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Assessing long-term metocean data variability for optimal energy system planning via static robust optimization approach

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ABSTRACT

Small, non-interconnected island systems are at the forefront of the energy transition but their isolated condition makes them exposed to the natural variability of renewable resources. This work develops a static robust optimization framework to design multi-technology portfolios that explicitly account for the inter-annual variability of the wave climate. The methodology couples the EnergyPLAN simulation tool with a MATLAB-based NSGA-II algorithm. The design vector includes the installed capacities of onshore and offshore wind, photovoltaics, two different wave energy converters (Pelamis and CorPower) and a battery energy storage system (BESS). Robustness is assessed over a discrete uncertainty set composed of twenty years of hourly meteomarine data from Copernicus reanalysis for La Gomera (Canary Islands). Three system-level indicators are optimized in a worst-case sense: annual CO_2 emissions, a demand-generation mismatch metric ϕ, and the BESS exploitation index. A post-processing step selects all robust portfolios that satisfy a stringent emissions target, corresponding to roughly a 70% reduction with respect to the validated reference configuration. Within this low-carbon subset, CO_2 is treated as a saturated objective and the remaining trade-offs are explored in the two-dimensional ϕ-R_{BESS} plane, where a secondary Pareto front is identified. The resulting portfolios reveal a clear interaction between storage use and temporal balancing, with different BESS levels but a quite constant wave contribution. The framework is generic and transferable to other island systems and renewable technology combinations, providing a practical tool for integrating long-term resource variability and explicit decarbonization targets into energy system planning.

1. Introduction

The global urgency to mitigate climate change has placed a premium on optimal energy system planning and on the diversification of renewable energy source (RES) portfolios (IEA, 2025). Achieving high shares of renewables while maintaining reliability requires strategic deployment of complementary and diversified resources and careful long-term planning (Said et al., 2025; Cairella et al., 2025). This challenge is particularly acute for isolated, non-interconnected island grids (Cabrera et al., 2018, 2021; Meschede et al., 2018, 2019). In such non-interconnected island systems, the balancing area is inherently small, and the set of available flexibility providers is limited to local assets. Consequently, deviations of RES availability can represent a vulnerability to steadily meet the demand, while the lack of interconnection removes a primary mechanism for reserve sharing and net power exchange. Moreover, island systems cannot rely on mainland interconnections for balancing and have historically depended on imported fossil fuels (European Commission, 2022), yet they are now committed to ambitious decarbonization targets (*e.g.*, European Union, 2024; Europeean Commission, 2019; ITC Canarias, 2021) despite currently having often only a modest fraction of demand met by renewables. Under these conditions, renewable variability is not merely a forecasting issue but a structural planning driver (*i.e.* RES cannot be programmed): achieving high-RES operation requires portfolios that combine complementary resources and explicitly sized flexibility (*e.g.*, storage) to maintain adequacy across plausible realizations of the resources.

In this sense, a pivotal role is played by marine renewables, as shown by Lavidas et al. in Lavidas et al. (2025), where their inclusion in a 100% renewable European scenario allowed for significant reductions in required storage capacity (on the order of 70%) while still meeting demand. This outcome highlights the system-level benefits of considering marine energy resources in long-term energy planning alongside more established renewables. Among the various RES options, wave

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energy converters (WECs) have been identified as a valuable complement to other variable renewables, and their integration at the system level can enhance overall supply reliability (Lavidas and Blok, 2021; Giorcelli et al., 2025a). Rather than eliminating zero-generation periods, the integration of wave energy into hybrid systems primarily contributes by smoothing variability and improving predictability relative to wind and solar, which in turn can moderate storage and balancing needs (Said and Ringwood, 2021). In islands systems, the lack of interconnection limits balancing options and amplifies the operational impact of renewable variability. Consequently, supply-side diversification becomes strategically valuable. Therefore, including wave energy within candidate RES portfolios can improve system performance in a small, non-interconnected grid for an island system, where the wave resource is abundant.

However, a key complication in planning for marine renewables lies in the uncertainty and inter-annual variability inherent in meteo-marine resource data. An example of the sensitivity of energy system performance to data accuracy/resolution is pointed out by Lavidas et al. (2025). In fact, energy system planners often rely on numerical reanalysis datasets (*e.g.*, Copernicus Marine Service, 2025) to characterize long-term wave resources, especially in regions where in-situ measurements are sparse. While reanalysis products provide extensive spatial and temporal coverage, they come with uncertainties and biases that introduce spatial and resource assessment uncertainty. Different wave reanalysis, hindcast products and numerical models can yield divergent estimates of wave energy data and therefore to its potential (Politecnico di Torino et al., 2025). In literature, to handle these errors different bias-correction techniques (Peñalba et al., 2023; Penalba et al., 2023) and data-driven approaches are employed (Gambarelli et al., 2024, 2023; Gamabrelli et al., 2025).

Long-term climatic variability of metocean states is a major source of uncertainty in wave energy performance assessments (Guo and Ringwood, 2021; Ringwood and Brandle, 2015; Mackay et al., 2010; Neill and Hashemi, 2013; Gunn and Stock-Williams, 2012; Webb et al., 2020), also being a key driver in WEC design (Martinez-Iturricastillo et al., 2024; Ulazia et al., 2020), influencing geometry, control strategies, survivability, reliability and estimates of power and energy production (Orszaghova et al., 2022; Carreno-Madinabeitia et al., 2024; Guo and Ringwood, 2021; Ulazia et al., 2023; Penalba et al., 2020; Ulazia et al., 2019; Ambühl et al., 2015b; Nielsen and Sørensen, 2011; Ambühl et al., 2015a). Therefore, ignoring long-term resource variability may also misalign system's design with target operative conditions and lead to over-dimensioning (Ulazia et al., 2020). While high-energy and low-variability sites remain preferable, recent work shows that cost-effectiveness also depends on the intended application and dominant sea states (Coe et al., 2021). Smaller WECs targeting persistent, moderate-energy conditions can be advantageous (Davidson and Nava, 2024; Lavidas et al., 2021; Giorcelli et al., 2025b). In moderate climates, resource variability can be included in techno-economic assessments and site-selection tools to identify viable deployment strategies (Lavidas and Blok, 2021; Abaei et al., 2017; Guanche et al., 2014).

From the literature arises a clear need for planning models that can optimize energy systems under these uncertainties, ensuring robust performance over a range of possible resource conditions. In this context, robust optimization (RO) (Ben-Tal et al., 2009; Gorissen et al., 2015; Bertsimas and Sim, 2004) emerges as a suitable approach to incorporate uncertainty in energy planning by identifying solutions that remain feasible and near-optimal under various realizations of uncertain parameters. In the context of renewable energy planning, a static robust optimization framework can be employed to hedge against long-term variability in RES outputs by optimizing the capacity of deployed RES for worst-case conditions. By accounting for resource variability within the optimization, the resulting energy infrastructure plan is less sensitive to any single year's anomalies or to biases in a particular dataset. This robust planning approach is especially pertinent for island systems: overestimating the available wave resource in a given year could lead to overbuilt RES capacity that underperforms in other years, whereas underestimating it might mean missing an opportunity to improve resilience and reduce costs through a more diversified portfolio.

In this study, it is proposed a static-single-stage RO framework for long-term energy system planning that explicitly addresses meteo-marine resource variability. Our approach leverages long-term wave climate data from Copernicus reanalysis dataset (Gómez et al., 2025) (spanning decades) to capture a representative range of wave conditions in the planning model. By optimizing the RES portfolio over this ensemble of scenarios, the solution is designed to be resilient to inter-annual fluctuations in the wave climate. The application of this framework is demonstrated for the case study of La Gomera, in the Canary Islands, a region emblematic of insular energy challenges and rich in renewable resources. The model determines an optimal mix of RES generation technologies, including WECs alongside onshore and offshore wind (OWT and WT, respectively), photovoltaics (PV), such that the island energy system can reliably meet demand under varying wave climate scenarios while reducing the CO_2 emissions. The results show that using a long-term robust approach can markedly mitigate the sensitivity of planning outcomes to single-year assumptions about resource availability. In doing so, this work provides a pathway for more reliable and cost-effective integration of wave energy into island energy systems, highlighting how a RO paradigm can improve renewable energy resource strategic planning.

1.1. Motivation

Despite the growing body of work on decision-making and strategic energy planning under uncertainty, the explicit treatment of the natural inter-annual variability of renewable resources is still limited, and in particular of marine resources. In the proposed RO framework, rather than relying on a single-year-based nominal representation, the method evaluates each candidate design across a set of perturbed realizations of metocean data, each corresponding to a distinct year or climatic condition. This choice enables the optimizer to account for both intra-annual dynamics and interannual variability, thereby enhancing the usability of available metocean datasets and to synthesize performance via a robustness criterion targeting the worst-case outcome.

Accounting for real-world inter-annual variability is especially important for non-interconnected systems such as island grids, where limited flexibility options and the absence of reserve sharing can amplify the system-level consequences of renewable variability. Explicitly stress-testing candidate RES portfolios against multiple admissible metocean realizations therefore provides a structured way to reduce the risk of suboptimal performances under real-world uncertain and variable operating conditions and to support more defensible long-term investment decisions Accordingly, the remainder of the paper first positions the proposed approach within the state of the art on RO for energy system planning, then presents a workflow that embeds multi-year wave-resource variability into the optimal capacity planning stage, with the aim of identifying RES portfolios that preserve satisfactory performance across a representative set of plausible meteocean inter-annual fluctuations.

1.2. Notation

For clarity, the symbols and conventions adopted in this work are summarized below. The set of real numbers is indicated by $\mathbb{R}$, while $\mathbb{C}$ denotes the complex domain. For any complex quantity, $\mathrm{Re}(\cdot)$ and $\mathrm{Im}(\cdot)$ specify its real and imaginary parts, respectively, and the imaginary unit is written as j. The symbol 0 is used for a null quantity, independently of its dimension. The set of positive integers up to n is written as $\mathbb{N}_n = \{1, 2, \dots, n\}$. Vectors are written in bold lowercase letters and matrices in bold uppercase letters. Given a matrix $\mathbf{M} \in \mathbb{R}^{r\times c}$, its element in row a and column b is denoted by $M_{a,b}$, where $a \in \mathbb{N}_r$

and $b \in \mathbb{N}_c$. Likewise, if $\mathbf{v} \in \mathbb{R}^s$ is a column vector with s entries, its ath component is written as v_a, with $a \in \mathbb{N}_s$. The transpose of a matrix or vector is indicated by the superscript ^{T}. When a vector is normalized with respect to the maximum value among its components (for instance, the peak of a time series), the resulting quantity is marked with a hat $\hat{\cdot}$.

1.3. Structure of the manuscript

The remainder of this manuscript is organized as follows. Section 2 provides a concise overview of RO theory and reviews its main applications to energy system planning, highlighting the gap related to the treatment of long-term metocean variability and therefore the positioning of the present study. Building on this background, Section 2.3 clarifies the specific research questions addressed in this work, outlines the novelty of the proposed framework with respect to previous studies, and summarizes the main contributions. Section 3 details the methodological development: the optimization problems formulation, the coupling between EnergyPLAN and the MATLAB-based optimizer, and the construction of the uncertainty set from multi-year wave data. Section 4 presents the La Gomera case study in detail, including the identification and validation of the reference energy system, the characterization of metocean variability, and the set-up of the optimization problem. The numerical outcomes of the nominal and robust formulations, together with the post-processing of robust portfolios under a stringent decarbonization target, are analysed in Section 5. Finally, Section 7 discusses the main findings, draws broader implications for island energy planning, and outlines limitations and directions for future research.

2. Literature review: robust optimization approaches for energy system planning

2.1. Brief introduction to robust optimization

Classical optimization approaches assume that all model inputs, system parameters and operational conditions are known and remain unchanged throughout the simulation horizon. Under this assumption, the decision maker selects a single configuration of the system that maximizes performance or minimizes cost, and feasibility is evaluated only at such nominal condition. In real-world energy system planning problem, however, this assumption is rarely justified. Load and demand profiles fluctuate, technology costs trajectories may differ from projections the over time horizon, renewable generation depends on resources which naturally vary across different years and whose forecast or measured data can involve a degree of uncertainty, and also policy or infrastructure developments may unexpectedly deviate from expectations. These aspects do not imply that energy system models cannot represent hourly renewable variability dynamics or are unable to cope with time-varying technology costs (*e.g* via learning rates), but rather that when a solution optimized under deterministic assumptions (*e.g.*, a selected representative year) operates under alternative realizations outside the expected conditions (*e.g.*, different years and consequently different meteorological conditions) can return suboptimal performances outcomes. In other words, portfolios are often optimized with respect to a representative year, while operation may occur under alternative plausible realizations outside the selected period and this can affect the expected performances. As a result, solutions derived under deterministic assumptions may become suboptimal when confronted with inter-annual variability or RES data uncertainty.

