TECHNO-ECONOMIC BI-LEVEL OPTIMIZATION OF BATTERY STORAGE FOR WIND FARM EXPANSION

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ABSTRACT

Wind farm expansion is increasingly constrained by existing grid assets, where export limits and transformer thermal loading can force curtailment and reduce project value. This study presents a flexible techno-economic optimization framework that integrates a Battery Energy Storage System (BESS) into an existing wind farm to enhance investment efficiency without reinforcing transmission infrastructure. Wind uncertainty is represented probabilistically by using a Weibull model and converted to power through a utility-scale turbine power curve. A bi-level structure is adopted: at the upper level, Harris Hawks Optimization (HHO) determines the BESS energy and power ratings to maximize Net Present Value (NPV) over a 20-year lifetime; at the lower level, Pattern Search refines the day-ahead charge/discharge schedule under sequential SOC dynamics, operational limits, and an end-of-day energy neutrality condition. The framework is evaluated on the IEEE 30-bus system with wind plants connected at buses 5 and 11 and a transformer thermal model enforced at a 3-min resolution. Results show that wind expansion improves NPV from 4.29M€ to 10.58M€, while adding a 72MWh BESS further increases NPV to 14.10M€, corresponding to a ~33.3% gain over wind-only expansion at the same 90MW wind capacity. The proposed framework provides a practical pathway to improve wind project economics under uncertainty and grid thermal constraints using moderate storage sizing.

Keywords: *Wind farm expansion; Battery energy storage; Net present value; Bi-level optimization.*

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1. INTRODUCTION

In the context of global climate change, the transition toward clean energy sources such as Wind power has become a central pillar in decarbonization strategies [1], yet its economic performance is increasingly challenged when projects are developed under export constraints and reduced policy support [2]. In practical grids, wind farm expansion is not solely limited by resource availability, but also by the hosting capacity of existing transmission corridors and the thermal capability of step-up transformers. When wind generation exceeds the deliverable limit, curtailment becomes unavoidable; conversely, when production falls below market commitments, imbalance penalties may apply. These factors jointly reduce profitability and discourage private investment even in regions with favorable wind conditions [3].

BESS provides a direct flexibility option for mitigating wind variability. By absorbing surplus power and releasing energy during deficits, BESS can reduce curtailment, lower penalty exposure, and exploit temporal price signals [4]. However, BESS requires substantial upfront investment, and over-sizing storage can increase financial risk. Therefore, a coordinated planning-and-operation strategy is required to determine "just-enough" storage capacity that maximizes long-term value while respecting grid operating constraints [5].

Existing literature has been widely investigated either BESS sizing or operational scheduling for wind integration. Nevertheless, many studies adopt simplified grid constraints or do not explicitly leverage spare export capability under transformer thermal limits for wind expansion decisions. Moreover, degradation-aware operation is often omitted despite its relevance to lifecycle cost. Motivated by these gaps, this paper evaluates wind farm development strategies with and without BESS under seasonal wind conditions and grid feasibility constraints, using NPV as the core financial metric.

Table 1. Comparison of studies on wind power integration

Paper	IEEE system	Capacity Degradation	Profit	NPV
[6]	x	x	✓	x
[7]	x	✓	x	x
[8]	x	x	✓	✓
[9]	x	✓	✓	✓
[5]	30 Bus	x	✓	x
[10]	30 Bus	x	✓	x
This paper	30 Bus	✓	✓	✓

The main contributions are summarized as follows:

(1) A bi-level optimization structure is proposed in which HHO optimizes BESS sizing to maximize NPV, while Pattern Search determines day-ahead charge/discharge scheduling under SOC dynamics and practical operational rules.

(2) Battery degradation is incorporated via a cycle-aging cost condition, enabling economically meaningful dispatch decisions that balance short-term gains against lifetime impacts.

(3) The approach is validated on the IEEE 30-bus system with wind integration and transformer thermal constraints, demonstrating measurable NPV improvement under wind expansion cases.

2. MATERIALS AND METHODS

This section formulates the techno-economic optimization problem for wind farm expansion with battery storage integration. The model integrates wind power uncertainty, battery operational dynamics, grid feasibility constraints, and long-term financial evaluation into a unified bi-level framework. The objective is to maximize NPV of the project over its lifetime while respecting operational and infrastructure limits.

