Multi-Objective Optimal Design of Distributed Energy Systems for Resilience and Sustainability

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Abstract*—This research article highlights the critical role of Distributed Energy Systems (DES) in the global energy transition towards carbon neutrality. While much existing work focuses on optimizing DES for economic and environmental benefits under normal conditions, it often overlooks the importance of resilience to extreme events, such as natural disasters. This paper addresses that gap by proposing a multi-objective optimization design framework that integrates resilience as a key objective alongside economic efficiency and environmental performance. The framework centers on three main goals: System Resilience: Resilience is quantified by the Expected Energy Not Supplied (EENS) during an extreme event scenario, specifically a prolonged grid outage caused by a typhoon. This measures how well the system can maintain energy supply during disruptions. Economic Efficiency: The economic performance is evaluated through the Total Annualized Cost (TAC), which reflects the financial feasibility of the system. Environmental Performance: Environmental impact is assessed by the total annual CO2 emissions associated with the system. The optimization problem is solved using the Non-dominated Sorting Genetic Algorithm II (NSGA-II), a method commonly used in multi-objective optimization problems. The case study focuses on a coastal industrial park in southeastern China, which is highly susceptible to typhoons. By using reproducible load and renewable energy resource profiles, the study demonstrates the trade-offs between these three objectives. Key findings include: Resilience and Investment Costs: Enhancing resilience requires larger capacities of energy storage and renewable generation, leading to higher initial investment costs. Cost-Optimal Configurations: A system designed purely for cost optimization might be vulnerable during extreme events due to insufficient reliability in energy supply. Pareto-Optimal Frontier: The analysis provides a set of optimal system configurations that offer a balance between resilience, cost, and environmental performance, allowing decision-makers to make choices based on their specific risk preferences. The study makes a significant contribution by elevating resilience from a mere constraint or post-assessment metric to a primary optimization objective, placing it on equal footing with economic and environmental goals. This approach offers a scientific and quantitative tool for designing DES that are not only economically viable and environmentally sustainable but also resilient, which is crucial for ensuring energy security in the face of climate change. This framework is valuable for decision-makers in planning and designing future energy systems that need to be robust, sustainable, and resilient, especially in regions vulnerable to extreme weather events like typhoons.

Keywords—Distributed Energy Systems; Multi-objective Optimization; Resilience; Sustainability; Energy System Design

I. INTRODUCTION

As the world confronts the growing pressures of climate change and surging energy demand, a global energy transformation is accelerating—one defined by cleaner, low-carbon, and highly efficient systems [1]. In this context, China has pledged to peak carbon emissions before 2030 and achieve carbon neutrality before 2060, establishing a clear strategic pathway for restructuring its energy landscape [2]. Within this transition, Distributed Energy Systems (DES) are gaining prominence as a key alternative to traditional centralized supply models. By delivering integrated energy solutions close to end users and enabling the coordinated use of multiple energy resources, DES play an essential role in shaping next-generation power systems [3, 4]. Through the integration of renewable technologies such as photovoltaics (PV) and wind power with flexible solutions like energy storage and hydrogen systems, DES not only help reduce carbon emissions and improve overall efficiency but also strengthen grid flexibility and operational security [5].

At the same time, the rising frequency and severity of extreme weather events worldwide — including typhoons, snowstorms, and prolonged heatwaves — are placing unprecedented stress on energy infrastructure [6]. Conventional centralized grids are particularly vulnerable during large-scale natural disasters, as damage to critical assets such as transmission lines can trigger widespread power outages, leading to significant economic disruption and social consequences. Although DES have the inherent capability to operate independently, their performance can also be severely compromised if they are not specifically designed to withstand such extreme conditions. Consequently, enhancing the resilience of DES — ensuring that they can maintain essential functions during and after external disturbances — has emerged as a critical scientific and engineering challenge in the energy sector [7].

