



Degradation-aware multi-objective optimization of wind-battery energy systems using NSGA-II

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ABSTRACT

Battery energy storage systems (BESS) are increasingly integrated with wind power plants to mitigate production variability and enhance economic performance in electricity markets. However, optimal battery sizing requires simultaneous consideration of economic profitability, operational smoothing capability, and lifecycle degradation, which inherently represent conflicting objectives.

This study proposes a degradation-aware multi-objective optimization framework for wind-battery energy systems using the Non-Dominated Sorting Genetic Algorithm II (NSGA-II). The framework integrates dynamic state-of-charge modeling, equivalent full cycle (EFC) based degradation estimation, and capital recovery factor (CRF) based economic evaluation within a continuous optimization structure. Real operational data consisting of 744 h of wind generation and electricity price information from a 70 MW wind power plant are employed to evaluate system performance.

The optimization results reveal a well-defined three-dimensional Pareto surface representing nonlinear trade-offs among net profit, grid injection variance, and battery degradation. The deterministic benchmark identifies a profit-maximizing configuration with a storage capacity of approximately 5.0 MWh and a net profit of approximately \$632,687 over the analyzed period. In contrast, the NSGA-II optimization generates a diverse Pareto solution set enabling flexible trade-off analysis.

The TOPSIS-based compromise solution selected using weights of 0.50 for profit, 0.25 for variance, and 0.25 for degradation, corresponds to a battery capacity of 10.18 MWh and a power rating of 2.00 MW, achieving a net profit of approximately \$266,189 over the simulation period. Pareto quality evaluation yields a hypervolume value of 66,038,808 and a spread indicator of 0.455. The results demonstrate that degradation-aware multi-objective optimization provides a complementary framework for wind-battery system planning, offering diverse Pareto trade-offs unavailable to deterministic sizing approaches.

1. Introduction

The large-scale deployment of wind energy has significantly reshaped modern power systems over the past two decades. However, the intrinsic intermittency and stochastic nature of wind generation continue to pose substantial operational and economic challenges for

grid operators and market participants [1,2]. Variability in wind output introduces power fluctuations, imbalance penalties, and revenue uncertainty in electricity markets, particularly in systems with high renewable penetration [3,4].

Battery Energy Storage Systems (BESS) have emerged as a key enabling technology to mitigate these challenges by enhancing

Abbreviations: BESS, Battery Energy Storage System; CAPEX, Capital Expenditure; CRF, Capital Recovery Factor; EFC, Equivalent Full Cycle; HV, Hypervolume; IEA, International Energy Agency; IRR, Internal Rate of Return; MOPSO, Multi-Objective Particle Swarm Optimization; NSGA-II, Non-Dominated Sorting Genetic Algorithm II; NPV, Net Present Value; PJM, PJM Interconnection (electricity market); PV, Photovoltaic; SOC, State of Charge; TCMB, Central Bank of the Republic of Turkey; TOPSIS, Technique for Order of Preference Similarity to Ideal Solution; TurkStat, Turkish Statistical Institute; WACC, Weighted Average Cost of Capital; $P_{grid}(t)$, Grid power output at time t [MW]; $P_{wind}(t)$, Wind generation at time t [MW]; $P_{dis}(t)$, Battery discharge power at time t [MW]; $P_{ch}(t)$, Battery charging power at time t [MW]; SOC_t , State of charge at time step t [—]; SOC_{min} , Minimum SOC limit [—]; SOC_{max} , Maximum SOC limit [—]; η_c , Charging efficiency [—]; η_d , Discharging efficiency [—]; E_{max} , Battery energy capacity [MWh]; $E_{dis,total}$, Cumulative discharge energy [MWh]; C_E , Battery energy cost [\$/MWh]; C_P , Battery power (converter) cost [\$/MW]; r , Discount rate (WACC) [—]; $Price(t)$, Electricity market price at time t [\$/MWh]; w_j , TOPSIS objective weight for objective j [—]; C_i , TOPSIS relative closeness coefficient [—].

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dispatchability, reducing output variability, and enabling energy arbitrage [5–7]. Early studies demonstrated that integrating storage with renewable generation improves system flexibility and reduces balancing costs [8], while subsequent research quantified the economic value of arbitrage and regulation services [9,10]. Comprehensive reviews of storage technologies further highlight lithium-ion batteries as a dominant solution due to high efficiency, modularity, and declining costs [11,12].

Despite technological advances, the economic viability of wind-integrated storage strongly depends on optimal sizing and operational strategy design [13,14]. Incorrect sizing may either lead to underutilization or excessive capital expenditure, thereby undermining project profitability. Consequently, optimal battery sizing for wind applications has become an active research area [15–17].

Traditional sizing approaches often rely on deterministic simulations or discrete parameter sweeps [18,19]. While such methods provide useful insights, they may fail to capture nonlinear trade-offs among profit, power variance reduction, and battery degradation [20,21]. Moreover, deterministic searches may overlook intermediate optimal solutions in continuous design spaces [20].

To address these limitations, multi-objective optimization techniques have been increasingly adopted in renewable energy system design [22,23]. Among these, the Non-Dominated Sorting Genetic Algorithm II (NSGA-II) remains one of the most widely applied algorithms due to its elitist sorting mechanism and diversity preservation capability [24]. NSGA-II has been successfully used in hybrid renewable system optimization and microgrid operation problems [25], demonstrating its suitability for complex nonlinear energy system planning tasks.

However, critical gaps remain in wind–battery co-optimization literature, particularly regarding integrated degradation modeling, economic lifecycle analysis, and quantitative Pareto performance evaluation.

2. Related works

2.1. Wind–battery sizing and power smoothing

Initial research on storage integration focused primarily on operational strategies and power smoothing. Korpaas et al. [8] investigated optimal operation and sizing of storage for wind power plants, highlighting the importance of balancing storage capacity and operational constraints. Teleke et al. [15] proposed dispatch strategies for wind farm battery integration, while Abbey and Joos [5] explored storage applications for renewable variability mitigation.

Power smoothing through battery coordination has been extensively studied [6,26,27], demonstrating that properly sized storage can significantly reduce output fluctuations and improve grid compliance. Nevertheless, many of these studies emphasize technical smoothing performance without fully integrating long-term economic trade-offs [8,28].

Hybrid renewable system design studies expanded the scope toward multi-objective optimization [12,13,15,29]. For example, Huang et al. [29] applied NSGA-II to microgrid operation, illustrating the algorithm's capability to balance conflicting objectives. However, these works often focus on hybrid PV-wind systems rather than wind-dominant market participation scenarios. In addition, our previous study [30] presented a strategic design framework for integrating wind energy with battery storage to enhance operational efficiency and sustainability. This work provides foundational insights on battery sizing and energy dispatch strategies that are extended in the present study by explicitly incorporating degradation-aware multi-objective optimization and Pareto front analysis.

2.2. Degradation-aware modeling

Battery degradation significantly affects long-term project

economics. Lithium-ion aging mechanisms have been extensively characterized in electrochemical studies [21,22]. Subsequent modeling approaches incorporated degradation into lifecycle assessment frameworks [23,24].

Calendar aging and cycling degradation models demonstrate strong dependence on depth-of-discharge and throughput [15,31]. Electrochemical modeling approaches further quantify capacity fading dynamics [32,33]. Despite these advances, only a limited number of wind-storage optimization studies explicitly integrate degradation cost into the objective function [34,35].

