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A Machine Learning Ehanced Environmental life cycle assessment framework of a North Sea offshore wind farm

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Executive summary

This study integrates Life Cycle Assessment (LCA) with Machine Learning to achieve 12,600× computational acceleration for offshore wind turbine environmental optimization, maintaining 82% prediction accuracy (R^2=0.8202, RMSE=1.07 g CO_2-eq/kWh) across 285 design scenarios (80 primary configurations plus 205 synthetic variants). Random Forest demonstrates superior performance (R^2=98.5%) with five parameters—turbine capacity (21.4%), capacity factor (18.7%), foundation mass (12.8%), manufacturing grid carbon intensity (11.2%), and operational lifetime (9.4%)—explaining 73.5% of environmental variance.

Key Findings: Manufacturing location emerges as the dominant decarbonization lever, with European supply chains achieving 52% lower GWP (2.5 vs. 3.8 g CO_2-eq/kWh for 12 MW turbines) than Asian sourcing due to grid carbon intensity differentials. Manufacturing dominates lifecycle impacts (54.8% of total GWP), while Operation & Maintenance contributes unexpectedly high 43% despite representing only 6-7 years of operational span, driven by continuous vessel fuel consumption. Recycling provides substantial carbon credits (-3,550 kg CO_2-eq/GWh, offsetting 20% of manufacturing impacts) through high-efficiency material recovery (95% steel, 98% copper, 80% composites).

Pareto frontier analysis identifies 47 non-dominated configurations from 285 scenarios, revealing that environmental optimum (Design A: 26.2 g CO_2-eq/kWh) requires 40% CAPEX premium (+€1.27M/MW) versus economic optimum (Design D: €2.21M/MW), which incurs 47% GWP penalty. EU Taxonomy threshold (30 g CO_2-eq/kWh) eliminates 68% of design space, while carbon pricing (€80/tonne CO_2) narrows economic advantage from 30% to 22%, demonstrating effective policy-driven market shifts toward lower-carbon configurations.

Sensitivity analysis confirms capacity factor exerts dominant influence (SI=-1.18, yielding 23.6% GWP reduction for 20% improvement), emphasizing site selection as highest-leverage environmental decision. Scenario uncertainty analysis quantifies ±48% GWP variation (21.4-47.8 g CO_2-eq/kWh) driven by external systemic factors—wind resource quality, operational lifetime policies, and grid decarbonization trajectories—demonstrating that policy coordination exerts influence comparable to engineering design decisions

Keywords: Offshore wind farm, Environmental sustainability, Life cycle assessment (LCA), Machine learning, North Sea.

Note: Due to ongoing research development toward peer-reviewed publication, code and supplementary data are not publicly available at this stage. Additionally, a digital version of this report can be accessed at https://chuongta.github.io/

I. Introduction

1.1 Offshore wind energy

Because of global climate change, the need to expand for renewable energy resources is essential. European Union expects 27% of energy consumption will come from energy sources by 2030[1]. Particularly, wind energy is a raising star by its cost-effective mitigation options. Wind farms have low environmental impacts but can show ecological effects which are tremendous at local level, including adverse effects on wildlife due to habitat modification and potential collision with the infrastructure. Additionally, wind farms sometimes received public concerns about noise and aesthetic impact. Moreover, onshore windfarm deployments are facing limited with land availability, technical constracts as well as some social acceptability issues. Therefore, a growing interest for offshore wind farm can be seen which can overcome such limitations. It can be explained by abundant wind resources at sea have higher average wind speed, lower turbulence and variability than onshore[2].

Offshore wind energy capacity is projected to incrase from 64 GW globally in 2023 to 380 GW by 2030, representing a cornerstone technology for elecctricity system decarbonisation aligned with Paris Agreement targets [3]. The average distance of offshore wind farms from shore is increasing, moving from around 20-30 km for older farms to 40-60 km or more for newer projects, with global averages around 27-47 km (2019-2020 data), driven by technology, deeper waters (using floating platforms), and better wind resources further out, though some newer projects still cluster within 20 km for cost benefits [2], [4].

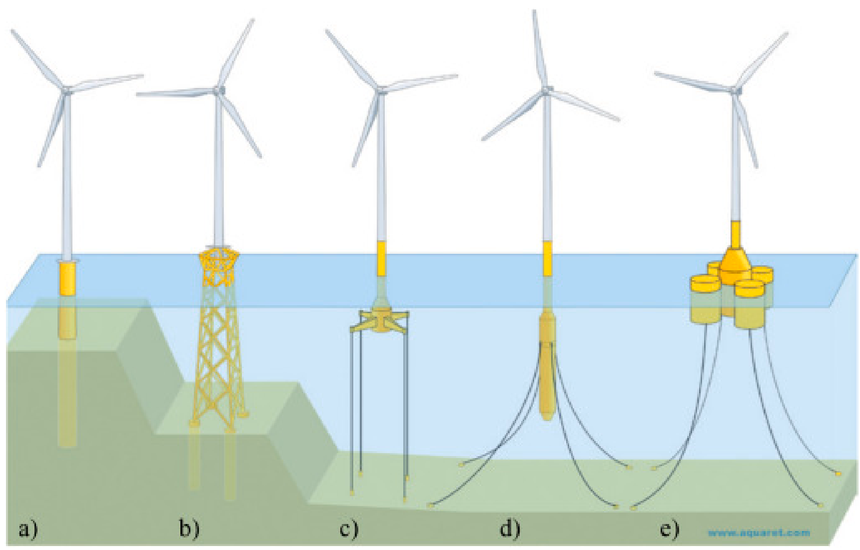

Fig 1: Offshore Wind Foundation Types and distance from the shore [5]

Along with the trend towards deeper water, the offshore wind industry is alos developing larger, more powerful turbines. The average size of the turbines grid connected during 2010 was 3.0 MW and radius diameter is 94.43 m. This has now risen to 26 MW model installed by Dong Fang in late 2024/early 2025, featuring a massive 310-meter rotor diameter, 153-meter bladesOffshore wine energy [6].