Extensive research has explored the optimal design of DES, with most studies emphasizing multi-objective trade-offs. Common optimization goals typically include economic indicators (such as life-cycle cost and return on investment) and environmental metrics (such as carbon emissions and pollutant outputs) [8, 9]. For example, Fonseca et al. [10] introduced a multi-objective optimization framework incorporating economic, environmental, and social sustainability criteria. However, their treatment of the social dimension focused mainly on grid reliance and intrinsic safety, without directly evaluating system performance under disruptive events. Some researchers have incorporated reliability metrics — such as Loss of Power Supply

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Probability (LPSP) or average annual energy deficit—often applying them as constraints within optimization models [11, 12]. Yet reliability primarily reflects system behavior under normal operating conditions and frequent, low-impact failures. In contrast, resilience addresses the system's capacity to withstand, adapt to, and rapidly recover from rare but high-impact extreme events. These two concepts differ substantially in both interpretation and evaluation methodology [13].

Overall, several gaps remain in existing DES design research. First, quantitative frameworks for assessing resilience are still insufficiently developed, particularly in terms of metrics capable of realistically simulating extreme weather scenarios and integrating seamlessly into design optimization processes. Second, there is a lack of comprehensive optimization frameworks that treat resilience, economic performance, and environmental sustainability as equally weighted objectives. In many cases, resilience or reliability is imposed merely as a constraint, limiting the exploration of broader design possibilities. Finally, most current applications focus on residential or commercial contexts where supply continuity requirements are relatively moderate. For critical facilities — such as industrial parks, data centers, and hospitals — where uninterrupted energy supply is essential, resilience-oriented DES design is far more urgent, yet research in this area remains limited.

To address these challenges, this study proposes a novel multi-objective optimization framework for DES that integrates resilience and sustainability as central design principles. Specifically, the objectives of this research are threefold: first, to develop a quantitative resilience assessment metric based on representative extreme event scenarios and incorporate it as a primary objective within a multi-objective optimization model; second, to construct a comprehensive decision-making framework that simultaneously optimizes resilience, economic performance, and environmental outcomes; and third, to validate the proposed methodology through a case study of a coastal industrial park in southeastern China, using transparent and reproducible data assumptions to generate practical optimal design strategies for high-reliability applications. The remainder of this paper is organized as follows: Section 2 reviews relevant literature; Section 3 introduces the system model, objective functions, and optimization methods; Section 4 presents and analyzes the results; and Section 5 concludes with key findings and future research directions.

II. Literature Review

A. *Sustainability Assessment of Distributed Energy Systems*

Sustainable development emphasizes the need to balance economic viability, environmental protection, and social responsibility in system planning and decision-making [14]. Within the field of distributed energy, multi-criteria decision-making (MCDM) approaches have been extensively reviewed and applied to support more comprehensive evaluations [15]. For example, mixed-integer linear programming (MILP) models have been developed to enable integrated planning and performance assessment of distributed energy systems (DES) [16]. In practical regional case studies, multi-objective optimization techniques have been employed to support system configuration and capacity design under real-world constraints [17]. Beyond technical and economic considerations, social dimensions — such as public acceptance of energy technologies — have also been examined through qualitative approaches including factor analysis, highlighting the growing recognition of social sustainability in energy transitions [18].

B. *Research on Energy System Resilience*

Resilience engineering provides a theoretical foundation for enhancing the capacity of energy systems to withstand and recover from disruptions [19]. In recent years, considerable attention has been devoted to improving power system resilience under extreme weather and other high-impact events [20]. This body of research has led to the development of various assessment methodologies and enhancement strategies aimed at strengthening system robustness and recovery capability [21]. The deployment of microgrids has emerged as a key strategy for improving the resilience of distribution networks, enabling localized operation during grid disturbances [22]. To support such configurations, bi-level optimization models have been proposed for resilient distribution system design incorporating microgrids [23]. In addition, energy storage technologies play a crucial role in maintaining supply-demand balance and enhancing operational flexibility within microgrids, further reinforcing system resilience [24].

