

Original article

Sizing for survival: Building resilient off-grid LVDC PV-storage systems against long-return-period climate events

T. Castillo-Calzadilla ^a, A.M. Macarulla ^b, C. Olivares-Rodríguez ^c, C.E. Borges ^b, E. Olías Ruiz ^d^a Escuela Superior de Ingeniería y Tecnología, Departamento de Ingeniería Industrial, Universidad de La Laguna, Camino San Francisco de Paula s/n, 456, 38200, San Cristóbal de La Laguna, Spain^b Facultad Ingeniería, Universidad de Deusto, Avda. Universidades, 24, 48007, Bilbao, Spain^c Facultad Ingeniería, Universidad Alberto Hurtado, Alameda 1825, Santiago, Chile^d Escuela de Ingeniería, Departamento de Tecnología Electrónica, Universidad Carlos III de Madrid, Avenida de la Universidad, 30, Postal Code 28911, Leganés, Madrid, Spain

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ABSTRACT

The increasing severity of extreme weather events demands enhanced resilience in off-grid photovoltaic and energy storage systems. This study aims to integrate quantitative risk analysis into the system sizing process to quantify and mitigate the probability of operational failure under long-return-period weather extremes, under the hypothesis that risk-based sizing can improve reliability without disproportionate cost escalation. A surrogate model is constructed from real and synthetic performance data to efficiently explore the design space and identify a Pareto frontier of robust system configurations. A Monte Carlo simulation is then applied to a case-study building in Bilbao, evaluating 100 candidate configurations against 100 bootstrapped weather patterns, representing 120 years of historical and projected climate data. The results show that fewer than 25% of the investigated systems maintain continuous operation under the most extreme conditions considered. The most cost-effective configuration achieving 100% reliability for a 100-year return period event combines an 80% oversized photovoltaic array with a 20% undersized storage system. These findings provide actionable sizing guidelines for resilient off-grid DC systems and underscore the significant economic trade-offs associated with designing for full climatic reliability in future applications and standards development.

Introduction

The ongoing energy transition, driven by policies such as the EU Green Deal and the United Nations “Zero Carbon Buildings for All (ZCB)” initiative, is rapidly increasing the share of renewable generation in power systems [1]. While this shift is essential for decarbonisation and achieving the Sustainable Development Goals (SDG), it also exposes electricity networks to greater sensitivity to weather variability and extreme climate events [2].

Maintaining the generation-demand balance becomes increasingly challenging as electrification progresses and weather-dependent resources gain prominence [3]. Climate-intensified events and prolonged periods of low renewable output (e.g., Dunkelflaute [4]) pose serious risks to security of supply, causing extended energy deficits [4,5]. In this context, off-grid and weakly connected systems are especially vulnerable, as they cannot rely on strong interconnections to buffer local shortages [6,7].

Off-grid photovoltaic systems coupled with battery energy storage systems (PV-BESS) are a key technology for enhancing resilience by decoupling generation and consumption over time [8]. Through advanced control strategies, these systems can perform peak shaving and energy arbitrage, and provide ancillary services, thereby improving reliability and enabling higher renewable penetration [8,9]. However, most sizing methodologies still rely on historical climate data and focus on techno-economic optimisation under typical conditions, potentially underestimating the increasing frequency and severity of climate-change-induced extremes.

Existing studies on climate risk in energy systems have mainly addressed large-scale networks or AC-based infrastructures, while the resilience of off-grid low-voltage DC (LVDC) microgrids in urban buildings remains comparatively under-explored [6,7]. In particular, there is a lack of sizing approaches that explicitly integrate long-return-period events into the design of off-grid LVDC PV-storage systems [10,11],

* Corresponding author.

E-mail addresses: tony.castillo@ull.edu.es (T. Castillo-Calzadilla), ana.macarulla@deusto.es (A.M. Macarulla), colivares@uahurtado.cl (C. Olivares-Rodríguez), cruz.borges@deusto.es (C.E. Borges), olias@ing.uc3m.es (E.O. Ruiz).<https://doi.org/10.1016/j.seta.2026.105166>

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Nomenclature

AC	Alternating current
AEMET	Spanish state meteorological agency
BESS	Battery energy storage systems
BOS	Balance of system
CESM-LENS	Community earth system model-Large ensemble project
CMIP	Coupled model intercomparison project phase
CORDEX	Climate downscaling experiment
DC	Direct current
dSoC	Variation of state of charge
EBOS	electrical balance of system
ESS	Energy storage system
IPCC	Intergovernmental panel on climate change
IR	Global irradiance of the day
IRR	Internal rate return
LVDC	Low voltage direct current
NPV	Net present value
NREL	National renewable energy laboratory
PV	Photovoltaic
RCP	Representative concentration pathways
ROI	Return over investment
SBOS	structural balance of system
SoC	State of Charge
SSP	Shared socioeconomic pathways

prioritising operational survival before conventional techno-economic assessment [8].

This work addresses this gap by proposing a risk-aware sizing methodology for off-grid LVDC PV-storage systems that explicitly accounts for 100-year return period climate events in the design process. The method combines a detailed simulation model of a service building (hall of residence in Bilbao) with a surrogate model derived from real and synthetic performance data, and applies it to long-term weather series (1980–2100) generated from historical measurements and climate projections.

In contrast to traditional sizing tools (such as HOMER or XENDÉE) that rely on typical meteorological years (TMY) or short historical series, this study introduces a machine-learning-based sizing framework that accounts for long-term climate variability and extreme weather events. Accordingly, the scientific contribution of this work is twofold:

1. The integration of synthetic IPCC future projections (up to 2100) with historical reanalysis (from 1980) to model extreme climate risks with 100-year return periods, and
2. The development of a multi-objective sizing optimisation that quantifies blackout risks (via daily State of Charge, $dSOC$, dynamics) to identify cost-effective, resilient configurations on a Pareto frontier.

To validate this framework, the methodology is applied to a building-scale, low-voltage direct current (LVDC) off-grid system as a representative case study. This work builds directly upon our previously established DC sizing methodology [10–12], expanding it to incorporate a novel resilience constraint and long-horizon climate scenarios. Weather variations and rare climate events are captured by pairing historical AEMET data with Meteorom-based projections via bootstrapping.

The remainder of this paper is organised as follows. Section “Related Work” provides a comprehensive review of relevant literature.

Section “System diagram & description” details the implemented system configuration, while Section “Methodology implemented” formally introduces the risk-aware optimisation methodology. The experimental results and case study evaluation are presented in Section “Results and discussion”. Finally, Section “Conclusions, future work & limitation” outlines the main conclusions, limitations, and paths for future work.

Related work

A limited number of studies explicitly integrate risk analysis and long-horizon climate projections into the design of renewable energy systems, and even fewer focus on low-voltage DC architectures. A first line of research investigates the impact of climate change on atmospheric dynamics and solar resource availability using 100-year simulations and scenarios from CESM-LENS, CORDEX, CMIP, and RCP/SSP frameworks [13–15]. These works show that global warming is likely to reduce average PV potential and increase the frequency of extreme low-yield events, potentially destabilising power systems.

A second group of contributions analyses how extreme weather events and natural disasters affect PV generation, storage operation, and system resilience at regional or national scales [4,14,16,17]. These studies often rely on long-term projections and scenario analysis to evaluate the role of battery and hydrogen storage in mitigating outages during emergencies, and highlight the importance of flexible storage strategies under conditions of deep uncertainty. While highly relevant, they primarily address large-scale or AC-based systems rather than off-grid LVDC microgrids in buildings.

Other works focus on urban energy resilience, modelling the behaviour of city districts and energy communities under extreme weather scenarios, and assessing the contribution of PV and BESS to reducing vulnerability and outage duration [18–22]. These analyses typically employ multi-criteria decision-making and resilience indicators to quantify performance and demonstrate that integrating PV and storage can significantly improve the robustness of urban energy systems. However, they do not provide a dedicated sizing methodology for off-grid LVDC PV-ESS systems that explicitly targets long-return-period events.

Finally, there is a strand of literature on techno-economic risk assessment of LVDC distribution networks, which evaluates efficiency gains, net present value (NPV), and internal rate of return (IRR) under different investment scenarios [23–25]. These studies confirm the potential benefits of LVDC in terms of efficiency and economic performance, but they generally treat risk in financial terms (e.g., price and cost uncertainty) and do not embed explicit climatic resilience constraints into the sizing process of PV and storage capacities.

