



Is a cost-optimal wind farm also carbon-optimal? A layout optimization and control co-design study

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Abstract. Wind farm design and operation are traditionally driven by economic objectives, often overlooking environmental impacts. Although greenhouse gas emissions associated with wind energy are substantially lower than those of fossil-fuel-based plants, they are not negligible when assessed over the entire life cycle. This study investigates the impact of introducing a carbon-related objective alongside classical objectives, such as annual energy production and levelized cost of energy, into wind farm optimization. The analysis considers wind farm layout optimization, wind farm flow control, and the combined optimization of layout and control strategies, namely co-design. A range of case studies is examined, from illustrative examples to a large-scale offshore wind farm under varying site conditions. The results indicate that selecting a carbon-related objective yields economic performance very similar to the one obtained with conventional economic objectives, and vice versa, a significant (unexpected) finding with potentially far-reaching implications. This suggests that economic and environmental goals are largely aligned, and that prioritizing one does not necessarily compromise the other. Despite similar overall performance metrics, the resulting layouts differ in terms of turbine positions depending on the chosen objective and on whether layout and control are optimized jointly or sequentially.

1 Introduction

The rapid expansion of offshore wind energy is a key pillar of the global energy transition towards a climate-neutral energy system. Ambitious renewable energy expansion targets have been established worldwide, and offshore wind installations are expected to increase substantially over the coming years and decades (Mc Govern et al., 2025; Global Wind Energy Council, 2025). To meet these targets efficiently, future wind farms must be economically profitable and minimize their environmental impacts.

The design of an offshore wind farm directly affects its technical, economic, and environmental performance. Wind farm layout optimization (WFLO) is therefore a key step during the early development phase, where the turbine positions are selected to maximize the overall wind farm performance (Mosetti et al., 1994). Once the layout has been fixed, sequentially optimized wind farm flow control (WFFC) can further improve the wind farm performance. In particular, wake steering increases the overall energy production by intentionally redirecting turbine wakes to reduce wake interactions (Meyers et al., 2022). More recently, wind farm co-design optimization (WFCO), in which the layout and control strategy are optimized simultaneously



rather than sequentially, has emerged as an alternative to the traditional sequential design process (Stanley et al., 2023). The integration of WFFC into WFLO requires the development of computationally efficient surrogate functions to approximate WFFC set points, such as yaw misalignment angles, thereby avoiding the curse of dimensionality and ensuring tractability. By accounting for the interactions between WFFC and WFLO during the optimization process, WFCO has the potential to further enhance the overall wind farm performance. To date, most WFCO studies have focused on wake steering as the integrated WFFC strategy.

The optimal layout and control strategy depend on the selected objective function. Traditionally, wind farm optimization has focused on maximizing the annual energy production (AEP) or minimizing the economic cost of energy (denoted COE_e in this work and also referred to as the levelized cost of energy). Both metrics are well-established quantities for evaluating the technical and economic performance of a wind farm (Veers et al., 2023; Meyers et al., 2022). While AEP considers only the energy yield, COE_e extends this perspective by relating the total life-cycle costs (TLCC) of the wind farm to its lifetime energy production.

In the context of WFLO, AEP and COE_e are commonly used to determine optimal turbine positions (Tao et al., 2020; Hou et al., 2019). For WFFC, a major research focus has been the mitigation of wake losses to increase power production, and consequently AEP, with wake steering emerging as one of the most effective control strategies. While improving the economic performance of a wind farm is a primary objective, the full economic impacts of control actions are difficult to quantify because of the complex relation between structural loads, component reliability, and operation and maintenance costs (Meyers et al., 2022). Nevertheless, changes in AEP directly influence COE_e , providing a measurable – although incomplete – pathway to assess the economic impact of WFFC actions. Existing WFCO studies have largely focused on AEP or revenue maximization, while the direct optimization of COE_e through a WFCO approach remains unexplored. Overall, the benefits of WFCO are still not well established. Reported AEP gains relative to sequential optimization approaches vary significantly, ranging from negligible improvements to increases of up to 0.8% (Stanley et al., 2023; Dirik et al., 2025; Baricchio et al., 2026). Furthermore, the effectiveness of WFCO has been shown to depend strongly on site-specific characteristics, including the number of turbines, power density, and the heterogeneity of the wind resource (Baricchio et al., 2024).

While AEP and COE_e have supported the rapid deployment of wind energy, they do not explicitly account for the life-cycle greenhouse gas emissions associated with a wind farm. These emissions arise throughout the entire life cycle, from material extraction and component manufacturing to installation, maintenance, and end-of-life treatment. Although substantially lower than those of fossil-based electricity generation, they are not negligible (Dolan and Heath, 2012). As wind deployment accelerates, reducing these life-cycle emissions becomes increasingly important (Veers et al., 2023).

Analogously to COE_e , the environmental cost of energy (denoted COE_{CO_2} in this work and also referred to as the carbon footprint) relates the total life-cycle emissions (TLCE) to the lifetime energy production. However, COE_{CO_2} has received little attention as a design metric for wind farm optimization. While numerous studies have assessed the environmental impacts of wind farms after the design has been established (Arvesen and Hertwich, 2012; Dolan and Heath, 2012; Bonou et al., 2016), only a limited number have investigated environmental objectives as optimization criteria during the design process. Canet et al. (2023) introduced COE_{CO_2} in wind turbine design and showed that minimizing COE_{CO_2} can lead to different



60 design choices than minimizing COE_ϵ . Kainz et al. (2024) developed a fully parameterized and automated toolchain for the simultaneous assessment of COE_ϵ and COE_{CO_2} for varying offshore wind farm configurations. The study investigated the impact of different turbine and wind farm design choices on both metrics, showing that design changes do not necessarily affect economic and environmental performance in the same way. However, the authors neither investigated varying layout configurations nor included wind farm control in their performance assessment. This toolchain is leveraged in the present
65 study to extend the assessment of COE_ϵ and COE_{CO_2} towards optimization-based wind farm design. To the best of the authors' knowledge, COE_{CO_2} has not yet been formulated as an optimization objective for WFLO, WFFC, or WFCO.

Because WFLO, WFFC, and WFCO influence the lifetime energy production as well as TLCC and TLCE of a wind farm, they may affect COE_ϵ and COE_{CO_2} differently. However, whether these two objectives are aligned or conflicting remains an open question. If minimizing COE_ϵ also minimizes COE_{CO_2} , the economic and environmental objectives are aligned, and
70 optimizing for economic performance simultaneously improves the environmental performance. In contrast, if the objectives conflict, improving economic performance may come at the expense of environmental performance, potentially requiring a deliberate trade-off between the two. Such conflicts have been demonstrated by Canet et al. (2023) in the design of an eco-conscious wind turbine, where substantial trade-offs between economic and environmental performance were identified. Understanding the relationship between the two objectives is therefore important for assessing whether economic optimization
75 alone promotes low-emission wind farm designs or whether dedicated design strategies or policy incentives are required. Consequently, it is important to understand whether different objectives lead to distinct optimal layouts and control strategies, and whether these differences result in significant trade-offs between economic and environmental performance.

Taken together, the existing literature highlights the presence of three key gaps. First, it remains unclear whether economic and environmental objectives are aligned or conflicting when considered within WFLO, WFFC, and WFCO. Second, the
80 differences between layouts optimized for maximizing AEP, minimizing COE_ϵ , and minimizing COE_{CO_2} , as well as the underlying design drivers, have not yet been comprehensively investigated. Third, the potential benefits of sequential WFFC and WFCO for improving the technical, economic, and environmental performance of offshore wind farms under different site conditions remain insufficiently understood.

This paper addresses these gaps by systematically investigating WFLO, WFFC, and WFCO for maximizing AEP, mini-
85 mizing COE_ϵ , and minimizing COE_{CO_2} . Single-objective optimizations are performed to compare the resulting layouts and identify the underlying design drivers, whereas multi-objective optimizations quantify potential trade-offs between economic and environmental objectives. A scaled version of the Hollandse Kust Noord (HKN) wind farm, populated with 69 IEA 22-MW reference turbines, serves as the case study. To assess the robustness of the findings, additional parametric studies investigate the influence of bathymetry and wind farm power density on potentially resulting design trade-offs.

90 Unexpectedly – at least for these authors – all results of this study clearly point to the fact that economic and carbon indicators are to a very large extent well aligned. In the context of layout and layout-control co-design, this means that a wind farm designed for a minimum LCOE also achieves a minimal carbon footprint, a lucky example of the rare feat of killing two birds with one stone. Therefore, this study demonstrates that the trade-offs observed by Canet et al. (2023) at the turbine-design level are not present during the layout optimization and control co-design stage.



95 The remainder of this paper is structured as follows. Section 2 describes the methodology, including the formulation of the
performance metrics and the optimization approaches for WFLO, WFFC, and WFCO. Section 3 introduces the case studies
and presents the corresponding results. The case studies include illustrative examples with a few turbines, the scaled HKN wind
farm, and parametric studies used to investigate the influence of different site conditions. The analysis of the results focuses
on design differences, including variations in objective performance, optimal layouts, and the drivers governing the observed
100 trade-offs. Section 4 discusses the observed trends and their implications for wind farm design. Finally, Section 5 summarizes
the main conclusions of the study.

2 Methodology

This section describes the methodology of this study. First, four different performance metrics are presented. Second, the
different wind farm design and operation optimization problems are defined, namely, WFLO, WFFC, and WFCO. Third, the
105 entire toolchain that enables the use of these metrics in the different optimization problems is summarized.

2.1 Wind farm performance metrics

Four key metrics serve as performance indicators and optimization objectives for the wind farm layout and control designs:
(1) the AEP of the farm considering wake interactions among the turbines, (2) the net AEP considering additional losses
beyond those due to wakes, denoted AEP_{net} , (3) COE_{ϵ} to measure the economic performance of the farm, and (4) COE_{CO_2}
110 to quantify the environmental performance.

2.1.1 Annual energy production

The AEP is calculated as

$$AEP = 8760 \text{ h yr}^{-1} \sum_{\theta=1}^{N_{\theta}} \sum_{u=1}^{N_u} P_{\theta,u}(\mathbf{x}, \mathbf{y}, \gamma_{\theta,u}) \rho_{\theta,u}, \quad (1)$$

where N_{θ} and N_u represent the discretization of the wind farm operating range in wind direction θ and wind speed u , respec-
115 tively, $P_{\theta,u}$ denotes the total wind farm power for the layout $(\mathbf{x}, \mathbf{y})$ and the setpoints for yaw misalignment of each turbine
 $(\gamma_{\theta,u})$ under the ambient inflow condition (θ, u) , and $\rho_{\theta,u}$ is the probability of occurrence for that inflow condition. The wind
farm simulation software PyWake (Pedersen M M et al.) is used to calculate the AEP. Wake interactions among turbines
are calculated with the TurbOPark wake model, as suggested by Nygaard (2022) due to its suitability for deep-array effects,
together with the Jiménez deflection model (Jiménez et al., 2010). The default parameter settings of the implemented PyWake
120 version are adopted.

2.1.2 Net annual energy production

While the classical AEP metric considers only wake-induced losses, additional loss mechanisms occur in real wind farms.
These losses must be included to obtain realistic values for COE_{ϵ} and COE_{CO_2} . While some losses can be represented by



fixed (layout independent) factors, others depend explicitly on the wind farm layout, most notably electrical losses in the
 125 collection system and availability losses associated with component failures. Consequently, AEP_{net} is introduced as a second
 design objective to isolate the influence of these additional layout-dependent losses on the optimal wind farm design before
 investigating the more comprehensive objectives COE_{ϵ} and COE_{CO_2} .

A constant loss factor of $f_p = 0.98$ is applied to account for non-ideal operating conditions (Clifton et al., 2016). Next,
 power-dependent cable losses are considered using a resistive loss model for three-phase alternating current (AC) cables fol-
 130 lowing Worzyk (2009). For each array cable section a in the wind farm, the transmitted active power per inflow condition is
 determined by summing the power generated by all supplied downstream turbines as calculated with PyWake. The correspond-
 ing phase current is calculated as

$$I_a = \frac{P_a}{\sqrt{3} V \cos \phi_a}, \quad (2)$$

where P_a is the transmitted active power, V is the array voltage, and $\cos \phi_a$ is the power factor of the installed cable type. The
 135 instantaneous resistive power loss of each cable section is then computed as

$$P_{a,\text{loss}} = 3I_a^2 R_a L_a, \quad (3)$$

where R_a is the AC resistance per unit length and L_a is the length of the cable section. The total cable losses per inflow
 condition are obtained by summing the losses over all cable sections, from which a power- and inflow-dependent array cable
 loss factor is defined as

$$140 \quad f_{\text{ar},\theta,u} = 1 - \frac{\sum_a P_{a,\text{loss}}}{P_{\theta,u} f_p}. \quad (4)$$

After correcting for the offshore substation efficiency, f_{off} , the losses of each export cable e are calculated similarly to array
 cabling losses, resulting in the export cable loss factor

$$f_{\text{ex},\theta,u} = 1 - \frac{\sum_e P_{e,\text{loss}}}{P_{\theta,u} f_p f_{\text{ar},\theta,u} f_{\text{off}}}. \quad (5)$$

After consideration of the onshore substation efficiency, f_{on} , the available power delivered to the connected electricity grid
 145 can be calculated.

