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# Review and quantification of major risks in wind farm development and operation

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**Abstract.** With declining subsidies and tightening project margins, wind energy investments are increasingly exposed to a wide range of technical, operational, market, and system-level risks. Understanding the combined economic and technical relevance of these risks, and how they interact across project lifecycle phases, is essential for translating them into economic impact metrics. This study combines expert elicitation, structured survey results, and targeted literature review to identify and categorize the major risks affecting wind energy projects during both development and operation. These risks are clustered into four overarching sector challenges spanning long-term asset viability, component reliability, operation and maintenance performance, and rapid technology upscaling. To illustrate the potential economic relevance of these challenges, simplified scenario-based techno-economic impact assessments are conducted using a representative offshore wind farm case study. The analysis offers order-of-magnitude insights into how different risk categories propagate into economic performance indicators such as net present value and levelized cost of energy. The results demonstrate that different risks exhibit different economic signatures, including asymmetric downside risk, long-tailed loss distributions. Overall, this work does not propose a complete solution for capturing the full complexity of wind energy risks. Instead, it demonstrates the limitations of fragmented risk treatment and motivates the need for integrated, de-risking and decision-support frameworks capable of addressing interacting uncertainties. The study provides a structured starting point for future research aimed at developing such tools and supporting more robust investment, design, and operational decisions in the wind energy sector.

## 1 Introduction

With decreasing or non-existent subsidy levels, continued wind energy project investments are conditional on securing project profitability at low risk. The wind energy value chain often operates on small margins, and the economic feasibility of wind power under such conditions is sensitive to risks leading to unexpected costs or other disruptions. Over the last year there have been multiple failed auctions in Germany, France, the Netherlands, Denmark and Lithuania. At the same time many projects that won auctions over the last 3 years are now struggling to get the necessary investments approved (WindEurope (2025b)).

Recent industry assessments underscore the urgent need to de-risk the wind energy sector. The latest GWEC report highlights growing exposure to market and system-level risks, including a sharp increase in hours with negative electricity prices and

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persistent supply chain disruptions (Global Wind Energy Council (GWEC) (2025)). Without appropriate market design and effective de-risking instruments, these developments risk undermining investor confidence and increasing financing costs. The report further emphasizes the critical role of grid infrastructure in mitigating bottlenecks, reducing congestion and curtailment, enhancing energy security, and improving the economic viability of new projects. In parallel, supply chain uncertainties are identified as a major source of cost, schedule, and performance risk for wind energy projects (Council and Group (2023)).

It is therefore essential for investors to systematically identify and quantify the risks that can affect wind energy projects. These risks span technical, regulatory, environmental, socio-economic, and financial dimensions and are characterized by multidisciplinary interactions and feedback involving multiple actors and decision layers (Abba et al. (2022)). While existing studies have provided reviews of risk sources, there remains a gap in linking identified risk drivers to quantitative modeling parameters that allow for a systematic assessment of their economic impacts. In this study, we move beyond risk identification from literature by explicitly translating risk categories into modeling assumptions within a quantitative impact assessment tool chain and by evaluating their implications through scenario-based economic indicators.

The present study employs expert elicitation, structured polling, and analysis of publicly available data to identify, categorize, and quantify the major risks affecting wind energy projects across both development and operational phases. The objectives of this paper are:

- to identify and categorize the major risks currently facing the wind energy industry during the development and operation of wind energy projects;
- to review the identified risk categories and provide an overview of the most significant risks and their interdependencies;
- to quantify the economic impacts of these risks using a dedicated impact assessment tool chain.

Methodologically, this work combines expert-based risk categorization with quantitative cost and revenue modeling to illustrate the propagation of uncertainties into economic outcomes. Scenario definitions are informed by data and existing literature to represent plausible developments under current market and technological conditions. The economic impacts of risk-induced uncertainties are illustrated through a representative offshore wind farm case study based on the 22MW IEA (Zahle et al. (2024)) reference wind turbine.

Through this contribution, we aim to highlight the complex and interconnected nature of wind energy risk drivers across research domains and project life-cycle phases. For example, supply chain risks may interact with technical aspects of turbine design and propagate into construction, operation, and maintenance performance. By demonstrating how such interactions can be quantified, this study provides a first step toward developing de-risking tools that capture complex risk interdependencies and support informed decision-making across the financing, design, operation, and end-of-life phases of wind energy projects.

## 2 Methodology

In this study, we adopt a mixed qualitative and quantitative methodology to identify, categorize, and assess the economic relevance of major risks in wind farm development and operation. The approach combines a survey on major risks, expert

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elicitation, synthesis of sector challenges, literature review, and scenario-based quantitative impact assessment using the impact assessment tool WINPACT (Gräfe et al. (2025)).