Other studies address renewable-energy system design through simulation and techno-economic optimisation. In [26], it is shown that temporal resolution materially affects sizing accuracy and reliability in self-sufficient systems, while [27] optimises an off-grid university-campus HRES with PV, batteries, and hydrogen under economic criteria. However, they do not consider a climate-risk-aware sizing framework for off-grid LVDC PV-ESS systems, nor do they explicitly evaluate resilience against long-return-period weather events using historical and projected climate series, bootstrapping, and a surrogate model.

In summary, while the existing literature separately addresses long-horizon climate trends, large-scale system resilience, and the economic assessment of LVDC networks, a critical research gap remains at their intersection. Current sizing frameworks for building-scale off-grid LVDC systems lack mechanisms to ingest multi-decade climate projections or to quantify physical asset resilience against rare, long-return-period weather anomalies. This study directly addresses this gap. By extending a foundational DC sizing framework to incorporate synthetic IPCC future projections up to 2100 alongside daily State of Charge ($dSOC$) dynamics, this work provides a novel, risk-aware optimisation methodology. It effectively moves beyond traditional TMY-based sizing, enabling the identification of cost-effective configurations explicitly optimised for long-term climate resilience on the Pareto frontier.

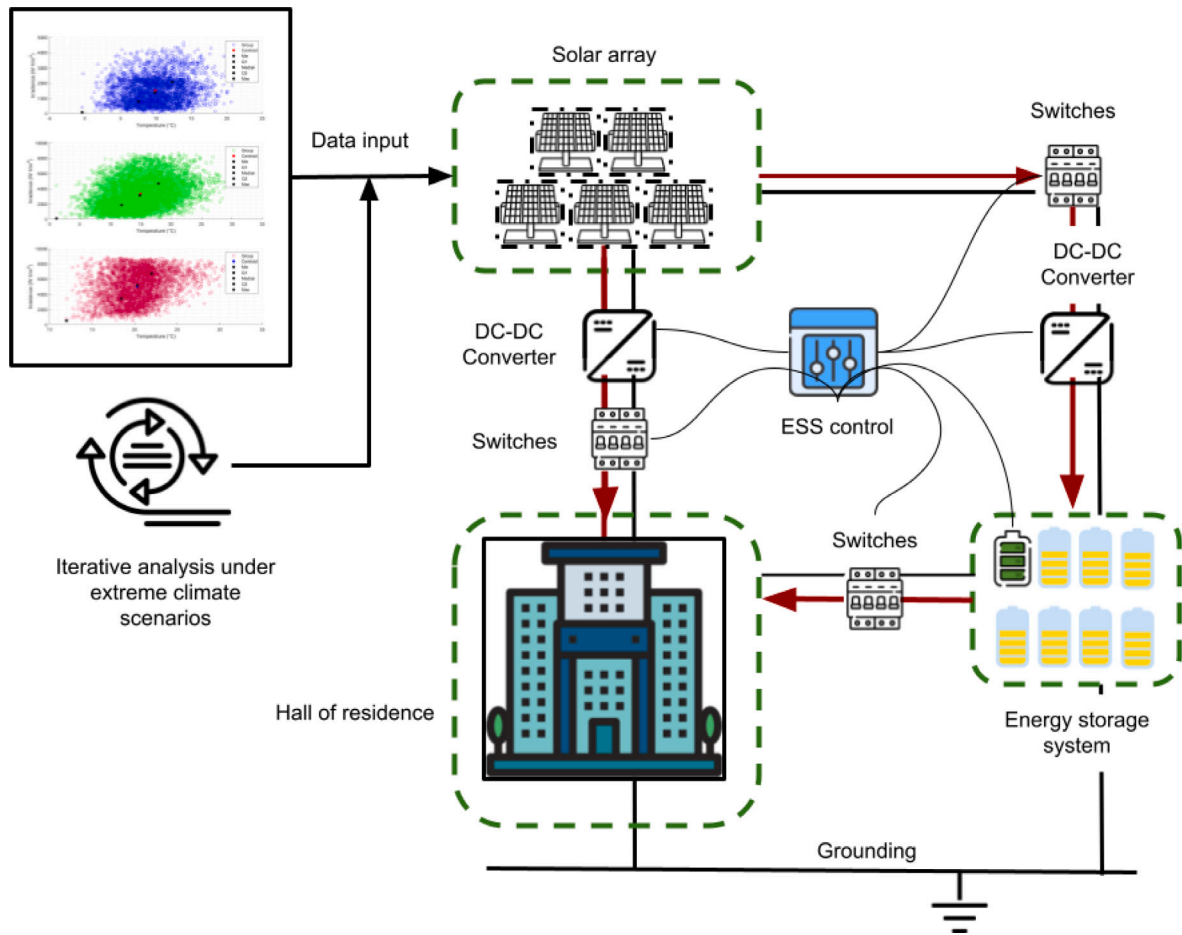


Fig. 1. Schematic diagram of the simulation framework used to evaluate the off-grid PV-ESS system under iterative climate scenarios.

System diagram & description

The off-grid system comprises a PV array, DC-DC converters, a battery ESS, control systems, and an electrical load (see Fig. 1) representing a hall of residence at the University of Deusto, Bilbao.

Fig. 1 illustrates the core architecture of the pilot system. The solar PV array model simulates electrical behaviour based on time-series inputs of solar irradiance and temperature, capturing thermal sensitivity during extreme weather events. A 24 V battery bank serves as the Energy Storage System (ESS), managed by an SoC-driven control loop that regulates charging and discharging cycles via DC-DC converters. Finally, the demand side is modelled using real, measured consumption profiles from a University of Deusto hall of residence; this load block is modular and can be adapted to simulate alternative electrical demands such as residential buildings, motors, or electric vehicles (EVs).

Methodology implemented

This section introduces key modifications to the foundational sizing algorithms established in [10,11] to explicitly incorporate infrastructure resilience. The updated optimisation framework balances two primary objectives: determining the optimal PV array capacity to meet the building's core energy demand and sizing the energy storage system to maintain operational continuity during extended periods of zero generation.

To evaluate system performance under long-return-period extremes, synthesising off-grid weather archetypes introduces limitations due to temporal dependencies; microgrid operations depend heavily on cumulative state of charge (SoC) built up over extended preceding periods.

Consequently, this framework generates continuous climate scenarios to capture long-term cumulative dynamics.

The second paradigm involves generating multiple long-term, continuous climate scenarios to evaluate the system over extended horizons. This approach eliminates arbitrary window selection and captures the long-term cumulative dynamics essential for realistic resilience modelling. However, this method introduces a substantial computational burden, requiring the evaluation of nearly one million operational days. Because the core sizing simulation is highly detailed and computationally intensive, executing it across such massive datasets presents a significant tractability challenge.

To handle the computational burden, the methodology is structured into two sequential phases: building infrastructure simulation (Section "Building infrastructure simulation"), which establishes the baseline operational model, and blackout resilience assessment (Section "Blackout resilience assessment"), which uses an efficient surrogate model [28] trained on baseline data to evaluate long-term resilience under extensive synthetic climate scenarios.

Eq. (1) present the surrogate model proposed. This model uses a logistic model to map meteorological data (temperature and global irradiance) to the $dSoC$ of the ESS of the pilot, depending on the actual configuration.

$$dSoC(X_{PV}, X_{ESS}; IR, T) := d + \frac{a - d}{(1 + (IR/c)^b)^f} + \beta_1 T + \beta_2 X_{PV} + \beta_3 X_{ESS}, \quad (1)$$

where:

- IR , T , X_{PV} , and X_{ESS} represent the daily global irradiance, mean ambient temperature, normalised PV capacity, and normalised energy storage capacity, respectively.
- c and d are the horizontal asymptotes representing operational $dSoC$ boundaries.
- b , e , and s govern the curve's slope transition, location, and asymmetry relative to solar irradiance.
- β_1 , β_2 , β_3 are the linear coefficients quantifying the independent impacts of thermal sensitivity, PV scaling, and ESS capacity on daily storage variations.