To formally account for parameter deviations, the optimization problem can be posed in an uncertain setting, where decision variables and uncertain quantities are treated separately. Let $\mathcal{X} \subseteq \mathbb{R}^{N_x}$ denote the design space of design vectors $\boldsymbol{x}$ and let $\mathcal{Z} \subseteq \mathbb{R}^{N_\zeta}$ represent the domain of the uncertain parameters $\boldsymbol{\zeta}$. A generic multi-objective uncertain optimization problem reads

$$\begin{aligned} \min_{\boldsymbol{x}\in\mathcal{X},\,\boldsymbol{\zeta}\in\mathcal{Z}} \quad & \boldsymbol{f}(\boldsymbol{x},\boldsymbol{\zeta}) \\ \text{s.t.} \quad & h_i(\boldsymbol{x},\boldsymbol{\zeta}) \le 0, \quad \forall i \in \mathbb{N}_m, \end{aligned} \tag{1}$$

where $\boldsymbol{f} : \mathcal{X} \times \mathcal{Z} \to \mathbb{R}^{N_F}$ collects all the N_F the objective functions and $h_i : \mathcal{X} \times \mathcal{Z} \to \mathbb{R}$ are the constraint functions defining the feasible region. In this formulation, deviations in $\boldsymbol{\zeta}$ capture modelling inaccuracies, forecast errors, or implementation imperfections. However, since neither the true realization of $\boldsymbol{\zeta}$ nor its probability distribution may be known with confidence, solving Eq. (1) directly is generally impractical.

Stochastic programming (SP) is the traditional framework for decision-making and optimization under uncertainty, where the objective is optimized in expectation over a scenario tree and probability density functions (PDFs) of the uncertain parameters are assumed to be known (Babonneau et al., 2009; Gorissen et al., 2015). However, SP use is often restricted by the difficulty of defining reliable PDFs and by the rapid growth of problem size.

A common strategy is to adopt a worst-case interpretation, leading to a RO problem formulation via the robust counterpart of Eq. (1). RO provides an alternative that seeks solutions protected against worst-case realizations of uncertainty without relying on probability calculus, thus mitigating data requirements and the curse of dimensionality. As discussed by Moret (2017) and Gorissen et al. (2015), early formulations by Soyster (1973) were overly conservative, a limitation later alleviated by the approaches of Ben-Tal et al. (2009) and Bertsimas and Sim (2004). Further developments include recourse-based extensions such as adjustable RO (Kuhn et al., 2011) and distributionally RO (Wiesemann et al., 2014), in which the uncertainty set definition is considered to be uncertain itself.

In this setting, the decision vector is chosen before $\boldsymbol{\zeta}$ materializes, and the optimization seeks protection against all admissible parameter variations. The corresponding robust problem can be written as

$$\begin{aligned} \min_{\boldsymbol{x}\in\mathcal{X}} \quad & \left\{ \max_{\boldsymbol{\zeta}\in\mathcal{Z}} \boldsymbol{f}(\boldsymbol{x},\boldsymbol{\zeta}) \right\} \\ \text{s.t.} \quad & h_i(\boldsymbol{x},\boldsymbol{\zeta}) \le 0, \quad \forall i \in \mathbb{N}_m. \end{aligned} \tag{2}$$

In other words, the solution must remain feasible for every realization of the uncertain parameters within the prescribed set, and the objective is safeguarded against its most adverse outcome. This perspective implicitly addresses two design requirements: performance should not deteriorate excessively when parameters deviate from nominal values under the most adverse condition, and any feasible configuration must withstand all allowable perturbations in $\boldsymbol{\zeta}$.

When applied to energy system planning, this worst-case view could help to mitigate the risks of underestimating resource variability. Although the resulting solutions may be more conservative than their nominal counterparts, they offer enhanced reliability by ensuring feasibility under any possible uncertain parameters realization. In practice, the trade-off between robustness and nominal optimality is shaped by how the uncertainty set $\mathcal{Z}$ is defined and how each constraint reacts to deviations. Consequently, RO provides a structured bridge between idealized planning assumptions and the uncertain dynamics that characterize real energy systems. The formulations described before are adapted from established references in RO field (*e.g.* Ben-Tal et al., 2009; Bertsimas and Hertog, 2022; Sun et al., 2021), to which interested readers are referred to for a deeper analysis of the topic.

2.2. Robust optimization approaches for energy system planning

Historically, as reported by Moret (2017), since its introduction by Dantzig, in the 1950s (Dantzig, 1955), SP has been applied to multistage and long-term planning problems in the energy sector (*e.g.* Usher and Strachan, 2012; Quitoras et al., 2021) but its use is often restricted by the difficulty of defining reliable PDFs and by the rapid growth of problem size (Babonneau et al., 2009). While more recent cases of application of RO strategies in the energy system planning sector are presented in the work of Moret et al. *e.g.* Moret et al. (2020) and Moret (2017). In particular, their results show that robust strategies tend to favour portfolios with relevant shares of renewables technologies, while incurring only moderate additional system costs. Building on this framework, Guevara et al. (2020) explicitly introduce a machine-learning assisted distributionally RO scheme, where specific ambiguity sets are constructed around empirical distributions. The resulting long-term investment plans for the Swiss power system are less sensitive to arbitrary probabilistic assumptions, illustrating how RO and DRO can provide computationally tractable yet uncertainty-aware support for strategic energy planning.

The growing complexity of energy system optimization models (ESOM) and their central role in supporting long term strategic decisions make uncertainty management a fundamental requirement for ensuring reliable results. As shown by Yue et al. (2018), ESOMs are subject to various forms of uncertainty that are difficult to capture through deterministic approaches or simple sensitivity analyses. In this context, RO has emerged as a particularly relevant approach in energy planning, as it offers an effective compromise between uncertainty representation and computational tractability. Yue et al. (2018) also report that RO is especially suitable when the number of uncertain parameters is large, when reliable data for constructing probabilistic models are lacking, and when the objective is to directly quantify the trade off between cost and solution robustness. A number of studies therefore employ RO in ESOMs. The works surveyed in the literature, including those from Labriet et al. (2015), Lorne and Tchung-Ming (2012), and Babonneau et al. (2012), highlight recurring effects of RO in energy system applications, such as increases in system costs (the so-called cost of robustness), but also the generation of more diversified solutions that are less sensitive to adverse parameter variations, thereby improving the resilience of energy plans. Although the studies cited by Yue et al. (2018) also encompass a wide spectrum of economic and technological uncertainties, the existing literature has predominantly applied RO to parameters such as investment costs, fossil resource availability, and demand trajectories. Subsequent scientific contributions have largely remained aligned with this focus. Early developments include the decision making frameworks of Loulou and Kanudia (1999), based on minimizing the maximum deviation from the best possible outcome across alternative futures, while more recent works such as Patankar et al. (2022) from Patankar et al. employ RO to inform national decarbonization strategies under uncertain cost and demand projections. In addition, RO has been coupled with scenario analysis to enhance the resilience of energy system plans and to support investment decisions in high-risk environments.

However, despite the growing interest in variable renewable technologies such as wind and photovoltaics, RO has been applied only rarely to the variability of natural resources over multi decadal climatic horizons (Bylling et al., 2020; Verástegui et al., 2019; Das et al., 2018). This represents a particularly relevant gap for emerging technologies such as WEC, whose energy availability is characterized by strong seasonal and interannual variability. Current literature shows that RO has been used only marginally in the context of wave energy, and primarily at the device design and control level (*e.g.* Giorcelli et al., 2022; García-Violini and Ringwood, 2019; Garcia-Violini and Ringwood, 2021; Faedo et al., 2019, 2022; Faedo and Celesti, 2024), for example, to develop robust control algorithms, rather than for energy mix planning or capacity expansion. As also noted by Giorgi and Bonfanti (2024), a systematic treatment of robustness in WEC system planning is lacking, and even more so regarding their integration into islanded energy systems. It is within this context that the contribution of the present study is situated, extending the use of RO to long-term metocean variability. Unlike previous studies that focus on costs and economic parameters of WECs, this approach adopts uncertainty sets based on actual fluctuations in wave climate. The methodology allows the identification of an optimal and robust portfolio of renewable technologies (WEC, PV, WT, and OWT) capable of meeting demand even under significant interannual variations in metocean conditions. The results show that a RO approach based on long-term data can significantly reduce the sensitivity of planning decisions to climatic scenarios, providing a more solid basis for the integration of wave energy into island systems. Overall, this work demonstrates how RO logic can be extended to the variability of renewable resources (especially wave energy), offering a promising pathway to enhance the resilience and reliability of energy planning in highly variable and vulnerable contexts such as island systems.

2.3. Novelty and contribution

Section 2.2 indicates that only a limited number of studies explicitly incorporate the natural inter-annual variability of RES within robust planning formulations, and that this limitation is even more evident for marine resources. Within this context, the key novelty of the present study is the extension of RO logic to long-term wave resource variability, building uncertainty sets from observed fluctuations in the renewable availability. Leveraging multi-year data within a RO structure, the proposed framework reduces the dependence of planning outcomes on the particular climatic realization adopted for the nominal simulation and supports the identification of portfolios that remain feasible and effective under year-to-year changes in metocean conditions. Overall, the proposed approach contributes a methodological advancement towards the consistent integration of resource uncertainty in energy system planning, proving how RO can be systematically used to enhance the resilience and reliability of long-term energy planning in highly variable and vulnerable contexts such as islands. The present study, therefore, introduces a methodological advancement over previous optimal energy planning frameworks by embedding the inter-annual variability of marine renewable resources directly into the optimization routine via a static-single stage RO framework.

From an optimization perspective, the framework adopts a static single-stage robust counterpart, where the planning vector is chosen once and then stress-tested against an uncertainty set of admissible wave resource conditions. The robust objective is constructed through a worst-case operator: for any candidate portfolio, an inner maximization selects the boundary condition within the uncertainty set that produces the most adverse value of the selected performance indicators, while the outer minimization searches for the portfolio that performs best under this adversarial selection. In this sense, “robust optimal” refers to portfolios that minimize the worst-case performance across the entire uncertainty set, thereby providing the strongest guarantee against any represented uncertainty vector. This differs from a deterministic (nominal) formulation, where the uncertainty set collapses to a single assumed realization (*e.g.*, a representative year) and optimality is conditional on that specific input.

3. Methodology

This section presents the methodological framework developed in this study for the RO of energy systems. The proposed approach builds upon previous deterministic frameworks (Cabrera et al., 2018, 2021; Giorcelli et al., 2025a), which coupled the energy system’s simulations in EnergyPLAN environment with a MATLAB-based optimization routine. Here, the methodology is extended to explicitly account for parametric uncertainty through a dedicated RO formulation.

3.1. Framework overview and robust optimization formulation

The overall workflow of the presented investigation, schematically illustrated in Fig. 1, is organized into five main phases. Such a proposed framework follows a structured process ensuring coherence between modelling, optimization, and uncertainty evaluation:

1. *Identification of reference energy system.* A baseline configuration of the energy system is defined based on real operational and statistical data, available from official government reports (*i.e.* the so-called Anuario Energeticos de Canarias Gobierno de Canarias, 2025) and from open-source real-world data of the local transmission system operator (TSO) (Red Eléctrica, 2025), which in this case is Red Eléctrica de España (REE). The system boundaries, main sectors, and representative technologies are established at this stage.
2. *Reference energy system model validation.* The reference configuration model is simulated in EnergyPLAN and iteratively adjusted until the computed energy balances and outputs align with observed and references values of official reports (Gobierno de Canarias, 2025) and data from the TSO (Red Eléctrica, 2025).
3. *RO problem formulation.* Following the model validation, the candidate energy-system configurations to be explored are defined, thereby identifying the design space $\mathcal{X}$. In parallel, the set of admissible wave resource conditions is characterized and their series of long-term annual realizations are collected into a dedicated uncertainty set $\mathcal{Z}$, to represent the natural variability in renewable resources. On this basis, the RO problem for the energy system is then cast according to Eq. (2).
4. *RO run.* The optimization problem is embedded into a MATLAB routine. Each candidate solution is perturbed across the set of admissible wave resource annual realizations, and the system model is simulated independently for each year of operation. In this way, the RO routine explores the design and uncertainties' set spaces $\mathcal{X}$ and $\mathcal{Z}$ until the maximum number of generations is exceeded. Each scenario (*i.e.* each individual) is simulated within EnergyPLAN, and the aggregated performance is evaluated through a robustness operator, *i.e.* the worst-case performance across all the simulated year of operations.
5. *Outcomes analysis.* The algorithm outputs a Pareto-optimal set of robust configurations, which are subsequently analysed.