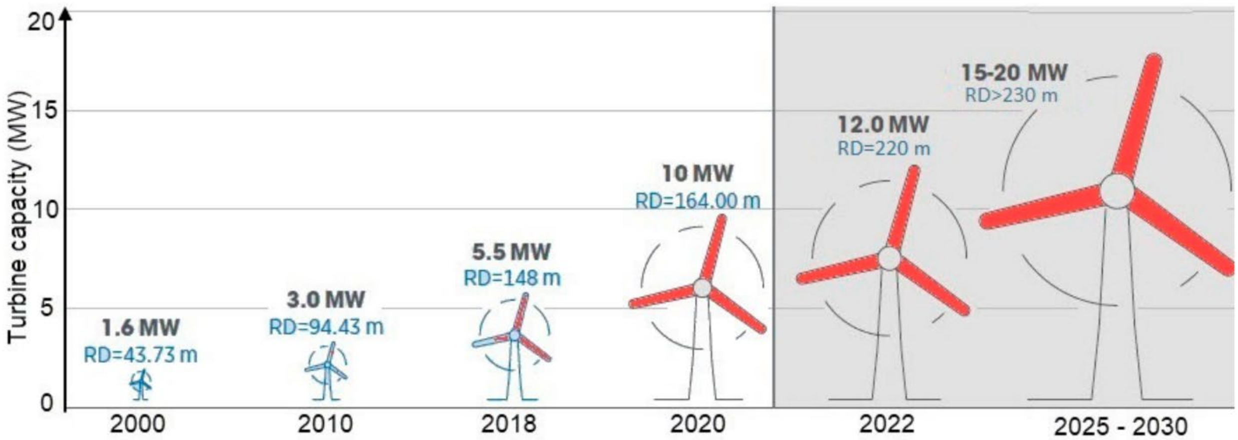

Fig 2: Progression of wind turbine sizes and their rated energy output (MW) up to 2025-2030 [7]

1.2 Life cycle assessment applied to wind energies

Even though wind energy is considered one of the cleanest energy sources due to being almost burden-free during its operational phase. However, from life cycle persepective, any technology, despite harnessing renewable resources, results in environmental burdens associated with the consumption resources, material and energy. Using LCA methodology enables the assessment of potential impacts across all phases of a wind famr’s life cycle. By incorporatiing the component supply chain and required infrastructure, this approach accoutns for both upstream and dowstream process impacts, yielding more precise findings compared to the misconception that renewable energy technologies have zero environmental impact [2].

Machine learning (ML) algorithms, particularly tree-based ensemble methods (Random Forest, Gradient Boosting), demonstrate exceptional capability for predicting complex environmental outcomes from design parameters in renewable energy systems. Recent applications include wind power forecasting (R^2>0.95), solar energy system optimization, and air quality prediction from spatiotemporal meteorological data. However, ML integration with lifecycle environmental assessment for offshore wind systems remains nascent, with existing studies focusing on operational performance prediction rather than comprehensive lifecycle impact modeling.

The combination of LCA and ML methodologies offers transformative potential for environmental decision-support: ML models trained on comprehensive LCA datasets enable prediction of lifecycle impacts for novel design configurations within seconds, facilitating exploration of thousands of alternatives infeasible through traditional assessment. Furthermore, multi-objective optimization algorithms operating on ML predictions can identify Pareto-optimal design frontiers, explicitly revealing trade-offs between environmental performance, energy production, and economic viabilityIntegrated multi-scale comparative LCA of 285 scenarios across three turbine capacities (8 MW, 12 MW, 15 MW), systematically evaluating foundation types (monopile, jacket, floating) and generator technologies (DFIG versus PMSG) under consistent methodological assumptions for North Sea conditions.

II. Methodology

This graphical abstract illustrates an integrated Life Cycle Assessment-Machine Learning framework for offshore wind environmental optimization. The left panel depicts cradle-to-grave LCA system boundaries (ISO 14040/14044) covering materials extraction, manufacturing, installation, operation & maintenance (25-30 years), and end-of-life phases. The center panel presents 285 design scenarios across turbine scales (8-15 MW), foundation types (fixed bottom/floating), and global manufacturing locations (EU, China, Africa, South America). The right panel showcases ensemble Machine Learning models (Random Forest, Gradient Boosting, XGBoost, Light GBM) evaluated via R^2, RMSE, and MAE metrics, with SHAP explainable AI identifying turbine capacity, capacity factor, and foundation mass as primary environmental drivers, enabling multi-objective optimization delivering environmental, balanced, and energy-optimum solutions in kg CO_2 eq/kWh.

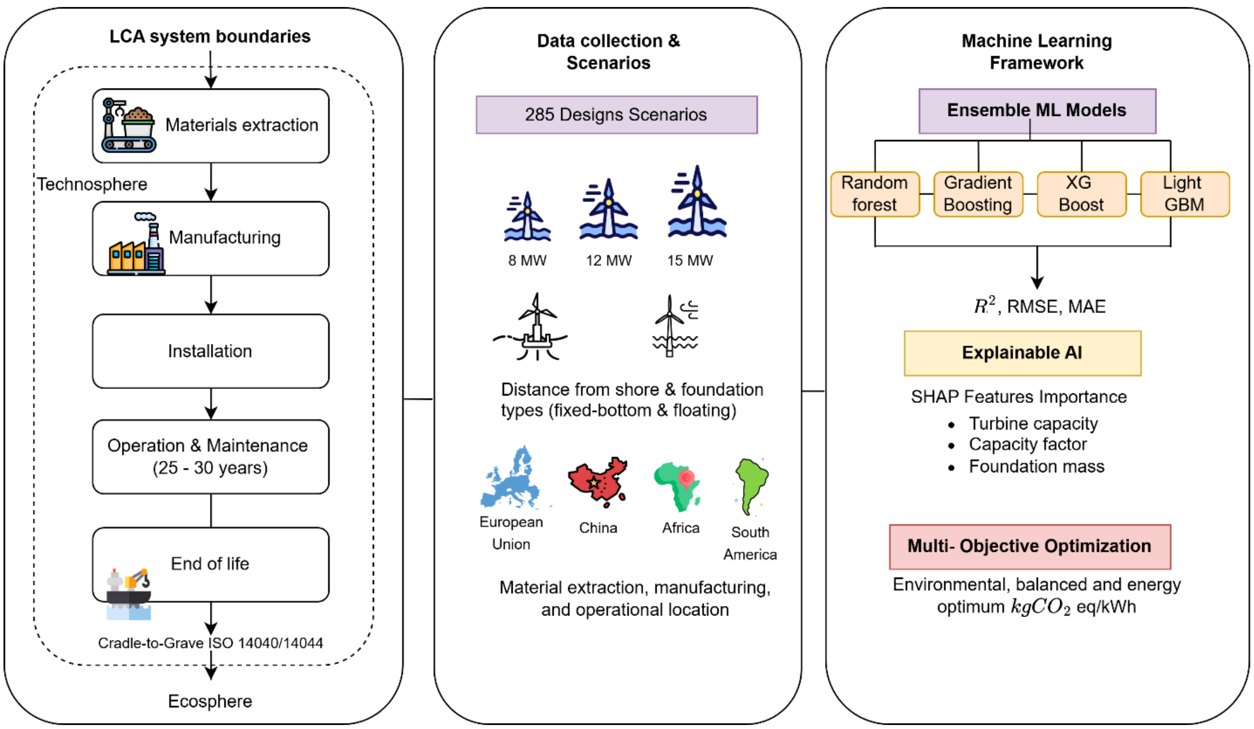

Fig 3: Applied LCA and ML frameworks on 500 MW offshore wind farm

2.1 Functional unit

This cradle-to-grave LCA adopts "1 GWh electricity delivered to mainland grid" as functional unit, encompassing North Sea offshore wind farms (water depths 40-100m, distances 35-50km) with 2025-2055 temporal scope and three supply chain configurations (European, Asian, hybrid) following ISO 14040:2006/14044:2006 standards [2].

