

Towards 100% renewable-powered offshore oil and gas platforms: Techno-economic evaluation of optimal power plant configurations

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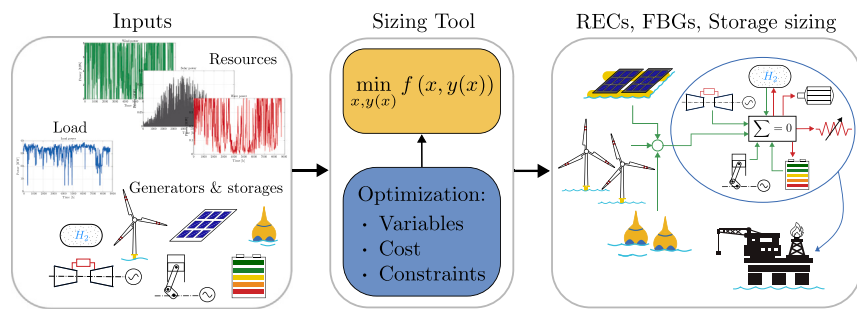
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HIGHLIGHTS

- Optimal sizing of multi-resource isolated power system for offshore O&G.
- 100% REC is feasible today, but costs about 8× current fuel-based setups.
- Combining renewable and thermal units cuts the emissions with a limited cost increase.
- Findings inform decision makers on the present and future decarbonization potential.
- Open-source tool enables extended analyses beyond the study's boundaries.

GRAPHICAL ABSTRACT



ARTICLE INFO

Keywords:

Oil & gas platforms
Decarbonization
Mixed integer linear programming
Risk management
Demand response
Multi-resource
Battery energy storage system

ABSTRACT

This paper introduces a method for the techno-economical sizing of a pool of Renewable Energy Converters (RECs), Fuel-Based Generators (FBGs), and Energy Storage Systems (ESSs) to meet the load power demand of a target Isolated Power System (IPS) offshore. The problem is formulated as Mixed Integer Linear Programming (MILP), with a cost function accounting for the risk aversion of decision makers. The framework considers already mature technologies, such as Wind Turbines (WTs), Gas Turbines (GTs), Diesel Generators (DGs) and Battery Energy Storage Systems (BESSs), as well as innovative ones, such as floating Photo-Voltaic Panels (PVs), Wave Energy Converters (WECs) and Hydrogen Storage Systems (HSSs). A load side Demand Response (DR) mechanism is also proposed. The methodology is applied to the test case of offshore Oil and Gas (O&G) platforms, in which the reduction of the emissions produced by FBGs supplying electricity and heat is urgent. The results show that, for current costs, the 100% Fuel-Based Generator (FBG)-based solutions are cheaper than any other hybrid solution, but the deployment of RECs alongside just one Gas Turbine (GT) reduces the emissions by 70% while increasing the costs by only 6%. It is also shown that a tenfold carbon tax increase is required to make a combined FBG/Renewable Energy Converter (REC)-based solution financially advantageous compared to a solely FBG-based one. Furthermore, the flexible management of 10% of the load can lead to a cost reduction of around 4%. Sensitivity of the solution from Photo-Voltaic Panel (PV), Wave Energy Converter (WEC), and BESS costs, user's risk aversion, and platform deployment locations are also analyzed.

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Acronyms

BESS	Battery Energy Storage System
CAPEX	CAPital EXpenditure
COP30	United Nations Climate Change Conference
CVaR	Conditional Value-at-Risk
DG	Diesel Generator
DoD	Depth of Discharge
DR	Demand Response
EL	Electrolyzer
EoL	End of Life
ESS	Energy Storage System
FBG	Fuel-Based Generator
FC	Fuel Cell
GA	Genetic Algorithm
GHG	Greenhouse Gas
GT	Gas Turbine
HSS	Hydrogen Storage System
IPS	Isolated Power System
LP	Linear Programming

MG	Micro Grid
MILP	Mixed Integer Linear Programming
MPPT	Maximum Power Point Tracking
NG	Natural Gas
O&G	Oil and Gas
O&M	Operational and Maintenance
OP	Offshore Platform
OPEX	OPERative EXpenditures
PLA	Piecewise Linear Approximation
PSO	Particle Swarm Optimization
PV	Photo-Voltaic Panel
RA	Risk Averse
REC	Renewable Energy Converter
RES	Renewable Energy Source
RN	Risk Neutral
WEC	Wave Energy Converter
WF	Wind Farm
WIS	Water Injection System
WS	Wind Speed
WT	Wind Turbine

1. Introduction and innovations**1.1. Motivation**

With the increasing concern about the impact of human activities on the environment, the decarbonization of heavy industrial processes plays a crucial role, as recently discussed in the 2025 United Nations Climate Change Conference (COP30) [1]. In this context, the O&G sector is particularly critical, considering that in 2023 O&G operations accounted for around 15% of the total energy-related emissions globally [2]. In Norway the situation is even more severe, as the sector is responsible for almost a quarter of the aggregate national Greenhouse Gas (GHG) emissions [3], mainly coming from the combustion of Natural Gas (NG) in turbines (83.6%), and diesel in engines and boilers (11.3% combined). To contribute to the goal of reducing the carbon footprint of Offshore Platform (OP) operations, this article develops a sizing tool that can be freely used for the techno-economic allocation of a pool of RECs, FBGs, BESSs, and HSSs, to supply the energy demand of an OP.

Isolated Offshore Platforms (OPs) share some similarities with classical Micro Grids (MGs), enabling the use, upon proper adaptation, of some mathematical tools and methods already developed in such proximal field (for example, in the electrification of rural installations [4] or islands [5]). On the other hand, isolated OP and general Micro Grid (MG) also present multiple distinctive features. In fact, general MGs can operate both in grid-connected and islanded modes, while OPs have to rely only on local generation and storage since they are frequently located far from the coastline, making the electrical connection to the mainland grid unfeasible for technical or economical reasons.

1.2. Literature review

Several studies address with the decarbonization of OPs. They can be categorized in three broad groups according to their objectives: (i) increasing the efficiency of existing assets by proper control [6–17], (ii) refurbishing already functioning fossil-based plants by integrating RECs and ESSs [18–23], (iii) and designing new installations while taking into account the goals of increased sustainability [4,5,24–37]. In the first group of studies, [9,11] considers the presence of GTs as generators, while [8,10] additionally consider WTs.

Among the studies dealing with the refurbishment, [19,20,22] size the Battery Energy Storage System (BESS) considering GTs already in operation, but only [21] adds the BESS' degradation cost to the picture, while [23] jointly sizes BESS and Diesel Generator (DG). Differently,

[18] optimizes the interconnection and energy sharing of closely connected OPs.

Within the studies focusing of the design of new OP IPS, [28–33] still consider the presence of FBG, in the pool of generators that can be installed.

Among the studies including FBGs, [28] considers a fixed presence of GTs and optimizes the number of installed WTs only, while [29] optimizes the number of both GTs and WTs. [30–32] address the sizing of a GTs + WTs plant with an Energy Storage System (ESS), considering BESS only [30], Hydrogen Storage System (HSS) only [31], or both of them [32].

Among offshore RECs, WTs are the most widely deployed ones due to their high level of technological maturity. On the other hand, other marine technologies such as floating PVs and WECs have a high theoretical energy potential but are still not frequently considered, due to their relatively low technological maturity. For example, Cipolletta et al. [33] uses WECs alongside GTs in a hybrid plant. The use of these innovative RECs has been proposed as necessary in order to achieve 100% renewable plants [24–27]. In particular, Zhao and Li [25] and Oliveira-Pinto et al. [26] consider the hybridization of at least two RECs (i.e., WTs + WECs in Oliveira-Pinto et al. [26], and WTs + PVs in addition to BESS + HSS for Zhao and Li [25]), while Su et al. [24] designs an OP IPS composed by WTs and grid-forming undersea pumped storage system as ESS. None of the previous studies consider Wind Turbine (WT), PV, and WEC at the same time, as done in this study. On the other hand, Toms et al. [27] uses a broad range of RECs (i.e., WTs, PVs, WECs, and tidal generators) but simplifies the load profile to just 1 day of operation, whereas the yearly operation with hourly resolution used in this study seems more appropriate for capturing dynamics happening at different scales.

Among the papers targeting applications different from the O&G ones, Kazemi-Robati et al. [37] proposes an optimization model for hybridizing an existing and grid-connected offshore WT parks installing PVs and WECs, to reduce power variability and improve the economics of the whole system.

Some control-oriented studies explicitly model the degradation cost of BESS and incorporate it into the optimal operational planning of MGs [7] or grid-connected BESS [13,14]. Although the degradation model adopted in this study follows the same principle as the one employed in Keske et al. [13] and Wang et al. [14], its application is extended here to the design phase. This represents a fundamentally different problem,

Table 1
Comparative summary of the reviewed studies and their main features.

Ref.	O&G	Type	GT	DG	WT	PV	WEC	BESS	BESS deg	HSS	DR	Risk	Year
[6]	✓	C	✗	●	✗	✗	✗	●	✗	✗	✓	✗	2021
[7]	✓	C	✗	●	✗	●	✗	●	✓	✗	✗	✗	2023
[8]	✓	C	●	✗	●	✗	✗	✗	✗	●	✗	✗	2023
[9]	✓	C	●	✗	✗	✗	✗	✗	✗	✗	✗	✗	2017
[10]	✓	C	●	✗	●	✗	✗	●	✗	✗	✗	✗	2022
[11]	✓	C	●	✗	✗	✗	✗	●	✓	✗	✗	✗	2022
[12]	✓	C	●	✗	●	✗	✗	✗	✗	✗	✓	✗	2017
[18]	✓	R	●	✗	✗	✗	✗	✗	✗	✗	✗	✗	2021
[19]	✓	R	●	✗	●	✗	✗	✓	✗	✗	✗	✗	2019
[20]	✓	R	●	✗	●	✗	✗	✓	✗	✗	✗	✓	2022
[21]	✓	R	●	✗	●	●	✗	✓	✓	✗	✓	✗	2025
[22]	✓	R	●	✗	●	✗	✗	✓	✗	✗	✗	✗	2023
[23]	✓	R	●	✓	●	✗	✗	✓	✗	✗	✗	✗	2021
[24]	✓	D	✗	✗	✓	✗	✗	✗	✗	✗	✗	✗	2025
[25]	✓	D	✗	✗	✓	✓	✗	✓	✗	✓	✗	✗	2022
[26]	✓	D	✗	✗	✗	✓	✓	✗	✗	✗	✗	✗	2020
[27]	✓	D	✗	✗	✓	✓	✓	✓	✗	✗	✗	✗	2023
[28]	✓	D	●	✗	✓	✗	✗	✗	✗	✗	✗	✗	2025
[29]	✓	D	✓	✗	✓	✗	✗	✗	✗	✗	✗	✗	2023
[30]	✓	D	✓	✗	✓	✗	✗	✓	✗	✗	✗	✗	2024
[31]	✓	D	✓	✗	✓	✗	✗	✗	✗	✓	✗	✗	2020
[32]	✓	D	✓	✗	✓	✗	✗	✓	✗	✓	✗	✗	2021
[33]	✓	D	✓	✗	✗	✗	✓	✗	✗	✗	✗	✗	2023
[13]	✗	C	✗	✗	✗	✗	✗	●	✓	✗	✗	✗	2024
[14]	✗	C	✗	✗	●	✗	✗	●	✓	✗	✗	✗	2016
[15]	✗	C	✗	●	✗	●	✗	●	✗	✗	✓	✗	2019
[16]	✗	C	✗	✗	✗	✗	✗	●	✗	✗	✗	✓	2018
[4]	✗	D	✗	✓	✗	✗	✗	✓	✗	✗	✗	✗	2019
[5]	✗	D	✗	✓	✗	✓	✗	✓	✗	✗	✗	✗	2016
[34]	✗	D	✗	✗	✓	✓	✗	✓	✗	✗	✗	✓	2021
[35]	✗	D	✗	✗	✓	✓	✗	✓	✗	✗	✗	✓	2024
[36]	✗	D	✗	✗	✗	●	✗	✗	✗	✗	✗	✓	2022
[37]	✗	D	✗	✗	✓	✓	✓	✗	✗	✗	✗	✗	2024
[17]	✗	C	●	✗	●	●	✗	●	✗	✗	✗	✓	2020
This work	✓	D	●	✓	✓	✓	✓	✓	✓	✓	✓	✓	

✓ present (and size optimized); ✗ not present; ● present, but size not optimized; C = Control; R = Refurbishment; D = Design.

as the optimal BESS size is not known a priori and must be determined within the optimization process.

A generally under-investigated opportunity is to exploit DR load-side flexibility for OP decarbonization. Although this was generally recognized as an important strategy to enhance RECs penetration in industrial [38–40] or civil [15] sectors, its application in IPS has been included only in control-oriented studies in the OP domain [6,12,21], while this study includes it in the design phase as well.

For what concerns the management of the challenges regarding uncertainties from different sources (e.g., RECs, and load), Risk Averse (RA) formulations have been applied in studies dealing with cross-regional energy systems [17], grid connected energy system design [35,36], control of civil building [16], refurbishment of OPs [20], and design of IPS [34], but only our study presents an articulated analysis of the risk associated to the design of an OP.