Similarly to the previously mentioned works from Cabrera et al. (2018, 2021) and Giorcelli et al. (2025a), three complementary indicators are adopted in this framework to evaluate system-wide performance:

- the total annual CO_2 emissions,
- the root of the mean squared error (MSE) between the renewable energy production annual time history $\boldsymbol{E_{RES}} \in \mathbb{R}^{N_h}$ and the total annual energy demand $\boldsymbol{D_e} \in \mathbb{R}^{N_h}$, here denoted as

$$\phi = \sqrt{\frac{\left\|\boldsymbol{E_{RES}} - \boldsymbol{D_e}\right\|^2}{N_S}}, \tag{3}$$

  where N_S is the number of samples, N_h is the number of hour in one yar of simulation, and $\|\cdot\|$ indicates the Euclidian norm of a vector,
- the battery energy storage system (BESS) exploitation parameter, defined as the ratio between the energy discharged in the grid by the BESS over the sum of the one that could be ideally discharged in the grid each hour along one year of simulation:

$$R_{BESS} = \frac{E_{dis}}{E_{dis}^{ID}}. \tag{4}$$

The first metric directly reflects the progress towards carbon neutrality and thus represents the primary optimization objective. However, the sole minimization of CO_2 emissions may lead to an excessive expansion of RES. Especially in small or isolated systems, unconstrained capacity growth can result in inefficient overdimensioning and high (and unmotivated) costs. This trade-off highlights the need for the second objective function ϕ capable of balancing the system by penalizing mismatches between RES generation and electricity demand. To this end, ϕ measures the annual imbalance between renewable production and system demand. Conceptually, it quantifies how far the system operates from an ideally balanced configuration in which the RES generation is fully utilized and perfectly synchronized with the system's demand with a hourly resolution, thus making the operation of the thermal power plant (PP) unnecessary. This indicator therefore complements CO_2 minimization by discouraging renewable oversizing and encouraging optimal coordination between clean and conventional generation assets. At the same time, the third objective function, R_{BESS}, was introduced to constrain the oversizing of the BESS. Without such a penalization or cost term, the optimization algorithm would systematically favour the installation of the maximum available storage capacity, since BESS integration would always appear beneficial for reducing renewable curtailment and emissions in the absence of explicit trade-offs. Introducing R_{BESS} as an objective therefore ensures that storage deployment is balanced against its actual utilization and system-level benefit, preventing unrealistic or economically inefficient oversizing.

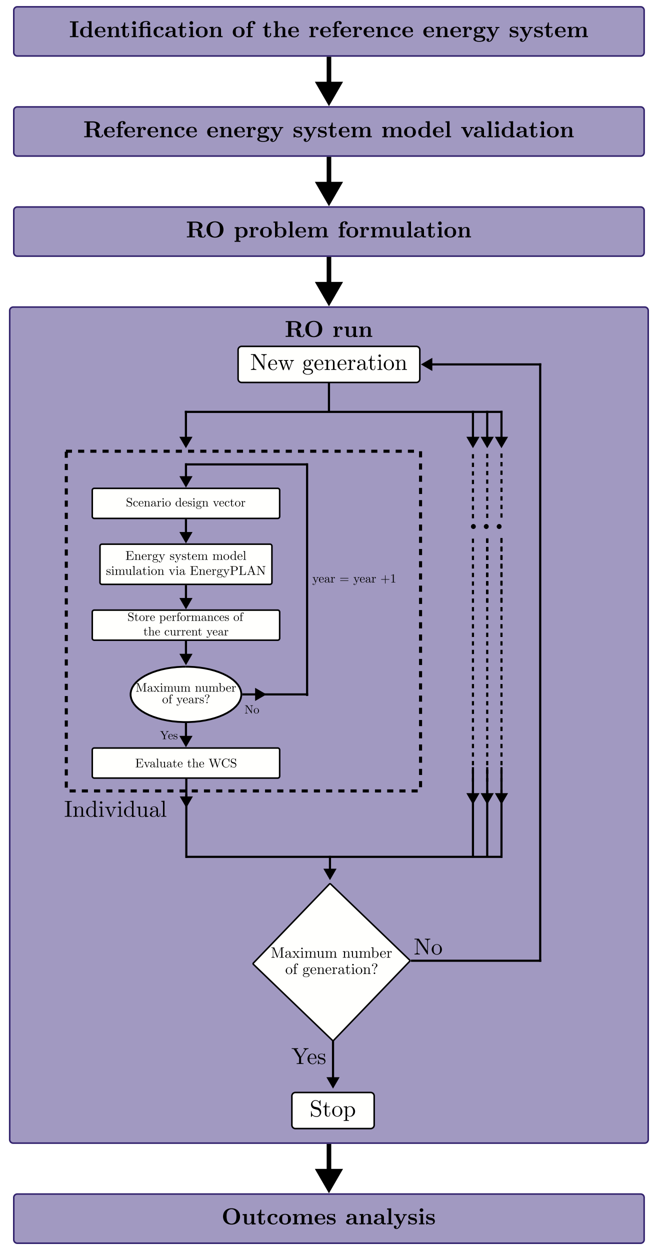


Fig. 1. Schematization of the proposed RO-based framework of the present investigation.

In the end, considering the objective functions vector of Eq. (2) ($\boldsymbol{f}(\boldsymbol{x},\boldsymbol{\zeta})$) as the vector whose elements are the three described performances indicators (*i.e.* $[\mathrm{CO}_2(\boldsymbol{x},\boldsymbol{\zeta}),\ \phi(\boldsymbol{x},\boldsymbol{\zeta}),\ -R_{BESS}(\boldsymbol{x},\boldsymbol{\zeta})]$) the robust multi-objective optimization problem can be expressed as follows:

$$\begin{aligned}
&\min_{\boldsymbol{x}\in\mathcal{X}} \left\{ \max_{\boldsymbol{\zeta}\in\mathcal{Z}} \left[\mathrm{CO}_2(\boldsymbol{x},\boldsymbol{\zeta}),\ \phi(\boldsymbol{x},\boldsymbol{\zeta}),\ -R_{BESS}(\boldsymbol{x},\boldsymbol{\zeta})\right] \right\}\\
&\text{s.t.}\\
&\boldsymbol{X}_\mathrm{l} \le \boldsymbol{x} \le \boldsymbol{X}_\mathrm{u},\\
&\mathcal{Z} = \{\boldsymbol{\zeta}^{(1)}, \boldsymbol{\zeta}^{(2)}, \dots, \boldsymbol{\zeta}^{(N_y)}\}.
\end{aligned} \tag{5}$$

Here, $\boldsymbol{x} \subseteq \mathcal{X} \in \mathbb{R}^{N_x}$ denotes the design vector, whose elements represent the decision variables of the energy system (*e.g.*, installed capacities and storage size), bounded by the lower and upper limits $\boldsymbol{X}_\mathrm{l}$ and $\boldsymbol{X}_\mathrm{u}$, respectively. The symbol $\boldsymbol{\zeta} \subseteq \mathcal{Z} \in \mathbb{R}^{2\times N_h}$ represents the vector of uncertain parameters, accounting for metocean environmental data variability (*i.e.* consisting in the peak wave period T_p and the significant wave height H_s). Each $\boldsymbol{\zeta}^{(y)}$ corresponds to a distinct realization (*i.e.*, an annual time series of the N_h hours of the year of metocean resources), so that the inner maximization captures the worst-case performance across the finite uncertainty set $\mathcal{Z}$, composed by a set of N_y uncertain realization $\boldsymbol{\zeta}^{(y)}$ with N_y the number of investigated years.

To make the exploration of the uncertainty set and the subsequent worst-case aggregation explicit, a pseudocode description of the procedure is reported below:

Algorithm 1: Robustness evaluation of a candidate portfolio within the optimization loop.

```
Input: Candidate design vector x; uncertainty set
       Z = {ζ^(1), ζ^(2), ..., ζ^(N_y)}
Output: Objective vector f(x, ζ)
for y = 1, ..., N_y do
    Build hourly wave resource profile using ζ^(y);
    Run EnergyPLAN and compute
      f(x, ζ^(y)) = [CO2(x, ζ^(y)), φ(x, ζ^(y)), −R_BESS(x, ζ^(y))];
max_{y∈{1,...,N_y}} f(x, ζ^(y)) return f(x, ζ);
```

3.2. Energy system simulation environment and model

Among the different developed energy system modelling tool (Connolly et al., 2010; Openmod, 2025), the simulation core of the framework is provided by the EnergyPLAN tool developed at Aalborg University (Lund et al., 2021; Lund, 2024), freely available from the developer research group website in EnergyPLAN (2025a,b).

EnergyPLAN is an hourly-resolution based, input–output energy system model capable of representing electricity, transport, heating, cooling, and other end-use sectors. The tool receives as inputs the total annual energy demands (D_e, D_c, D_h respectively for electricity, cooling and heating), their hourly normalized distributions $\{\hat{\boldsymbol{D}}_e, \hat{\boldsymbol{D}}_c, \hat{\boldsymbol{D}}_h\} \subset \mathbb{R}^{N_h}$, installed capacities of RES, and their corresponding hourly generation profiles. These profiles can be derived from measurements or modelled from local resource data, enabling a detailed and location-specific characterization of system-wide energy balances and flows, CO_2 emissions, and fuel consumption by following different simulation strategies. In addition to conventional PP, the model allows for the inclusion of alternative supply technologies, such as waste-to-energy, biofuels, or hydrogen, and can simulate regulation strategies for handling excess production and import/export exchanges. The computational efficiency of the tool allows for annual simulations to be completed within seconds, making it suitable for iterative analyses and optimization workflows. In literature, the software is widely used for analysing energy systems with high renewable energy penetration (Østergaard et al., 2022; Lund and Mathiesen, 2009; Cabrera et al., 2018, 2021; Jiménez et al., 2024; Meschede et al., 2018), as it provides hourly-resolution simulations capturing the interactions among multiple sectors, including electricity, heating, cooling, transport, and industry.

EnergyPLAN's deterministic nature and computational efficiency make it well suited for iterative analyses. However, as it does not include an internal optimizer, external coupling is required. This integration is achieved through the MATLAB toolbox developed by Cabrera et al. (2020), which enables direct control of EnergyPLAN simulations, parameter sweeping, and automatic data exchange between the two environments. In this framework, each energy system configuration is defined by a state vector $\boldsymbol{x}$, whose elements correspond to the installed capacities of BESS (C_{BESS}) and of the considered RES technologies: onshore wind (C_{WT}), offshore wind (C_{OWT}), solar photovoltaic (C_{PV}), and wave energy (C_W). Consistently, their normalized generation profiles with hourly resolution are named as $\{\hat{\boldsymbol{P}}_{WT}, \hat{\boldsymbol{P}}_{OWT}, \hat{\boldsymbol{P}}_{PV}, \hat{\boldsymbol{P}}_W\} \subset \mathbb{R}^{N_h}$ respectively. Hourly energy production for each ith RES technology ($E^h_{RES_i}$) is computed as:

$$E^h_{RES_i} = C_{RES_i} \cdot \hat{P}^h_{RES_i}, \tag{6}$$

where $\hat{P}^h_{RES_i}$ is the normalized hourly generation profile and C_{RES_i} is the effective installed capacity for the ith RES. The annual energy production of each RES is then given by:

$$AEP_{RES_i} = \sum_{h=1}^{N_y} E^h_{RES_i}. \tag{7}$$

During each simulation, EnergyPLAN balances generation and demand at every hour. When renewable generation is insufficient ($\sum_i E^h_{RES_i} < D^h_e$), a conventional PP, defined by its capacity C_{PP} and efficiency η_{PP}, compensates for the deficit. As anticipated, the model also accounts for a BESS characterized by its energy capacity C_{BESS}, charge/discharge power limits (S_{ch}, S_{dis}), and corresponding efficiencies (η_{ch}, η_{dis}). CO_2 emissions are evaluated from PP production, transport fuel consumption (F_t), and natural gas demand (N_{gas}).

