



Assessing the eco-efficiency of offshore wind energy using a combined life cycle assessment and data envelopment analysis approach

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Abstract

This study develops an integrated Life Cycle Assessment (LCA)–Data Envelopment Analysis (DEA) framework to evaluate the material eco-efficiency of 20 operational offshore wind farms in the United Kingdom. The framework incorporates a contribution-analysis step to identify the most environmentally relevant inventory flows before efficiency assessment. Harmonised cradle-to-grave inventories were constructed from the MEAOW model and remapped to ecoinvent v3.12 background processes. Environmental impacts were quantified using ReCiPe 2016 Midpoint (H), covering 18 impact categories, in SimaPro. Contribution analysis identified five dominant physical material inputs: low-alloy steel (49.37%), copper (21.99%), chromium steel (2.98%), glass fibre (2.26%), and aluminium (2.05%). These materials were incorporated into an input-oriented Slack-Based Measure DEA model under variable returns to scale, using lifetime electricity generation as the output. Nine wind farms were classified as efficient, whereas the remaining eleven obtained efficiency scores between 0.584 and 0.795. Material-specific reduction targets were transferred to the corresponding life-cycle inventories while holding electricity generation and non-DEA inventory flows constant. A second LCA showed reductions across all 18 impact categories for every inefficient wind farm. Median improvements ranged from 8.85% for fossil resource scarcity to 30.32% for terrestrial and freshwater ecotoxicity, while maximum reductions reached 59.18%. Sensitivity analysis indicated high stability in efficiency classifications, rankings, and reduction targets. The proposed framework links environmental hotspot identification, efficiency benchmarking, and impact reassessment, providing material-focused improvement potentials for offshore wind planning and design. These targets should be interpreted as comparative benchmarks rather than directly implementable engineering prescriptions.

Keywords DEA · LCA · Renewable energy · Offshore wind farm · Sustainability

1 Introduction

Over recent decades, the EU has undertaken a significant transition toward cleaner and more sustainable energy sources, aligning with its broader environmental and climate goals. This transformation is a central pillar of the European Green Deal (Commission, 2019), which envisions a carbon-neutral continent by 2050. Within this context,

offshore wind energy has emerged as a cornerstone technology for achieving long-term climate neutrality. This priority is clearly reflected in the EU Strategy on Offshore Renewable Energy, which sets an ambitious target of reaching 300 GW of installed offshore wind capacity by 2050 (European Commission, 2020a).

Offshore wind power is embedded within the broader framework of the Blue Economy, contributing directly to its sustainability objectives (Peña et al., 2024). As a key industry in the renewable energy generation, it supports decarbonization, technological advancement, and climate change mitigation (European Commission, 2014). However, the increasing deployment of offshore wind also raises legitimate environmental concerns. These include disruptions to marine ecosystems, such as seabed alterations and wildlife collisions, thereby underscoring the urgent need for sustainability-oriented planning and impact mitigation strategies

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(Abramic et al., 2022; European Commission et al., 2021; May et al., 2021).

Beyond ecological impacts during operation, significant environmental burdens also arise from the extraction and manufacturing of offshore wind farm components, including turbines, foundations and interconnection/export cables (Faizan & Afgan, 2025). The weight of an offshore wind farm is distributed across concrete foundations and structural steel, followed by cast iron and steel used in the nacelle and hub, fiberglass composites with epoxy resin for blades, and to a lesser extent, copper in cables and electrical equipment, often accompanied by plastic coatings (Chen et al., 2022; Kouloumpis & Azapagic, 2021; Wang et al., 2018; Yang et al., 2018).

Metallic and composite materials used in offshore wind farms contribute to several life-cycle environmental impacts, including climate change, resource depletion, human toxicity, ecotoxicity, and water consumption (Izydorczyk et al., 2021; Liu & Barlow, 2017; Rueda-Bayona et al., 2022; Tablein et al., 2021; Watari et al., 2020). These burdens are mainly associated with the extraction, processing, manufacturing, and end-of-life treatment of materials such as steel, copper, aluminium, and fibre-reinforced composites. However, these materials also fulfil essential structural, electrical, fatigue-resistance, and corrosion-resistance functions, particularly under demanding marine conditions. Consequently, their environmental impacts cannot generally be addressed through simple material elimination or uniform substitution. Instead, relevant improvement strategies include reducing material intensity through structural and component optimisation, extending component service life, increasing the use and recovery of secondary metals where technically feasible, improving maintenance and repair, designing components for disassembly, and developing more effective recycling routes for composite materials (European Commission, 2020b; Liu & Barlow, 2017; Sovacool et al., 2020). Within this context, identifying the materials that dominate the life-cycle environmental profile and determining whether comparable offshore wind farms achieve the same electricity output with lower material requirements are essential steps toward improving material eco-efficiency.

Following the general concept of eco-efficiency (World Business Council for Sustainable Development [WBCSD], 2000), this study defines material eco-efficiency as the ability of an offshore wind farm to generate a given amount of lifetime electricity while minimising the use of the materials that dominate its life-cycle environmental profile. LCA is used to compile the material and energy inventories associated with each offshore wind farm (ISO, 2006a, b) and to translate them into environmental impact indicators, thereby identifying the principal material hotspots and reducing the risk of burden shifting across impact categories (Ederer, 2014; Ewertowska et al., 2017). These hotspot materials are

then used as DEA inputs to benchmark the relative performance of the wind farms and estimate material-reduction targets while maintaining the same level of lifetime electricity generation.

The combination of LCA and DEA (known as the LCA+DEA methodology) was studied by Vázquez-Ibarra et al. (Vázquez-Ibarra et al., 2020). This approach is typically structured in three, four, or five stages. While they differ in how and when environmental, operational, and economic variables are integrated into the DEA model, they all share the common goal of measuring and optimizing the eco-efficiency of the systems being analyzed. These methods have been successfully applied across various sectors, including agri-food systems (Rebolledo-Leiva et al., 2017; Vázquez-Rowe et al., 2012), seafood production (Vázquez-Rowe et al., 2011), and energy (Iribarren et al., 2013). Although LCA and DEA have been jointly applied to assess eco-efficiency in several sectors and renewable energy technologies, their integrated application to offshore wind farms remains limited. Moreover, existing LCA–DEA studies commonly incorporate environmental and operational variables directly into the DEA model, often using aggregated indicators, which can obscure the role of the most environmentally relevant inputs and hinder the interpretation of efficiency drivers (Vázquez-Ibarra et al., 2020).

In addition, the application of DEA to offshore wind systems is often constrained by the limited availability of fully comparable decision-making units, which restricts the number of input variables that can be robustly included without compromising the discriminatory power of the model. As a result, variable selection becomes a critical methodological issue, particularly when environmental relevance and interpretability are key objectives (Ederer, 2014; Ewertowska et al., 2017).

This study addresses these limitations by proposing an enhanced LCA–DEA framework that incorporates a contribution-analysis stage prior to efficiency optimization. This step enables the identification of the material hotspots that dominate the environmental profile of offshore wind farms across the full set of midpoint impact categories and allows the DEA model to focus exclusively on these key inputs. By restricting the analysis to environmentally dominant materials, the proposed approach improves the interpretability and environmental relevance of the resulting efficiency targets while preserving robustness under small-sample conditions.

In addition, the study extends conventional LCA–DEA applications by translating DEA-derived material reduction targets into adjusted life cycle inventories and re-evaluating them through a second LCA, enabling a quantitative verification of the environmental benefits associated with efficiency improvements.