Risk identification is initiated through a structured survey targeting experts from industry and academia. The survey captures perceptions of dominant risks for both currently operating and future wind farms, as well as perceived priorities for risk mitigation and research. Responses are analyzed quantitatively to identify dominant risk drivers and qualitatively to understand emerging themes and shifts in risk relevance as we move from operating wind energy assets to developing new ones. Survey results are complemented by expert judgment and targeted consultations to cluster individual risk drivers into four sector challenges. These challenges reflect structural issues that affect wind energy projects across technologies, markets, and lifecycle phases.

For each identified sector challenge, a literature review is conducted to summarize the current state of knowledge, data availability, and known sources of uncertainty. Building on this review, the economic relevance of each challenge is explored through scenario-based impact assessments. These assessments are not intended to provide detailed, project-specific risk quantification, but rather to estimate the order of magnitude of potential economic impacts and to illustrate how uncertainties, data limitations, and knowledge gaps propagate into project-level economic metrics. Scenarios are designed to span plausible ranges of uncertainty and structural change, grounded in literature, empirical evidence, and forward-looking assumptions.

### 2.1 Quantitative impact assessment

For the quantification of risks in terms of aggregated economic metrics, we use the wind energy project impact assessment tool WINPACT (Gräfe et al. (2025)). WINPACT is a modular, scenario-based impact assessment framework designed to quantify how uncertainties and design or operational choices in wind energy projects propagate through the full project life cycle to affect technical performance and economic value. The tool integrates interacting sub-models for wind farm operation, reliability-driven operation and maintenance, capital and operational cost structures, market conditions and price formation, revenue generation, and financial valuation within a unified simulation environment. Alternative assumptions on technical characteristics, cost parameters, market environments, or external constraints are introduced as scenario overrides and evaluated across all modules, enabling coupled effects, such as reliability changes influencing operation and maintenance (O&M) costs, revenues, and ultimately LCOE or NPV to be captured. Simulations can be executed as single cases or scenario ensembles with stochastic replicates.

Hereafter, we summarize the functionality of WINPACT modules used in this study.

The **CAPEX module** in WINPACT follows a bottom-up cost modeling approach in which total capital expenditure is assembled from explicitly defined project phases, cost categories, subcategories, and individual cost items. Each cost item consists of fixed cost terms and material-dependent cost terms and can be assigned at the turbine level or the project level. Material-dependent costs are calculated by combining prescribed material quantities with unit prices that are sampled stochastically at the beginning of each simulation and then applied consistently across all CAPEX items. Unit prices are generated from parametric stochastic price models, evaluated over a specified prediction horizon. A single vector of correlated random shocks can be applied across materials using a user-defined correlation matrix, allowing joint price movements to be represented. All

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capital cost items are time stamped according to the project schedule and stored at item level, enabling transparent aggregation to turbine and project CAPEX and propagation of material price uncertainty into valuation results.

The **WindFarm module** provides the baseline electrical production time series that serves as input for downstream modules. In this study, wind farm production is represented using the fixed-response option, in which a constant power output is generated over the operational lifetime based on the installed capacity and an assumed capacity factor.

The **OPEX module** represents wind farm operation and maintenance at an aggregated, project-relevant level, linking component reliability and maintenance processes to availability losses and operational costs. Operation and maintenance activities are modeled using an analytic continuous-time Markov chain (CTMC) formulation, in which turbine components transition between an operational state and downtime states associated with corrective and preventive maintenance actions, capturing the combined effects of failures, scheduled maintenance, access constraints, logistics delays, and repair activities. The steady-state solution of the CTMC yields expected component and turbine availability, which is applied to energy production, while the implied maintenance intervention frequencies determine operational expenditures for labor, logistics, vessels, and spare parts. Uncertainty in reliability and O&M process parameters is reflected through sampling from defined probability density functions, allowing variability in failure behavior and maintenance processes to propagate into availability and cost outcomes. The resulting availability and OPEX results feed into to energy yield, revenue, and financial valuation modules.

The **End of Life module** represents continued operation beyond the nominal design life as a scenario-based modification of production, reliability, and cost assumptions over an extended operating horizon. The module extends the baseline wind farm production time series and applies an aggregated energy yield modifier to the extension period to represent performance degradation and changing operating conditions. Ageing-related effects on operation and maintenance are captured through deterministic mean-shift overrides to the analytic CTMC-based OPEX model, applied during the extended lifetime to reflect changes in component reliability. In addition, the module introduces specific costs, such as inspection, analysis, and refurbishment expenditures, at the start of the extension period. Uncertainty in production performance, refurbishment effort, and selected reliability and process parameters is represented through sampling from defined probability density functions at the scenario level.