As shown, the role of our surrogate model is to serve as a deterministic surface-fitting (or interpolation) proxy over a closed, structured grid of known physical simulation points. The underlying data-generating process is a deterministic engineering simulation framework, meaning there is no stochastic noise, random measurement error, or unobserved real-world variance in the dataset. Please note that this methodology could be used for any other type of dwelling or building in any location worldwide by using the data described in this section. In particular, the procedure requires time series for radiation, temperature, and consumption to emulate the behaviour of the new building under study.

Building infrastructure simulation

This framework adopts the foundational sizing workflow developed in [10,11], as illustrated in Fig. 2. Although the physical facility is located in an urban area, the framework models the system as a fully off-grid microgrid. Consequently, the sizing algorithm optimises the PV array and ESS capacity to achieve total self-sufficiency, forcing the battery bank to absorb all surplus generation and bridge all generation deficits dynamically.

The reference system configuration yielded by the baseline sizing algorithm comprises a 464 kWp PV array (1115 modules) and a 4018 kWh battery bank (186 cells) [10,11]. To preserve asset health and ensure operational safety, the ESS control loop enforces strict manufacturer-recommended operational limits, restricting the State of Charge (SoC) strictly between 10% and 98.5% [29,30]. The detailed specifications for these components are compiled in Tables B.3 and B.4. We will consider this as the reference configuration (100%).

The foundational climate dataset comprises 43 years (1980–2023) of hourly solar irradiance and temperature records from a weather station located approximately 4 km from the study site. Following data preprocessing and quality control, an unsupervised k -means clustering technique was applied to partition the weather data into three distinct seasonal cohorts representing spring/autumn, summer, and winter; these clusters were subsequently used to impute missing values. The resulting descriptive statistics and characteristic irradiance profiles for each cluster are detailed in Table B.2 and Fig. A.7, respectively (with full methodological details provided in Section Appendix F).

On the other hand, we have four years of energy consumption data (2015–2019). The dataset was clustered using the same procedure as for the weather data, and thus a representative day for each season was selected to perform the simulations. Fig. A.8 present the load profile of the representative days selected. The energy demand follows a typical Spanish household load profile, exhibiting characteristic midday and nocturnal consumption peaks.

To assess performance under different configurations, a parametric reduction of the PV and ESS capacities was carried out in steps of 10%, ranging from 180% to 60% of the reference size. This procedure was implemented through a double iteration loop, resulting in 169 unique combinations of PV and ESS capacities (13×13 possible size).

Each sizing combination was simulated under the three climate scenarios (winter, autumn/spring, and summer) across the five representative statistical cohorts for irradiance and temperature (see Fig. 3). This structured approach generated 845 unique configurations per climate scenario, yielding a uniform dataset of 2535 deterministic

simulation points. Because this matrix was populated via a systematic parametric grid search rather than passive observation, the input vector space features a perfectly equal distribution of design configurations. Consequently, traditional dataset classification artefacts—such as class imbalance—are absent in this framework, eliminating the need for artificial resampling or algorithmic class weighting. This balanced design space forces the surrogate model to map the physical resilience boundary with global fidelity, ensuring its structural robustness across all operational regimes. Model parameters show stable fits ($p < 0.001$, Appendix D).

We are only focused on the difference of the State of Charge ($dSoC$) of the ESS. The $dSoC$ is calculated as the difference between the SoC at the end of the 24-hour simulation cycle and the initial SoC , defined as the SoC at the beginning of the cycle. A graphical example can be seen on Fig. A.9. See Appendix C for more details.

Blackout resilience assessment

To evaluate the resilience of the proposed solution under extreme weather conditions with a return period of at least 100 years, it was necessary to extend the analysis beyond the available 43-year historical dataset. For this purpose, estimations of solar irradiance and temperature for the period 2023–2100 were required. This extension not only enables the characterisation of extreme events with a return period of at least 100 years, but also allows such estimates to incorporate the expected influence of climate change on their probability of occurrence. It should be emphasised that this temporal horizon does not correspond to the lifetime of individual system components (e.g., photovoltaic modules, batteries), which is typically estimated at 20–30 years, but rather provides a framework to assess the capacity of the initial system design to withstand long-term climatic challenges Section Appendix B.

In this paper, we have used Meteororm 8 [31]. Meteororm provides three types of future data based on the Intergovernmental Panel on Climate Change (IPCC) scenarios RCP 2.6, 4.5, and 8.5, derived from 10 global climate models based on CMIP5. The RCP 2.6 pathway was deliberately selected as the baseline climate scenario for this resilience assessment. While higher-emission pathways (e.g., RCP 8.5) typically simulate more extreme global warming, they project an overall increase in average solar irradiance for the target region due to reduced cloud cover. Consequently, the lower-emissions scenario serves as a more conservative “worst-case” benchmark for off-grid PV generation availability and system stress testing.

Because Meteororm provides only one typical meteorological year per decade (Fig. A.10), a bootstrapping technique [32] was employed to populate the remaining years, yielding continuous multi-decade testing timelines. Subsequently, the AEMET observational data were conditioned to ensure consistency with the time series, enabling the datasets to be concatenated. Given the stochastic nature of the bootstrapped samples, 100 unified datasets, covering the period 1980–2100, were then prepared for modelling in order to evaluate both the performance of the sizing methodology and the overall system operation.

Finally, the last step of the methodology is to use the surrogate model over the bootstrapped time series. In this way, the model approximates the behaviour of the overall system given the irradiation of the day and the initial SoC of the system using the following recurrent equation:

$$SoC(0) := 70\% + dSOC(X_{PV}, X_{ESS}; IR(0), T(0))$$

$$SoC(t+1) := \min(SoC(t) + dSOC(X_{PV}, X_{ESS}; IR(t), T(t)), 98.5\%) \quad (2)$$

where:

- t represents the day of the simulation,
- $IR(t)$ and $T(t)$ represent the global irradiance (respectively the temperature) of the day, and
- $dSOC(\cdot)$ is the surrogate model fitted in Eq. (1).