While the present study represents storage through a generic BESS, consistent with common practice in high-RES planning studies, other flexibility technologies may be attractive for mountainous islands. In particular, hydraulics storage can be highly effective in non-interconnected systems, as demonstrated by the El Hierro experience (ManagEnergy, 2025). Despite that La Gomera's orography may offer opportunities for a similar approach, in the context of the present manuscript, BESS is adopted as a generic flexibility option that can be parameterized consistently at hourly resolution and compared across scenarios within the proposed optimization loop. The study does not intend to claim that BESS is the only or necessarily the preferred storage solution for La Gomera. Rather, BESS is used as a representative storage technology, enabling a transparent assessment of the interactions between variable RES, storage sizing and worst-case performance.

3.3. Integration with MATLAB-based optimization and uncertainty layer

The optimization is carried out in MATLAB using a multi-objective genetic algorithm (GA), implemented through the `gamultiobj` function. The EnergyPLAN model simulation, as anticipated, is handled via the EnergyPLAN MATLAB toolbox (Cabrera et al., 2020). Each individual in the GA population represents a potential configuration of the system, described by a design vector $\boldsymbol{x} \subseteq \mathcal{X} \in \mathbb{R}^{N_x}$. For each candidate solution, EnergyPLAN simulations are automatically executed, and the resulting performance metrics are used to evaluate the objective functions.

To include uncertainty, an additional loop is introduced inside the GA evaluation phase. For every $\boldsymbol{x}$, a set of $N_y = 20$ annual realizations (from March 2004 to April 2024) is generated by sampling a series of N_y uncertainty vectors $\boldsymbol{\zeta} \in \mathbb{R}^{2\times N_h}$, reflecting variability in the metocean data and therefore in wave renewable resource. Each realization is simulated independently, and the corresponding objective functions

Table 1
Selected configuration of the reference OWT employed in the present study.
Source: Data from Yanez-Rosales et al. (2024).

Parameter	Unit	Value
Rotor diameter - D_{V95}	(m)	164
Hub height - H_{V95}	(m)	100
Rated power - P^0_{V95}	(MW)	9.5
Cut-in speed - c_{V95}	(m/s)	3.0
Cut-out speed - c_{V95}	(m/s)	25.0

are aggregated by means of the worst-case outcome, which quantifies overall solution performance under uncertainty.

In particular, in the present study, the wave energy installed capacity is differentiated with respect to two different WECs: the 750 kW Pelamis (Said et al., 2025) (C_P) and the 400 kW HiWave-5 CorPower (Santiago et al., 2023) (C_{CP}). The motivation to rely on two representative WECs is the intention to avoid biasing the planning outcomes towards a single device archetype and to capture technology-dependent conversion characteristics under the same metocean forcing. In Fig. 2, the two WECs power matrices employed to derive each annual operational curve of the two WECs ($\hat{\boldsymbol{P}}_P$ and $\hat{\boldsymbol{P}}_{CP}$, respectively) are reported. This passage is straight forward: for each hour of year of simulation, the corresponding actual sea state is directly linked to the harvested wave energy by means of the interpolation of all the discrete points defined in the two WECs power matrices. In this way, a sea state is univocally correlated to a energy production and therefore from the H_s-T_p time series it is possible to derive the time series of the extracted WEC's energy. Therefore, in the end, the dimensions of the design space of the present study are $N_x = 6$. The devices' distinct power matrices map sea-state sequences into different production profiles. Therefore, allowing both options enables the optimization to select (or combine) WEC technologies that best support robust-optimal portfolios under inter-annual wave-resource variability.

Hourly WT production data were obtained directly from REE (Red Eléctrica, 2025), solar irradiation from the dataset given in OpenMeteo (2025), and offshore wind profiles derived form the relative offshore wind resource combined with the power curve of the WT proposed by Yanez et al. in Yanez-Rosales et al. (2024) The set of technical parameters for the reference turbine is reported in Table 1. The Vestas V164-9.5 MW turbine has been adopted in order to remain aligned with the analysis carried out by Yanez-Rosales et al. (2024) and the area indicated in the study as potentially suitable for offshore renewables deployment in La Gomera (*i.e.* the same adopted in the current study).

It is worth noting that, given the bathymetric slope of the Canary Islands, in the present study, the already mentioned offshore area identified in Yanez-Rosales et al. (2024) explicitly includes bathymetric thresholds. Therefore, the rapid depth increase close to the coastline is already accounted for at the area-selection stage. A schematic overview of the simulation complete list of model parameters and input data is reported in Table 2.

4. Case study

4.1. Small islands as testbench for energy transition pathways: La Gomera case study

European islands have long been recognized as strategic laboratories for energy transition due to their structural dependence on imported fossil fuels and their favourable conditions for renewable deployment (European Commission, 2022; Cross et al., 2017; Meschede et al., 2018). Their limited size allows for complete energy system representation and rapid implementation of innovative technologies, while their isolation highlights the importance of self-sufficiency and energy security. As emphasized by the EU's Clean Energy for All Europeans packages (Euroopean Commission, 2019; European Union, 2024), non-interconnected islands are considered priority regions for accelerating renewable integration and demonstrating the feasibility of sustainable, decentralized energy systems.

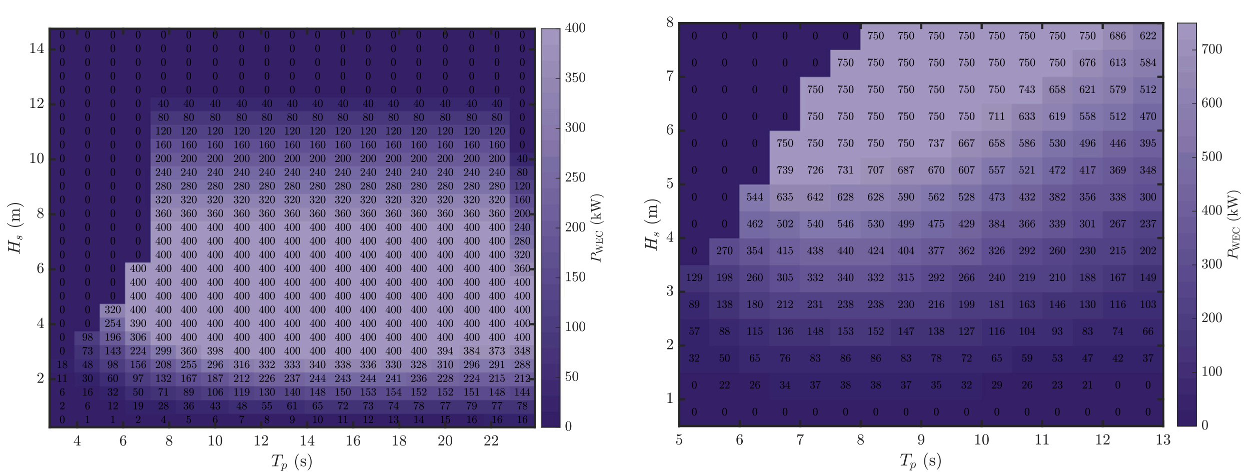
Among these, the Canary archipelago stands out as a pioneering example. Despite a historical dependence on petroleum imports, the islands possess abundant solar and wind resources. Their diversity in morphology and energy configuration (from flat, arid islands such as Fuerteventura and Lanzarote to mountainous ones such as El Hierro and La Gomera) makes the region particularly suitable for comparative analyses. El Hierro, in particular, has become a national and European benchmark for decarbonization through its wind-pumped hydro hybrid system, which now covers most of the island's annual electricity demand (ManagEnergy, 2025; Boda et al., 2022). While this case is valuable for assessing the operation and control of a specific legacy configuration, the present work targets an uncertainty-aware capacity-planning optimization problem in an island context where the portfolio is still dominated by conventional generation and where multiple candidate technologies (including offshore/marine options) remain under consideration. La Gomera (Fig. 3), selected as a case study, matches this objective because it is currently transitioning from imported diesel-based supply (primarily consumed at the El Palmar thermal power plant in San Sebastián de La Gomera Gobierno de Canarias, 2022), has recently (2023) commissioned onshore wind capacity, is embedded in an institutional programme (*La Gomera 100% Sostenible* ITC Canarias, 2021) targeting full sustainability, and has been reported to possess the largest offshore area suitable for marine renewable deployments within the archipelago (Yanez-Rosales et al., 2024). These characteristics make La Gomera a representative and relevant testbed for evaluating robust portfolio designs under renewable-resource variability. Therefore, La Gomera was chosen as an exemplary case for testing the proposed RO framework because it provides an effective balance between representativeness and constraint. The island exhibits all the key characteristics of small, isolated power systems (limited interconnection, high diesel dependency, and rapidly growing renewable penetration) while offering access to high-resolution metocean and operational datasets. These features enable realistic data-driven modelling. Moreover, the island's ongoing transition process provides an ideal setting to investigate uncertainty-aware planning strategies. Applying the RO framework to La Gomera allows assessing how the natural interannual variability of renewable resources affects the optimal configuration of a real-world, small-scale energy system, thereby demonstrating the applicability and robustness of the proposed methodology beyond theoretical conditions.

4.2. Reference energy system model identification and validation

The reference energy system of La Gomera was developed to ensure internal consistency across sectors and alignment with officially reported data. The validation of such model allows, in the optimization phase, a RES portfolio and cross-sector re-design of the system. The model structure and validation procedure follow the same approach adopted by Giorcelli et al. (2025a), where the EnergyPLAN-MATLAB framework was first calibrated and verified using observed operational data. Official information from *Anuario Energético* of the Canary Government (Gobierno de Canarias, 2025), statistics from the Canary Institute of Statistics (ISTAC) (Gobierno de Canarias, 2022, 2025a), together with hourly demand and generation data from the Spanish TSO (Red Eléctrica, 2025), served as the main data sources. When needed, additional parameters such as temperature or solar radiation were derived from established datasets (OpenMeteo, 2025; Copernicus Marine Service, 2025) to shape end-use and renewable generation profiles. According to the reference model validated in Giorcelli et al. (2025a), the period from April 2023 to March 2024 was selected as the reference time horizon, corresponding to the first full cycle of wind operation of the installed 12 MW WTs plant. However, to date, only 2.23 MW of such plant are operative. Hourly electricity demand profile for this period is shown in Fig. 4, and the normalized wind generation distribution used for validation is reported in Fig. 5.

Table 2
Model parameters and input data employed in the EnergyPLAN simulation for the present work.

RES capacity	Unit	Description
C_P	(MW)	Pelamis wave energy installed capacity
C_{CP}	(MW)	CorPower wave energy installed capacity
C_{PV}	(MW)	PV installed capacity
C_{WT}	(MW)	Wind turbine installed capacity
C_{OWT}	(MW)	Offshore wind turbine installed capacity
C_{PP}	(MW)	Conventional PP installed capacity
C_{BESS}	(MWh)	BESS installed energy capacity
Annual total demand	Unit	Description
D_e	(GWh)	Annual electricity demand
D_c	(GWh)	Annual cooling demand
D_h	(GWh)	Annual heating demand
Distribution	Unit	Description
$\hat{\boldsymbol{D}}_e$	(/)	Annual electricity demand normalized distribution
$\hat{\boldsymbol{D}}_c$	(/)	Annual cooling demand normalized distribution
$\hat{\boldsymbol{D}}_h$	(/)	Annual heating demand normalized distribution
$\hat{\boldsymbol{P}}_{WT}$	(/)	Annual wind energy production normalized distribution
$\hat{\boldsymbol{P}}_{OWT}$	(/)	Annual offshore wind energy production normalized distribution
$\hat{\boldsymbol{P}}_{PV}$	(/)	Annual solar energy production normalized distribution
$\hat{\boldsymbol{P}}_{P}$	(/)	Annual Pelamis wave energy production normalized distribution
$\hat{\boldsymbol{P}}_{CP}$	(/)	Annual CorPower wave energy production normalized distribution
System parameter	Unit	Description
η_{PP}	(/)	PP conversion efficiency
N_{gas}	(GWh)	Natural gas demand
F_t	(GWh)	Fuel consumption for transport sector
S_{ch}	(kW)	Storage charge capacity
S_{dis}	(kW)	Storage discharge capacity
η_{ch}	(kW)	Storage charge efficiency
η_{dis}	(kW)	Storage discharge efficiency



(a) HiWave-5 CorPower power matrix. Data from Santiago et al. (2023).

(b) Pelamis power matrix. Data from Said et al. (2025)

Fig. 2. Employed WECs power matrix.