C. *Application of Multi-Objective Optimization in Energy System Design*

Given the inherent trade-offs among economic, environmental, and technical objectives, multi-objective optimization offers a robust mathematical framework for resolving such conflicts [25]. Among available algorithms, the Non-dominated Sorting Genetic Algorithm II (NSGA-II) has been widely adopted due to its efficiency and elite preservation mechanism in handling complex energy system optimization problems [26]. Comprehensive reviews have summarized techno-economic and environmental analyses of distributed energy systems, reflecting the maturity of multi-objective design approaches in this field [27]. Several studies have proposed integrated multi-objective methods to optimize both the design and operational strategies of DES [28]. Furthermore, frameworks incorporating technical, economic, and environmental indicators for evaluating resilient distributed energy systems have been established [29], alongside systematic methodologies for system design and performance analysis [30]. The effectiveness and applicability of these multi-objective optimization techniques have been broadly recognized within the energy research community [31]. With ongoing updates in energy technology data and cost parameters, system modeling inputs have become increasingly accurate, providing a more reliable basis for optimization-based design [32].

D. *Positioning and Innovation of This Study*

Building upon the existing body of literature, this study advances a multi-objective optimization framework for distributed energy systems that explicitly integrates resilience and sustainability as core design objectives. By systematically incorporating resilience assessment into the optimization process alongside economic and environmental criteria, the proposed framework aims to address current methodological gaps and provide a more balanced and forward-looking approach to DES planning and design.

III. METHODOLOGY

This chapter presents the research methodology applied to evaluate and optimize the distributed energy system. It begins with a description of the system ' s physical configuration and the mathematical models representing its technological components. It then introduces the multi-objective optimization framework, which incorporates resilience, economic performance, and environmental impact as key objectives. Finally, it explains the solution algorithm and outlines the specific parameter settings adopted in the case study.

A. System Description and Modeling

1) Physical System Architecture

The distributed energy system developed in this study, as shown in Figure 1, is designed to satisfy the integrated energy demands — electricity, heating, and cooling — of an industrial park. A primary focus of the design is to strengthen system resilience, particularly under extreme conditions. To achieve high efficiency and coordinated operation, multiple energy technologies are integrated into a unified framework.

a) Renewable Power Generation Units:

The system incorporates large-scale photovoltaic (PV) arrays and wind turbines (WT) as its main sources of clean electricity, forming the foundation of green power supply.

b) Energy Storage Units:

Both electrochemical storage (lithium-ion batteries) and hydrogen-based storage are included. Lithium-ion batteries handle short-term power balancing and load shifting. The hydrogen subsystem — comprising an electrolyzer, high-pressure hydrogen storage tank, and fuel cell — provides large-capacity, long-duration energy storage, which plays a critical role in enhancing long-term system resilience.

c) Flexibility and Regulation Units:

A dispatchable biomass-based generation unit is considered as an optional low-carbon flexibility resource, modeled using a simplified conversion efficiency. This unit represents a generic on-site controllable power source and may be replaced in practice by other low-carbon firm generation technologies. The system also remains connected to the external utility grid, enabling electricity trading during normal operations and providing backup power during extreme events, provided that grid supply remains available.

d) Energy Conversion and Utilization:

Electricity generated within the system directly serves the industrial park ' s loads, while any surplus energy is stored. Additionally, waste heat recovered from the fuel cell and gas turbine is captured through a heat recovery unit to meet heating and hot water demands, thereby enabling cascaded energy utilization and improving overall efficiency.

Figure 1. Physical layout of the distributed energy system examined in this study. Blue arrows indicate the flow of electricity, green arrows represent hydrogen flow, red arrows denote heat transfer, and brown arrows illustrate the flow of biomass or syngas.

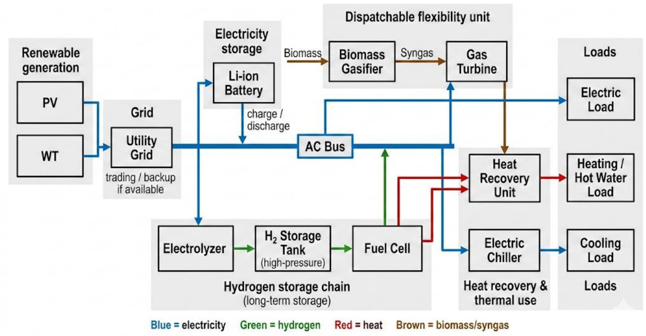

Fig. 1. Physical architecture of the distributed energy system studied.