The **Curtailment module** accounts for system-level production losses by modifying the wind farm power time series to reflect market-driven, grid-related, or externally imposed curtailment. Curtailment is modeled as a fractional reduction of potential energy production applied at a monthly resolution. Curtailment fractions are drawn from prescribed probability density functions and applied uniformly to all production values within each month. Epistemic uncertainty in long-term curtailment conditions is represented through sampling of the distribution parameters at the simulation level, while aleatory variability in short-term system conditions is captured through repeated sampling of monthly curtailment fractions. The resulting production reductions are applied directly to the wind farm output and propagate to energy yield, revenue, and financial valuation modules.

The **FINEX and valuation modules** translate technical and operational model outputs into project-level financial performance and investment metrics. The FINEX module represents project financing, capital structure, and depreciation, debt amortization schedules, equity cost, and depreciation cash flows. These outputs are combined with CAPEX, OPEX, revenue, and lifetime extension cost records within the valuation module, which constructs cash-flow time series over the full project

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horizon. Cash flows are aggregated and discounted to derive valuation metrics, including net present value at the firm and equity level, internal rate of return, debt service coverage ratios, and levelized cost of energy. This approach ensures that changes in technical performance, operational strategies, financing assumptions, or lifetime extension scenarios are reflected in project value metrics.

### 2.2 Wind farm definition & scenario definition

As a basis for the quantitative impact analysis in the individual Risk categories in section 4, we define a generic wind farm representing a large-scale next generation European offshore wind farm project. The wind farm is assumed to consist of 34 22MW wind turbines located in the North Sea. Table 1 summarizes the main characteristics of the wind farm.

**Table 1.** Description of the study case.

| | **Wind farm** |
|---|---|
| Location | Offshore |
| Installed capacity $P_{\text{farm}}$ | 880 MW |
| Turbine rating $P_{\text{unit}}$ | 22 MW |
| Number of turbines $N_{\text{turb}}$ | 34 |
| Base design life $t_0$ | 25 years |
| Funding scheme | Contract for Difference |
| Strike price | 86 €/MWh |

In the impact assessment subsections of Section 4, scenarios are defined to represent different parameter ranges governing each modeled process. For each risk category, multiple scenarios are developed based on literature, available data, and the judgment of the authors. The scenarios are evaluated in a Monte Carlo manner, with the tool chain run 3000 times for each experiment. To ensure comparability across risk categories, a common baseline scenario is defined, representing operation of the reference wind farm under baseline assumptions and without stochastic variation of model parameters. Scenario labels are defined within each risk category. For example, “SC1” denotes the first scenario within the supply chain risk category.

## 3 Risk identification and categorization

### 3.1 Survey results

To identify the dominant risk drivers affecting wind energy projects across different lifecycle stages, a targeted survey was conducted as part of this study. The survey was conducted during multiples conference events organized by the Electrical Power Research Institute (EPRI) and included participants from both industry and academia. In total, approximately 100 respondents participated, primarily from the United States and Europe, with additional representation from South America, Asia, and Australia, providing a snapshot of current expert judgments across different markets.

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The survey was designed around three complementary questions addressing (i) risks affecting currently operational wind projects, (ii) risks expected to affect future wind projects, and (iii) research directions and innovations perceived as most effective for risk mitigation. Each participant was asked to select up to three predefined answers per question to avoid a bias toward the single most important issue. Together, these questions allow the identification of dominant risk categories and an assessment of how risk perceptions evolve when changing the perspective from operational to new projects and how these risks are expected to be addressed.

Figure 1 presents the distribution of responses to the first question, focusing on operational wind energy projects. The results show a clear dominance of reliability-related concerns. In total, 49% of responses identify reliability as the primary economic risk driver, comprising reliability of major non-redundant components (26%), reliability of replaceable components (8%), and premature degradation of components (17%).