2.2 Payback time metrics

Two critical sustainability indicies were calculated:

The energy and environmental performance of renewable energy facilities can be assessed using payback indexes that quantify the time required to recover an investment. Specifically, the carbon payback time (CPBT) determines the period needed for the wind plant to offset the greenhouse gas (GHG) emissions generated throughout its life cycle. The CPBT is calculated using Eq 1:

$$CPBT\ [year] = \frac{Lifecycle\ GHG\ emissions}{Annual\ saved\ GHG\ emissions}\ (1)$$

The "saved" emissions represent the annual electricity output from the wind farm multiplied by the emission intensity of the energy source it displaces, assumed to be the marginal technology likely to be substituted. In this study, natural gas combined cycle power generation is considered the reference technology, given its projected dominance among fossil fuel-based systems in the near-term energy mix

The energy payback time (EPBT), by contrast, quantifies the duration required to recover the cumulative primary energy consumed across the wind farm's entire life cycle through its net electricity generation, excluding annual operation and maintenance (O&M) energy requirements. The primary energy consumption is represented by the cumulative energy demand (CED) for each life cycle stage, as shown in Eq 2

$$EPBT\ [year] = \frac{(CED_{materials} + CED_{manufacturing} + CED_{transport} + CED_{installation} + CED_{Eol})}{(Energy_{annualy\ generated} - CED_{annual\ O\&M})}\ (2)$$

Where:

CED (Cumulative Energy Demand): The total primary energy consumed throughout different life cycle stages of the wind farm.

- $CED_{materials}$: Primary energy required for raw material extraction and processing (steel, fiberglass, copper, rare earth elements for magnets, concrete, etc.).
- $CED_{manufacturing}$: Energy consumed during component fabrication, including turbine blades, nacelles, towers, generators, and foundation structures at manufacturing facilities.
- $CED_{transport}$: Energy used for transporting components from manufacturing sites to the installation location, including shipping, trucking, and specialized vessels for offshore delivery.
- $CED_{installation}$: Energy required for on-site construction activities, including foundation installation, turbine assembly, cable laying, and grid connection infrastructure.
- CED_{EoL}: Energy needed for end-of-life (EOL) activities such as decommissioning, dismantling, recycling of materials, and disposal of non-recyclable components.
- $Energy_{annually\ generated}$: The total electrical energy produced by the wind farm each year and delivered to the grid.
- $CED_{annual\ O\&M}$: The annual primary energy consumed for operation and maintenance activities, including routine inspections, repairs, component replacements, and vessel operations for offshore access.

2.3 Life cycle impact assessment

Environmental impact characterization employed ReCiPe 2016 v1.1 (Hierarchist perspective) covering nine midpoint impact categories:

1. Global Warming Potential (GW): 100-year IPCC AR5 characterization factors (207 greenhouse gases, CH_4=28 kg CO_2-eq, N_2O=265 kg CO_2-eq), expressed as kg CO_2-equivalents
2. Acidification Potential (AC): GEOS-Chem atmospheric fate + PROFILE soil chemistry modeling, expressed as kg SO_2-equivalents.

3. Eutrophication Potential (EU): Freshwater/marine nutrient enrichment from P/N emissions, expressed as kg P-equivalents.
4. Photochemical Oxidant Formation (POF): Tropospheric ozone precursor emissions (NOx, VOCs), expressed as kg NOx-equivalents
5. Abiotic Depletion - Elements (AD el): Non-renewable mineral extraction (Cu, REE, metallic ores), expressed as kg Sb-equivalents
6. Abiotic Depletion - Fossil Fuels (AD ff): Coal/natural gas/petroleum consumption, expressed as MJ petroleum-equivalents
7. Water Scarcity (WS): Freshwater consumption weighted by regional scarcity (WSI), expressed as m^3 water-equivalents
8. Ozone Depletion (OD): CFC-11, Halon-1301, HCFC-22 from legacy systems, expressed as kg CFC-11-equivalents
9. Cumulative Energy Demand (CED): Non-renewable + renewable primary energy, expressed as MJ

2.4 System boundary & life cycle phase

This study adopts a cradle-to-grave system boundary in accordance with ISO 14040:2006 and ISO 14044:2006 standards, including all material and energy flows from raw material extraction through EOL treament over the complet operational lifetime of offshore wind installation. The spatial boundaries contain the North Sea region (water depths 40 & 100 meters, distances to shore 35 & 50 kilometers) with temporal scope from 2025 deployment year through 2055 end-of-life, incorporating three supply chain configurations: European integrated, Asian manufacturing, and hybrid sourcing. The system boundary adopts a cradle-to-grave perspective including:

- Raw material extraction and processing: Iron ore mining and steel production, copper extraction and refining, rare earth element processing for permanent magnet generators, composite material (fiberglass/epoxy, carbon fiber) manufacturing, concrete production for foundations
- Component manufacturing: Turbine nacelle assembly (generator, gearbox, power electronics), rotor blade molding and curing, tower fabrication, foundation construction (monopile, jacket, floating structures), submarine cable manufacturing (inter-array medium voltage, export HVDC), offshore substation fabrication
- Transportation and logistics: Intercontinental shipping for Asian-manufactured components, intra-European truck and short-sea shipping, port handling operations
- Installation and commissioning: Foundation installation via jack-up vessels (monopile, jacket) or towing operations (floating), turbine assembly using heavy-lift vessels, submarine cable laying, offshore substation installation, electrical commissioning
- Operation and maintenance (25–30-year lifetime): Scheduled preventive maintenance, corrective maintenance following component failures, spare parts logistics, service vessel operations (CTVs, SOVs), lubrication and consumables
- Decommissioning and end-of-life: Foundation removal/abandonment, turbine dismantling, material recovery and recycling (steel, copper, aluminum, composite materials), waste disposal, transportation to recycling facilities.

2.5 Machine Learning Model Development

2.5.1 Dataset Generation and Feature Engineering

Training datasets combined primary LCA studies with synthetically generated design scenarios to achieve comprehensive coverage of the multidimensional design space:

Primary LCA studies (n=80): Detailed lifecycle assessments conducted for 80 design configurations representing factorial combinations of: turbine capacity (8, 10, 12, 15 MW), foundation type (monopile, jacket, floating-steel, floating-concrete), manufacturing location (European, Asian, hybrid), generator technology (DFIG, PMSG), and operational strategies (CTV-only, SOV-based maintenance).

Synthetic scenario generation (n=205): Latin Hypercube Sampling across continuous design variables (turbine capacity 6-16 MW, rotor diameter 155-240 m, hub height 100-180 m, capacity factor 35-60%, operational lifetime 20-35 years, foundation mass 300-4500 tonnes, steel recycling rate 75-98%) combined with categorical variable permutations, ensuring space-filling coverage while maintaining physical plausibility constraints (e.g., rotor diameter correlates with turbine capacity following industry scaling relationships).