2) System Mathematical Model

To conduct the optimization analysis, a mathematical model was established under a pseudo-steady-state assumption with an hourly time resolution. The model assumes that each energy conversion unit responds instantaneously, without considering internal energy storage dynamics. The input – output relationships of all components are characterized using constant efficiency parameters and linear formulations, following the modeling approach proposed by Fonseca et al. [10, 30].

a) PV and Wind Models:

The power output of photovoltaic (PV) panels and wind turbines is calculated based on local solar irradiance and wind speed data, as well as the rated capacity and conversion efficiency of the equipment.

b) Energy Storage Model:

The State of Charge (SOC) of each storage unit is represented by a discrete-time state transition equation that accounts for charging and discharging efficiencies along with self-discharge effects:

$$SOC(t) = SOC(t-1) \times (1-\sigma) + (P_{ch}(t) \times \eta_{ch} - P_{dis}(t)/\eta_{dis}) \times \Delta t / C_{rated} \quad (1)$$

where σ denotes the self-discharge rate; P_ch and P_dis represent charging and discharging power, respectively; η _ch and η _dis are the charging and discharging efficiencies; and C_rated is the rated storage capacity.

c) Hydrogen System Model:

The electrolyzer, hydrogen storage tank, and fuel cell are modeled to describe the processes of electricity-to-hydrogen conversion, hydrogen storage, and hydrogen-to-electricity/heat reconversion. Their efficiencies are defined according to corresponding performance characteristics.

d) Biomass Gasification and Gas Turbine Model:

This model relates the dry biomass input to the resulting electricity and heat output through an overall efficiency coefficient, capturing the integrated conversion performance.

B. Multi-Objective Optimization Framework

The central contribution of this study is the construction of a multi-objective optimization framework designed to simultaneously optimize system resilience, economic performance, and environmental impact. The framework incorporates three inherently conflicting objective functions.

1) *Objective Functions*

a) *Economic Objective (J_eco): Minimize Total Annualized Cost (TAC)*

This objective seeks the most cost-effective system configuration. The Total Annualized Cost (TAC) consists of annualized capital investment (CAPEX) and annual operating expenses (OPEX), expressed as:

$$Min\ J_{eco} = TAC = CAPEX \times CRF + OPEX \quad (2)$$

Here, CAPEX includes the procurement and installation costs of all equipment (e.g., PV panels, wind turbines, energy storage systems, hydrogen infrastructure), determined by their respective capacities and unit costs. OPEX covers maintenance expenses, fuel costs (such as purchased biomass), and electricity purchases from the external grid. The Capital Recovery Factor (CRF) is applied to convert the one-time capital investment into an equivalent annual cost over the project's lifetime.

b) *Environmental Objective (J_env): Minimize Annual CO_2 Emissions*

This objective evaluates the system's environmental performance. Carbon emissions mainly arise from indirect emissions associated with electricity imported from the grid and, in general cases, direct on-site fossil fuel consumption (though fossil fuels are not included in the present model).

$$Min\ J_{env} = E_{grid_import} \times e_{grid} \quad (3)$$

where E_grid_import represents the total annual electricity imported from the grid, and ef_grid denotes the grid's carbon emission factor (kgCO_2 /kWh).

c) *Resilience Objective (J_res): Minimize Expected Energy Not Supplied (EENS)*

This objective represents the core innovation of the study and quantifies system reliability under extreme conditions. A scenario-based approach is adopted to assess resilience. Specifically, a 48-hour super typhoon scenario is simulated with the following assumptions:

- Complete outage of the external utility grid.
- PV output reduced to 20% of normal levels due to heavy cloud cover and rainfall.
- Wind turbines shut down for safety reasons under excessive wind speeds, resulting in zero generation.