Finally, beyond efficiency benchmarking, the proposed framework provides explanatory insight by examining the

relationship between eco-efficiency outcomes, the use of dominant materials, and key wind farm characteristics, such as scale-related parameters. This integrated analysis contributes to a better understanding of the structural and material drivers underlying efficiency differences among offshore wind farms, enhancing the practical relevance of the results for planning, design, and policy-making.

This study aims to assess the environmental efficiency of 20 operational offshore wind farms (OWFs) in the United Kingdom using an integrated LCA-DEA methodology. The combination of these approaches allows for the identification of technical and environmental inefficiency sources, while also providing targeted recommendations to guide policy development, promote circularity, and support more sustainable decision-making within the offshore wind sector.

The scope of this work is deliberately restricted to offshore wind technology and to a single, internally consistent national dataset, in order to preserve inventory comparability across DMUs and to avoid the harmonisation biases associated with combining heterogeneous data sources. Extending the comparison to other renewable energy technologies or to a broader international sample of offshore wind farms falls outside the scope of the present study.

2 Methodology

This study adopts an integrated methodological framework based on the five-step LCA+ DEA approach, proposed by Vázquez-Rowe et al. (Vázquez-Rowe et al., 2010) (see Fig. 1). This approach allows to assess the resources and environmental efficiency of complex systems, such as offshore wind farms.

This study applies LCA and DEA as an integrated, iterative framework rather than as two independent assessment methods. The methodology comprises five sequential stages,

with the output of each stage providing the input required for the next. First, a harmonised life-cycle inventory is developed to ensure comparability among the offshore wind farms, which are treated as decision-making units (DMUs). Second, a baseline LCA quantifies the environmental profile of each wind farm and uses contribution analysis to identify the inventory flows that contribute most to the overall impacts. These environmental hotspots are then used to define a parsimonious DEA model that remains appropriate given the limited number of DMUs. Third, DEA benchmarks material inputs against lifetime electricity generation and estimates material-specific reduction targets for inefficient wind farms. Fourth, these targets are incorporated into the corresponding life-cycle inventories and evaluated through a second LCA. This reassessment is necessary because reductions in material inputs do not necessarily translate into proportional reductions in environmental impacts. Finally, the original and adjusted environmental profiles are interpreted together with the DEA results and the technical characteristics of the wind farms to identify the main drivers of eco-efficiency and assess potential improvement strategies.

The methodology is developed according to the following steps: i) data collection or life cycle inventory; ii) LCA performance; iii) efficiency assessment (through DEA); iv) environmental assessment of optimized resource data; and v) interpretation. This section is presented according to each step of the LCA+DEA methodology as follow:

2.1 Data collection

The initial stage consisted of compiling the input and output data required to represent each offshore wind farm as a DMU. The input inventory included the quantities and types of materials used in the main wind farm components, energy requirements, transport activities, maintenance operations and end-of-life treatments. The output variable

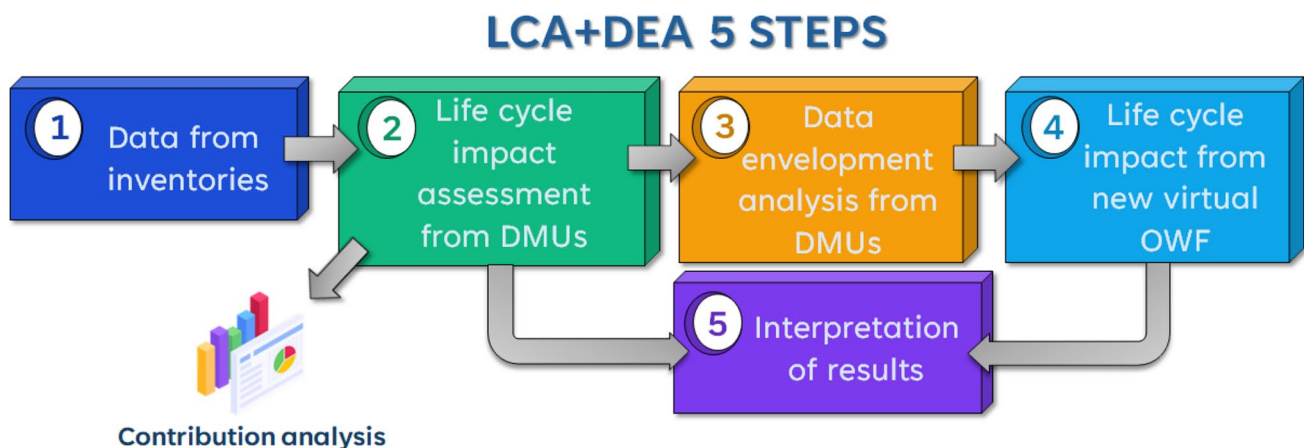


Fig. 1 Procedure of the five-steps LCA+DEA method (adapted from Vázquez-Rowe et al., 2010)

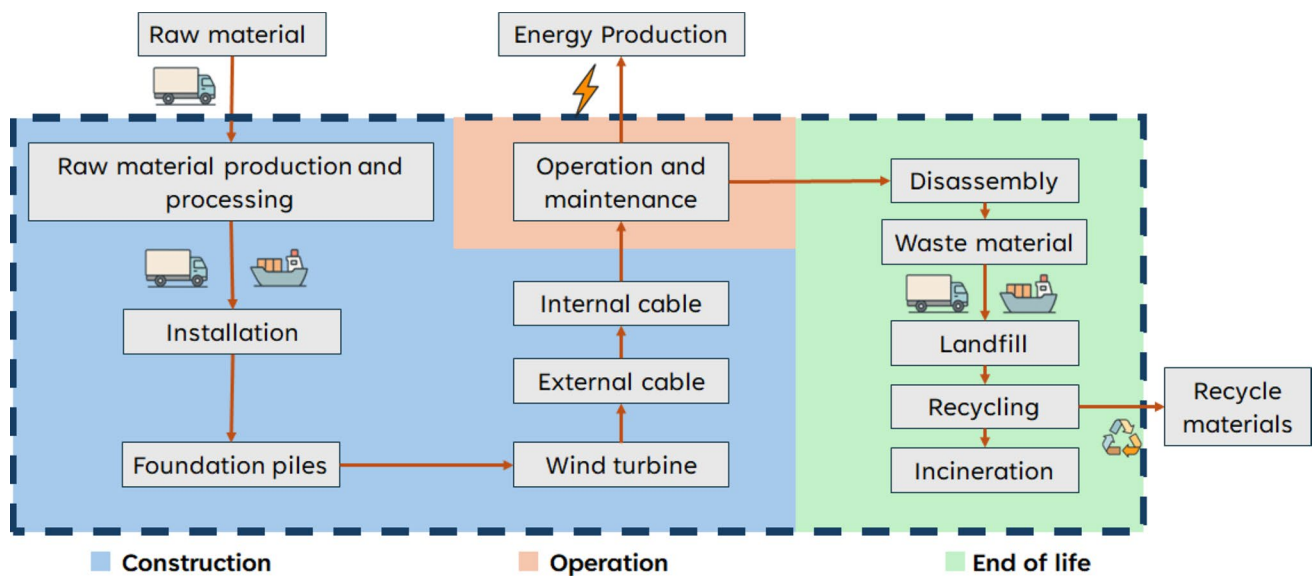


Fig. 2 System boundaries

corresponded to the total electricity generated over the assumed operational lifetime of each wind farm, expressed in kilowatt-hours.

