –
γ	Weighting factor for degradation cost in objective, –	CVaR	Conditional Value-at-Risk, –
<i>Decision Variables</i>		DA / RT	Day-Ahead / Real-Time, –
P_t^{batt}	Battery dispatch power (+ Discharge, - Charge), MW	DER	Distributed Energy Resource, –
$P_{DA}^{sell/buy}$	Energy sold/bought in Day-Ahead market, MW	GARCH	Generalized Auto-Regressive Conditional Heteroskedasticity–
$R_t^{up/dn}$	Regulation Up/Down capacity committed, MW	PFR	Primary Frequency Response, –
$SOC_{t,s}$	State of Charge at time t in scenario s , %	SEI	Solid Electrolyte Interphase, –
E_t	Energy stored in the battery, MWh	VPP	Virtual Power Plant (Aggregated DER Node), –
C_t^{deg}	Real-time marginal degradation cost, \$/MWh		

Table 1
Comparison of the Proposed VPP Framework with Recent Literature.

Feature	[22]	[12]	[14]	[33]	Proposed Model (This Work)
Two-Stage (DA + RT) Stochastic Scheduling	✓	✓	✓	✓	✓
High-Fidelity Battery Degradation Model	×	×	×	×	✓ (Electrochemical)
Sophisticated Uncertainty Modeling	×	✓	×	✓	✓ (ARIMA–GARCH)
Multi-Objective Optimization	✓	×	✓	×	✓ (Profit–Aging–Reliability)
Probabilistic Grid Reliability Constraint	×	×	×	×	✓ (CVaR-based PFR)

reliability services.

The critical role of battery degradation

Battery systems provide significant flexibility in DER portfolios as a way to manage uncertainty; however, managing this flexibility results in an ongoing cost associated with degradation through repeated charge/discharge cycles (and others) [3]. Cycle aging and degradation mechanisms and forecasting studies have illustrated that omitting physical wear from model development can result in batteries failing prematurely, resulting in reduced profitability [9,16]. As such, similar concerns regarding degradation have been expressed for other applications of battery systems including microgrid operation, energy arbitrage, economic dispatch, and battery life-cycle management.

As a result of these concerns, numerous researchers have developed degradation aware dispatch and scheduling algorithms [17], which

include battery sizing and scheduling considering the effects of aging, cycle count pricing, and degradation aware dispatch in distribution networks [18]. Previous studies have demonstrated that the incorporation of simple aging cost models into economic dispatch improves both the longevity of assets and profit compared to those that do not consider degradation [19]. More recent research focuses on developing physical models of the degradation process itself. The use of State of Health (SOH) based operational strategies have been demonstrated to provide stable revenue streams over time [11,20,21], and multi-layered, and multi-objective optimization frameworks that utilize electrochemical degradation models demonstrate the need to accurately quantify high fidelity degradation costs to ensure the long-term health of assets, while maximizing short term profitability [22,23,17]. Additionally, advancements in data driven and physics informed approaches enable the efficient and accurate quantification of the impact of temperature, C-rate, and state-of-charge on degradation, thus enabling more effective battery utilization [24–26].

Managing uncertainty with advanced forecasting

In addition to improvements in degradation modeling, the sophistication of methods used to manage uncertainties in the market and renewables has increased significantly. The application of statistical and machine learning techniques has now become common place for forecasting PV output and electricity prices [17,27]. Hybrid ARIMA-GARCH models are among the most popular of such approaches for the purposes of forecasting PV output and volatility in electricity prices and renewable generation [12,28]. Seasonal ARIMA models have demonstrated high effectiveness for the day-ahead planning of PV yields [26,29] while hybrid ARIMA-GARCH models have become the standard for describing both the time-varying means and volatility in electricity prices [30]. Frameworks for power systems that utilize multi-variate ARIMA-GARCH models for forecasting show high performance when using uncertain data for uncertainty aware dispatch problems [31,32,18]. The forecasting is then commonly reduced to discrete scenarios for use in

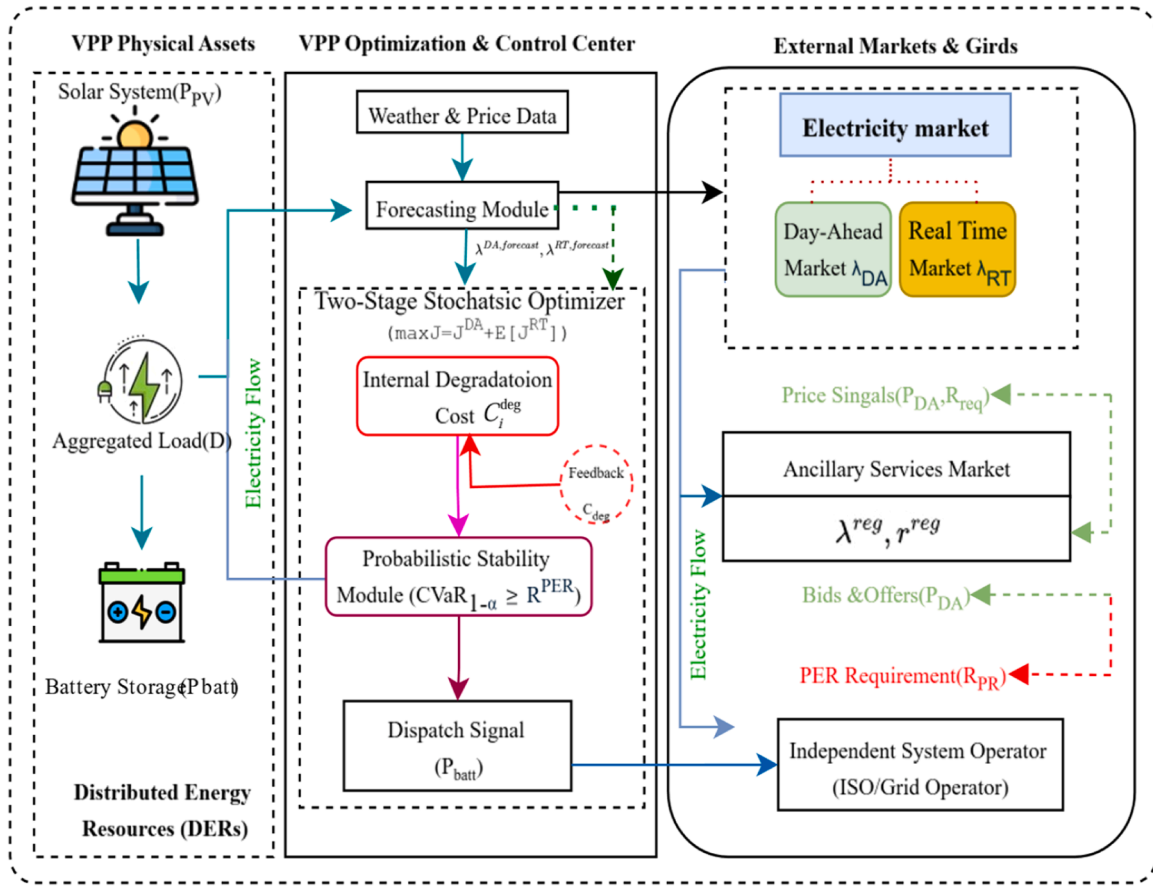


Fig. 1. Conceptual framework of the multi-scale VPP optimization model, showing the flow of information and decisions between day-ahead scheduling and real-time dispatch, including degradation and stability.

stochastic optimization [33]. In general, the use of data driven scenario generation for stochastic VPP optimization and scenario based stochastic programming for renewable energy integration in an environment with forecast uncertainty, have yielded near perfect foresight performance; therefore, it is critical to apply rigorous techniques for generating and reducing scenarios. Table 1 compares the proposed VPP optimization framework with recent literature, highlighting its unique integration of electrochemical battery degradation modeling, ARIMA-GARCH-based uncertainty handling, and CVaR-based probabilistic grid reliability constraints.

Collectively, the literature points toward an integrated framework combining high-fidelity battery degradation modeling with multi-stage stochastic dispatch. However, existing work lacks a single, cohesive framework integrating four critical features: a two-stage stochastic market model, a high-fidelity electrochemical degradation model, an ARIMA-GARCH uncertainty scenario model, and a probabilistic stability constraint. This paper fills that gap by proposing a holistic VPP optimization framework that unites these contributions.

1. This includes a new two-stage stochastic programming model that simultaneously optimizes profit, battery life-span, and grid reliability through the integration of degradation-costs that are based on real-time physics, and CVaR-stability guarantees that are probabilistically constrained.
2. Through use of historical data in a case study, we quantify both the economic benefits of being aware of degradation and the explicit costs of maintaining grid reliability.
3. The presented framework gives operators an actionable way to strategically traverse the Pareto frontiers of aggressive profit-driven strategies and conservative longevity-maintaining strategies.

The paper is structured as follows, Section 2 presents the mathematical modeling of the proposed framework. Section 3 describes the experimental setup and case study. Section 4 discusses the results and provides a detailed analysis. Finally, Section 5 concludes the paper and outlines future research directions.

Mathematical modeling

The VPP aggregates a portfolio of distributed energy resources (DERs) for market participation and grid services. Key asset sets include grid-scale battery storage (BESS), photovoltaic (PV) systems, and fixed or price-responsive loads. The multi-scale optimization framework and its component interactions are illustrated in Fig. 1.

VPP asset aggregation model

The VPP under consideration aggregates a diverse portfolio of distributed energy resources (DERs) to participate in volatile electricity markets and provide essential grid services. We define the following sets for these resources: $\mathcal{B} = \{1, \dots, N_b\}$ for grid-scale Battery Energy Storage Systems (BESS), $\mathcal{P} = \{1, \dots, N_p\}$ for photovoltaic (PV) systems, and $\mathcal{L} = \{1, \dots, N_l\}$ for aggregated fixed and price-responsive loads. The overarching conceptual framework of our multi-scale VPP optimization model, illustrating the main components and their interactions, is presented in Fig. 1.

The total available power from stochastic resources and the total aggregated load are given by:

$$P_{\text{total}}^{\text{PV}}(t) = \sum_{j \in \mathcal{P}} P_j^{\text{PV}}(t) \quad (1)$$

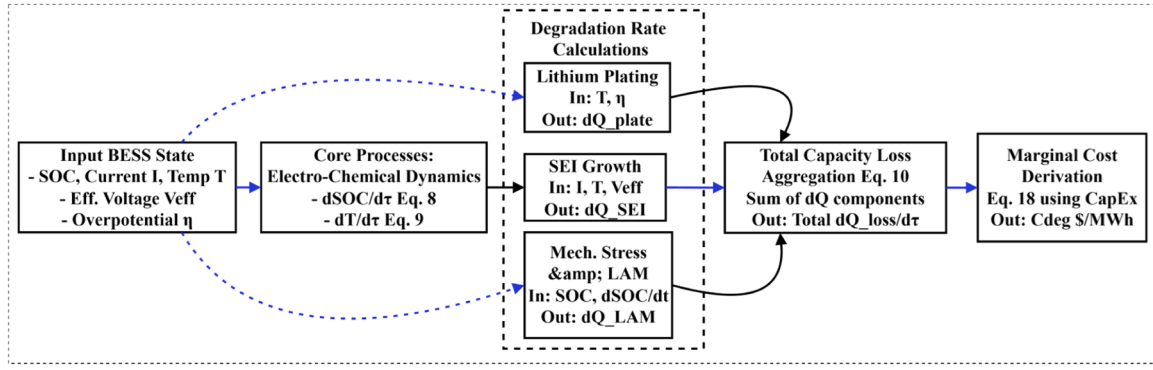


Fig. 2. Block diagram of the multi-mechanism degradation model. The model uses the real-time BESS state to calculate individual degradation rates, which are then aggregated and converted into a marginal cost (\$/MWh) for the economic optimization.

$$D_{\text{total}}(t) = \sum_{k \in \mathcal{K}} D_k(t) \quad (2)$$

To establish the VPP's net position at any moment, the framework first uses Eq. (1) to consolidate the power generation from every individual PV system (j) in its portfolio (P). In parallel, Eq. (2) calculates the total electricity demand the VPP must satisfy by aggregating the loads (D_k) from all participating consumers (k).

Electrochemistry-informed battery degradation model

A core contribution is a high-fidelity, electrochemistry-informed battery degradation model. This model, detailed in Fig. 2, moves beyond simple empirical methods to provide precise, real-time degradation costing based on instantaneous operation. It directly embeds physical wear into the economic optimization by calculating capacity loss and deriving a real-time marginal degradation cost for each battery unit.

Uncertainty modeling via scenario generation

To manage operational uncertainty, we employ a scenario-based stochastic programming approach [18]. This enables robust day-ahead decisions by modeling a set of plausible real-time scenarios S , each with a probability π_s . The method focuses on three key stochastic parameters: PV generation, real-time electricity price (λ^{RT}), and the real-time regulation signal (r^{reg}). Each is modeled as a deterministic day-ahead forecast plus a stochastic deviation

$$P_{\text{total}}^{\text{PV}}(t, s) = P_{\text{total}}^{\text{PV,forecast}}(t) + \Delta P_s^{\text{PV}}(t) \quad (3)$$

$$\lambda^{RT}(t, s) = \lambda^{RT, \text{forecast}}(t) + \Delta \lambda_s^{RT}(t) \quad (4)$$

$$r^{\text{reg}}(t, s) \in [-1, 1] \quad (5)$$

The actual P_s^{PV} power and real-time price λ_s^{RT} in scenario s are defined by their forecast plus a scenario-specific deviation (Eqs. 3, 4). The regulation signal is bounded by operational limits (Eq. 5). Generating realistic scenarios for the correlated deviations ΔP^{PV} and $\Delta \lambda^{RT}$ requires capturing their temporal dependencies and volatility clustering. We therefore employ a multivariate ARIMA-GARCH model.