Beyond the electricity sector, all other energy-consuming sectors were represented to ensure system-wide balance and proper accounting of CO_2 emissions and diesel fuel consumptions F of the El Palmar PP:

- *Transport:* road transport represents the only local mode, consuming 5.1 kt of gasoline and 6.8 kt of diesel annually, with electricity contributing only 0.13 GWh (Gobierno de Canarias, 2025). Aviation and maritime transport were excluded as extra-insular activities.
- *Natural gas:* total consumption in 2022 amounted to 10.42 GWh/y (Gobierno de Canarias, 2022). As no breakdown was available, it was assumed that households use gas exclusively for cooking, while the hotel and service sectors employ it partially for heating (Gobierno de Canarias, 2025a; University of La Laguna, 2017). Because no official government report was released for 2023, the data on N_{gas} and transport consumption are taken from the 2022 government report and assumed to remain valid for the period under analysis.
- *Heating and cooling:* based on statistical data from ISTAC and University of La Laguna (Gobierno de Canarias, 2025a; University of La Laguna, 2017), thermal energy use was divided between households and hotels/services. Household electricity demand was 27.3 GWh, with 10.9% for cooling and 13.3% for domestic hot water. The tertiary sector consumed 29.71 GWh of electricity and 5.41 GWh of NG, with 30.8% for cooling and 22% for heating (domestic hot water, pool maintenance, and space heating). Heating demand was evenly distributed throughout the

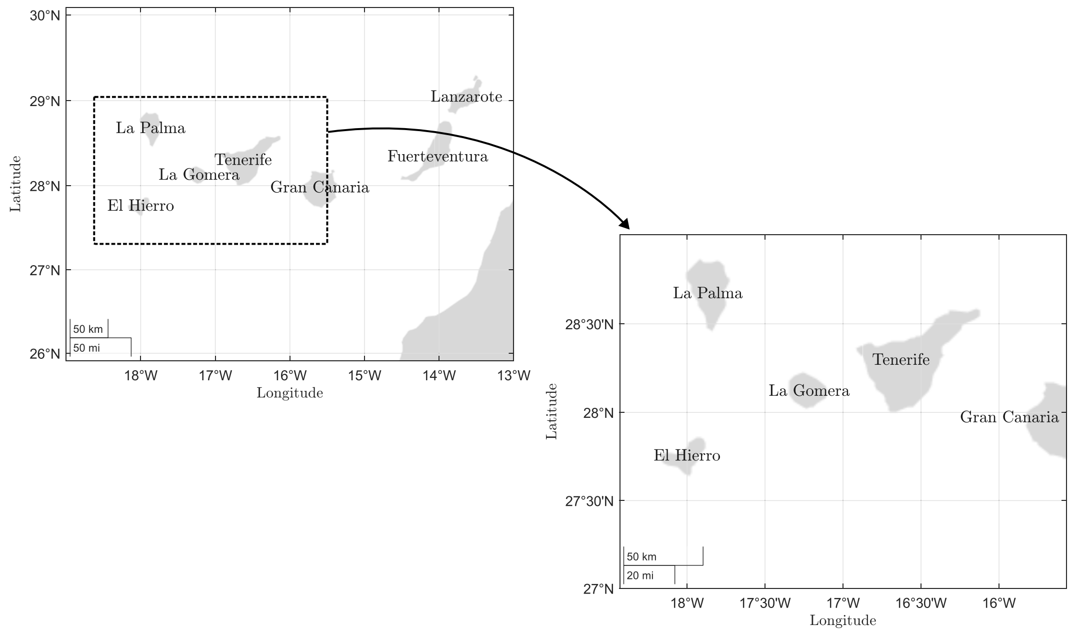


Fig. 3. Geographical map of La Gomera island in the canary archipelago.

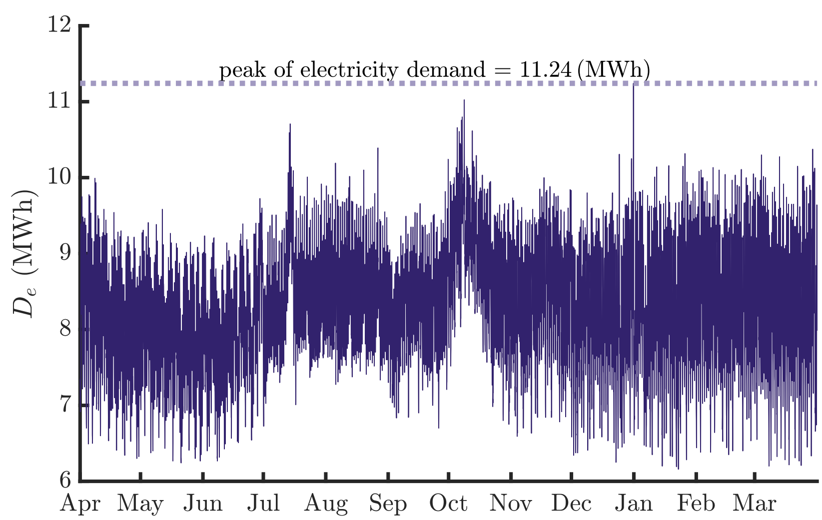


Fig. 4. Electricity demand (D_e) in La Gomera from 2023 to 2024. Data achieved from Red Eléctrica (2025). Adapted from Giorcelli et al. (2025a).

year, while cooling was derived from hourly temperature data, activated above 22 °C and weighted 65% towards continuous air conditioning in service facilities.

- *Water treatment:* the new desalination plant, operational since 2024, was added to the electricity demand, while wastewater treatment (1.03 hm^3/y) accounts for approximately 0.9 GWh/y (Cabrera et al., 2021; Gobierno de Canarias, 2025b).

At first, a 2022 energy system model of La Gomera was developed and calibrated using the El Palmar PP fuel consumption (F) and the total system CO_2 emissions as reference indicators. Reference values were derived from Gobierno de Canarias (2025), considering an annual electricity demand of 69 GWh (data from Red Eléctrica (2025)), while household and service-sector consumptions were set at 37.4 GWh and 34.1 GWh, respectively, following the same statistical proportions reported in the description above. The model outcomes show good agreement with reported data, as summarized in Table 3.

For the 2023–2024 configuration (which is the targeted time-horizon for the present work), the validation exploit the observed hourly PP generation and CO_2 data from Red Eléctrica (2025). The annual fuel consumptions of the El Palmar plant are estimated from the energy injected into the grid, as reported by the TSO (Red Eléctrica, 2025), and converted into input fuel energy using the efficiency values previously validated in the 2022 year of operation. The simulated CO_2 emissions and fuel consumption match the reference data within 3% deviation (Table 4), confirming the model's accuracy.

Table 3
Validation of CO_2 emissions (from transport and PP electricity generation) and fuel consumption (F) for 2022.
Source: Reference values obtained from Gobierno de Canarias (2025).

Parameter	EnergyPLAN model	Reference value	Error
CO_2	92.9 kt	98.3 kt	5.5%
F	186.5 GWh/y	186.2 GWh/y	0.2%

Overall, the validation process demonstrates that the EnergyPLAN model reliably reproduces the real operation of La Gomera's energy system across two consecutive years. The agreement between simulated

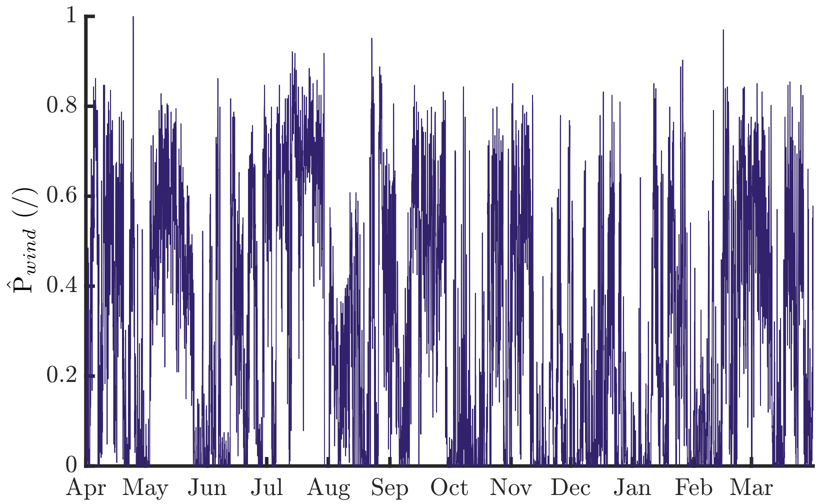


Fig. 5. Normalized wind energy production distribution ($\hat{P}_{WT}$) between 2023 and 2024 in LA Gomera. Data from downloaded from Red Eléctrica (2025). Adapted from Giorcelli et al. (2025a).

Table 4
Validation of CO_2 emissions (from transport and PP electricity generation) and fuel consumption (F) for 2023–2024.
Source: Reference values obtained from Red Eléctrica (2025).

Parameter	EnergyPLAN model	Reference value	Error (%)
CO_2	888.6 kt_{eq}	882.3 kt_{eq}	0.71%
F	177.4 GWh/y	173.1 GWh/y	2.5%

and observed fuel use and CO_2 emissions confirms both the internal consistency of the sectoral assumptions and the suitability of the reference configuration as a baseline for the RO analysis performed in this study.

Once validated, the reference EnergyPLAN model can be adapted to represent a more advanced stage of La Gomera's energy transition, serving as the baseline for the RO routine presented in this work. In this extended configuration, a progressive electrification of the transport sector was assumed, corresponding to a 50% substitution of conventional vehicles with electric ones. This assumption reflects plausible medium-term policy targets under the *La Gomera 100% Sostenible* programme and allows for the assessment of system flexibility and storage requirements under increased electricity demand. Moreover, in order to exploit the high offshore potential of the island, OWTs' capacity has also been added to the RES portfolio to be optimized.

4.3. Metocean data inter-annual natural variability

As stated, for small and non-interconnected systems such as La Gomera, realistic wave energy planning requires that the natural variability of the marine resource be explicitly represented. In our case study, wave energy is a promising complement to wind and PV, but its availability fluctuates both seasonally and from year to year. This section quantifies such variability and re-call how it is embedded in the RO framework introduced in Section 3.

Hourly significant wave height (H_s) and peak period (T_p) are retrieved from the Copernicus reanalysis (Gómez et al., 2025), at the ocean grid node adopted nearest to the point (28.20°N, 17.47°W), within the suitable offshore deployment area for La Gomera identified by Yanez-Rosales et al. (2024). This ensures that the metocean data used for WEC assessment are consistent with a decision-relevant, feasibility-driven offshore area. The data cover a time period from March 2004 to April 2024. Each record has been then re-mapped to an April–March annual window to match the first year of operation of the new WT plant in La Gomera. The equivalent energy period T_e was derived via WAFO toolbox (WAFO-group, 2011) and the wave power flux J_{wave} was computed as

$$J_{wave} = 0.49\, T_e\, H_s^2. \tag{8}$$

Moreover, for every hour and for every April–March year, the expected value operator $E^{\mathbb{P}}[\cdot]$ of H_s, T_p and J_{wave} are calculated. Despite acknowledging the relevant north/south metocean differences in the Canary Islands, in the present study, spatial heterogeneity around the coastline is not explicitly modelled: a single offshore node is adopted for the wave energy characterization and the actually produced wind data from REE (Red Eléctrica, 2025) are used to characterize the wind operational curve. To cope with such limitations and assumptions is a relevant extension for possible future works.

Fig. 6(a) shows the inter-annual sequence of the annual expected wave energy flux $E^P[J_{wave}]$: the series oscillates from roughly 11 kW/m to 17 kW/m, indicating moderate but non-negligible year-to-year variability. Fig. 6(b), instead, reports the intra-annual pattern of J_{wave}: winter months are characterized by higher and more variable fluxes, while summer exhibits lower (and more shrinked) values.

Fig. 7 details the metocean drivers. Also in this image, the shaded bands display the inter-annual bounds for H_s and T_p, while the dark violet lines plot their hourly expected values $E^P[H_s]$ and $E^P[T_p]$. Winter peaks exceed 5 m in H_s and reach 20 s in T_p, consistent with the Canary wave climate reported in previous regional studies. Consistently with Fig. 6(b), higher variability across years for both H_s and T_p is revealed for the winter months.