The foreground inventory was obtained from the work of Kouloumpis and Azapagic (Kouloumpis & Azapagic, 2021), who developed the Model for Environmental Assessment of Offshore Wind (MEAOW) for 20 offshore wind farms located in the United Kingdom. The MEAOW model provides disaggregated information on the material composition and process requirements of the principal wind farm components, including turbines, foundations, inter-array and export cables, offshore substations, transport, installation, maintenance and end-of-life operations.

The original MEAOW inventory was compiled using information from wind turbine manufacturers, industrial reports, technical literature and background process originally associated with ecoinvent v2.2. In the present study, only the physical foreground inventory reported in MEAOW was retained, including materials, energy requirements, transport distances, operational inputs and waste flows. The original ecoinvent v2.2 background inventories, environmental impact results and characterisation results were not transferred directly to the new LCA model.

Site-specific parameters were obtained from the same sources used in the original MEAOW model. These included installed capacity, number and rated power of turbines, distance to shore, and capacity factor. A common operational lifetime of 20 years was assumed, together with the transport, maintenance, and end-of-life assumptions reported in the original study. The principal technical characteristics of the 20 offshore wind farms are presented in Supplementary Information S11 Table S1.

To ensure consistency between the foreground inventory and the current background database, all foreground flows were independently remapped to equivalent activities in ecoinvent v3.12. The detailed harmonisation procedure is described in the Life Cycle Inventory section, while the complete process-level correspondence is provided in Supplementary Information S11 Table S2.

2.1.1 Life Cycle Assessment of offshore wind systems

In the second stage, a Life Cycle Assessment is conducted for each DMU to determine its environmental performance profile. The LCA follows the methodological framework established by ISO 14040 and ISO 14044 (Ederer, 2014; Ewertowska et al., 2017), structured into four key phases:

- Goal and Scope Definition:** This phase defines the purpose of the study, the functional unit (FU), and the system boundaries. This research considers a FU was the construction of one offshore wind farm and follows a cradle-to-grave boundary (see Fig. 2), including stages such as raw material extraction, manufacturing, transport, installation, operation, maintenance, and end-of-life treatment (e.g., dismantling and recycling). The construction of electrical sub-stations was excluded due to their absence in several of the sites analyzed.
- Life Cycle Inventory (LCI):** The Life Cycle Inventory included the material and energy inputs, transport activities, emissions, waste flows and treatment processes associated with each offshore wind farm. The physical foreground data were retained from the

MEAOW inventory, while all background processes were reconstructed exclusively using ecoinvent v3.12 under the Allocation, cut-off by classification system model.

The original ecoinvent v2.2 processes were first linked to the activity and reference-product structure introduced in ecoinvent v3.0 and subsequently verified against the nomenclature, geography, and reference units available in ecoinvent v3.12 (ecoinvent Association. ecoinvent Database & Version 3.12. Zürich:ecoinvent Association, 2025. 2025). Equivalent activities were selected based on reference product, function, technology, geography, unit, and position within the supply chain. Production datasets were preferred for factory-gate processes, whereas market datasets were used for regional supply or supply-mix processes. Unit conversions and documented proxy datasets were applied where no direct alternative was available. The complete process-level correspondence is provided in Supplementary Information SI1 Table S2.

- iii. Life Cycle Impact Assessment (LCIA): The inventory data are translated into environmental impact indicators across several categories. The selection of impact categories and assessment method was ReCiPe 2016 Midpoint (H) v1.11 in SimaPro v10.2.0.1 (PRé Sustainability. SimaPro & Version 10.2.0.1 [computer software]., 2025). ReCiPe 2016 is a harmonised impact assessment method that offers midpoint and endpoint characterisation Huijbregts et al. (Huijbregts et al., 2016). The use of SimaPro ensures consistent application of characterisation factors and traceability of modelling, in accordance with the ILCD/JRC recommendations and ISO 14040 and ISO 14044 standards European Commission, 2011 (European Commission, 2011). In addition, ReCiPe 2016 provides 18 midpoint categories relevant to energy systems (e.g., climate change, acidification, eutrophication, toxicities, land use, and resource scarcity), enabling specific diagnoses by impact mechanism. In this study, all ReCiPe 2016 midpoint categories (H perspective) will be quantified.
- iv. Interpretation: The environmental results are thoroughly analyzed to identify the key contributors to the overall environmental burden within the system. Additionally, the analysis seeks to uncover opportunities for environmental improvements by highlighting inefficiencies and areas where changes could lead to significant reductions in resource use and emissions. The interpretation phase provides essential insights that inform decision-making, guiding both technical optimizations and strategic planning to enhance the sustainability performance of the system under study.

2.2 Eco-efficiency assessment through DEA

Mathematical optimization tools, such as Data Envelopment Analysis (DEA), enhance resource-allocation decisions by benchmarking the relative performance of decision-making units (DMUs) against an empirical “best-practice” frontier built from observed data (Cooper et al., 2007; Tone, 2017). Since its introduction in 1978, DEA has evolved into a range of complementary models designed to accommodate different production assumptions and analytical objectives. The original CCR model evaluates radial efficiency under the assumption of constant returns to scale (Charnes et al., 1978), whereas the BCC model extends this framework by allowing for variable returns to scale, thereby separating pure technical inefficiency from scale inefficiency (Banker et al., 1984). The additive model identifies non-radial slacks when proportional adjustments are unrealistic (Charnes et al., 1985), while the Slack-Based Measure (SBM) directly accounts for input excesses and output shortfalls, providing a more detailed assessment of inefficiencies (Cook & Seiford, 2008; Tone, 2001).

The third step involves applying DEA to assess the relative operational efficiency of each wind farm under study. In DEA, input- and output-oriented perspectives can be considered, depending on whether the goal is to reduce inputs or maximize outputs. Additionally, DEA models establish an efficient frontier, where the reference DMUs are located to establish performance targets to inefficient DMUs (Cooper et al., 2007). This study used a Slack-Based Measure (SBM) model, which considers a non-radial measurement of inefficiency, and explicitly incorporates input and output slacks into the efficiency score (Tone, 2001). Additionally, its unit-invariance ensures that inputs with different physical units (e.g., kilograms, MJ, CO₂-eq) can be used without distorting the efficiency scores (Cooper et al., 2007). Finally, input-oriented SBM model has superior discriminatory power compared to traditional radial models, enabling it to uncover inefficiencies that may go undetected by more basic methods (Cooper et al., 2007).

An important scope clarification concerns the interpretation of the efficiency concept applied in this study. The scores derived from the model reflect material eco-efficiency, defined as the intensity of material inputs required to deliver a given level of electricity output, rather than a comprehensive measure of technical or economic performance. Because the DEA specification does not incorporate site-specific, exogenous conditions, such as distance to shore, wind resource quality or capacity factor, as explicit control variables, part of the variability captured by the efficiency scores may reflect locational and design-related conditions rather than resource-management performance alone.

It should be noted that the rule established by Cooper et al. (Cooper et al., 2007) was followed to select the

quantity of inputs and outputs. This states that the number of decision units (n) must exceed the greater of the following two limits: the product of the number of input variables (m) and the number of output variables (s), or three times the sum of inputs and outputs, i.e., $n > \max \{m \times s, 3(m + s)\}$. This rule is commonly used as a minimum adequacy criterion to reduce the risk of limited discriminatory capacity. However, satisfying the criterion does not by itself guarantee the stability of the DEA frontier, particularly when the number of DMUs is close to the recommended threshold.