1.3. Research gaps

To provide a structured overview of the contributions in the existing literature and to highlight current research gaps, the previously discussed papers are compared in Table 1. They are categorized according to whether they target an O&G application, the type of study performed (i.e., control of already installed assets, refurbishment of currently operating OPs, or the design of new energy systems), the FBGs/RECs/ESSs that are considered, the exploitation of DR mechanism, and the economic risk-aware formulation of the problem.

Overall, it can be noticed that the design of an OP IPS considering a broad range of generator and storages (i.e., GTs, DGs, WTs, PVs, WECs, BESS, and HSS), using long term data with hourly time resolution, and

assessing the impact of both DR and varying levels of user's risk aversion is missing.

1.4. Paper innovations

Considering the main research gaps described in the previous section, the main contributions of this paper are the following:

- (I) to propose a sizing methodology for identifying the best techno-economical combination of a wide range of different RECs/FBGs/ESSs for supplying an OP IPS;
- (II) to quantify the CO₂ emissions reduction and costs variations currently attainable through the use of RECs and ESSs instead of -or combined with- FBGs.
This highlights how far the O&G sector is from reaching 100% REC-based power generation;
- (III) to assess the impact on the optimal solution of internal parameters (i.e., dependent on where and how the owner operates the IPS), such as: (a) load side flexibility, (b) geographical location of the OP (affecting the relevance of different RECs), (c) user's risk aversion (trading-off total cost minimization for the risk of very high costs in the worst cases);
- (IV) to assess the impact on the optimal solution of external parameters (i.e., dependent on the market or regulator's decisions), such as: (a) PV cost reduction, (b) WEC cost reduction, (c) BESS cost reduction, (d) carbon tax increase.
This can serve as guidance for decision and policy-makers and/or OP operators for decarbonization projections;

(V) to make the developed design tool freely available to the user community in an openly accessible repository.

The remainder of the work is organized as follows. Section 2 describes the target OP in terms of load characteristic and available assets, Section 3 reports the mathematical formulation of the proposed solution, Section 4 describes the investigated test cases, while Section 5 reports the results obtained. Finally, conclusions are drawn in Section 6.

2. Isolated platform power system description

The OP is supposed to become part of an energy hub comprising FBGs like GTs and DGs, as well as Renewable Energy Sources (RESs) like WTs, PVs, WECs and is equipped with BESS and HSS and a dump load to dissipate excess power, as illustrated in Fig. 1.

2.1. Load

From an electrical point of view, an offshore OP can, in most cases, be seen as an IPS with power rating in the range of tens to hundreds of MW [41], consumed primarily as electricity in pumps and compressors, and heat for separation purposes [12]. In this study, we consider an OP located in the North Sea whose rated power is $P_L^{rated} = 50$ MW.

The OP load is composed of two types of electrical consumption. One part is fixed and dominated by 24/7 industrial operations, while the rest is more flexible, and represented, for example, by the Water Injection System (WIS). The latter can be used by DR to reduce the operation costs [21], or to reduce their emissions [12].

In this study, the analysis of DR effects on solution cost assumes that up to 10% of the rated load power is flexible. This is in line with the ranges reported in previous literature. For example, in Adeyemo et al. [21] a flexible WIS load of 6 MW (corresponding to 7.5% of the installed FBG power) in a setup with 4×20 MW GTs, WT, PV, BESS is suggested, while the flexible load used in Sanchez et al. [12] accounts for 0.18 [pu], and it is actively controlled according to the available WT power. Finally, in Jabari et al. [6] the base load can be increased/decreased by up to 30%.

In line with the most recent practices for OP decarbonization [42], it is assumed that all the thermal units for heat production are decommissioned and the entire heat demand for O&G operation is met by electrical boilers. Consequently, no distinction is made between heat and electricity demands and the total power consumption covers both needs.

2.2. FBGs

A typical arrangement of OP in the North Sea uses two identical GTs operated by equally sharing the load to increase reliability [9,19,43]. On the other hand, in this study, more configurations will be evaluated.

Typically, a DG is installed on OP for emergencies and backup for unfavorable conditions [18]. In this study, DGs can be used not only

as a backup, but also as a conventional, highly-flexible energy source (e.g., faster ramp-up and no minimal off-time before a startup compared to GTs).

2.3. Renewable energy converters

Since the time scale resolution used in the sizing studies is relatively large (i.e., the range of hours) [19,20], all intra-hour variations of the resources can be neglected, and static models of WT, PV, and WEC can be considered. While there does not exist consensus or any consolidated method to include RECs' degradation in planning algorithms, in this study an operational technology-dependent cost is assigned to account for wear and tear of the RECs components.

The selected WT model has a rated power of 8 MW in line with the widely used models for offshore applications [44]. The WT power curve is used for transforming the hub height-adjusted (h_{hub}) Wind Speed (WS) into power

$$v_{hub} = v_r \left(\frac{h_{hub}}{h_r} \right)^{\alpha_s} \quad (1)$$

where v_r is the measured WS, α_s is the shear coefficient. Wake effects among WTs are considered out of scope for this study, but the interested reader can find more information on the subject in Refs. [29,45].

In recent years the possibility of deploying PV panels over the water has been tested in some commercial-size plants [46–48]. The power output of a PV is modelled as in Ref. [49]:

$$P_{PV} = \eta_{STC} \bar{A} G \eta_{AC} \quad (2)$$

where η_{STC} is the efficiency in Standard Testing Conditions (i.e., when the PV is irradiated with 1 kW m^{-2}), $\bar{A}$ is the surface of 1 PV, G is the solar irradiance, and η_{AC} is the conversion efficiency from the DC to the AC side. This model is considered sufficient with respect to the time scale of the analyses in this study.

Unlike WT and PV, the technology of WECs is far from consolidated because none of the prototypes proposed so far has proved to be clearly superior to the others. Furthermore, only a few concepts reached the commercial deployment stage. Among all of them CorPower reported having proved reliability and power delivery capabilities in ocean tests [50,51], so it was selected for this application. The output power of the WEC is obtained from the power matrix reported in de Santiago et al. [52] for the values of significant wave height and energy period of the target location.

In terms of cost modelling, the developed methodology uses CAPital EXpenditure (CAPEX) and OPERative EXpenditures (OPEX), as commonly done in sizing problems, both in the design of energy systems [53–55] and also in other fields [56].

3. Mathematical formulation of the optimal sizing problem

The sizing of the energy hub can be mathematically formulated as a constrained minimization, and different methodologies and algorithms have been proposed in the literature to solve it, such as Linear Programming (LP), Genetic Algorithm (GA), and Particle Swarm Optimization (PSO) [57,58]. Among various approaches, MILP has been selected in this study because it allows incorporation of uncertainty (modeled using stochastic process variables ξ related to environmental and operational conditions) as a widely adopted approach [19,20, 49,59,60].

It is important to note that the actual operating conditions of the plant—both in terms of resource availability and load—are unknown during the design phase. Therefore, the common underlying assumption is that future environmental conditions will resemble historical patterns, and that the load profile will be similar to that of comparable installations.

The optimization workflow is represented in Fig. 2, with a summary of the most relevant variables, cost components, constraints, and output of the developed method.

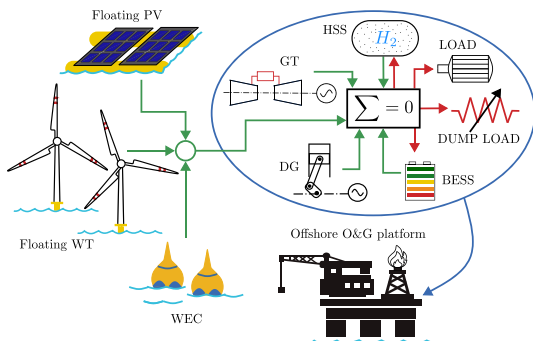


Fig. 1. Schematic representation of the target IPS.

The code implementing the sizing methodology described in this paper in Matlab is available at Andreetta [61].

3.1. Objective function

3.1.1. Risk-neutral formulation

The objective function f contains three different costs:

- A) f_I : installation expenditures, associated to the variable $\mathbf{x}$ (also called first stage variable) which defines the presence and/or the size of the assets, and their costs $\mathbf{c}$;
- B) f_O : operational expenditures, associated to the use of the available assets;
- C) f_{SC} : soft constraints expenditures, modeling the possibility to violate some limits, associated with the variable $\mathbf{z} \geq 0$, and a price $\mathbf{w}$.

Furthermore, the f_O can be divided into two subcategories:

- B.1) $f_{O,M}$: operational expenditures for which an explicit dependency between the control variable $\mathbf{y}$ (also known as second stage variables) and the related costs $\mathbf{q}$ is modelled (M) (e.g., the fuel cost of a GT, under the assumption of proportionality with the power output);
- B.2) $f_{O,NM}$: operational expenditures with a non-modelled (NM) relationship with a control variable, so expressed as a single value o but accounting for the operation during a specific time period (e.g., the WT operation cost given in dollars per year).

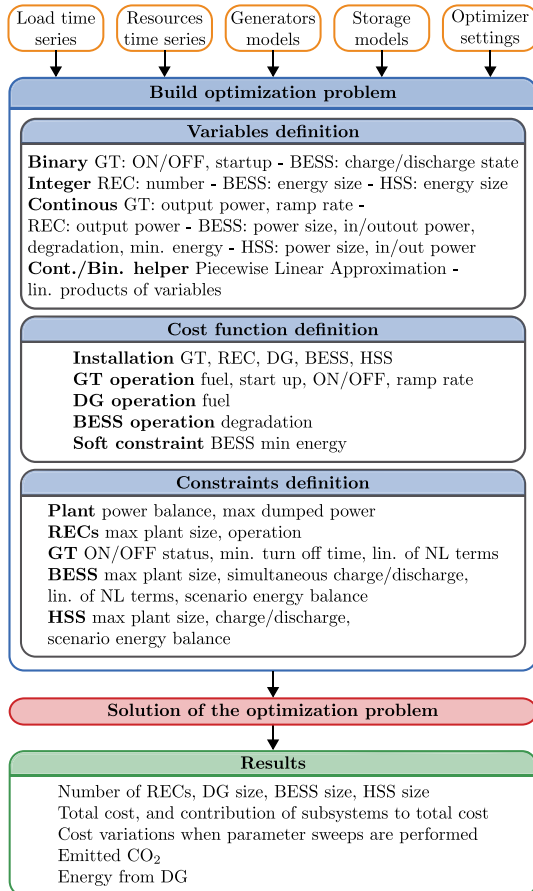


Fig. 2. Graphical representation of the optimization workflow, with summary of variables, costs, constraints, and obtainable results.

Combining the cost functions, the minimization problem can be generally formulated as:

$$\begin{aligned} \min_{\mathbf{x}} \{ & \mathbb{E} [f(\mathbf{x}; \tilde{\xi})] \} \\ \text{with: } f(\mathbf{x}; \tilde{\xi}) = & f_I(\mathbf{x}) + f_{O,NM}(\mathbf{x}) + f_{SC}(\mathbf{x}) + \min_{\mathbf{y}} \{ f_{O,M}(\mathbf{x}; \tilde{\xi}) \} \\ \text{s.t. } & \mathbf{Ax} + \mathbf{By} + \mathbf{C}\tilde{\xi} \leq \mathbf{0} \end{aligned} \quad (3)$$

where $\mathbf{A}$, $\mathbf{B}$, and $\mathbf{C}$ are the matrices expressing the constraints of the problem, that will be addressed in Section 3.3, in general form.

The MILP formulation can be obtained by discretizing $\tilde{\xi}$ over a set, Ω , containing all the possible realizations of the uncertain parameters called scenarios ω [20] having a specific scenario length h (in this paper $h = 24$ h or $h = 365 \cdot 24$ h depending on the test case), and whose probability of occurrence is π_ω . The discretized version of $\tilde{\xi}$ is denoted with $\hat{\xi}$. The scenario-based formulation enables future applications of the proposed methodology, for example by considering synthetic-generated dataset instead of real recorded ones, enhancing the flexibility and computational efficiency in the management of the uncertainty of the resources and load, as done for example in Ref. [20].

Eq. (3) is defined as Risk Neutral (RN) problem, because it is mathematically insensitive to the impact of extreme scenarios on the solutions, therefore the risk associated to them cannot be managed by the user [62].

An important aspect to consider relates to the timeline of the expenditures and how they should be accounted for. In fact, both f_I and f_{SC} are usually paid at one specific time instant, for assets that are then used over a time period (e.g., the installation cost of a BESS), while other costs are paid during the operation. To account for this effect, all expenditures must be referred to an equivalent time length h^* ($h^* = 24$ h in this paper), such that the physical meaning of the cost function to be optimized will be the cost of operating the OP for a time window h^* , also accounting for the fixed expenditures and regardless of the scenario length chosen in the optimization. The other quantities related to time discretization are: τ namely the (minimum) time resolution used in the formulation (in our case $\tau = 1$ h), $T = h/\tau$ i.e., the number of time frames τ forming a scenario (in this paper $T = 24$ or $T = 365 \cdot 24$), p i.e., the number of periods of length h^* contained in the project lifetime L , d_L i.e., the conversion factor for unifying the measurement units of L and h^* (in our case $p = L \cdot d_L / h^* = 10 \cdot (365 \cdot 24) / 24 = 3650$), d_o namely the number of reference periods of length h^* in the time frame in which o is expressed (if o is an annual cost, then $d_o = 365$).