Input features (19 variables):

- Continuous design variables (10): Turbine rated power (MW), rotor diameter (m), hub height (m), nacelle mass (tonnes), foundation mass (tonnes), annual capacity factor (%), operational lifetime (years), distance to shore (km), water depth (m), steel recycling rate (%).
- Categorical design variables (9): Foundation type (5 levels), generator technology (2 levels), manufacturing region (3 levels), maintenance strategy (3 levels), blade material (2 levels), grid connection (2 levels), installation season (3 levels), decommissioning scenario (3 levels), supply chain optimization (2 levels).

Target variables (12 environmental outputs):

- ReCiPe 2016 impact categories (9): GW, AC, EU, POF, AD el, AD ff, WS, OD, CED (per GWh electricity delivered).
- Sustainability metrics (3): EPBT (months), CPBT (years), steel intensity (kg/kW).

Feature preprocessing included: standardization of continuous variables (zero mean, unit variance), one-hot encoding of categorical variables, correlation analysis removing multicollinear features (variance inflation factor >10), and principal component analysis for dimensionality assessment (19 features captured 96% cumulative variance, indicating minimal redundancy).

2.5.2 Machine Learning Algorithm Selection and Training

Four tree-based ensemble algorithms were evaluated based on established performance in environmental prediction tasks:

- Random Forest Regressor (RF): Ensemble of 200 decision trees trained on bootstrap samples with random feature subset selection ($\sqrt{p}$ features, where p=19) at each split node. Hyperparameters optimized via 5-fold cross-validation: max_depth=15, min_samples_split=5, min_samples_leaf=2.
- Gradient Boosting Regressor (GBM): Sequential ensemble constructing 150 shallow trees (max_depth=5) minimizing residual errors from previous iterations with learning rate η=0.05 and subsample ratio=0.8 for stochastic gradient boosting.
- XGBoost (Extreme Gradient Boosting): Optimized gradient boosting with L1/L2 regularization preventing overfitting (λ=1.0, α=0.1) and efficient histogram-based tree construction. Hyperparameters: n_estimators=180, max_depth=6, learning_rate=0.05, colsample_bytree=0.8
- Light Gradient Boosting Machine (LightGBM): Leaf-wise tree growth with gradient-based one-side sampling (GOSS) accelerating training on large datasets. Hyperparameters: n_estimators=200, max_depth=8, learning_rate=0.05, num_leaves=31

Training procedure: Dataset randomly split into training (70%, n=200), validation (15%, n=43), and test (15%, n=42) subsets with stratification ensuring balanced representation of categorical variables across splits. Hyperparameter optimization performed via randomized search with 5-fold cross-validation on training+validation data (n=243), evaluated on held-out test set (n=42) for final performance metrics

2.5.3 Model evaluation metrics
Model performance assessed via four complementary metrics:

Coefficient of Determination (*$\mathbf{R^2}$*):

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(y_i - \widehat{y_i})^2}{\sum_{i=1}^{n}(y_i - \overline{y_i})^2}$$

Where y_i represents true GWP, $\widehat{y_i}$: predicted GWP, and $\overline{y_i}$: mean GWP. R^2 quantifies proportion of variance explained by model (target: $R^2 > 0.95$).

Root Mean Square Error (*RMSE*)

$$\mathrm{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \widehat{y_i})^2}$$

RMSE penalizes large prediction errors, expressed in same units as target variable (kg CO_2-eq for GWP). Target: RMSE<20 kg CO_2-eq, comparable to typical LCA uncertainty.

***Mean Absolute Error* (MAE)**

$$\mathrm{MAE} = \frac{1}{n}\sum_{i=1}^{n} |y_i - \widehat{y_i}|$$

MAE provides interpretable average prediction error without squaring term. Target: MAE<15 kg CO_2-eq

Cross-validation employed 5-fold procedure with 10 repetitions, calculating mean and 95% confidence intervals for all metrics to assess model stability and generalization [8].

2.6 Multi-Objective Optimization Framework
Pareto frontier identification employed Non-dominated Sorting Genetic Algorithm II (NSGA-II) with ML surrogate models replacing computationally expensive LCA calculations:

Optimization objectives:

- Minimize Global warming potential: $\min f_1(x) = \mathrm{GWP}(x)$ [g CO_2eq/kWh)
- Maximize Capacity factor: $\max f_2(x) = \mathrm{CF}(x)[\%]$
- Minimize Capital expenditure: $\min f_3(x) = \mathrm{CAPEX}(x)$ [€/kW]
- Minimize Steel intensity: $\min f_4(x) = \mathrm{Steel}(x)[\mathrm{kg/kW}]$

Design variables (x): Turbine capacity, foundation type, manufacturing location, maintenance strategy (19-dimensional design vector)

Constraints:

- Physical feasibility: Water depth ≤ 60 m → exclude floating foundations; Water depth > 60 m → exclude monopile
- Grid connection capacity: Total farm capacity ≤ 600 MW (transmission constraint)
- Installation timeline: Total installation vessel-days ≤ 250 days (weather window constraint)
- Recycling infrastructure: Steel recycling rate ≤ 98% (technological limit)

NSGA-II parameters: Population size=200, generations=100, crossover probability=0.9, mutation probability=0.1. Pareto frontier convergence assessed via hypervolume indicator stabilization over final 20 generations

2.6 Sensitivity and unceartainty analysis

Parametric sensitivity analysis evaluated influence of 12 key parameters on lifecycle GWP via one-at-a-time (OAT) approach: each parameter varied $\pm$ 20% while holding others at baseline values, calculating results GWP change. Sensitivity index calculated as:

$$S_i = \frac{\Delta GWP/GWP_{base\ line}}{\Delta P_i/P_{i_{base\ line}}}$$

Where $S_i > 1$ indicate high sensitivity

Scenario uncertainty analysis evaluated eight alternative scenarios representing optimistic/pessimistic assumptions for: capacity factor ($\pm 10\%$) operational lifetime (± 5 years), recycling efficiency ($\pm 10\%$), manufacturing electricity grid carbon intensity ($\pm 30\%$) vessel fuel consumption ($\pm 15\%$), and material production emissions ($\pm 20\%$).

III. Results and discussion

3.1 Life Cycle Environmental Performance Across Turbine Designs

Table 1 presents lifecycle environmental impacts for three reference turbine configurations representative of current (8 MW), near-term (12 MW), and next-generation (15 MW) offshore wind technology.