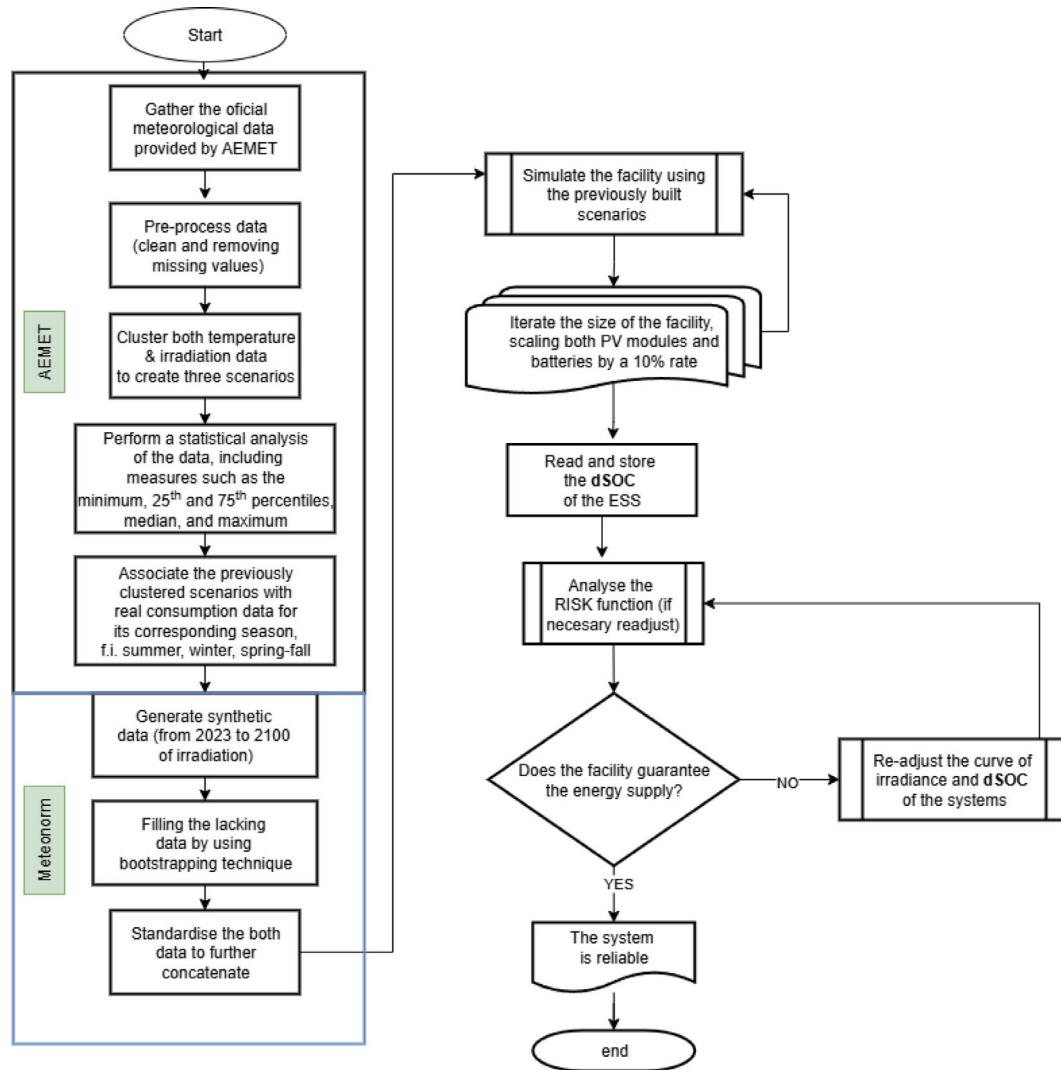


Fig. 2. Workflow of the proposed risk-based sizing methodology under historical and future climate scenarios.

To test the system's resiliency, we now just need to use Eq. (2) with the bootstrapped weather time series generated in Section "Blackout resilience assessment" to produce a time series of expected S_oC for the installation. If the $S_oC(t)$ time series falls below the manufacturer's lower safe-operating limit (10%), we record the time step at which it occurs. Finally, this value is defined as the system's resilience. Because these calculations rely on the explicit logistic surrogate, simulating millions of operational days requires only minutes of computation.

This metric is directly linked to the design objective of guaranteeing survival under long-return-period climate events; the complementary blackout rate is defined as 1-resilience. From a techno-economic perspective, we use IRR, ROI, and NPV, with cost assumptions based on NREL Q1-2023 benchmarks, as standard indicators to assess the economic viability of PV-ESS investments.

Results and discussion

Fig. 4 illustrates the resilience landscape across the evaluated sizing variations, serving as a comprehensive component-level ablation study of the physical infrastructure assets. The horizontal and vertical axes represent the capacities of the PV array and the ESS, respectively, expressed as percentages relative to the baseline scenario. Each cell quantifies system resilience as the percentage of operational days wherein the facility successfully guarantees an uninterrupted electricity

supply to the hall of residence. A value of 1.0 denotes a completely resilient configuration that operates across the entire 47,321-day horizon without experiencing a supply deficit. Note that while configurations ranging from 60% to 180% were comprehensively tested, results for capacities at or below 70% are excluded from the heatmap to prevent inaccuracies arising from surrogate model extrapolation boundaries.

As shown in Fig. 4, 39 fully resilient configurations (achieving a value of 1.0) concentrate in the lower-left region of the design space. Within this set, the configurations highlighted in red define the *Pareto frontier*. Along this frontier, an almost inverse linear relationship emerges between optimal PV and ESS sizes. Crucially, the traditional sizing baseline derived from TMY methods [10,11] lies entirely outside this high-resilience region. This behaviour is explained by the fact that additional PV capacity is relatively inexpensive and has a longer operational lifespan than electrochemical storage; thus, oversizing the PV array cost-effectively mitigates risk during prolonged low-irradiance periods, leaving the ESS to bridge short-term diurnal deficits.

To determine the final optimal configuration from the Pareto frontier, a techno-economic assessment was conducted using regional cost benchmarks from the National Renewable Energy Laboratory (NREL) [33], summarised in Appendix E. The specific trade-offs of the Pareto-optimal points are detailed in Table E.6. Assuming no physical space constraints for installation, the most techno-economically viable configuration features an 80% oversized PV array combined with a

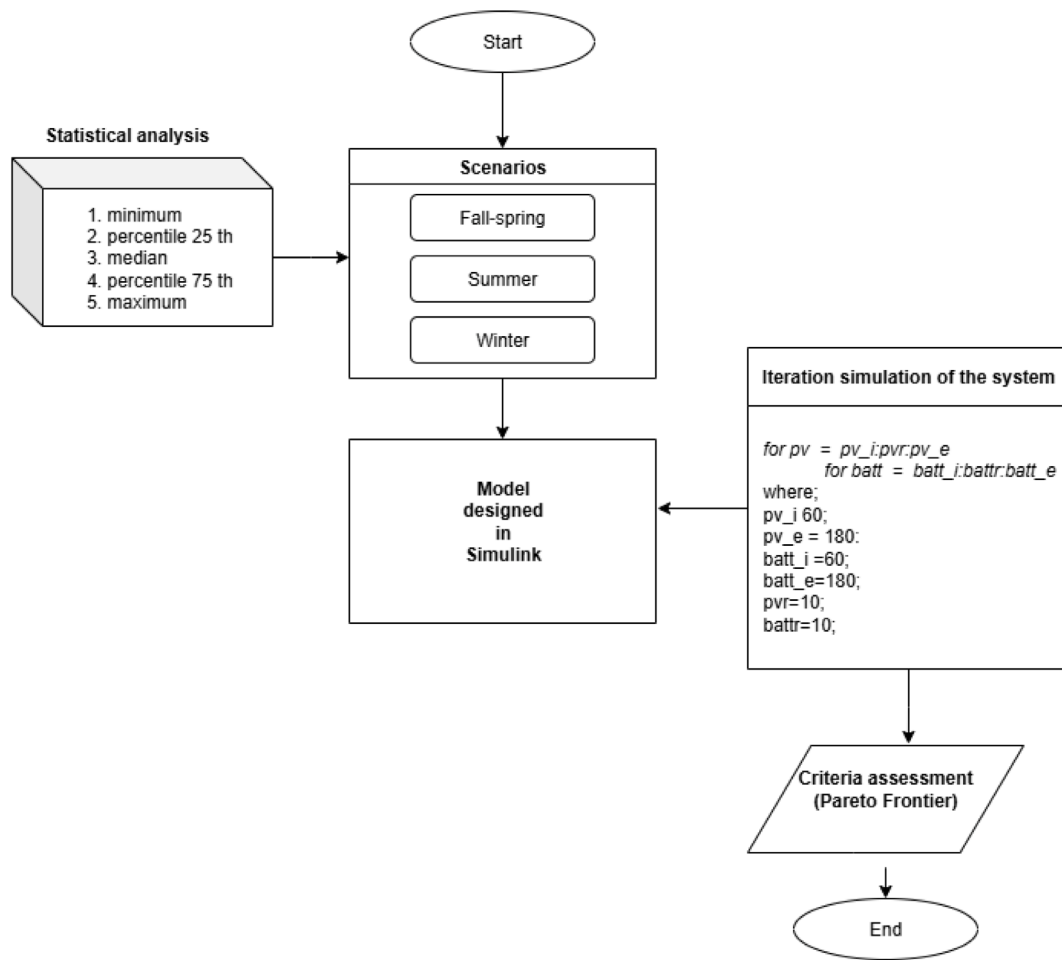


Fig. 3. Simulation workflow for the proposed risk-based assessment, including scenario selection, model simulation, iterative sizing, and Pareto-frontier evaluation.

Table 1

Techno-economic metrics: Traditional sizing baseline vs. proposed pareto-optimal configuration.

Metric	Traditional baseline [11]	Optimised configuration
PV Capacity Sizing	100%	180% (Oversized)
ESS Capacity Sizing	100%	80% (Undersized)
Climate Resilience	Fails on extreme events	100% Guaranteed
Relative CapEx	Baseline Cost	+17%
ROI	–	8 Years
IRR	–	14.55%
NPV	–	\$3.14 M USD

20% undersized ESS. This configuration yields a Return on Investment (ROI) of 8 years, an Internal Rate of Return (IRR) of 14.55%, and a Net Present Value (NPV) of 3.14 M USD. Notably, the baseline configuration (100% PV, 100% ESS) is only 17% less expensive than this maximum-resilience configuration, demonstrating that substantial climate robustness can be achieved with a marginal increase in capital expenditure.