Further clarifying the need for the previous definitions, one may be interested in comparing the costs of operating a certain asset over horizons of different lengths (i.e., $h = 1, 3, 12, 24, 96$ h), by referring to a common reference (base) period h^* (i.e., $h^* = 24$ h). On the other hand, one might want to discretize the same time horizon h with different time resolutions (i.e., $\tau = 0.5, 1, 2$ h).

Hence (3) can be rewritten as (4), calling $\hat{f}_{O,M}(\mathbf{y})$ the discretized operational expenditures:

$$\begin{aligned} \min_{\mathbf{x}, \mathbf{y}(\omega)} \{ & f_{RN}(\mathbf{x}, \hat{\xi}) \} = \min_{\mathbf{x}, \mathbf{y}(\omega)} \left\{ \underbrace{\left(\frac{r(1+r)^p}{(1+r)^p - 1} \mathbf{c}^T + \frac{1}{d_o} \mathbf{o}^T \right) \mathbf{x}}_{\hat{\mathbf{c}}^T} \right. \\ & \left. + \frac{r(1+r)^p}{(1+r)^p - 1} \mathbf{w}^T \mathbf{z} + \underbrace{\frac{h^*}{h} \sum_{\omega \in \Omega} \pi_\omega \sum_{t=1}^T \mathbf{q}(\omega, t)^T \mathbf{y}(\omega, t) \tau}_{\hat{f}_{O,M}(\mathbf{y})} \right\} \\ \text{s.t. } & \mathbf{A}(\omega) \mathbf{x} + \mathbf{B}(\omega) \mathbf{y}(\omega) + \mathbf{H}(\omega) \hat{\xi}(\omega) \leq \mathbf{0} \quad \forall \omega \in \Omega \end{aligned} \quad (4)$$

where $\mathbf{H}$ replaces the constraint matrix $\mathbf{C}$ in the case of $\hat{\xi}$, r is the interest rate over the reference period (obtained from the annual interest rate r_a as $r = r_a \cdot h^* / d_L$).

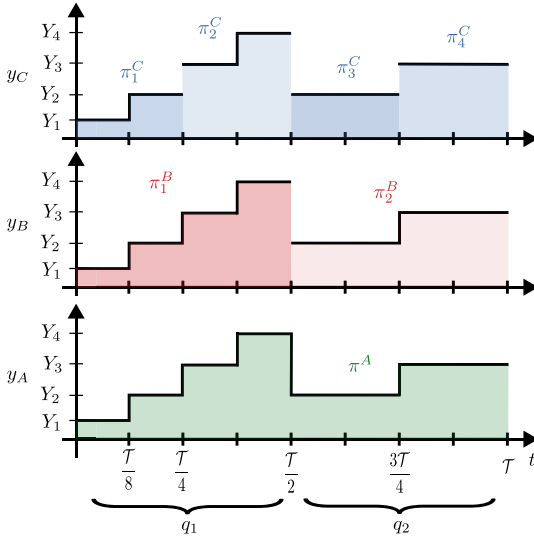


Fig. 3. Example of three possible subdivisions of the same time series y .

The effect of the rescaling factor h^*/h in (4) can be better understood by computing $\hat{f}_{O,M}(y)$ for the three cases (named A, B, and C) in Fig. 3. They represent the same time series of a variable $y \in \mathcal{Y}$ of total length $\mathcal{T}$, but divided according to three different scenario lengths $h_A = \mathcal{T}$, $h_B = \mathcal{T}/2$, and $h_C = \mathcal{T}/4$ respectively. The discretization period $\tau = \mathcal{T}/8$ h, and $h^* = 24$ h are common. The costs are $q(\omega, t) = q_1$ for $0 < t \leq \mathcal{T}/2$ and $q(\omega, t) = q_2$ for $\mathcal{T}/2 < t \leq \mathcal{T}$.

Assuming that all the scenarios are equally probable irrespective of their length (i.e., $\pi^A = 1$, $\pi_1^B = \pi_2^B = 1/2$, and $\pi_1^C = \pi_2^C = \pi_3^C = \pi_4^C = 1/4$), then:

$$\begin{aligned} \hat{f}_{O,M}(y_A) &= \hat{f}_{O,M}(y_B) = \hat{f}_{O,M}(y_C) = \\ &= 3 [q_1 (Y_1 + Y_2 + Y_3 + Y_4) + 2q_2 (Y_2 + Y_3)] \end{aligned}$$

3.1.2. Risk-management formulation

A MILP problem formulated as (3) and (4) does not inherently consider the fact that some unfavorable scenarios may lead to very high values of the cost functions [20,62]. In order to avoid this, a *risk-measure* (i.e., a function that assigns to a given random number representing the cost a real number characterizing the risk associated with that cost) is usually introduced [20,62]. In this work the extreme cases are penalized using the Conditional Value-at-Risk (CVaR), i.e., given an α -quantile, the CVaR represents the expected value of the cost for the $1-\alpha$ percentage of worst scenarios. In other words, having a 95% CVaR of 1 M\$ means that the expected cost of the worst 5% scenarios is, on average, 1 M\$. Then, the RA cost function f_{RA} can be introduced and the problem can be stated as:

$$\begin{aligned} \min_{\mathbf{x}, \mathbf{y}(\omega), \zeta, s(\omega)} & \left\{ f_{RA}(\mathbf{x}, \hat{\xi}) \right\} \\ \text{with: } f_{RA}(\mathbf{x}, \hat{\xi}) &= (1 - \beta) \left(f_{RN}(\mathbf{x}, \hat{\xi}) \right) + \\ & + \beta \left(\zeta + \frac{1}{1 - \alpha} \sum_{\omega \in \Omega} \pi_{\omega} s(\omega) \right) \end{aligned} \quad (5)$$

$$\text{s.t. } \mathbf{A}(\omega) \mathbf{x} + \mathbf{B}(\omega) \mathbf{y}(\omega) + \mathbf{H}(\omega) \hat{\xi}(\omega) \leq \mathbf{0}$$

$$f_{RN}(\mathbf{x}, \hat{\xi}) - \zeta \leq s(\omega), \forall \omega \in \Omega$$

$$s(\omega) \geq 0, \forall \omega \in \Omega$$

where ζ is a helper variable, $s(\omega)$ is a continuous scenario-dependent non-negative slack variable. It is worth emphasizing that (5) contains

two independent parameters that the users can tune according to their risk aversion. In particular, $\alpha \in [0, 1]$ controls how many adverse scenarios have to be monitored, while $\beta \in [0, 1]$ weights the impact of the extreme cases' costs into a risk-neutral formulation. The problem is RN for $\beta = 0$ and totally risk dominated for $\beta = 1$.

Typical values of α in the financial sector (also adopted in nonfinancial cases) are between 0.90 and 0.99 (corresponding to considering the worst 10%–1% scenarios, respectively) [63]. Ref. [34] investigates the planning of an energy hub with RECs and ESSs by varying α between 0.8 and 0.99. Yu and Zheng [17] optimally schedules a cross-regional energy system analyzing the change of the solution's cost for α between 0.1 and 0.90. Chapaloglou et al. [20] uses $\alpha = 0.80$ in the design of an OP's IPS. Lin et al. [35] proposes the planning of an energy system analyzing different α between 0.6 and 0.9. Mu et al. [36] uses $\alpha = 0.90$ for measuring the loss risk in the design of a grid connected system. Roustai et al. [16] uses α between 0.80 and 0.99 for the optimization of the operation of the energy system of a civil building.

The reviewed literature justifies the choice of $\alpha \in [0.80, 0.95]$, which is used in the test cases in Section 5.7.

3.2. Variables and costs modelling

3.2.1. First stage

The vector of first-stage variables includes the number and rated power/energy of the assets that can be installed as a result of the optimization, that is:

$$\mathbf{x} = [n_{PV}, n_{WT}, n_{WEC}, n_{BESS}, \bar{P}_{BESS}, n_{HSS}, \bar{P}_{el}, \bar{P}_{fc}, \mathbf{x}_{GT}, \bar{P}_{DG}]^T \quad (6)$$

where n_{PV} , n_{WT} , n_{WEC} are the (integer) number of PV, WT, and WEC, respectively; n_{BESS} and n_{HSS} are the (integer) number of BESS and HSS modules with capacity E^u and H^u (i.e., the total BESS and HSS capacities are $\bar{E} = n_{BESS} E^u$ and $\bar{H} = n_{HSS} H^u$), $\bar{P}_{BESS}$ is the BESS rated power (continuous variable), and $\bar{P}_{el}$ and $\bar{P}_{fc}$ are the Electrolyzer (EL) and Fuel Cell (FC) rated power (continuous). The GT is modeled with a binary vector $\mathbf{x}_{GT} \in \mathbb{R}^{N_G \times 1}$, where $x_{GT}^g = 1$ if the g -th GT is installed, and 0 otherwise. N_G is maximum number of GTs that can be installed, and it is a parameter defined by the user beforehand, remembering that the higher it is, the more binary and integer variables are introduced and the more complicated the problem becomes. $\bar{P}_{DG}$ is the rated power of the DG (continuous).

The corresponding first stage costs are expressed as:

$$\mathbf{c} = [c^{PV}, c^{WT}, c^{WEC}, c^{BESS_E}, c^{BESS_P}, c^{HSS_E}, c^{HSS_P_{el}}, c^{HSS_P_{fc}}, c^{GT_g}, c^{DG}]^T \quad (7)$$

The operational costs without an explicit dependency on the dynamics are expressed as $\mathbf{o}$:

$$\mathbf{o} = [o^{PV}, o^{WT}, o^{WEC}, o^{BESS_E}, o^{BESS_P}, o^{HSS_E}, o^{HSS_P_{el}}, o^{HSS_P_{fc}}, 0, 0]^T \quad (8)$$

$\mathbf{c}$ and $\mathbf{o}$ costs are reported in Table C.1.

3.2.2. Second stage

The second-stage variables that contribute to the operational cost are related to the operation of the GT, DG, and BESS:

$$\mathbf{y}(\omega) = \left[\mathbf{p}_{GT,\omega}^g, \mathbf{u}_{GT,\omega}^g, \frac{\mathbf{z}_{GT,\omega}^g}{\tau}, \mathbf{RR}_{GT,\omega}^g, \mathbf{P}_{DG,\omega}, \theta_{\omega} \right]^T \quad (9)$$

$$\mathbf{q}(\omega) = [\mathbf{C}_{GT}, \mathbf{C}_{GT}^{\text{on}}, \mathbf{C}_{GT}^{\text{start}}, \mathbf{C}_{RR}, \mathbf{C}_{DG}, \mathbf{C}_{BESS,\text{deg}}]^T \quad (10)$$

where, for the g -th GT, $\mathbf{p}_{GT,\omega}^g$ is the vector of output power (continuous), $\mathbf{u}_{GT,\omega}^g$ the ON/OFF status (binary), $\mathbf{z}_{GT,\omega}^g$ is a binary variable that is 1 only at the instant when the GT is turned on (and since it is an event-dependent variable it should not be affected by the τ selected for the analysis, as done for the other variables directly in (4)), $\mathbf{RR}_{GT,\omega}^g$ is a

continuous helper used (alongside the constraint (49)) for penalizing the ramp up and down of the GT. $P_{DG,\omega}$ is the output power of the DG (continuous). θ_{ω} is the BESS's degradation percentage, such that $\theta = 0$ means that the BESS is new, while $\theta = 1$ means that it reached end-of-life, which happens when its nominal capacity is reduced by a certain percentage [13].

The costs associated with the operation of GTs are:

$$C_{GT} = \left\{ \left(\frac{C_{NG}}{\rho_{NG}} + \mu_{GT} C_{CO_2} \right) \alpha^g + C_{O\&M}^g \right\}_{t \in T} \quad (11)$$

$$C_{GT}^{on} = \left\{ \left(\frac{C_{NG}}{\rho_{NG}} + \mu_{GT} C_{CO_2} \right) \beta^g \right\}_{t \in T} \quad (12)$$

$$C_{GT}^{start} = \left\{ C_{GT}^{start,g} \right\}_{t \in T} \quad C_{RR} = \left\{ C_{RR}^g \right\}_{t \in T} \quad (13)$$

where C_{NG} is the cost of the NG per normal meter cube, ρ_{NG} is the density of the NG at standard temperature and pressure conditions, μ_{GT} is the ideal combustion coefficient of NG to CO_2 , C_{CO_2} is the tax per kg of released CO_2 (i.e., the so called *carbon tax*), $C_{O\&M}^g$ is the Operational and Maintenance (O&M) cost per generated amount of energy, $C_{GT}^{start,g}$ is the estimated startup cost of a GT per event, and α^g and β^g are the coefficients for the linear regression approximating the fuel consumption mass rate $\dot{m}_f$ as $\dot{m}_f^g = \alpha^g \cdot P_{GT}^g + \beta^g$ [19]. C_{RR}^g is the cost associated to the ramp rate of the GT.

For the DG the cost is represented as:

$$C_{DG} = \left\{ \left(\frac{C_{DG}}{\rho_{DG}} + \mu_{DG} C_{CO_2} \right) \alpha^d + C_{O\&M}^d \right\}_{t \in T} \quad (14)$$

where C_{DG}/ρ_{DG} is the cost of diesel per kilogram, and μ_{DG} is the ideal combustion coefficient of diesel to CO_2 . In this formulation no costs for the startup of the DG are imposed, and the fuel consumption is supposed to be purely proportional to the energy output as $\dot{m}_f^d = \alpha^d \cdot P_{DG}$.