2.1. Wind revenue model under uncertainty

In competitive electricity markets, wind power producers are typically required to submit day-ahead generation schedules. As a result, total wind revenue can be decomposed into a scheduled component and a deviation-related component, as expressed in (1) [11].

$$\mathrm{R_w(P_w) = R_{ws}(P_{ws}) + R_{wu}(\Delta P_w)} \quad (1)$$

where $\mathrm{R_{ws}(P_{ws})}$represents the guaranteed revenue from offering wind power to the electricity market, as defined in Equation (2), and $\mathrm{R_{wu}(P_w)}$denotes the uncertain revenue resulting from deviations between the actual wind power output and the scheduled (offered) power, as described in Equation (3).

$$\mathrm{R_{ws}(P_{ws}) = \lambda * P_{ws}} \quad (2)$$

$$\mathrm{R_{wu}(\Delta P_w)} = \begin{cases} \mathrm{R_{Rw}(\Delta P_w)} & \mathrm{, if\ P_w > P_{ws}} \\ \mathrm{C_{Pw}(\Delta P_w)} & \mathrm{, if\ P_w < P_{ws}} \end{cases} \quad (3)$$

When actual production surpasses the committed amount, the additional revenue $\mathrm{R_{Rw}(\Delta P_w)}$ is assumed to be zero in this study, reflecting the practical situation in which surplus energy is either curtailed or compensated at negligible prices to preserve system stability. Conversely, when generation is below the scheduled level, a penalty cost $\mathrm{C_{Pw}(\Delta P_w)}$ is incurred. This penalty is evaluated according to (4).

$$\mathrm{C_{Pw}(\Delta P_w) = k_P.\lambda.\int_0^{P_{ws}} (P_w - P_{ws}).f_w(P_w).dP_w} \quad (4)$$

where $\mathrm{k_P}$ is the penalty coefficient, set to 2 in the present study, and $\mathrm{f_w(P_w)}$ denotes the probability density function of wind power output. Wind speed uncertainty is represented using a two-parameter Weibull distribution, widely adopted for wind resource modeling due to its adaptability to various climatic conditions [12]. The wind speed samples are subsequently converted into electrical power using the characteristic curve of the Enercon E82-E4 turbine (rated at 3MW) [11]. The resulting probabilistic generation profiles form the basis for the techno-economic evaluation of wind expansion strategies.

2.2. BESS model and degradation-aware operation

The integration of wind generation into modern power systems introduces substantial variability, which requires additional flexibility resources to maintain operational reliability. Among available technologies, Battery Energy Storage Systems (BESS) provide a practical means of mitigating short-term fluctuations by temporally shifting energy from surplus intervals to deficit periods [13, 14]. Rather than increasing installed capacity, storage enhances the controllability of renewable output, enabling improved compliance with export limits and market commitments.

To realistically represent storage behavior over the project lifetime, the proposed model explicitly accounts for battery aging effects. The available energy capacity of a BESS gradually declines due to both calendar aging and cycle-induced degradation [15]. In operationally intensive applications such as wind balancing, cycle aging plays a dominant role and is therefore incorporated through a degradation metric denoted as Cycledegrad [%], adapted from [16]. This degradation component is linked to the depth of discharge (DoD) and the corresponding charge/discharge rate, both derived from successive variations in the state of charge, [SOC(t) − SOC (t − 1), across time intervals.

Within the optimization framework, storage dispatch decisions are not based solely on short-term revenue maximization. Discharging is permitted only when the anticipated economic benefit exceeds the associated degradation cost, ensuring that immediate gains do not compromise long-term asset value. At any given time step, the battery operates in a mutually exclusive mode either charging or discharging subject to SOC limits and rated power constraints. Charging is triggered when available wind generation surpasses deliverability or market limits and the SOC remains below its upper threshold. Conversely, discharging occurs when generation is insufficient and the SOC is above its minimum bound. Both processes are constrained by the rated power (P_{BESS}) and efficiency parameters. Charging and discharging efficiencies are assumed to be approximately 95%, resulting in an effective round-trip efficiency of about 90%. Furthermore, the operational SOC window is restricted to 20%–90% to prevent excessive cycling stress, reflecting practical battery management strategies that mitigate accelerated degradation and preserve lifecycle performance. When surplus wind power is available, the excess energy is first absorbed by the BESS, subject to the maximum charging power and the available storage margin defined by the current SOC. If the surplus exceeds the BESS absorption capability, the upper-level HHO algorithm determines whether increasing the BESS size is economically justified based on the NPV objective function in (15). Otherwise, the remaining surplus power is curtailed through wind turbine control.