By just posing the baseline configuration against the optimised design space, the definitive advantages of the proposed framework become clear. Table 1 provides a direct comparative summary of the traditional sizing baseline versus the selected Pareto-optimal configuration.

Nevertheless, the robustness of the solution depends on the cost structure presented in Table E.5. To provide a more generalised and robust assessment, we performed two distinct sensitivity analyses on the final optimal configuration. First, we analysed the impact of the

relative costs of the PV modules and the ESS. We repeated the final assessment by testing cost multipliers ranging from 0.05% to 200% for both PV panels and ESS cells, following the Pareto frontier. The results, detailed in Fig. 5, demonstrate a high degree of solution stability. Only two optimal configurations were selected across this wide range:

- The reference configuration: 180% PV Array and 80% ESS (the default solution found at current costs).
- An alternative configuration: 120% PV Array and 170% ESS.

However, the economic conditions required to switch from the default solution to the alternative are not highly unrealistic. The shift would require a 70% reduction on the price of the ESS. While this is a sharp price reduction, PV panels have experienced similar reductions in the past, and the price reduction for ESS has exceeded even the most optimistic forecasts [34].

Second, we contrasted the impact of labour costs (Office work, Fieldwork, and Other) against infrastructure costs (PV module, ESS, SBOS, and EBOS). As before, the final assessment was repeated using cost multipliers ranging from 0.05% to 200% for both cost blocks. The results, detailed in Fig. 6, show that even that moderate reduction in labour costs (up to 30%) does not affect the best solution selected by the methodology. Moreover, if the cost of PV panels and ESS cells continues to drop, it would require even bigger reductions in labour cost to switch to the best configuration. This result suggests that changes in the relative proportion of labour versus material costs, given that labour cost is the only cost with an increasing trend in the sector (due to inflation), will not affect the optimal system sizing (provided the critical internal relationship between the cost of PV panels and the cost of the ESS cells remains constant).

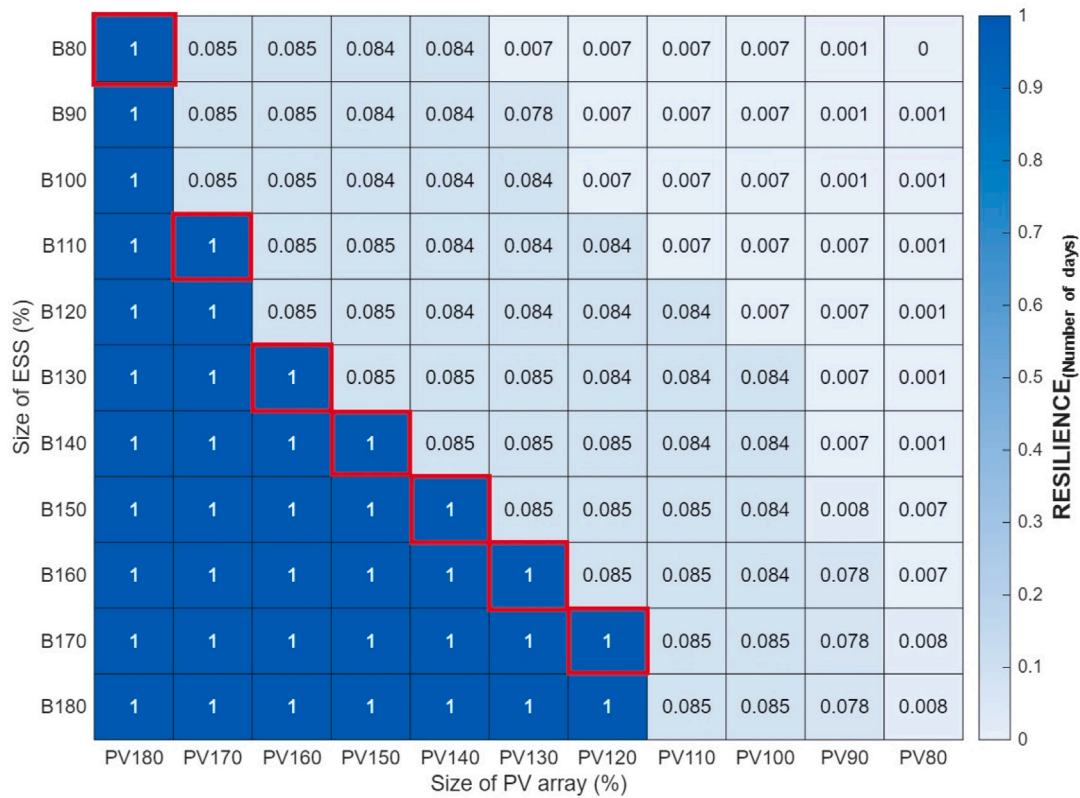


Fig. 4. Resilience results for the PV-ESS sizing combinations.

The structural superiority of the identified Pareto-optimal configurations over traditional sizing baselines stems from an explicit synergy between the power-electronic control framework and asset-level economic trade-offs. Physically, traditional sizing methods are bounded by conservative energy storage safety cushions. By implementing a dual-window control loop that actively regulates both SoC and V_{bats} , the proposed model safely capitalises on an extended depth-of-discharge window (down to 10% SoC) without accelerating capacity degradation. This optimisation effectively unlocks latent electrochemical capacity, allowing the system to shrink the expensive battery bank by 20%. Mechanistically, the model mitigates the risk of extreme, long-return-period climate anomalies by executing a strategic asset substitution: it aggressively oversizes the PV array (+80%) to guarantee adequate generation even under severe, low-irradiance multi-day cloud covers. Because photovoltaic modules represent a low-cost, long-lifespan capital asset relative to electrochemical storage, this configuration cost-effectively satisfies the zero-deficit resilience constraint while maximising NPV .

Conclusions, future work & limitation

In this research, we introduced a novel, risk-aware sizing methodology that successfully bridges the gap between blackout risk analysis and traditional design methods for resilient, off-grid LVDC PV-storage systems. By utilising an extensive simulation framework that integrates both real-world variability and extreme climate data, the study achieved a high degree of reliability in the results.

Applying this methodology to an urban hall of residence in Bilbao, we demonstrated that a viable and resilient off-grid solution requires significant component over-sizing: specifically, an 80% oversized PV array and a 20% undersized ESS to guarantee 100% reliability against 100-year return period weather events. The subsequent economic analysis suggests a promising outlook, with an IRR of 6.55% and a 16-year ROI, highlighting the financial appeal despite the initial investment

(this scenario does not include subsidies). In contrast, when subsidies (30%) are considered, the facility increases IRR of 14.62% and an 8-year ROI.

Furthermore, the Pareto frontier analysis revealed a key design principle: there is a quasi-inversely linear relationship between the optimal sizing of the PV panels and the batteries. Given the lower cost and longer lifecycle, the logic dictates that solutions with larger PV arrays should be proffered. This rule of thumb is confirmed by the methodology presented in the paper.

Nevertheless, by considering only ESS, we are over-constraining the system's solution space. To correct this, future research should consider system coupling by integrating surrogate models of a cogeneration unit based on a fuel cell and electrolyzers or the use of EV with V2X technology as storage [35]. This will enable us to remove the curtailment cap on energy generation (and likely reduce oversizing of the PV array) and simultaneously assess the facility's electrical, heating, and transportation requirements. Finally, the assessment could be enriched by incorporating degradation models and more complex control strategies for the PV and ESS. This allows us to determine the effects of long-term degradation factors (such as temperature, ageing, and oxidation) on the overall system performance.

The financial viability of such large-scale installations is heavily dependent on the regional context. While the high reliability of European utility grids currently restricts such installations to critical infrastructure, the model demonstrates significant value in developing countries or regions with unstable power grids, where ensuring uninterrupted electricity supply is paramount, and large-scale battery systems provide essential security. For this reason, it would be relevant if future research replicates the study across diverse building typologies in various climate zones, with different loading profiles, generation potentials and weather extremes.