The operation cost of the BESS is given by the difference between the cost of a new BESS and the corresponding cost when it has been used until end of live (called c^{BESS_E} and $c^{BESS_E_eol}$ respectively). For one BESS module, the OPEX cost would be:

$$C_{BESS,deg}^u = \{c^{BESS_E} - c^{BESS_E_eol}\}_{t \in T-1} \quad (15)$$

but in this formulation where n_{BESS} modules are installed, the total cost becomes:

$$C_{BESS,deg} = n_{BESS} C_{BESS,deg}^u \quad (16)$$

It must be noted that when (16) is substituted back in (5) the product between an integer term (i.e., n_{BESS}) and a continuous one (i.e., $\theta_{t,\omega}$) is present and must be linearized using (B.12).

The operational expenses for the HSS are supposed to be included in fixed OPEX in (8), and be independent by its use.

3.2.3. Soft constraints

To reduce the degradation of BESS, it is frequently advised that the stored energy should never be below a threshold. Since this requirement is not driven by a physical limitation of the device, but mainly from a preferred operating condition, the discharge of the BESS is formulated such that any excess below a reference minimum stored energy (ζ_{BESS}) is penalized with an expenditure ($w^{BESS,MIN}$). Such soft constraint formulation uses the cost:

$$w = [w^{BESS,MIN}] \quad (17)$$

$$z = [\zeta_{BESS}] \quad (18)$$

and the constraints (24)–(26).

3.3. Constraints

3.3.1. REC plant limits

For the proper sizing of the RECs, two important aspects are considered. First, the REC system does not necessarily need to operate in the Maximum Power Point Tracking (MPPT) condition, but it can be deloaded if needed. Thus, calling $P_{l,t}^{unitary}$ (with $l = \{PV, WT, WEC\}$) the maximum power produced by a single unit of REC at instant t , which is computed from the raw environmental data using the REC model, the l -th REC power output is computed including its deloading capability as:

$$P_{l,t,\omega} \leq n_l P_{l,t}^{unitary} \quad (19)$$

In order to restrict RECs plant sizes to values compatible with realistic installations [64,65], their power capacities are limited according to:

$$n_l P_l^u \leq P_l^{MAX} \quad (20)$$

where P_l^u is the rated power of one REC, P_l^{MAX} is the maximum plant size.

The total power produced by the REC is:

$$P_{REC,t,\omega} = P_{PV,t,\omega} + P_{WT,t,\omega} + P_{WEC,t,\omega} \quad (21)$$

3.3.2. BESS size and operation

The model of BESS assumes that a constant power is exchanged during the discretization period τ and that the energy stored at each time E follows the dynamic (22), while the total power is subject to a scenario cycle constraint (23):

$$E_{t,\omega} = E_T + \sum_{j=1}^t \left(\eta_{CH} P_{CH,j,\omega} - \frac{P_{DC,j,\omega}}{\eta_{DC}} \right) \tau \quad (22)$$

$$\sum_{j=1}^T \left(\eta_{CH} P_{CH,j,\omega} - \frac{P_{DC,j,\omega}}{\eta_{DC}} \right) \tau = 0 \quad (23)$$

where $P_{CH,t,\omega}$ and $P_{DC,t,\omega}$ are the BESS charging and discharging powers, and E_T the energy at the end of each scenario.

The energies E and E_T are lower and upper bounded by (24) and (25), where E^{MAX} is the maximum allowed plant size, and λ_B is the fraction of capacity $\bar{E}$ that should preferably not be exceeded (i.e., soft constraint formulation):

$$\lambda_B \bar{E} - \zeta_{BESS} \leq E_t \leq \bar{E} \leq E^{MAX} \quad (24)$$

$$\lambda_B \bar{E} - \zeta_{BESS} \leq E_T \leq \bar{E} \leq E^{MAX} \quad (25)$$

$$0 \leq \zeta_{BESS} \leq \lambda_B \bar{E} \quad (26)$$

The power that can be exchanged by the BESS is upper limited by the installed power, which, in turn, is limited by the power allowed by feasibility considerations P_{BESS}^{MAX} :

$$0 \leq P_{CH,t,\omega} \leq \bar{P}_{BESS} \cdot \delta_{CH,t,\omega} \leq P_{BESS}^{MAX} \quad (27)$$

$$0 \leq P_{DC,t,\omega} \leq \bar{P}_{BESS} \cdot \delta_{DC,t,\omega} \leq P_{BESS}^{MAX} \quad (28)$$

where $\delta_{CH,t,\omega}$ and $\delta_{DC,t,\omega}$ are binary variables that are 1 if the BESS is charging or discharging respectively, and the products $\bar{P}_{BESS} \cdot \delta_{CH,t,\omega}$ and $\bar{P}_{BESS} \cdot \delta_{DC,t,\omega}$ can be linearized as explained in (B.7) [66]. Furthermore, the concurrent charge and discharge of the BESS is avoided by:

$$\delta_{CH,t,\omega} + \delta_{DC,t,\omega} \leq 1 \quad (29)$$

3.3.3. BESS degradation

The BESS degradation at time t , i.e., θ_t is computed as the maximum between the shelf degradation θ_t^{sh} (i.e., only dependent on time) and the cycle degradation θ_t^{cy} (i.e., only dependent on its operation):

$$\theta_t = \max(\theta_t^{sh}, \theta_t^{cy}) \quad (30)$$

The max function is linearized as described in Appendix B.2.

The shelf degradation is assumed to be linear, but its cost has to be accounted for if and only if the BESS is installed, therefore it depends on the value of a binary variable δ_{BESS} , such that $\delta_{BESS} = 1$ if and only if $n_{BESS} \geq 1$:

$$\theta_t^{sh} = \frac{\tau}{L_{sh}} \delta_{BESS} \quad \forall t \in T \quad (31)$$

where L_{sh} is the shelf lifetime of the BESS.

The cycle degradation θ^{cy} is defined as:

$$\theta_t^{cy} = \frac{|\Psi_t - \Psi_{t-1}|}{2} \quad (32)$$

where Ψ_t is the degradation function evaluated at time t , describing the BESS's degradation as a function of the state of charge SoC reached at that cycle:

$$\Psi_t = A_{BESS} \sigma_t^{B_{BESS}} = A_{BESS} (1 - SoC_t)^{B_{BESS}} \quad (33)$$

with A_{BESS} and B_{BESS} fitting parameters [13]. However, being the faced problem a sizing one, both the energy capacity and the energy contained at each time step are unknowns, therefore the SoC results to be the ratio between two decision variables and cannot be included in the formulation, and have to be handled as described in Appendix A.

To avoid excessive wear, the maximum allowed degradation during each scenario is limited by an upper value $\theta_{max,s}$ as:

$$\sum_{t=1}^{T-1} \theta_t \leq \theta_{max,s} \quad (34)$$

3.3.4. Hydrogen storage

The HSS requires size and dynamic constraints:

$$H_{t,\omega} = H_T + \sum_{j=1}^t \left(\eta_{el} P_{el,j,\omega} - \frac{P_{fc,j,\omega}}{\eta_{fc}} \right) \tau \quad (35)$$

$$\sum_{j=1}^T \left(\eta_{el} P_{el,j,\omega} - \frac{P_{fc,j,\omega}}{\eta_{fc}} \right) \tau = 0 \quad (36)$$

$$\lambda_H \bar{H} \leq H_t \leq \bar{H} \leq H^{MAX} \quad (37)$$

$$\lambda_H \bar{H} \leq H_T \leq \bar{H} \leq H^{MAX} \quad (38)$$

$$P_{el} \leq \bar{P}_{el} \leq P_{el}^{MAX} \quad (39)$$

$$P_{fc} \leq \bar{P}_{fc} \leq P_{fc}^{MAX} \quad (40)$$

where H is the stored energy in the hydrogen tank (and H_T the one at the end of the scenario), P_{el} and P_{fc} are the power exchanged by the EL and the FC, respectively, $\bar{P}_{el}$ and $\bar{P}_{fc}$ their installed capacities, η_{el} and η_{fc} their efficiencies. H^{MAX} , P_{el}^{MAX} , and P_{fc}^{MAX} are the maximum allowed sizes of the storage tank, the EL and the FC, respectively.

3.3.5. Gas turbine

The model of the GT is in line with Chapaloglou et al. [20].

In order to avoid an excessive number of start-up events which may provoke excessive wear and tear of the GT, it is imposed that the GT

can be turned on again after a minimum off-time, T_{off} , from the last shutdown:

$$u_{GT,t-1,\omega}^g - u_{GT,t,\omega}^g \leq 1 - u_{GT,k,\omega}^g \quad \forall g \in N_G \quad (41)$$

$$k = \{t+1, \dots, \min\{t+T_{off}-1, T\}\} \quad (42)$$

The model of the start up event is:

$$u_{GT,t-1,\omega}^g - u_{GT,t,\omega}^g \leq z_{GT,t,\omega}^g \quad \forall g \in N_G \quad (43)$$

The power output of the g -th GT depends on whether it is both installed and turned on:

$$P_{GT,t,\omega}^{g,MIN} = x_{GT,t,\omega}^g u_{GT,t,\omega}^g \gamma^g P_{GT,t}^{g,M} \quad (44)$$

$$P_{GT,t,\omega}^{g,MAX} = x_{GT,t,\omega}^g u_{GT,t,\omega}^g P_{GT,t}^{g,M} \quad (45)$$

$$P_{GT,t,\omega}^{g,MIN} \leq P_{GT,t}^g \leq P_{GT,t,\omega}^{g,MAX} \quad \forall g \in N_G \quad (46)$$

where γ^g is the minimal operational ratio when the GT is turned on. The nonlinear terms in (44) and (45) are linearized using (B.7).

The ramping rate $RU_{t,\omega}^g$ of the GT, defined as in (47), is constrained by the maximum allowed ramping rate R^g (which is a GT characteristic) (48):

$$RU_{t,\omega}^g = \frac{(P_{GT,t,\omega}^g - P_{GT,t-1,\omega}^g)}{\tau} \quad \forall g \in N_G \quad (47)$$

$$|RU_{t,\omega}^g| \leq R^g \quad \forall g \in N_G \quad (48)$$

The cost of the absolute value on the GT ramping rate uses the following constraint:

$$RU_{t,\omega}^g \leq RR_{t,\omega}^g, -RU_{t,\omega}^g \leq -RR_{t,\omega}^g \quad \forall g \in N_G \quad (49)$$

preventing abrupt transitions in the GT power output, that could otherwise occur when multiple GTs are operated in parallel.

3.3.6. Diesel generator

The output power of the DG should be lower than the installed one, as:

$$P_{DG,t,\omega} \leq \bar{P}_{DG} \quad (50)$$

Since the DG can be turned ON/OFF, and reach its rated power in a few minutes [67] no minimum time between start-ups has to be respected.

3.3.7. Demand response

The possibility of shifting a fraction of the rated load η_{IL} (associated with interruptible loads) from a time interval to another can be an important factor in reducing the total cost because some operations (e.g., the use of Water Injection Systems (WISs) or some thermal loads) can be delayed or anticipated within a scenario without adverse consequences for the OP, to better align the power production and patterns [59,68]. Following the idea schematized in Fig. 4, such DR logic is modelled as:

$$P_{L,t,\omega}^{DR} = P_{L,t,\omega}^{original} + P_{ADD,t,\omega} - P_{REM,t,\omega} \quad (51)$$

$$P_{ADD,t,\omega} \geq 0, P_{REM,t,\omega} \geq 0 \quad (52)$$

$$P_{L,t,\omega}^{DR} \leq \eta^{OL} P_L^{rated} \quad (53)$$

$$P_{ADD,t,\omega} \leq \eta^{IL} P_L^{rated}, P_{REM,t,\omega} \leq \eta^{IL} P_L^{rated} \quad (54)$$

$$P_{L,t,\omega}^{DR} \geq \eta^{FL} P_L^{rated} \quad (55)$$

$$\sum_{t=1}^T (P_{ADD,t,\omega} - P_{REM,t,\omega}) \tau = 0 \quad (56)$$

where $P_{ADD,t,\omega}$ and $P_{REM,t,\omega}$ are the helper variables used for the DR mechanism.

Eq. (53) prescribes that the reshaped load does not exceed a fraction η^{OL} of the nominal load, (55) prescribes that the fraction of fixed load η^{FL} is always supplied, while (56) imposes the energy stationarity within a scenario.

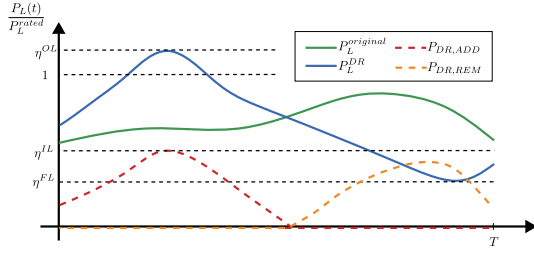


Fig. 4. Schematic representation of the load reshaping performed by the DR.