To assess the influence of model dimensionality, three DEA scenarios were estimated. The baseline scenario included five material inputs: low-alloy steel, aluminium, copper, chromium steel, and glass fibre. The four-input scenarios excluded aluminium, which had the lowest average environmental contribution among the five selected materials. The three-input scenarios additionally excluded glass fibre, leaving low-alloy steel, copper, and chromium steel as inputs. The order of exclusion was therefore based on the contribution-analysis results rather than on the efficiency scores obtained from the DEA models.

Efficiency is defined here as the capacity of each wind farm to minimize resource inputs (e.g., material, embodied energy) while maintaining a given level of output (e.g., electricity generation), i.e., follows an input-oriented approach. Additionally, a Variable Returns to Scale (VRS) assumption was adopted to reflect the heterogeneity in scale among the DMUs, given the significant variation in installed capacities across the offshore wind farms. The input-oriented SBM model is presented in Eq. 1.

$$\begin{aligned} \text{Min } \rho &= \frac{1}{m} \sum_{i=1}^m \frac{S_i^-}{x_{io}} \\ \text{subject to } &\begin{cases} X_0 = X\lambda + S^- \\ y_0 \leq Y\lambda \\ \lambda \geq 0, S^- \geq 0 \end{cases} \end{aligned} \quad (1)$$

where S_i^- represents the slack, or the excess amount, of input i ; that is, the extent to which the input can be reduced without affecting output levels. X_{io} is the actual value observed of input i for the DMU under evaluation. m is the number of input variables. Y and y_0 denote the output matrix and output vector for the DMUs and the evaluated DMU, respectively. Finally, λ is a vector of weights assigned to peer DMUs during the efficiency comparison and must be non-negative.

The DEA model produced efficiency scores ranging from 0 to 1, where a score of 1 indicates that the DMU (i.e., wind farm) is efficient, and lower values reflect that the unit is inefficient. The DEA modelling was conducted in DEA-Solver-PRO (professional version 16.0) Software (SAITECH & Inc., 2025).

2.3 Environmental reassessment using DEA-optimized data

In this step, the DEA results are not interpreted as a new physically observed or technically validated offshore wind farm design. For each inefficient DMU, the input-oriented VRS-SBM model identifies a joint projection onto the empirical efficient frontier. This projection is constructed using the same set of peer weights simultaneously for all inputs and outputs. Therefore, the target values for low-alloy steel, aluminium, copper, chromium steel and glass fibre are not obtained by independently selecting the lowest observed value for each material. Instead, they are valuable as a single, internally consistent benchmark derived from the efficient offshore wind farms included in the reference set of the evaluated DMU.

To quantify the environmental implications of the estimated material-efficiency gap, the observed quantities of the five selected material inputs are replaced by their corresponding DEA target values in the life-cycle inventory of each inefficient DMU. The observed lifetime electricity generation and all inventory flows not included as DEA inputs are held constant. A second LCA is then conducted using these target inventories. Consequently, the reassessment represents a conditional counterfactual scenario that estimates how environmental impacts would change if the material-efficiency gap identified by DEA were closed, while all other conditions remained unchanged. These results should therefore be interpreted as benchmarking-based improvement potentials rather than as engineering prescriptions or evidence that the projected material reductions can be directly implemented without further technical validation.

2.4 Interpretation of results

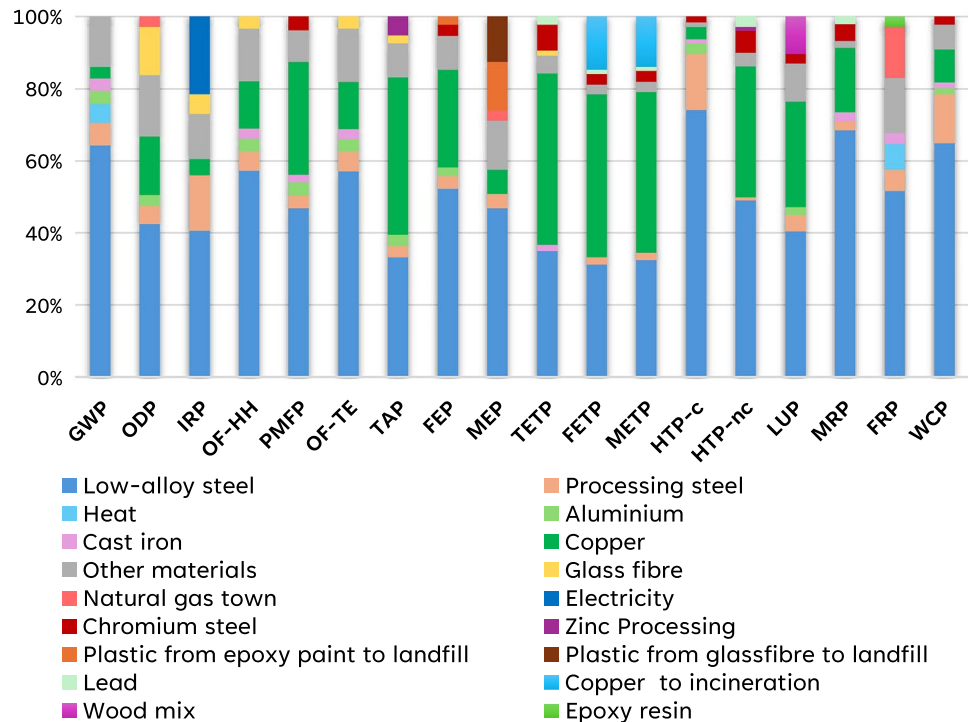
The final stage consists of comparing the original and DEA-optimized environmental impact results for each DMU. This comparison reveals the extent to which environmental performance could be improved by enhancing resource efficiency. By linking environmental impact categories with operational efficiency levels, this step provides critical insights into the trade-offs and synergies between operational and environmental performance. It also allows wind farms to be classified according to performance levels, and to identify hotspots in each farm to reduce their environmental impacts.

3 Results

3.1 Data collection

The life cycle inventory data used in this study were compiled from the work of Kouloumpis and Azapagic

Fig. 3 Normalized contribution of the main inventory flows to the 18 ReCiPe 2016 Midpoint (H) impact categories. The data for Fig. 3 can be found in Supplementary Information S11 Table S4



(Kouloumpis & Azapagic, 2021). Based on the information broken down by component presented in that manuscript, the inventory was harmonised by adding equivalent materials to obtain a final inventory broken down by material type. When the same material was associated with different elements of the turbine or infrastructure, its quantities were added together to estimate total consumption; for example, the steel low alloy used in the manufacture of the tower and hub was consolidated into a single category, thus obtaining the total steel consumption considered in the analysis. The complete harmonised life-cycle inventory is provided in Supplementary Information S11 Table S3.

3.2 Eco-efficiency assessment through DEA

After consolidating the inventory, a contribution analysis was performed to identify which materials have the greatest influence on the environmental impact of the OWF. The results of this phase are presented in Fig. 3, which shows the contribution analysis by impact category, normalized to 100%, allowing the main inventory hotspots that determine the environmental profile of the park to be identified.