$$R_{w,BESS}\text{-}R_w \geq \text{Cycledegrad} \tag{5}$$

where $R_{w,BESS}$ denotes the wind power revenue with BESS integration.

$$P_{bess} = \frac{E_{bess}}{\text{duration}} \tag{6}$$

$$E_{cha} = P_{cha}.t \tag{7}$$

$$E_{dis} = P_{dis}.t \tag{8}$$

where E_{cha} is the charging energy, E_{dis} is the discharging energy, and P_{cha}, P_{dis} are the charging and discharging power of the BESS, respectively.

$$P_{cha} = \int_{P_t^{bid}}^{P^{wr}} \begin{pmatrix} p_t^{wp} \\ -P_t^{bid} \end{pmatrix}. f_w(p_t^{wp}). dp_t^{wp}, \quad P_{cha} \leq P_{BESScha} \tag{9}$$

$$P_{dis} = \int_0^{P_t^{bid}} (p_t^{wp} - P_t^{bid}). f_w(p_t^{wp}). dp_t^{wp}, \quad P_{dis} \leq P_{BESS} \tag{10}$$

2.3. Transformer Thermal Model

The transformer plays a critical role in determining the feasible export capability of the wind farm, since its thermal performance directly limits the amount of power that can be transferred to the grid. In practice, sustained or repeated overload may accelerate insulation aging and reduce transformer lifetime. Therefore, the transformer is represented in this study through a thermal constraint model, in which the operating condition must satisfy the allowable limits of both hot-spot temperature and top-oil temperature. These limits can be expressed as

$$\theta_t^{hst} \leq \theta_t^{hst,max} \tag{11}$$

$$\theta_t^{top} \leq \theta_t^{top,max} \tag{12}$$

where θ_t^{hst} is the winding hot-spot temperature and θ_t^{top} is the top-oil temperature at time t. Both variables vary with the transformer loading level and are commonly used to evaluate the thermal admissibility of transformer operation [17]. In addition to the instantaneous thermal limits, the transformer aging effect can also be considered through the loss-of-life index, so that the transformer is operated not only within short-term thermal boundaries but also within an acceptable lifetime degradation range. This modeling approach allows the proposed optimization framework to reflect the practical thermal constraints of the transformer under wind power fluctuation and BESS dispatch.

3. METHODOLOGY

Section 3 presents the proposed methodology to quantify the economic impact of alternative wind farm development pathways under existing grid and transformer constraints. Representative system configurations are defined and evaluated under a consistent techno-economic setting to ensure fair comparability. The assessment focuses on long-term investment performance using NPV, emphasizing the incremental value created by wind capacity expansion and storage integration relative to baseline operation.

3.1. Scenario Descriptions

Three development cases are defined to assess the economic and operational impacts of wind expansion and storage integration under identical grid conditions.

1) Case A - Baseline Operation

The wind power plant operates at its existing installed capacity of 75MW at Bus 5 of the IEEE 30-bus system. No infrastructure modification or storage integration is introduced. This case establishes the reference NPV level.

2) Case B - Wind-Only Expansion

Wind capacity is increased to 90MW while maintaining the original transmission and transformer constraints. No storage system is installed, and system feasibility is evaluated through power flow simulation under export limits.

3) Case C - Storage-Integrated Expansion

Wind capacity is maintained at 90 MW and complemented by a Battery Energy Storage System. The storage size and rated power are determined via HHO to maximize NPV, while dispatch is optimized at the lower level. The BESS mitigates curtailment and reduces imbalance exposure without reinforcing the grid.