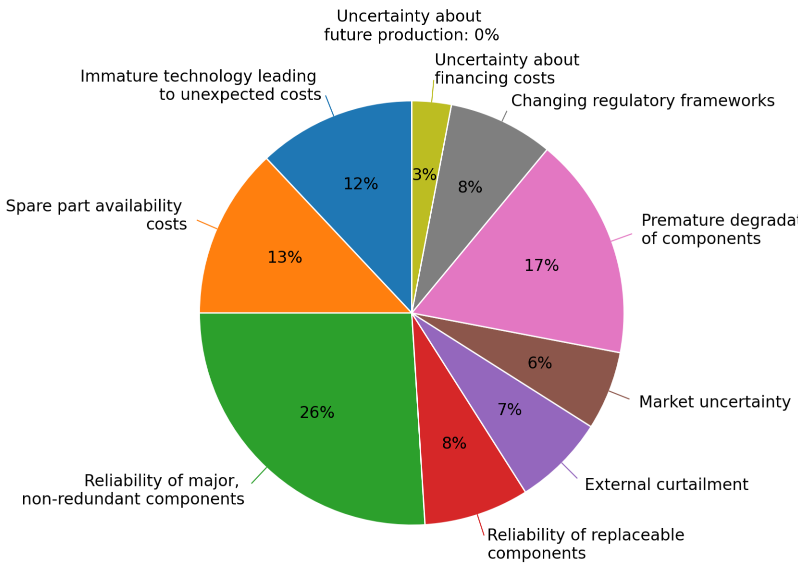


**Figure 1.** Survey results: What are the biggest risks for the economy of operational wind energy projects?

An additional 12% of respondents cite immature technology leading to unexpected costs, a concern that is closely linked to reliability and operational robustness. Other risk categories, including market and curtailment uncertainty, regulatory changes, and financing conditions, receive noticeably lower shares. Notably, uncertainty in future production receives no votes, indicating that wind resource uncertainty is generally perceived as well understood and adequately managed for existing projects.

Taken together, these results indicate that for operational wind farms, economic risk is dominated by asset-level performance and reliability, rather than by external system or market factors. This finding motivates a detailed examination of reliability modeling, failure-rate uncertainty, and O&M process inefficiencies in the subsequent sections of this paper.

Figure 2 shows the responses to the second question, addressing future wind energy projects. Reliability-related issues remain the most prominent risk category, accounting for 34% of responses. Although the relative weight is lower than for

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operational projects, concerns about major component reliability, replaceable components, and premature degradation continue to dominate expert perceptions.

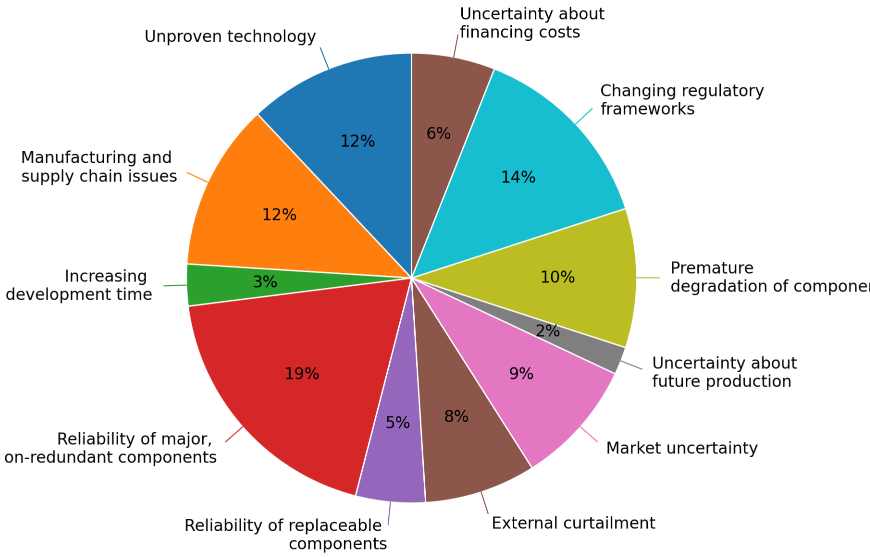


**Figure 2.** Survey results: What are the biggest risks for the economy of future wind energy projects?

However, in contrast to operational projects, the survey reveals a broader risk landscape for future developments. Unproven or immature technology again accounts for 12% of responses, reflecting concerns about larger turbines, accelerated upscaling, and reduced operational experience at the time of deployment. In addition, external and system-level risks gain substantially more importance. Market uncertainty and curtailment (together accounting for approximately 17%), changing regulatory frameworks (14%), financing uncertainty (6%), and manufacturing and supply-chain constraints (12%) are all perceived as significant contributors to future project risk.

This shift highlights an important temporal distinction: while operational projects are primarily exposed to technical and O&M-related risks, future projects are increasingly affected by system integration, market evolution, regulatory stability, and supply-chain robustness. These emerging risks are linked to longer planning horizons and reflect uncertainty about how power systems, markets, and policies will evolve as wind and renewables penetration continue to increase.