In conclusion, this research not only provides a technically and economically validated resilient design for off-grid LVDC PV-storage systems but also lays a solid foundation for future research in LVDC

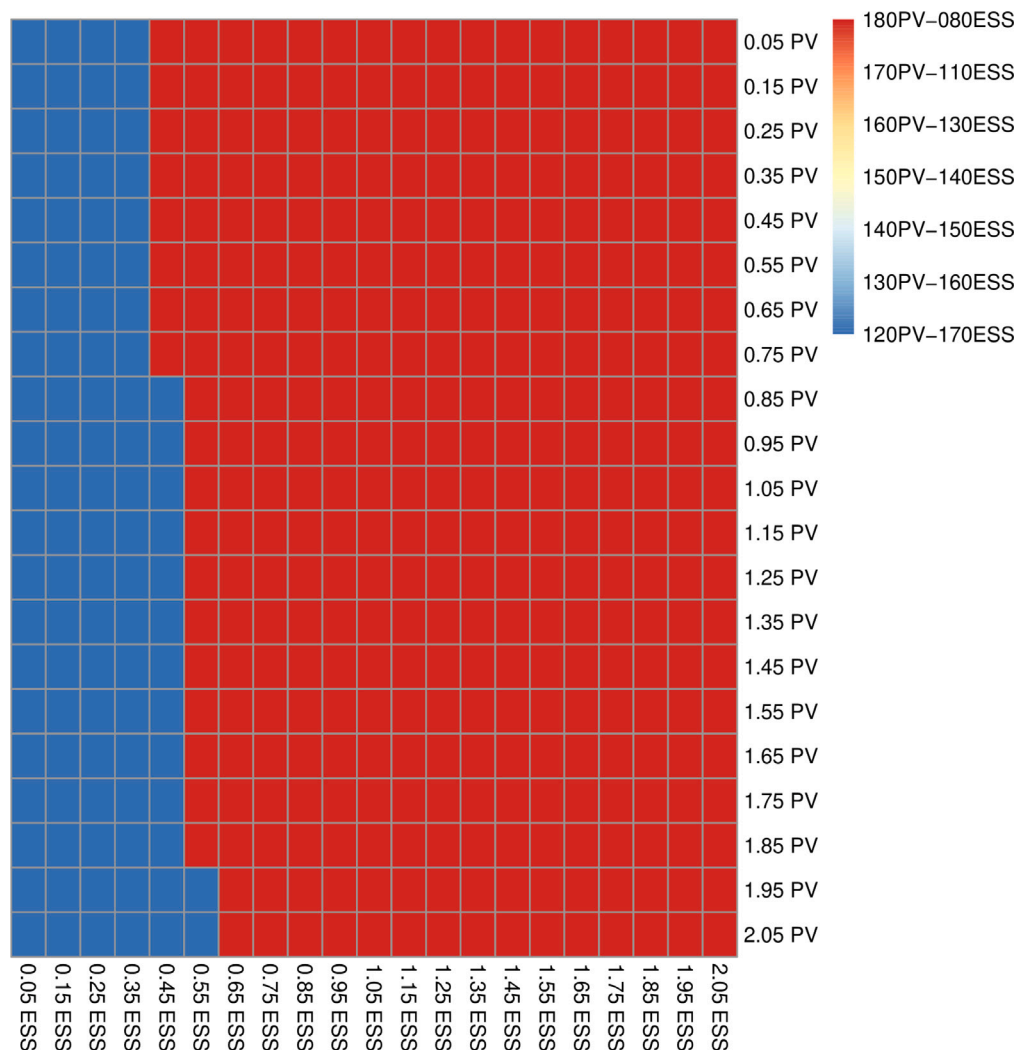


Fig. 5. Best solution selected depending on cost structure.

energy systems, paving the way for the development of more robust, efficient, and context-aware solutions in renewable energy generation.

CRediT authorship contribution statement

T. Castillo-Calzadilla: Writing – review & editing, Writing – original draft, Visualization, Software, Methodology, Investigation, Formal analysis. **A.M. Macarulla:** Writing – original draft, Validation, Supervision, Resources, Funding acquisition, Conceptualization. **C. Olivares-Rodríguez:** Writing – review & editing, Visualization, Software, Data curation. **C.E. Borges:** Writing – review & editing, Visualization, Validation, Supervision, Software, Funding acquisition, Formal analysis, Conceptualization. **E. Olías Ruiz:** Writing – review & editing, Validation, Supervision, Project administration.

Declaration of competing interest

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

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Appendix A. Supplementary figures

All data employed in the experimental analysis are documented in the appendices. For transparency and reproducibility, the complete data set has been organised in graphical form and is presented as a series of figures in Section Appendix A

Appendix B. Supplementary data for the experimentation

More supplementary information supporting the experimental analysis is provided in the appendices. For completeness, the additional material has been organised in tabular form and is presented as a series of tables in Section Appendix B.

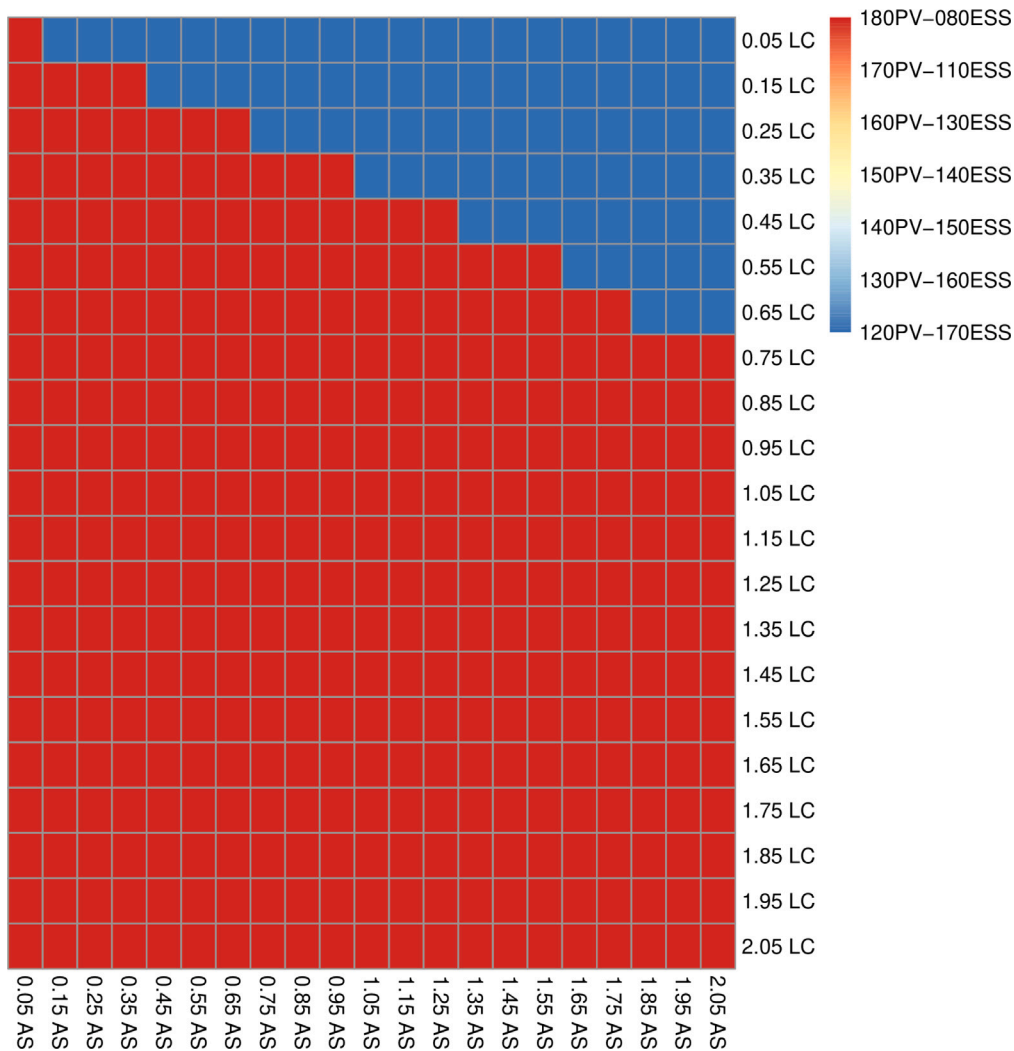


Fig. 6. Best solution selected depending on labour cost.

Table B.2
Descriptive statistics of the clustered weather dataset used to define the seasonal simulation groups.