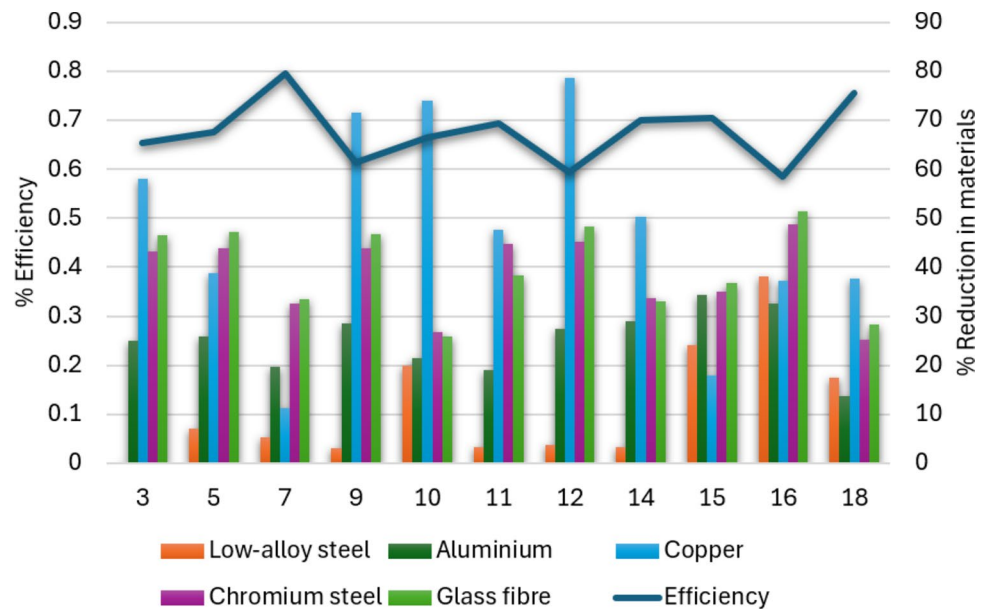
The ReCiPe midpoint impact categories are abbreviated as follows: global warming potential (GWP), stratospheric ozone depletion (ODP), ionizing radiation (IRP), ozone formation–human health (OF-HH), fine particulate matter formation (PMFP), ozone formation–terrestrial ecosystems (OF-TE), terrestrial acidification (TAP), freshwater eutrophication (FEP), marine eutrophication (MEP), terrestrial

ecotoxicity (TETP), freshwater ecotoxicity (FETP), marine ecotoxicity (METP), human carcinogenic toxicity (HTP-c), human non-carcinogenic toxicity (HTP-nc), land use (LUP), mineral resource scarcity (MRP), fossil resource scarcity (FRP), and water consumption (WCP).

Overall, low-alloy steel is the predominant contributor across most impact categories, reflecting the large quantities required for structural components such as towers, foundations, hubs, and other supporting elements. It is the main contributor to categories including GWP, ODP, IRP, OF-HH, PMFP, OF-TE, FEP, MEP, HTP-c, HTP-nc, LUP, MRP, FRP, and WCP. Copper also plays a major role in the environmental profile. It is particularly relevant in toxicity- and ecotoxicity-related categories and becomes the largest contributor to TAP, TETP, FETP, and METP. Copper also makes a substantial contribution to HTP-nc, LUP, and FEP, reflecting the environmental burdens associated with its extraction, refining, and use in electrical equipment and cabling.

Among the remaining materials, chromium steel shows smaller but consistent contributions across several categories, with increased relevance in TETP, HTP-nc, and MRP. Glass fibre is especially important in ODP and also contributes to IRP and ozone-formation-related categories, reflecting the environmental burdens associated with composite production for turbine blades. Aluminium presents a more moderate but relatively consistent contribution, particularly in GWP, OF-HH, PMFP, OF-TE, TAP, and HTP-c. In addition, some impact categories remain sensitive to specific

Fig. 4 DEA results: relative efficiency scores and material reduction targets for inefficient offshore wind farms. The data for Fig. 4 can be found in Supplementary Information S11 Table S5



inventory flows and end-of-life processes. For example, plastic waste from glass-fibre and epoxy components contributes substantially to MEP, whereas wood mix is particularly relevant to LUP.

Based on the average contribution across all 18 impact categories, five physical materials were selected as input variables for the DEA model: low-alloy steel (49.37%), copper (21.99%), chromium steel (2.98%), glass fibre (2.26%), and aluminium (2.05%). Together, these materials account for 78.65% of the average environmental contribution and therefore represent the main physical material hotspots of the system. Although steel processing also showed a relevant average contribution, it was not included as an independent DEA input because it represents a manufacturing activity rather than a physical material and could be strongly associated with the quantity of steel used. Its inclusion alongside low-alloy steel could therefore introduce redundancy into the model.

Focusing the DEA analysis on these five material inputs improves the environmental relevance and interpretability of the efficiency assessment. It enables the model to distinguish the performance of individual OWFs according to their use of the most environmentally influential materials and to establish material-specific reduction targets without decreasing electricity generation.

Low-alloy steel is the predominant contributor across most impact categories, primarily due to its extensive use in towers, foundations, hubs, and other structural components. Copper contributes most to terrestrial acidification as well as terrestrial, freshwater, and marine ecotoxicity, reflecting the environmental burdens associated with its extraction, refining, and application in electrical systems and cables. Glass fiber is the main contributor to stratospheric ozone depletion

and ionizing radiation, while aluminum and chromium steel exhibit smaller but consistent contributions across multiple impact categories. Overall, the results identify low-alloy steel and copper as the main environmental hotspots of the offshore wind farms assessed.

3.3 Environmental reassessment using DEA-optimized data and input-sensitivity analysis

After applying Data Envelopment Analysis (DEA) to the 20 offshore wind farms evaluated, nine facilities were identified as fully efficient and therefore acted as reference units within the sample. Specifically, OWFs 1, 2, 4, 6, 8, 13, 17, 19, and 20 achieved an efficiency score of 1.00. The remaining eleven facilities OWFs 3, 5, 7, 9, 10, 11, 12, 14, 15, 16, and 18 obtained scores below unity and were therefore considered relatively inefficient. These results are summarized in Fig. 4, which also presents the estimated reduction targets for the five prioritized material inputs: low-alloy steel, aluminium, copper, chromium steel, and glass fibre. In all cases, the projected electricity generation remains unchanged, meaning that the proposed material reductions could theoretically be achieved without decreasing the lifetime energy output of the farms.

Figure 4 presents the results for the eleven inefficient OWFs, showing both the efficiency score and the estimated percentage reductions required for each of the five prioritized materials. Efficiency scores range from 0.584 for OWF 16 to 0.795 for OWF 7, indicating different levels of deviation from the efficient frontier. OWF 16 exhibits the lowest relative efficiency and requires substantial reductions in all material inputs: 38.05% for low-alloy steel, 32.56% for

aluminium, 37.16% for copper, 48.65% for chromium steel, and 51.42% for glass fibre. These results indicate that the inefficiency of OWF 16 is not associated with a single material but rather with comparatively high consumption across the complete set of prioritized inputs.

Copper presents the largest individual reduction targets in several facilities. The greatest reduction is observed for OWF 12, with a target of 78.66%, followed by OWF 10 with 73.92% and OWF 9 with 71.56%. Glass fibre also shows substantial improvement potential, particularly in OWF 16, OWF 12, OWF 5, and OWF 9, with required reductions of 51.42%, 48.36%, 47.12%, and 46.70%, respectively. Chromium steel follows a similar pattern, reaching its highest reduction target in OWF 16 at 48.65%. In contrast, low-alloy steel generally requires more moderate adjustments and no reduction is projected for OWF 3, indicating that its inefficiency is primarily associated with the other four material inputs. Among the inefficient facilities, OWF 7 and OWF 18 are comparatively closer to the efficiency frontier and therefore generally require more moderate material adjustments.

3.3.1 Input-sensitivity analysis

The baseline five-input scenario satisfied the Cooper et al. criterion with a margin of two DMUs. Reducing the number of inputs increased this margin to five DMUs in the four-input scenario and eight DMUs in the three-input scenario. The number of efficient units decreased only slightly, from nine units in the baseline model to eight units in both reduced-input specifications.