Most economic optimization studies assume fixed lifetime or simplified cycle limits, potentially leading to optimistic profitability projections [10]. Thus, embedding degradation cost directly within multi-objective optimization remains an open challenge.

2.3. Economic optimization and arbitrage

The economic value of energy storage has been widely examined in electricity markets [10,36]. Walawalkar et al. [10] quantified arbitrage value under market price volatility, while He and Sioshansi [37] provided deeper economic insights into storage investment decisions.

Broader system-level studies demonstrated that storage facilitates renewable integration and increases system flexibility [38,39]. Reviews of lifecycle cost and technology comparison further emphasize the importance of accurate economic modeling [40,41].

However, many studies treat arbitrage as a single-objective maximization problem without considering grid variance reduction or degradation simultaneously. Integrated tri-objective formulations remain limited in the literature.

2.4. Multi-objective optimization and pareto quality metrics

Multi-objective evolutionary algorithms provide a structured approach to exploring trade-offs among conflicting objectives [20,42,43]. NSGA-II has become a benchmark algorithm due to its non-dominated sorting and crowding distance mechanisms [1].

Pareto front quality evaluation metrics such as hypervolume and diversity indicators are well established in evolutionary computation literature [44–46]. Nevertheless, many applied renewable energy studies report Pareto fronts qualitatively without rigorous convergence assessment.

Furthermore, benchmarking evolutionary algorithms against deterministic approaches remains uncommon in wind-battery sizing literature [20,47]. Such comparisons are essential to evaluate whether heuristic search provides tangible improvements over structured grid exploration.

3. Research gap

Based on the reviewed literature, several gaps are identified:

First, the integration of profit maximization, variance minimization, and degradation minimization within a unified tri-objective framework remains limited in existing studies [17,37]. Second, lifecycle degradation models are rarely embedded directly within optimization loops, which may lead to unrealistic lifetime estimations [15,23–26,32,33]. Third, rigorous Pareto front quality evaluation using metrics such as hypervolume and diversity indicators is still uncommon in renewable energy storage optimization studies [2,45]. Furthermore, systematic benchmarking between deterministic sizing approaches and evolutionary multi-objective optimization methods remains scarce in wind–battery system design literature [20,47]. Finally, only a limited number of studies employ real operational wind production and electricity price data within degradation-aware optimization frameworks [9,38].

To address these gaps, this study proposes a degradation-aware tri-objective optimization framework for wind–battery integration. The proposed model employs the NSGA-II algorithm to optimize continuous

battery capacity and power rating variables while explicitly incorporating cycling-based degradation grounded in lithium-ion aging literature [15,21–24,26,27,32–34]. The framework also integrates an economic evaluation structure consistent with electricity market participation models [9,10,36,37]. In addition, the quality of the obtained Pareto solutions is quantitatively evaluated using hypervolume and diversity metrics [2,45], and the performance of the evolutionary optimization approach is benchmarked against deterministic grid-search sizing methods [20,42].

Although NSGA-II has been widely applied in energy system optimization, the novelty of this study lies in the proposed degradation-aware tri-objective optimization framework. Unlike previous studies that focus solely on technical smoothing, profit maximization, or simplified cycle limits [34,37], our framework explicitly integrates battery degradation cost into the optimization model, capturing the long-term economic impact of cycling and capacity fading. The optimization simultaneously considers profit maximization, power variance reduction, and degradation minimization, providing a more realistic and comprehensive assessment of wind–battery systems. Furthermore, the study benchmarks the performance of the evolutionary multi-objective optimization against deterministic sizing approaches [20,42], allowing a systematic comparison of solution quality and Pareto diversity. By combining wind power variability, battery operational constraints, and economic performance metrics within a unified structure, the proposed methodology offers a practically applicable planning tool for wind–battery integration and highlights trade-offs that are often overlooked in single- or dual-objective analyses.

4. Optimization framework and system modeling

This section describes the proposed optimization framework for the coordinated design of wind power generation and battery energy storage systems. The framework integrates wind generation profiles, battery operational dynamics, degradation modeling, and economic evaluation within a multi-objective optimization structure.

The objective is to identify optimal battery sizing configurations that balance economic profitability, power fluctuation mitigation, and battery lifetime degradation. The proposed framework combines simulation-based system evaluation with evolutionary optimization techniques.

4.1. System configuration

The system considered consists of a wind power plant integrated with a battery energy storage system (BESS). The wind power plant represents the primary renewable energy source, while the battery storage unit provides operational flexibility through energy buffering

and price-based dispatch.

The wind power output is represented by a time-series production profile, reflecting the intermittent nature of wind resources. The battery system is connected to the grid through a bidirectional power converter, enabling both charging and discharging operations.

The power delivered to the grid is therefore expressed as

$$P_{grid}(t) = P_{wind}(t) + P_{dis}(t) - P_{ch}(t) \quad (1)$$

where

$P_{wind}(t)$ represents wind generation,

$P_{dis}(t)$ denotes battery discharge power, and.

$P_{ch}(t)$ represents charging power.

This configuration enables the battery system to reduce power fluctuations while simultaneously exploiting electricity price variations. The overall architecture of the wind–battery integrated system considered in this study is illustrated in Fig. 1.

The simulation is conducted over a 744-hour (31-day) dataset from an operational 70 MW wind power plant, capturing real wind generation profiles and spot electricity market prices. While a longer dataset would improve the statistical representativeness of the results, the one-month period captures meaningful intra-month wind variability and price dynamics sufficient for battery sizing optimization. This temporal scope is acknowledged as a limitation; the annualized financial projections in Section 6 assume stationary wind resource and price conditions and should therefore be interpreted as indicative estimates rather than strict long-term forecasts.

4.2. Battery operation model

The battery energy storage system is modeled using a simplified state-of-charge (SOC) representation.

The SOC dynamics are defined as

$$SOC_{t+1} = SOC_t + \eta_c P_{ch}(t) \Delta t - \frac{P_{dis}(t) \Delta t}{\eta_d} \quad (2)$$

where

SOC_t is the state of charge at time step t ,

η_c and η_d represent charging and discharging efficiencies.

The SOC is constrained within the operational limits of the battery system:

$$SOC_{min} \leq SOC_t \leq SOC_{max} \quad (3)$$

Additionally, charging and discharging power levels are restricted by inverter capacity constraints.

To simulate realistic operational behavior, the battery dispatch

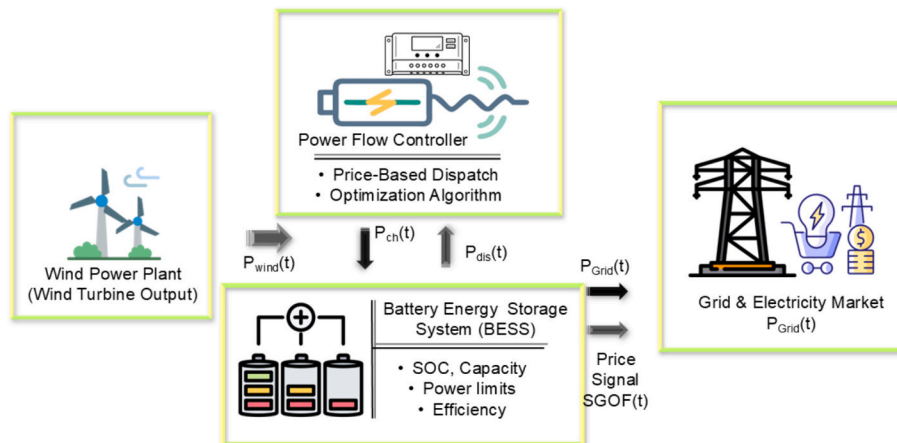


Fig. 1. Overall architecture of the wind–battery system.

strategy follows a price-driven operational logic, where charging occurs during relatively low electricity prices and discharging is prioritized during higher price periods. Advanced reinforcement learning-based control strategies have demonstrated superior adaptability in complex energy dispatch problems [48]; the price-driven approach adopted here provides a tractable and interpretable baseline consistent with energy arbitrage literature. The main technical and economic parameters used in the simulation model are summarized in Table 1.