3.3.8. Power balance and dumped power constraints

Calling P_{GEN} the total power produced by all generators (57), the power balance (58) ensures the equilibrium between power production and consumption at any time. Furthermore, (59) limits the maximum dumped power $P_{CT,\omega}$ to a values of $\bar{P}_{CT}$:

$$P_{GEN,t,\omega} = \sum_{g=1}^{N_G} P_{GT,t,\omega}^g + P_{DG,t,\omega} + P_{REC,t,\omega} \quad (57)$$

$$P_{GEN,t,\omega} + P_{DC,t,\omega} = P_{L,t,\omega}^{DR} + P_{CH,t,\omega} + P_{CT,t,\omega} \quad (58)$$

$$P_{CT,t,\omega} \leq \bar{P}_{CT} \quad (59)$$

3.3.9. Energy generation and consumption metrics

The annual energies produced by FBGs and DG are quantified through the metrics E_{FBG} and E_{DG} respectively, while the total energy consumed by the load is E_{LOAD} :

$$E_{FBG} = \sum_g \sum_{\omega \in \Omega} \sum_{t=1}^T P_{GT,t,\omega}^g \cdot \tau + \sum_{\omega \in \Omega} \sum_{t=1}^T P_{DG,t,\omega} \cdot \tau \quad (60)$$

$$E_{DG} = \sum_{\omega \in \Omega} \sum_{t=1}^T P_{DG,t,\omega} \cdot \tau \quad (61)$$

$$E_{LOAD} = \sum_{\omega \in \Omega} \sum_{t=1}^T P_{L,t,\omega}^{original} \cdot \tau \quad (62)$$

4. Numerical analyses and simulation studies

4.1. Platform power load and environmental datasets

A realistic load profile, corresponding to 1 year of operation of an offshore OP located in the North Sea is used as input in this study. Data sets for solar irradiance and WS in the considered location for one whole year are obtained from [69], while the wave resources are obtained from [70]. Since the input parameters come from direct measurements on the field, then the probability of each scenario is $\pi_\omega = 1/365 \forall \omega \in \Omega$.

4.2. Description of the test cases and corresponding parameters

The analysis is carried out on 9 base test cases that are reported in Table 2. It must be remarked that in each of them the general mathematical formulation presented in Section 3 is adapted to the subset of considered assets.

The first two cases, GT24 and GT365 are cases where the load is supplied by up to two GTs and the only cases where no ESS is envisaged. They are considered as reference cases since they represent the most common configurations. They differ from each other in the length of the considered scenario(s), ($T = 24$ or $T = 24 \cdot 365$, respectively), and consequently in the implications on the operational constraints (e.g., the ESSs energy balance).

In the following cases (1GT + WT + DG and 1GT + REC + DG) it is considered that only one GT is kept in operation and power production is

Table 2
Investigated test cases.

CASE	REC	BESS/HSS	Cstr.	GT	DG	T
GT24	No	No	–	≤ 2	Yes	24
GT365	No	No	–	≤ 2	Yes	$365 \cdot 24$
1GT + WT + DG	WT	Yes	Yes	1	Yes	24
1GT + REC + DG	WT,WEC,PV	Yes	Yes	1	Yes	24
WT + DG	WT	Yes	Yes	No	Yes	24
REC-U	WT,WEC,PV	Yes	No	No	No	24
REC-U + DG	WT,WEC,PV	Yes	Yes	No	Yes	24
REC-C + DG24	WT,WEC,PV	Yes	Yes	No	Yes	24
REC-C + DG365	WT,WEC,PV	Yes	Yes	No	Yes	$365 \cdot 24$

possibly complemented to a bounded maximum by WTs only, in the former case, and WTs, PVs and WECs in the latter one. In both cases, the presence of a DG is admitted and its size optimized in order to determine the cheapest solution.

The case WT + DG excludes the presence of GTs and aims at the installation of a Wind Farm (WF) (whose size is constrained) to cover the load consumption. Recognizing that the absence of wind would jeopardize the security of the supply to the OP load, the use of a DG, whose size is also optimized, is enabled. The case REC-U is similar to the previous one except for the larger pool of allowed RECs, which includes WT, PV and WEC farms of unconstrained size and that allows excluding the DG, thus attaining a 100%-renewable solution. The case REC-U-DG resembles the previous one, except for the fact that the use of DG is also allowed and optimized.

Finally, compared to the previous case REC-U-DG, the last cases REC-C + DG24 and REC-C + DG365 study the effect of constraining the size of the RECs farms as detailed above, while also studying the impact of changing the length of the considered scenario(s) from $T = 24$ in the former case to $T = 24 \cdot 365$ in the latter.

The technical and economical parameters used in the simulations are collected in Table C.1.

4.3. Solution software

The optimization has been performed in MATLAB, using the GUROBI 13 solver on a desktop computer equipped with an Intel(R) Core(TM) i7-1355U CPU and 16 GB of RAM.

The solution method proposed in this paper primarily targets IPS which are usually deployed in location with clear geographical boundaries (e.g., OPs, remote communities, or islands), therefore it is not expected that the dimensions of the problem can grow unbounded. Larger problems can be handled by simplifying the components' models, applying more efficient mathematical computing methods, increasing the convergence rate for the solution, or reducing the size of the input either by increasing the time step in operation stage (e.g., from $\tau = 1$ h to $\tau = 2, 3, 5$ h) or by generating a reduced amount of scenarios equivalently representing the stochastic nature of the original dataset [20,28,34,71–73].

5. Results

An initial experiment has been conducted to compare the different configurations according to some performance indicators such as the equivalent daily cost f_{RA} expressed in (5), the total amount of energy generated by FBG, and the yearly emitted CO_2 for some current values of techno/economical input in a location in the North Sea. Later on, several tests have been done to investigate how the current results will change due to modifications on relevant external and internal parameters, analyzing them one by one while keeping the others fixed. Among the external parameters, there are costs depending on the market, or the decisions of the regulator authorities, while among the internal parameters there are effects depending on how the OP owner will operate it, such

as the range of the flexible load control, the deployment location, and user's risk aversion.

5.1. Analysis of the base cases

Initially, the optimization has been performed for all the cases described in Table 2. Fig. 5 contains the daily cost of the solution and the yearly emitted CO₂ for the different cases, while the associated solutions in terms of installed REC/FBG power and ESS power and energy are reported in Figs. 6 and 7 respectively. Details of the values in Fig. 5 are given in Figs. 8 and 9. The former breaks down the relative contributions of the cost and emission sources, while the latter reports in a bar plot the total CO₂ emissions and the details of the fractions due to the GTs and DG (left axis), and the share of FBG-based energy E_{FBG} and DG-based energy E_{DG} over the total energy consumed by the load E_{LOAD} (right axis).

Comparing the investigated cases from an economic perspective based on the equivalent daily cost f_{RA} (Fig. 5), of each solution, the fully GT-driven cases are the cheapest. This is not surprising, considering the still high cost of offshore RECs. However, hybrid solutions

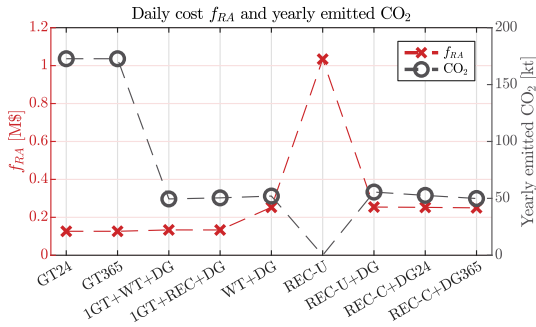


Fig. 5. (Daily equivalent) cost f_{RA} on the left axis, and yearly emitted CO₂ on the right axis.

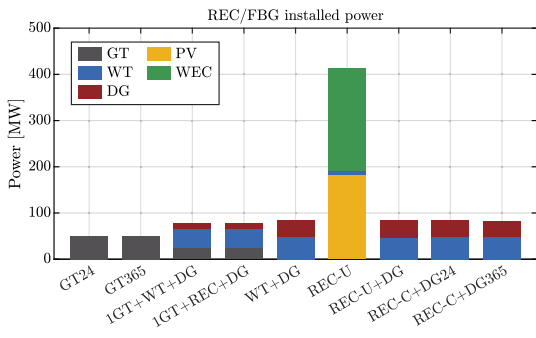


Fig. 6. RECs and FBGs installed power.

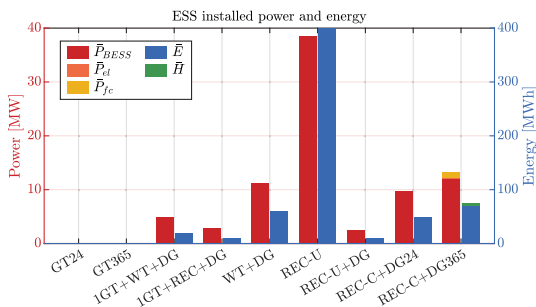


Fig. 7. ESS installed power (left axis) and energy (right axis).

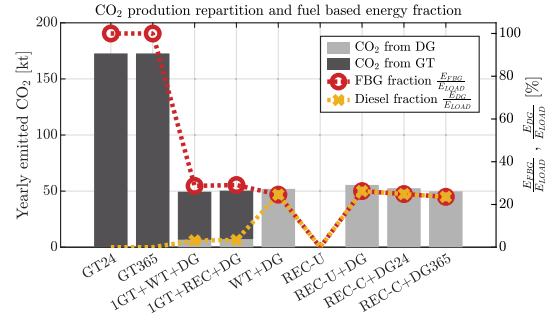


Fig. 8. Yearly CO₂ emission from the different sources (left axis) and fraction of fossil fuel based energy over the total energy consumption (right axis).

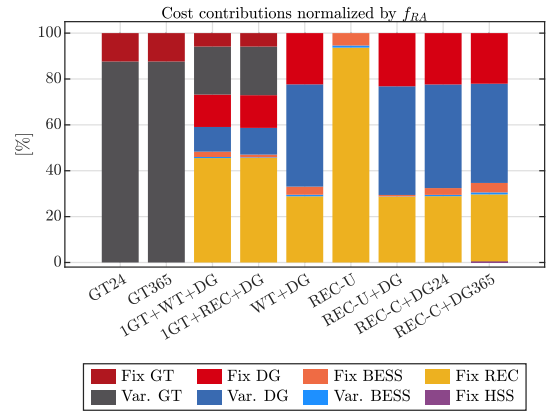


Fig. 9. Relative contribution of the different costs to the equivalent daily cost f_{RA} (5). Fix costs include CAPEX and fixed OPEX (i.e., accounted in the $\hat{c}^T x$ term in (4)), whereas Var. costs depend on how the assets are operated (i.e., accounted in the $q^T y$ in (4)).

1GT+WT+DG and 1GT+REC+DG (i.e., operating a single GT coupled to RECs, and using DGs to supply otherwise non-satisfied load), are only 6% more expensive than the reference case GT24, but they allow to reduce the CO₂ emissions by more than 70%. It is worth noting that the results of these two hybrid solutions 1GT+WT+DG and 1GT+REC+DG include only WTs among the RECs, although in the second case other RECs would be allowed, suggesting that for the considered location and costs, PVs and WECs are not economically advantageous. Configurations 1GT+WT+DG and 1GT+REC+DG have almost identical costs and generator solutions (see Fig. 6) even though the installed BESS are different (Fig. 7). This often happens in large optimization problems, where similar costs can be associated to different solutions [74].

Solutions that exclude the use of GTs while allowing DG (named WT+DG, REC-U+DG, REC-C+DG24, and REC-C+DG365) are typically 2 times more expensive than the reference configuration GT24. In this case, PV and WEC are not part of the optimal solution, because for current costs the installation and operation of DGs (supplying around 25% of the load energy, as visible in Fig. 8) are more economical than the installation of emerging RECs.

Our analysis also suggests that a 100%-REC-based solution could be technically feasible, provided that multiple types of RECs are considered. However, not only would this require a massive REC installation (i.e., 414 MW, more than 8 times the nominal load power), but it would also cost more than 8 times more than the GT24 case. The REC-U case also proves the importance of RECs complementarity, since it has been verified that, if only WTs were deployed, it would not be possible to satisfy

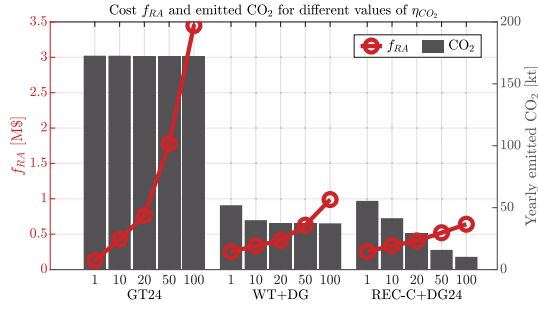


Fig. 10. Cost and emitted CO₂ for the carbon tax sensitivity analysis.

the power balance for a 100% REC-based solution in some scenarios with low WS.

On the other hand, if the RECs/ESS are size-limited (in cases REC-C + DG24 and REC-C + DG365), the installation of flexible FBG, such as DGs, becomes necessary from the technical point of view while still being viable from an economic perspective.

From a methodological standpoint, it can be observed that the case REC-C + DG365 allows a cost reduction by 1% compared to REC-C + DG24, suggesting that increasing the optimization time horizon T may be beneficial: in particular, even though the RECs capacity remains the same, REC-C + DG365 has larger BESS power and energy capacity and includes the additional installation of HSS, allowing to store more energy during periods of high production to use it during longer periods with lower production. It is important to note that the energy capacities of both the BESS and HSS reach the defined upper limits, indicating that an even lower cost might be possible if relaxing the corresponding constraints.