Lastly, component downtimes due to failures are captured through the loss factor f_d . Average annual failure rates r and
 associated mean time to repair t_{mttr} per turbine component are sourced from Carroll et al. (2016) and updated with values
 suggested by Donnelly et al. (2024). For array and export cables, values reported by Worzyk (2009) for the Baltic Cable are
 adopted. For the calculation of f_a , a conservative approach is taken, in which the downtime of individual components i is added
 150 up:

$$f_d = 1 - \frac{\sum_i r_i t_{\text{mttr},i}}{8760 \text{ h}}, \quad (6)$$

which assumes that failures never occur concurrently.

Finally, the AEP considering all described losses, denoted AEP_{net} , can be calculated:

$$AEP_{\text{net}} = f_d 8760 \text{ h yr}^{-1} \sum_{\theta=1}^{N_{\theta}} \sum_{u=1}^{N_u} P_{\theta,u}(\mathbf{x}, \mathbf{y}, \gamma_{\theta,u}) f_p f_{\text{ar},\theta,u}(\mathbf{x}, \mathbf{y}, \gamma_{\theta,u}) f_{\text{off}} f_{\text{ex},\theta,u}(\mathbf{x}, \mathbf{y}, \gamma_{\theta,u}) f_{\text{on}} \rho_{\theta,u}. \quad (7)$$

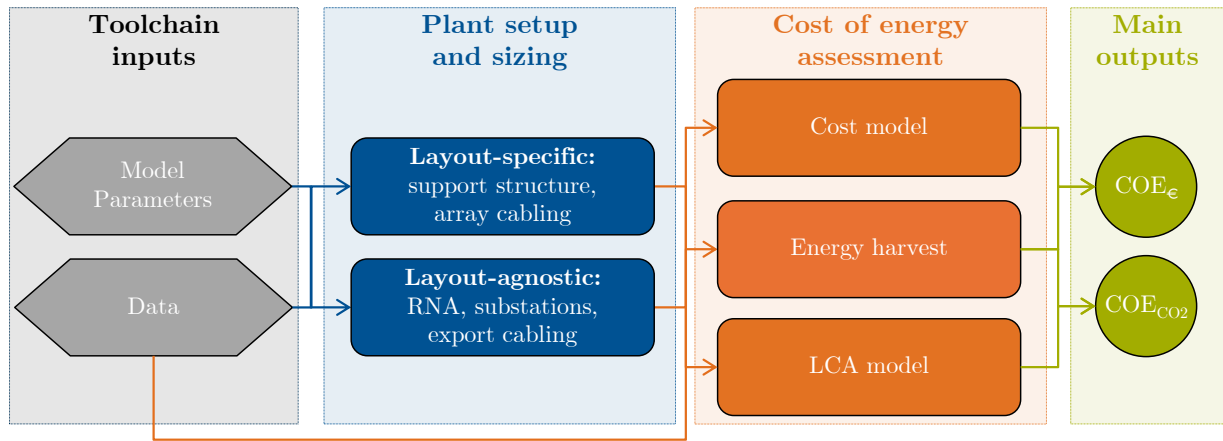


Figure 1. Workflow of the DETECT toolchain.

155 2.1.3 Economic and environmental cost of energy

To determine COE_e and COE_{CO_2} , the TLCC and the TLCE must be assessed first. Both quantities are calculated using the Design and Evaluation Toolchain for Emission and Cost Tracing (DETECT) as described by Kainz et al. (2024). DETECT is a fully parameterized toolchain that quantifies the TLCC and TLCE of offshore wind farms for varying design choices – including the wind farm layout – by combining engineering, economic, and Life Cycle Assessment (LCA) models.

160 Figure 1 shows the data and model flow for the forward analysis. After adjusting the model parameters to the regarded case study, the masses of the individual plant components are calculated. In the context of layout optimization, two categories of components are distinguished: (1) layout-dependent components, whose configuration and logistics vary with the turbine positions within the wind farm, and (2) layout-independent components, which remain unaffected by the optimization. In the following, the focus lies on the calculation procedure for the layout-dependent components. Costs and emissions related to
 165 layout-independent components are calculated as described by Kainz et al. (2024) and considered as fixed quantities.

A first layout-dependent component is the support structure. Per turbine, its mass scales with the local water depth and is determined using a bathymetry-dependent mass surrogate model (McWilliam et al., 2022). A lookup table for monopile and tower masses is generated by evaluating the surrogate model over the site bathymetry range in water depth increments of 0.1 m. Since the surrogate model is available only for rated turbine powers up to 20 MW, masses for the IEA 22-MW turbine
 170 are obtained by linear extrapolation of the mass–power relationship at each evaluated water depth, following the approach proposed by Kainz et al. (2026).

A second layout-dependent component is the array cabling network, whose configuration depends on the relative distances between the turbines and the substation. For a given layout, the cable connections within the farm are optimized using the electrical network design tool OptiWindNet (Souza de Alencar et al., 2026), which minimizes the total cabling network length.
 175 During the WFLO and the WFCO, a nested cabling optimization is performed using the Hybrid Genetic Search (HGS) meta-



Table 1. Available 110kV array cabling types (ABB, 2010; Kainz et al., 2026).

Parameter	Unit	Cable type		
Cross section	mm ²	185	400	1000
Current capacity	A	420	590	825
Max. turbines supplied	-	3	5	7
Mass factor	kg m ⁻¹	40.9	47.2	80.5
Cost factor	€ m ⁻¹	368.9	428.9	737.1

heuristic solver. The HGS is limited to a runtime of 0.3 s, as suggested by Kainz et al. (2026), to provide a sufficiently good approximation of the optimal cabling solution without imposing an excessive computational burden on the outer optimization loop. The cabling plans for the final layouts obtained from the WFLO and the WFCO are further refined using an integer linear programming optimizer (IBM, 2024). Following the optimization of the cabling configuration, each array cable section
 180 is equipped with a cable type from Table 1. Specifically, the cable type is assigned that has the lowest current-carrying capability when all transmitting turbines are operating at rated power. The capacitive reactive power contribution of the cables is disregarded.

Based on the determined component masses, the TLCC and TLCE are calculated following the DETECT methodology described in detail by Kainz et al. (2024). The methodology is briefly summarized below, with emphasis on layout-specific
 185 costs and emissions.

State-of-the-art cost models are used to calculate the TLCC. The TLCE are calculated using the standardized LCA method, which quantifies the environmental impacts associated with a product or service over its entire life cycle. Only the climate change impact category is considered in this study, quantified as the 100-year global warming potential (GWP) according to the IPCC-2013 characterization method (Intergovernmental Panel on Climate Change, 2013) and expressed in kilogram carbon
 190 dioxide equivalents (kgCO₂eq). Consequently, the environmental assessment is limited to a carbon footprint analysis and does not account for other environmental impact categories. More than 100 reference activities and their associated GWP, selected from the Ecoinvent database version 3.9.1. (Wernet et al., 2016), are used to approximate the life cycle inventory and related emissions of the wind farm. While the Ecoinvent *allocation, cut-off by classification* system model is used for background data extraction, the circular footprint formula (European Commission, 2021) is applied to account for recycling-related burdens
 195 and credits, including recycled content of incoming materials and recycling benefits associated with end-of-life materials. This approach enables a design-oriented assessment by rewarding both the use of recycled and recyclable materials.

The following life phases are considered during the calculation of the TLCC and TLCE:

1. **Component production.** To determine the production costs of all wind farm components, mass-dependent cost factors are used. The emissions related to material extraction, processing, and component manufacturing are determined via



- 200 material-specific emission factors. The masses of all components are broken down by their respective materials using average shares by weight documented in the literature.
2. **Transport to port.** Based on component masses and average transport distances per component reported in the literature, the associated transportation costs and emissions are calculated using mass- and distance-dependent cost and emission factors.
- 205 3. **Installation.** The costs and emissions linked to the installation phase are determined by means of the logistics of the involved vessels, specifically via the calculated operational hours per vessel type. Vessel-specific cost rates are used to determine the installation costs. For the emission calculation, vessel-specific fuel rates are used and further translated into installation emissions via the associated well-to-wake emission factors. The operational hours per vessel depend on the component masses, considering vessel-specific maximum cargo, deck load, and deck space.
- 210 4. **Operation & Maintenance.** Based on the component-specific failure rates discussed in Sect. 2.1.2, the spare parts for component replacements, and vessel logistics for replacement, repair, and service activities are determined. The associated costs and emissions are calculated as described for life phases 1–3. However, only layout-agnostic components in the rotor-nacelle-assembly are considered due to missing data for layout-dependent components.
- 215 5. **Decommissioning.** The wind farm decommissioning is modeled as a reversed installation process, except for the scour protection, which is assumed to be left on the seabed. All components are then transported by trucks to a local end-of-life facility. The associated transportation costs and emissions are calculated as in life phase 2 (transport to port).
6. **End-of-life treatment.** Component- and material-specific recycling rates from literature are used to model the end-of-life costs and emissions associated with recycling, landfill, and incineration.
- 220 7. **Project management.** Additional to life-phase dependent costs, project-related costs, such as land lease and insurance, are considered. However, these costs are independent of the layout-specific components. Emissions linked to project management are neglected.

A nominal discount rate of 6.61 % (Stehly et al., 2024) is used to discount costs occurring throughout the project lifetime to the year of installation. Once the TLCC and TLCE are determined, COE_ϵ and COE_{CO_2} are calculated as

$$\text{COE}_\epsilon = \frac{\text{TLCC}}{\text{AEP}_{\text{net}} n}, \quad (8a)$$

$$225 \quad \text{COE}_{\text{CO}_2} = \frac{\text{TLCE}}{\text{AEP}_{\text{net}} n}, \quad (8b)$$

where n is the project lifetime assumed as 25 years.

In this study, TLCC and TLCE are sensitive to the wind farm layout, but not to the selected WFFC strategy. Differences in WFFC affect the cost metrics only through their influence on AEP_{net} , while potential differences in costs and emissions resulting from WFFC-induced changes in component loads, failures, and O&M activities are not considered. This limitation



230 reflects an existing research gap arising from the complexity of quantifying the full economic and environmental effects of WFFC actions (Meyers et al., 2022).

2.2 Wind farm layout optimization

The WFLO problem considered in this study aims to minimize an objective function f by optimizing the positions of the turbines defined by the couples of coordinates $(\mathbf{x}, \mathbf{y})$. Two constraints are considered, namely a minimum spacing $d_{\min}$ between the turbines and a boundary constraint that enforces the turbines to be positioned within the designated wind farm area, indicated by Ω . Therefore, the optimization is formulated as

$$\begin{aligned} \min_{\mathbf{x}, \mathbf{y}} \quad & f(\mathbf{x}, \mathbf{y}), \\ \text{subject to} \quad & (\mathbf{x}, \mathbf{y}) \in \Omega, \\ & \sqrt{(x_i - x_j)^2 + (y_i - y_j)^2} \geq d_{\min} \quad \forall i, j \in [1, N_{wt}], i \neq j, \end{aligned} \quad (9)$$

where N_{wt} denotes the number of turbines in the wind farm.

The performance metrics described in Sect. 2.1 are utilized as objective functions f within this study, resulting in different versions of the WFLO problem. When the scope of the WFLO is to maximize a performance metric, the objective is expressed with the opposite sign in Eq. (9). The optimal solution, i.e. the optimal position of the turbines, is indicated by $(\mathbf{x}_{\text{opt}}, \mathbf{y}_{\text{opt}})$.

This study also considers a multi-objective WFLO problem, which is formulated as shown in Eq. (9), except that two objective functions are considered instead of one. In this case, the solution consists of a Pareto front containing the non-dominating solutions. The extent of a Pareto front can be calculated as the difference in the objectives at the extremes of the front. In case the two objectives are not competing, the Pareto front comprises only a single solution, as occurs for the single objective optimization case. In this case, the extent of the Pareto front is equal to zero.

The WFLO is solved with the Layout Optimization Genetic Algorithm (LO-GA) developed by Baricchio et al. (2024), which exploits the specific properties of the WFLO through a tailored genetic algorithm. Each layout of the initial population is initialized randomly using OptiWindNet (Souza de Alencar et al., 2026). The hyperparameter settings of the LO-GA are summarized in Table 2. Specifically, the percentage and the step of mutation decrease linearly and exponentially, respectively, as the population of solutions evolves through the generations. This allows a gradual transition from an “aggressive” exploration of the design space to a refinement phase within the optimization process. Therefore, Table 2 includes the minimum and maximum values for these two hyperparameters.

2.3 Wind farm flow control

255 In this work, WFFC is based on wake steering. The benefits of WFFC are compared to the baseline operation, in which the yaw misalignment angles are assumed to be equal to zero for all the flow conditions. Wake steering is implemented by interpolating within a lookup table $\gamma_{\text{LUT}, \text{opt}}$ of optimized yaw misalignment angles, obtaining the angles $\gamma_{\theta, u}$ corresponding to the flow conditions (θ, u) , which are then used to calculate the AEP according to Eq. (1).



Table 2. Hyperparameters of LO-GA adopted in this study.