4.3. Economic model

The economic performance of the system is evaluated through electricity market participation. Revenue is generated by selling electricity delivered to the grid based on time-dependent electricity prices.

The total revenue over the simulation horizon is defined as

$$\text{Revenue} = \sum_{t=1}^T P_{\text{grid}}(t) \cdot \text{Price}(t) \quad (4)$$

where $\text{Price}(t)$ represents the electricity market price at time t .

The investment cost of the battery system consists of energy capacity and power capacity components:

$$\text{CAPEX} = C_E E_{\text{max}} + C_P P_{\text{max}} \quad (5)$$

where

C_E denotes the cost per unit energy capacity and

C_P denotes the cost per unit power rating.

The annualized investment cost is calculated using the capital recovery factor.

The system profit is obtained by subtracting investment costs and degradation-related expenses from the operational revenue.

The system profit is obtained by subtracting investment costs and degradation-related expenses from the operational revenue. The discount rate of 0.2145 in Table 1 reflects the nominal weighted average cost of capital (WACC) expressed in Turkish lira, consistent with the real project financing data of the wind facility under study. Turkey's persistently elevated inflation — averaging 53.86% in 2023 [50] — drives nominal financing costs substantially above international benchmarks, a pattern well-documented for Turkish wind investments [51]. A sensitivity analysis across discount rates of 8%, 15%, 21.45%, and 25% is presented in Section 6 to demonstrate robustness.

4.4. Battery degradation model

Battery degradation is incorporated to reflect the impact of cycling on battery lifetime and economic performance.

In this study, degradation is quantified using an equivalent full cycle (EFC) approach, which estimates cumulative battery usage based on total discharge energy.

The equivalent full cycle metric is expressed as

$$\text{EFC} = \frac{E_{\text{dis,total}}}{2E_{\text{max}}} \quad (6)$$

where

$E_{\text{dis,total}}$ represents cumulative discharge energy and

E_{max} denotes battery energy capacity.

The degradation cost is assumed to be proportional to the battery investment cost and cumulative cycle usage.

This formulation enables the optimization algorithm to avoid excessive battery cycling that may negatively affect long-term economic viability.

While higher-fidelity electrochemical models can capture capacity fading mechanisms such as solid-electrolyte interphase growth and lithium plating with greater accuracy [32,33], the EFC metric provides a computationally tractable and widely validated proxy for cycling degradation that is sufficient for system-level sizing optimization. The limitations of the EFC approach relative to electrochemical models are acknowledged, and more detailed degradation modeling is identified as a direction for future research.

4.5. Multi-objective optimization problem

The system design problem is formulated as a tri-objective optimization problem involving economic, operational, and degradation-related objectives.

The first objective maximizes system profit:

$$f_1 = \max(\text{Profit}) \quad (7)$$

The second objective minimizes the variance of the grid power output:

$$f_2 = \min(\text{Var}(P_{\text{grid}})) \quad (8)$$

This objective represents the smoothing capability of the battery system.

The third objective minimizes battery degradation:

$$f_3 = \min(\text{EFC}) \quad (9)$$

These objectives create a trade-off between economic performance, power stability, and battery lifetime.

To select a single compromise solution from the Pareto front without subjective bias, the Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) multi-criteria decision-making method is applied. TOPSIS identifies the solution closest to the positive ideal solution and farthest from the negative ideal solution using min-max normalized objective values. The weights assigned to the three objectives are: profit = 0.50, grid variance = 0.25, and EFC = 0.25, reflecting the primary economic focus of the study while accounting for operational and degradation objectives. Multi-criteria decision frameworks have been applied across diverse energy system optimization problems to balance competing objectives [52].

The TOPSIS procedure is implemented as follows. Let x_{ij} denote the value of objective j for solution i . Each objective is first normalized using min-max scaling:

$$r_{ij} = \frac{x_{ij} - x_j^{\min}}{x_j^{\max} - x_j^{\min}} \quad (10)$$

Weighted normalized values are then computed as:

$$v_{ij} = w_j \cdot r_{ij} \quad (11)$$

where w_j denotes the weight assigned to objective j (profit: $w_1 = 0.50$; grid variance: $w_2 = 0.25$; EFC: $w_3 = 0.25$). The positive ideal solution A^+ and negative ideal solution A^- are defined as:

$$A^+ = \{v_1^{\max}, v_2^{\min}, v_3^{\min}\} \quad (12)$$

Table 1

Simulation parameters.

Parameter	Value	Unit	Description
Wind plant capacity	70	MW	Installed wind capacity
Simulation horizon	744	hour	One-month dataset
Battery capacity range	5–30	MWh	Optimization variable
Battery power range	2–25	MW	Optimization variable
Charge efficiency	0.80	—	Battery charging efficiency
Discharge efficiency	0.80	—	Battery discharging efficiency
SOC _{min}	0.1	—	Minimum SOC limit
SOC _{max}	0.9	—	Maximum SOC limit
Energy cost (C_E)	192,000	\$/MWh	Battery energy cost [49]
Power cost (C_P)	150,000	\$/MW	Converter cost [49]
Discount rate	0.2145	—	Financial parameter

$$A^- = \{v_1^{\min}, v_2^{\max}, v_3^{\max}\} \quad (13)$$

Note that profit is maximized while variance and EFC are minimized. The Euclidean distances from each solution to A^+ and A^- are:

$$d_i^+ = \sqrt{\sum_{j=1}^3 (v_{ij} - v_j^+)^2}, d_i^- = \sqrt{\sum_{j=1}^3 (v_{ij} - v_j^-)^2} \quad (14)$$

The relative closeness coefficient for each solution is:

$$C_i = \frac{d_i^-}{d_i^+ + d_i^-} \quad (15)$$

The solution with the highest C_i value is selected as the compromise solution, as it simultaneously minimizes distance to the positive ideal and maximizes distance from the negative ideal. This procedure is fully deterministic and reproducible, eliminating subjective bias in the selection process.

4.6. NSGA-II optimization procedure

The multi-objective optimization problem is solved using the Non-Dominated Sorting Genetic Algorithm II (NSGA-II), which is widely used for solving complex engineering optimization problems involving conflicting objectives.

The algorithm begins with an initial population of candidate solutions representing different battery sizing configurations. Each candidate solution is evaluated through the simulation model described in the previous subsections.

The population size is set to 50 individuals with a maximum of 50 generations, yielding 2,500 function evaluations. A sensitivity analysis conducted across three configurations (Pop = 30/Gen = 30, Pop = 50/Gen = 50, Pop = 100/Gen = 100) confirmed that hypervolume increases monotonically with population size (HV: 64,822,258 → 65,959,561 → 66,700,756), validating the adequacy of the selected configuration as a balance between solution quality and computational cost.

The NSGA-II algorithm applies genetic operators including selection, crossover, and mutation to iteratively improve the population. The non-dominated sorting procedure identifies Pareto-optimal solutions, while the crowding distance mechanism preserves diversity within the solution set.