During the event period T_event, hourly energy shortages L(t) are defined as the difference between load demand P_load(t) and total generation P_gen(t), when demand exceeds supply. The resilience objective minimizes total unmet energy demand over the entire event duration:

$$Min\ J_{res} = EENS = \sum_{t=1 to\ T_{event}} max\,(0,\, P_{load}(t) - P_{gen}(t)) \times \Delta t \quad (4)$$

2) *Decision Variables and Constraints*

a) *Decision Variables:*

The optimization primarily determines the optimal installed capacity of each technology. Key decision variables include:

- Total PV installation area (A_pv)
- Number of wind turbines (N_wt)
- Rated energy capacity and power of the Li-ion battery system (C_bat, P_bat)
- Rated power of the electrolyzer (P_el)
- Hydrogen storage tank capacity (C_h2)
- Rated power of the fuel cell (P_fc)
- Biomass generator capacity (C_bio)

b) *Constraints:*

The optimization process must satisfy several physical and operational constraints:

- Energy Balance Constraint: At every time step, total power generation (including generation units and storage discharge) must equal total consumption (including loads, storage charging, and conversion losses).
- Equipment Operational Constraints: The output of each device cannot exceed its rated capacity.
- Storage State Constraints: The State of Charge (SOC) of storage units must remain within a predefined safe operating range (e.g., 20% – 90%).
- Cyclic Energy Constraint: To ensure long-term operational stability, the storage energy level at the beginning and end of the annual optimization horizon must be identical.

C. *Solution Method and Case Study Setup*

1) *Solution Algorithm*

Because this study addresses a complex optimization problem characterized by nonlinearity, multiple objectives, and numerous constraints, conventional mathematical programming approaches are not well suited for obtaining effective solutions. To overcome these challenges, we adopted the Non-dominated Sorting Genetic Algorithm II (NSGA-II) [31], a heuristic optimization method known for its strong performance in solving multi-objective problems.

NSGA-II is inspired by the principles of natural evolution, incorporating selection, crossover, and mutation operations to conduct a global search within a complex solution space. Its main mechanisms include:

- Fast Non-dominated Sorting: This procedure ranks individuals in the population by stratifying them into different Pareto fronts, enabling rapid identification of superior and inferior solutions.
- Crowding Distance Calculation: Within the same Pareto rank, this metric evaluates the density of surrounding solutions to preserve diversity. By encouraging a well-distributed solution set, it reduces the risk of premature convergence to local optima.
- Elitism Strategy: The algorithm retains the best individuals from both parent and offspring generations, ensuring that high-quality solutions are preserved throughout the iterative process.

Through NSGA-II, the optimization yields a set of Pareto-optimal solutions rather than a single outcome. This

Pareto front defines the optimal trade-off boundary among resilience, economic, and environmental objectives, offering decision-makers flexible options aligned with their specific priorities.

2) Case Study Setup

To demonstrate the applicability of the proposed framework, a representative industrial park located in a coastal region of southeastern China was selected as the case study. This area frequently experiences typhoons during summer and autumn, making energy system resilience particularly critical.

- Load and Resource Data: Reproducible hourly electricity and heat demand profiles, along with representative annual solar irradiance and wind speed data for the region, were utilized. These datasets were either sourced from publicly available databases or constructed according to clearly defined rules. The total annual electricity demand of the industrial park is approximately 50 GWh.
- Economic and Technical Parameters: Capital costs, operation and maintenance expenses, conversion efficiencies, and equipment lifetimes were compiled from publicly accessible reports and relevant literature [10, 32], forming a transparent and reproducible parameter set. The grid electricity price followed a time-of-use tariff structure, and the carbon emission factor was defined based on a clearly stated grid-average assumption.
- Optimization Parameter Settings: For the NSGA-II algorithm, the population size was set to 200 and the maximum number of generations to 500. The random seed and key solver parameters were explicitly specified to ensure reproducibility. All optimization procedures were implemented within the MATLAB environment.

IV. Results and Discussion

This chapter presents the optimization results derived from the previously described methodology and offers a comprehensive discussion of the findings. It begins with an analysis of the Pareto-optimal solutions to explore the trade-offs among the three objectives. Next, three representative design schemes are selected for comparative evaluation, highlighting how system configurations and performance vary under different optimization priorities. Finally, a sensitivity analysis is conducted on a key parameter to examine its influence on overall system performance.

A. Pareto Frontier Analysis

By implementing the NSGA-II algorithm, a total of 200 non-dominated solutions were obtained, forming the Pareto-optimal frontier. Each solution in this set represents a system configuration that is non-inferior—meaning that improving one objective would inevitably lead to the deterioration of at least one other objective.