The responses to the third survey question, summarized in Figure 3, provide a direct link between the identified risks and perceived mitigation pathways. The prioritization of research and innovation areas closely mirrors the challenges identified in the first two questions.

Reliability-focused solutions dominate the responses. Advanced digital solutions for failure prediction (19%) and advanced sensing technologies for component health assessment (16%) underscore the perceived need for improved understanding and prediction of degradation processes and remaining useful lifetime during operation. These technologies are seen as essential enablers for more effective maintenance planning and risk-informed O&M strategies. Closely related, advanced O&M

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decision-making tools (16%) are highlighted as a key priority, emphasizing the need to translate diagnostic and prognostic information into economically optimal operational decisions.

Beyond operational mitigation, respondents also highlight the importance of upstream interventions. Novel design methodologies for improved reliability (11%) point to the need to explicitly integrate reliability objectives into turbine and wind farm design. Technology qualification and risk assessment frameworks (12%) are identified as critical tools for managing uncertainty associated with rapid technology upscaling and deployment. Supply-chain modeling and risk assessment (6%) address vulnerabilities identified for future projects, while market modeling, resource assessment, and policy innovation receive smaller but non-negligible attention.

Overall, the survey results reveal a pattern across project phases. Reliability emerges as a risk driver, influencing both operational performance and long-term economic outcomes. At the same time, the relative importance of external, system-level risks increases for future projects, reflecting longer planning horizons and greater exposure to market, regulatory, and supply-chain uncertainty.

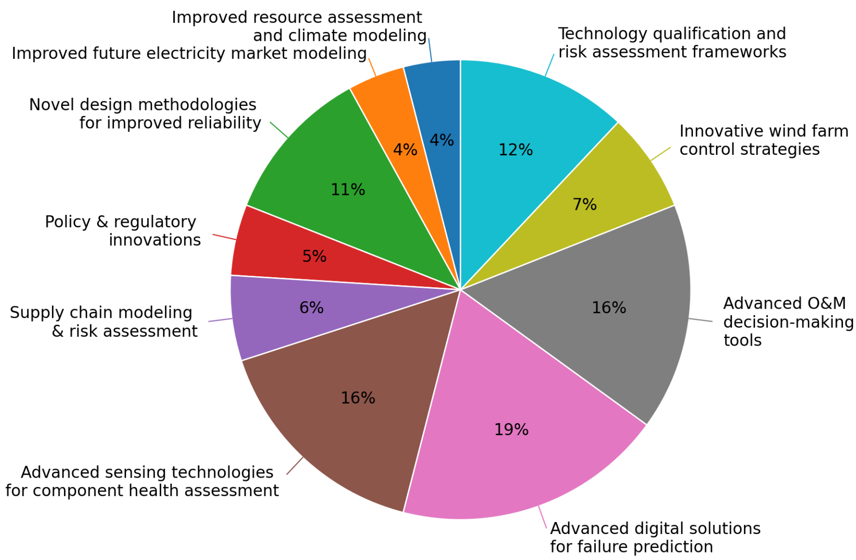


**Figure 3.** Survey results: What research areas or innovations could most effectively help mitigate risks in wind energy projects?

### 3.2 Risk categorization

While the survey responses identify individual risk drivers and mitigation priorities, they also reveal consistent clusters of challenges that affect wind energy projects across lifecycle stages. Building on the survey results, targeted consultations with experts from industry and academia, and the judgment of the authors, we identify four overarching sector challenges. These challenges are summarized in this section.

**Sector Challenge 1: Long-term asset viability under environmental and market dynamics** This challenge arises primarily from responses to future wind energy projects, where external and system-level risks become more important. While

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reliability remains a relevant concern, market uncertainty and curtailment, changing regulatory frameworks, financing uncertainty, and supply-chain constraints are identified as key risk drivers. These factors are inherently long-term and interdependent, influencing revenue stability, cost structures, and investment decisions over the project lifetime. The survey results indicate a shift from predominantly technical and physical uncertainties toward system-level uncertainties driven by external conditions and institutional factors.

**Sector Challenge 2: Reliability gaps in major non-redundant components** The dominance of reliability-related responses across both operational and future projects motivates this challenge. Reliability remains the single largest risk category for both project phases. In particular, failures of major non-redundant components are critical due to their potential to cause long outages, high repair costs, and significant reductions in availability and revenue.