The optimization process produces a Pareto front representing trade-offs between profit, grid power stability, and battery degradation. This configuration is further supported by recent data-driven optimization studies demonstrating the importance of adequate population diversity in multi-objective evolutionary algorithms [53].

4.7. Deterministic benchmark approach

To evaluate the effectiveness of the evolutionary optimization approach, a deterministic grid-search method is also implemented.

In this approach, battery capacity and power rating are systematically varied within predefined ranges. For each configuration, the system simulation is executed to compute profit, power variance, and degradation metrics. The deterministic search results provide a baseline for evaluating the performance of NSGA-II in terms of solution diversity, convergence quality, and overall system performance. The overall workflow of the proposed optimization framework is summarized in Fig. 2.

4.8. Optimization algorithm

To solve the multi-objective optimization problem, the Non-Dominated Sorting Genetic Algorithm II (NSGA-II) is employed due to its strong capability in handling nonlinear and conflicting objectives. The algorithm operates by evolving a population of candidate solutions

representing different combinations of battery capacity and power ratings. For each solution, the system simulation evaluates three objective functions: economic profit, grid power variance, and battery degradation. The evolutionary search process iteratively improves the population through selection, crossover, and mutation operators while preserving diversity using the crowding-distance mechanism. Non-dominated sorting is applied to classify solutions according to Pareto dominance, enabling the identification of trade-offs among the objectives. The overall optimization procedure implemented in this study is summarized in Algorithm 1.

Algorithm 1 NSGA-II based multi-objective optimization

Input:
 Wind production time series **Pwind**(*t*)
 Electricity market price **Price**(*t*)
 Battery capacity range $C_{\min} \leq C \leq C_{\max}$
 Battery power range $P_{\min} \leq P \leq P_{\max}$
 Output:
 Pareto optimal solution set
 1: Initialize population P with random battery capacity and power values
 2: Evaluate objective functions for each individual:
 f1 = **-Profit**(maximize economic performance)
 f2 = **Var(Pgrid**(*t*))(minimize power fluctuations)
 f3 = **EFC**(minimize battery degradation)
 3: Perform non-dominated sorting of population P
 4: Compute crowding distance for each solution
 5: while generation < MaxGeneration do
 6: Select parent solutions using tournament selection
 7: Apply crossover operator to generate offspring population
 8: Apply mutation operator to introduce diversity
 9: Evaluate objective functions for offspring population
 10: Combine parent and offspring populations
 11: Perform non-dominated sorting
 12: Select next generation based on:
 Pareto rank
 Crowding distance
 13: end while
 14: Output final Pareto optimal solution set

5. Case study and simulation setup

To evaluate the proposed optimization framework, a case study based on a wind energy system integrated with a battery storage unit was conducted. The system parameters were derived from the operational data used in the developed simulation model. Wind power production profiles and battery operational constraints were incorporated into the optimization process.

The battery system was characterized by two main decision variables: energy capacity and power rating. The capacity search range was defined between small-scale storage levels and large-scale installations to explore the economic and operational trade-offs associated with storage sizing. The battery power rating was constrained to maintain feasible charge–discharge operation within the system.

The proposed optimization framework was implemented using the NSGA-II algorithm with a population size of 50 individuals and a total of 50 generations, resulting in 2500 evaluations during the evolutionary search process. The algorithm aimed to simultaneously optimize three objectives:

- Maximizing system profit.
- Minimizing operational variance.
- Minimizing battery degradation through equivalent full cycles.

The optimization results were compared with a deterministic grid search approach to highlight the benefits of multi-objective evolutionary optimization. The trade-off between economic performance, operational stability, and battery degradation is illustrated by the three-dimensional Pareto front shown in Fig. 3.

As observed in the Pareto distribution, an increase in net profit generally corresponds to higher battery degradation levels and increased grid power variance. This behavior can be explained by the

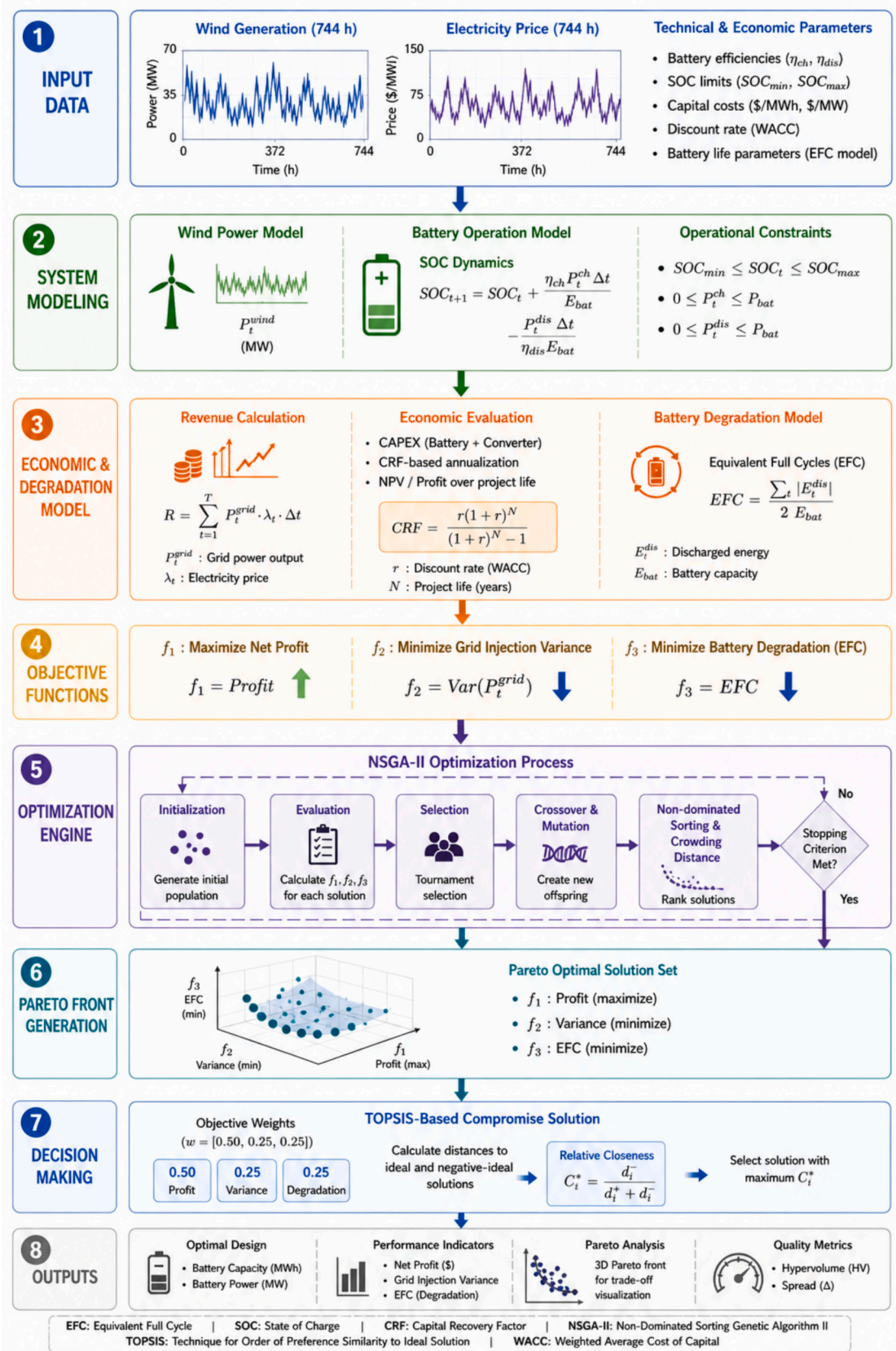


Fig. 2. Flowchart of the proposed optimization framework.