Hyperparameter name	Value
Number of generations	800
Size of the population	350
Number of parent solutions to keep	105
Percentage of selection	70%
Percentage of mutation	30% $\rightarrow$ 10%
Step of mutation	3 $D \rightarrow 0 D$
Distance limit	1 D

The performance improvements obtained through WFFC are incorporated into the cost- and emissions-related performance metrics solely through an increase in energy production. Moreover, the power calculations corresponding to different flow conditions (θ, u) are decoupled from one another, as shown in Eq. (1) and (7). Therefore, the optimization problem used to obtain $\gamma_{\text{LUT,opt}}$ is equivalent to solving $N_\theta \times N_u$ independent optimization problems, each of which optimizes $\gamma_{\theta,u}$ by maximizing the power $P_{\theta,u}$. Each optimization problem is therefore formulated as

$$\max_{\gamma_{\theta,u}} P_{\theta,u}(\mathbf{x}, \mathbf{y}, \gamma_{\theta,u}), \quad (10)$$

subject to $\gamma \in [\gamma_{\min}, \gamma_{\max}]$,

with $\gamma_{\min}$ and $\gamma_{\max}$ indicating the lower and upper bounds for the yaw misalignment angles. This process is repeated for all wind speeds and directions to obtain the complete lookup table $\gamma_{\text{LUT,opt}}$.

The optimization problems described in Eq. (10) are solved with the Serial-Refine optimization algorithm (Fleming et al., 2022). The algorithm is tailored to the optimization of yaw misalignment angles and is based on repeated iterations from the most upstream to the most downstream turbines, ensuring fast convergence. Specifically, the number of values tested during each farm iteration and the total number of such iterations are set to 5 and 3, respectively, while the yaw misalignment angles are bounded within -30° and 30° .

2.4 Wind farm control-layout co-design optimization

The co-design of the wind farm layout and control strategy combines the two optimization problems defined in the previous sections. The direct integration of these two problems would require prohibitive computational resources and may lead to convergence issues due to the high dimensionality of the problem. Therefore, in this study, the co-design approach is implemented using the “Geometric Yaw” concept (Stanley et al., 2023). This method approximates the optimal yaw misalignment angles through an analytical relation embedded within the WFLO, rather than relying on monolithic or nested optimizations. As a result, the dimensionality and computational time of the WFLO remain unchanged.



The specific analytical relation adopted in this study is the method referred to as “Exponential Corrected,” introduced by Baricchio et al. (2024). This method represents an improved version of the analytical relation originally proposed by Stanley et al. (2023). Specifically, the optimal yaw misalignment angle of each turbine is expressed as a function of the relative positions of all downstream turbines in the wind farm and the effective wind speed at each turbine location under baseline operation. Moreover, the coefficients of this method are re-tuned for the present study, adapting the values to the specific turbine and wake models selected for this work. As a result, lookup tables containing the approximated yaw misalignment angles $\gamma_{\text{LUT,geom}}$ are obtained as functions of the turbine positions $(\mathbf{x}, \mathbf{y})$, i.e. $\gamma_{\text{LUT,geom}}(\mathbf{x}, \mathbf{y})$.

The co-design optimized layouts are obtained by solving the optimization problem formulated as

$$\begin{aligned} \min_{\mathbf{x}, \mathbf{y}} \quad & f(\mathbf{x}, \mathbf{y}, \gamma_{\text{LUT,geom}}(\mathbf{x}, \mathbf{y})), \\ \text{subject to} \quad & (\mathbf{x}, \mathbf{y}) \in \Omega, \\ & \sqrt{(x_i - x_j)^2 + (y_i - y_j)^2} \geq d_{\min} \quad \forall i, j \in [1, N_{wt}], i \neq j. \end{aligned} \quad (11)$$

In this formulation, the yaw misalignment angles of the turbines are set equal to their geometric values when computing the power production of the wind farm, which is evaluated within the objective function f as shown in Eq. (1), for all the performance metrics considered in this study. Consequently, the layout of the wind farm is optimized considering the application of wake steering during operation.

To ensure a consistent comparison with the sequential optimization of WFLO and WFFC, the optimal yaw misalignment angles corresponding to the WFCO-optimized layouts are computed by solving the optimization problem formulated in Eq. (10), following the approach adopted in previous studies (Stanley et al., 2023; Baricchio et al., 2024). Therefore, the only difference between sequential and co-design optimization lies in the objective function adopted for layout optimization. In the sequential approach, the layout optimization is unaware of the wake steering operation adopted in the subsequent control optimization stage. In contrast, the co-design approach accounts for wake steering during layout optimization, although only through an approximation rather than using the actual optimal yaw misalignment angles. Subsequently, for both the sequential and co-design approaches, the optimal yaw misalignment angles are optimized using the same method.

2.5 Overview of the toolchain

Figure 2 shows the overall toolchain used for this study. The $\mathbf{x}$ and $\mathbf{y}$ positions of the turbines are the design variables and determine the layout to be assessed by the cost model. In the case of WFCO, the yaw misalignment angles per turbine and inflow condition are approximated using geometric relations of the analyzed layout. For WFLO, the angles are set to zero. Subsequently, PyWake is called to calculate the power production per turbine and inflow condition, and the associated AEP considering wake interactions. Next, the electrical network of the current layout is optimized as a nested optimization using OptiWindNet. Then, DETECT is run to calculate AEP_{net} as well as $\text{COE}_{\text{€}}$ and COE_{CO_2} . Depending on the studied single- or multi-objective optimization objectives, the corresponding outputs are handed over to the LO-GA. During the optimization process, the LO-GA adapts the design variables to converge towards optimal layouts, until the last generation is reached. Then, a WFFC optimization is executed for the final layouts. In the case of WFCO, this provides optimized yaw misalignment angles

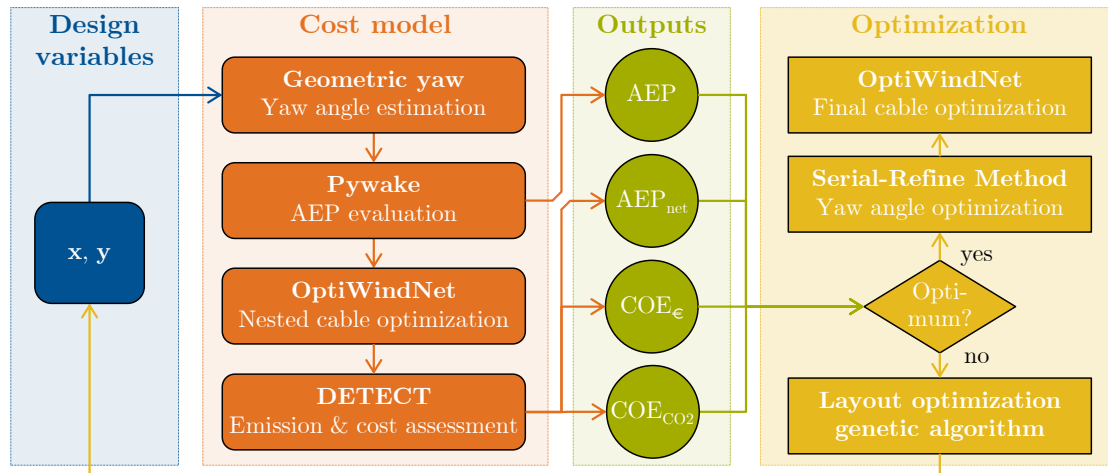


Figure 2. Overview of the proposed wind farm design optimization framework.

rather than the approximations obtained from the geometric relations used during the WFCO process. Finally, a detailed cabling network optimization is performed.

3 Results

This section presents the results of this study through a series of case studies. First, a few illustrative examples based on two- and three-turbine wind farms are presented to provide an intuitive understanding of the methodology and establish a basis for interpreting the results of the more complex cases.

Second, the re-design of a 69-turbine wind farm is investigated using a scaled version of the HKN wind farm, located off the coast of the Netherlands in the North Sea. This is adopted as the baseline scenario in this study. The analysis of this reference case is then followed by a series of parametric studies investigating the influence of different site characteristics. For the HKN-based cases, the results are first presented in terms of the statistical distributions of the different optimization performance metrics, investigating the impact of WFLO, WFFC, and WFCO. For the best-performing layouts, the impact of the design on the different wind farm components is then analyzed in terms of energy losses, costs, and emissions, examining the drivers of the optimization outcomes under different objectives and approaches.

The turbine type adopted in this study is the IEA 22-MW reference turbine (Zahle et al., 2024), which is characterized by a hub height of 170 m and a rotor diameter (D) of 283.2 m. The same turbine type is used consistently across all cases considered in this study.



Table 3. Main characteristics of the illustrative examples.

Case study name	Number of turbines	Bathymetry range
Two turbines - low bathymetry difference	2	19 m – 28 m
Two turbines - high bathymetry difference	2	20 m – 60 m
Three turbines - low bathymetry difference	3	19 m – 28 m
Three turbines - high bathymetry difference	3	20 m – 60 m

3.1 Illustrative examples

3.1.1 Description of the case studies

Four illustrative examples based on a limited number of turbines are presented. These examples explore whether different performance metrics lead to different optimal turbine positions in simple, intuitive cases. The turbines are located in a single-dimensional domain, characterized by a length of $10D$ and a regular bathymetry pattern. The characteristics of each case are summarized in Table 3, which highlights the number of turbines and the bathymetry range of the domain.

A simplified wind resource is considered in this example, consisting of a single wind direction from the west, corresponding to the direction along which the turbines are aligned, and wind speeds described by the average Weibull distribution of the HKN site. The latter is described in more detail for the baseline case study in Sect. 3.2.1.

The first two examples refer to a wind farm consisting of two turbines. One turbine is kept fixed, while the position of the second turbine is varied along one dimension to investigate the impact of such a layout choice on the selected performance metrics. In both of these two-turbine examples, the bathymetry profile varies linearly as the distance from the fixed turbine increases. Whereas the first example is characterized by bathymetry values from 19 m to 28 m, in the second example, the bathymetry limits are set to 10 m and 60 m, respectively. These water depth values are representative of the HKN site and the parametric studies described in the next sections.

The third and fourth examples consist of a three-turbine wind farm with two turbines located at $10D$ distance from each other and a third turbine whose position is varied along the direction of alignment. These examples are respectively characterized by the same bathymetry profile as the previous cases. In all four examples, the varying position of the turbine is constrained to maintain a minimum distance of $2D$ between turbines. Therefore, the design space is limited in the range $2 - 8D$ from the left turbine. These four examples are visualized in Fig. 3.

3.1.2 Two-turbine wind farm

The results for the two-turbine wind farm examples are presented in Fig. 4. The plots show the relative changes in the performance metrics indicated on the y-axis as a function of the normalized distance between the turbines in D . The relative changes are calculated with respect to the turbine position at a distance of $2D$. In each of these plots, two lines are included, with the solid line indicating the performance metric values calculated without considering wake steering and the dashed line

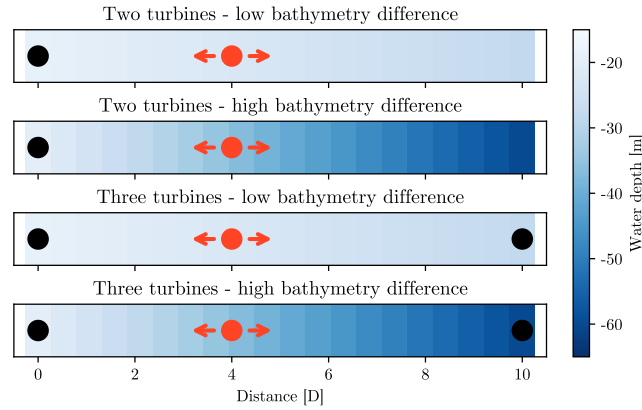


Figure 3. Turbine positions and bathymetry profile in the illustrative examples. Black dots indicate fixed turbines, and red dots indicate the varying-position turbine.

representing values obtained by applying the yaw misalignment angles obtained through the Serial-Refine optimization algorithm. Therefore, the dashed line indicates the solution obtained with a control-layout co-design approach. Additionally, the changes in TLCE and TLCC with increasing turbine distance are plotted to provide insight into the behavior of COE_{ϵ} and COE_{CO_2} , with the contributions of the most significant components shown separately. These two metrics are independent of

355 the application of wake steering.

Since the AEP calculation is not sensitive to water depth, the results regarding this performance metric are identical for both bathymetry cases. Specifically, the AEP increases with the distance from the first turbine, as a consequence of reduced wake effects. This behavior occurs in both the baseline and wake steering cases, with wake steering resulting in a higher AEP for distances $\geq 5D$ due to the increased overall wind farm power production. Therefore, in all cases, the optimal position of the

360 second turbine is identical and equal to $8D$. This identical outcome indicates that the co-design approach has no impact in this simplified example when the objective is the maximization of the AEP.

The trends for AEP_{net} are almost identical to those observed for AEP. The contribution of non-wake losses to the relative performance changes is limited. In particular, changes in array cable length appear to have a negligible impact on cable availability losses compared with the corresponding improvements in wake losses, at least for the range of cable lengths investigated.

The COE_{ϵ} in the low-bathymetry-difference case shows an inverse trend compared with AEP, indicating that AEP dominates the metric, whereas TLCC has only a minor influence. Cable and support structure costs increase with increasing turbine distance and water depth, respectively, while the costs of the tower and other components of the turbine remain largely unchanged with turbine position. However, their influence on COE_{ϵ} is negligible compared with the impact of AEP. Although these cost increases oppose the corresponding trends in AEP, they have only a minor influence on COE_{ϵ} and are not large

370 enough to offset the benefits of increased AEP. In the high-bathymetry-difference case, however, the higher support-structure costs, particularly those associated with the monopile, start to influence the results more strongly. In the baseline case, the opposing trends in TLCC and AEP result in a trade-off and lead to an optimum turbine spacing of approximately $6D$. When wake



steering is enabled, however, the increase in AEP remains the dominant effect, and no trade-off is observed. The difference in the optimal turbine positions indicates a potential for a co-design approach when COE_{ϵ} is used as the optimization objective, particularly in cases with significant bathymetry differences.