In terms of relative cost contributions (as depicted in Fig. 9), it can be seen that the *Fix* costs (i.e., including CAPEX and fixed OPEX, and accounted in the $\hat{c}^{Tx}$ term in (4)) and *Var.* costs (i.e., dependent on how the assets are operated, and accounted in the q^{Ty} in (4)) of the DGs significantly contribute to the total cost in cases WT + DG, REC-U + DG, REC-C + DG24 and REC-C + DG365, implying that the reduction of DGs' usage is a key point for future studies. Although this highlights that the elimination of FBG can have a significant impact on reducing total expenditures, at the same time a high cost will still be present if no other backup solution is identified for periods with low RECs production. Furthermore, in all the cases that include a BESS, its *Fix* has a small relative contribution, and its *Var.* even smaller. However, even though the *Var.* are not so relevant to justify the increased model complexity in the selected test cases, they might become more relevant for BESSs with different operational costs (i.e., different A_{BESS} and B_{BESS} in (33), or costs in (16)) or when the contributions of the FBG will decrease and therefore the relative contributions of the other resources will increase.

5.2. Sensitivity analysis on the carbon tax

Observing the high cost of the REC-based case compared to the GTs driven ones, it is considered relevant to investigate the sensitivity of the solution to the C_{CO_2} . This was done by setting $C_{CO_2} = \eta_{CO_2} C_{CO_2}^{ref}$ with $\eta_{CO_2} = \{1, 10, 20, 50, 100\}$, where $C_{CO_2}^{ref}$ has been selected according to the carbon tax presently applied by the Norwegian state [75].

Fig. 10 reports the (daily) cost of the solution f_{RA} and the (yearly) emitted CO₂, Fig. 11 displays the power of RECs/FBGs installed as solution and the fraction of power provided by the DG (i.e., E_{DG}), and Fig. 12 the power and energy of the installed BESS.

In the GT24 (i.e., when up to 2 GT can be installed and no RECs are allowed), as expected, the cost increases with the increase in carbon tax since all the power has to be produced via FBGs. Interestingly, the solver finds convenient to deploy one additional DG when the carbon tax increases significantly. This behavior could be driven by the larger DG

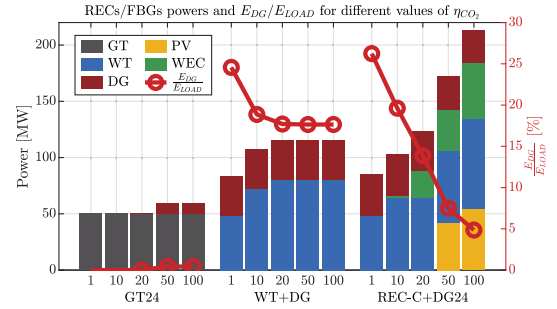


Fig. 11. Solution of the power-related variables for RECs/FBGs, along with the energy provided by the DG, for the carbon tax sensitivity analysis.

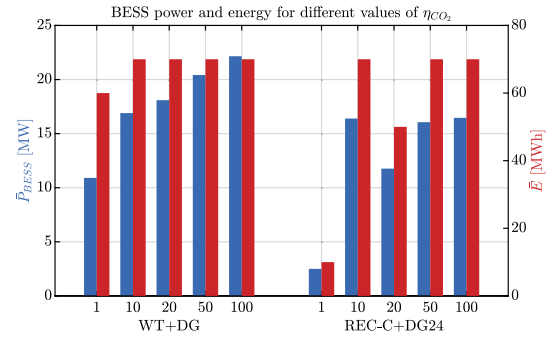


Fig. 12. Solution of the power and energy related variables for BESS for the carbon tax sensitivity analysis.

operational flexibility (i.e., no startup time, no minimum operational output), that might be more efficient by offering better granularity to match power production with the demand patterns.

In the WT + DG case the increase of the C_{CO_2} favors the installation of WTs and BESS, while reducing the E_{DG} . On the other hand, $\bar{P}_{DG}$ remains almost constant, suggesting that the DG size is mostly defined/dominated by specific days with low wind power generation. Furthermore, it can be seen that for $\eta_{CO_2} \geq 20$ the WF and BESS energy capacity reach their maximum allowed size, showing that the share of DG-based energy generation of 17.7% is the technical minimum required to make the solution feasible (given the maximum plant size constraints), which would be selected irrespectively of the cost.

For the case REC-C + DG24 where $\eta_{CO_2} \geq 10$, WECs and PVs enter the optimal generation-mix along with WTs, revealing their competitiveness compared to DGs, for high carbon taxes. As a result, $\bar{P}_{DG}$ is further reduced in this case. Furthermore, the cost of the solution for $\eta_{CO_2} \geq 20$ (i.e., when larger share of PV power is deployed), is smaller than in the WT + DG case, further emphasizing/stressing the benefit brought by the hybridization of the RECs pool.

None of the proposed solutions includes HSS in the optimal pool, suggesting that for the current cost of the technology their inclusion is not economically beneficial yet.

Finally, we can observe that from a 10-fold increase of the carbon tax, the GT24 solutions become less competitive compared to the ones including RECs.

5.3. Sensitivity analysis on the PV cost

Given that the cost of PV modules in the market has declined by an average of 35% between January and November 2024 [76] it is considered relevant to investigate the effect of a PV cost reduction up to 60% (values that are evidently plausible in the future [77]). This test has been performed on the REC-C + DG24 case, by modifying the PV cost as $c^{PV} = (1 - \gamma_{PV})c^{PV,ref}$, $\sigma^{PV} = (1 - \gamma_{PV})\sigma^{PV,ref}$, with $\gamma_{PV} \in [1, 0.6]$. The

test has been performed both in the reference location in the North Sea and in another one in the South China Sea. The comparison of the two locations reveals the expected benefits in areas where PV installation is more favorable (i.e., South China Sea), since the global horizontal irradiation of 1800 kWh m^{-2} is more than double the one in the North Sea location [78]. The same load time series has been used in both cases for a fair comparison.

Fig. 13 reports the (daily) cost of the solution f_{RA} and the (yearly) emitted CO_2 , Fig. 14 displays the power of RECs/FBGs obtained as solution and the fraction of power provided by the DG E_{DG} , and Fig. 15 the solutions of power and energy of the BESS.

From the result in Fig. 14 it can be seen that the installation of PVs in the North Sea is not recommended by the algorithm unless the cost is reduced by at least 60%, while in the South China Sea a cost reduction of 20% favors the installation of a PV farm larger than the WT one. This suggests that the best mix of installed RECs is highly dependent on the installation site, and there is no univocal optimal share.

It must be highlighted that WECs are not included in the solution because they won't make f_{RA} lower for these cases.

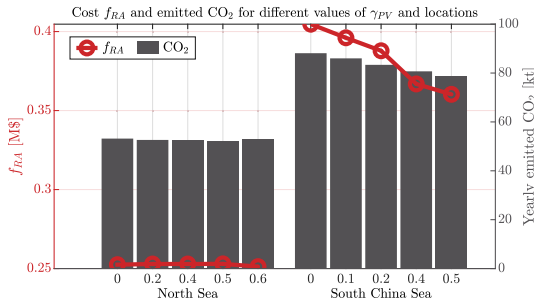


Fig. 13. Cost and emitted CO_2 for the PV cost sensitivity analysis.

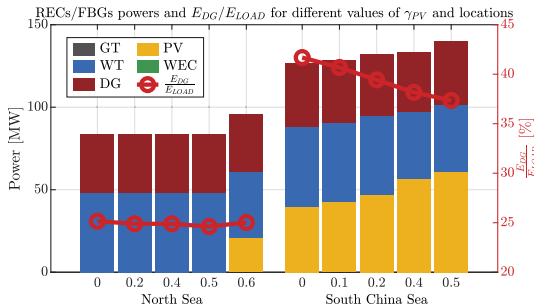


Fig. 14. Solution of the power-related variables for RECs/FBGs, along with the energy provided by the DG, for the PV cost sensitivity analysis.

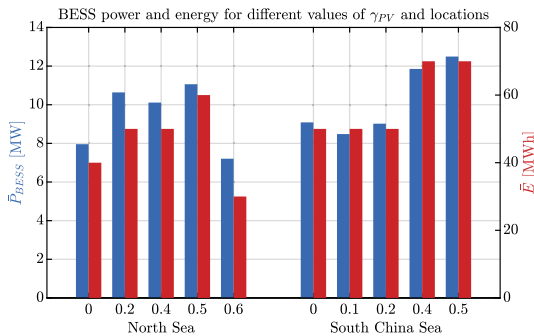


Fig. 15. Solution of the power and energy related variables for BESS for the PV cost sensitivity analysis.

5.4. Sensitivity analysis on the WEC cost

To study the location effect along with the WEC cost sensitivity, a similar sensitivity analysis to the one done for PV in Section 5.3, was performed. The WEC's cost has been modified as $c^{WEC} = (1 - \gamma_{WEC})c^{WEC,ref}$, $\sigma^{WEC} = (1 - \gamma_{WEC})\sigma^{WEC,ref}$, with $\gamma_{WEC} \in [1, 0.60]$.

Fig. 16 shows the (daily) cost of the solution f_{RA} and the (yearly) emitted CO_2 , Fig. 17 displays the power of RECs/FBGs obtained as solution and the fraction of power provided by the DG E_{DG} , and Fig. 18 the solutions of power and energy of the BESS.

The effect of WECs cost reduction shows that WEC installation will be overall more challenging than the PV one, since it is envisaged by the optimizer only for the North Sea location and for a cost decrease of at least 40%. On the other hand, none of the investigated improvements seems to be beneficial in the South China Sea location, mostly because the resource has a low availability in that part of the world. Again, the sensitivity of the results from the location is highlighted.

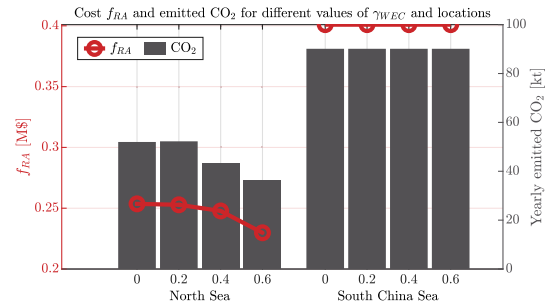


Fig. 16. Cost and emitted CO_2 for the WEC cost sensitivity analysis.

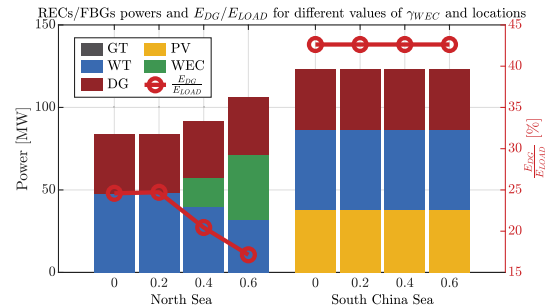


Fig. 17. Solution of the power-related variables for RECs/FBGs, along with the energy provided by the DG, for the WEC cost sensitivity analysis.

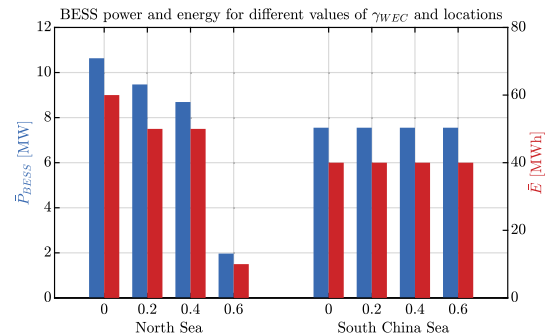


Fig. 18. Solution of the power and energy related variables for BESS for the WEC cost sensitivity analysis.

5.5. Sensitivity analysis on the BESS cost

To study the location effect along with the BESS cost sensitivity, a similar sensitivity analysis to the one done for PV in Section 5.3, and WEC in Section 5.4 was performed. Both BESS's power and energy costs have been modified as $c^{BESS_E} = (1 - \gamma_{BESS})c^{BESS_E.ref}$, $c^{BESS_P} = (1 - \gamma_{BESS})c^{BESS_P.ref}$, $o^{BESS_E} = (1 - \gamma_{BESS})o^{BESS_E.ref}$, $o^{BESS_P} = (1 - \gamma_{BESS})o^{BESS_P.ref}$, with $\gamma_{BESS} \in [1, 0.60]$.

Fig. 19 shows the (daily) cost of the solution f_{RA} and the (yearly) emitted CO₂, Fig. 20 displays the power of RECs/FBGs obtained as solution and the fraction of power provided by the DG E_{DG} , and Fig. 21 the solutions of power and energy of the BESS.

The reduction in BESS costs leads to a decrease in f_{RA} at both locations. When comparing this cost reduction with the sensitivities of the RECs, f_{RA} in the North Sea decreases less than in the WEC case, whereas in the South China Sea it decreases less than in the PV case. In both locations, from a 30% reduction in BESS costs the maximum allowable energy capacity is installed, suggesting that potentially an even larger cost reduction might be possible by increasing this upper bound.