First, a Vector ARIMA model captures the conditional mean and linear temporal structure, providing the day-ahead forecast and a series of historical residuals ε_t . A general formulation is [12]:

$$\Phi(L)(1-L)^d Y_t = c + \Theta(L)\varepsilon_t \quad (6)$$

The multivariate ARIMA model for the forecast vector $Y_t = [P_t^{\text{PV}}, \lambda_t^{RT}]^T$ is given by $\Phi(L)Y_t = \Theta(L)\varepsilon_t$ where $\theta(L)$ and $\Phi(L)$ are matrix polynomials for the autoregressive and moving average components, and ε_t is the residual vector [12]. These residuals are then modeled using a

multivariate GARCH process [28] to capture time-varying volatility and correlation:

$$\Sigma(t) = \Omega + \sum_{i=1}^{\text{top}} A_i (\varepsilon_{t-i} \varepsilon_{t-i}^T) + \sum_{j=1}^{\text{top}} B_j \Sigma(t-j) \quad (7)$$

where Ω , A_i , and B_j are coefficient matrices capturing past shocks (ARCH) and past volatility (GARCH). The forecast deviations for PV power and real-time price are drawn from a multivariate normal distribution with zero mean and the predicted covariance $\Sigma(t)$:

$$(\Delta P_s^{\text{PV}}(t), \Delta \lambda_s^{RT}(t)) \sim \mathcal{N}(0, \Sigma(t)) \quad (8)$$

$$\Sigma(t) = \begin{bmatrix} \sigma_{\text{PV}}^2(t) & \rho \sigma_{\text{PV}}(t) \sigma_{\lambda}(t) \\ \rho \sigma_{\text{PV}}(t) \sigma_{\lambda}(t) & \sigma_{\lambda}^2(t) \end{bmatrix} \quad (9)$$

Here, $\sigma_{\text{PV}}^2(t)$ and $\sigma_{\lambda}^2(t)$ are the time-varying variances, and ρ is their correlation coefficient. The regulation signal $r^{\text{reg}}(t, s)$ is modeled separately by sampling from a historical distribution, subject to the bounds in Eq. (5).

Governing electro-chemical dynamics

The internal state of each BESS $Bi \in \mathcal{B}$ is described by a set of coupled differential equations foundational to battery modeling [11]. These states include its State of Charge (SOC), instantaneous current (I_i), core temperature (T_i), and effective electrode voltage $V_{\text{eff},i}$. The evolution of these states over a small-time interval τ is governed by:

$$\frac{d\text{SOC}_i(\tau)}{d\tau} = -\frac{I_i(\tau)}{Q_i^{\text{nom}}} \quad (10)$$

$$\frac{dT_i(\tau)}{d\tau} = \frac{1}{C_{\text{th}}} (I_i^2(\tau) R_i^{\text{int}} - hA(T_i(\tau) - T^{\text{amb}})) \quad (11)$$

The optimizer's dispatch decision, the current $I_i(\tau)$, directly relates to the change in the battery's stored energy level. This dynamic is governed by the rate of change of the State of Charge, as formulated in Eq. (10). Concurrently, the core temperature dynamics for BESS i are modeled in Eq. (11), which accounts for internal heat generation and heat exchange with the ambient environment T_{amb} .

Multi-mechanism degradation rate modeling

Our novel approach models the total capacity fade of each BESS $Bi \in \mathcal{B}$ as the superposition of three dominant and well-understood degradation mechanisms: Solid Electrolyte Interphase (SEI) growth, lithium plating, and mechanical stress [22]. These mechanisms contribute cumulatively to the overall capacity loss. The set of equations defining these individual and total degradation rates are as follows:

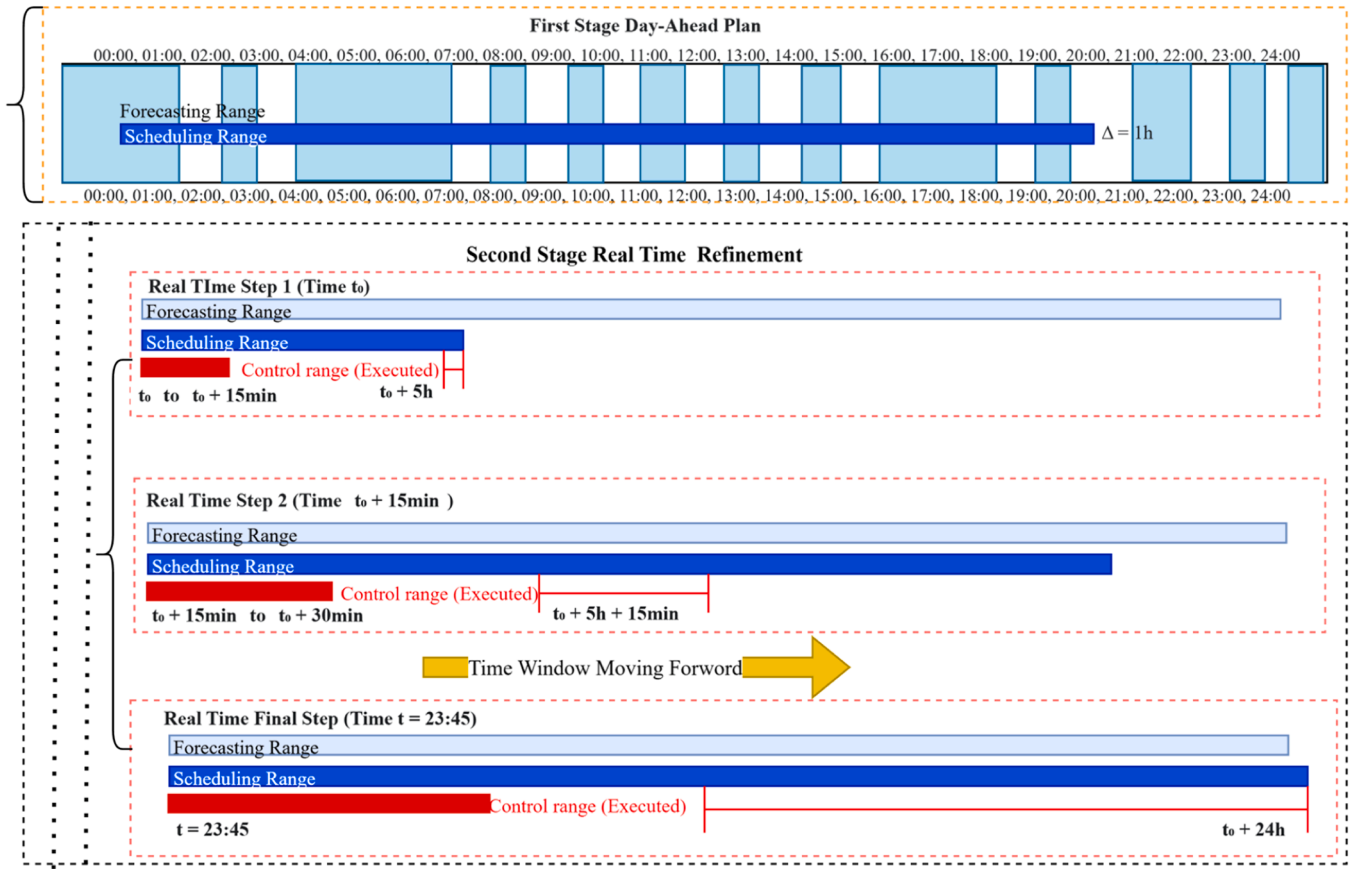


Fig. 3. Principle of the Multi-Time-Scale Rolling Horizon. The model first establishes a 24-hour Day-Ahead Plan. This plan is then refined in the Real-Time Stage, where the optimization window continually moves forward, executing only the immediate 15-minute control actions.

$$\frac{dQ_i^{\text{loss}}(\tau)}{d\tau} = \frac{dQ_i^{\text{SEI}}(\tau)}{d\tau} + \frac{dQ_i^{\text{plate}}(\tau)}{d\tau} + \frac{dQ_i^{\text{LAM}}(\tau)}{d\tau} \quad (12)$$

$$\frac{dQ_{\text{SEI},i}(\tau)}{d\tau} = A_{\text{SEI}} \exp\left(-\frac{E_{\text{SEI}}}{RT_i(\tau)}\right) V_{\text{eff},i}(\tau) \quad (13)$$

$$\frac{dQ_i^{\text{plate}}(\tau)}{d\tau} = A^{\text{plate}} \exp\left(-\frac{E_a^{\text{plate}}}{R_g T_i(\tau)}\right) \max\left(0, \eta_i(\tau) - \eta^{\text{crit}}\right) \quad (14)$$

$$\frac{dQ_i^{\text{LAM}}(\tau)}{d\tau} = A^{\text{mech}} \left(\frac{\sigma_i(\tau)}{\sigma^{\text{crit}}}\right)^m \quad (15)$$

$$\sigma_i(\tau) = Y \left| \frac{d\text{SOC}_i(\tau)}{d\tau} \right| (\text{SOC}_i(\tau) - \text{SOC}^{\text{ref}}) \quad (16)$$

The total degradation rate for BESS i (Eq. 12) aggregates three electrochemical mechanisms: solid electrolyte interphase (SEI) growth, lithium plating. The primary cause of capacity fade, the rate of SEI growth, is defined in Eq. (13) with an Arrhenius dependence on battery core temperature and the effective electrode voltage, consistent with established calendar aging models [16]. Lithium plating rate (Eq. 14) occurs when the charging overpotential exceeds a critical threshold. The mechanical stress-induced LAM rate (Eq. 15) is a function of stress relative to a critical threshold [34], approximated (Eq. 16) using the SOC and its rate of change. Key electrochemical and thermal parameters for an NMC cell, sourced from literature [24], the full list of electrochemical parameters is provided in Appendix A.

Proposed marginal degradation cost function

The pivotal innovation of our degradation model is its translation

into a real-time marginal cost function. This transformation allows the physical degradation model to become a dynamic economic signal directly embedded within the VPP's optimization objective. To quantify this, the battery's (SOH) for BESS $_i$ at time τ is defined as the remaining capacity relative to its nominal capacity:

$$\text{SOH}_i(\tau) = 1 - \frac{1}{Q_i^{\text{nom}}} \int_0^\tau \frac{dQ_i^{\text{loss}}(\tau)}{d\tau} d\tau \quad (17)$$

The condition of the battery is quantified by means of the SOH of the battery system BESS $_i$ at time τ . It is defined as the remaining capacity of the battery system relative to its nominal capacity; it is given by the expression (15), where the SOH declines with increasing cumulative capacity loss which causes the effective nominal capacity to decline. On the basis of this physical state, we define the marginal degradation cost (C_i^{deg}) in \$/MWh. It is determined by the Eq. (17); this term defines an amortized capital cost for each MWh of energy that has been dispatched due to capacity loss. Thus, the marginal degradation cost directly reflects the costs associated with the wear and tear of the battery. In terms of the formulation of the marginal degradation cost, it is based upon the instantaneous total capacity degradation rate from (12) and the magnitude of the energy dispatched.

$$C_i^{\text{deg}}(\tau) = \frac{\text{CapEx}_i}{E_{\text{LEOL}}^{\text{throughput}}} \frac{dQ_i^{\text{loss}}(\tau)}{d\tau} \frac{1}{|I_i(\tau)| + \epsilon} \quad (18)$$

Eq. (18) calculates the real-time marginal degradation cost of the BESS $_i$. CapEx_i is the capital cost of the BESS, and for which $E_{\text{LEOL}}^{\text{throughput}}$ is its warranted lifetime energy throughput prior to reaching end-of-life. The term in the equation for marginal degradation cost, $\frac{dQ_{\text{loss},i}(\tau)}{d\tau}$, is the instantaneous total capacity degradation rate from Eq. (12). In addition,