Similar trends observed for COE_{ϵ} are also registered for COE_{CO_2} . Here, the relative increase in TLCE follows the same trend as TLCC, but is approximately twice as large. Particularly, the relative increase in support structure emissions is more pronounced. Consequently, in the high-bathymetry-difference case, the optimal position of the second turbine shifts further to the left, favoring shorter turbine spacing. However, for this metric, the optima obtained considering and neglecting wake steering coincide in both cases. This indicates that, even when wake steering is enabled, the increase in AEP does not dominate the increase in TLCE.

Comparing the optimal positions of the second turbine for the different performance metrics, it can be observed that, in the high-bathymetry-difference case, these differ when COE_{ϵ} or COE_{CO_2} are considered. This difference indicates a conflict between the two metrics and therefore suggests the presence of a Pareto front when both metrics are optimized simultaneously. In the baseline case, the difference in the performance metrics between the different optimal layouts is equal to 0.68% and 1.26%, for COE_{ϵ} and COE_{CO_2} , respectively. With wake steering, these values change to 2.46% and 0.70%, respectively.

3.1.3 Three-turbine wind farm

The same procedure as in the previous examples is applied to the three-turbine case, aiming to assess whether trade-offs between COE_{ϵ} and COE_{CO_2} and the potential for the co-design approach are present.

Figure 5 presents the results for the three-turbine cases. In the case of baseline operation, the second turbine is generally positioned near the midpoint between the two fixed turbines to reduce wake effects. This behavior is evident when AEP or AEP_{net} are the performance metrics, whereas the turbine is shifted left for the other metrics. The higher TLCC and TLCE associated with larger support structures at greater water depths cause these trade-offs, while the contribution of the array cables is negligible in this scenario because the total horizontal cable distance remains unchanged. The trade-offs are more pronounced for COE_{CO_2} than for COE_{ϵ} and are amplified in the high-bathymetry-difference case.

For most performance metrics, the optimal position differs between the baseline and wake steering solutions, highlighting the potential of the co-design approach. Especially for the AEP and AEP_{net} optima, this difference is evident, as wake steering shifts the optimal turbine position away from the upstream turbine. However, the objective functions remain relatively flat across the domain, indicating little design trade-off between the optimal solutions.

Moreover, the position of the turbine obtained considering COE_{ϵ} differs from the one obtained based on COE_{CO_2} . However, in the high-bathymetry-difference case, for which large differences are observed in the two-turbine case, the discrepancy becomes smaller. In general, the curves remain relatively flat around the optima. Consequently, the performance difference between the layouts optimized for either objective is small. In the baseline case with a high bathymetry difference, the maximum differences in COE_{ϵ} and COE_{CO_2} are only 0.27% and 0.34%, respectively, while even smaller differences are observed in the other cases. Therefore, although the optimal turbine spacing differs noticeably between the two single-objective optima, each

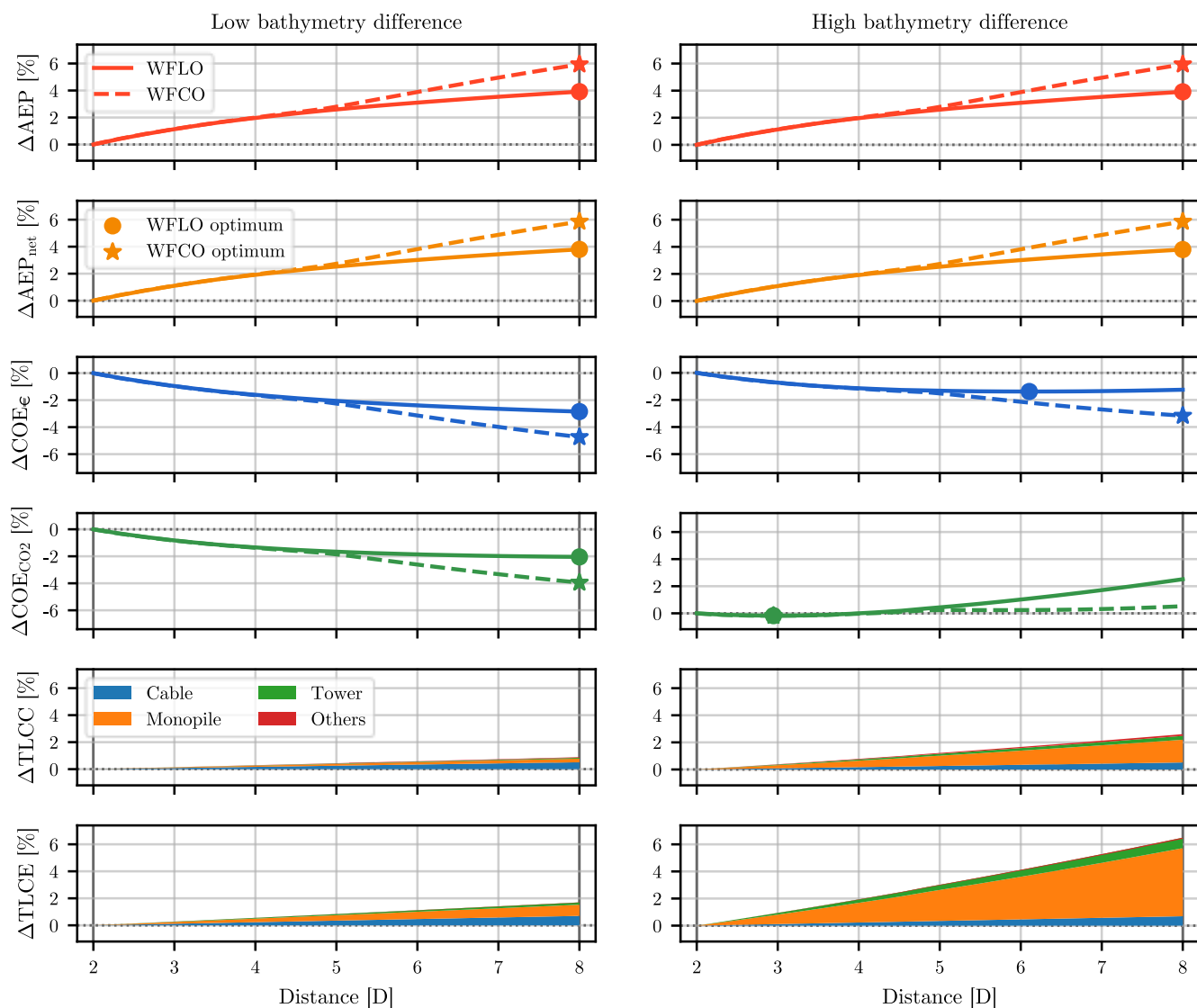


Figure 4. Two-turbine wind farm example: performance metric values as functions of the normalized position of the second turbine. The optimal position is indicated by a dot (baseline operation) or a star (wake steering). All relative changes are reported with respect to a turbine located at 2D.



design solution performs similarly with respect to the other objective. This suggests that, when both objectives are optimized simultaneously, the resulting Pareto front is relatively limited.

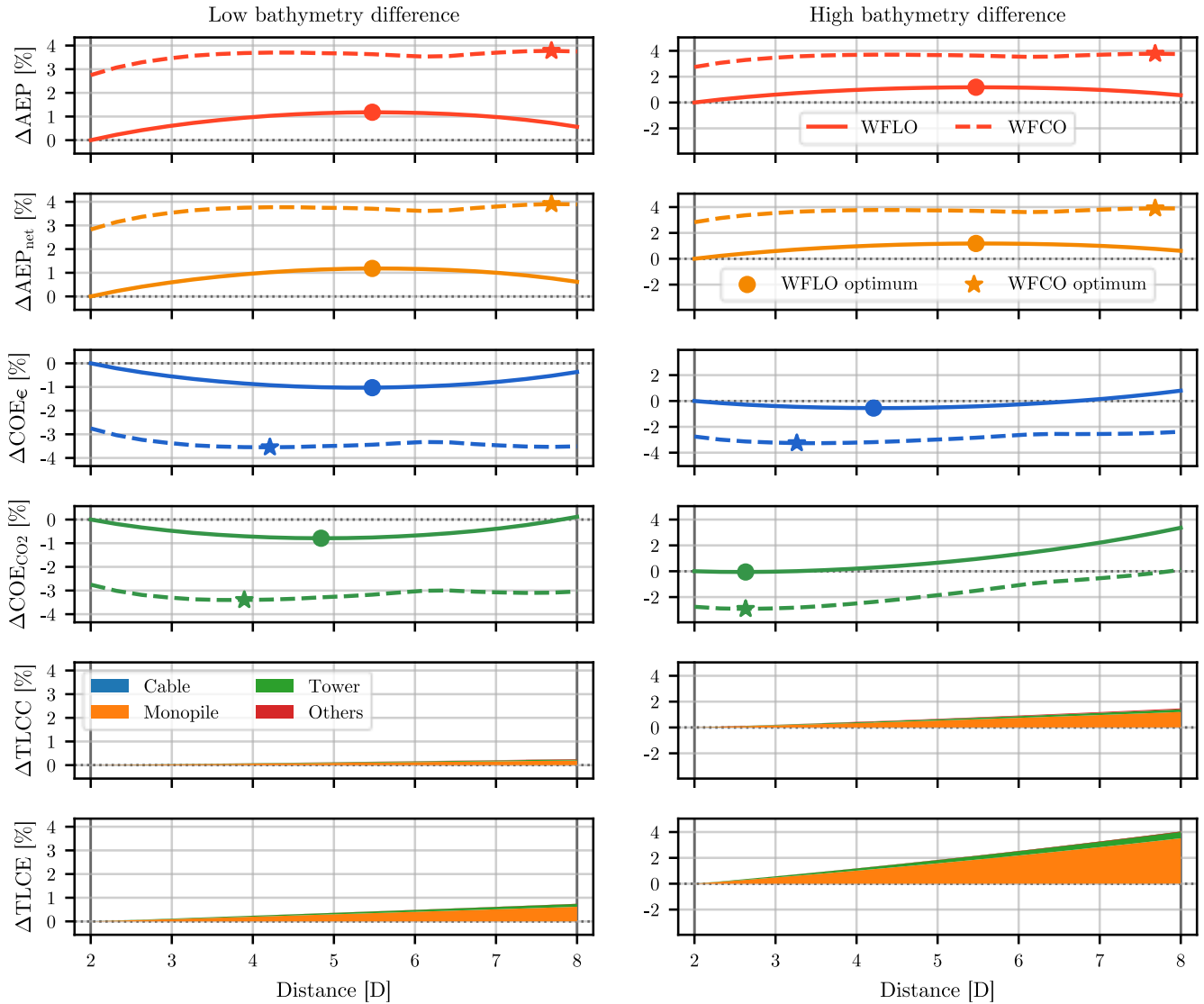


Figure 5. Three-turbine wind farm example: performance metric values as functions of the normalized position of the second turbine. The optimal position is indicated by a dot (baseline operation) or a star (wake steering). All relative changes are reported with respect to a turbine located at $2D$.

Overall, the two- and three-turbine examples show that minimizing COE_e and COE_{CO_2} during the layout design process involves trade-offs between wake losses, total array cable length, and support structure dimensions. These trade-offs may lead to different optimal turbine spacings when optimizing the individual metrics both with and without co-design. However, the



flat objective functions around the optima limit the associated trade-offs, and the differences in objective values between the resulting layouts remain small.

3.2 Re-design of the scaled HKN wind farm

3.2.1 Description of the case study

415 The second case study is a scaled representation of the offshore HKN wind farm, which serves as a baseline scenario for the rest of this study. The farm consists of 69 IEA 22-MW reference turbines. The available area Ω is obtained by scaling the distance between the original farm boundaries and the substation location according to the ratio between the diameters of the IEA 22-MW turbine and the one actually installed at HKN. This approach preserves the original power density of 6 MW km^{-2} . A similar procedure is applied to derive the bathymetry based on the original site data from EMODnet (EMODnet Bathymetry Consortium, 2024), maintaining both the spatial pattern and the depth variations of the original site, as shown in Fig. 8. The bathymetry exhibits a few shallow regions, while the overall depth range within the domain remains limited to 19–28 m.

The wind resource is described by the wind rose in Fig. 6 and the heterogeneous wind speed map in Fig. 7, based on data from Vortex (Vortex FDC, 2024). These are obtained by scaling the original HKN data to match both the hub height of the selected turbine and the resized domain, while preserving the underlying spatial patterns. The site is characterized by a dominant south-westerly wind direction, and higher average wind speeds are observed in the north-western part of the domain, which is located further offshore. For the computation of AEP and AEP_{net} , as described in Eq. (1) and Eq. (7), respectively, the wind rose is discretized with resolutions of 3° and 1 ms^{-1} for the wind direction and speed values, respectively. These resolutions provide a balance between a sufficiently detailed representation of wake interactions and computational cost during optimization.

430 Finally, the minimum inter-turbine spacing constraint is set to $d_{\min} = 4D$, to avoid mechanical interference and excessive structural loads in the near wake while maintaining sufficient design flexibility.