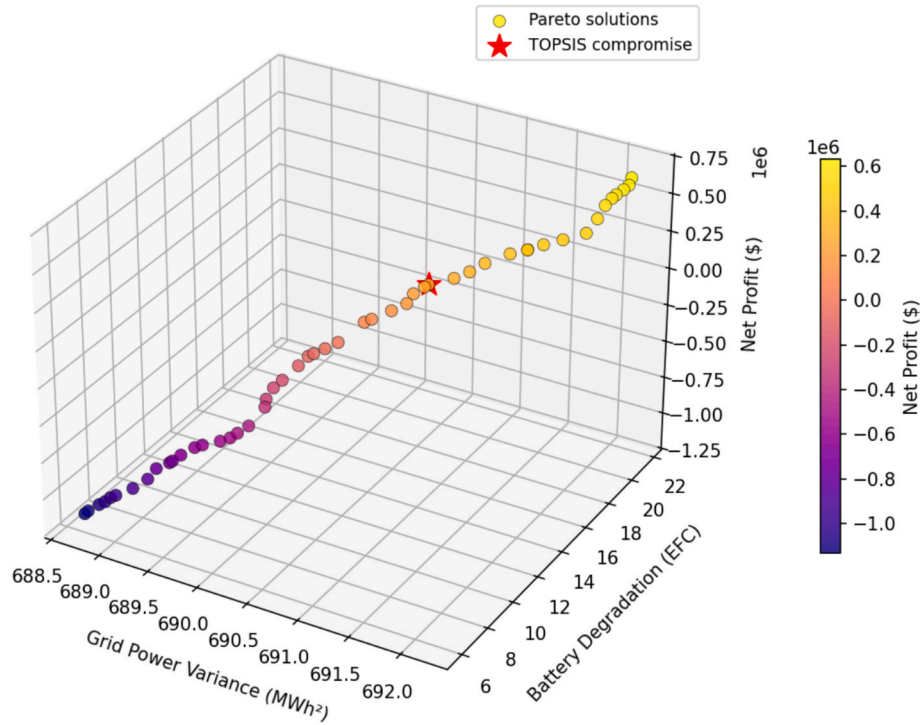


Fig. 3. Three-dimensional Pareto front obtained from the NSGA-II optimization illustrating the trade-off among net profit, grid power variance, and battery degradation (equivalent full cycles, EFC).

fact that more aggressive charge–discharge strategies enable the battery system to exploit electricity price fluctuations more effectively, thereby increasing economic returns. However, such operational strategies also lead to higher cycling intensity, which accelerates battery degradation and slightly increases variability in grid injection. Solutions located in the lower-degradation region of the Pareto front correspond to more conservative battery operation strategies. These configurations reduce cycling stress and improve long-term battery sustainability, but they result in slightly lower economic profits due to reduced participation in price arbitrage opportunities.

The smooth and continuous distribution of solutions along the Pareto surface indicates that the NSGA-II algorithm successfully captured the nonlinear relationships between the three objectives. This provides decision-makers with a wide range of feasible design alternatives, enabling the selection of battery configurations that best balance economic performance, operational stability, and battery lifetime considerations.

Also, the best deterministic configuration obtained from the grid search is summarized in Table 2.

Representative Pareto-optimal solutions obtained from the NSGA-II optimization are listed in Table 3.

Table 2
Deterministic optimization result.

Capacity (MWh)	Power (MW)	Profit (\$)
5	2	632,687

Note: The deterministic result is obtained from a 20×20 discrete grid search optimizing a single objective (profit). The NSGA-II algorithm explores a continuous two-dimensional design space under three simultaneous objectives; consequently, the TOPSIS compromise solution differs from the deterministic optimum (see Section 6.3).

Table 3
Pareto optimal solutions (Top 10).

Capacity (MWh)	Power (MW)	Profit (\$)	Variance	EFC
5.00	2.00	632,580	692.17	21.51
5.20	2.00	618,338	692.19	21.07
5.37	2.00	606,647	692.17	20.77
5.56	2.00	592,737	692.14	20.41
5.70	2.00	583,314	692.13	20.18
5.97	2.00	564,269	692.11	19.75
6.49	2.00	527,482	692.12	19.04
7.06	2.00	486,970	692.11	18.24
7.36	2.00	466,020	691.96	17.56
7.62	2.00	447,514	691.84	17.04

6. Results and discussion

6.1. Deterministic optimization results

Before applying the evolutionary optimization approach, a deterministic grid search was performed to identify the best single solution based solely on profit maximization. The deterministic optimization produced a solution with a battery capacity of approximately 5.00 MWh and a power rating of 2.0 MW, yielding a total net profit of approximately \$632,687 over the analyzed period. This result represents the highest profit achievable when only a single objective is considered.

However, deterministic optimization ignores the trade-offs between profit, operational stability, and battery degradation. As a result, the obtained solution may lead to higher cycling stress on the battery and increased variability in system performance. These limitations motivate the use of multi-objective optimization to explore a broader range of feasible design alternatives and to identify balanced solutions among conflicting objectives.

It is worth noting that the deterministic optimum of \$632,687 is achieved at the minimum capacity bound (5.00 MWh), indicating that profit maximization alone favors minimal battery investment under the updated cost parameters. This arises because the deterministic grid

search is restricted to a discrete 20×20 candidate grid, whereas NSGA-II explores a fully continuous design space, accessing off-grid configurations unavailable to the discrete search. The TOPSIS-selected compromise solution (10.18 MWh, Section 6.3) accepts a modest reduction in profit relative to the highest-profit Pareto solutions in exchange for substantially lower battery degradation and grid variance — the intended behavior of a multi-objective framework.

6.2. NSGA-II Pareto front analysis

The NSGA-II algorithm successfully generated a diverse set of Pareto-optimal solutions representing different trade-offs among the considered objectives. The optimization process reached convergence after approximately 50 generations, producing a set of 50 non-dominated solutions forming the Pareto front. The evolutionary search demonstrated stable convergence behavior throughout the optimization process. The final hypervolume value reached 66,038,808, indicating a well-distributed Pareto front and adequate solution diversity. The hypervolume reference point is defined as the nadir point plus 10% of the nadir–ideal range, ensuring consistency and reproducibility across runs.

The Pareto solutions obtained show a clear relationship between storage capacity and overall system performance. The optimal compromise solution identified by the NSGA-II algorithm corresponds to a battery capacity of approximately 10.18 MWh with a 2 MW power rating, achieving a net profit of approximately \$266,189, while maintaining moderate grid variance and battery degradation levels. Smaller battery capacities tend to maximize economic profit but result in significantly higher cycling intensity. In contrast, larger storage capacities reduce degradation stress at the expense of reduced profitability due to higher investment costs. These results highlight the inherent trade-offs among economic performance, operational stability, and battery lifetime. The trade-offs among the three objectives can be observed in Fig. 3, where the three-dimensional Pareto front illustrates the relationship between net profit, grid power variance, and battery degradation (EFC). Fig. 4 shows the relationship between battery capacity and net profit across Pareto-optimal solutions, providing additional insight into the economic implications of storage sizing. This figure emphasizes the diminishing returns of increasing battery capacity beyond a certain point, where additional investment yields marginal improvements in stability and degradation mitigation, but at a higher cost. Together, these figures underscore that no single configuration simultaneously optimizes all objectives, reinforcing the importance of

multi-objective optimization for wind–battery system design.