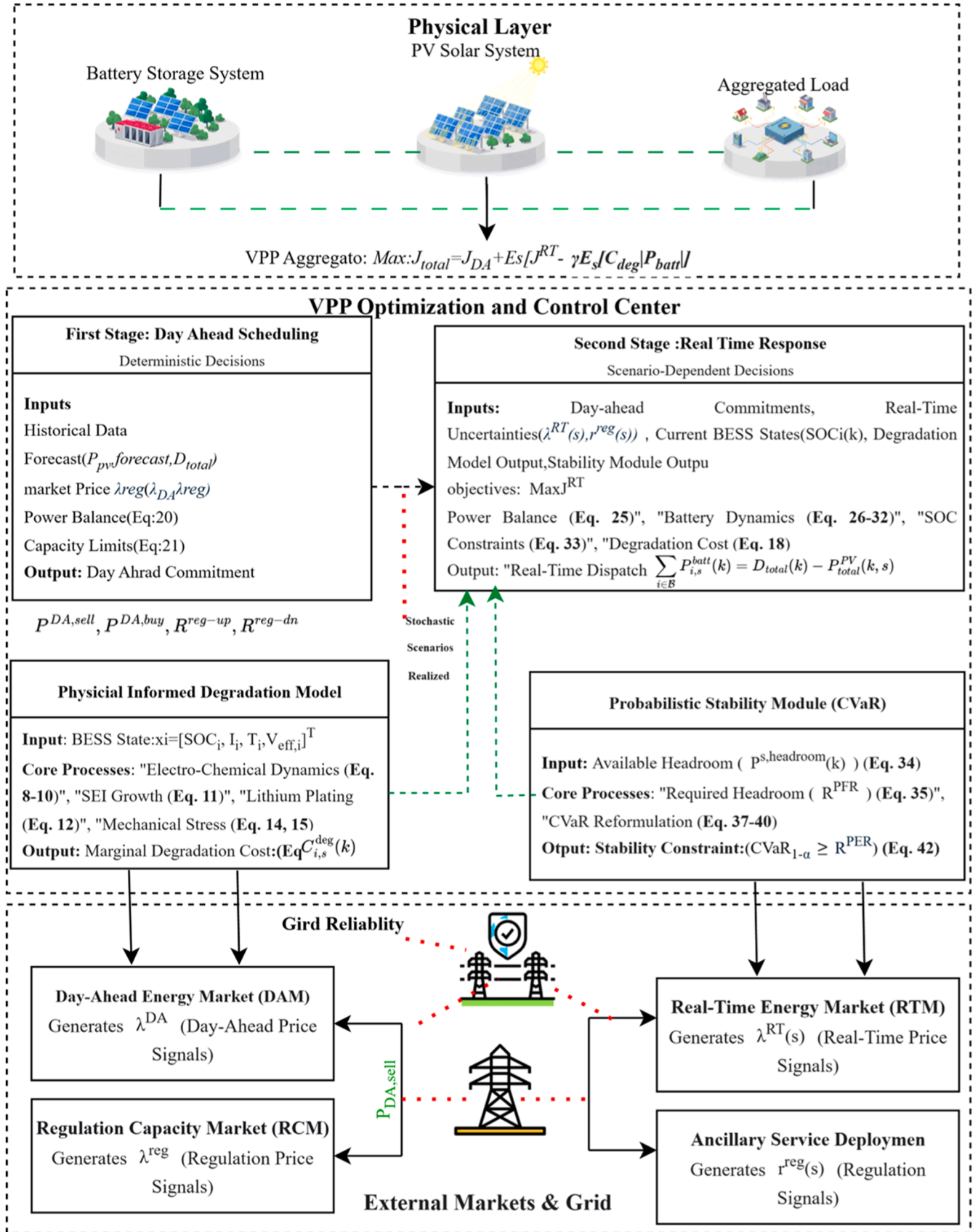


Fig. 4. Detailed architecture of the VPP optimization framework. This diagram outlines the complete flow of information, from the physical assets and market signals to the specific modules including the two optimization stages, the degradation model, and the probabilistic stability module that constitute the VPP's control center.

Table 2

VPP Asset Specifications.

Parameter	Component	Value	Unit	Description
Rated Power	BESS	5	MW	Maximum charge/discharge rate
Usable Capacity	BESS	20	MWh	Total usable energy storage capacity
Round-trip Efficiency	BESS	92	%	AC-to-AC conversion efficiency
SOC Min / Max	BESS	10 / 90	%	Operational State of Charge limits
Rated Capacity	PV System	8	MWp	DC peak capacity of the solar array
Location	PV System	Bakersfield, CA	-	Geolocation for solar irradiance data
Peak Demand	Commercial Load	6	MW	Maximum daily power consumption
Profile Type	Commercial Load	Commercial	-	Standard commercial load profile

the last part of the equation for marginal degradation cost is $|I_i(\tau)| + \epsilon$, where ϵ is a very small positive number added to the absolute value of the energy dispatched to prevent dividing by zero. This formulation provides a continuous, differentiable and physical representation of the marginal degradation cost of the BESS, and enables true degradation-aware decision making through explicit valuation of the trade-off between immediate profit and long-term asset longevity.

Two-stage stochastic optimization formulation

To optimize and co-optimize VPP operation across all possible time scales with an acceptable level of uncertainty, we use a two-stage

stochastic program. The two-stage nature of this program is significant because it allows day-ahead commitment to be optimally integrated into real-time decision-making processes that incorporate dynamic degradation costs and satisfy system stability requirements; see Fig. 3 for the flow of information through the two stages.

First stage: day-ahead scheduling (deterministic decisions)

Before the actual realization of uncertainties in the day-ahead period, day-ahead commitments are made. The main goal of this day-ahead stage is to achieve the maximum expected day-ahead market revenue by balancing the VPP's asset dispatch, demand response commitments, and market bids with the best available forecasts. The objective function for the day-ahead scheduling is:

$$J^{DA} = \sum_t (\lambda^{DA}(t) (P^{DA,sell}(t) - P^{DA,buy}(t)) + \lambda^{reg}(t) (R^{reg-up}(t) + R^{reg-dn}(t))) \quad (19)$$

The first-stage objective is to maximize the day-ahead revenue by optimizing the VPP's market commitments. This is achieved through the objective function shown in Eq. (19), which comprises profits from energy sales ($P^{DA,sell}(t)$) and purchases ($P^{DA,buy}(t)$) at the day-ahead price $\lambda^{DA}(t)$, as well as revenue from providing regulation reserves $R^{reg-up}(t)$ and ($R^{reg-dn}(t)$).

$$P^{DA,sell}(t) - P^{DA,buy}(t) + P_{total}^{PV,forecast}(t) + \sum_{i \in \mathcal{B}} P_{i,t}^{batt,ch} - \sum_{i \in \mathcal{B}} P_{i,t}^{batt,dn} = D_{total}(t) + D^{DR}(t) \quad (20)$$

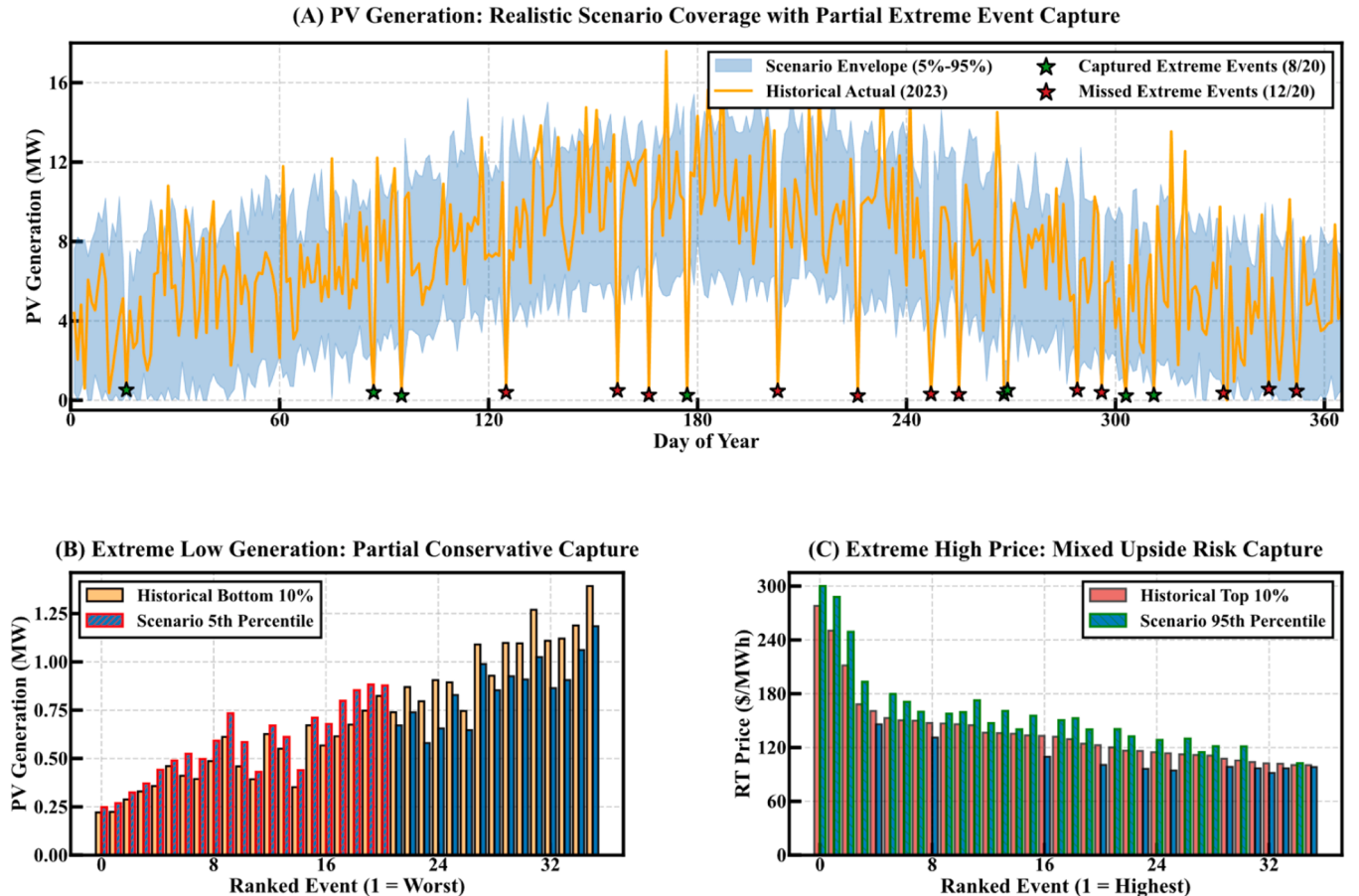


Fig. 5. Scenario coverage validation and extreme event capture analysis over a 365-day horizon.

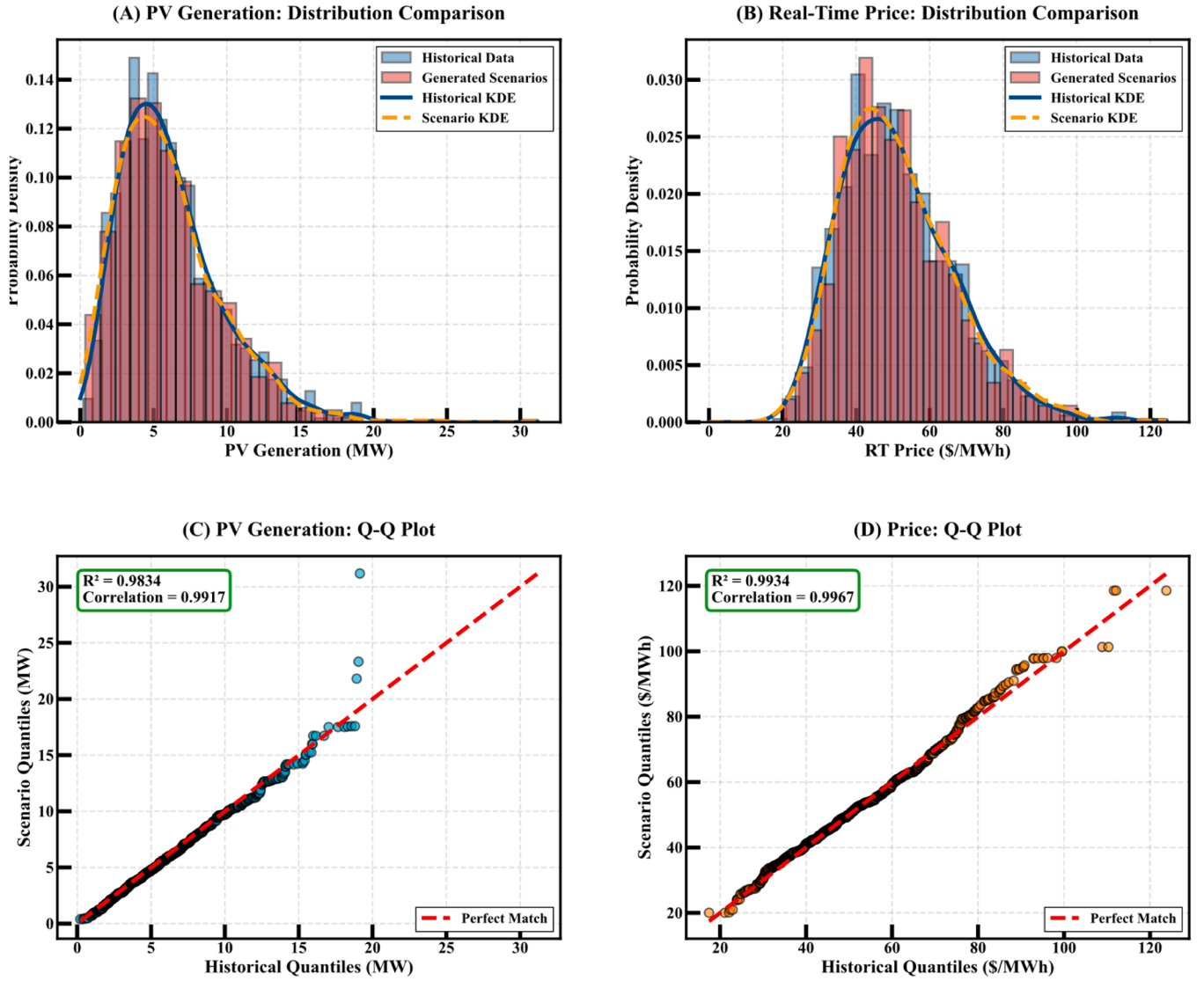


Fig. 6. Statistical validation of scenario generation quality via distribution matching.

$$0 \leq R^{\text{reg-up}}(t) \leq R^{\text{max,up}} \quad (21)$$

$$0 \leq R^{\text{reg-dn}}(t) \leq R^{\text{max,dn}} \quad (22)$$

$$0 \leq p_{i,t}^{\text{batt,ch}} \leq p_i^{\text{max,ch}} \forall i \in \mathcal{B} \quad (23)$$

$$0 \leq p_{i,t}^{\text{batt,dis}} \leq p_i^{\text{max,dis}} \forall i \in \mathcal{B} \quad (24)$$

$$SOC_i^{\min} \leq SOC_i(t) \leq SOC_i^{\max} \forall i \in \mathcal{B} \quad (25)$$

$$E_i(t) = E_i(t-1) + \left(p_{i,t}^{\text{batt,ch}} \eta_i^{\text{ch}} - p_{i,t}^{\text{batt,dis}} / \eta_i^{\text{dis}} \right) \Delta t \quad \forall i \in \mathcal{B} \quad (26)$$

$$SOC_i(t) = E_i(t) / E_i^{\text{nom}} \quad (27)$$

To ensure physical and operational feasibility, the first-stage objective is subject to several deterministic constraints. The Day-Ahead Power Balance, presented in Eq. (20), ensures that at each time step, the net market exchange, forecasted PV generation, and BESS power balance the total aggregated load and demand response. The VPP's commitments for regulation reserves must not exceed maximum capacities, as defined by the limits in Eqs. (21) and (22). Furthermore, the charging and discharging power of each BESS are constrained by the BESS Day-Ahead

Operational Limits in Eq. (23) to (25). The SOC for each BESS must be maintained within a predefined safe range, mandated by Eq. (26). Finally, the BESS Day-Ahead Energy Capacity dynamics are described in Eq. (27), which updates the stored energy based on its previous state and current dispatch.