Eight OWFs 1, 2, 4, 6, 8, 13, 17, and 20 were classified as efficient under all three scenarios. In addition, all eleven OWFs classified as inefficient in the baseline scenario remained inefficient in the four- and three-input models. OWF19 was the only DMU whose classification changed: its efficiency score decreased from 1.000 in the five-input scenario to 0.776 and 0.768 in the four- and three-input scenario, respectively. Consequently, classification agreement was 95% between the baseline and each reduced scenario and 100% between the four- and three-input scenario.

Efficiency rankings were also highly consistent. Spearman rank correlations were 0.976 between the five- and four-input scenario, 0.968 between the five- and three-input scenario, and 0.992 between the four- and three-input scenario. The mean absolute score differences were 0.022, 0.024, and 0.014, respectively. The largest differences involving the baseline model corresponded to OWF19.

For the eleven DMUs classified as inefficient in the baseline scenario, the slack values for low-alloy steel, copper, and chromium steel were identical across the three specifications, to the precision reported by DEA-Solver. The glass-fibre slacks were also identical between the five- and four-input scenario. Therefore, although the aggregate SBM

scores changed slightly when the number of inputs was modified, the material-reduction targets for the common inputs remained unchanged.

3.4 LCA of optimally adjusted inputs

Once the slack variables were calculated, a new LCA was conducted by modifying the observed life-cycle inventories according to the resource-reduction targets obtained through DEA. The objective was to compare the environmental profiles of the offshore wind farms before and after the application of the DEA-based optimization.

Figure 5 shows, for each initially inefficient offshore wind farm, the percentage reduction achieved across the 18 impact categories after recalculating the LCA using the target inventories proposed by the DEA model. Two main findings can be observed. First, the DEA-derived adjustments lead to reductions in all impact categories for every inefficient OWF. Second, the magnitude of these improvements varies considerably across both farms and environmental indicators. OWF 12 and OWF 10 show the highest overall reductions, particularly in toxicity-, ecotoxicity-, acidification-, and land-use-related categories. In contrast, OWF 7 exhibits the lowest and most consistent reductions, generally below 11%, indicating more limited room for environmental improvement. OWF 16 presents relatively high and homogeneous reductions across most categories, with values generally ranging from approximately 23% to 36%.

The heat map also identifies the impact categories that are most sensitive to the optimized material inventories. The highest individual reductions are observed for terrestrial ecotoxicity (TETP) and freshwater ecotoxicity (FETP), both reaching 59.18% in OWF 12. Terrestrial acidification (TAP) also shows a substantial maximum reduction of 56.97% in OWF 12, followed by land use (LUP), which decreases by up to 51.31% in the same facility. Marine ecotoxicity (METP) and human carcinogenic toxicity (HTP-c) reach maximum reductions of 50.18% and 50.16%, respectively, also in OWF 12. Overall, these results indicate that the environmental benefits of DEA-based material optimization are particularly pronounced in categories strongly influenced by copper, chromium steel, glass fibre, aluminium, and low-alloy steel consumption.

Figure 6 complements this analysis by summarising, for each impact category, the distribution of the reductions obtained across the inefficient offshore wind farms, including the median, interquartile range, extreme values, mean values, and individual observations. Overall, the reductions show considerable variability among impact categories. Median reductions range from 8.85% for fossil resource scarcity (FRP) to 30.32% for both terrestrial ecotoxicity (TETP) and freshwater ecotoxicity (FETP).

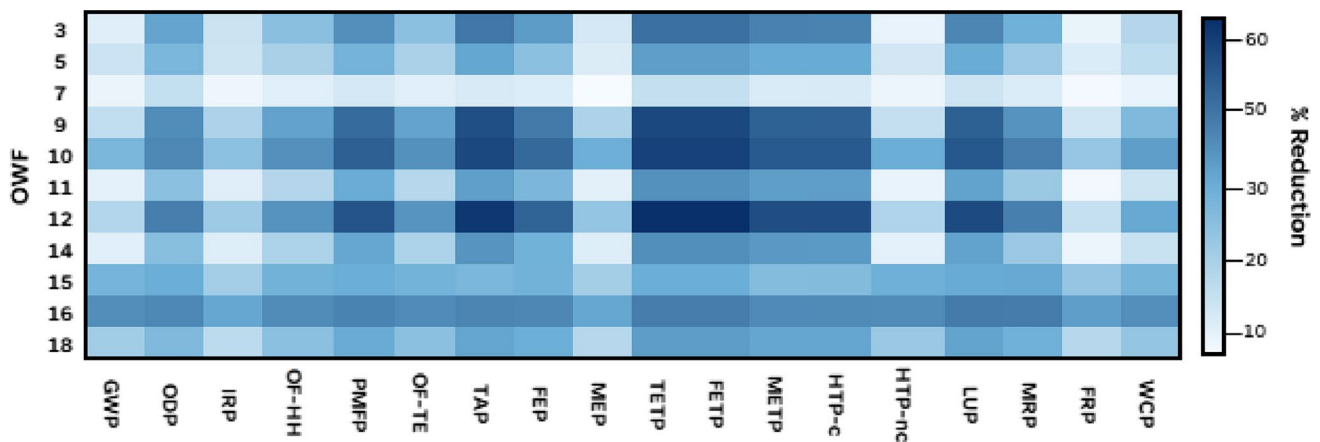


Fig. 5 Heat map of percentage reductions in 18 impact categories following DEA optimisation of the inventory. Global Warming (GWP), Stratospheric Ozone Depletion (ODP), Ionizing Radiation (IRP), Ozone Formation – Human Health (OF-HH), Fine Particulate Matter Formation (PMFP), Ozone Formation – Terrestrial Ecosystems (OF-TE), Terrestrial Acidification (TAP), Freshwater Eutrophication (FEP), Marine Eutrophication (MEP), Terrestrial Ecotoxicity (TETP),

Freshwater Ecotoxicity (FETP), Marine Ecotoxicity (METP), Human Carcinogenic Toxicity (HTP-c), Human Non-Carcinogenic Toxicity (HTP-nc), Land Use (LUP), Mineral Resource Scarcity (MRP), Fossil Resource Scarcity (FRP), and Water Consumption (WCP). The data for Fig. 5 can be found in Supplementary Information S11 Table S6