**Sector Challenge 3: Inefficiencies in operation and maintenance (O&M)** While reliability determines failure occurrence, the survey responses also highlight the importance of how failures are managed. The strong prioritization of advanced sensing, failure prediction, and O&M decision-support tools indicates recognition that operational inefficiencies and limited predictability in O&M processes materially affect project economics. This challenge captures issues that are not reflected in failure behavior alone, including uncertainty in repair times, logistics delays, access constraints, data availability for operational and end-of-life decisions, and the difficulty of translating condition-monitoring information into effective operational actions.

**Sector Challenge 4: Design and operational risks from rapid technology upscaling** The identification of immature or unproven technology as a risk across both operational and future projects motivates the fourth sector challenge. Risks associated with technology novelty include unexpected costs, reduced availability, delayed commissioning, and increased uncertainty in performance and maintenance behavior. These risks are amplified by rapid upscaling trends, including increasing turbine size, new drivetrain concepts, evolving grid-code requirements, and associated changes in turbine operating modes.

## 4 Review and quantification

In this section, each sector challenge is examined in more detail. For each challenge, existing literature on the underlying risk categories is reviewed, and the order of magnitude of economic impacts arising from uncertainty in modeling assumptions and data availability is quantified.

### 4.1 Long-term asset viability- Supply chain uncertainty

#### 4.1.1 Review

The growth of the wind energy industry has been enabled by a robust and globalized supply chain that supported the installation of around 100 GW of capacity per year from 2020 - 2024 (IRENA (2025)). However, this existing supply chain is inadequate to support growth targets that require higher deployment rates, expansion into new markets, diversifying suppliers to mitigate geopolitical risks, and meeting the needs of evolving technologies such as floating offshore wind (Costanzo et al. (2025)).

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Although many of these challenges could be mitigated by strengthening supply chain resilience through expanded networks of manufacturers, infrastructure, and skilled labor, investors remain cautious due to heightened risk perceptions stemming from market volatility, inconsistent policy signals, and trade-offs between local capacity building and reliance on established global suppliers (Shields et al. (2023); Council and Group (2023)). This uncertainty slows supply chain investment, which subsequently limits the ability of future wind energy projects to source and install components in a timely, cost-effective, and politically acceptable manner.

The elements of a global supply chain that are relevant for wind energy projects include raw materials, manufactured components, specialized infrastructure, and a skilled workforce (Shields et al. (2023)). These present themselves as risks to wind energy projects primarily as:

- *Material and component bottlenecks*. Construction of a wind turbine requires specialized materials, products, and manufacturing processes. Manufacturing facilities are designed only to produce components that are specific to the wind industry (and often, specific to a single manufacturer) and can not easily diversify their production base. Installing wind turbines - particularly offshore - requires specialized logistics and facilities that have a limited global supply. Constrained supply of these components or capabilities can drive higher costs and delays for wind projects that compete for a scarce set of resources.

- *Geopolitical and trade risks*. In recent years, policy-makers have emphasized the need for supply chain localization to increase reliability and stimulate economic growth (Shields et al. (2023); Council and Group (2023)). Strategically critical materials, such as rare earth elements (used in generators) and balsa wood (used in blades), have highly concentrated supplier networks and limited global manufacturing capacity. Governments have used industrial policy to create import barriers (i.e. tariffs), limiting the availability of global supply chain components.

Supply chain uncertainties affect project design and decision-making through a complex network of interrelated factors, which we summarize in Table 2.

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**Table 2.** Key uncertainty dimensions in decision-making based on supply chain risk, mapped to uncertainty type, decision risk, and time aspects.

| Dimension | Uncertainty source | Type | Risk | Time horizon |
|---|---|---|---|---|
| Financing costs | Financing parameters (i.e., cost of debt, cost of equity, debt share) under different supply chain risk scenarios | E | Higher LCOE, reduced bankability | Pre-construction |
| Cost volatility | Short- and long-term variations in key commodities, including shocks from externalities | E | Higher LCOE | Pre-construction |
| Supply uncertainty | Component price equilibria attributed to supply / demand dynamics | E | Higher LCOE | Pre-construction |
| Geopolitical pressures | Changes in availability of critical materials or resources; magnitude of subsidies, tariffs and local content requirements | E | Project delays, possibility for higher costs | Pre-construction |
| Limited infrastructure | Uncertain availability of resources such as ports and vessels for offshore wind | E | Project delays, increased financing costs | Pre-construction through operation |
| Technology evolution | Readiness level of current supply chain to produce new technologies | E | Higher LCOE | Pre-construction |

In this study, we provide a simple assessment of the first two uncertainty dimensions to demonstrate the potential impact on LCOE driven by supply chain uncertainty. Further research is required to fill the knowledge gap of how future supply chain risks impact project design and cost decisions, such as developing dynamic supply chain investment models, causal relationships between perceived risks and financing costs, detailed accounting of industrial policies, and readiness levels of existing supply chain infrastructure.