Second stage: real-time recourse (scenario-dependent decisions)

The second stage of our optimization problem involves real-time recourse actions. After an uncertainty scenario $s \in \mathcal{S}$ is revealed, recourse actions are taken at each intra-hour time step $k \in \mathcal{T}^{\text{RT}}$. The objective in this stage is to maximize real-time revenue while minimizing the incurred degradation costs associated with BESS operation. The objective function for the real-time recourse stage is:

$$\begin{aligned} \max J^{\text{RT}}(s) = & \sum_{k \in \mathcal{T}^{\text{RT}}} \left[\lambda^{\text{RT}}(k, s) * (p^{\text{RT}}, + (k, s) - p^{\text{RT}}, - (k, s)) \right. \\ & \left. - \sum_{i \in \mathcal{B}} C_i^{\text{deg}} \text{eg}(k, s) * \left| p_{i,k,s}^{\text{batt}} \right| * \Delta \tau \right] \end{aligned} \quad (28)$$

The objective in the second stage is to maximize real-time revenue while minimizing the incurred degradation costs associated with BESS operation. This recourse action is formulated in Eq. (28), which

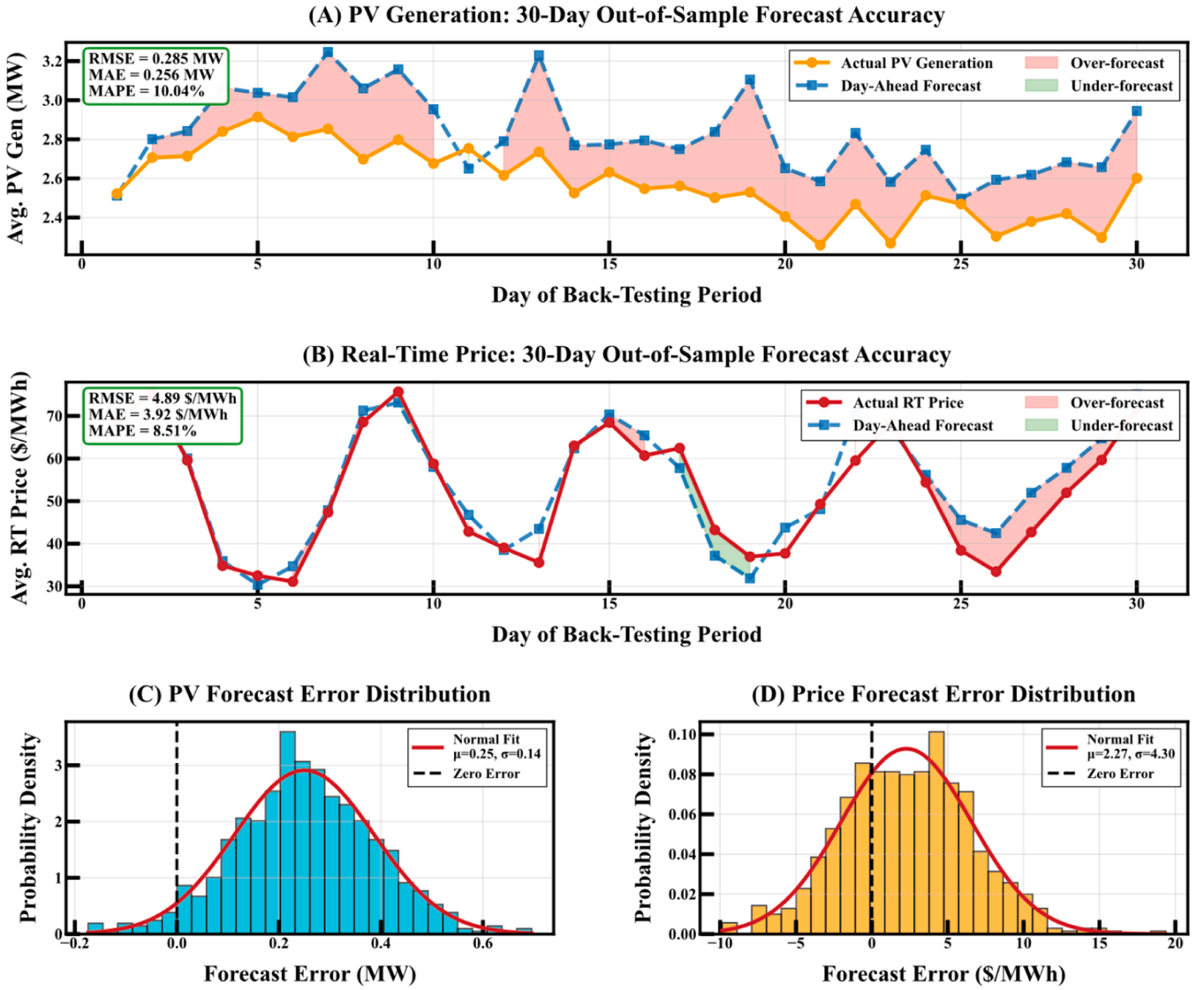


Fig. 7. Out-of-sample back-testing and forecast accuracy assessment over a 30-day horizon.

optimizes market sales and purchases at the real-time price while simultaneously penalizing the marginal degradation cost $C_i^{\text{deg}}(k, s)$, as derived from Eq. (19) incurred by each BESS. This second-stage objective is subject to the following constraints for all scenarios s and time steps k .

$$P^{RT,+}(k, s) - P^{RT,-}(k, s) + P_{\text{total}}^{\text{PV}}(k, s) + \sum_{i \in \mathcal{B}} (P_{i,k,s}^{\text{batt},\text{ch}} - P_{i,k,s}^{\text{batt},\text{dis}}) = D_{\text{total}}(k) + D^{\text{DR},\text{RT}}(k, s) \quad (29)$$

$$P_{i,k,s}^{\text{batt}} = P_{i,k,s}^{\text{batt},\text{dis}} - P_{i,k,s}^{\text{batt},\text{ch}} \forall i \in \mathcal{B} \quad (30)$$

$$P_{i,k,s}^{\text{batt},\text{dis}} = \max(0, P_{i,k,s}^{\text{batt}}) \forall i \in \mathcal{B} \quad (31)$$

$$P_{i,k,s}^{\text{batt},\text{ch}} = \max(0, -P_{i,k,s}^{\text{batt}}) \forall i \in \mathcal{B} \quad (32)$$

$$P_i^{\text{min},\text{ch}} \leq P_{i,k,s}^{\text{batt},\text{ch}} \leq P_i^{\text{max},\text{ch}} \forall i \in \mathcal{B} \quad (33)$$

$$P_i^{\text{min},\text{dis}} \leq P_{i,k,s}^{\text{batt},\text{dis}} \leq P_i^{\text{max},\text{dis}} \forall i \in \mathcal{B} \quad (34)$$

$$SOC_{i,s}(k+1) = SOC_{i,s}(k) + \frac{\eta_i^{\text{ch}} P_{i,k,s}^{\text{batt},\text{ch}} - P_{i,k,s}^{\text{batt},\text{dis}} / \eta_i^{\text{dis}}}{E_i^{\text{nom}}} \Delta \tau \quad \forall i \in \mathcal{B} \quad (35)$$

$$SOC_i^{\text{min}} \leq SOC_{i,s}(k) \leq SOC_i^{\text{max}} \forall i \in \mathcal{B} \quad (36)$$

$$R_{i,k,s}^{\text{reg-up}} \leq R_i^{\text{max},\text{up}} \cdot r_{k,s}^{\text{reg}} \forall i \in \mathcal{B} \quad (37)$$

$$R_{i,k,s}^{\text{reg-dn}} \leq R_i^{\text{max},\text{dn}} \cdot (-r_{k,s}^{\text{reg}}) \forall i \in \mathcal{B} \quad (38)$$

Real-time operations for each scenario (s) enforce the power balance (Eq. 29) between market positions, generation, BESS dispatch, demand response, and load. BESS power is decomposed into charge and discharge components with operational bounds (Eqs. 30–34), while its State of Charge (SOC) is governed by dynamics and limits (Eqs. 35–36). Regulation reserve provision (Eqs. 37–38) ensures upward and downward capacity respects real-time availability, scaled by the signal ($r_{k,s}^{\text{reg}}$). The architecture of the complete two-stage optimization, integrating all inputs, modules, and constraints, is summarized in Fig. 4.

The total expected profit for the VPP across all stages and scenarios is then computed as:

VPP Operational Summary

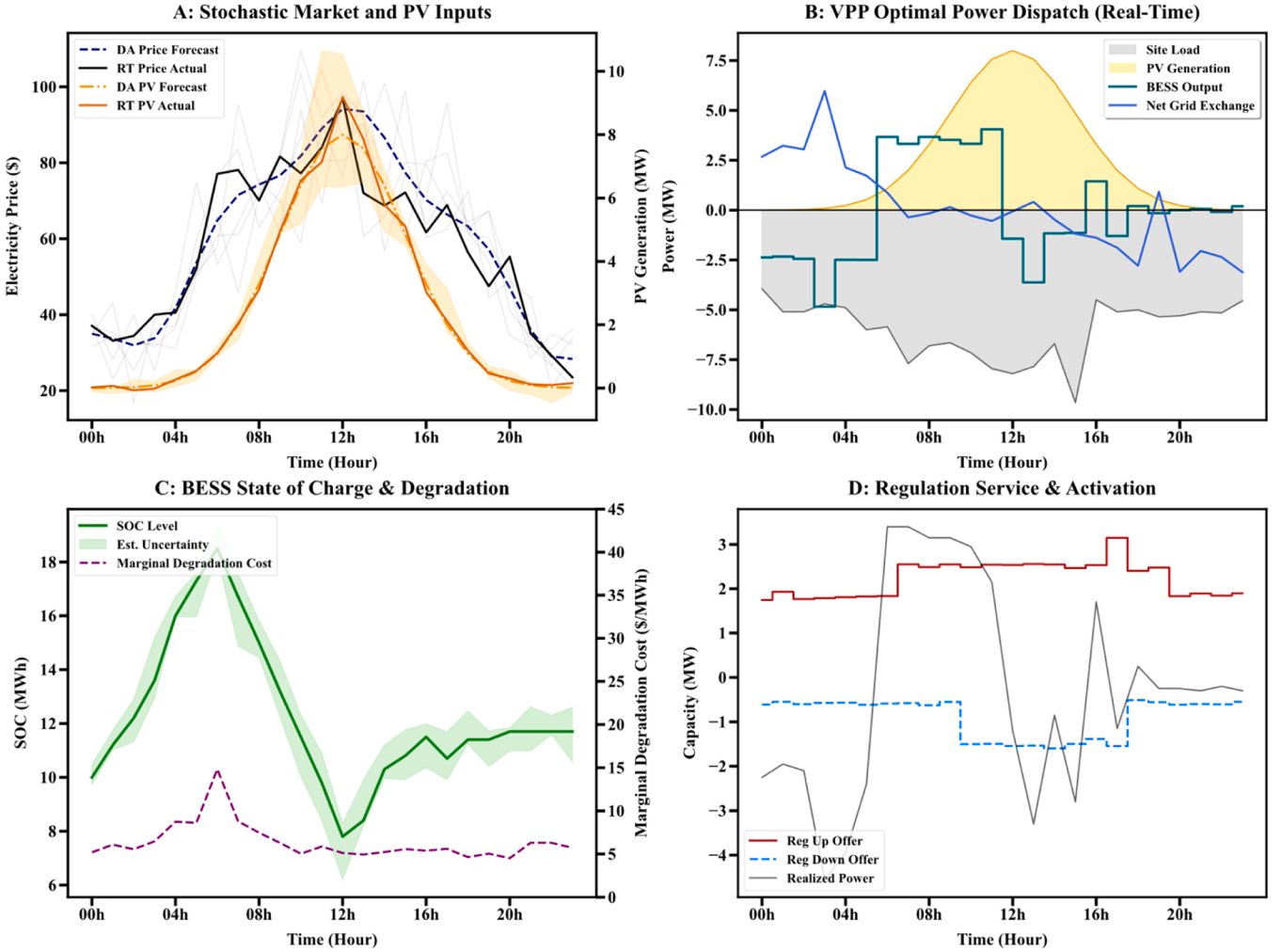


Fig. 8. Operational results of the VPP over a 24-hour horizon. Panel (A) shows day-ahead forecasts and real-time stochastic realizations for prices and PV generation. Panel (B) presents the resulting recourse-based optimal dispatch, including PV utilization, BESS charge/discharge, and grid interaction. Panel (C) illustrates BESS SOC evolution and the corresponding marginal degradation cost. Panel (D) shows regulation up/down capacity provision and net BESS power.

$$\max J^{\text{total}} = J^{\text{DA}} + \sum_{s \in \mathcal{S}} \pi_s J^{\text{RT}}(s) \quad (39)$$