Cluster	Freq. (%)	Temperature (°C)					Irradiation (kWh/m ² /day)				
		Min	Q1	Med	Q3	Max	Min	Q1	Med	Q3	Max
Winter	46.30	−0.40	7.55	9.85	12.3	20.75	0.09	0.80	1.39	2.09	4.65
Fall-spring	32.08	1.15	11.85	14.85	17.9	30.20	0.11	1.86	3.14	4.67	8.67
Summer	21.61	12.00	18.45	20.30	22.0	32.15	0.54	3.44	5.20	6.73	8.90

Table B.3
Technical specifications of the selected PV module (TS-420TA1).

Feature	Value
Power Output (Wp)	420
Open circuit Voltage (V)	60.65
MPP Voltage (V)	48.73
Short circuit Current (A)	9.12
MPP Current (A)	8.62
Efficiency (%)	16.38
Tolerance	0+3
Cells per module	96

Table B.4
Technical specifications of the selected PV module (Raylite 3MIL 25 S).

Feature	Value
C100 (A)	900
Nominal Voltage (V)	6
Deep cycle	Yes
Approx. Battery Mass (kg)	120
Acid Volume per Cell (litres)	8.1

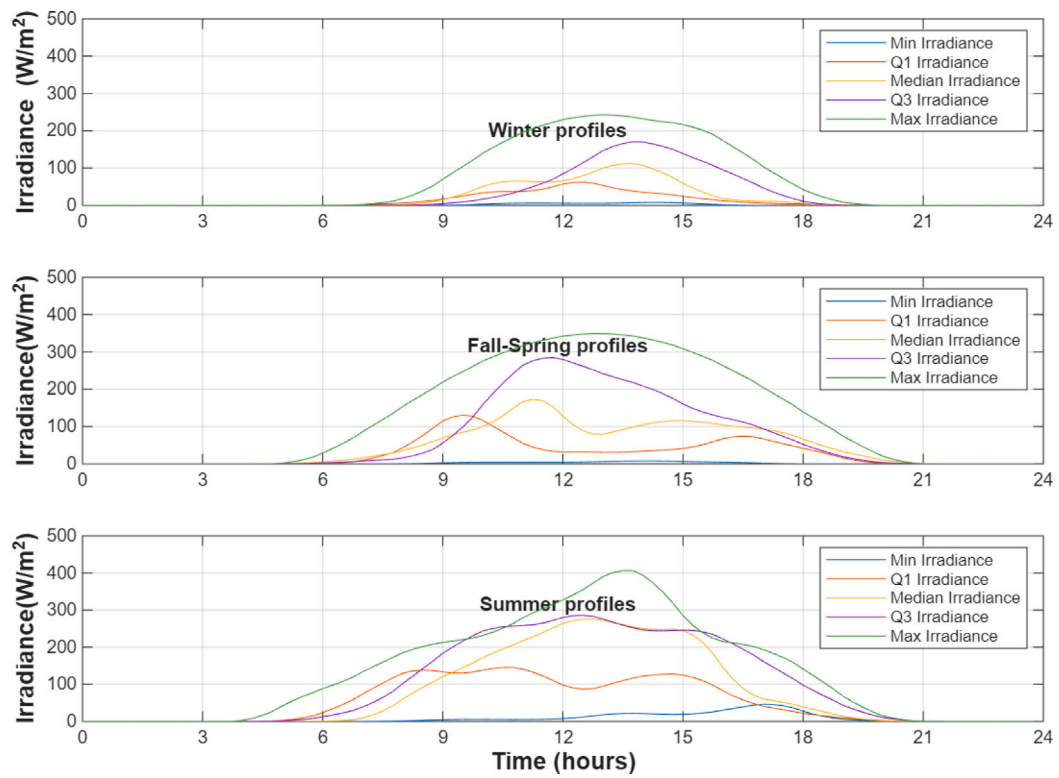


Fig. A.7. Representative irradiation profiles used to test the sizing algorithm under winter, fall-spring, and summer conditions.

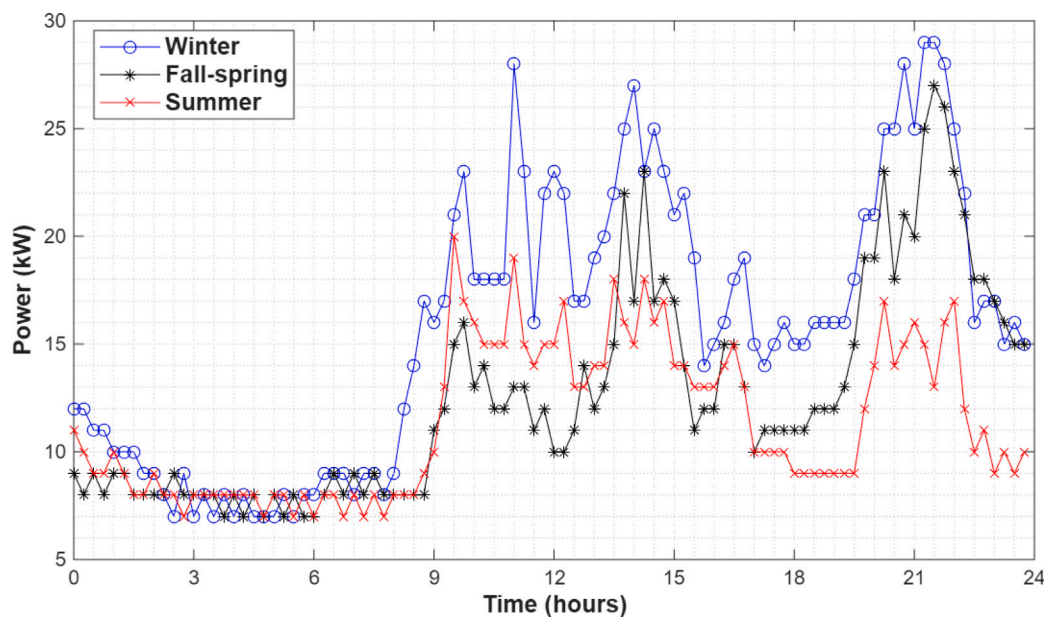


Fig. A.8. Representative consumption profiles of the hall of residence for winter, fall-spring, and summer conditions.

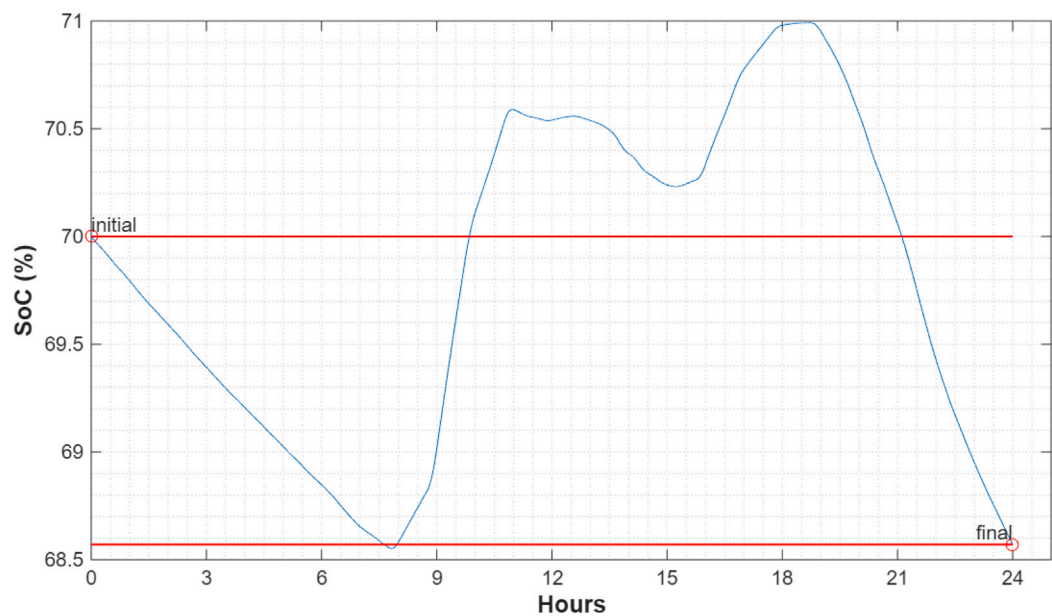


Fig. A.9. State-of-charge evolution during the fall-spring scenario.