The Pareto frontier is illustrated in a three-dimensional space defined by cost, carbon emissions, and Expected Energy Not Supplied (EENS), as shown in Figure 2. Each point on the surface corresponds to a distinct optimal configuration. The resulting surface clearly reveals the significant trade-offs among economic efficiency, environmental performance, and system resilience.

Figure 2. The three-dimensional Pareto frontier of system planning results.

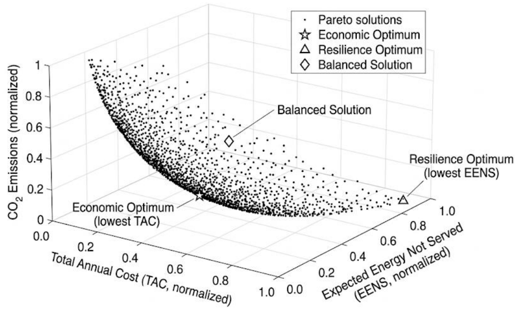

Fig. 2. 3D Pareto-optimal frontier showing the trade-offs between resilience, economic, and environmental objectives.

Figure 2. Three-dimensional Pareto-optimal frontier illustrating the trade-offs among resilience, economic performance, and environmental impact. The color of each point reflects the corresponding level of Expected Energy Not Supplied (EENS). The red star, blue triangle, and green square denote the Economic Optimum, Resilience Optimum, and Balanced Solution, respectively.

To better visualize the pairwise trade-offs between objectives, the three-dimensional Pareto frontier was projected onto three two-dimensional planes, as presented in Figure 3.

Figure 3. Two-dimensional projections of the three-objective Pareto frontier.

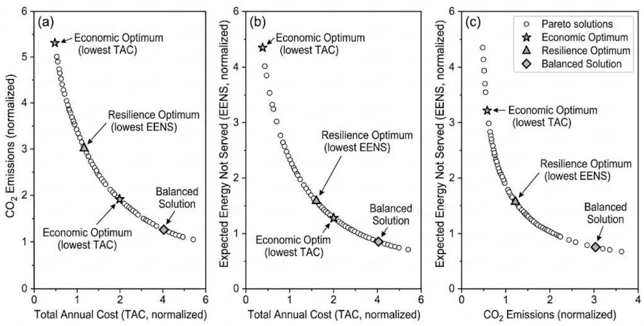

Fig. 3. 2D projections of the Pareto frontier between the three objectives.

Figure 3. Two-dimensional projections of the Pareto frontier illustrating the trade-offs among the three objectives: (a) Economic vs. Environmental; (b) Economic vs. Resilience; and (c) Environmental vs. Resilience. The markers representing the three selected solutions are the same as those shown in Figure 2.

Economic vs. Environmental Trade-off (Figure 3a): This projection highlights the relationship between Total Annualized Cost (TAC) and annual CO_2 emissions. A clear positive correlation can be observed: achieving lower emissions generally requires higher system costs. This trend arises because emission reductions depend on increased deployment of renewable energy technologies such as PV and wind, which involve higher upfront capital investment, as well as reduced reliance on grid electricity purchases. This observation aligns with findings from prior research on distributed energy system optimization [26].

Economic vs. Resilience Trade-off (Figure 3b): This represents one of the study ' s central findings. The figure reveals a pronounced conflict between minimizing cost and enhancing system resilience (i.e., reducing EENS).

Improving resilience requires larger investments in energy storage—particularly long-duration hydrogen storage—and dispatchable generation capacity to withstand extended grid outages and unfavorable weather during extreme events. These additional "resilience-oriented" investments significantly increase total system cost. In contrast, a purely cost-driven design results in a substantially higher EENS, indicating considerable energy shortfalls and an inability to reliably supply critical loads during extreme conditions.