The overall objective of the two-stage stochastic program is to maximize the total expected profit, which is defined in Eq. (39) as the sum of the day-ahead profit (J^{DA}) and the expected value of the real-time profits (J^{RT}) across all scenarios

Probabilistic stability constraint formulation

In order to position the VPP as an effective and reliable element of the power grid, a new probabilistic constraint for stability was developed which ensures that Primary Frequency Response (PFR) can be provided with a high degree of certainty. The addition of this feature will allow the VPP to function as a stable resource on the grid. The overall two-stage stochastic optimization model representing the interaction between Day-Ahead decisions and Real-Time Recourse Actions is presented in Fig. 3. The VPP's ability to provide PFR is determined by its available headroom, the amount of PFR required, and the resulting probabilistic constraint are as follows:

$$p_s^{\text{headroom}}(k) = \sum_{i \in \mathcal{B}} (p_i^{\text{max}, \text{dis}} - p_{i,k,s}^{\text{batt}}) + (p_{\text{total}}^{\text{PV}, \text{max}} - p_{\text{total}}^{\text{PV}}(k, s)) \quad (40)$$

$$R^{\text{PFR}} = X^{\text{VPP}} \cdot \Delta P^{\text{loss}} \quad (41)$$

$$\Pr\{p_s^{\text{headroom}}(k) \geq R^{\text{PFR}}\} \geq 1 - \alpha \quad (42)$$

$$\text{VaR}_\beta = \min z : F(z) \geq \beta \quad (43)$$

$$\text{CVaR}_\beta \approx \max \left(\zeta - \frac{1}{1 - \beta} \sum_{s \in \mathcal{S}} \pi_s u_s \right) \quad (44)$$

$$u_s \geq \zeta - p_s^{\text{headroom}}(k) \forall s \in \mathcal{S}, u_s \geq 0 \forall s \in \mathcal{S} \quad (45)$$

$$\text{CVaR}_\alpha \geq R^{\text{PFR}} \quad (46)$$

For reliability of power system, primary frequency response (PFR) constraint on probability of stability is introduced. Available headroom of PFR in each scenario s is defined in Eq. (40) and compared to required PFR capacity as given in Eq. (41). Reliability is defined in the form of a chance constraint in Eq. (42) to ensure availability of PFR headroom at least at a high confidence level of α . Due to intractable nature of chance constraints, they are converted into CVaR based constraints in the linear approximation as shown in Eq. (44). CVaR formulation introduces auxiliary target variable ζ and a set of non-negative scenario specific deficit variables u_s as defined in Eq. (45). In this way, originally

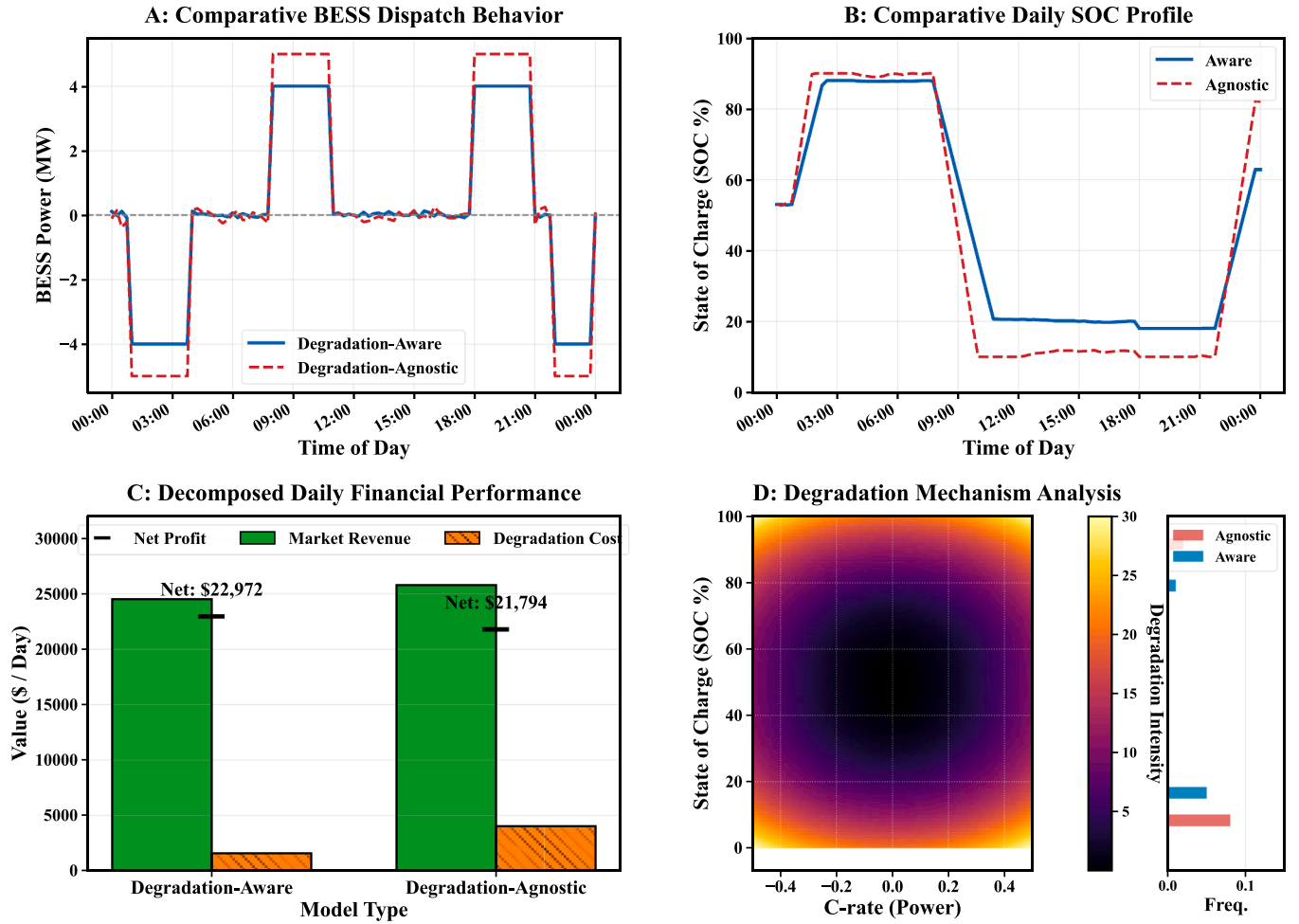


Fig. 9. Comparison of degradation-aware vs. agnostic model performance: (A) BESS power dispatch, (B) State of Charge profiles, (C) financial breakdown (market revenue, degradation cost, net profit), and (D) operational stress analysis via high-stress zone heatmap and occupancy histogram.

Table 3
Annualized Performance Comparison: Degradation-Aware vs. Agnostic Model.

Metric	Degradation-Aware (Proposed)	Degradation-Agnostic	% Change
Financial Performance			
Annual Gross Revenue	\$8950,000	\$9415,000	-4.9 %
Annual Degradation Cost	(\$565,000)	(\$1460,000)	+ 61 %
Annual Net Profit	\$8385,000	\$7955,000	+ 5.4 %
Physical Performance			
Daily BESS Throughput (MWh)	35.2	58.1	-39.4 %
Daily Capacity Fade (%)	0.0044 %	0.0114 %	+ 159 %
Projected BESS Lifetime (Years)	12.4	4.8	+ 158 %

formulated chance constraint in Eq. (42) is substituted by the single linear CVaR based constraint in Eq. (46) ensuring availability of adequate reliable capacity across all possible adverse scenarios.

Complete multi-objective problem statement

The optimization seeks to maximize the total expected Net Present Value (NPV) of VPP operation. The objective function J^{Total} is formulated as:

$$\text{Maximize } J^{\text{Total}} = J^{\text{DA}} + \sum_{s \in S} \pi_s (J_s^{\text{RT}} - \gamma \cdot J_s^{\text{Deg}}) \quad (47)$$

Where:

1. Day-Ahead Revenue (J^{DA}):

$$J^{\text{DA}} = \sum_t [\lambda_t^{\text{DA}} (P_t^{\text{DA, sell}} - P_t^{\text{DA, buy}}) + \lambda_t^{\text{reg}} R_t^{\text{reg}}] \quad (48)$$

2. Real-Time Recourse Profit (J_s^{RT}):

$$J_s^{\text{RT}} = \sum_t [\lambda_{k,s}^{\text{RT}} (P_{k,s}^{\text{RT, sell}} - P_{k,s}^{\text{RT, buy}})] \quad (49)$$

3. Degradation Cost Penalty (J_s^{Deg}):

$$J_s^{\text{Deg}} = \sum_k C_i^{\text{deg}}(k, s) \cdot |P_{i,k,s}^{\text{batt}}| \cdot \Delta \tau \quad (50)$$

The comprehensive objective function for the VPP is presented in Eqs. (46–49). This function seeks to maximize the sum of the day-ahead profit (J^{DA}) from Eq. (19) and the expected real-time profit across all scenarios ($J^{\text{RT}}(s)$ from Eq. (28)), while subtracting a weighted sum of the expected real-time degradation costs. This degradation cost term directly incorporates the marginal degradation cost ($C_i^{\text{deg}}(k, s)$) from Eq. (18) and is scaled by the weighting factor γ . This complete optimization problem is subject to all operational and stability constraints established in the preceding sections. These constraints ensure the physical

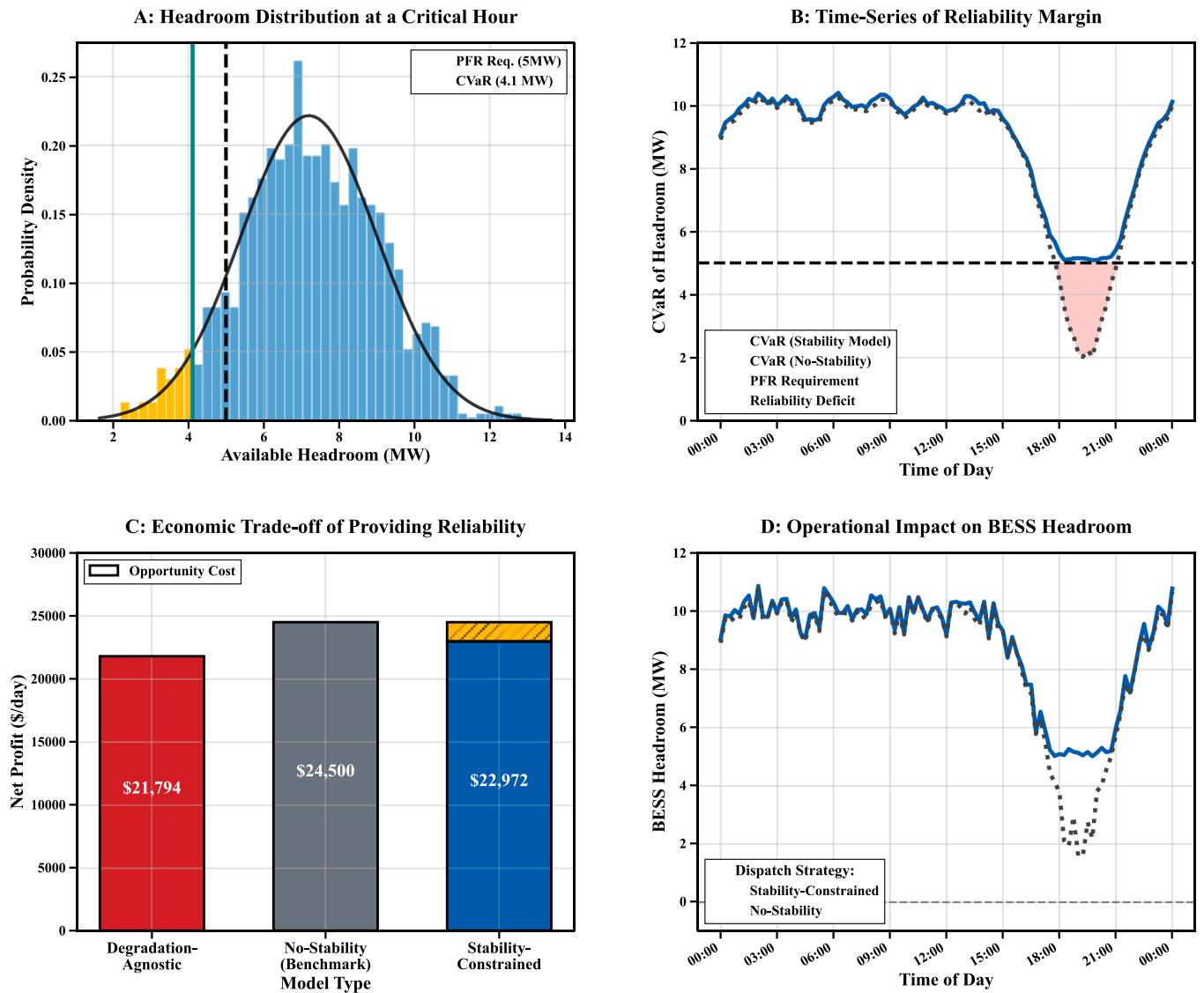


Fig. 10. Validation of CVaR-based stability constraint: (A) Distribution of available headroom showing the 5 % CVaR tail meeting the requirement. (B) Time-series CVaR comparison, highlighting the reliability deficit of the unconstrained model. (C) Economic trade-off bar chart with explicit "Opportunity Cost." (D) Operational reserve mechanism: constrained model reserves BESS headroom during peak hours.

feasibility of VPP operations and adherence to grid requirements:

- **First-Stage Constraints:** The operational limits and power balance requirements for day-ahead scheduling, as defined in Eqs. (20) through (26).
- **Second-Stage Constraints:** The real-time recourse actions for each scenario, governed by Eqs. (29) through (38).
- **Stability Constraint:** The probabilistic requirement for PFR, enforced through the CVaR-based reformulation in Eqs. (44) through (46).