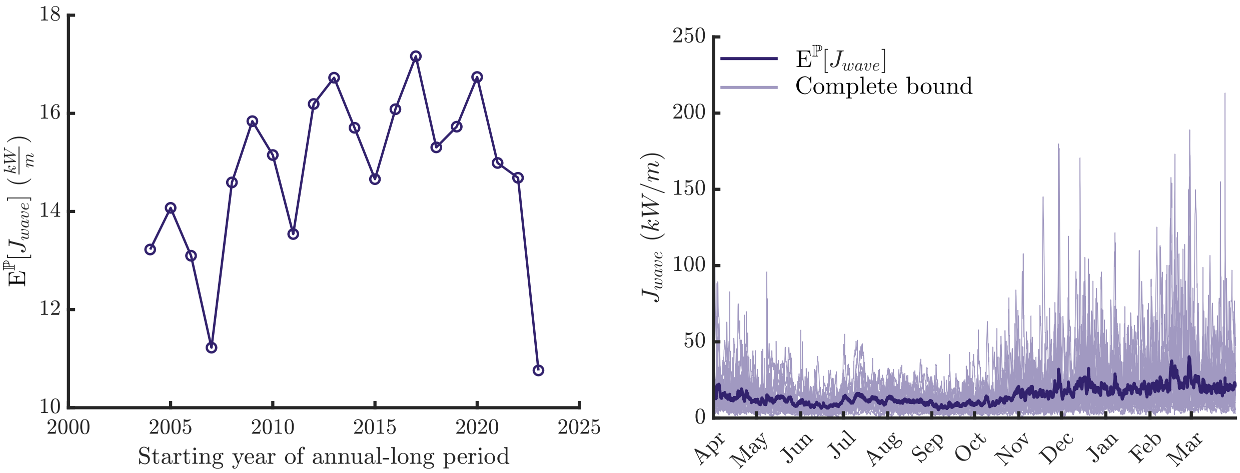
It worth nothing to re-call here that the twenty April–March realizations (from 2004–2005 to 2023–2024) constitute the finite uncertainty set

$$\mathcal{Z} = \{\zeta^{(1)}, \dots, \zeta^{(N_y)}\}, \qquad \zeta^{(y)} = \{H_s^{(y)}(h), T_p^{(y)}(h)\}_{h=1}^{N_h},$$

which drives the wave power time series through the WEC power matrices of Section 3 (see Fig. 2).

4.4. Optimization set-up

In this study, the Non-Dominated Sorting Genetic Algorithm II (NSGA-II) (Deb et al., 2002) is employed as the multi-objective optimization framework. NSGA-II has become a standard choice for practical engineering problems thanks to its ability to generate a well-distributed approximation of the Pareto front. Its population-based exploratory capabilities are particularly attractive for renewable energy system planning problems, where the objective functions are often



(a) Cumulative wave energy flux inter-annual variability.

(b) Wave energy flux intra-annual variability.

Fig. 6. Wave energy annual natural variability in La Gomera. In (b), thin light violet lines represent the wave energy flux trend for each year from March 2004 to April 2024, while bold dark violet line is its derived hourly expected value.
Source: Data from Gómez et al. (2025).

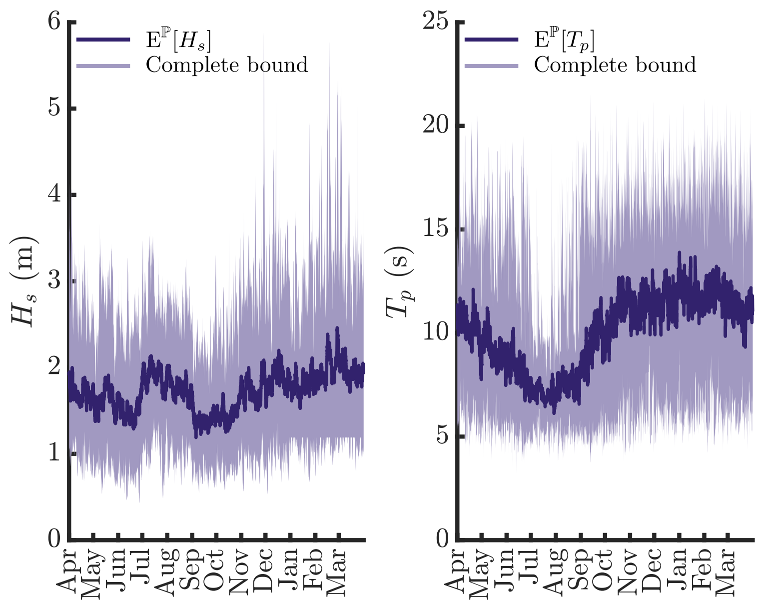


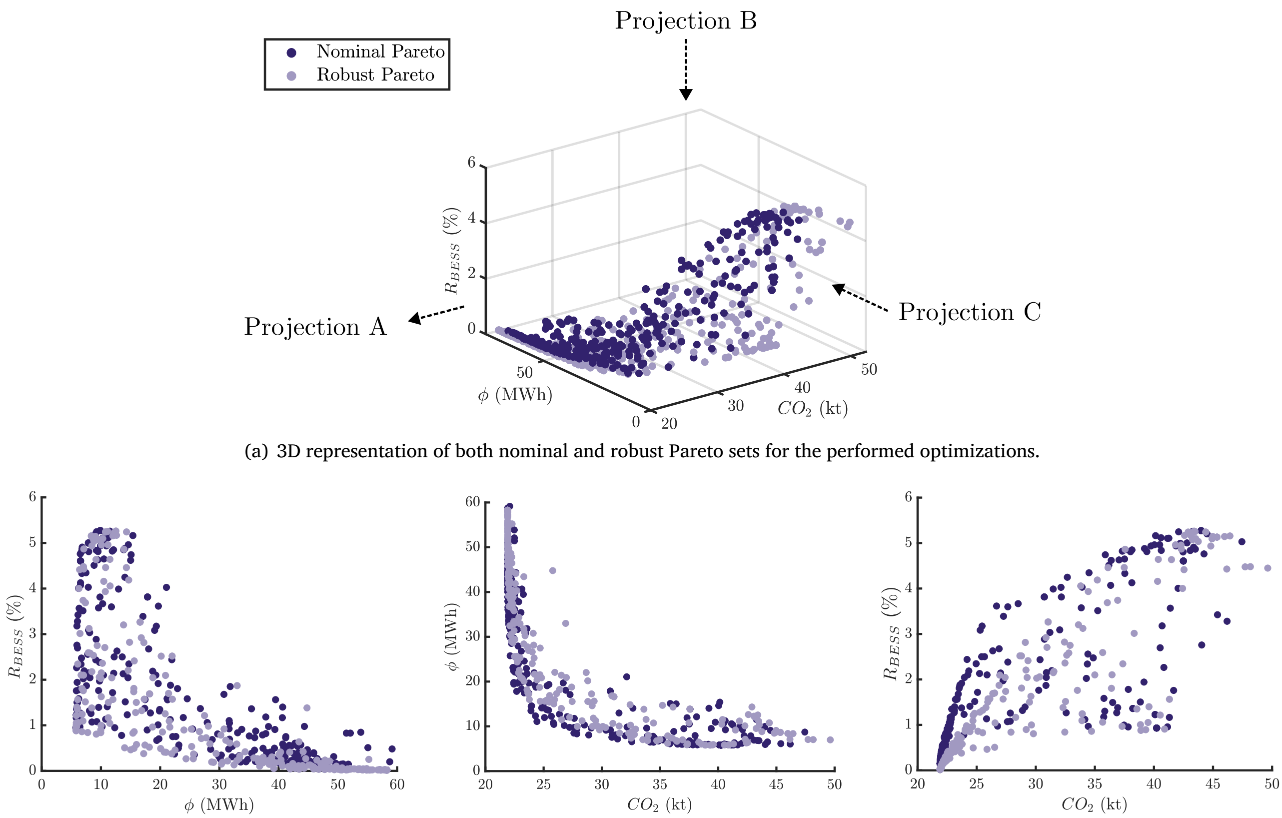
Fig. 7. Meteomarine natural variability in La Gomera from March 2004 to April 2024. Thin light violet lines represent the H_S and T_p trends for each year from March 2004 to April 2024, while bold dark violet lines are their derived hourly expected value.
Source: Data from Gómez et al. (2025).

non-convex, highly nonlinear, and not amenable to gradient-based optimization methods.

The algorithm proceeds by repeatedly applying the usual genetic operators (selection, crossover, and mutation), while introducing two key features: a fast non-dominated sorting procedure, used to classify individuals into successive Pareto dominance fronts, and the crowding-distance metric, which promotes diversity along the front. At each of the N_{gen} generation, each of the N_{ind} individuals are ranked with respect to the current non-dominated set, and the elitist strategy embedded in NSGA-II ensures that the best-performing solutions are preserved across generations. This mechanism mitigates the risk of convergence to poor local optima and encourages a more thorough exploration of the decision space. Furthermore, the population-based nature of the algorithm naturally supports parallel evaluation of candidate solutions, which can be efficiently exploited on multi-core computational platforms.

As anticipated, here the optimization is carried out using the `gamultiobj` routine from the MATLAB Global Optimization Toolbox, which implements a variant of NSGA-II (MathWorks, 2025), considering the default settings of the `gamultiobj` function, which provide a robust compromise between exploitation of promising regions and exploration of alternative designs, leading to a stable and representative collection of Pareto-optimal portfolios.

Unless otherwise stated, the algorithm is run for $N_{gen} = 100$ generations with a population size of $N_{gen} = 25$ individuals. The decision space comprises six continuous design variables, corresponding to the installed capacity of each generation technology and the energy storage



(a) 3D representation of both nominal and robust Pareto sets for the performed optimizations.

(b) Projection A of both nominal and robust Pareto sets for the performed optimizations in the plane.

(c) Projection B of both nominal and robust Pareto sets for the performed optimizations.

(d) Projection C of both nominal and robust Pareto sets for the performed optimizations.

Fig. 8. Nominal and robust Pareto sets for the performed optimizations.

Table 5
Design space with decision variables and bounds for the multi-technology portfolio optimization.

Design parameter	Unit	X_l	X_u
C_{WT}	(MW)	12	50
C_{PV}	(MW)	0	50
C_{OWT}	(MW)	0	50
C_{CP}	(MW)	0	50
C_P	(MW)	0	50
C_{BESS}	(MWh)	0	50

size. Their lower and upper bounds, reported in Table 5, are chosen to reflect realistic deployment limits for the considered islanded power system.

5. Results

To characterize the overall performance of the modelling framework, the analysis first compares the multi-objective results obtained with the RO formulation with those derived from the conventional representative year approach. A three dimensional Pareto front is used to visualize the trade-offs between the three objectives selected in the complete set of simulations. As shown in Fig. 8, the solutions produced by the RO formulation occupy a restricted region of the objective space, indicating a loss of overall improvement in performance compared to the representative year benchmark, *i.e.* the cost of robustness previously mentioned in Section 2.

To facilitate a more detailed interpretation of these differences, the 3D surface is supplemented by two-dimensional projections of each of its faces, shown in the same Fig. 8, allowing for a clearer inspection of how the two approaches diverge between individual pairs of objectives. In particular, the two lateral projections show that the battery exploitation parameter is markedly lower under the RO formulation, pointing out the relevance of BESS within the RES portfolio when the system request for guarantees of performances in terms of robustness along the various years examined. These outcomes of the RO process are, however, supported by the behaviour of the mismatch metric ϕ, which reaches values under RO that are comparable with those achieved when the nominal optimization problem is solved, indicating a smooth alignment between renewable generation and demand. Aligned with ϕ, the reduction in annual CO_2 emissions further confirms that RO achieves a favourable compromise across all three performance metrics. In fact, the difference between the two approaches is much smaller in the top projection of Fig. 8, which displays the relationship between ϕ and total annual CO_2 emissions. Here, the Pareto fronts obtained with the RO method and the representative year approach lie much closer together, indicating that robustness has a stronger influence on storage related metrics for the selected case study.

Fig. 9 presents the outcomes for two selected optima scenarios, from both the robust and nominal optimization, showing how each optimized variable behaves over the entire simulation period. The design vector for the two chosen (nominal and robust) scenarios are reported in Table 6.

For every variable, the plots include the fitness value identified by the optimizer and highlight the corresponding suboptimal region, represented by the red band indicating performance levels worse than that reference value. What emerges from these results is a consistent and significant difference between the two optimization strategies. In the robust case, all simulated years remain at or improve the fitness

Table 6
Design vector and performances of the identified robust and nominal optima.

Parameter	Unit	Nominal optima	Robust optima
C_{WT}	(MW)	12	12
C_{PV}	(MW)	41	9
C_{OWT}	(MW)	0	0
C_{CP}	(MW)	20	44
C_{P}	(MW)	0	0
C_{BESS}	(MWh)	50	23
CO_2	(kt)	25.27	23.93
ϕ	(MWh)	15.86	14.44
R_{BESS}	(%)	1.28	1.23

value, never entering the suboptimal region. This demonstrates that the robust solutions maintain the expected performance across time, without unexpected degradations. Conversely, the representative year solutions frequently fall within the red area, exceeding their fitness value and thus performing worse than anticipated when assessed over multiple years. Looking across the variables, η_{BESS} shows similar boundary behaviour in both approaches. The situation differs for annual CO_2 emissions, where the fitness values themselves diverge noticeably. The most evident contrast appears for ϕ: although both approaches achieve comparable fitness values, the representative year optimization exhibits a highly variable trend over the subsequent years, almost entirely within the suboptimal region, while the RO maintains a stable and consistently acceptable performance profile. Overall, the results demonstrate the greater reliability of RO than nominal optimization strategies, which avoids the performance drops clearly visible in the nominal solutions when assessing the long-term performance of a energy system planning scenario.