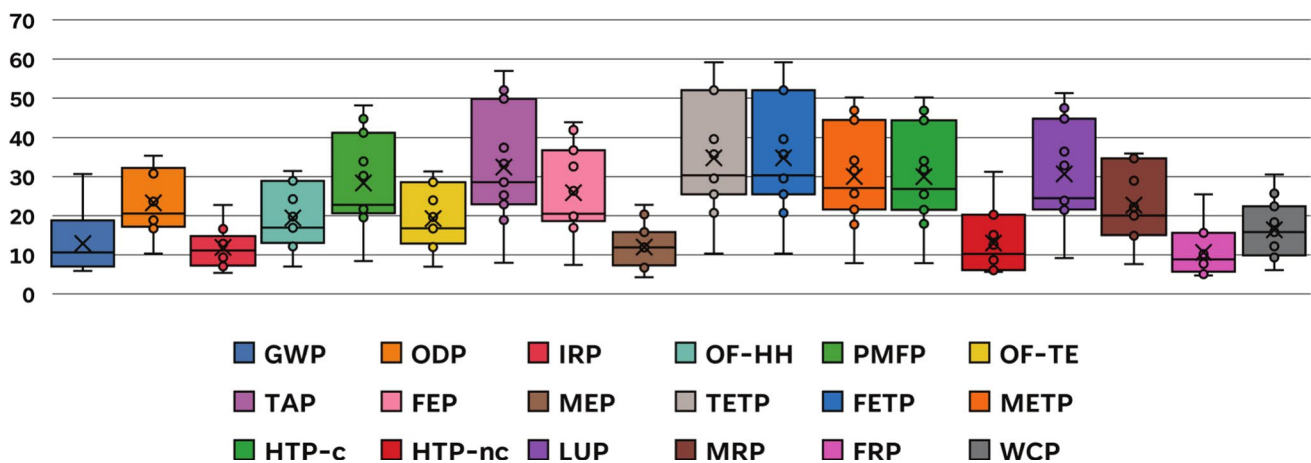


Fig. 6 Box plots and whiskers of the distribution of percentage reductions by impact category following DEA optimisation of the inventory. Global Warming (GWP), Stratospheric Ozone Depletion (ODP), Ionizing Radiation (IRP), Ozone Formation – Human Health (OF-HH), Fine Particulate Matter Formation (PMFP), Ozone Formation – Terrestrial Ecosystems (OF-TE), Terrestrial Acidification (TAP), Freshwater Eutrophication (FEP), Marine Eutrophication (MEP), Ter-

restrial Ecotoxicity (TETP), Freshwater Ecotoxicity (FETP), Marine Ecotoxicity (METP), Human Carcinogenic Toxicity (HTP-c), Human Non-Carcinogenic Toxicity (HTP-nc), Land Use (LUP), Mineral Resource Scarcity (MRP), Fossil Resource Scarcity (FRP), and Water Consumption (WCP). The data for Fig. 6 can be found in Supplementary Information S11 Table S6

Other categories with relatively high median reductions include terrestrial acidification (TAP, 28.59%), marine ecotoxicity (METP, 27.09%), human carcinogenic toxicity (HTP-c, 26.85%), and land use (LUP, 24.51%). In contrast, lower median reductions are observed for human non-carcinogenic toxicity (HTP-nc, 10.25%), global warming potential (GWP, 10.62%), ionizing radiation (IRP, 11.10%), and marine eutrophication (MEP, 11.90%).

These distributions are consistent with the corresponding average reductions, which range from 10.62% for FRP to 34.82% for TETP and FETP.

3.5 Interpretation of results

To evaluate the association between efficiency and the other characteristics of the offshore wind farms, bivariate

correlation matrices were calculated using IBM SPSS Statistics Version 29.0.2.0 (Corp xxxx). Pearson correlation coefficients (r) were estimated to examine linear relationships between continuous variables, whereas Spearman rank correlation coefficients (ρ) were used to assess monotonic associations and provide a measure that is more robust to potential deviations from normality and the influence of outliers. In both cases, two-tailed significance tests were applied, and the correlation coefficients were reported together with their corresponding significance levels (p) and sample size ($N=20$).

The Pearson analysis identified a statistically significant moderate positive association between global efficiency and distance from shore ($r = 0.485$, $p = 0.030$). This result suggests that, within the analysed sample, offshore wind farms located farther from the coast tended to achieve higher DEA efficiency scores. Efficiency also showed moderate positive correlations with the number of wind turbines ($r = 0.432$, $p = 0.057$), estimated electricity generation ($r = 0.428$, $p = 0.060$), and total installed capacity ($r = 0.408$, $p = 0.074$). Although these relationships did not reach the conventional 5% significance level, their direction and magnitude indicate a possible tendency for larger offshore wind farms to exhibit higher relative efficiency. In contrast, efficiency was practically unrelated to turbine capacity ($r = -0.057$, $p = 0.811$), rolling load factor ($r = 0.014$, $p = 0.953$), and year of commissioning ($r = 0.001$, $p = 0.995$).

The Spearman analysis produced a similar pattern and identified two statistically significant monotonic associations. Global efficiency was positively associated with distance from shore ($\rho=0.541$, $p = 0.014$) and with the number of wind turbines ($\rho=0.484$, $p = 0.030$). These findings indicate that farms located farther offshore and those comprising a greater number of turbines tended to occupy higher positions in the efficiency ranking. Moderate but non-significant positive associations were also observed between efficiency and estimated electricity generation ($\rho=0.415$, $p = 0.069$) and total installed capacity ($\rho=0.379$, $p = 0.099$). No statistically significant monotonic relationships were found for rolling load factor ($\rho=0.256$, $p = 0.277$), turbine capacity ($\rho=-0.116$, $p = 0.625$), or year of commissioning ($\rho = 0.103$, $p = 0.666$).

4 Discussion

The results show that differences in offshore-wind eco-efficiency arise from farm-specific combinations of structural metals, electrical materials and composites rather than from a single, uniform source of inefficiency. The analytical contribution of the proposed framework lies in the explicit coupling of its stages: the baseline LCA identifies the inventory

flows that are environmentally relevant, those results define a focused DEA specification, and the DEA projections are subsequently returned to the inventories for environmental verification. This sequential use of evidence addresses a recurrent concern in combined LCA–DEA studies, namely that variable selection and efficiency targets must remain environmentally interpretable rather than being treated as independent outputs of two separate methods (Martín-Gamboa et al., 2017; Vázquez-Ibarra et al., 2020).

The contribution analysis provided a clear empirical basis for selecting the DEA inputs. Low-alloy steel and copper accounted for 49.37% and 21.99%, respectively, of the average contribution across the 18 midpoint categories, while chromium steel, glass fibre and aluminium increased the combined coverage of the selected materials to 78.65%. This pattern is consistent with previous offshore-wind LCAs, which identify structural steel, foundations, electrical infrastructure and composite blades as major sources of life-cycle burdens (Benitez et al., 2024; Faizan & Afgan, 2025; Kouloumpis & Azapagic, 2021; Rueda-Bayona et al., 2022; Yang et al., 2018). Importantly, the dominance of low-alloy steel was broad but not universal: copper was particularly influential in acidification, toxicity and ecotoxicity categories, in line with the environmental burdens associated with extraction and metallurgical processing (Izydorczyk et al., 2021; Tablein et al., 2021). Using these hotspot materials as separate physical inputs, rather than relying on a single aggregated environmental indicator, preserved the connection between the efficiency scores and the material flows that can ultimately be addressed through design, procurement, maintenance or end-of-life strategies (Martín-Gamboa et al., 2017; Vázquez-Ibarra et al., 2020).

The DEA results further show that material inefficiency is heterogeneous across the analysed fleet. Nine OWFs defined the empirical frontier, whereas the remaining eleven obtained efficiency scores between 0.584 and 0.795. The largest individual gaps were observed for copper in OWFs 12, 10 and 9, with projected reductions of 78.66%, 73.92% and 71.56%, respectively, while OWF 16 exhibited substantial excesses across all five selected materials. Consequently, the observed performance gaps cannot be explained by a single material or corrected through a uniform reduction factor. This finding is consistent with earlier LCA–DEA research showing that wind farms with comparable energy functions can differ markedly in their resource requirements (Iribarren et al., 2013), but the present analysis advances that approach by linking the benchmark directly to contribution-selected materials and by retaining material-specific slacks for subsequent environmental reassessment.

The DEA analysis identified material inefficiencies, particularly for copper, glass fibre, chromium steel, aluminium and low-alloy steel. These reduction targets should be interpreted as comparative benchmarks rather than directly

applicable engineering prescriptions, since the model does not account for structural, geotechnical or site-specific constraints.