Environmental vs. Resilience Trade-off (Figure 3c): The relationship between CO_2 emissions and EENS is more nuanced, forming an "L-shaped" or "J-shaped" curve. On one side, highly resilient systems often incorporate substantial renewable energy capacity, which simultaneously reduces carbon emissions, suggesting a synergistic effect. On the other side, if renewable capacity is inadequate, achieving very high resilience (extremely low EENS) may require extensive deployment of dispatchable generation resources. If these resources are not fully carbon-neutral, emissions may increase. This indicates that environmental and resilience objectives can align under optimized conditions, but achieving such synergy requires careful system design and strategic capacity allocation.

B. *Analysis of Representative Solutions*

To more clearly demonstrate how system configurations vary under different optimization priorities, three representative solutions were selected from the Pareto frontier for detailed comparison: the Economic Optimum (with the lowest Total Annualized Cost), the Resilience Optimum (with the lowest Expected Energy Not Supplied), and a Balanced Solution that achieves a compromise among the three objectives. All three solutions were derived under the same reproducible data inputs and parameter assumptions.

Table I presents a comparative overview of the system configurations and key performance indicators for these representative solutions.

TABLE I. COMPARISON OF CONFIGURATIONS AND PERFORMANCE FOR THE THREE REPRESENTATIVE SOLUTIONS.

Parameter	**Unit**	**Economic Optimum**	**Balanced Solution**	**Resilience Optimum**
System Configuration				
PV Capacity	MWp	8.2	15.5	24.8
Wind Capacity	MW	4.1	9.3	14.9
Battery Capacity	MWh	6.5	22.1	39.5
H2 Storage Capacity	MWh	5.2	85.6	198.7
Performance Indicators				
Total Annualized Cost (TAC)	k$/year	281.4	453.8	715.2
Annual CO2 Emissions	tonnes/year	1485	650	55
Expected Energy Not Supplied (EENS)	MWh/event	17.8	4.2	0.06
Renewable Penetration	%	41.2	75.8	97.5
Self-Sufficiency	%	45.1	80.3	98.9

[a] results are illustrative under stated assumptions

Economic Optimum: This configuration focuses exclusively on minimizing overall cost. Consequently, it features the smallest installed capacities of renewable generation and energy storage, with a strong dependence on grid electricity. Although it achieves the lowest Total Annualized Cost, its resilience performance is extremely weak, reflected in a very high EENS value. This indicates that the system would be nearly incapacitated during a severe extreme event. In addition, its environmental performance is the poorest among the three solutions due to its substantial reliance on grid-supplied electricity.

Resilience Optimum: This configuration prioritizes maintaining energy supply during extreme conditions. It includes significantly expanded capacities of PV, wind power, and particularly hydrogen storage. The large-scale hydrogen storage system serves as a long-duration energy buffer, enabling the system to maintain near-zero energy shortages even during a 48-hour grid outage. However, this high level of resilience requires substantial investment, with the Total Annualized Cost exceeding 2.5 times that of the Economic Optimum. Its environmental performance is outstanding, supported by its very high share of renewable energy generation.

Balanced Solution: This configuration represents a strategic compromise among economic, environmental, and resilience objectives. Both its installed capacities and performance metrics fall within moderate ranges. Compared to the Economic Optimum, it reduces EENS by more than 75% while incurring only a moderate cost increase. For decision-makers who seek a practical and well-rounded solution rather than extreme optimization of a single objective, this balanced approach often provides the greatest real-world applicability.

C. *Sensitivity Analysis of Key Parameters*

To further examine how key design parameters influence overall system performance, a sensitivity analysis was carried out. Since hydrogen storage plays a pivotal role in strengthening long-term system resilience, we specifically evaluated how varying hydrogen storage capacity affects both the Total Annualized Cost (TAC) and the Expected Energy Not Supplied (EENS).

As illustrated in Figure 4, increasing hydrogen storage capacity leads to an exponential decline in EENS, reflecting a substantial enhancement in resilience. In contrast, TAC rises in an almost linear manner as storage capacity expands. This trend highlights the phenomenon of diminishing marginal returns on resilience investment. When hydrogen storage capacity is relatively low, modest increases in investment can produce significant resilience improvements. However, beyond a certain threshold, additional investments result in progressively smaller reductions in EENS, while system costs continue to grow steadily.