Remark 1. The reader should note that robustness can be interpreted in two complementary ways. On the one hand, it may be understood as a low sensitivity of a candidate scenario to perturbations, *i.e.*, a limited deviation from the target performance when the system is slightly altered within the prescribed uncertainty set. On the other hand, robustness can be defined, as in the optimization problem of Eq. (5), in a worst-case sense: as the ability of a scenario to guarantee the best possible performance under the most adverse realization of the uncertainties compatible with that set. Depending on which of these perspectives is adopted, the same performance-sensitivity results can be interpreted differently, and this should be borne in mind when drawing conclusions on performance under uncertainty and when comparing alternative scenarios.

Fig. 10 provides a disaggregated view of the robust portfolios that meet a stringent emissions target. Starting from the full optimization outcomes dataset, in the 3D objective space, all configurations with annual CO_2 emissions lower than or equal to 25 kt (approximately a 70% reduction with respect to the validated reference system, that in line to the proposed plans of carbon footprint reduction of the local government (Cabildo insulare de La Gomera, 2025)) are first selected. Within this low-carbon subset, CO_2 is treated as a saturated objective: every scenario is equally attractive from an emissions viewpoint. The remaining trade-offs are then examined by projecting the solutions onto the two-dimensional ϕ-R_{BESS} plane, where a secondary Pareto front is identified (red markers and line).

Although several capacity combinations populate the feasible region, the colour maps in Fig. 10 reveal clear structural trends. Portfolios on the 2D Pareto front combine relatively low mismatch ϕ with an efficient use of storage, reflected by higher R_{BESS}, and are systematically associated with larger BESS capacities and a significant presence of CorPower as shown in Fig. 11. Moving away from the front towards higher ϕ values, the maximum attainable R_{BESS} decreases and the mix gradually shifts towards less storage and more dispersed allocations among PV and wind. Pelamis and OWT capacities remains modest across the entire set, indicating a limited contribution under the investigated resource and technology assumptions.

As anticipated, these patterns are summarized in Fig. 11, which reports the absolute capacity (top panel) and the installed-capacity share (bottom panel) of technologies for representative points along the 2D robust front. At low ϕ, deep decarbonization is achieved through higher BESS and a diversified mix that includes a strong wave energy component of CorPower device. As ϕ increases, storage shrinks and its relative share declines, while onshore wind increases its relevance, yet wave energy remains a persistent element of the robust portfolio. Overall, the post-processed 2D front clarifies how, once a strict CO_2 target is imposed, robust planning hinges on balancing temporal mismatch and storage exploitation.

Remark 2. Notably, wave energy is not imposed a priori: the optimizer is allowed to select zero installed WECs. Therefore, the fact that non-zero wave capacity appears in the (robust-)optimal portfolios confirms that wave energy can provide a net system-level value within the considered uncertainty set and constraints. However, it is worth stressing that the wave energy capacities identified along the Pareto-optimal front would, under present technology characteristics, imply the deployment of a relatively large number of individual WEC units. This is mainly a consequence of the still modest rated power of commercial devices, rather than an intrinsic limitation of the resource. Despite being allowed to select zero wave capacity, the optimizer systematically includes WECs in the optimal portfolios, indicating that, even at current performance levels, wave energy provides a net systemic benefit in terms of temporal balancing, storage utilization and emission reduction. This outcome offers a technical argument in favour of continued research and development on WECs and on control and design strategies aimed at unlocking the still largely untapped wave energy potential. In the specific case of La Gomera, the planned subsea interconnection with Tenerife (Red Eléctrica de España (REE), 2021, 2025), combined with the island's extensive suitable offshore areas for marine renewables (Yanez-Rosales et al., 2024), further strengthens the strategic value of wave energy, as future configurations could exploit both local demand coverage and green electricity export towards the wider Canarian system.

6. Discussion

Within the present section, the outcomes derived from the proposed framework are discussed and benchmarked against the current literature.

Multi-objective optimization is a widely employed method for the exploration of trade-offs among performances in islanded energy systems. In common formulations, a limited set of time series (or a single representative year) is used to simulate system operation and then to rank candidate designs, *e.g.* see Cabrera et al. (2018, 2021), Giudici et al. (2019) and Groppi et al. (2021). Such workflows are valuable for mapping structural trade-offs and for supporting stakeholder-facing decision-making, but they may hide configuration-dependent sensitivities to the evolution of RES (or possible other variables) across different years. However, when the inter-annual variability of time-evolving parameters, such as RES, is compressed or confined to a single-year representation, the resulting Pareto set may not preserve its optimality under alternative years. In such cases, considering as an uncertain parameter the inter-annual RES variability, the presented RO formulation can be employed to explicitly prioritize solution that maintain acceptable performance under the most adverse admissible resource realizations. This distinction is particularly relevant when the planning question aim to disclose also which portfolio remains acceptable across multiple years, where RES can become unfavourable. The latter aspect becomes central for non-interconnected islands, where reserve sharing and cross-border balancing are unavailable and the consequences of low-resource years can be amplified. In this setting, the proposed RO

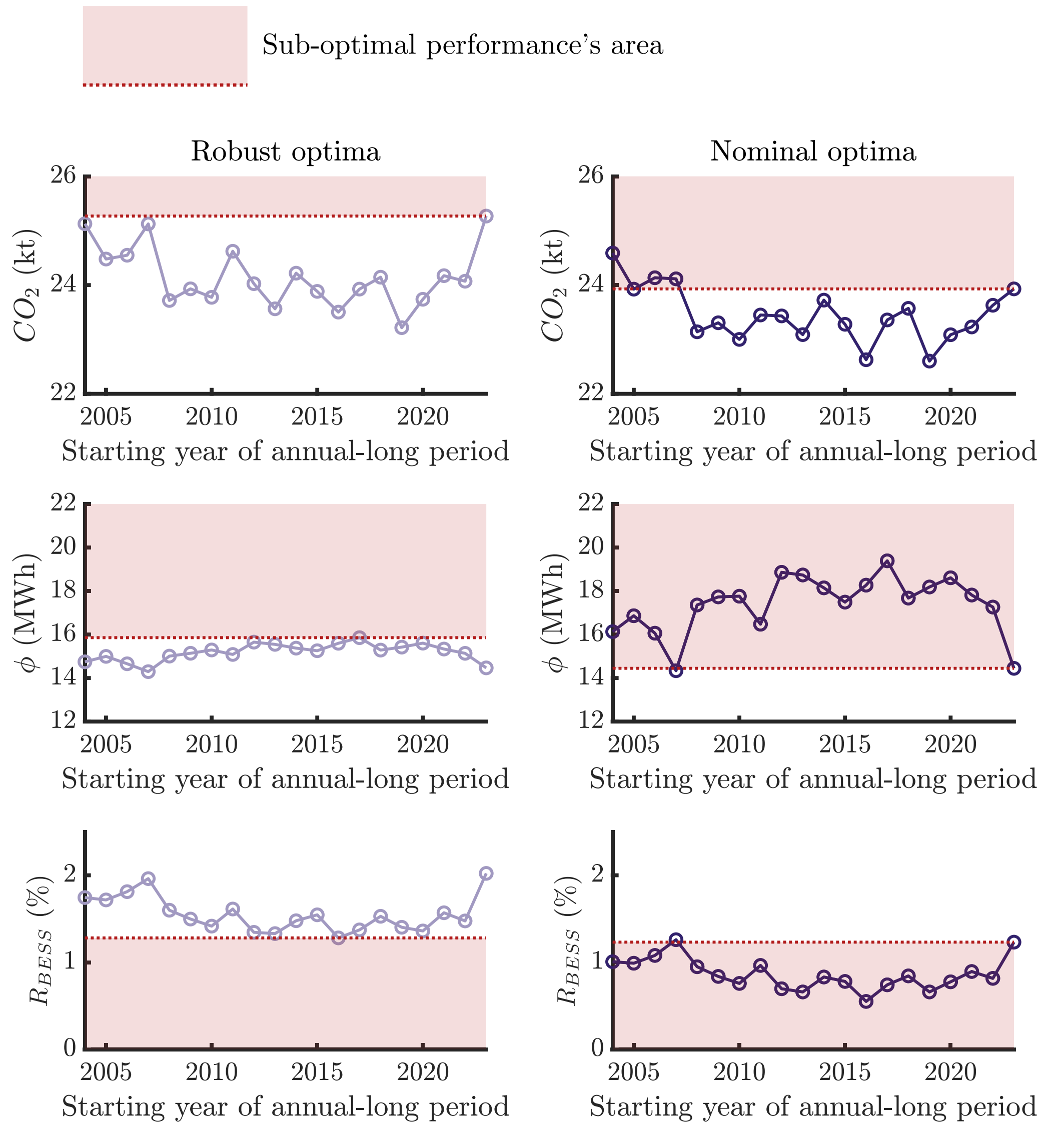


Fig. 9. Long-term performance's behaviour robust and nominal optima.

approach can be interpreted as an operationally resolved stress test applied to every candidate design during the search process.

In literature, transition planning for RES integration in islands is also addressed by means of SP models (Moschos et al., 2017). However, despite scenario-based stochastic approaches can account for uncertainty by optimizing expected performance across a probabilistic scenario set, they require probability assignments that may be unreliable for long-term renewable resource variability. At the same time, a worst-case aggregation can be conservative and may under-emphasize average-year benefits, but an expected performance indicator based on stochastic models could lead to an overestimation of their value. Moreover, MILP/LP capacity-expansion models can represent multi-year system evolution, but they often rely on clusterization approaches to remain tractable. Recent studies have shown that the use of grouped representative periods can significantly affect the assessment of flexibility options and that such modelling choices can influence the resulting transition plans (Marocco et al., 2023). In this context, a static, hourly-resolved RO framework represents a complementary tool: it does not aim to replace pathway models, but to provide a computationally practical, stress-tested portfolio design that is directly evaluated on multi-year hourly inputs. In representative-day clustering, as a result, higher-order intra-annual dynamics are not preserved exactly. Similarly, stochastic-based paradigms must operate on a finite set built from statistical models, these scenarios can reproduce selected distributions and correlations, yet they cannot guarantee that the full intra-annual chronology present in the underlying record, By contrast, the proposed RO workflow deliberately preserves intra-annual dynamics by evaluating each candidate portfolio through full hourly simulations for each admissible year in the multi-year dataset, and then synthesizing performance via a robustness criterion, at the expense of increased computational cost and problem complexity.

Consistently, in their study, Javed et al. (2023) solve the sizing problem over moving multi-year simulation windows of increasing length, demonstrating that extending the temporal horizon beyond a single representative year can potentially change capacity sizing (especially storage) outcomes in island energy systems. The results indicate that involving longer simulation periods systematically increases the energy system design robustness, because multi-year windows are more likely to include adverse renewable source conditions, highlighting how limited-year sizing can underestimate the severity of unfavourable periods and lead to optimistic assessments of system balancing. Instead, by construction, portfolios selected under multi-year worst-case evaluation are less exposed to this optimism bias and provide a more conservative (yet operationally consistent) coverage against inter-annual resource variability.