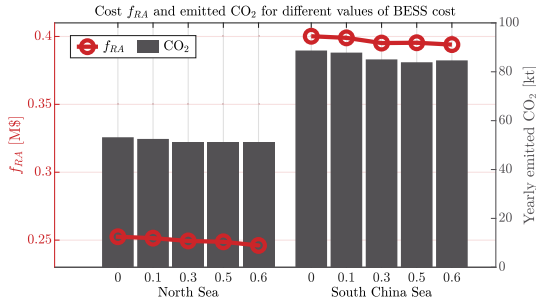


Fig. 19. Cost and emitted CO₂ for the BESS cost sensitivity analysis.

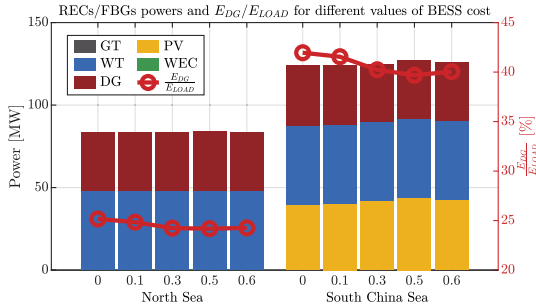


Fig. 20. Solution of the power-related variables for RECs/FBGs, along with the energy provided by the DG, for the BESS cost sensitivity analysis.

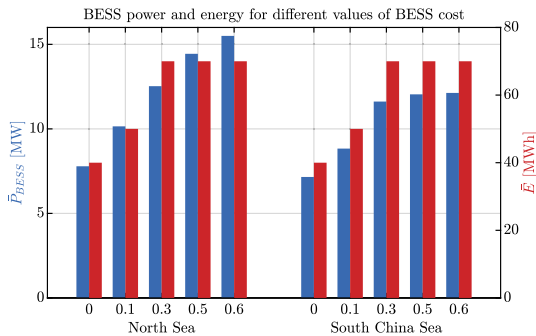


Fig. 21. Solution of the power and energy related variables for BESS for the BESS cost sensitivity analysis.

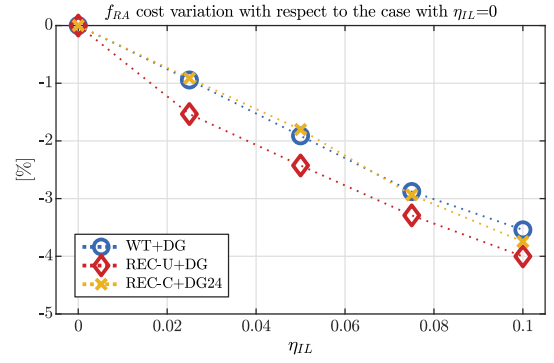


Fig. 22. f_{RA} cost (on the left axis) and CO₂ variations (right axis) with respect to the case $\eta_{IL} = 0$.

5.6. Load demand response mechanism

The possibility to move part of the load from one time period to another within the same scenario has been tested for cases including RECs (named WT + DG, REC-U + DG, and REC-C + DG24), considering 5 different values of the η^{IL} shifted power. These values have been chosen in a small range (i.e., $\eta^{IL} \in [0, 0.10]$) to take into account realistic operational limitations of the OP flexibility margins, as they could be inferred from the available literature. This analysis can serve as a guideline for OP managers to quantify the economic benefits associated with more advanced load management strategies. This prospective may be particularly valuable in the context of refurbishing industrial equipment, to evaluate the economic impact of upgrading existing plants towards more flexible loads. The results analyzing the cost and emission reductions with respect to the case where the load cannot be shifted in time are reported in Fig. 22.

It can be seen that incorporating load side flexibility in the sizing has a monotonic effect on the solution cost: the higher the fraction of load that can be shifted from one time period to another, the smaller the cost that can be achieved. Numerically, the total cost reduction amounts to 4% for all the investigated case study.

5.7. Risk management

The impact of the risk management has been assessed with two studies. The first one, has been conducted by varying the value of $\beta \in [0, 1]$, for a fixed value of $\alpha = 0.95$ for the REC-C + DG24 and WT + DG cases. $\beta = 0$ means that the cost function only accounts for the installation and operation costs of the assets, without taking into account the risk that the $1 - \alpha$ more adverse scenarios might lead to a high cost, while $\beta = 1$ accounts just for minimizing the effects of these less favorable conditions. The user can select α and β independently, according to its risk aversion, and the test cases analyzed in the paper might be taken as a reference for showcasing the effect of these two parameters.

Fig. 23 reports the (daily) cost of the solution f_{RA} and the (yearly) emitted CO₂, Fig. 24 displays the power of RECs/FBGs obtained as solution and the fraction of power provided by the DG E_{DG} , and Fig. 25 the solutions of power and energy of the BESS.

In case REC-C + DG24, as β increases from 0 to 1, the total cost of the solution increases due to the higher reliance on DG (as visible from the higher E_{DG}/E_{LOAD}), reaching an RA cost which is more than double the RN one. The RECs pool for $\beta \geq 0.60$ includes WECs and/or PVs, demonstrating that RECs hybridization can lead to a more reliable system when the most adverse scenarios are considered.

The case of WT + DG reveals similar trends in the resulting costs. Increasing β from 0 to 1, the total cost almost doubles and E_{DG} increases as well.

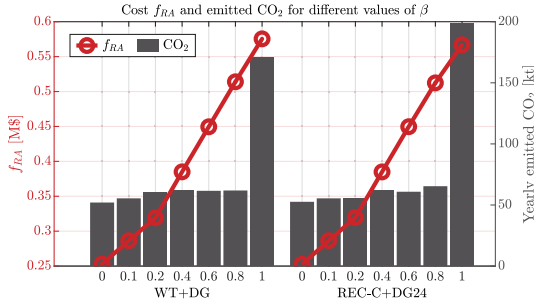


Fig. 23. Cost and emitted CO₂ for the analysis of the risk control parameter β .

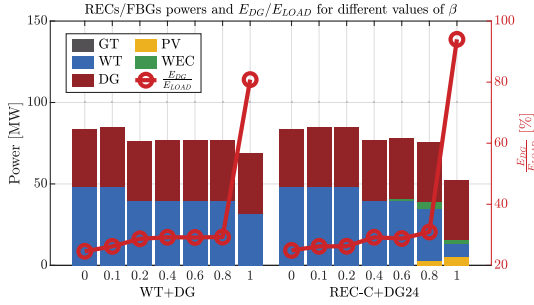


Fig. 24. Solution of the power-related variables for RECs/FBGs, along with the energy provided by the DG, for the analysis of the risk control parameter β .

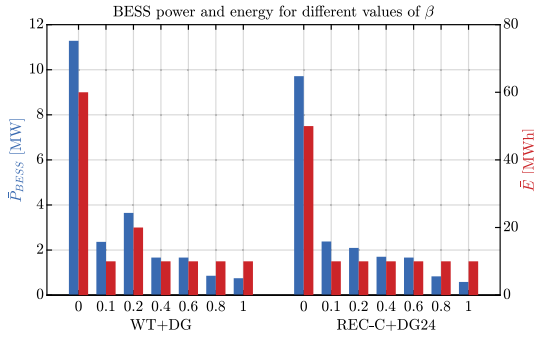


Fig. 25. Solution of the power and energy related variables for BESS for the analysis of the risk control parameter β .

Common to both cases is the almost constant DG size, suggesting that this is mainly determined by some operating conditions which are not affected by how much they are getting penalized through β .

The second risk-analysis study aims to derive the efficient frontier for different values of α and β , for the REC-C+DG24 case for different values of risk aversion parameter $\alpha \in \{0.80, 0.90, 0.95\}$ and weights β , Fig. 26. As visible, when α is fixed, the more β is increased, the larger the total cost of the solution, whereas the additional expected cost due to the worst case scenarios (quantified by CVaR), decreases. Note that the risk aware formulation has a beneficial effect for the user. It could be seen that for $\alpha = 0.95$ (0.9, 0.8) when β increases from 0 to 0.1, then CVaR decreases of 88% (78%, 61%), while f_{RA} increases of just 13% (12%, 10%). On the other hand, when fixing β , increasing α leads to both higher total cost and CVaR, since only the most critical worst-case scenarios are considered. This analysis highlights how the choice of the risk parameters α and β has a substantial effect on the resulting design, therefore the proposed graph can be useful for proper parameter selection.

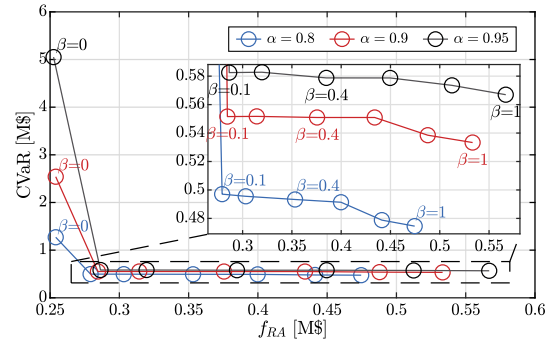


Fig. 26. Efficient frontiers for different risks parameters α and β , for case REC-C+DG24.

6. Conclusion

This paper presented an optimization methodology to identify techno-economically efficient combinations of RECs, FBG, and ESS for decarbonizing Isolated Power Systems (IPSS) while ensuring the security of supply irrespective of the stochastic load variations and intermittent environmental conditions. The proposed MILP-based sizing tool was initially applied to the case of an offshore OP located in the North Sea using realistic load and environmental input datasets. Various energy resources and their optimal participation in the total energy mix were analyzed, including traditional FBG (such as GT and DG), consolidated RECs (e.g., WT), emerging marine technologies like offshore PV and WECs, and different types of energy storage (BESS and HSS).

It was shown that, even though with current technology and cost levels, the cheapest solution is still maintaining the current industry practice of operating GTs only. However, it was shown that a configuration employing one GT alongside WTs, BESS and a small share of DG, cuts the yearly CO₂ emissions of more than 70% at a cost only 6% higher than the GTs driven one. A 100% REC-based solution would be technically possible thanks to RECs complementarity, but the required energy capacity would need to be more than 8 times the maximum OP load, leading to a cost more than 8 times higher than a GT-powered base case.

It was also shown that a GTs-less hybrid solution combining WT with more flexible FBG, such as DGs, providing around a quarter of the total energy required by the OP, would enable cutting the platform emissions by 70%, at a cost that is twice the one of GT powered case. The inclusion of other energy sources like WEC and PV at the current costs is marginally beneficial in terms of cost reduction, mainly due to prominent wind availability in the North Sea location. Overall, the results indicate that a hybrid RECs/FBGs solution still represents a good compromise towards decarbonizing heavy industrial processes in an economically reasonable way, while 100% are still not practical in the near future.

At least a tenfold increase in the carbon tax would be needed to make hybrid FBGs/RECs-based solutions competitive with purely GTs-driven ones.

The economic feasibility of offshore PVs has a strong location dependence. Although it was not particularly favorable for the North Sea location unless a 60% PV cost reduction takes place, in the location in the South China Sea, PV plants of size at least comparable to that of a WF seem promising with an affordable 20% PV cost reduction. An opposite trend is seen for WECs, as their cost decrease will make them more appealing only in the North Sea, and for higher relative cost reduction. Also the impact of BESS' cost decrease is case sensitive, but in general less important than the established RECs, due to its limited contribution to the daily costs.

From a different perspective, despite the limited potential for load side flexibility in an O&G, DR management up to 10% of the nominal

load power, can lead to cost reductions up to 4% in a hybrid configuration with RECs and DG.

Finally, decision-support guidelines are provided for dealing with uncertainty by quantifying design trade offs between lower expected cost solutions and risks of experiencing higher costs during rare events.

It is worth noting that the proposed methodology is general and can be applied, not only to OP, but also to other IPSs, such as critical infrastructures [79,80] or rural communities [81].

CRedit authorship contribution statement

Niccolò Andreetta: Writing – original draft, Software, Methodology, Investigation, Formal analysis, Conceptualization. **Spyridon Chapaloglou:** Writing – review & editing, Supervision, Software, Conceptualization. **Elisabetta Tedeschi:** Writing – review & editing, Supervision, Project administration, Funding acquisition, Conceptualization.

Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests:

The Norwegian University of Science and Technology received financial support from PETRONAS Research Sdn Bhd for sponsored research activities, including the PhD project of Niccolò Andreetta and supervision by Elisabetta Tedeschi.

Appendix A. Mathematical formulation of BESS degradation model

It is assumed that the BESS has been characterized by the manufacturer by charging and discharging it N_{eol} times, until End of Life (EoL). This test is done for different Depth of Discharges (DoDs) σ . The degradation is assumed to accumulate, and a cycle with a certain Depth of Discharge (DoD) degrades the BESS by $\frac{1}{N_{eol}(\sigma)}$ [13]. Therefore, it is possible to obtain a degradation function Ψ as a function of the state of charge SoC at that cycle:

$$\Psi_t = A_{BESS} \sigma_t^{B_{BESS}} = A_{BESS} (1 - SoC_t)^{B_{BESS}} \quad (A.1)$$

with A_{BESS} and B_{BESS} fitting parameters [13]. It must be noted that this method is valid even if an analytical expression like (A.1) is not available, and only a set of discrete values of Ψ for different σ are known, and one can use a Piecewise Linear Approximation (PLA) for approximating the degradation for any SoC .