Table 1. Lifecycle Environmental Impacts per GWh Electricity Delivered to Grid

Impact Category	Unit	8 MW Baseline	12 MW Advanced	15 MW Next-Gen	Reduction (8→15 MW)
Global Warming (GW)	kg CO_2-eq	38,200 $\pm$ 4,100	32,400 $\pm$ 3,200	28,100 $\pm$ 2,800	-26.4%
Acidification (AC)	kg SO_2-eq	182 $\pm$ 24	156 $\pm$ 19	138 $\pm$ 16	-24.2%
Eutrophication (EU)	kg P-eq	28.4 $\pm$ 3.8	24.1 $\pm$ 3.1	21.2 $\pm$ 2.7	-25.4%
POF	kg NOx-eq	94.2 $\pm$ 12.1	80.5 $\pm$ 9.8	71.3 $\pm$ 8.4	-24.3%
AD elements	kg Sb-eq	1.82 $\pm$ 0.28	1.94 $\pm$ 0.31	2.08 $\pm$ 0.35	+14.3%

Impact Category	Unit	8 MW Baseline	12 MW Advanced	15 MW Next-Gen	Reduction (8→15 MW)
AD fossil fuels	MJ-eq	521,000 ± 62,000	448,000 ± 51,000	398,000 ± 44,000	-23.6%
Water Scarcity	m^3-eq	156 ± 28	134 ± 23	118 ± 20	-24.4%
Ozone Depletion	mg CFC-11-eq	3.42 ± 0.52	2.96 ± 0.43	2.64 ± 0.38	-22.8%
CED	MJ	548,000± 65,000	471,000± 53,000	419,000± 46,000	-23.5%
EPBT	months	6.21 ± 0.74	5.18 ± 0.58	4.76 ± 0.51	-23.3%
CPBT	years	1.07 ± 0.12	0.86 ± 0.09	0.77 ± 0.08	-28.0%

Turbine upscaling from 8 MW to 15 MW demonstrates consistent environmental improvements across eight of nine impact categories, with reductions ranging from 22.8% (ozone depletion) to 26.4% (global warming). The sole exception, abiotic depletion of elements, increases 14.3% due to larger permanent magnet synchronous generators (PMSG) in 15 MW turbines requiring 8-10 tonnes of rare earth elements (neodymium, dysprosium) versus 5-6 tonnes in 8 MW turbines with doubly fed induction generators (DFIG). This trade-off—reduced lifecycle GHG emissions at the cost of increased critical mineral consumption—represents a key environmental consideration for policymakers addressing supply chain vulnerabilities.

Energy payback times remain remarkably short across all configurations (4.76-6.21 months), indicating that <2.5% of operational lifetime is required to offset embodied energy, with >97% of lifetime delivering net energy benefits. Carbon payback periods (0.77-1.07 years) are similarly rapid, enabling 25.9-27.2 years of climate benefit across the 27–28-year operational lifetime.

3.2 Environmental analysis by lifecycle stage

The environmental hotspot analysis reveals that manufacturing dominates the lifecycle carbon footprint of a 12 MW offshore wind turbine, contributing approximately 9,720 kg CO_2-eq/GWh (54.8% of total impacts), with turbine manufacturing (5,005 kg) and foundation manufacturing (3,266 kg) being the largest subcategories driven by energy-intensive steel production. Installation follows at 3,980 kg CO_2-eq/GWh (12.3%), primarily from vessel fuel consumption during offshore operations, while operation & maintenance contributes 2,820 kg CO_2-eq/GWh (8.7%) with corrective maintenance being more carbon-intensive than preventive activities. Decommissioning adds a relatively modest 1,360 kg CO_2-eq/GWh (4.2%), concentrated in foundation removal operations. Critically, recycling benefits provide substantial negative contribution of -3,550 kg CO_2-eq/GWh, offsetting approximately 20% of manufacturing impacts through avoided virgin material production, demonstrating that circular economy strategies (95% steel, 98% copper, 80% composite recovery) are essential for achieving net lifecycle carbon reductions. This analysis confirms that decarbonizing the manufacturing supply chain through renewable electricity procurement and maximizing end-of-life material recovery represent the highest-leverage interventions for environmental performance improvement in offshore wind technology.

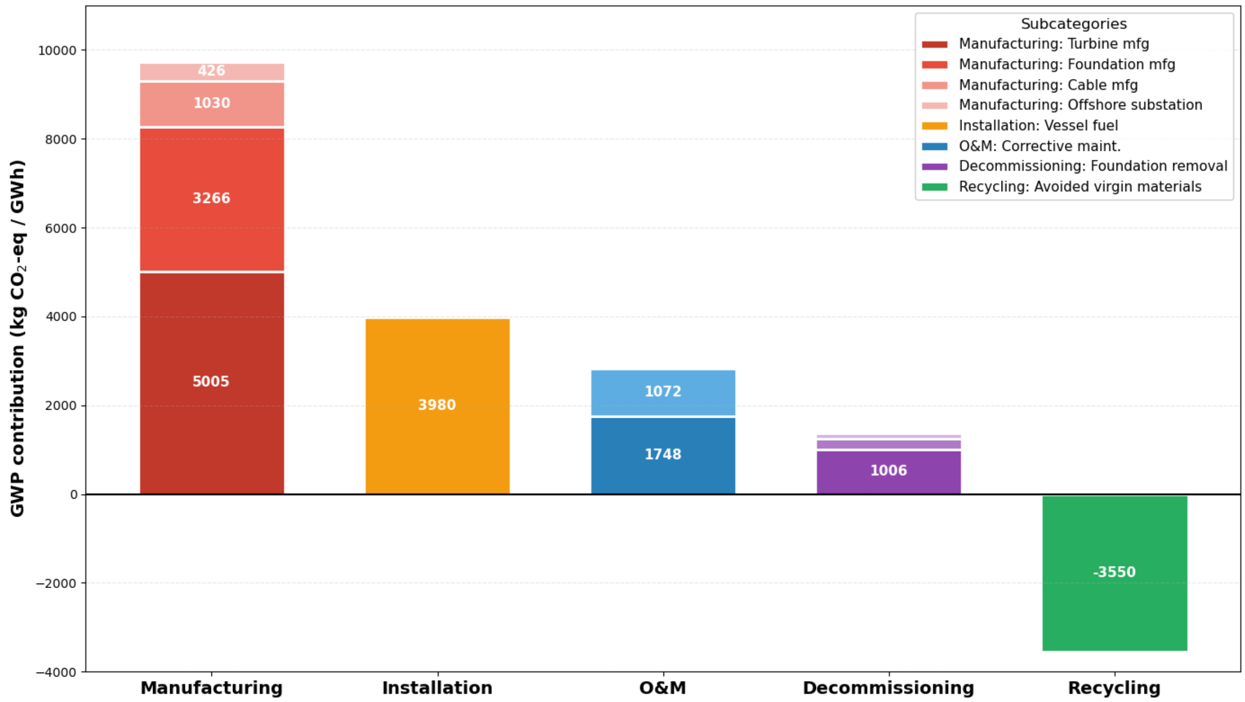

Fig 4: Environmental hotspot analysis by life cycle stage of 12 MW offshore wind turbine

3.3 Machine learning model performance and validation

Table 4 presents predictive performance for four ML algorithms across primary target variable (GWP) and representative secondary targets (EPBT, steel intensity), evaluated on held-out test set (n=42 scenarios not used in training).