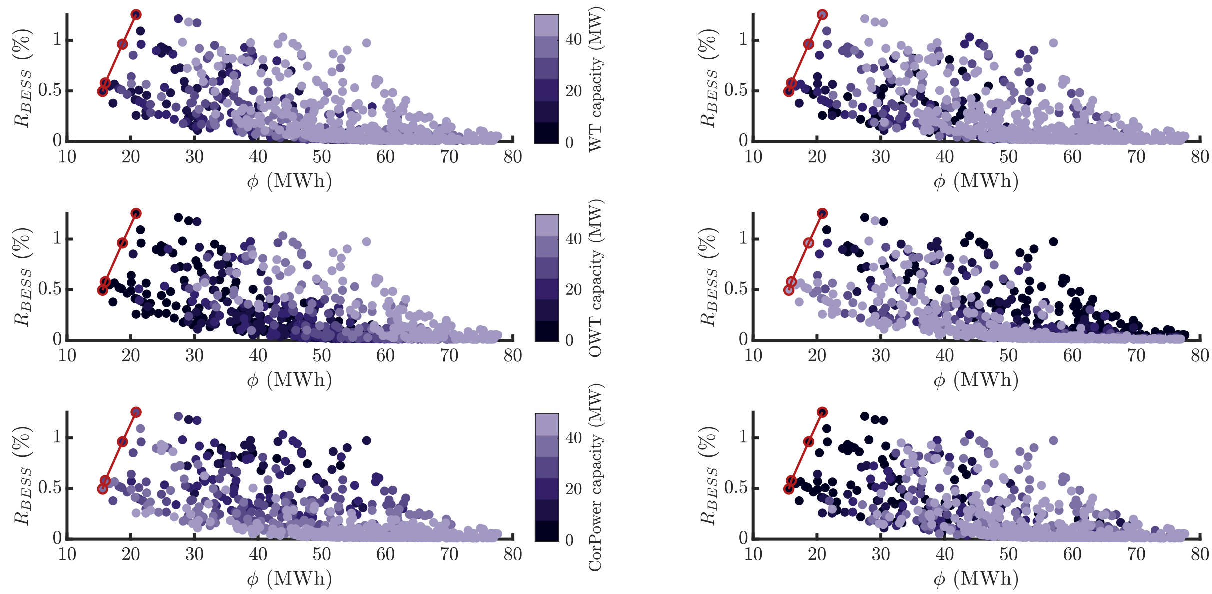


Fig. 10. Relationship between R_{BESS} and ϕ for all portfolios generated by the RO. All panels display the same set of solutions, while the colour scale highlights the design variables. Red markers denote the robust Pareto set.

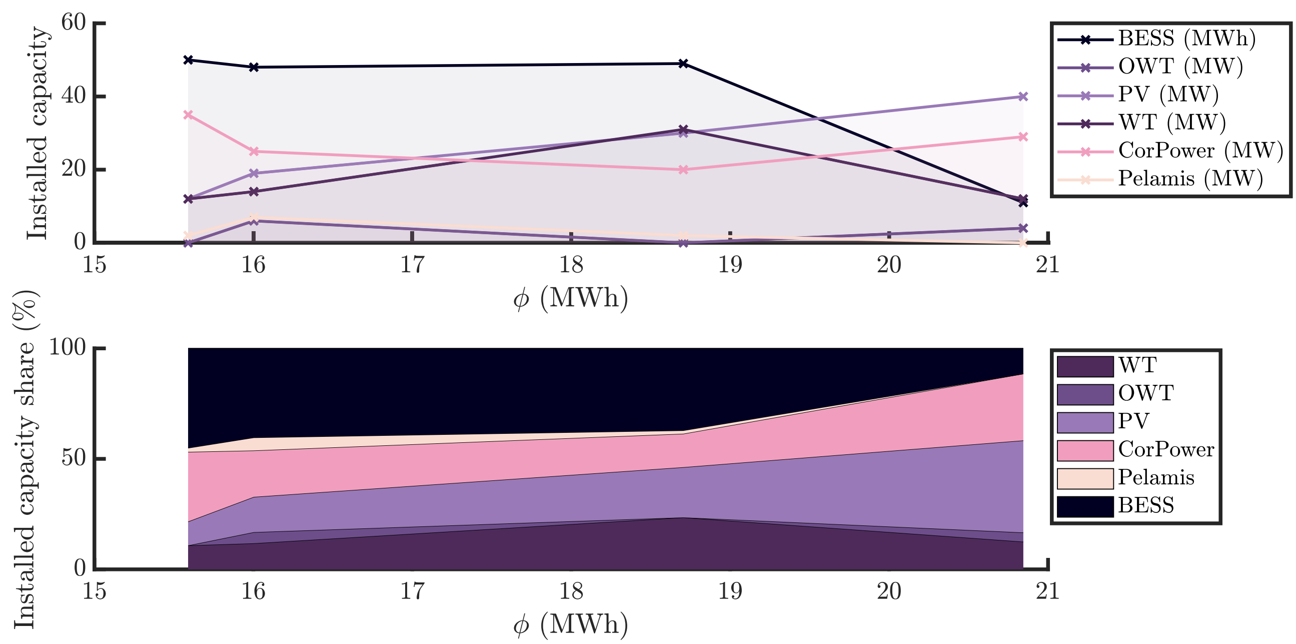


Fig. 11. Top panel: installed capacity of each technology along the robust Pareto front as a function of ϕ. Bottom panel: corresponding installed capacity share of each technology.

Overall, embedding multi-year stress testing into the optimization loop via RO formulation is shown to affect the decision-making stage of which portfolios are considered to be optimal. The proposed approach advances current island-planning optimization practice by explicitly including the natural RES variability (for the presented case study wave energy) in the optimization problem formulation, rather than treating it implicitly through a single representative year or approximating it via reduced temporal representations and clustering strategies required for tractability in long-term models. Here, robustness (intended as the best possible performance under the worst-case realization) becomes an optimization driver, while preserving the pre-defined intra-annual resolution and system behaviour for each of the simulated years. The resulting framework is appropriate when planning decisions need to be defensible under adverse, yet plausible, renewable conditions, and when the designer seeks to retain hourly operational detail without relying on probabilistic or stochastic modelling assumptions.

7. Conclusions

This paper has introduced a static single-stage RO framework for the long-term planning of islanded energy systems under meteomarine variability. The approach extends previous deterministic EnergyPLAN-MATLAB couplings by embedding an explicit uncertainty layer based on twenty years of hourly wave data for La Gomera. Within this framework, the installed capacities of WT and OWT, PV, two WEC technologies and BESS are jointly optimized via GA. Robustness is formalized in a worst-case scenario sense: each candidate portfolio is evaluated over all annual realizations within the discrete uncertainty set, and the objectives correspond to the most adverse outcome in terms of: renewable production-energy demand mismatch ϕ, storage efficiency R_{BESS}, CO_2 emissions.

The posed RO problem converges towards a robust Pareto set which occupies a more restricted region of the objective space than the representative-year (nominal) set, indicating that guaranteeing performance over the full uncertainty set comes at the expense of reduced achievable improvement in the three objectives (*i.e.*, the cost of robustness). Moreover, when the solutions optimized on a single representative year are assessed over multiple years, their performance can deteriorates beyond the nominal fitness, evidencing sensitivity to the particular year used for optimization. Conversely, despite the price paid, the robust solutions are guaranteed to remain at or improve their fitness across all simulated years, avoiding the systematic performance drops observed in the representative-year designs.

Beyond a primary 3D robust Pareto front in terms of annual CO_2 emissions, mismatch ϕ and BESS exploitation R_{BESS}, a second layer of analysis is carried out by explicitly enforcing a deep decarbonization target. All robust portfolios with $CO_2 \leq 25$ kt, corresponding to roughly a 70% reduction relative to the validated reference configuration, are treated as equally optimal with respect to emissions. Within this low-carbon subset, the trade-off space is re-expressed in the two dimensional ϕ-R_{BESS} plane, where a secondary Pareto front is identified.

The resulting portfolios show that robust low-ϕ configurations rely on significant BESS capacity and a relevant contribution from wave energy, especially CorPower, while maintaining a diversified mix across wind and PV. As larger mismatch levels are accepted, storage capacity and exploitation gradually decrease, and the system transitions towards wind-dominated configurations, yet wave energy remains a structural element of the mix. Importantly, these robust solutions display markedly reduced performance variability over the historical dataset when compared to deterministic portfolios optimized on a single representative year, confirming the added value of embedding resource variability directly into the optimization loop.

It is worth noting that robust-optimal portfolios can differ in composition from representative-year optima because they are designed to preserve performance under adverse realizations of the uncertainty set (worst-case multi-year) rather than to be optimal for a single representative year. This is exemplified in Table 5, where the robust optimum features lower PV capacity, higher CorPower wave capacity, and a different BESS sizing. A broad technology-by-technology generalization across the entire Pareto sets is not straightforward, as the two formulations span different temporal scopes and occupy different regions of the objective space. Consequently, systematic statements on the comparison of individual technology trends between the two entire sets could be misleading due to the different optimization problems posed.

From a broader perspective, the proposed framework is generic and computationally tractable and it can be readily transferred to other islands, microgrids or mainland regions. The EnergyPLAN-MATLAB coupling is implemented in a location-agnostic manner: once an EnergyPLAN model is built and calibrated for a given system, the optimization loop interacts with it only through the set of decision variables (installed capacities and storage size in the presented case study) and the resulting performance indicators extracted from the EnergyPLAN outputs. In the NSGA-II iterations, for each candidate solution, MATLAB generates a candidate vector, writes it into the EnergyPLAN input files, executes EnergyPLAN and returns the objective values to the optimizer. Therefore, the framework is directly transferable to any other location (including continental European systems) by replacing the EnergyPLAN case model and its input time series/constraints, while keeping the optimization wrapper unchanged. Moreover, the presented formulation allows for extension of the model to include additional sources of uncertainty such as demand growth, other RES variability or technology costs. By turning long-term resource records into an explicit uncertainty set and combining them with an emissions threshold, the methodology bridges detailed resource assessment and decision-oriented planning, supporting the design of energy transition pathways that are not only low-carbon but also robust to the natural variability of renewable resources.

7.1. Limitation and further works

Although the insights provided by the proposed framework, certain limitations must be taken into account in order to contextualize the scope and validity of the results. These limitations do not compromise the main findings, but they highlight aspects that merit caution in interpretation and indicate directions for future research.

A first limitation of this work is that the entire analysis is performed in hindcast, meaning that the optimization is tested using historical data rather than explicit forecasts (with its related prediction's error that should be included in the RO formulation) of future conditions which may be affected by climate change (see Guerra et al. (2019), Li et al. (2016) and Donk et al. (2023) as examples of optimization under uncertainty dealing with climate change effects). This allow to observe how robust and nominal solutions behave under a wide range of past variability, but it does not provide a formal guarantee that the same performance will be maintained under future, potentially different conditions. In practical terms, although robust optima are statistically more likely to generalize well, the adopted framework cannot quantify the exact level of reliability associated with this prediction, nor it can establish a mathematical limit to the possible deterioration in performance for scenarios that are still unknown. Together, another important limitation is related to the treatment of data uncertainty. The present work does not explicitly account for potential inaccuracies in the input data or model parameters. Although this choice simplifies the analysis, it also means that the results do not reflect uncertainties inherent to the data generation process. Future works should therefore incorporate structured approaches for representing and propagating such uncertainties through the optimization model and possibly their evolution in time or uncertainty on the uncertainty set definition itself (*e.g.* employing distributionally or adaptive RO strategies Guevara et al., 2020). Finally, the uncertainty considered in this study is limited to a narrow subset of system parameters. Extending the uncertainty space to include, for example, future energy demand, technology costs, or technology performance trajectories would provide a more comprehensive assessment. However, such an extension would require a robust and well-validated modelling framework to characterize the uncertainty of these additional parameters.

In conclusion, constrained eligible areas for RES deployment are not explicitly modelled in the current work. The resulting capacities should therefore be interpreted as planning indicators of technology and system potential, not as site-ready layouts. In fact, although the optimization framework allows each technology to be set to zero capacity, the optimizer systematically retains a diversified RES shares in the optimal solutions, indicating advantages in terms of system-level performances. The present work addresses a system-level capacity-planning problem under uncertainty, accordingly, port logistics and micro-siting choices are not explicitly modelled, and the optimal offshore (and portfolios) returned by the optimization should not be interpreted as site-ready layouts. Nevertheless, the generalizability of the quantitative results depends on how adequately the target energy system is modelled. Beyond the limitations already stated, the present case study describes a non-interconnected island grid and thus does not represent interconnection-driven dynamics. For interconnected locations, such as continental countries, the EnergyPLAN model should be extended to capture inter-area interactions (*e.g.*, import/export exchanges and related interconnection constraints), which can affect system operation. Hence, while the proposed RO workflow is transferable, the underlying system model must be carefully adapted to each case study.

Future works should also integrate land-use and regulatory boundaries within the optimization problem formulation, *e.g.* via explicit spatial constraints or technology-specific upper bounds on maximum installable capacity.

CRediT authorship contribution statement

Filippo Giorcelli: Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Viola De Clerck:** Writing – review & editing, Writing – original draft, Visualization, Methodology, Investigation, Data curation. **Edoardo Pasta:** Writing – review & editing, Writing – original draft, Validation, Supervision, Project administration, Investigation, Funding acquisition, Formal analysis, Data curation, Conceptualization.

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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Data availability

Data will be made available on request.

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