However, being the faced problem a sizing one, both the energy capacity and the energy contained at each time step are unknowns, therefore the SoC results to be the ratio between two decision variables and cannot be included in the formulation. Therefore, some additional steps are required:

1. The map describing Ψ has to be reformulated in terms of stored energy for a BESS module with capacity E^u , as in Fig. A.1.

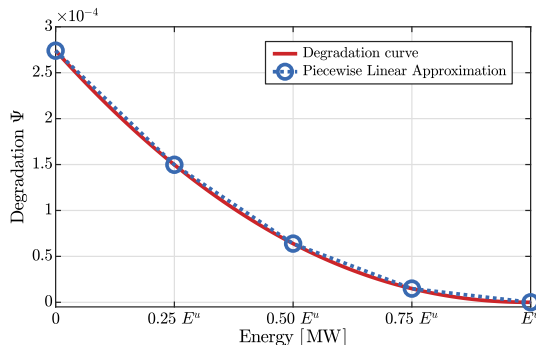


Fig. A.1. BESS degradation curve and its PLA defined in 5 breakpoints.

2. Since the total capacity of the BESS becomes $n_{BESS} E^u$, the x-axis points for which the function Ψ has been defined in the previous step have to be rescaled by the decision variable n_{BESS} .
3. The procedure described in Appendix B.7 has to be used to perform the PLA.

It can be noted that the inclusion of BESS degradation into the sizing problems requires the definition of multiple helper variables, that increase the computational complexity.

Appendix B. Mathematical equivalent formulations

In this section, some useful mathematical formulations used for modeling nonlinear functions into integer linear programming are reported, following what originally proposed by Bemporad and Morari [66] and Wei et al. [82].

B.1. Notation

We call $x \in \mathbb{X} \subset \mathbb{R}$ a scalar variable, and

$$M = \max(x) \quad (B.1)$$

$$m = \min(x) \quad (B.2)$$

The *logical variable* u is a binary variable (i.e., $u \in \{0, 1\}$) having value $u = 1$ if the statement associated to it is true, $u = 0$ otherwise. u denotes a vector of binary variables.

The *connectives* $\rightarrow$ and $\leftrightarrow$ define the logical statements “implies” and “if and only if” respectively.

B.2. Maximum between two values

The maximum between two values $x = \max(A, B)$ is given by:

$$x \geq A \quad (B.3)$$

$$x \geq B \quad (B.4)$$

B.3. “If and only if” statement

$$[x \leq 0] \leftrightarrow [u = 1] \quad (B.5)$$

is equivalent to:

$$\begin{cases} x \leq M(1 - u) \\ x \geq \epsilon + (m - \epsilon)u \end{cases} \quad (B.6)$$

where ϵ is a small constant.

B.4. Product of binary and integer variables

Defining $\varphi = u \cdot x$, the product $u \cdot x$ can be linearized as:

$$\begin{cases} \varphi \leq M \cdot u \\ \varphi \geq m \cdot u \\ \varphi \leq x - m(1 - u) \\ \varphi \geq x - M(1 - u) \end{cases} \quad (B.7)$$

B.5. Product of continuous and linear variables

A generic integer variable $i \in [i^L, i^U]$ can be represented with the following binary expansion:

$$i = i^L + \sum_{k=1}^{K_i} 2^{k-1} u_k \quad (B.8)$$

$$K_i = \lceil \log_2 (i^U - i^L) \rceil \quad (\text{B.9})$$

$$\mathbf{u} = [u_1, u_2, \dots, u_{K_i}]^T \quad (\text{B.10})$$

$$\mathbf{b} = [2^0, 2^1, \dots, 2^{K_i-1}]^T \quad (\text{B.11})$$

The product $x \cdot i$ is:

$$y = xi = x \left(i^L + \sum_{k=1}^{K_i} 2^{k-1} u_k \right) = xi^L + \sum_{k=1}^{K_i} 2^{k-1} xu_k = xi^L + x\mathbf{b}^T \mathbf{u} \quad (\text{B.12})$$

then the product xu_k can be linearized as explained in the Eq. (B.7).

B.6. Piecewise linear approximation of a function

Defining a vector $\mathbf{x}_{ref}$ of breakpoints $\mathbf{x}_{ref} = [x_{ref_1}, \dots, x_{ref_n}]^T \in \mathbb{R}^n$, a continuous variable α_j for each breakpoint j $\alpha_j \in [0, 1] \forall j = 1, \dots, n$. h_j is a binary variable associated with the $j - th$ interval $[x_j, x_{j+1}] \forall j = 1, \dots, n-1$, with $h_0 = h_n = 0$. Then, the function $f(x)$ can be approximated in the point $\bar{x}$ using:

$$\sum_{j=1}^{n-1} h_j = 1 \quad (\text{B.13})$$

$$\alpha_j \leq h_{j-1} + h_j \quad (j = 1, \dots, n) \quad (\text{B.14})$$

$$\sum_{j=1}^n \alpha_j = 1 \quad (\text{B.15})$$

$$\bar{x} = \sum_{j=1}^n \alpha_j x_j = \alpha^T \mathbf{x}_{ref} \quad (\text{B.16})$$

$$f^a = \sum_{j=1}^n \alpha_j f(x_{ref_j}) \quad (\text{B.17})$$

B.7. Piecewise linear approximation of a function rescaling the breakpoints by an integer variable

The concepts presented in Appendices B.5 and B.6 can be combined in order to express the PLA for discrete rescaling of the breakpoints. In particular, if the new discretization points are $\tilde{\mathbf{x}}_{ref} = I \cdot \mathbf{x}_{ref}$ with $I \subseteq [I^L, I^U] \in \mathbb{I}$ an integer variable, (B.16) can be rewritten as:

$$\begin{aligned} \bar{x} &= \alpha^T \tilde{\mathbf{x}}_{ref} = \alpha^T \mathbf{x}_{ref} I = \alpha^T \mathbf{x}_{ref} (I^L + \mathbf{b}^T \mathbf{u}) = \\ &= \alpha^T \mathbf{x}_{ref} I^L + \alpha^T \mathbf{x}_{ref} \mathbf{b}^T \mathbf{u} = \\ &= \alpha^T \mathbf{x}_{ref} I^L + [\alpha_1 \quad \dots \quad \alpha_n] \begin{bmatrix} x_{ref_1} \\ \vdots \\ x_{ref_n} \end{bmatrix} [b_1 \quad \dots \quad b_{K_i}] \begin{bmatrix} u_1 \\ \vdots \\ u_{K_i} \end{bmatrix} = \\ &= \alpha^T \mathbf{x}_{ref} I^L + b_1 x_{ref_1} \alpha_1 u_1 + \dots + b_{K_i} x_{ref_1} \alpha_1 u_{K_i} + \dots + b_{K_i} x_{ref_n} \alpha_n u_{K_i} \end{aligned} \quad (\text{B.18})$$

and then each of the products $\alpha_j u_k \forall j = 1, \dots, n$ and $\forall k = 1, \dots, K_i$ can be linearized as explained in (B.7). It must be highlighted that there are $K_i \times n$ of this nonlinear terms, and each linearization requires four constraints.

Appendix C. Used parameters

$\beta = 0$, $\eta^{IL} = 0$, $C_{CO_2}^{ref} = C_{CO_2}$, $c^{PV} = c^{PV,ref}$, and $o^{PV} = o^{PV,ref}$ unless otherwise specified.

Table C.1

Physical parameters and costs.

Parameter	Symbol	Value	Unit	Source
WT				
Rated power	P_{WT}^u	8	[MW]	
Wind shear exponent	α_S	0.11	[-]	[83]
Turbine hub height	h_{hub}	112	[m]	
Wind measurement height	h_r	10	[m]	
Max. farm power	P_{WT}^{MAX}	80	[MW]	
PV				
Area	$\bar{A}$	1.663	[m ²]	[84]
Efficiency	η_{STC}	0.144	[-]	[84]
Inverter efficiency	η_{AC}	0.95	[-]	
Rated DC power	P_{PV}^u	240	[W]	[84]
Max. farm size	P_{PV}^{MAX}	200	[MW]	
WEC				
Rated power	P_{WEC}^u	400	[kW]	[85]
Max farm size	P_{WEC}^{MAX}	50	[MW]	[86]
BESS				
Module energy	E^u	10	[MW h]	
Min. energy fraction	λ_B	0.10	[-]	
Max. Energy	E^{MAX}	70	[MW h]	
Max. Power	P_{BESS}^{MAX}	50	[MW]	
BESS degradation factor	A_{BESS}	$2.7 \cdot 10^{-4}$		[13]
BESS degradation exponent	B_{BESS}	2.1		[13]
PLA Interp. breakpoints		3		
BESS shelf lifetime	L_{sh}	15	[yr]	
Max deg. per scenario	$\theta_{max,s}$	$1.82 \cdot 10^{-4}$	[day ⁻¹]	
Charging efficiency	η_{CH}	1	[-]	
Discharging efficiency	η_{DC}	1	[-]	
HSS				
Module energy	H^u	2	[kg]	
Min. energy fraction	λ_H	0.0	[-]	
Max. Energy	H^{MAX}	20	[kg]	
Max. FC Power	P_{fc}^{MAX}	2	[MW]	
Max. El. Power	P_{el}^{MAX}	2	[MW]	
FC efficiency	η_{fc}	0.6	[-]	
El efficiency	η_{el}	0.6	[-]	
GT				
Max. power	$P_{GT}^{S,u}$	25	[MW]	[20]
Min. offtime	T_{off}^S	2	[h]	[20]
Min. op. fraction	γ^S	0.20		[20]
Max ramp rate	RR	25	[MW h ⁻¹]	[20]
Fuel cost	C_{NG}	0.317	[\$m ⁻³]	[87]
Fuel density	ρ_{NG}	0.77	[kg m ⁻³]	[20]
NG comb. coeff	μ_{GT}	2.682	[kg _{CO₂} kg _f ⁻¹]	[20]
Carbon tax	C_{CO_2}	0.071	[\$kg ⁻¹]	[75]
Fuel coeff.	α^S	181	[kg MW ⁻¹ h ⁻¹]	
Fuel coeff.	β^S	765	[kg h ⁻¹]	
O&M cost	$C_{O\&M}^S$	6	[\$MW ⁻¹ h ⁻¹]	[20]
Startup cost	C_{GT}^{start}	1339	[\$]	[20]
Ramp rate cost	C_{RR}^S	0.5	[\$MW ⁻¹]	
DG				
Fuel cost	C_{DG}	2.31	[\$L ⁻¹]	[88]
Fuel density	ρ_{DG}	0.85	[kg L ⁻¹]	
Diesel combustion coeff	μ_{DG}	3.17	[kg _{CO₂} kg _f ⁻¹]	[89]
Fuel coeff.	α^d	245	[kg MW ⁻¹ h ⁻¹]	
O&M cost	$C_{O\&M}^d$	6	[\$MW ⁻¹ h ⁻¹]	
Load				
OP rated power	P_{L}^{rated}	50	[MW]	
Overpower	η^{OL}	1.1	[-]	
Fixed load	η^{FL}	0.1	[-]	
Simulation				
Time frame	τ	1	[h]	
Ann. Interest rate	r_a	0.07	[-]	
Project lifetime	L	10	[years]	
Risk quantile	α	0.8		
Max curtailment	$\bar{P}_{CT}$	1	[MW]	

(continued on next page)

Table C.1 (continued)

Parameter	Symbol	Value	Unit	Source
Installation costs				
WT CAPEX	c^{WT}	25.6	[M\$]	[90]
WT OPEX	o^{WT}	0.88	[M\$/yr]	[90]
PV CAPEX	c^{PV}	528	[\$]	[91]
PV OPEX	o^{PV}	79.2	[\$/yr]	[91]
WEC CAPEX	c^{WEC}	2.2	[M\$]	[50]
WEC OPEX	o^{WEC}	112	[k\$/yr]	[50]
BESS Energy CAPEX	$c^{BESS,E}$	2.5	[M\$]	[92]
BESS Energy OPEX	$o^{BESS,E}$	0.125	[M\$/yr]	[92]
BESS Power CAPEX	$c^{BESS,P}$	0.20	[\$W ⁻¹]	[92]
BESS Power OPEX	$o^{BESS,P}$	0.010	[\$W ⁻¹ yr]	[92]
BESS EoL Energy CAPEX	$c^{BESS,E_{eol}}$	0.25	[M\$]	
GT unitary cost	$c^{GT,g}$	20.5	[M\$]	[93]
DG unitary cost	c^{DG}	2.1	[\$W]	[93]
HSS E. CAPEX	$c^{HSS,E}$	1.02	[k\$]	[94]
HSS E. OPEX	$o^{HSS,E}$	25.4	[\$/yr]	[94]
HSS FC CAPEX	$c^{HSS,P_{fc}}$	2.4	[\$/W]	[95]
HSS FC OPEX	$o^{HSS,P_{fc}}$	0.024	[\$/kW yr]	[95]
HSS EL CAPEX	$c^{HSS,P_{el}}$	1.87	[\$/W]	
HSS EL OPEX	$o^{HSS,P_{el}}$	0.019	[\$/kW yr]	
Min bat. energy	w_{BESS}^{MIN}	0.001	[\$/Wh]	

Data availability

Used research data cannot be publicly disclosed because they include confidential information.

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