3.2.2 Impact on the performance metrics

The WFLO, WFFC, and WFCO are implemented using the different performance metrics considered in this study as optimization objectives. The results are presented in Fig. 9 in terms of COE_ϵ and COE_{CO_2} values. These metrics are reported both in absolute terms (left and bottom axes) and as percentage differences (right and top axes).

Three objective formulations are investigated. First, a multi-objective formulation based on COE_ϵ and COE_{CO_2} is considered, which represents the main focus of this study and enables the analysis of the trade-off between these metrics. The best-performing layouts related to each metric correspond to the extremes of the resulting Pareto front. Second, a single-objective formulation based on AEP is adopted to facilitate comparison with previous literature, as this is one of the most commonly used objectives for WFLO, WFFC, and WFCO studies. Third, AEP_{net} is considered as an intermediate single-objective to investigate the influence of layout-dependent loss mechanisms beyond wake effects on the optimal wind farm design. The latter two cases are also formulated as multi-objective optimizations that combine either AEP or AEP_{net} with COE_ϵ . The solution

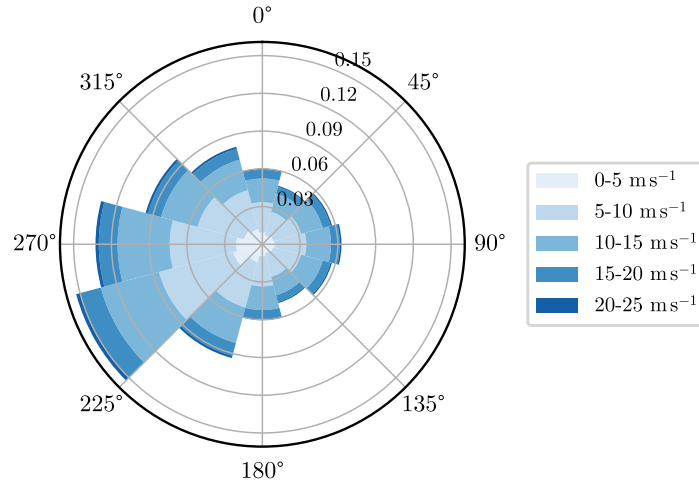


Figure 6. Wind rose for the selected case study, referred to the location of the substation.

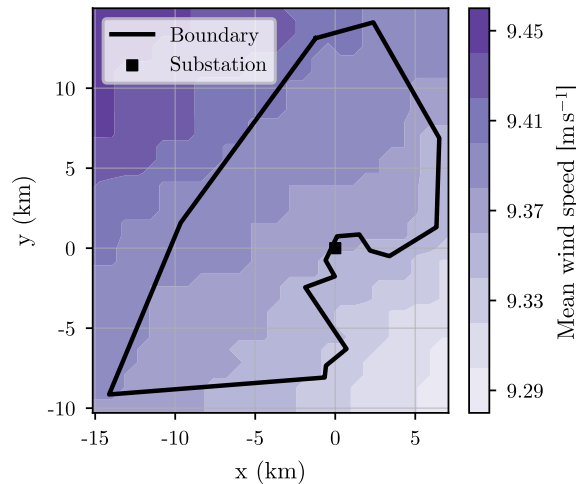


Figure 7. Average wind speed profile for the selected case study.

characterized by the highest AEP or AEP_{net} is then selected from the resulting Pareto front. This approach avoids potential biases when comparing single- and multi-objective formulations, whose implementations differ slightly within the LO-GA.

445 For each case, 10 independent optimization runs are performed to account for the multimodality of the optimization problem and reduce the dependence of the results on the initial populations. This results in 10 solutions, or 10 Pareto fronts for the multi-objective cases. Among these solutions, the best-performing one is identified according to the performance metric adopted as objective and is highlighted in Fig. 9. In case a Pareto front is present, both extrema of the Pareto front are highlighted. Since AEP is widely used in the context of WFLO, WFFC, and WFCO, the best-performing AEP-optimized layout is used as a
 450 reference to calculate the percentage difference for all the results included in Fig. 9, as highlighted by the dotted lines.

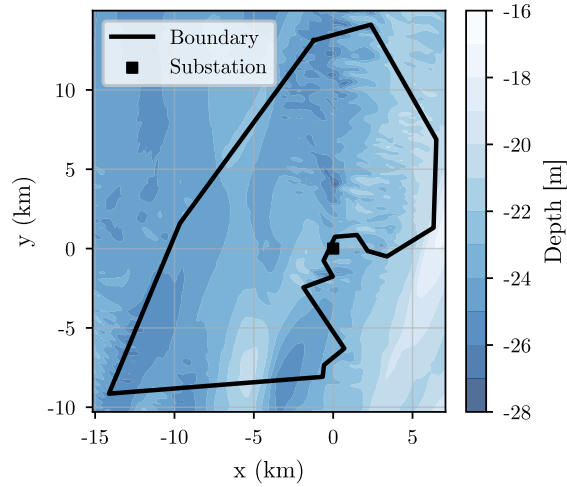


Figure 8. Bathymetry profile for the selected case study.

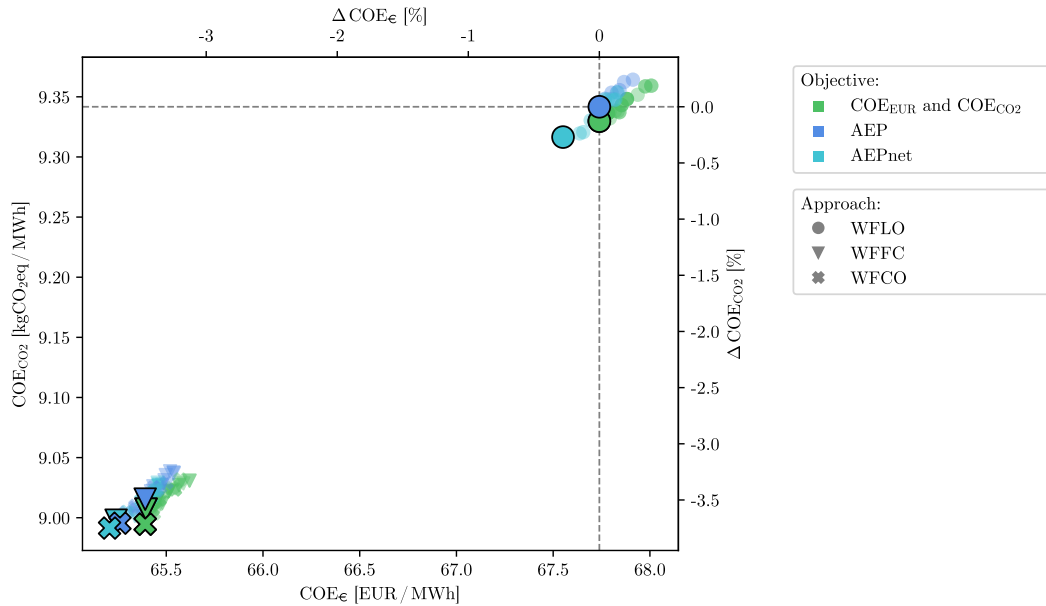


Figure 9. Impact of WFLO, WFFC, and WFCO on the COE_e and COE_{CO_2} . Each datapoint corresponds to a layout obtained from WFLO without WFFC (dots), the same layout with WFFC (triangles), or a layout obtained from WFCO with WFFC (crosses). The color of each datapoint indicates the objective adopted during the optimization. The best-performing layout is highlighted with larger markers and darker edges for each case.

The results of the WFLO are shown in the top-right corner of Fig. 9. First, no distinct Pareto front emerges for the multi-objective optimization of COE_e and COE_{CO_2} . Instead, the extreme solutions coincide, as indicated by the single visible green



marker, demonstrating that minimizing either objective results in the same design solution. Therefore, these two objectives appear to be strongly correlated, with no trade-off between them. When analyzing the results associated with the AEP objective, it is observed that the best-performing layout yields higher values of COE_{ϵ} and COE_{CO_2} than those obtained from the multi-objective COE_{ϵ} – COE_{CO_2} optimization, indicating a slightly worse performance. This confirms that optimizing using a simplified objective based solely on AEP (derived from wake losses) leads to suboptimal solutions when evaluated against COE_{ϵ} and COE_{CO_2} . However, these differences remain negligible, on the order of 0.13% for both metrics. Conversely, the best-performing layout obtained from the AEP_{net} optimization exhibits lower values of COE_{ϵ} and COE_{CO_2} compared to the multi-objective case, indicating improved performance. This behavior can be attributed to two main factors. First, the inclusion of additional components in the COE_{ϵ} and COE_{CO_2} formulations increases the complexity of the design space, thereby enhancing the multimodality of the optimization problem and potentially hindering convergence. Similar effects have been reported in the WFLO literature, for example, by Dirik et al. (2025), when incorporating yaw approximations or electricity price variations into the AEP calculation. Second, the structure of the LO-GA favors objective functions that can be expressed as a linear sum of turbine-wise contributions, as is the case for AEP and AEP_{net} (Baricchio et al., 2024). This property does not hold for more complex aggregated metrics such as COE_{ϵ} and COE_{CO_2} , which may further explain the observed differences in performance, especially during the refinement stage. Overall, the best-performing layouts obtained with the different objectives are within 0.28% in COE_{ϵ} and COE_{CO_2} , demonstrating that the choice of the studied objective functions for the WFLO has limited impact in terms of these performance metrics.

Figure 9 also quantifies the impact of WFFC on the performance metrics COE_{ϵ} and COE_{CO_2} . The corresponding values, obtained by applying WFFC to the layouts generated by WFLO, are indicated by triangular markers, following the same color and size conventions used for the WFLO results. A trend consistent with the WFLO outcomes regarding the choice of objective function is observed. This is expected, as WFFC only increases AEP, which contributes in a similar way to all considered metrics. As a result, reductions of up to 3.69% and 3.58% are achieved for COE_{ϵ} and COE_{CO_2} , respectively, highlighting the substantial benefits of WFFC. These percentage differences are reported relative to an AEP-optimized layout in which WFFC is not applied. Furthermore, the improvement relative to the WFLO-only results appears to be systematic. The clusters of data points associated with WFFC are clearly separate from those corresponding to WFLO alone, regardless of the selected optimization objective or the specific optimization run. This consistent separation indicates that the application of WFFC robustly enhances performance across all cases considered for this particular wind farm.

Lastly, Fig. 9 includes the results obtained with the WFCO approach, indicated by cross-shaped markers. These correspond to new layouts compared to those obtained with WFLO and subsequently evaluated with WFFC. It can be observed that the best-performing layouts are slightly shifted towards the bottom-left region of the plot, indicating an overall improvement compared to the sequential application of WFLO and WFFC. However, this improvement is negligible, with a maximum reduction of 3.74% in COE_{ϵ} and 3.75% COE_{CO_2} , achieved with respect to the AEP-optimized layout under baseline operation. Furthermore, no clear separation can be observed between the clusters of points obtained with WFLO followed by WFFC and those obtained with WFCO. This suggests that the additional benefits introduced by WFCO are not systematic, but rather depend on the specific optimization run.

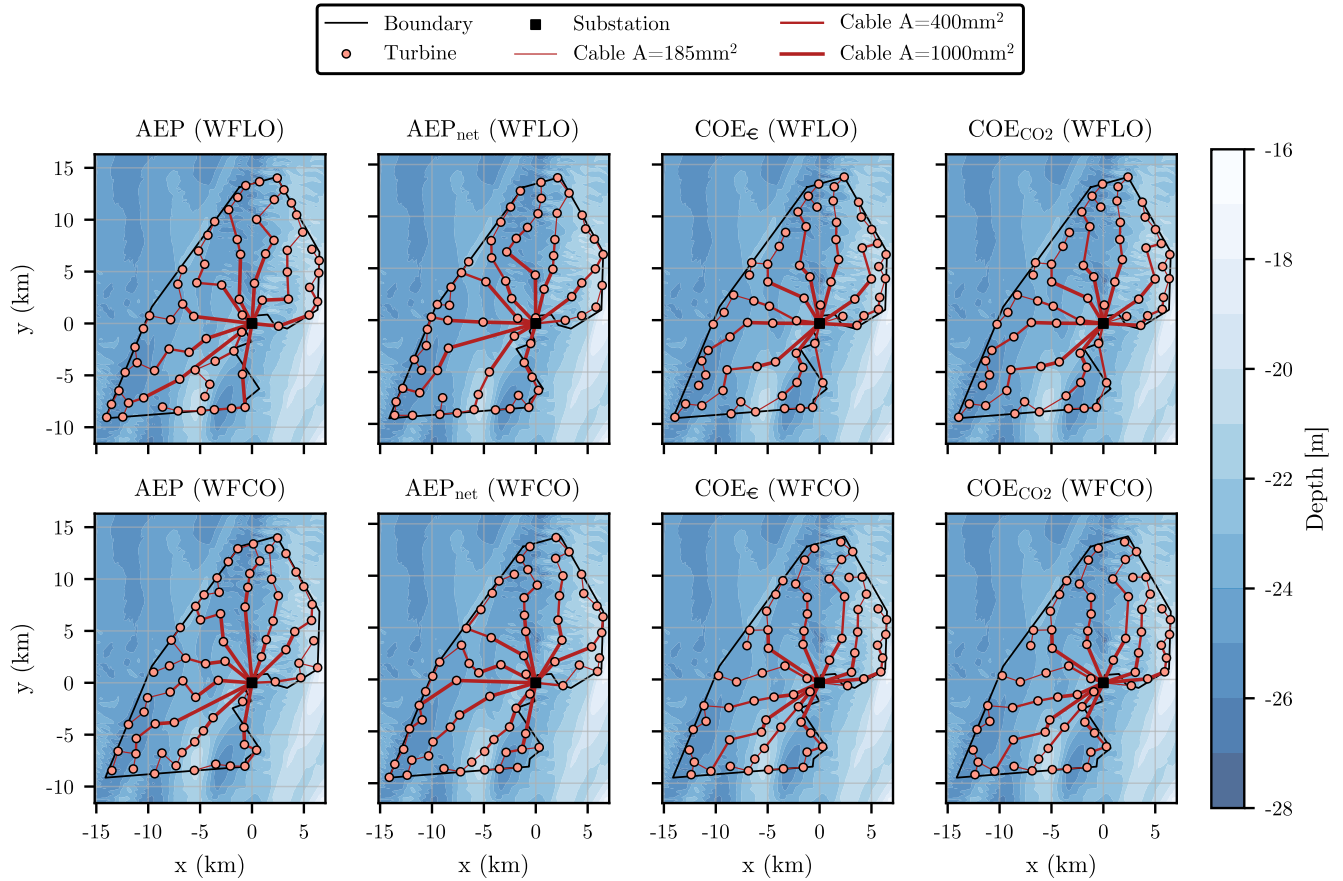


Figure 10. Best-performing layouts obtained for the four objective functions using the WFLO approach (first row) and the WFCO approach (second row).