The figure also identifies an "optimal investment region" (for example, approximately 35 – 70 MWh in the illustrated case), within which a favorable balance between cost and resilience can be achieved. This finding offers a quantitative reference for decision-makers in determining an appropriate and economically justified level of resilience investment.

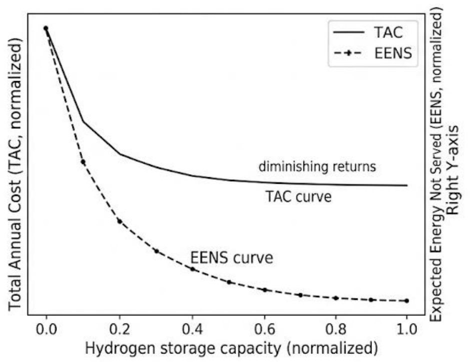

Figure 4. Sensitivity analysis of hydrogen storage capacity on EENS.

Fig. 4. Sensitivity analysis of the impact of hydrogen storage capacity on system cost and resilience.

Figure 4. Sensitivity analysis illustrating the effect of hydrogen storage capacity on system cost (Total Annualized Cost, TAC) and resilience (Expected Energy Not Supplied, EENS). The results indicate that expanding hydrogen storage capacity markedly enhances resilience, while simultaneously increasing overall cost, with clear evidence of diminishing returns at higher capacity levels.

V. Conclusion

This paper addresses a key gap in distributed energy system design by introducing a multi-objective optimization framework that positions system resilience as a primary objective, on equal footing with economic and environmental considerations. Through the development of a comprehensive hybrid DES model and the application of the NSGA-II algorithm, the study systematically quantifies and evaluates the intricate trade-offs among resilience (measured by EENS), economic performance (measured by TAC), and environmental impact (measured by CO_2 emissions).

The main conclusions are summarized as follows:

- There is a pronounced trade-off between system resilience and economic cost. Achieving high resilience requires significant investment in renewable energy capacity and especially in long-duration storage technologies such as hydrogen. These investments substantially increase the Total Annualized Cost. In contrast, a design focused solely on minimizing cost is highly vulnerable to extreme events and cannot reliably supply critical loads during disruptions.
- The relationship between resilience and environmental performance is both synergistic and complex. Increasing renewable energy penetration can simultaneously strengthen resilience and reduce carbon emissions. However, configurations that maximize resilience are not always the most environmentally optimal, underscoring the importance of coordinated, multi-objective optimization.
- The proposed framework serves as an effective decision-support tool. By generating a Pareto-optimal frontier, it provides a spectrum of optimal design solutions, ranging from cost-prioritized to resilience-prioritized configurations, along with balanced alternatives. This enables stakeholders to select solutions aligned with their specific objectives, budget limitations, and risk preferences.
- Hydrogen storage is pivotal for enhancing long-term resilience, yet its investment demonstrates diminishing marginal returns. Sensitivity analysis indicates that while hydrogen storage significantly reduces energy shortages during extended outages, there exists an optimal investment range beyond which additional capacity yields progressively lower cost-effectiveness.

The primary innovation of this study lies in redefining resilience from a secondary constraint to a central design objective. This conceptual shift offers a more comprehensive and scientifically grounded approach to designing next-generation distributed energy systems that are not only economically and environmentally sustainable but also robust against increasing climate-related uncertainties. The results hold important practical implications for planning energy infrastructure in critical facilities such as industrial parks, data centers, and hospitals.

Future research may expand on this work in several ways. First, more diverse and complex extreme event scenarios—such as compound disasters or cascading failures—could be incorporated to strengthen resilience assessment. Second, uncertainties in renewable generation and load demand could be modeled using stochastic or robust optimization techniques. Finally, the social dimension of sustainability could be integrated into the framework by including additional objectives, such as employment impacts and public health benefits.

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AVAILABILITY OF DATA

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AUTHOR CONTRIBUTIONS

Gehao Xie: Conceptualization, Methodology, Software, Formal analysis, Visualization, Writing – original draft. Wenjing Yuan: Data curation, Validation, Investigation, Writing – review & editing. Wanliu He: Supervision, Project administration, Resources, Funding acquisition, Writing – review & editing. All authors have read and approved the final manuscript.

COMPETING INTERESTS

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