#### 4.1.2 Impact assessment

We define a two-part risk assessment to evaluate the impact of supply chain risks on the LCOE of representative wind projects. First, we quantify uncertainty in key material prices and propagate this uncertainty through the CAPEX calculations of the

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wind project. Second, we vary the cost of capital to reflect changing levels of perceived risk from global and geopolitical drivers. The LCOE scales with the product of these factors, showing how supply chain risks can create nonlinear impacts.

The commodity prices that have the greatest impact on the variance of capital costs of a wind project are steel, copper, and carbon fiber which contribute some of the highest mass fractions to onshore and offshore wind projects (Eberle et al. (2023)). Although there are other key commodities that are notable supply chain risks for wind energy projects, such as rare earth elements and iron ore, these commodities are a relatively minor part of the capital stack of a project and price fluctuations will not greatly affect CAPEX (availability risk will be addressed through the cost of capital). Other commodities such as fiberglass used in blades have higher mass fractions but relatively low historic volatility, making them less relevant for stochastic modeling (U.S. Bureau of Labor Statistics (2026a)). Therefore, we primarily assess stochastic CAPEX uncertainty due to the variability in these primary cost drivers.

We obtain long-term price indices for these commodities from the U.S. Bureau of Labor Statistics (U.S. Bureau of Labor Statistics (2026c, b, b, c)) and derive the following stochastic parameters from the historical data:

- the *drift* (long-term trend) of commodity prices,
- the *volatility* (short-term uncertainty),
- the *jump intensity* (frequency of large, discrete price shocks).

We fit these parameters using a Merton jump-diffusion model as the frequency of short term shocks to commodity prices results in large tails in the log returns, leading to poor Gaussian fits to the data. The resulting parameters are provided in Table 3. Log-likelihood assessments show reasonable fits to the underlying historic data and a clear improvement over Gaussian models. The linear correlations between the parameters are low (under 0.1), but are still included in the Monte Carlo simulation.

**Table 3.** Stochastic commodity price parameters drift $\mu_{\text{hist}}$, volatility $\sigma_{\text{hist}}$ and jump intensity $\lambda_{\text{hist}}$ derived from historic data.

| Commodity | Drift $\alpha_s^\mu$ | Volatility $\alpha_s^\sigma$ | Jump intensity $\alpha_s^\lambda$ |
|---|---|---|---|
| Steel | 0.258 | 0.288 | 1.96 |
| Copper | 0.422 | 0.422 | 0.915 |
| Carbon fiber | 0.521 | 0.250 | 1.05 |

Financing risk is one of the most significant drivers of LCOE, although the magnitude of the impact of supply chain disruptions and geopolitical risks on financial parameters is not well established in the public literature. We address this by selecting values of the weighted average cost of capital (WACC) that correspond to different levels of project risk, but do not attempt to draw a causal link with factors such as regional dependencies, global concentrations of scarce elements, localization preferences, trade barriers, or other risk factors that could impact the deliverability and costs of a wind project. Modeling these dependencies is a promising direction for future research.

The WACC is calculated based on the debt-equity ratio, tax rate, and cost of debt and equity. We assume a constant value for the first two parameters. We select values for the cost of debt and equity based on historical comparisons between these

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project-specific financing terms and the risk-free rate of a 10 year bond; because historical wind project data are most readily available for U.S. projects, we determine the spread between wind-specific financing terms and a U.S. Treasury bond, and assume that this increment is broadly reflective of supply chain risk to the reference projects considered in this study.

Based on historical data between 2015 - 2024 from Mirletz et al. (2024), we calculate that the cost of debt is 1.73% higher than the risk-free rate for the period between 2017 - 2020, corresponding to a relatively stable period of wind energy deployment in the U.S. (Wiser et al. (2024)). In 2023, when prices spiked due to global supply chain constraints, this premium jumped to 3.5%. From the same data, we estimate that the cost of equity is around 5 percentage points higher than the cost of debt for all years. These estimates are relatively similar for both onshore and offshore wind projects, although in some markets we would expect offshore wind projects to face an additional premium due to the immaturity of the technology. We select a value of 2,7%, corresponding to the German 10-year bond yield, as the risk-free debt rate[1] for the baseline scenario (Deutsche Finanzagentur (2026)), and add an equity premium of 5%. We increase the debt premium based on the historical spreads from Mirletz et al. (2024) to reflect increasing risk profiles, keeping the equity premium at 5 percentage points above the cost of debt.