3.2.3 Cost and emission breakdown and impact on the layouts

Figure 10 presents the best-performing layouts corresponding to the four different objective functions following the WFLO approach (first row) and the WFCO approach (second row). For each of the best-performing layouts, Fig. 11 presents a detailed breakdown of the performance metrics, expressed as percentage changes relative to the AEP-optimal layout obtained from WFLO, which serves as the baseline. To relate the relative changes achieved through the WFCO approach to the sequential WFLO-WFFC design approach, the performance of the sequentially optimized baseline layout (WFFC) is included. The first row shows the changes in the key design indicators identified in the two- and three-turbine examples, namely the array cable length and the masses of the monopiles and towers. The second row presents the corresponding changes in the main contributors to the performance metrics, including the TLCC and TLCE broken down by components, as well as the AEP_{net} decomposed into the individual energy-loss contributions, where higher values correspond to lower losses in the respective category.

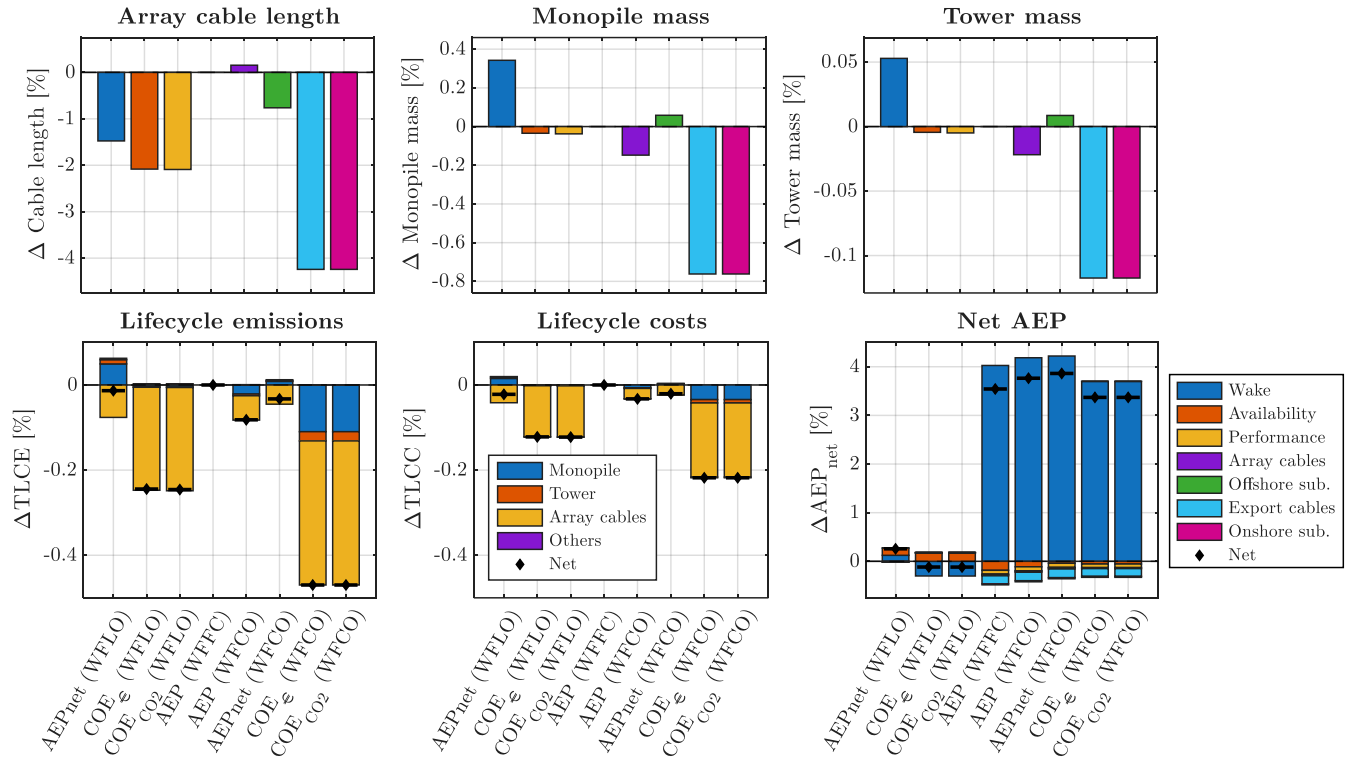


Figure 11. Breakdown of the different objective functions and design approaches by their key design indicators and contributors, compared to the AEP-optimal solution following the WFLO approach. The first row shows the changes in the key design indicators, namely array cable length and the masses of the monopiles and towers. The second row presents the corresponding changes in TLCC and TLCE, broken down by component, as well as the changes in the individual energy-loss contributions to AEP_{net} . Diamond markers indicate the corresponding net change for each objective. The performance of the sequentially optimized baseline layout (WFFC) is included for comparison to relate the relative changes achieved through the WFCO approach.

For both the AEP and AEP_{net} objectives, the optimized layouts follow the classic perimeter-weighted design, where turbines are preferentially placed along the boundary of the wind farm. The minimum spacing constraint of $4D$ limits the extent to which this pattern can be realized. Compared with the AEP-optimal layout, the AEP_{net} -optimal layout exhibits straighter array cable connections, resulting in a shorter total cable length and lower availability losses associated with the array cables. In addition, wake interactions are slightly reduced. Since the objective does not account for the support structure, the monopile dimensions – and thus the associated costs and emissions – can increase without penalty.

The layouts optimized for COE_{ϵ} and COE_{CO_2} are identical. Compared with the AEP-based layouts, the turbines are positioned slightly further inside the wind farm and are less concentrated along the perimeter, particularly in regions of greater water depth. This redistribution reduces the total array cable length and the dimensions of the support structures, thereby



Table 4. Case studies for the sensitivity analysis

Case study name	Abbreviation	Power density	Bathymetry pattern	Bathymetry range
Baseline (scaled HKN)	BL	6 MW km^{-2}	Same as HKN	19 m – 28 m
Low power density	LPD	3 MW km^{-2}	Same as HKN	19 m – 28 m
High power density	HPD	18 MW km^{-2}	Same as HKN	19 m – 28 m
High bathymetry difference	HBD	6 MW km^{-2}	Same as HKN	20 m – 60 m
High sloped bathymetry difference	HSBD	6 MW km^{-2}	Sloped	16 m – 56 m

decreasing the associated costs, emissions, and cable availability losses. These improvements are achieved at the expense of increased wake losses, reflecting the trade-off between energy production and infrastructural emissions and costs.

Applying the sequentially optimized WFFC approach increases the AEP of the baseline by approximately 3.5 % through reduced wake losses. This additional energy production is accompanied by small increases in other energy losses, which, however, remain substantially smaller than the reduction in wake losses. Since the objective function formulations used in this study do not account for the impact of WFFC on TLCE and TLCC, these quantities remain unchanged.

For the co-designed layouts optimized for AEP and AEP_{net} , the turbines are distributed more evenly across the design space, with fewer turbines located along the perimeter and more in the interior of the wind farm. This control-aware distribution reduces wake interactions and provides a small improvement compared with the sequential optimization approach.

The co-designed layouts optimized for COE_e and COE_{CO_2} are again identical. Compared with the WFLO approach, the control-aware optimization allows turbines to be placed in shallower water and in configurations with shorter array cables while maintaining low wake losses. This reduces the costs and emissions associated with the support structures and array cables. Although the AEP is substantially improved through wake steering, the infrastructure-related cost and emission reductions are achieved at the expense of some AEP gains that could be obtained when solely maximizing AEP during the design optimization.

3.3 Parametric studies

3.3.1 Description of the case studies

Four additional case studies are considered to investigate potential conflicts between the different performance metrics and their corresponding layouts. These consist of modified versions of the baseline case study, i.e., the scaled HKN wind farm, either related to the power density or to the bathymetry profile. The relevant characteristics of each case study are summarized in Table 4, which also includes those corresponding to the baseline case study to facilitate comparison. Table 4 also introduces abbreviations for each case study that are adopted in the remainder of the manuscript.

First, the power density of the baseline case study is modified, obtaining both a low and a high power density scenario. This is achieved by re-scaling the position of the boundary edges for the designated wind farm area with respect to the position of the substation, as shown in Fig. 12. In the high density case, the minimum distance constraint d_{min} is reduced to $2D$. Second,

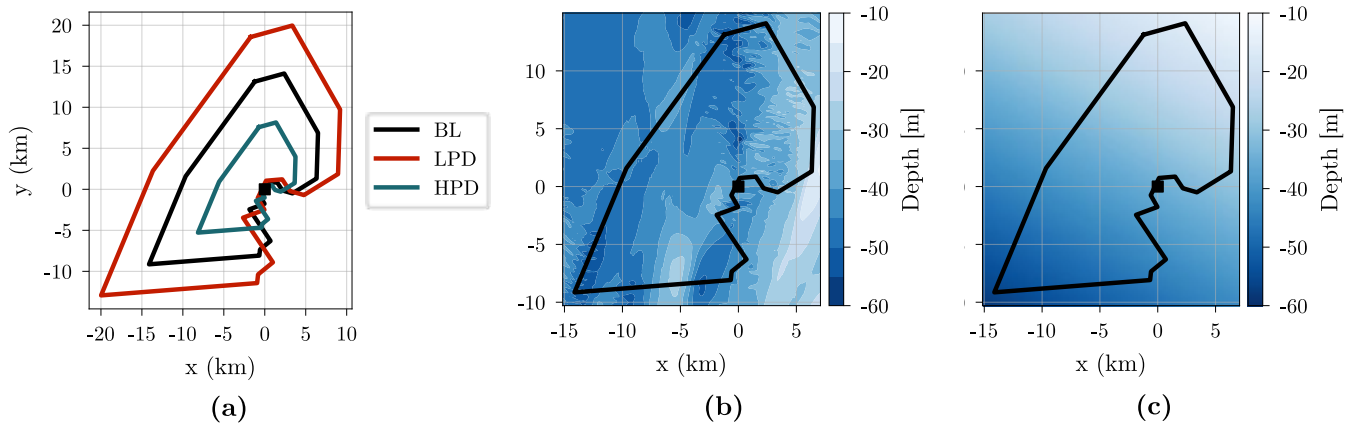


Figure 12. Relevant characteristics of the case studies introduced for the sensitivity analysis: (a) farm boundaries for the HPD and LPD case studies compared to the BL, (b) bathymetry profile of the HBD case study, and (c) bathymetry profile of the HSBD case study.

the bathymetry profile of the domain is modified, increasing the difference in water depth between the different regions, as depicted in Fig. 12. In this case, the bathymetry pattern from the baseline domain is preserved, and the magnitude of the water depth is varied from 10m to 60m over the region where the farm is located, resulting in a range of 20 – 60m within the farm designated area. Lastly, the bathymetry pattern is also modified, introducing a sloped bathymetry profile aligned with the dominant wind direction. Specifically, the bathymetry range of this case study amounts to 16 – 56m within the farm designated area, and is shown in Fig. 12.

These characteristics for the case studies are chosen to allow for a sensitivity analysis on the variables that are relevant to the scope of this study. Specifically, Baricchio et al. (2024) showed that the power density of a wind farm significantly affects the benefits introduced by a control-layout co-design approach targeting AEP maximization. On the other hand, since the water depth plays a pivotal role in both the cost and the emission of the support structures of the turbines, different ranges and profiles are tested.

3.3.2 Impact on the performance metrics

The results are obtained following the same procedure adopted for the baseline scenario described in Sect. 3.2.2, with the difference that only one objective formulation is considered, namely the multi-objective optimization of COE_{ϵ} and COE_{CO_2} . Unlike Sect. 3.2.2, the results are not combined into a single figure but are presented separately in two figures described in the next paragraphs. Specifically, Fig. 13 shows the WFLO results for the different case studies, while Fig. 14 illustrates the impact of WFFC and WFCO on the resulting COE_{ϵ} and COE_{CO_2} values.