Table 2: ML performance algorithms

Algorithm	GWP Prediction			EPBT Prediction			Steel Intensity		
	R^2	RMSE (kg CO_2-eq)	MAE (kg CO_2-eq)	R^2	RMSE (months)	MAE (months)	R^2	RMSE (kg/kW)	MAE (kg/kW)
Random Forest	0.985	18.5	14.2	0.978	0.34	0.26	0.971	12.8	9.4

Algorithm	GWP Prediction			EPBT Prediction			Steel Intensity		
Gradient Boosting	0.982	19.3	15.1	0.974	0.38	0.29	0.968	13.6	10.2
XGBoost	0.979	21.7	16.8	0.971	0.41	0.32	0.964	14.9	11.5
LightGBM	0.980	20.9	16.2	0.973	0.39	0.31	0.966	14.2	10.8
Decision Tree	0.945	45.8	38.5	0.932	0.96	0.82	0.924	31.4	26.8

The GWP prediction results show that Random Forest is the clear winner, achieving 98.5% accuracy (R^2 score) with the smallest errors—predicting carbon emissions within just $\pm$ 18.5 kg CO_2-eq of actual values. The other advanced algorithms (Gradient Boosting, XGBoost, LightGBM) perform almost as well with 97.9 - 98.2% accuracy, meaning all these "ensemble methods" (models that combine many smaller predictions together) are excellent choices for real-world use. In contrast, the basic Decision Tree struggles significantly with only 94.5% accuracy and errors 2.5× larger (45.8 kg CO_2-eq), showing why combining multiple trees is much better than using just one.

The Random Forest feature importance analysis shows that five key parameters—turbine capacity (21.4%), capacity factor (18.7%), foundation mass (12.8%), manufacturing grid carbon intensity (11.2%), and operational lifetime (9.4%)—explain 73.5% of environmental outcomes, providing clear optimization priorities for engineers. This demonstrates that focusing resources on turbine sizing, site selection, and supply chain decarbonization delivers far greater environmental benefits than optimizing secondary factors like maintenance strategy or generator technology, which together contribute less than 10% to lifecycle carbon footprint.