3.2. Study Setup and Input Assumptions

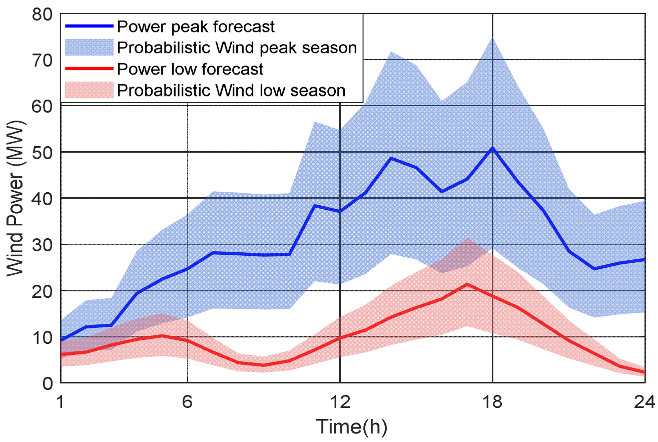

Figure 1. Forecasted Wind Energy in Peak and Low Seasons in Bus 5

The techno-economic assessment is conducted under unified financial assumptions to ensure consistency across cases. The wind power plant (WPP) installation cost is assumed to be €950,000/MW (excluding O&M), with annual operation and maintenance expenses estimated at 1.5% of the capital investment and a project lifetime of 20 years [18].

Although wind generation is modeled at Buses 5 and 11 to reflect system-level renewable penetration, the proposed BESS sizing and dispatch optimization is performed for the wind plant connected at Bus 5. Wind variability is represented using two seasonal operating modes (high-wind and low-wind) based on forecasted data [19]. The low-wind season is primarily observed during May–July according to meteorological statistics [20]. Wind speed is modeled using a Weibull distribution and converted into power output profiles corresponding to a maximum installed capacity of 75 MW. The seasonal generation patterns used in the simulation are illustrated in Figure 1.

3.3. Bi-Level Optimization Framework

To coordinate long-term storage planning with short-term operational decisions, a bi-level optimization framework is adopted. The upper level determines the optimal BESS size in terms of energy capacity and rated power, while the lower level identifies the economically optimal day-ahead charge/discharge schedule under operational and grid constraints. This hierarchical structure separates investment decisions from dispatch control, ensuring that storage sizing reflects its operational contribution to project profitability.

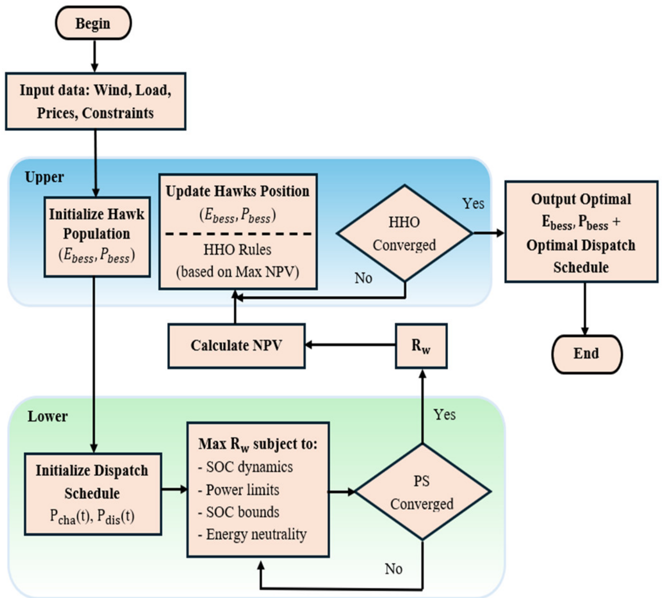

Figure 2. Bi-Level Optimization Procedure for BESS Sizing and Dispatch

The overall solution process is illustrated in Figure 2. For each candidate BESS size generated by the upper-level optimizer, the lower-level dispatch problem is solved to obtain the optimal daily revenue, which is then annualized and used to compute the corresponding NPV. The resulting NPV value serves as the objective function for the upper-level HHO search, and the nested evaluation continues iteratively until convergence is achieved.

Upper-Level Optimization Using HHO

The upper-level problem focuses on determining the optimal BESS energy capacity E_{bess} and rated power P_{bess}, that maximize the project's NPV over its lifetime. Harris Hawks Optimization (HHO) is employed due to its ability to balance global exploration and local exploitation without requiring gradient information [21].

Each hawk in the population represents a candidate pair **(**E_{bess}, P_{bess}) within predefined technical limits. For every candidate solution, the lower-level dispatch optimization is executed to estimate annual revenue and compute the corresponding NPV. Based on the escaping energy mechanism and position update rules of HHO, the candidate solutions are iteratively refined. The process continues until the maximum number of iterations is reached or the improvement in NPV becomes negligible.