Figure 13 presents the WFLO results for the different case studies, including the baseline scenario (BL). The BL results correspond to the COE_{ϵ} and COE_{CO_2} values shown in the top-right corner of Fig. 9. Analogously to Fig. 9, the best-performing layouts in terms of COE_{ϵ} and COE_{CO_2} are highlighted for each case study. These correspond to the extrema of a Pareto

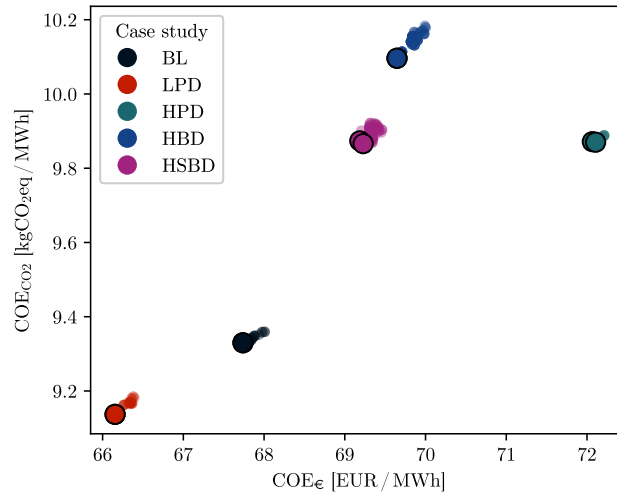


Figure 13. Impact of WFLO on the COE_e and COE_{CO_2} for the different case studies. Each data point corresponds to a layout resulting from a multi-objective optimization using COE_e and COE_{CO_2} as targets. The best-performing layouts in terms of both metrics are highlighted with larger markers and darker edges for each case.

front obtained from 10 independent optimization runs. Similar to the BL case, it can be observed that no distinct Pareto front is obtained for all case studies. Specifically, the layouts achieving the best COE_e and COE_{CO_2} values almost overlap, as each optimization run either converges towards a single solution or produces a Pareto front confined within a narrow region. Therefore, the conclusions drawn from the BL analysis can be extended to the additional case studies: the choice between COE_e and COE_{CO_2} as WFLO objectives has a negligible influence on the resulting layouts when evaluated according to these performance metrics.

Figure 14 presents the benefits of applying WFFC and WFCO compared to the WFLO-only approach. The BL results are also included to enable a direct comparison with the additional case studies. In contrast to Fig. 9, the multiple optimization runs are represented using boxplots, with the impact on COE_e and COE_{CO_2} shown in the first and second rows, respectively. To ensure a consistent comparison among Pareto fronts with different numbers of solutions, though characterized by nearly identical COE_e and COE_{CO_2} values, the boxplots in Fig. 14 are generated using the following procedure. Each boxplot contains 10 data points, each corresponding to one independent optimization run. For each run, the best-performing layout is selected according to the performance metric considered in the corresponding row, namely COE_e for the first row and COE_{CO_2} for the second row. This approach does not consider potential trade-off solutions between COE_e and COE_{CO_2} . However, Fig. 13 shows that such trade-offs are not significant for the considered case studies. The results are expressed both in absolute terms and percentage differences. In the latter case, these are calculated with respect to the best-performing layout obtained from WFLO under baseline operation. In addition to the boxplots, the best-performing layouts obtained with WFLO, WFFC, and WFCO are highlighted, enabling conclusions both from a statistical perspective, by assessing whether observed trends are systematic, and from a practical perspective, where only the best achievable layout is relevant.

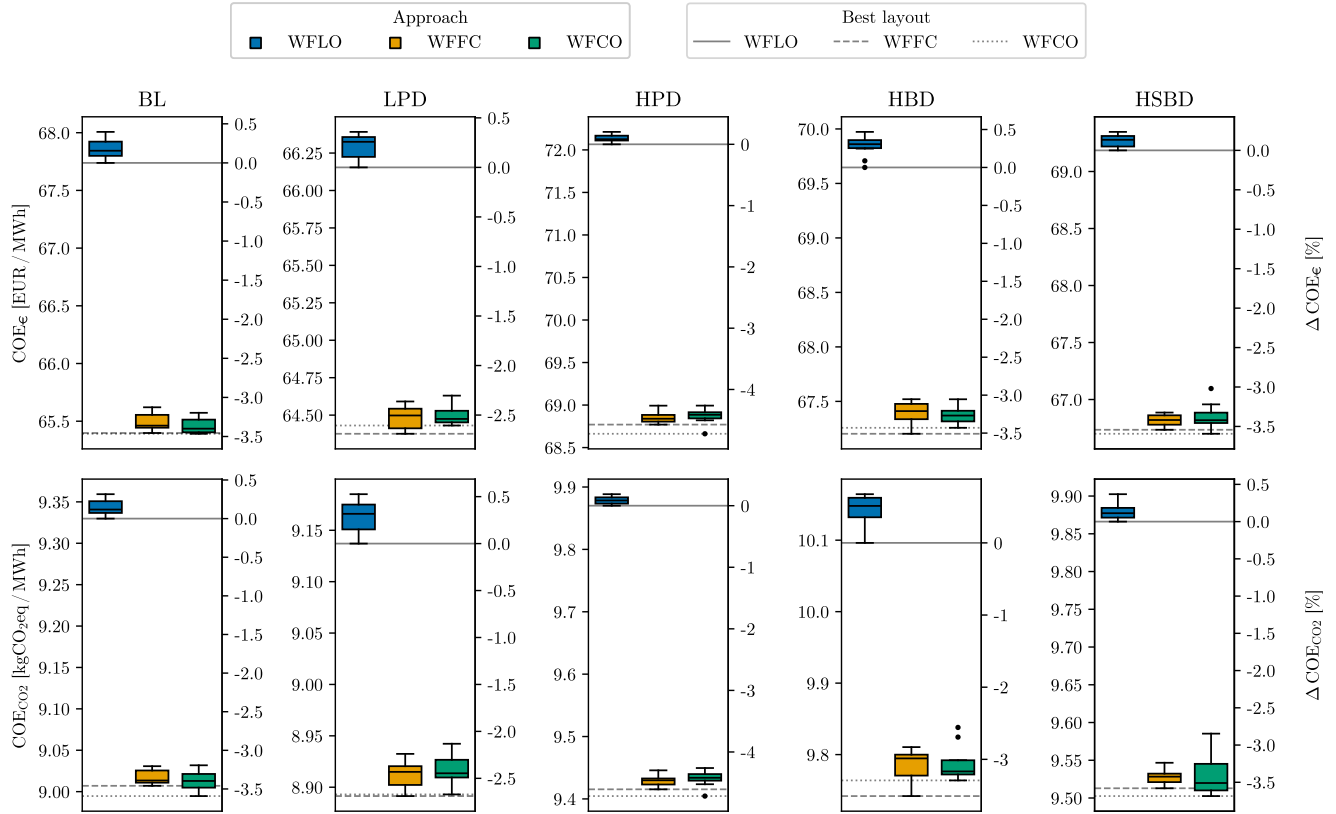


Figure 14. Impact of WFFC and WFCO on the COE_e (first row) and COE_{CO_2} (second row) for the different case studies. The boxplots originate from 10 independent optimization runs. The WFLO-, WFFC-, and WFCO- resulting values are distinguished using different colors, and the best-performing layouts for each approach are indicated using horizontal lines.

570 The results shown in Fig. 14 indicate that WFFC provides significant reductions in both COE_e and COE_{CO_2} for all investigated case studies. However, the magnitude of these reductions depends on the specific site characteristics, particularly the wind farm power density. Specifically, reductions of up to 4.57% in COE_e and 4.61% in COE_{CO_2} are obtained for the HPD case, whereas the improvement is limited to 2.69% for both metrics in the LPD scenario. The clear separation between the boxplots obtained with WFLO and WFFC demonstrates both the effectiveness and the robustness of WFFC across different

575 optimization runs and performance metrics.

Conversely, the impact of WFCO is negligible compared with the sequential WFLO–WFFC approach across all investigated cases. As already observed in Fig. 9, the best-performing layouts of the BL obtained with WFCO yield slightly lower COE_e and COE_{CO_2} , but the additional improvement is minimal. Moreover, the BL results shown in Fig. 14 indicate that this trend is also reflected in the median values. This suggests that, from a statistical perspective, adopting WFCO leads to a performance

580 increase, but the difference in median values remains minimal (below 0.04%). However, these trends are not consistent across



all cases. Whether the best performance is achieved using the sequential WFLO–WFFC approach or WFCO depends on the specific case, the chosen metric, and whether best-performing or median values are considered. For instance, in the HPD case, a comparison of the best-performing layouts shows that WFCO can enhance the gains from WFFC, leading to an additional reduction of up to 0.15% in COE_{ϵ} and 0.11% in COE_{CO_2} . However, this effect is not observed when comparing median values. Therefore, it can be concluded that, even when present, the additional benefits of WFCO are not consistent across different optimization runs.

3.3.3 Cost and emission breakdown and impact on the layouts

Figure 15 shows the best-performing layouts obtained for each parametric study and objective function using both the WFLO and WFCO approaches. Figure 16 presents the corresponding breakdowns of the TLCC, TLCE, and AEP_{net} for each layout, expressed as relative changes with respect to the COE_{ϵ} -optimal layout following the WFLO approach, which serves as the baseline. The TLCC and TLCE are further decomposed into their component contributions, while the AEP_{net} is decomposed into the individual energy-loss contributions responsible for the differences in energy production.

For the LPD scenario, the larger design area allows the turbines to spread further apart, thereby reducing wake interactions. Consequently, the relative importance of the array cable length and monopile dimensions increases, resulting in less perimeter-weighted layouts. The COE_{ϵ} and COE_{CO_2} optima are identical. For the co-designed COE_{ϵ} optimum, the AEP increases by approximately 2.8% through reduced wake interactions. This gain comes at the expense of larger support structures and longer array cables, resulting in higher associated costs and emissions. The co-designed COE_{CO_2} optimum achieves a smaller AEP gain of approximately 2.5%, but significantly reduces the monopile dimensions by moving turbines towards shallower water. This results in a more favorable balance between wake losses and emissions related to the support structure. The array cable length remains largely unchanged.

For the HPD scenario, the smaller design area results in stronger wake interactions. Thereby, wake losses become more dominant in the layout optimization, whereas infrastructure-related effects become less influential. Consequently, the layouts show a strong perimeter weighting, with turbines placed preferentially along the boundary to reduce wake interactions. The COE_{CO_2} optimum differs from the COE_{ϵ} optimum. The associated monopile dimensions are smaller, but wake interactions are increased, reflecting a different trade-off between infrastructure requirements and energy production. The co-designed layouts are identical for both objectives, with the main gains resulting from reduced wake interactions.

For the HBD scenario, the COE_{ϵ} and COE_{CO_2} optima are identical and clearly avoid the deeper regions of the designated area, with two particularly pronounced areas on the left that remain unoccupied. The layouts indicate that avoiding deeper waters, associated with increased support structure costs and emissions, is more beneficial than placing turbines there to reduce wake interactions. The co-designed layouts are similar but not identical. An AEP gain of approximately 3.6% is achieved by moving several turbines towards deeper waters. In this case, the benefit of increased energy production outweighs the additional support structure costs and emissions up to the resulting optimum. Furthermore, these layouts result in a more favorable array cable configuration, which further offsets the additional support structure requirements associated with relocating turbines to deeper waters.