This integrated formulation provides a novel and rich framework for the optimal management of a stability-constrained, degradation-aware VPP, allowing for sophisticated trade-offs between profitability, longevity, and grid reliability.

Case study: experimental setup

To validate the performance and demonstrate the practical applicability of the proposed stability-constrained, degradation-aware VPP optimization framework, we conduct a comprehensive case study using

real-world data. The simulation is designed to reflect a realistic operational environment for a VPP participating in a competitive electricity market, such as the California Independent System Operator (CAISO) market, a common benchmark in energy research [35]. This section details the VPP configuration, the parameters of the integrated models, the market and generation data used, and the computational environment.

Table 4

Reliability and Economic Performance of Stability-Constrained Model.

Metric	Stability-Constrained (Full Model)	No-Stability Benchmark	Degradation-Agnostic
PFR Requirement (MW)	5.0	5.0	N/A
Reliability Level (% of Time)	99.8 %	78.5 %	N/A
Min. Headroom CVaR (MW)	5.1	3.4	N/A
Daily Net Profit	\$24,500	\$26,250	\$17,500
Opportunity Cost	\$1750 (6.7 %)	-	-

Table 5
Comprehensive Performance Comparison of Operational Strategies.

Key Performance	Degradation-Agnostic (Profit Maximizing)	No-Stability Benchmark (Degradation-Aware)	Proposed Model
Financial Performance			
Annual Gross Revenue	\$9415,000	\$9581,250	\$8942,500
Annual Degradation Cost	(\$1460,000)	(\$565,000)	(\$565,000)
Annual Net Profit	\$7955,000	\$9016,250	\$8385,000
Asset Longevity			
Projected BESS Lifetime (Years)	4.8	12.4	12.4
Daily BESS Throughput (MWh)	58.1	35.2	< 35.2
Grid Reliability			
PFR Reliability (%) of Time)	N/A	78.5 %	99.8 %
Opportunity Cost of Reliability	N/A	-	\$1528 / day

VPP configuration

Our case study considers a VPP portfolio comprising co-located distributed energy resources designed to serve a commercial load profile. The VPP is structured around:

- A grid-scale Battery Energy Storage System (BESS), leveraging advanced lithium-ion chemistry for flexibility.
- A Solar Photovoltaic (PV) array, representing distributed renewable generation.
- An aggregated Commercial Load, characterized by its daily demand patterns.

The key specifications of the VPP assets, including their rated capacities, operational limits, and other essential characteristics, are summarized in Table 3. This configuration mirrors typical VPP deployments aiming for both market participation and grid support.

BESS Degradation Model Parameters

The high-fidelity degradation model (as detailed in Section 3) requires specific electrochemical and thermal parameters for the BESS. The parameters used in this study are representative of a common Lithium Nickel Manganese Cobalt Oxide (NMC) grid-scale battery cell. These values, derived from established battery modeling literature [24], are crucial for accurately simulating the capacity fade and real-time degradation costs. A comprehensive list of these parameters was provided previously in Table 2.

Market data and input scenarios

The historical 2023 data set was utilized in order to create a realistic representation of market conditions and seasonal variations. The day-ahead and real time locational marginal prices (LMPs) and regulation market data was obtained from the CAISO OASIS Database [35]. The solar irradiance data for Bakersfield, CA was obtained from NREL [36], and converted into a 1-minute power output profile for the 8MWp PV array. The representative commercial load profile from the OpenEI Database was scaled to a 6 MW peak [36]. In order to model real-time uncertainty, 1000 scenarios for PV and price deviations were created via an ARIMA-GARCH Model [28]; then these 1000 scenarios were reduced to 20 representative scenarios by utilizing a fast-forward selection algorithm. A 5 MW Primary Frequency Response (PFR) requirement (R^{PFR}) was defined to represent a typical ancillary service obligation.

To test the performance of the approach across seasonal variation and extreme tail risk, the method has been thoroughly tested over an entire 365 days horizon. As shown in Fig. 5, Panel A shows that the

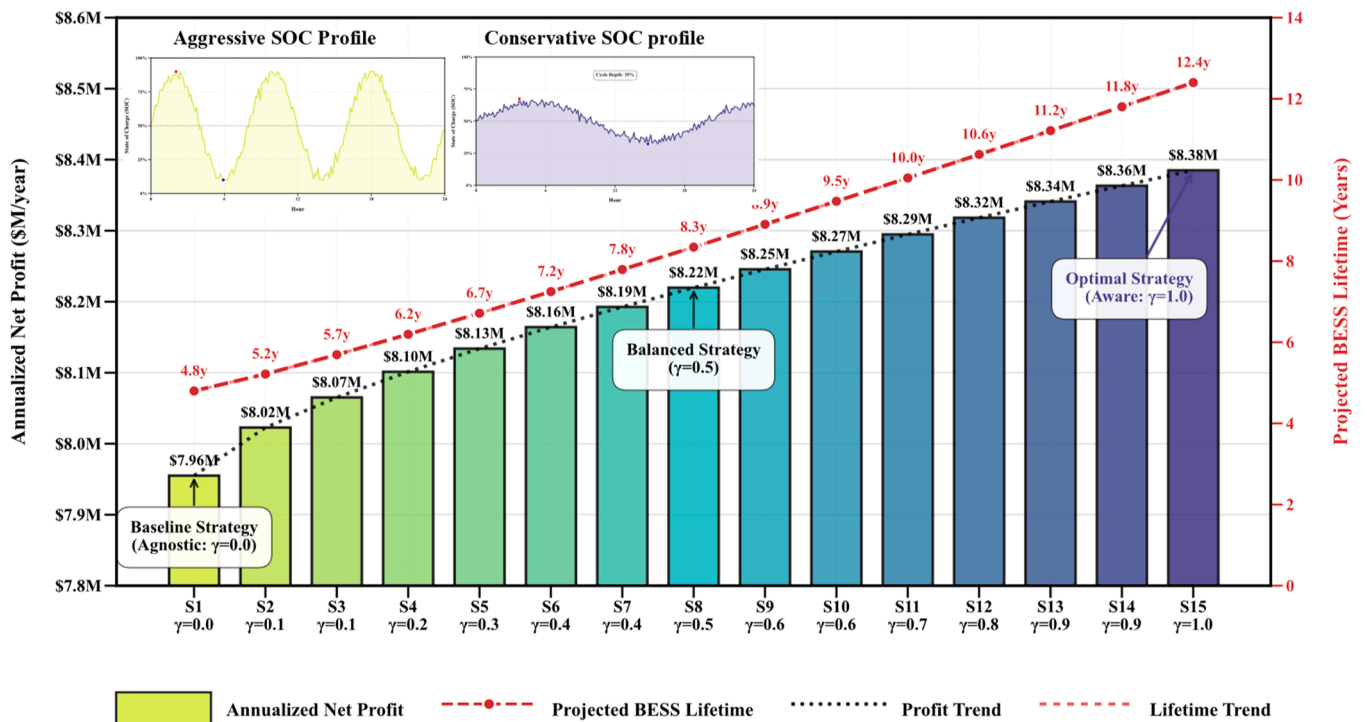


Fig. 11. Dashboard visualizing the trade-off between annual profit (bars) and projected BESS lifetime (line) across strategies. The color gradient indicates the degradation cost weight (γ). Embedded plots compare the aggressive daily SOC cycle for a maximum-profit strategy with the conservative cycle for a maximum-longevity strategy.

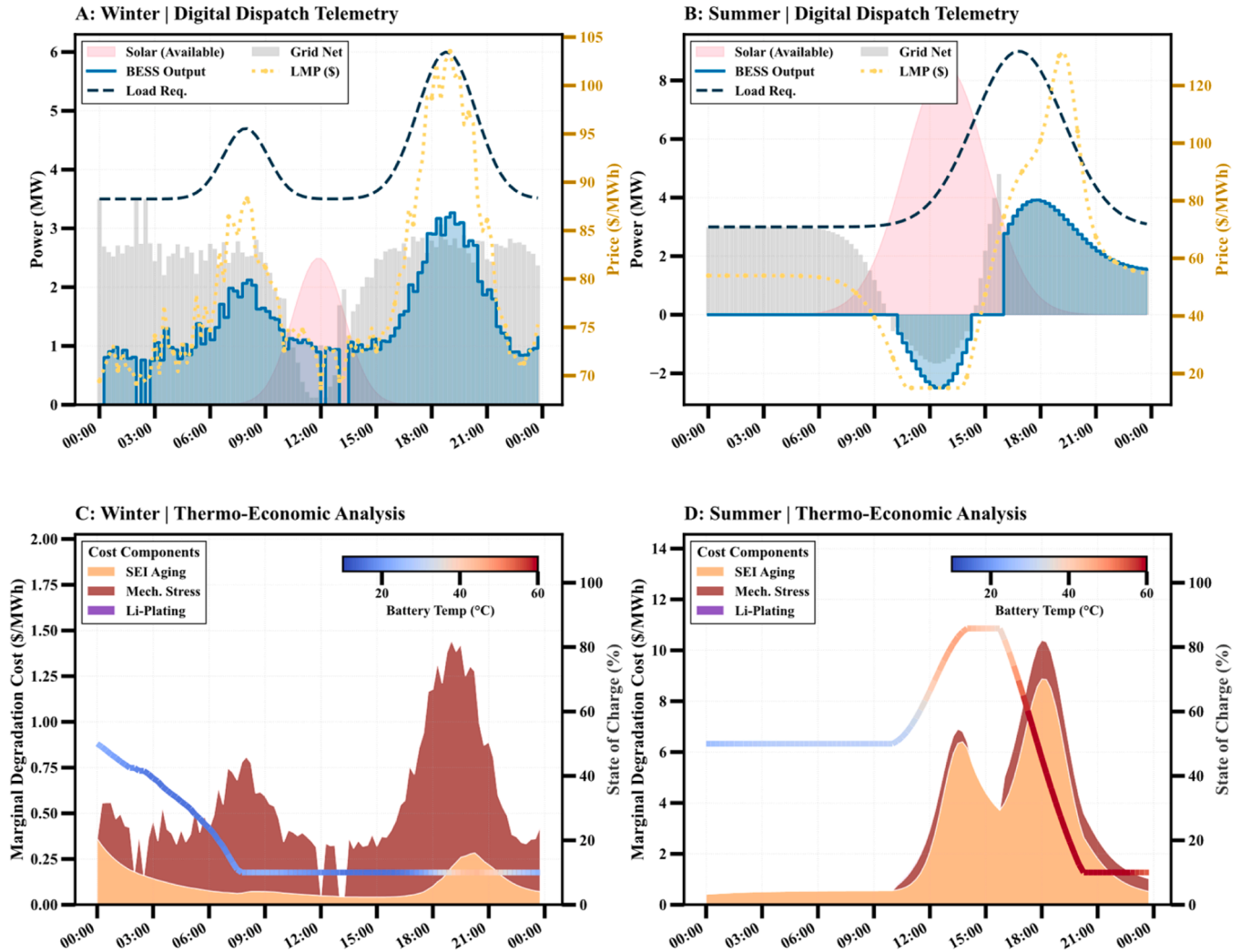


Fig. 12. A Seasonal adaptability and thermo-economic analysis of the VPP optimization framework.

generated scenario envelop (5th-95th percentiles) covers 89.0 % of historical observation points. This demonstrates the multivariate ARIMA-GARCH model has successfully modeled both seasonal behavior at longer time frames and daily volatility at shorter time frames. Most importantly, Panels B & C demonstrate the models ability to predict extreme events. The worst case PV scenarios that were generated using the model follow the trends of historical PV shortages; as such, this improves the model's ability to prevent over estimation of available solar PV power when there is significant shortages. In addition, the model also identifies extreme high price events. As such, the CVaR stability constraints (Eq. 45) can be trained with realistic worst-case conditions to avoid over commitment of ancillary services under adverse market or weather conditions.

The stochastic scenarios were rigorously validated against 2023 historical data Fig. 6. Panels A and B show the probability density functions for PV generation and real-time price closely match historical observations. This is confirmed quantitatively by Kolmogorov-Smirnov tests, with p-values of 0.6478 (PV) and 0.9883 (Price) exceeding the $\alpha = 0.05$ significance level, indicating the scenarios and historical data are drawn from the same distribution. Furthermore, Q-Q plots (Panels C and D) align exceptionally along the unit diagonal, with correlation coefficients exceeding 0.99, confirming the model accurately reproduces central tendencies and critical tail quantiles for realistic volatility in the optimization.

Prior to scenario generation, the accuracy of the deterministic Day-Ahead forecasts forming the optimization's conditional mean was validated via a 30-day out-of-sample back-test Fig. 7. Panels A and B show the ARIMA-based forecasts track actual diurnal patterns closely. For PV generation, the model achieves a MAPE of 10.04 % and RMSE of 0.285 MW, demonstrating strong performance. Price forecasting achieves a MAPE of 8.51 % and RMSE of \$4.89/MWh. Panels C and D confirm the forecast errors for both parameters are approximately normal and centered near zero, indicating an unbiased model. This high-fidelity baseline enables the GARCH variance model to add meaningful stochastic scenarios.

Simulation environment and benchmarking

The multi-objective optimization model developed as a two-stage stochastic program was efficiently computable to be deployed on-line. It was able to solve the approximately 22,000 variable/26,500 constraint per-day problem in less than 45 s for day-ahead scheduling and less than 2 s for real-time recourse.