This approach ensures that storage sizing decisions are evaluated based on their full operational and economic impact rather than on simplified assumptions.

Lower-Level Dispatch Optimization Using Pattern Search

Given a fixed BESS size from the upper level, the lower-level problem optimizes the 24-hour dispatch trajectory at a 3-minute resolution. Pattern Search is adopted as a derivative-free method suitable for non-smooth, simulation-driven objective functions [22]. For each candidate dispatch vector, SOC is updated sequentially while enforcing power limits, SOC bounds, and end-of-day energy neutrality. The resulting feasible dispatch schedule is used to compute daily wind-related revenue, including penalty and degradation considerations, and the optimal revenue is returned to the upper level.

$$\max \mathrm{R_w} = \mathrm{R_w}(\mathrm{P_{charge}}, \mathrm{P_{discharge}}) \tag{13}$$

$$\sum_{t=1}^{T} \eta_c \mathrm{P_{charge}}(t) - \frac{1}{\eta_d} \mathrm{P_{discharge}}(t) = 0 \tag{14}$$

3.4. Financial Evaluation Procedure

For each candidate configuration, daily revenue obtained from the lower-level optimization is annualized considering seasonal wind profiles. Annual operating and maintenance costs are deducted, and green certificate revenues are included where applicable. NPV is then computed over a 20-year horizon using a predefined discount rate. This procedure ensures that both operational performance and investment scale are consistently reflected in long-term economic assessment. In addition, because the BESS capacity is subject to degradation over time, the economic model may include the replacement cost of the storage system when its usable capacity falls below an acceptable operational threshold. In such a case, a reinvestment cost can be introduced at the corresponding replacement year. Otherwise, if reinvestment is not economically feasible, the degraded BESS may continue operating with reduced usable capacity, which will be reflected in the subsequent cash flow.

$$\mathrm{NPV} = \sum_{y=1}^{Y} \frac{\mathrm{R_s}}{(1+r)^t} - \mathrm{I_s} \tag{15}$$

where $\mathrm{R_s}$ is the project cash flow calculated as in (16), T is the expected project lifetime, assumed to be 20 years for wind turbines, and r is the discount rate or interest rate (%). For scenarios involving BESS replacement, the corresponding reinvestment cost should be discounted to its occurrence year and incorporated into the NPV calculation.

$$\mathrm{R_s} = \mathrm{R_w} - \mathrm{C_s} + \mathrm{G_t} \tag{16}$$

where $\mathrm{R_w}$ is the revenue from WPP, $\mathrm{C_s}$ is the operation and maintenance (O&M) cost. $\mathrm{G_t}$ represents Green Certificates, which provide additional income and certify the renewable origin of the electricity. The registration fee in 2019 was 0.305 [€/MWh], as reported in [10]. If required, the replacement cost of the BESS can be treated as an additional lifecycle cost term in years when battery renewal is carried out.

4. RESULTS AND DISCUSSION

4.1. IEEE 30-Bus System

The IEEE 30-bus benchmark system is adopted as the analytical test platform to evaluate wind integration strategies and their corresponding economic impacts. This network comprises 30 buses, 41 transmission branches, and 6 generating units, consistent with the standard IEEE 30-bus configuration reported in [23, 24]. The test system provides a well-established framework for assessing both operational feasibility and techno-economic performance under realistic grid constraints.

In the baseline configuration, conventional thermal generation is installed on buses 1, 2, 8, and 13. To represent renewable integration, two of the original generating units at buses 5 and 11 are substituted with wind power plants (WPPs). Bus 5 accommodates 25 wind turbines and bus 11 integrates 20 turbines, each rated at 3MW. Wind resource variability is characterized using a two-parameter Weibull distribution, with the corresponding shape (k) and scale (c) coefficients obtained from [11] and listed in Table 2. The probabilistic wind speed model is subsequently transformed into electrical output through the turbine power curve, providing the time-dependent wind generation profiles employed in the optimization framework.