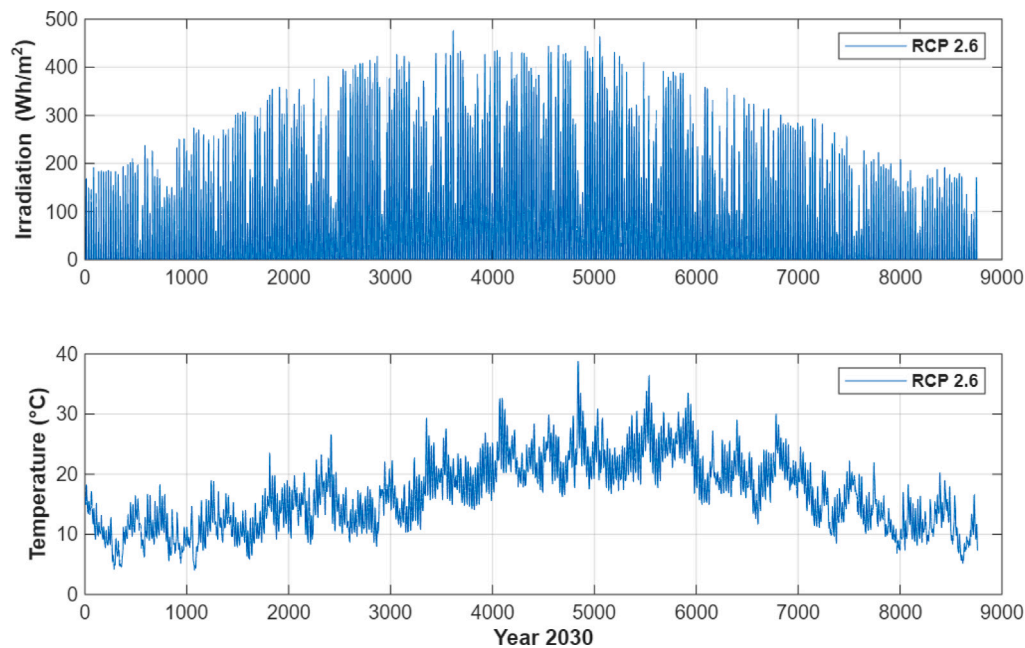


Fig. A.10. Projected irradiation and temperature profiles under the RCP 2.6 climate scenario from Meteonom 8.

Appendix C. Supplementary pseudocode

Algorithm 1 Overall risk assessment methodology

```

1: Input: Data acquisition (AEMET + building consumption) (1980-2023), Meteororm RCP projections (2023-2100)
2: Input: Building load profiles (hall of residence, 2014-2019)
3: Input: Sizing baseline PV+ESS sizing from [10]

4: Phase 1 - Climate data preparation:
5:   Preprocess AEMET data (remove NaNs, fill gaps with nearest value)
6:   Cluster into seasonal groups (k-means,  $k = 3$  selection rationale): winter, fall-spring, summer
7:   Extract 5 statistical days per season (min, Q1, median, Q3, max)
8:   Integrate Meteororm RCP 2.6 projections via bootstrapping (2023–2100)
9:   Surrogate model training (845 simulations per season → logistic fit)

10: Phase 2 – Simulation matrix:
11: for each PV size  $p \in \{60\%, 70\%, \dots, 180\%\}$  do
12:   for each ESS size  $b \in \{60\%, 70\%, \dots, 180\%\}$  do
13:     for each seasonal group  $s \in \{\text{winter, fall-spring, summer}\}$  do
14:       for each statistical day  $d \in \{\text{min, Q1, median, Q3, max}\}$  do
15:         Run Simulink simulation → record  $\Delta\text{SoC}_{p,b,s,d}$ 
16:       end for
17:     end for
18:   end for
19: end for ▶ Monte Carlo resilience assessment:  $13 \times 13 \times 3 \times 5 = 2,535$  simulations

20: Phase 3 – Resilience analysis:
21: Fit logistic model  $f_x = c + \frac{d-c}{1+e^{b(x-e)^s}}$  to  $\Delta\text{SoC}$  data
22: Identify configurations with 100% reliability across all scenarios
23: Extract Pareto frontier (configurations where no single parameter can be reduced)
24: Economic validation (IRR, ROI, NPV, sensitivity)
25: Output: Pareto frontier ordered by normalised cost; best configuration

```

Appendix D. Supplementary model parameters

parameter	value	confidence interval	p-value
a	19.88	[18.22, 21.97]	2×10^{-16}
b	-2.07	[-2.62, -1.62]	9.18×10^{-15}
c	3621.07	[2583.54, 4415.01]	2.07×10^{-14}
d	-15.70	[-16.53, -14.86]	2×10^{-16}
f	0.73	[0.48, 1.23]	3.58×10^{-5}
β_1	0.15	[0.11, 0.19]	2.64×10^{-14}
β_2	-0.03	[-0.03, -0.02]	2×10^{-16}
β_3	0.08	[0.08, 0.09]	2×10^{-16}
AIC	13 560.83		
BIC	13 613.38		
RMSE	3.50		
MAE	2.73		

Appendix E. Supplementary economic information

See Tables E.5 and E.6.

Appendix F. Supplementary preprocessing procedures and hyperparameter settings

This first subsection explicitly reports the preprocessing procedures:

Table E.5

Cost structure for the study [33].

Component	Unit	Cost
PV module	USD/kW	372
ESS	USD/kWh	323
SBOS	USD/m ²	35
EBOS	USD/kW	208
Office work	USD/kW	223
Fieldwork	USD/m ²	65
Other	USD/kW	839

Table E.6

Cost of the facility according to its size.

PV array (%)	ESS (%)	Cost (M USD)
120	170	3.30
130	160	3.26
140	150	3.22
150	140	3.18
160	130	3.14
170	110	2.98
180	80	2.68
100	100	2.21

• Size and source of the data:

- 43 years of hourly solar irradiance and temperature records (1980–2023) from the AEMET weather station 1082 located at the Bilbao airport (≈ 4 km from the case-study building);
- four years of building electricity demand data (2015–2019) measured by the electricity metre of the residence hall at the University of Deusto;
- and future climate projections generated with Meteororm 8 under the RCP 2.6 scenario, providing typical meteorological years per decade for 2023–2100 that are concatenated with the historical AEMET series.

- Types of features: For weather data, we use global solar irradiance (converted from deca-kJ/m² to kWh/m² per day) and air temperature in degrees Celsius; for the demand side, we use the hall of residence's active power consumption, aggregated to hourly time steps.
- Pre-processing steps: We remove NaNs from the historical records, apply k-means clustering to group days into three seasonal clusters (winter, fall-spring, summer), fill missing values using samples from the same cluster, and compute descriptive statistics (minimum, 25th percentile, median, 75th percentile, maximum) to construct representative days for each season. For future climate data, we employ a bootstrapping procedure on the Meteororm typical years to generate 100 continuous 120-year weather series (1980–2100), which are then used in the resilience assessment.

This second subsection explicitly reports the preprocessing procedures. The historical hourly climate dataset was preprocessed by applying linear interpolation for missing periods shorter than three hours and seasonal-average replacement for longer gaps. Prior to clustering, the input variables (irradiance and temperature) were standardised to zero mean and unit variance. For the K-means clustering of the 43-year climate series, the following hyperparameters were used:

1. Number of clusters: $k=3$, selected using the elbow method based on the within-cluster sum of squares, which exhibited a clear inflexion point at $k=3$.
2. Distance metric: Euclidean distance.
3. Initialisation method: The K-means algorithm was initialised using the k-means++ strategy, which selects well-separated initial centroids to improve convergence and reduce sensitivity to local minima.

4. Maximum number of iterations: 500.
5. Number of independent runs: 10 random initialisations to reduce the risk of convergence to local minima.
6. Final solution: the clustering result with the lowest total inertia was selected.

The optimisation and sizing procedure was performed through a parametric microgrid search. Starting from the baseline system configuration (1105 PV modules and 186 battery cells), both PV and battery capacities were varied independently within the range [60%, 180%] of the baseline values, with a uniform step size of 10%. This generated a total of 169 candidate configurations for evaluation.

For the dynamic simulations, the MATLAB/Simscape environment employed the variable-step solver ode23tb with a relative tolerance of 10^{-3} , providing a balance between computational efficiency and numerical stability during transient operating conditions.

Data availability

Data will be made available on request.

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