To quantify its benefit the DASC (Degradation-Aware, Stability-Constrained) framework is compared to two baseline frameworks:

- **Degradation-Agnostic Model ($\gamma=0$):** A profit-maximizing model where the degradation cost is entirely ignored. This is achieved by

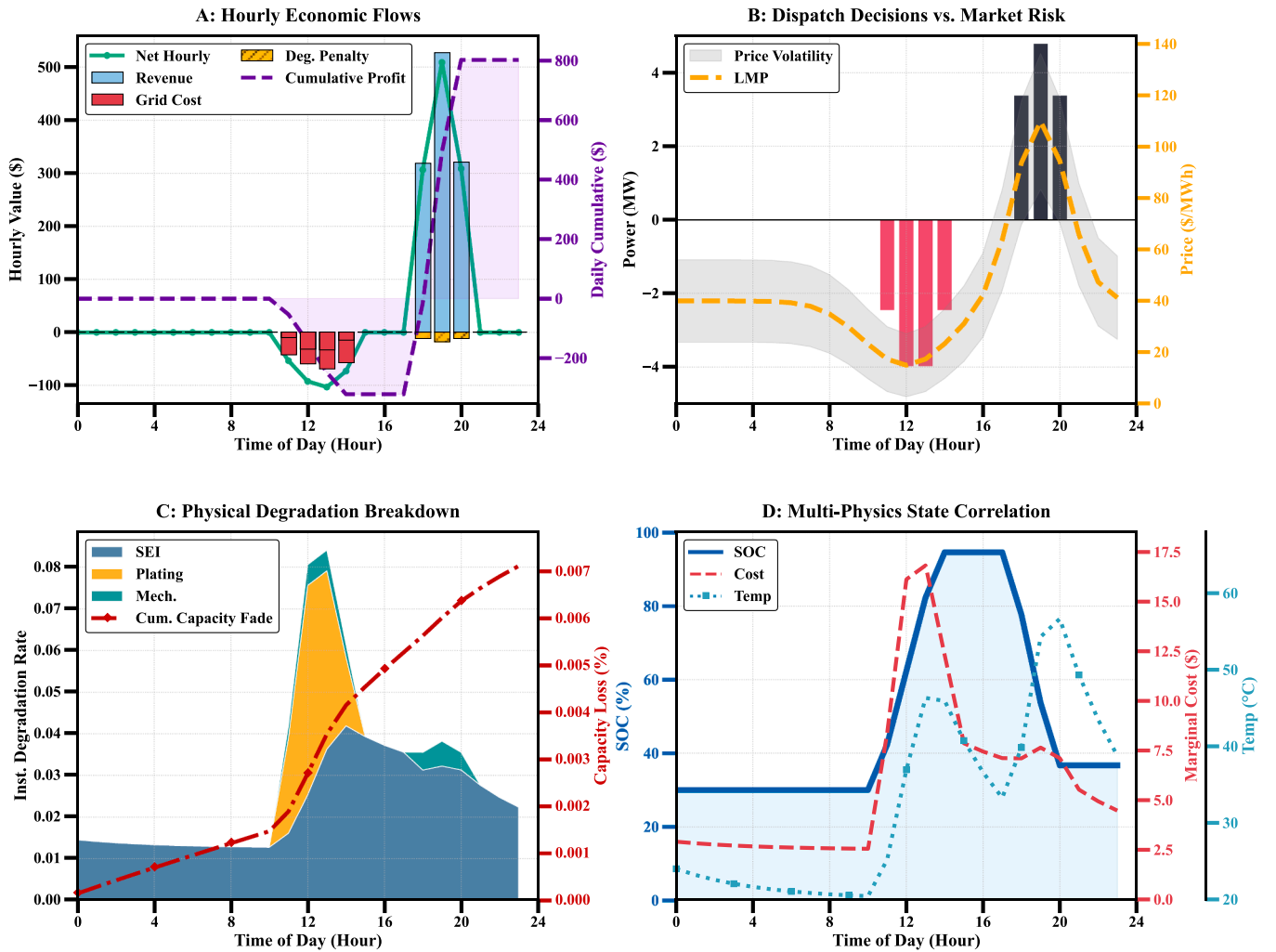


Fig. 13. High-resolution multi-physics and economic analysis of VPP operation over a representative 24-hour cycle.

setting the weighting factor γ in our complete objective function, Eq. (48), to zero. This baseline highlights the economic and operational trade-offs of neglecting asset longevity.

- **No-Stability Model (ignores PFR constraints):** A degradation-aware model ($\gamma = 1.0$) that participates in markets and considers degradation costs, but is not subject to the stability constraint. For this benchmark, the CVaR-based PFR stability constraint, Eq. (47), is relaxed. This comparative analysis highlights the economic and operational trade-offs of providing grid reliability.

This comprehensive benchmarking strategy allows us to highlight the improvements in economic performance, asset longevity, and grid reliability offered by our integrated framework.

Results and discussion

The proposed multi-scale stochastic optimization framework was implemented and tested in a comprehensive case study designed to reflect realistic market and operational conditions, as detailed in Section 5. The following results validate the key contributions of this work, demonstrating the framework's ability to perform holistic co-optimization under uncertainty, quantify and mitigate physical asset degradation, guarantee grid reliability, and adapt its strategy to diverse conditions.

Optimal co-optimization of VPP assets under uncertainty

The framework's core capability is its ability to co-optimize diverse assets across multiple timescales while hedging against uncertainty. Fig. 9 illustrates the model's operational dispatch on a representative day characterized by significant solar generation and price volatility.

Fig. 8 illustrates how the VPP operates in a coordinated manner when there is uncertainty. The VPP (Panel A) experiences price volatility (\$20 to >\$100/MWh) as well as fluctuating PV production (0–9 MW). In response, the VPP's BESS (Panel B) engages in price based arbitrage by charging/discharging at levels of 3–5 MW; meanwhile the BESS' SOC (Panel C) cycles from 10MWh to 20MWh. The increase to a marginal degradation cost of approximately 15\$/MWh due to the low SOC state during the morning hours indicates that the VPP has some degree of physical awareness. At the same time, the VPP offers ancillary services (Panel D); thus, it can provide Regulation capacity in amounts of up to 2.5 MW. The results illustrated here are indicative of the framework's ability to simultaneously and physically co-optimize energy arbitrage, degradation management and grid service.

The quantifiable value of physics-informed degradation modeling

A central contribution of this work is the integration of a high-fidelity degradation model. To validate its impact, the full framework (Degradation-Aware) was benchmarked against a conventional profit-

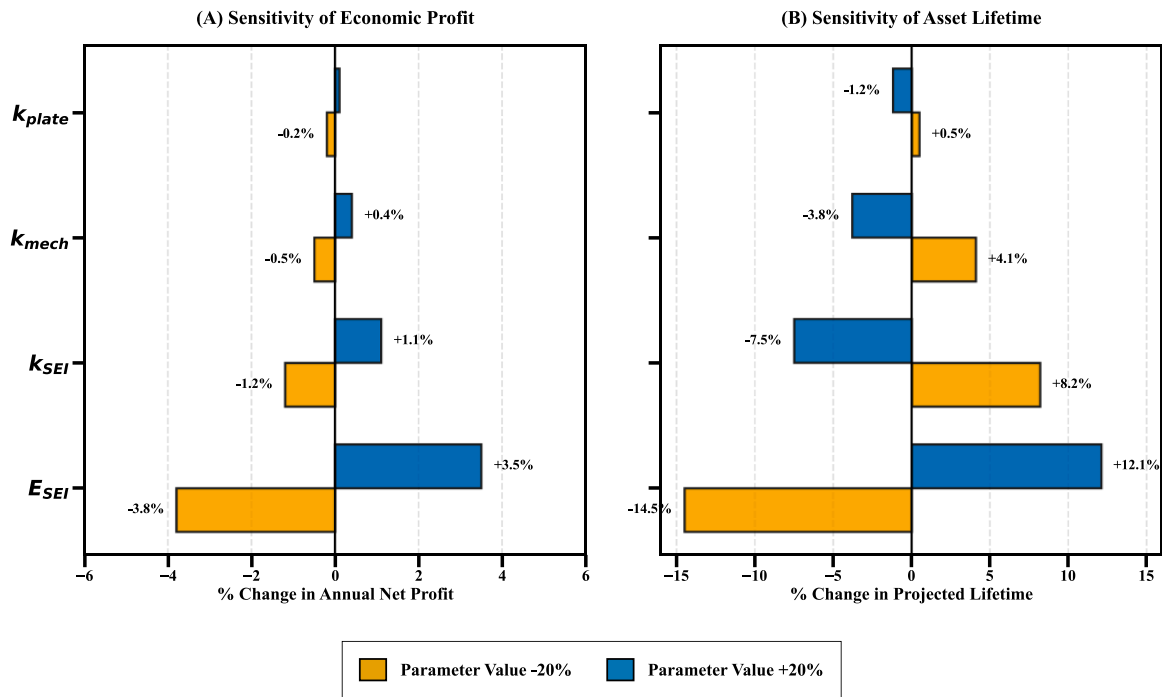


Fig. 14. Sensitivity analysis of VPP performance to electrochemical parameter uncertainty.

maximizing model that ignores degradation costs Degradation-Agnostic," $\gamma = 0$). Fig. 9 provides a compelling visual comparison of the operational and economic outcomes. To complement this, Table 3 presents a quantitative summary of the key performance indicators over an annualized simulation period.

As shown in Fig. 9, the key advantage of degradation-aware optimization is illustrated. Panel A compares the price-focused aggressive dispatch of the Agnostic Model with the more moderate dispatch of the Aware Model, where the latter limits the number of high-stress ramps. This leads to smoother, less aggressive state of charge (SOC) changes for the aware model, as shown in Panel B. Panel D further explains this behavior: the price-focused strategy uses significantly more degradation-inducing C-rates and operates more frequently in extreme SOC zones compared to the aware model. The financial outcome (Panel C) is clear: while the agnostic strategy generates slightly higher gross revenue, it incurs substantially greater degradation costs \$1.46 million annually resulting in a lower Annual Net Profit of \$7.95 million. In contrast, the degradation-aware model reduces wear costs to just \$0.56 million annually, yielding a higher total Net Profit of \$8.38 million. This demonstrates that true profitability is maximized not by ignoring degradation, but by strategically balancing revenue generation with asset preservation.

Guaranteed grid reliability and its economic trade-off

Beyond economics, modern VPPs must contribute to grid stability. Fig. 10 validates the effectiveness of our proposed probabilistic stability constraint by comparing the full model against a No-Stability benchmark. Table 4 provides the precise numerical results underpinning this analysis.

The Fig. 10 verifies the probabilistic stability constraint as it compares the full Stability-Constrained Model to a No-Stability benchmark. Panel A displays the probability density function of excess headroom (available generation above required generation) in an hour where the full Stability-Constrained model's conditional value at risk (CVaR) satisfies the 5.0 MW primary frequency response (PFR) obligation. Panel B shows that over 24 h the full model's CVaR (solid blue line) always satisfies the PFR obligation (99.8 % reliable) whereas the benchmark

does not, thus resulting in a Reliability Deficit. Panel D provides the physical explanation of how the model satisfies the reliability obligation; the model limits peak flow in order to preserve reserve capacity. Panel C measures the specific economic costs associated with the reliability obligation; the model provides this level of reliability for a daily opportunity loss of \$1750 (a 6.7 % decrease in profit). Table 5 shows the same results for both models; the full Stability-Constrained model has 99.8 % reliability compared to 78.5 % for the No-Stability benchmark.

Strategic adaptability and high-resolution validation

Finally, a truly robust framework must be both strategically flexible and tactically adaptive. Fig. 11 demonstrates the framework's use as a long-term strategic planning tool.

The Table 5 illustrates in detail how the various KPI's are related to each of the three operational strategies to allow for an easy comparison of both the financial performance, the lifetime and the reliability performance of the strategies. In this way, it is possible to quantify the differences in the different operational strategies and show that the degradation aware approach produces high value compared to the low additional cost of ensuring the grid stability (and thus the main contribution of the presented holistic framework).

The Seasonal Adaptability of the VPP is illustrated in Fig. 12 through a comparison of VPP Operations in Winter and Summer. In winter (Panel A), the low solar power output, and high price volatility cause the BESS to perform High Power Cycling for Arbitrage and Frequency Regulation. Although this creates Degradation (Panel C) from both Mechanical Stress and Lithium Plating, the optimizer controls it. By contrast, the summer "duck curve" (Panel B) causes a Solar-Soak Strategy, whereby the battery is charged during the middle of the day when prices are low and then discharged to meet the evening peak demand. As a result, the framework incurs a Thermodynamic Penalty (Panel D) by keeping the battery at a high State Of Charge (SOC) and Temperature; therefore, SEI Growth is the dominant degradation pathway. The Framework can dynamically adjust the operational strategy that best manages the different Thermo-Economic Tradeoffs between Revenue and Specific Degradation Pathways in each season.

To validate the internal logic of the proposed framework, Fig. 13. A

24-hour analysis linking market incentives to electrochemical consequences. Panel A shows the model achieves a net daily profit after explicit degradation penalties. Panel B confirms optimal dispatch, with discharge timed to price peaks and charging to troughs. Panel C reveals the physical cost: a spike in Lithium Plating risk during the high-current midday charge (hours 10–14), which the optimizer deems justified by revenue. Panel D explains the degradation profile: the non-linear Marginal Degradation Cost (red dashed line) spikes in correlation with rising Internal Temperature (teal dotted line) and high State of Charge (solid blue line). This demonstrates the framework internalizes multi-physics dynamics into a single economic dispatch signal.