6.3. Analysis of optimal compromise solution

To identify a practical design configuration, a compromise solution was selected from the Pareto front using a balanced trade-off criterion among the three objectives. The selected configuration corresponds to a battery capacity of approximately 10.18 MWh with a 2.0 MW power rating. This design achieves a net profit of approximately \$266,189, while maintaining a grid variance value of 691.10 and an equivalent full cycle value of 14.03.

Compared with the deterministic solution, the compromise design slightly reduces economic profit but significantly improves system stability and reduces battery cycling intensity. This result demonstrates the advantage of multi-objective optimization in identifying balanced solutions that are more suitable for long-term system operation.

Based on the IRENA cost parameters [49], the estimated simple payback period is approximately 0.72 years (approximately 9 months), indicating rapid investment recovery within the simplified economic framework. However, this value reflects the specific assumptions used in the economic model and should be interpreted as an indicative metric rather than a strict financial forecast. It should be noted that the monthly net profit of \$266,189 is extrapolated to an annual basis using a scaling factor of 365/31. This extrapolation assumes stationary wind resource and electricity price conditions, which may not hold over longer operational periods; the resulting financial metrics should therefore be interpreted as indicative upper bounds under the current modeling assumptions.

The variation of battery degradation across Pareto-optimal solutions is illustrated in Fig. 5, which depicts the relationship between battery capacity and equivalent full cycles (EFC). The figure depicts the relationship between installed battery capacity (MWh) and the corresponding equivalent full cycles (EFC), which serve as a quantitative measure of cumulative battery wear. As observed, smaller battery capacities tend to experience higher cycling intensity, leading to increased degradation, whereas larger capacities distribute energy throughput more evenly and exhibit lower EFC values. This trend underscores the inherent trade-off between short-term economic gains and long-term battery lifespan, emphasizing that system designers must balance investment cost, operational stability, and degradation when selecting an optimal battery configuration.

The figure demonstrates that moderate-capacity solutions can provide a compromise, achieve acceptable profit levels while limit

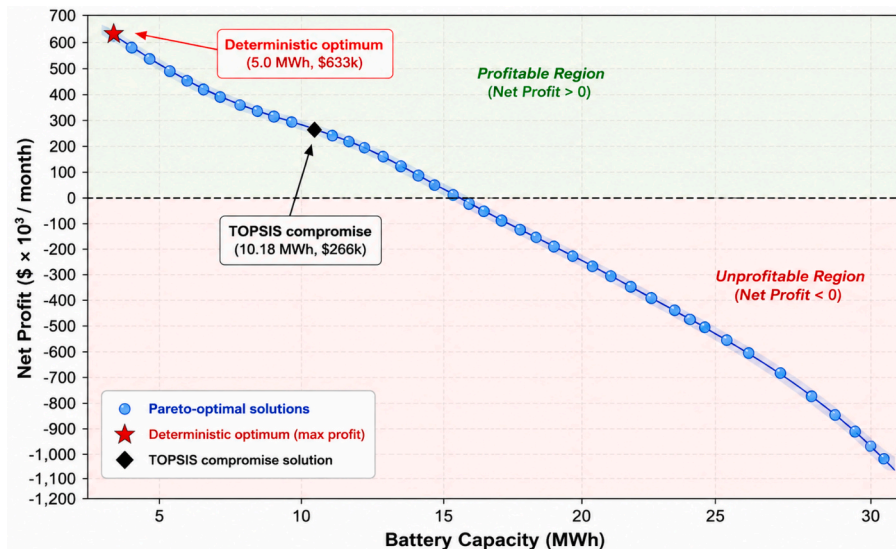


Fig. 4. Battery capacity vs net profit.

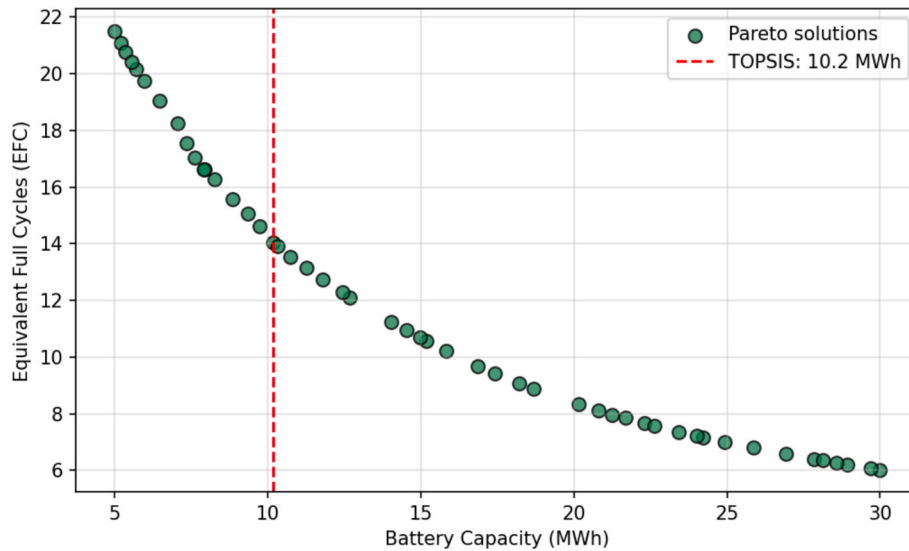


Fig. 5. Battery capacity vs battery degradation (EFC).

degradation, highlighting the utility of multi-objective optimization in identifying practically implementable solutions for wind–battery integrated energy systems. These findings highlight the importance of considering degradation and operational stability alongside economic objectives when designing wind–battery integrated energy systems.

The performance metrics of the selected compromise configuration are summarized in Table 4. The battery system is configured with an energy capacity of 10.18 MWh and a power rating of 2.0 MW, representing a balanced trade-off among economic, operational, and degradation objectives. The corresponding net profit is approximately USD \$266,189, indicating only a marginal reduction compared with the maximum-profit deterministic solution, while mitigating battery degradation and reducing grid power variance. The equivalent full cycle (EFC) metric of 14.03 demonstrates the lower cumulative cycling stress imposed on the battery, which contributes to prolonged system lifetime and operational stability. Furthermore, the estimated simple payback period of 0.72 years highlights the rapid recovery of the initial investment within the modeled economic framework. Collectively, these indicators confirm that the compromise solution achieves an effective balance between profitability, reliability, and battery sustainability, making it a practical choice for real-world wind–battery integration.

The financial performance of the selected compromise battery configuration is summarized in Table 5. Under Scenario A (4,000 EFC lifetime, no replacement), the NPV is estimated at \$12,260,439, while Scenario B (2,000 EFC lifetime with battery replacement at year 12) yields an NPV of \$12,041,504. Both scenarios assume a discount rate of 21.45% consistent with Turkish electricity market financing conditions and incorporate the battery cost parameters from IRENA (2025) [49] ($C_{bp} = \$150,000/\text{MW}$, $C_{be} = \$192,000/\text{MWh}$). The discounted payback period is 1 year in both scenarios, confirming rapid recovery of the initial capital investment. The IRR is 139.2% in both cases, indicating strong profitability while remaining within realistic bounds for renewable energy projects. These indicators collectively demonstrate the economic feasibility of the proposed optimization framework under current battery cost trends.