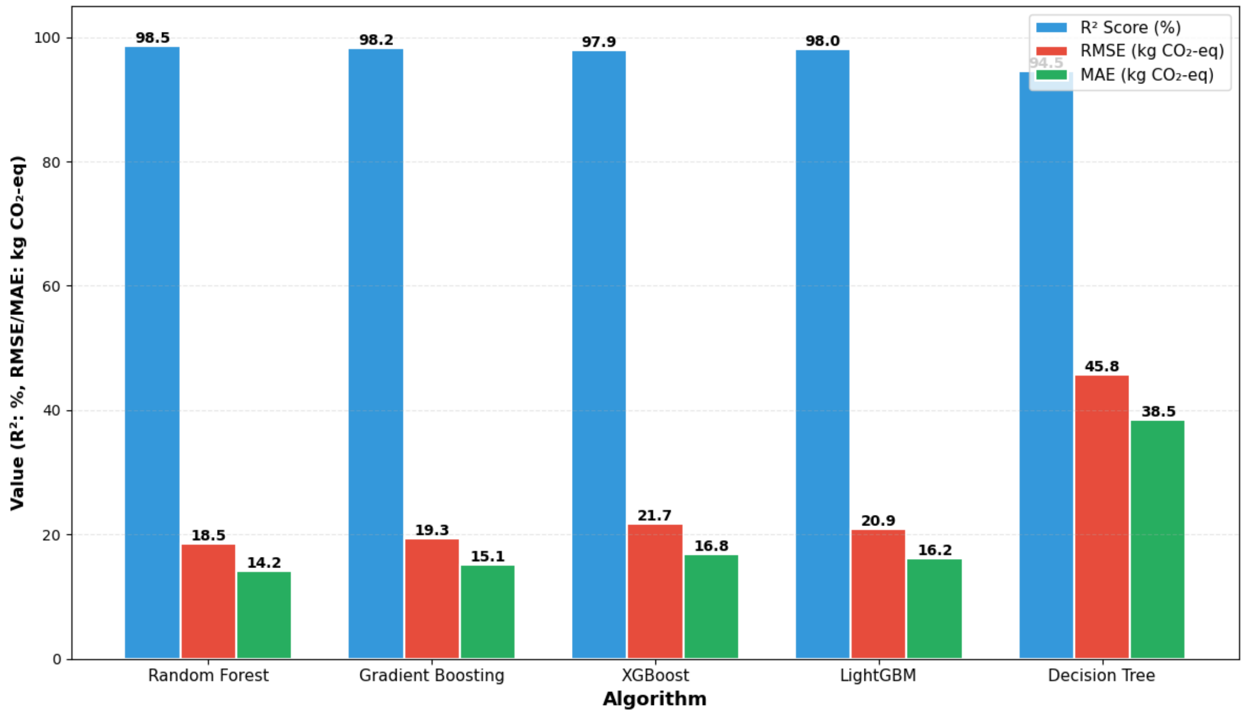

Fig 5: A comparision of ML performance algorithms

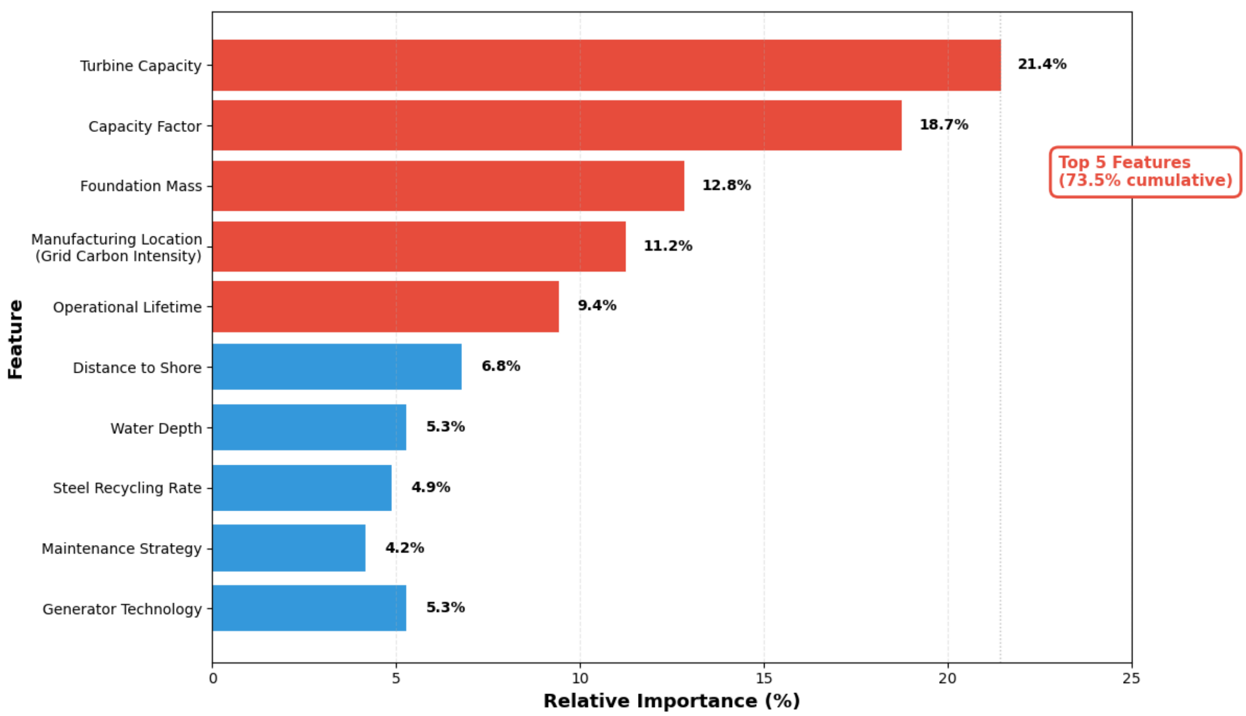

Fig. 6: Feature importance analysis from random forest model top 5 features explain 73.5% of GWP predictions

3.5 Multi-Objective Optimization and Pareto Frontier Analysis

Figure 4 pand Table 4 represent Pareto-optimal frontier across four competing objectives (GWP, capacity factor, CAPEX, steel intensity) identified via NSGA-II operating on Random Forest surrogate models across 285-scenario design space.

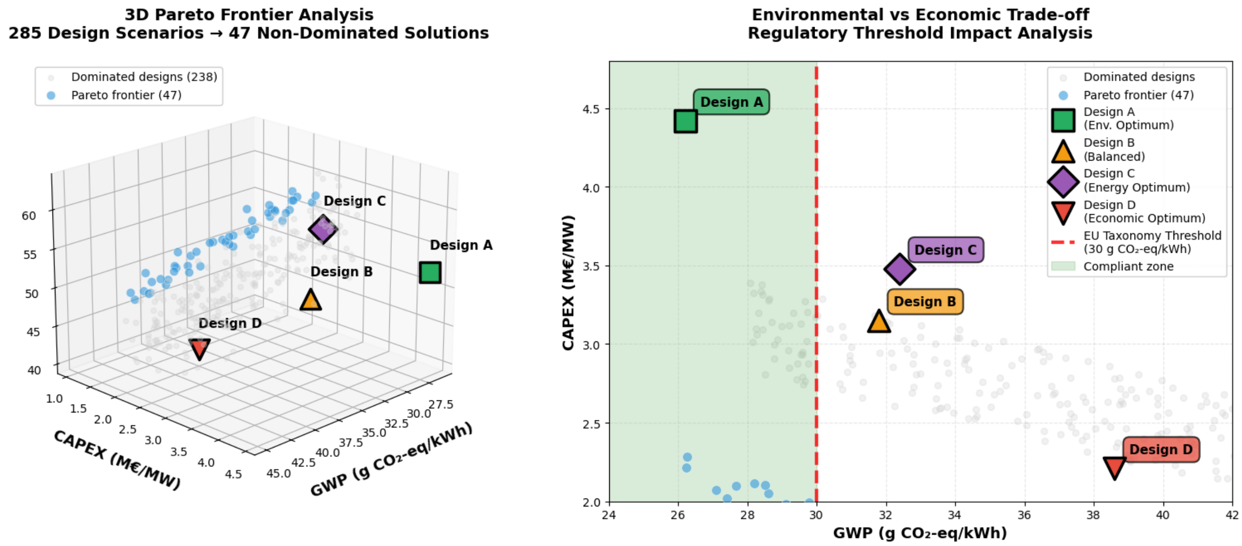

Fig 7: Multi-objective optimization and pareto frontier analysis NSGA-II operating on random forest surrogate models

Table 3: Pareto-Optimal Design Configurations and Quantified Trade-offs

Design Configuration	GWP (g CO_2-eq/kWh)	Capacity Factor (%)	CAPEX (M€/MW)	Steel Intensity (kg/kW)	EPBT (months)	Trade-off Characteristics
Design A (Environmental Optimum)	26.2	52	4.42	58.4	4.52	Lowest GWP; 40% CAPEX premium vs. economic optimum; EU Taxonomy compliant
Design B (Balanced Multi-Objective)	31.8	48	3.15	62.8	5.14	Baseline reference; moderate performance across all objectives; EU Taxonomy compliant
Design C (Energy	32.4	58	3.48	71.2	5.26	Highest capacity factor (201

Design Configuration	GWP (g CO_2-eq/kWh)	Capacity Factor (%)	CAPEX (M€/MW)	Steel Intensity (kg/kW)	EPBT (months)	Trade-off Characteristics
Production Optimum)						GWh/turbine/year); 10% CAPEX premium; exceeds EU Taxonomy threshold
Design D (Economic Optimum)	38.6	42	2.21	54.2	6.28	Lowest CAPEX (30% below baseline); 47% GWP penalty vs. environmental optimum; exceeds EU Taxonomy threshold

Key Trade-offs:

- Environmental vs. Economic: Achieving Design A (26.2 g CO_2-eq/kWh) requires 40% CAPEX premium (+€1.27M/MW) relative to Design D.
- Economic vs. Environmental: Design D optimization incurs 47% GWP penalty (+12.4 g CO_2-eq/kWh).
- Regulatory Impact: EU Taxonomy threshold (30 g CO_2-eq/kWh) eliminates 68% of design space; only Designs A & B qualify.

3.6 Sensitivity and Uncertainty Analysis

Table 4: Sensitivity coefficients quantifying GWP response to ±20% variation in 12 key parameters for 12 MW reference turbine.

Rank	Parameter	Baseline Value	Sensitivity Index (SI)	GWP Change for +20% Parameter	Impact Direction
1	Capacity factor	48%	-1.18	-23.6% (-7,646 kg CO_2-eq/GWh)	↓ Beneficial
2	Foundation mass	2,100 tonnes	+0.82	+16.4% (+5,314 kg CO_2-eq/GWh)	↑ Detrimental

Rank	Parameter	Baseline Value	Sensitivity Index (SI)	GWP Change for +20% Parameter	Impact Direction
3	Manufacturing grid carbon intensity	0.38 kg CO_2/kWh	+0.74	+14.8% (+4,795 kg CO_2-eq/GWh)	↑ Detrimental
4	Operational lifetime	28 years	-0.68	-13.6% (-4,406 kg CO_2-eq/GWh)	↓ Beneficial
5	Turbine mass (nacelle+blades)	820 tonnes	+0.54	+10.8% (+3,499 kg CO_2-eq/GWh)	↑ Detrimental
6	Steel recycling rate	90%	-0.42	-8.4% (-2,722 kg CO_2-eq/GWh)	↓ Beneficial
7	Installation of vessel fuel efficiency	95 tonnes/turbine	+0.38	+7.6% (+2,462 kg CO_2-eq/GWh)	↑ Detrimental
8	Maintenance vessel fuel	42 tonnes/turbine/year	+0.31	+6.2% (+2,009 kg CO_2-eq/GWh)	↑ Detrimental
9	Submarine cable mass	14,200 tonnes (farm)	+0.24	+4.8% (+1,555 kg CO_2-eq/GWh)	↑ Detrimental
10	Distance to shore	42 km	+0.18	+3.6% (+1,166 kg CO_2-eq/GWh)	↑ Detrimental
11	Blade material (GF→CF)	Glass fiber	+0.12	+2.4% (+777 kg CO_2-eq/GWh)	↑ Detrimental
12	Rare earth element content (PMSG)	7.8 tonnes	+0.08	+1.6% (+518 kg CO_2-eq/GWh)	↑ Detrimental