Sensitivity analysis and model robustness

To address the limitations associated with accurately defining the electrochemical properties of large-format batteries a sensitivity study was performed to identify how variations in uncertain parameters would affect the VPP's financial performance and ability to physically manage battery assets. A tornado chart (Fig. 14), displays how a $\pm 20\%$ variation in each of four key electrochemical parameters (rate constant for lithium plating (k_{plate}), rate constant for mechanical stress (k_{mch}), rate constant for SEI formation (k_{SEI}), and SEI activation energy (E_{SEI}) affects the Annual Net Profit (Panel A) and the calculated remaining useful life (Panel B) of the battery assets. The findings from the sensitivity analysis are two-fold. Firstly, the proposed method demonstrates a high degree of economic robustness as an error of $\pm 20\%$ in the parameter with the greatest sensitivity (E_{SEI}) would result in less than a 4 % difference in Annual Net Profit (Panel A). Therefore, the degradation aware dispatch strategy will remain economically viable despite errors in the model. Secondly, the sensitivity analysis reveals SEI to be the major source of battery degradation that influences the remaining useful life of battery assets. The sensitivity analysis shows a greater than 14.5 % difference in the projected remaining useful life of battery assets based upon a $\pm 20\%$ variation in the activation energy for SEI formation (E_{SEI}). While the inclusion of the rate constants for mechanical stress and lithium plating is required to ensure safe operation of battery assets, the inclusion of the rate constants for mechanical stress and lithium plating has a minimal impact on the calculation of the remaining useful life of battery assets.

Conclusion

This paper has developed an overall two-stage stochastic

optimization strategy for virtual power plants (VPP) that takes into account both battery aging and reliability of the electric grid in its endogenous valuation. The use of a physics-informed electrochemical model in the optimization process was shown to result in an increase of 5.4 % in net profit over a year as well as an increase in the life cycle of the battery of 150 % when compared to other non-degradation aware optimization strategies. The proposed method decreased total annual costs of battery degradation by 61 %, thus changing what was previously a large negative asset to a controllable operating cost. Finally, the integration of the CVaR based stability constraints ensured that primary frequency response was available at least 99.8 % of the time with a measurable opportunity loss of 6.7 %. Overall, the results of this study demonstrate the importance of including the effects of physical health and grid risk on the dispatching strategy of virtual power plants to ensure their long-term financial sustainability.

CRedit authorship contribution statement

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

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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.

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Appendix A

Parameter	Symbol	Value	Unit	Description
Nominal Cell Capacity	$Q_{nom,i}$	100	Ah	Total active material capacity
Thermal Capacitance	C_{th}	5000	J/K	Capacity to store thermal energy
Internal Resistance	R^{int}	0.0015	Ω	Ohmic resistance of the cell
Activation Energy (SEI)	E_{SEI}	30000	J/mol	Energy barrier for SEI growth
Activation Energy (Plating)	E_{plate}	40000	J/mol	Energy barrier for Lithium plating
Critical Overpotential	η_{crit}	0.05	V	Threshold for Lithium plating
SEI Growth Constant	A_{SEI}	0.00012	-	Pre-exponential factor for SEI growth
Lithium Plating Constant	A_{plate}	0.000095	-	Pre-exponential factor for Lithium plating
Mechanical Stress Constant	A_{mech}	0.0000021	-	Pre-exponential factor for mechanical stress
Critical Stress Threshold	σ_{crit}	0.5	MPa	Threshold for significant mechanical degradation
Mechanical Stress Exponent	m	2	-	Exponent for stress-induced degradation
Scaling Factor for Stress	γ	1.0	-	Scaling factor for SOC-based stress approximation
Universal Gas Constant	R	8.314	J/(mol·K)	Gas constant

Data availability

Data will be made available on request.

References

- [1] Y. Hu, F.J. Bahamonde-Birke, D. Ettema, Vehicle-to-grid, why not? An interview with battery electric vehicle users with various driving patterns in Utrecht, the Netherlands, *Transp. Policy* (Oxf.) 164 (Apr. 2025) 231–240, <https://doi.org/10.1016/j.tranpol.2025.02.009>.
- [2] A. Kouzelis, K. Linders, S. Bandyopadhyay, G.R.C. Mouli, Analysis of vehicle-integrated photovoltaics and vehicle-to-grid on electric vehicle battery life, *J. Power Sources* 631 (Mar. 2025) 236117, <https://doi.org/10.1016/j.jpowsour.2024.236117>.
- [3] Z. Long, N. Zhang, K. Feng, Y. Wang, J. Wang, Characterizing the Flexibility of Electric Vehicle Fleets Considering Battery Degradation Cost, *IEEE Trans. Ind. Appl.* (2025) 1–11, <https://doi.org/10.1109/TIA.2025.3587212>.
- [4] P. Höschele, S.F. Heindl, S. Erker, C. Ellersdorfer, Influence of reversible swelling and preload force on the failure behavior of a lithium-ion pouch cell tested under realistic boundary conditions, *J. Energy Storage* 65 (Aug. 2023) 107228, <https://doi.org/10.1016/j.est.2023.107228>.
- [5] J. Stekli, A. Ravi, U. Cali, A Cost Benefit Analysis of Vehicle-to-Grid (V2G) Considering Battery Degradation Under the ACOF-Based DLMP Framework, *Smart Cities* 8 (4) (Aug. 2025) 138, <https://doi.org/10.3390/smartcities8040138>.
- [6] S. Sagaria, M. van der Kam, T. Boström, Vehicle-to-grid impact on battery degradation and estimation of V2G economic compensation, *Appl. Energy* 377 (Jan. 2025) 124546, <https://doi.org/10.1016/j.apenergy.2024.124546>.
- [7] F. Reutter, P. Lehmann, Environmental trade-offs of (de)centralized renewable electricity systems, *Energy Sustain. Soc.* 14 (1) (Jun. 2024) 37, <https://doi.org/10.1186/s13705-024-00462-3>.
- [8] T.R. Rockafellar, S.P. Uryasev, Conditional Value-at-Risk for General Loss Distributions, *SSRN Electron. J.* (2001), <https://doi.org/10.2139/ssrn.267256>.
- [9] H.-G. Lee, J.-W. Choi, S.-T. Ryu, K.-J. Lee, Life Degradation of Lithium-Ion Batteries Under Vehicle-to-Grid Operations Based on a Multi-physics Model, *Int. J. Automot. Technol.* 26 (2) (Apr. 2025) 315–326, <https://doi.org/10.1007/s12239-024-00157-w>.
- [10] N. Naval, J.M. Yusta, Virtual power plant models and electricity markets - A review, *Renew. Sustain. Energy Rev.* 149 (Oct. 2021) 111393, <https://doi.org/10.1016/j.rser.2021.111393>.
- [11] R. Li, N.D. Kirkaldy, F.F. Oehler, M. Marinescu, G.J. Offer, S.E.J. O’Kane, The importance of degradation mode analysis in parameterising lifetime prediction models of lithium-ion battery degradation, *Nat. Commun.* 16 (1) (Mar. 2025) 2776, <https://doi.org/10.1038/s41467-025-57968-3>.
- [12] J. Contreras, R. Espínola, F.J. Nogales, A.J. Conejo, ARIMA models to predict next-day electricity prices, *IEEE Trans. Power Syst.* 18 (2003) 1014–1020, <https://doi.org/10.1109/TPWRS.2002.804943>.
- [13] X. Li, et al., Optimal Scheduling of Virtual Power Plants Under a Multiple Energy Sharing Framework Considering Joint Electricity and Carbon Trading, *Inventions* 9 (6) (Dec. 2024) 119, <https://doi.org/10.3390/inventions9060119>.
- [14] Z. Jiang, et al., Charging station layout planning for electric vehicles based on power system flexibility requirements, *Energy* 283 (Nov. 2023) 128983, <https://doi.org/10.1016/j.energy.2023.128983>.
- [15] C. Wen, et al., Design and verification innovative approach of dual-motor power coupling drive systems for electric tractors, *Energy* 247 (May 2022) 123538, <https://doi.org/10.1016/j.energy.2022.123538>.
- [16] M. Naumann, F.B. Spingler, A. Jossen, Analysis and modeling of cycle aging of a commercial LiFePO₄/graphite cell, *J. Power Sources* 451 (2020) 227666, <https://doi.org/10.1016/j.jpowsour.2019.227666>.
- [17] B. Wang, Y. Jiang, M. Jiang, K. Ma, Two-stage distributionally robust optimization operation of virtual power plant considering the virtual energy storage of electric vehicles, *Front Energy Res* 12 (Nov. 2024), <https://doi.org/10.3389/fenrg.2024.1495823>.
- [18] M. Emarati, F. Keynia, M. Rashidinejad, A two-stage stochastic programming framework for risk-based day-ahead operation of a virtual power plant, *Int. Trans. Electr. Energy Syst.* 30 (3) (Mar. 2020), <https://doi.org/10.1002/2050-7038.12255>.
- [19] M.A. Niazi, V. Kumar, M.U. Sadiq, Q. Sajid, M. Rizwan, S. Ahmad, Strategic management of forecast uncertainties to mitigate power imbalances in virtual power plants (vol), *IET Conf. Proc.* 2025 (3) (2025) 64–71, <https://doi.org/10.1049/icp.2025.1096>.
- [20] M.A. Niazi, et al., Optimal Scheduling of Electric Vehicle Aggregators in Residential Areas: A Cost Minimization Approach, *Sukkur IBA J. Emerg. Technol.* 8 (1) (2025) 62–69, <https://doi.org/10.30537/sjet.v8i1.1602>.
- [21] F. Mujjini, T. Betts, L.S. To, R.E. Blanchard, Resilience a means to development: A resilience assessment framework and a catalogue of indicators, *Renew. Sustain. Energy Rev.* 152 (Dec. 2021) 111684, <https://doi.org/10.1016/j.rser.2021.111684>.
- [22] H. Zhou, et al., Capacity degradation of NMC/graphite batteries based on electrochemical-mechanical-thermal coupling, *J. Energy Storage* 135 (2025) 118249, <https://doi.org/10.1016/j.est.2025.118249>.
- [23] V. Kumar, M.A. Niazi, Q. Sajid, M. Rizwan, S.A.A. Shah, S. Khatoun, Optimized Energy Management for EV Charging Stations Using Soft Actor-Critic Reinforcement Learning, 2025 International Conference on Emerging Technologies in Electronics, Computing, and Communication (ICETEC), IEEE, Apr. 2025, pp. 1–6, <https://doi.org/10.1109/ICETEC65365.2025.11070275>.
- [24] H. Chung, J. Kim, Y.S. Bae, J. Moon, Predictive modeling of lithium-ion battery degradation: Incorporating SEI layer growth and mechanical stress factors, *J. Mech. Sci. Technol.* 38 (11) (Nov. 2024) 6157–6167, <https://doi.org/10.1007/s12206-024-1031-y>.
- [25] V. Kumar, M.A. Niazi, M.U. Sadiq, M. Rizwan, Q. Sajid, S. Ahmad, Enhancing electric vehicle battery performance through Grey Wolf Optimization and Deep Reinforcement Learning integration, *IET Conf. Proc.* 2025 (3) (Sep. 2025) 72–79, <https://doi.org/10.1049/icp.2025.1097>.
- [26] M. Naumann, M. Schimpe, P. Keil, H.C. Hesse, A. Jossen, Analysis and modeling of calendar aging of a commercial LiFePO₄/graphite cell, *J. Energy Storage* 17 (2018) 153–169, <https://doi.org/10.1016/j.est.2018.01.019>.
- [27] S. Tao, K. Ding, Z. Li, H. Zhang, Development of a representative driving cycle for evaluating exhaust emission and fuel consumption for Chinese switcher locomotives, *Appl. Energy* 322 (Sep. 2022) 119499, <https://doi.org/10.1016/j.apenergy.2022.119499>.
- [28] L. Bauwens, Y. Xu, DCC- and DECO-HEAVY: Multivariate GARCH models based on realized variances and correlations, *Int. J. Forecast.* 39 (2) (Apr. 2023) 938–955, <https://doi.org/10.1016/j.ijforecast.2022.03.005>.
- [29] A. Yousefi, A. Hadi-Vencheh, Resiliency and reliability of the power grid in the time of COVID-19: An integrated ABC-K-means model for optimal positioning of repair crew, *Electr. Power Syst. Res.* 216 (Mar. 2023) 109022, <https://doi.org/10.1016/j.epr.2022.109022>.
- [30] T. Bollerslev, Generalized autoregressive conditional heteroskedasticity, *J. Econ.* 31 (3) (Apr. 1986) 307–327, [https://doi.org/10.1016/0304-4076\(86\)90063-1](https://doi.org/10.1016/0304-4076(86)90063-1).
- [31] J. Kumar K, S. Kumar, N. V.S., Standards for electric vehicle charging stations in India: A review, *Energy Storage* 4 (1) (Feb. 2022), <https://doi.org/10.1002/est2.261>.
- [32] Y. Zhan, B. Lin, C. Sun, How does pollution heterogeneity affect the role of cleaner production regulations? Evidence from Chinese enterprises’ domestic value-added in exports, *Energy Econ.* 122 (Jun. 2023) 106681, <https://doi.org/10.1016/j.eneco.2023.106681>.
- [33] A.J. Conejo, M. Carrión, J.M. Morales, Decision Making Under Uncertainty in Electricity Markets, Springer, 2010, <https://doi.org/10.1007/978-1-4419-7421-1>.
- [34] P. Huang, et al., Comprehensive investigation on the durability and safety performances of lithium-ion batteries under slight mechanical deformation, *J. Energy Storage* 66 (Aug. 2023) 107450, <https://doi.org/10.1016/j.est.2023.107450>.
- [35] California Independent System Operator, “Open Access Same-Time Information System (OASIS).” Accessed: Sep. 15, 2025. [Online]. Available: (<https://www.caiso.com>).
- [36] N.R.E.L Open Energy Data Initiative (OEDI), Commercial and Residential Hourly Load Profiles for all TMY3, (<https://data.openel.org/submissions/1>).