The trade-off between net profit and battery degradation is visualized in Fig. 6, highlighting the impact of cycling on economic

Table 5
Financial performance indicators.

Metric	Value
NPV – Scenario A (4,000 EFC)	\$12,260,439
NPV – Scenario B (2,000 EFC + replacement)	\$12,041,504
Discounted Payback	1 years
IRR	139.2%

performance. It is evident that aggressive energy arbitrage strategies, which aim to maximize short-term profit, lead to increased cycling and faster battery wear. On the other hand, conservative operational strategies reduce degradation but slightly compromise economic performance. These observations confirm the necessity of multi-objective planning to achieve balanced, sustainable system operation.

Grid power variance as a function of battery capacity for Pareto-optimal solutions is presented in Fig. 7. The results indicate that increasing battery capacity generally reduces the variability of power injections into the grid, enhancing operational stability. However, the rate of variance reduction diminishes at higher capacities, suggesting that beyond a certain point, additional investment provides limited operational benefit. This emphasizes the importance of evaluating both technical and economic performance metrics in storage sizing decisions.

The convergence of NSGA-II and the progression of hypervolume over generations are illustrated in Fig. 8, indicating algorithm performance and Pareto front quality. The plot demonstrates rapid initial improvement followed by gradual convergence, indicating that the algorithm effectively identifies a diverse set of high-quality solutions. This supports the reliability and robustness of the multi-objective optimization approach for planning wind–battery integrated energy systems.

6.4. Extended financial analysis

To provide a more rigorous economic assessment, NPV analysis is performed under two battery lifetime scenarios. Scenario A assumes the full 4,000 EFC manufacturer-rated lifetime (27.0 years at the optimized cycling rate). Scenario B assumes a 2,000 EFC lifetime with a battery replacement at year 12. At a discount rate of 21.45%, Scenario A yields an NPV of \$12.26 million and Scenario B yields \$12.04 million, with discounted payback within 1 year. A sensitivity analysis across discount rates confirms robustness (Table 6).

Table 4
Optimal compromise solution.

Capacity (MWh)	Power (MW)	Profit (\$)	Variance	EFC	Payback
10.18	2.0	266,189	691.10	14.03	0.72

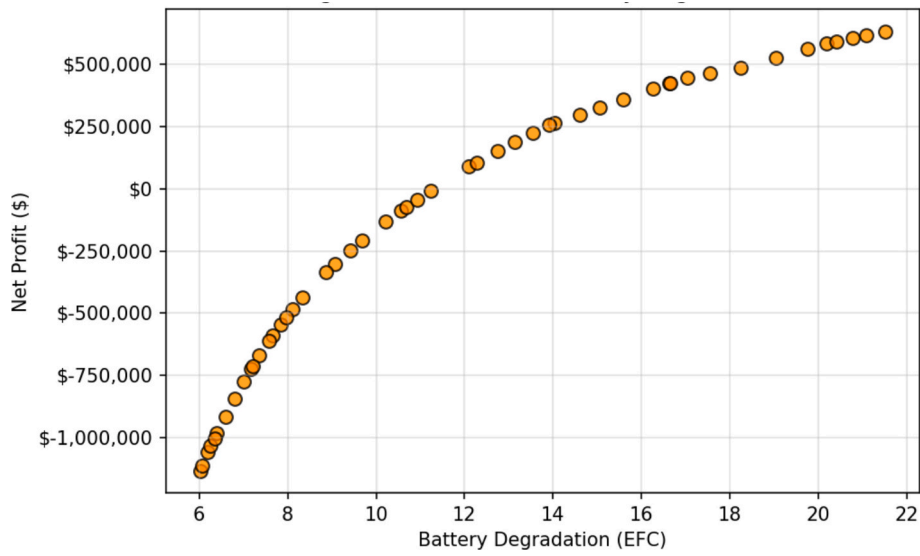


Fig. 6. Net profit vs battery degradation (EFC).

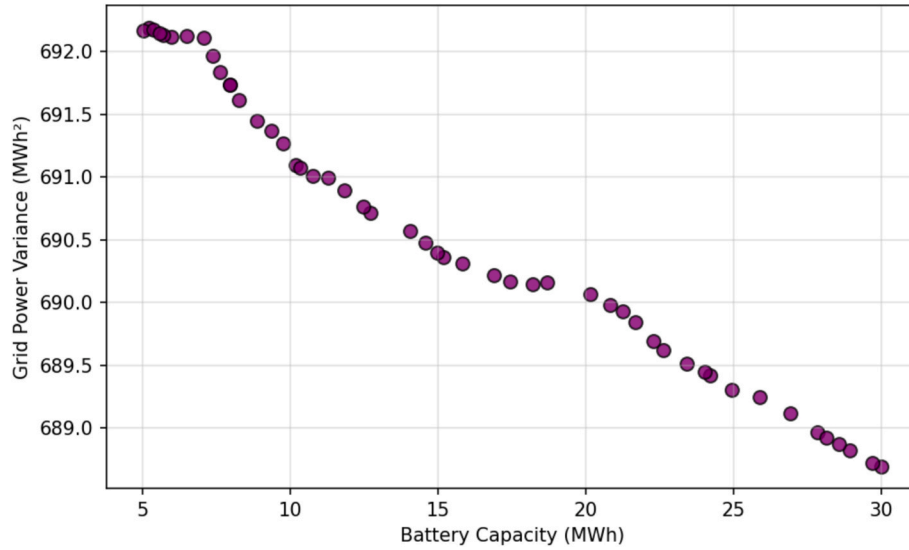


Fig. 7. Battery capacity vs grid power variance.

6.5. Statistical performance evaluation

To assess the reliability of the proposed degradation-aware NSGA-II optimization framework, multiple independent runs were conducted. The statistical evaluation reveals a mean net profit of approximately \$632,658, with a standard deviation of \$44.88, while the 95% confidence interval spans from \$632,618 to \$632,697. These narrow intervals indicate that the algorithm consistently identifies high-quality solutions across independent runs.

Performance metrics, including hypervolume (66,038,808) and spread Δ (0.455), demonstrate that the obtained Pareto front is both well converged and sufficiently diverse, capturing a wide spectrum of trade-offs among net profit, grid power variance, and battery degradation. The high hypervolume value indicates that the Pareto solutions dominate a large portion of the objective space, reflecting strong convergence toward optimal regions. Meanwhile, the spread Δ value confirms an adequate distribution of solutions along the Pareto front, preventing excessive clustering and preserving solution diversity. These results validate the robustness and stability of the NSGA-II approach in effectively balancing multiple conflicting objectives in wind–battery

system design. They also provide confidence that the selected compromise solutions reliably represent practical trade-offs between economic performance and operational considerations. The quantitative performance indicators used to evaluate the quality of the Pareto front are summarized in Table 7.

A Wilcoxon signed-rank test was conducted comparing the NSGA-II results against the deterministic benchmark across five independent runs. The test yielded a statistic of 0.0 with a p-value of 0.0625, indicating no statistically significant difference at $\alpha = 0.05$. It is noted that $n = 5$ constitutes a small sample, limiting test power; however, the low standard deviation and narrow 95% confidence interval confirm the convergence consistency of the algorithm.