Table 2. WPP parameters

Wind farm	No. of turbines	Rate power, P_{wr} (MW)	Weibull PDF parameter	Weibull mean, M_{wbl}
5	25	75	c = 9, k = 2	v = 7.976m/s
11	20	60	c = 10, k = 2	v = 8.862m/s

4.2. Simulation results

Table 3. Case-based economic comparison

Scenario	Baseline Operation	Wind-Only Expansion	Storage-Integrated Expansion	[3]	[25]
Wind Power rated (MW)	75	90	90	90	90
Test System	IEEE 30-bus	IEEE 30-bus	IEEE 30-bus	IEEE 30-bus	IEEE 30-bus
Transformer Thermal Model	✓	✓	✓	✓	✓
Storage Battery (MWh)	No	No	72	140	72
WT-BESS ratio (%)	x	x	80	155.56	80
NPV (M€)	4.29	10.58	14.1	17.28	13.61

The results in Table 3 reveal a clear escalation in project value as system flexibility is progressively introduced. Under the original 75MW configuration without storage support, the project attains an NPV of 4.29M€, indicating constrained economic adaptability when operating solely within fixed export and transformer thermal limits. Although technically viable, this configuration remains vulnerable to wind variability and imbalance exposure, limiting its long-term financial performance. Expanding the installed capacity to 90MW significantly elevates the NPV to 10.58M€, representing an increase of over 146% relative to the initial configuration and demonstrating that the existing infrastructure still offers exploitable hosting capability. However, capacity expansion alone does not mitigate temporal discrepancies between generation and grid deliverability, leaving residual curtailment and price-related inefficiencies. The integration of a 72MWh battery further enhances NPV to 14.10M€, corresponding to a 33.3% improvement compared with the wind-only expansion case. This additional value stems not from increased energy production per se, but from improved temporal redistribution of generation within operational and thermal constraints. By strategically absorbing excess output during constrained intervals and discharging during economically favorable periods, the storage system enhances effective infrastructure utilization while reducing imbalance exposure. The resulting 80% WT-BESS ratio captures a substantial portion of the economically recoverable flexibility without incurring the capital intensity associated with oversized storage deployments.

In comparison with prior studies, the proposed configuration yields a slightly higher NPV than that reported in [25] under the same 72MWh storage capacity. The comparisons with [3] and [25] are conducted under the same assumed project location, transformer constraints, and main input dataset, thereby ensuring a consistent basis for techno-economic evaluation. This improvement is mainly attributed to the lower-level Pattern Search optimization, which refines the BESS charging/discharging schedule beyond SOC-threshold-based operation and thereby improves the overall economic performance of the wind farm. Although the 140MWh configuration in [3] achieves a higher absolute NPV of 17.28M€, the associated storage-to-wind ratio exceeds 150%, implying significantly greater investment exposure. The marginal increase in NPV does not scale proportionally with storage capacity, indicating diminishing economic returns at higher storage sizes. From a practical investment perspective, the moderate storage configuration identified here represents a more balanced compromise between profitability enhancement and capital commitment under transformer thermal constraints. The 72MWh storage capacity and the corresponding WT–BESS ratio are not preselected values, but are obtained through the coordinated upper-level HHO sizing and lower-level Pattern Search dispatch optimization. Therefore, they should be interpreted as the optimal solution for the considered study scenario rather than as universally optimal values.

5. CONCLUSION

This paper proposed an integrated techno-economic optimization framework to evaluate wind farm expansion under export and transformer thermal constraints. By formulating the problem within a bi-level structure, long-term storage sizing and short-term dispatch decisions were coordinated rather than treated independently. The upper level employed Harris Hawks Optimization to determine the storage capacity that maximizes Net Present Value, while the lower level utilized Pattern Search to optimize day-ahead battery operation under SOC dynamics, degradation-aware conditions, and end-of-day energy neutrality. This hierarchical approach ensured that storage investment decisions were assessed based on their realized operational contribution.

Simulation results on the IEEE 30-bus system demonstrate that although wind capacity expansion alone substantially improves economic performance, additional value can be unlocked through the strategic integration of battery storage. The findings highlight that economic gains arise primarily from enhanced temporal utilization of existing infrastructure rather than from simple energy volume increase. Moreover, the analysis suggests that storage capacity exhibits diminishing marginal financial returns beyond a balanced WT–BESS ratio, indicating that optimal coordination is more critical than maximal deployment. Overall, the proposed framework offers a practical decision-support methodology for developers aiming to improve profitability within existing grid limits. Future work may extend the model to multi-day operational horizons, incorporate stochastic electricity price dynamics, and explore computational enhancements to improve scalability for larger transmission systems.

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