The results for low-alloy and chromium steel indicate that towers, transition pieces, and foundations should be prioritized for structural optimisation. Gentils et al. (Gentils et al., 2017) reported a 19.8% reduction in the mass of an offshore wind turbine support structure through integrated optimisation while satisfying vibration, stress, deformation, buckling, and fatigue constraints. Similarly, Moussavi et al. (Moussavi et al., 2023) found that an offshore wind farm incorporating an alternative foundation design achieved a life-cycle environmental single score 18% lower than that of an equivalent system using a conventional steel monopile. These studies demonstrate that reducing material use can provide both technical and environmental benefits when achieved through integrated, site-specific design optimisation rather than through uniform reductions in material quantities.

The structural implications of the DEA results should therefore be interpreted within a site-specific context. The optimal quantities and types of materials depend on turbine capacity, water depth, metocean conditions, seabed characteristics, fatigue requirements, and installation constraints. Accordingly, the efficient offshore wind farms identified by the model should not be regarded as designs to be directly replicated. Instead, they should be viewed as comparative benchmarks for identifying projects that achieve lower material intensity under broadly comparable technical and environmental conditions.

The second LCA confirms that the material-efficiency gaps identified by DEA are environmentally relevant, while also showing that their consequences differ substantially among impact mechanisms. Replacing the observed inputs with the joint DEA projections reduced all 18 midpoint indicators for every inefficient OWF. Median reductions ranged from 8.85% for fossil resource scarcity to 30.32% for terrestrial and freshwater ecotoxicity, and the largest reductions reached 59.18% for both ecotoxicity indicators in OWF 12. The strongest improvements occurred in categories that were highly sensitive to copper and other metal inputs, whereas the benefits associated with low-alloy steel were distributed across a broader range of categories because of its high mass contribution. These results are consistent with the material hotspots reported in offshore-wind LCAs (Kouloumpis & Azapagic, 2021; Rueda-Bayona et al., 2022; Yang et al., 2018) and with the well-documented environmental pressures of copper production and composite management (Izydorczyk et al., 2021; Liu & Barlow, 2017; Tablein et al., 2021). More importantly, they demonstrate why DEA slacks should not be interpreted as environmental gains without reassessment: material reductions of similar magnitude can produce very different changes across impact categories. Because all non-DEA inventory flows and electricity

generation were held constant, the resulting values represent conditional, benchmarking-based improvement potentials rather than predictions of the performance of a redesigned facility.

The correlation analysis provides additional, but necessarily exploratory, evidence on the characteristics associated with the efficiency ranking. Efficiency was positively related to distance from shore in both the Pearson and Spearman analyses, and the Spearman coefficient also indicated a significant association with the number of turbines. Positive but non-significant relationships with installed capacity and estimated generation point in the same direction. These patterns are broadly compatible with studies reporting lower specific material or emission requirements in larger wind-energy systems and positive relationships between project scale and DEA performance (Lenzen & Munksgaard, 2002; Tsolas, 2020). Nevertheless, the correlations do not establish economies of scale or causal effects. With only 20 observations and several bivariate tests, they should be regarded as hypothesis-generating evidence that helps interpret the DEA frontier, rather than as an independent basis for design or siting decisions.

These correlation results also carry a methodological implication for the interpretation of the efficiency concept used in this study. Because the DEA specification benchmarks material inputs against electricity output without embedding site-specific conditions as explicit control variables, part of the variability captured by the efficiency scores may reflect locational and generation-pattern differences rather than resource-management performance alone. In the present sample, the absence of a significant association between efficiency and the rolling load factor suggests that this particular driver does not materially distort the rankings; however, the significant association with distance from shore indicates that locational effects cannot be fully ruled out.

Accordingly, the relatively high proportion of frontier units should not be interpreted as evidence that the offshore wind sector is absolutely or universally highly efficient. DEA efficiency is relative to the analysed sample and model specification, and the high proportion of frontier units may partly reflect the limited number of comparable DMUs, model dimensionality, and the VRS assumption. The most robust implications therefore concern the consistently inefficient OWFs and their material-specific improvement targets, rather than the absence of further improvement opportunities among units receiving a score of 1.

The input-sensitivity analysis supports this more conservative interpretation. All eleven OWFs classified as inefficient in the baseline specification remained inefficient when aluminium and subsequently glass fibre were excluded; agreement between scenarios was 95–100%, Spearman rank correlations ranged from 0.968 to 0.992, and the slacks for the

inputs shared across specifications were unchanged. The only change in frontier status concerned OWF 19, which indicates that conclusions about individual units located on, or very close to, the frontier are more model-dependent than the improvement targets of the consistently inefficient farms. These results reduce concern that the principal findings are driven solely by the five-input specification, but they do not remove the uncertainty inherent in a deterministic DEA frontier estimated from a small sample (Cooper et al., 2007; ISO, 2006a).

The MEAOW inventory represents an earlier generation of UK offshore wind farms; therefore, the DEA efficiency scores and material-reduction targets obtained here should not be directly extrapolated to modern projects using 15+ MW turbines or floating foundations. Nevertheless, the proposed LCA–DEA framework remains applicable to newer technologies when updated and comparable inventories are available. Recent studies confirm that materials and manufacturing, particularly steel, floating structures, electrical cables, and composite blades remain major environmental hotspots in large floating wind farms (Brussa et al., 2023; Struthers et al., 2023). However, changes in turbine size, foundation design, water depth, lifetime, and operational conditions can substantially alter material requirements and environmental performance (Li et al., 2022; Sacchi et al., 2018). Thus, the present results should be interpreted as qualitative evidence of material-efficiency opportunities rather than as quantitative predictions for current mega-projects.

5 Conclusions

The main contribution of this work is the integration of LCA and DEA into a single framework for assessing the eco-efficiency of offshore wind farms, incorporating a contribution analysis that identifies the elements with the highest environmental impact and, therefore, guides optimisation toward the areas with the largest potential for improvement.

From an environmental perspective, the study identifies infrastructure and main component materials as the primary hotspots, making the optimisation of metals and structural materials the most effective improvement strategy. Applying DEA to these key materials enables the identification of reference facilities and the definition of material-specific reduction targets without affecting electricity production, while the subsequent LCA reassessment confirms that these optimisations lead to consistent improvements across impact categories without burden shifting.

Finally, the work emphasizes the need for comparable and consistent inventories to ensure robust benchmarking. Future work should include more diverse technological and end-of-life scenarios, and integrate additional criteria (such

as economic aspects or criticality) to enhance the applicability of the method in industrial planning and policy.

6 Summary

Supplementary Information S11 This supporting information provides the technical characteristics of the 20 offshore wind farms (Table S1), the correspondence between ecoinvent v2.2 and ecoinvent v3.12 datasets used for inventory harmonisation (Table S2), the harmonised life-cycle inventory (Table S3), the numerical data underlying Figure 3 (Table S4), the DEA efficiency scores and material reduction targets underlying Figure 4 (Table S5), and the environmental impact reduction data underlying Figures 5 and 6 (Table S6).

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Author contribution Adrian Sobral-Lores: Writing – original draft, Visualization, Methodology, Investigation, Formal analysis, Conceptualization. Ricardo Rebolledo-Leiva: Writing – review & editing, Supervision, Software, Investigation, Conceptualization. Gumersindo Feijoo: Writing—Review & Editing, Validation, Supervision. María Teresa Moreira: Writing—Review & Editing, Validation, Supervision.

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Data availability The authors declare that the data supporting the findings of this study are available within the paper and its Supplementary Information files. Should any raw data files be needed in another format they are available from the corresponding author upon reasonable request. Source data are provided with this paper.

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