Table 7 presents key performance metrics for evaluating the NSGA-II optimization outcomes. The hypervolume value of 66,038,808 indicates that the Pareto front covers a large portion of the objective space, demonstrating that the algorithm successfully identifies high-quality, non-dominated solutions that balance profit, grid stability, and battery degradation. The spread Δ of 0.455 reflects a well-distributed set of solutions along the Pareto front, ensuring diversity and preventing clustering around specific regions. The mean profit of \$632,658, with a

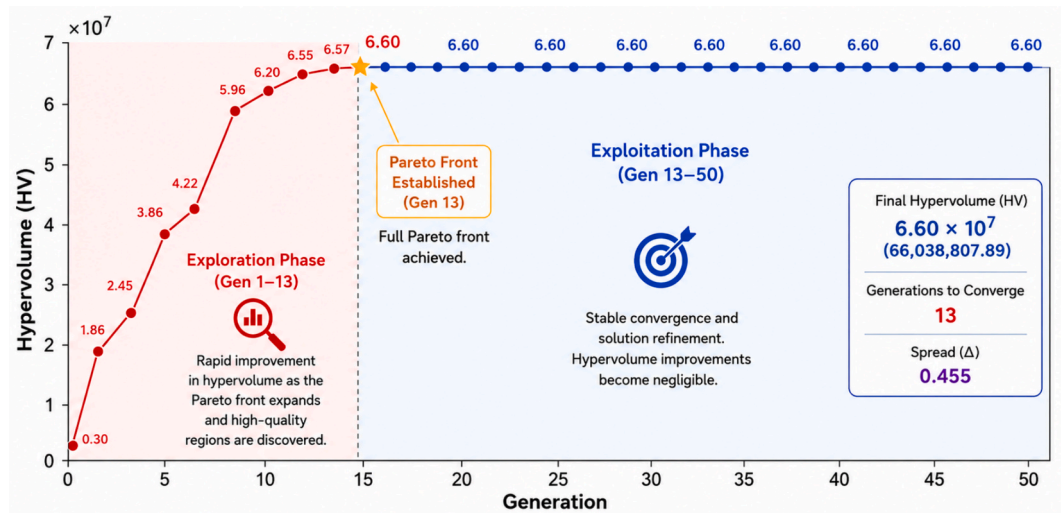


Fig. 8. NSGA-II hypervolume convergence.

Table 6

NPV sensitivity analysis across discount rates (Scenario A: 4,000 EFC lifetime).

Discount rate	NPV – Scenario A (\$)	Discounted Payback	IRR
8.0%	31,246,221	1 year	139.2%
15.0%	18,031,663	1 year	139.2%
21.45%	12,262,254	1 year	139.2%
25.0%	10,250,795	1 year	139.2%

Table 7

Optimization performance metrics.

Metric	Value
Hypervolume	66,038,808
Spread Δ	0.455
Mean Profit	\$632,658
Standard Deviation	\$44.88
95% CI	[\$632,618, \$632,697]
Wilcoxon p-value	0.0625

standard deviation of \$44.88, confirms the consistency and robustness

of the optimization across multiple independent runs. Collectively, these metrics validate the stability, convergence, and effectiveness of the proposed multi-objective optimization framework in identifying balanced trade-offs among conflicting objectives.

The effect of population size and generation count on Pareto front quality is illustrated in Fig. 9, where hypervolume increases monotonically from 64,822,258 (Pop = 30) to 66,700,756 (Pop = 100), confirming that the default configuration (Pop = 50, Gen = 50) provides a satisfactory balance between solution quality and computational cost.

7. Conclusion

This study presented a degradation-aware multi-objective optimization framework for the optimal sizing of battery energy storage systems integrated with wind power plants. The proposed methodology combines economic performance, grid power smoothing capability, and battery degradation considerations within a unified tri-objective optimization structure solved using the NSGA-II evolutionary algorithm. The deterministic grid-search analysis identified a profit-maximizing solution with a relatively small battery capacity of approximately 5 MWh. However, this configuration results in significantly higher cycling

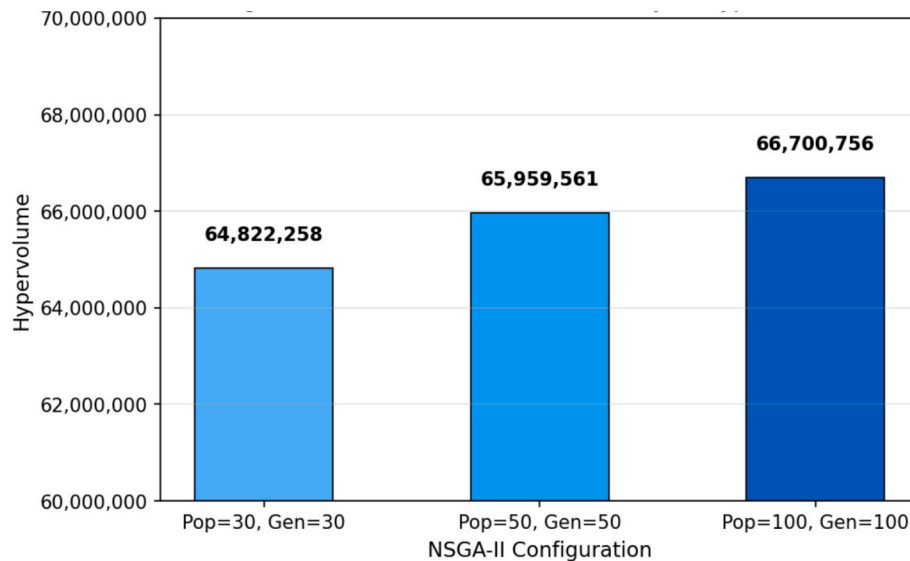


Fig. 9. Hypervolume indicator values obtained from NSGA-II under three population/generation configurations (Pop = 30/Gen = 30, Pop = 50/Gen = 50, Pop = 100/Gen = 100), demonstrating monotonic improvement in Pareto front quality with increasing computational budget.

intensity and does not explicitly account for long-term battery degradation effects. In contrast, the NSGA-II based optimization framework successfully generated a diverse set of Pareto-optimal solutions, revealing clear trade-offs among net profit, grid power variance, and battery degradation intensity.

The Pareto analysis demonstrated that smaller storage capacities tend to maximize short-term economic profit but lead to higher battery cycling intensity, whereas larger capacities reduce degradation stress at the expense of higher investment costs and slightly reduced profitability. The compromise solution obtained from the Pareto front corresponds to a battery capacity of approximately 10.18 MWh and a power rating of 2 MW, achieving balanced system performance with moderate profit, reduced degradation, and improved operational stability.

The evaluation of Pareto front quality using hypervolume and spread metrics confirmed the convergence stability and diversity of the obtained solution set. These results highlight the effectiveness of evolutionary multi-objective optimization for renewable energy storage planning and wind–battery system design.

Future research may extend the proposed framework by incorporating stochastic wind forecasting models, multi-market participation strategies, higher-fidelity electrochemical degradation models — including physics-constrained data-driven approaches such as theory-constrained neural networks with modular interpretability [54] — and multi-year or seasonal simulations to address the stationarity limitations of the current 744-hour dataset. These extensions would further enhance the realism and practical applicability of the optimization framework.

Declaration of generative AI and AI-assisted technologies in the writing process

The authors did not use generative AI tools in the preparation of this manuscript.

CRediT authorship contribution statement

Hasan Eroglu: Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Software, Resources, Project administration, Methodology, Investigation, Funding acquisition, Formal analysis, Data curation, Conceptualization.

Declaration of competing interest

The author declares 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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