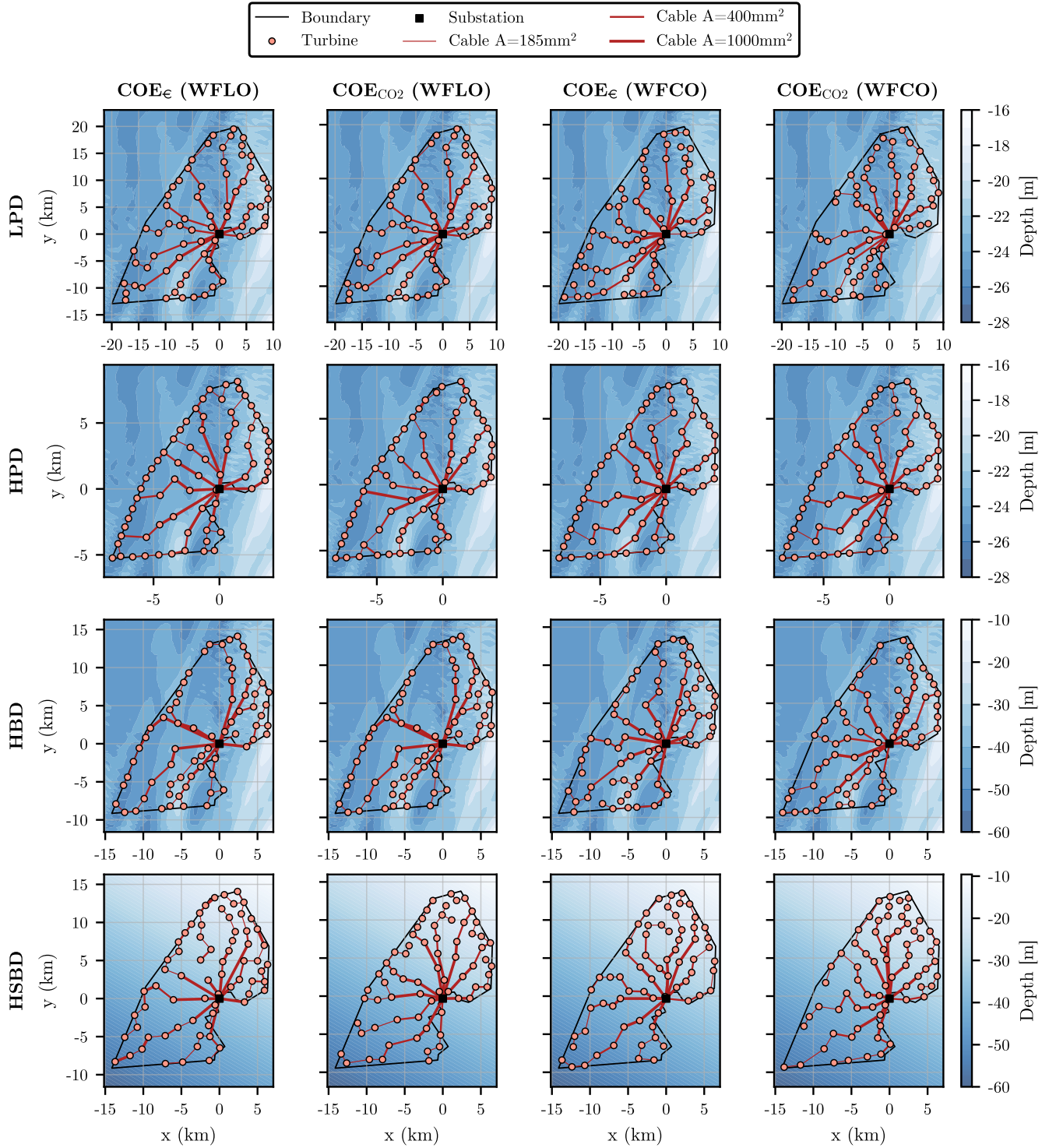


Figure 15. Best-performing layouts per parametric study obtained for the two objective functions using the WFLO and the WFCO approach.

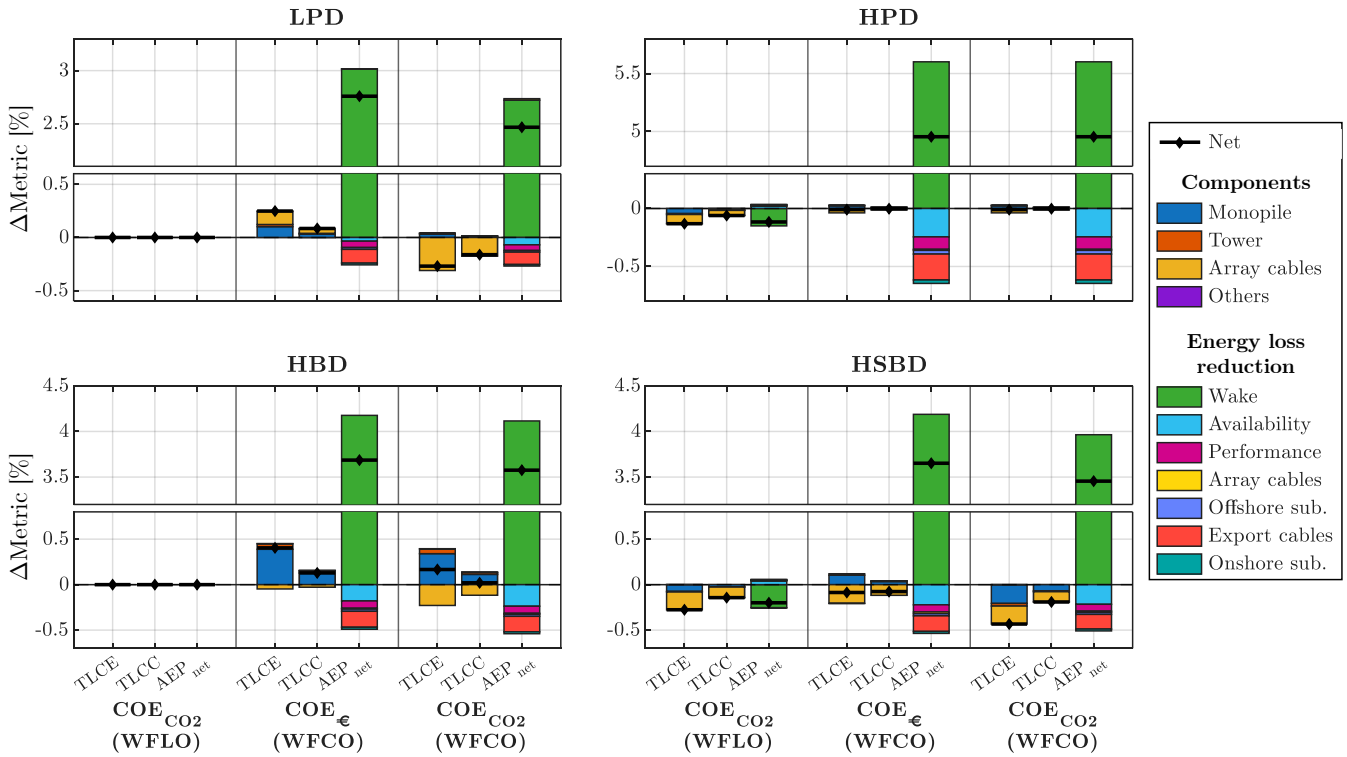


Figure 16. Relative changes in TLCC, TLCE, and AEP_{net} for the best-performing layouts following the different design approaches and objective functions per parametric study, compared to the respective best-performing COE_e -layout per parametric study designed under the WFLO approach. TLCC and TLCE are broken down by components, and AEP_{net} by the energy loss categories contributing to the variations. For improved readability, a discontinuous y-axis scale is used to accommodate the large range of values.

Similarly, the best layouts for the HSD scenario tend to avoid deeper waters, although some turbines remain in these regions to reduce wake interactions within the wind farm. The COE_{CO_2} optimum has lower array cable and monopile costs and emissions than the COE_e optimum, but also a lower AEP, reflecting a different trade-off between energy production and infrastructure requirements. The co-designed COE_e optimum achieves an AEP gain of approximately 3.6%, featuring shorter array cables, but causes slightly higher monopile costs and emissions. For COE_{CO_2} , the AEP gain is approximately 3.5%, while both array cable and monopile costs and emissions are further reduced. In this case, turbines appear to move further away from deeper waters, while wake steering reduces the associated wake interactions.

4 Discussion

The results presented in this study suggest that the considered optimization approaches for designing wind farm layouts have only a marginal influence on the performance of the resulting layouts. Regardless of the investigated objective formulation



(AEP, AEP_{net} , COE_{ϵ} , or COE_{CO_2}) or whether WFLO or WFCO is employed, the resulting wind farm layouts exhibit very similar performance across the considered metrics. This observation is consistent across all investigated case studies. In most cases, no clear Pareto fronts can be identified, or, when present, the differences between the solutions in terms of performance metrics remain negligible. Similarly, the benefits obtained from WFFC cannot be significantly increased through WFCO. Moreover, in some cases, adopting more complex objective formulations even leads to slightly lower performance values. This behavior is likely related to the increased complexity of the design space introduced by the additional terms included in the objective functions, which may hinder the convergence of the optimization algorithm.

However, analyzing only the objective function values does not fully capture the influence of the design approaches on the resulting layouts. When the turbine positions are directly investigated, it emerges that the optimized layouts are sensitive to both the selected objective formulation and the inclusion of wake steering during the layout design phase, even when the associated performance metrics are nearly identical. This behavior can already be observed in the simplified two- and three-turbine examples, where the gradients of the objective functions with respect to turbine positions become relatively flat around the optima. Therefore, multiple substantially different layouts can represent solutions that are almost equally optimal.

The same behavior is observed in the realistic case studies. Compared with AEP-optimized layouts, the adoption of AEP_{net} shifts the optimization towards layouts with reduced cable lengths, thereby decreasing electrical losses and downtime-related effects. When COE_{ϵ} or COE_{CO_2} are selected as objectives, lower bathymetry regions are increasingly favoured, with this effect being more pronounced for COE_{CO_2} . Finally, the additional energy yield obtained through WFCO further increases the importance of wake losses as a design driver: infrastructure-related costs and emissions become relatively less influential, allowing solutions with higher costs or emissions if they enable further improvements in energy production.

These observations remain valid when varying the wind farm characteristics. In general, the resulting layouts represent a trade-off between wake losses, support structure dimensions, and cable length. Wake losses are generally the dominant driver, although their relative importance decreases for low power density cases, where weaker wake interactions increase the influence of infrastructure-related costs and emissions. Conversely, for high power density cases, wake loss minimization becomes increasingly dominant. For larger bathymetry variations, support structure dimensions become more influential, leading to turbine positions that favour shallower regions at the expense of energy yield.

Overall, these results highlight the multimodal nature of the WFLO problem, where different turbine configurations can achieve comparable objective function values. Changes in the objective formulation or the inclusion of WFCO modify the structure of the design space and influence which of the multiple local optima is identified by the optimization algorithm. Therefore, apparently negligible differences in performance metrics can still correspond to relevant variations in the resulting turbine positions, with potential implications for subsequent design stages.

5 Conclusions

This study investigated the influence of incorporating carbon emissions into wind farm layout optimization and wind farm control-layout co-design, to move beyond a purely economic-driven wind farm design approach. Carbon emissions were in-



cluded through the COE_{CO_2} performance metric, whose impact was compared against more traditional alternatives, namely AEP, AEP_{net} , and $\text{COE}_{\text{€}}$. The analysis was performed across different case studies, ranging from illustrative examples involving two or three turbines to a realistic 69-turbine offshore wind farm. For the latter, additional case studies were investigated by varying relevant site characteristics, including power density and bathymetry variations.

The results showed that the choice of objective formulation has a limited impact on the resulting performance metrics. In particular, no significant conflict was observed between economic and environmental objectives, since layouts optimized for COE_{CO_2} achieved comparable performance to those optimized for AEP and $\text{COE}_{\text{€}}$. Similarly, the adoption of WFCO did not provide substantial additional improvements compared with the sequential application of WFLO and WFFC, indicating that these design choices have limited influence when evaluated solely based on aggregated performance metrics.

However, analyzing the resulting turbine positions revealed that these design choices do influence the optimized layouts. Compared with AEP-optimized solutions, layouts obtained with $\text{COE}_{\text{€}}$ and COE_{CO_2} tend to favor reduced cable lengths and lower bathymetry regions, with these effects being more pronounced when environmental impacts are included in the objective. Conversely, when WFCO is adopted, the additional energy yield obtained through wake steering becomes the dominant driver, leading the optimization to prioritize wake loss reduction over increased infrastructure-related costs and emissions.

Overall, the results demonstrate that, although the different design choices investigated in this study lead to different layouts, these differences do not translate into significant variations in the resulting performance metrics. This indicates that the investigated objectives are largely aligned, and that the AEP-optimal layout is generally close to the economic- and environmental-optimal solution. Therefore, incorporating carbon emissions into the WFLO objective does not introduce significant conflicts with conventional economic-based design approaches. Within the scope of the investigated layout design choices, this suggests that conventional wind farm design approaches inherently lead to layouts with favorable environmental performance. This is a significant finding, because it indicates that current wind farm design practices already support the decarbonization of the energy system to the extent possible. Additionally, this also means that it might not be necessary to economically incentivize the reduction of carbon emissions in the design of future wind farms, because a minimal carbon footprint is automatically achieved when pursuing the best economic performance. This appears to be a lucky – possibly rare – situation, because in general one might expect to have to pay a price in order to achieve a non-economic benefit. In fact, this was precisely the case of the eco-conscious wind turbine of Canet et al. (2023), who showed – for onshore wind turbine design – the existence of a significant reduction of the carbon footprint at the price of a slightly reduced economic performance.

However, important opportunities for further reductions in the environmental impact of wind farms do remain through technological advances beyond layout optimization, including low-carbon technologies and supply chains, such as low-emission steel production or sustainable fuels for installation vessels.

In the context of wind farm design, future work should investigate the impact of including carbon emissions – but, clearly, also additional environmental metrics – in other design decisions, such as turbine selection and the number of turbines, potentially combined with different operational strategies through WFCO. Furthermore, future optimization approaches should consider environmental value-oriented metrics beyond the limited horizon of a single wind farm, for example, by quantifying the displacement of fossil power generation through wind energy within the wider energy system.



Code and data availability. The software used in this study, together with the optimization results and the data underlying the figures, is available at <https://doi.org/10.5281/zenodo.23036193>.

695 *Author contributions.* Matteo Baricchio: conceptualization, methodology, software, validation, investigation, visualization, writing – original draft. Samuel Kainz: conceptualization, methodology, software, validation, investigation, visualization, writing – original draft. Matteo Baricchio and Samuel Kainz contributed equally to this study, with MB focusing mainly on the optimization framework and the co-design formulation, and SK on the economic and environmental performance metrics. Jan-Willem van Wingerden: conceptualization, methodology, investigation, supervision, resources, funding acquisition, writing – review & editing. Carlo L. Bottasso: conceptualization, methodology,
700 investigation, supervision, resources, funding acquisition, writing – review & editing.

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