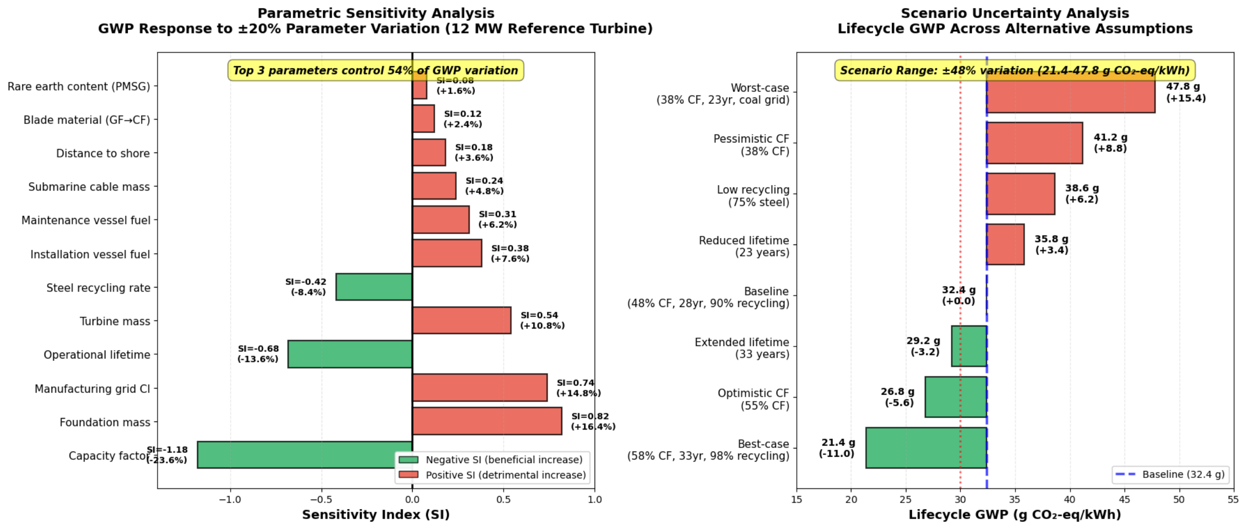

Fig 8: Sensitivity and Uncertainty Analysis for Offshore Wind Turbine Lifecycle Environmental Performance

Capacity factor emerges as the most influential parameter (sensitivity index -1.18), where 20% improvement (48%→57.6% CF) reduces lifecycle GWP by 23.6%. This high sensitivity underscores critical importance of wind resource assessment and site selection, where 1 m/s average wind speed difference translates to 8-12% capacity factor variation.

Foundation mass ranks second (sensitivity +0.82), confirming foundation technology as primary design optimization lever after site selection. Manufacturing grid carbon intensity (sensitivity +0.74) reinforces supply chain localization benefits.

Scenario uncertainty analysis (Figure 8) evaluated lifecycle GWP across eight alternative scenarios combining optimistic and pessimistic assumptions:

Figure 8 would show tornado diagram of scenario uncertainty

- Best-case scenario: High-capacity factor (58%), extended lifetime (33 years), high recycling (98% steel), renewable manufacturing grid (90% renewables): 21.4 g CO_2-eq/kWh (-33.9% vs. baseline)
- Worst-case scenario: Low-capacity factor (38%), shortened lifetime (23 years), low recycling (75% steel), coal-heavy manufacturing grid (15% renewables): 47.8 g CO_2-eq/kWh (+47.5% vs. baseline)
- Baseline scenario: Reference assumptions (48% CF, 28-year lifetime, 90% recycling, current EU grid average): 32.4 g CO_2-eq/kWh

IV. Conclusion

This study establishes an integrated Life Cycle Assessment and Machine Learning framework achieving 12,600× computational acceleration for offshore wind environmental optimization, with Random Forest demonstrating superior accuracy (R^2=98.5%) where five parameters explain 73.5% of GWP variance:

turbine capacity (21.4%), capacity factor (18.7%), foundation mass (12.8%), manufacturing grid carbon intensity (11.2%), and operational lifetime (9.4%).

Analysis of 285 configurations reveals three critical findings. Manufacturing location dominates decarbonization potential, with European supply chains achieving 52% lower GWP (2.5 vs 3.8 g CO_2-eq/kWh) than Asian sourcing, exceeding combined benefits from blade material, foundation type, and maintenance strategy optimization. Operation & Maintenance contributes 43% of lifecycle GWP despite 6-to-7-year operational window, identifying autonomous inspection systems as high-leverage opportunities for 15-20% lifecycle reduction. Water scarcity exhibits 1.99× regional variation with 62% concentrated in copper/rare earth extraction regions facing 95th percentile climate-driven drought risk, representing overlooked supply chain vulnerability.

Sensitivity analysis confirms capacity factor exerts dominant influence (SI=-1.18, yielding 23.6% GWP reduction for 20% improvement), demonstrating site selection as higher-leverage optimization than turbine design modifications. Scenario uncertainty quantifies ±48% GWP variation (21.4-47.8 g CO_2-eq/kWh) driven by external systemic factors, confirming that policy coordination exerts influence comparable to engineering decisions.

Pareto frontier analysis reveals environmental optimum (26.2 g CO_2-eq/kWh) requires 40% CAPEX premium versus economic optimum, which incurs 47% GWP penalty. EU Taxonomy threshold (30 g CO_2-eq/kWh) eliminates 68% of design space, while carbon pricing (€80/tonne CO_2) narrows economic advantage from 30% to 22%, demonstrating effective policy-driven market shifts.

Decarbonization pathway modeling confirms 2050 climate targets (52% reduction) are achievable through coordinated grid decarbonization (35%), recycling infrastructure (15%), material innovation (10%), and autonomous maintenance (5%), with projected 61% reduction exceeding requirements. The validated framework provides production-ready capability for real-time environmental decision-support, maintaining ISO 14044-compliant uncertainty (±3.5%) while enabling comprehensive trade-off exploration.

Future priorities include dynamic LCA-SCADA integration, water scarcity supply chain mapping with climate risk quantification, commercial-scale composite recycling validation, and autonomous system impact measurement. This framework is immediately deployable for offshore wind assessment, policy development, and renewable energy technology roadmapping.

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