The values for the stochastic CAPEX parameters and WACC are provided in Table 4. We define these for three separate scenarios with minimum, moderate, and substantial supply chain risk profiles. We also define a time horizon over which the stochastic cost pathways evolve, effectively representing the project's risk exposure to commodity price volatility (which has been identified as a major investment risk in some emerging markets (Ury et al. (2024))).

**Table 4.** Supply chain risk scenarios and associated financial and commodity price parameters. Values for drift $\mu_{\text{hist}}$, volatility $\sigma_{\text{hist}}$ and jump intensity $\lambda_{\text{hist}}$ are commodity-specific.

| **Scenario** | **Interpretation** | **WACC [%]** | **Drift $\alpha_s^\mu$** | **Volatility $\alpha_s^\sigma$** | **Jump intensity $\alpha_s^\lambda$** | **Time horizon** $t[years]$ |
|---|---|---|---|---|---|---|
| Baseline | Deterministic baseline assumptions | 5.2 | - | - | - | - |
| SC 1 - Minimum Risk | Risk free rates on debt; lower bounds on stochastic commodity parameters | 3,8 | $0.8 \times \mu_{\text{hist}}$ | $0.8 \times \sigma_{\text{hist}}$ | $0.8 \times \lambda_{\text{hist}}$ | 1 |
| SC 2 - Moderate risk | Historic averages on debt and equity; no multipliers on stochastic commodity parameters | 5,2 | $1.0 \times \mu_{\text{hist}}$ | $1.0 \times \sigma_{\text{hist}}$ | $1.0 \times \lambda_{\text{hist}}$ | 2 |
| SC 3 - Substantial risk | Debt rates from supply chain shocks: higher bounds on stochastic commodity parameters | 6,7 | $1.2 \times \mu_{\text{hist}}$ | $1.2 \times \sigma_{\text{hist}}$ | $1.2 \times \lambda_{\text{hist}}$ | 3 |

[1] In reality, it is unlikely that a wind project would achieve a debt rate equal to a risk-free government bond rate. We use this value as a minimum threshold for the impacts of supply chain risk-based financing costs on LCOE.

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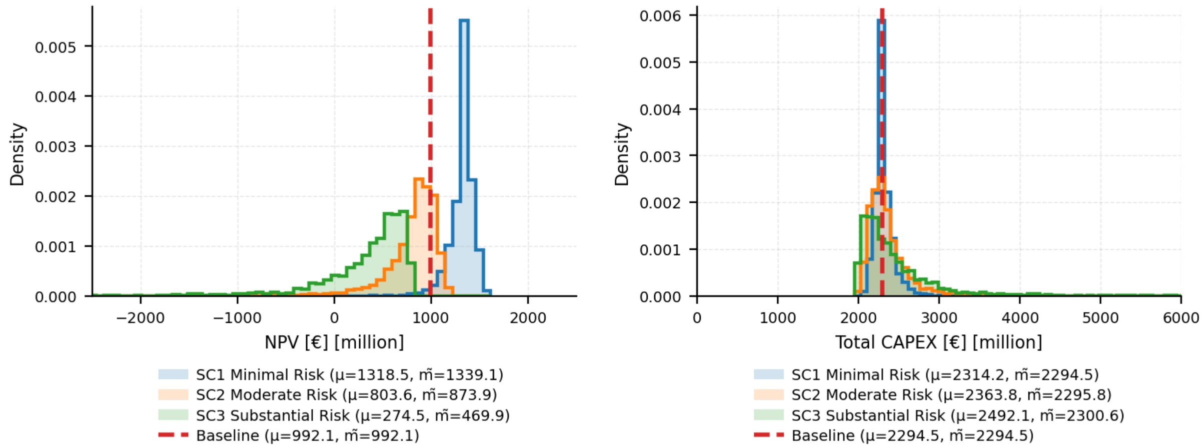


**Figure 4.** NPV (left) and total CAPEX (right) distributions for different scenarios.

The NPV, total CAPEX, and LCOE simulation results for the scenarios in Table 4 are provided in Figs. 4 and 5, respectively. The effects of the commodity price volatility and increasing time exposure increase the tails of the distribution while slightly reducing the peak cost. A greater impact is noticeable in NPV, which shows a clear shift in the mean of the distribution driven by favorable or unfavorable financing costs coupled with increasing negative tails for the SC3 scenario. When combined into the LCOE calculation, it is clear that increasing risk profiles drive a fundament shift in the cost structure of the project. The median of the SC 2 scenario is near the (deterministic) baseline LCOE of €67.3/MWh with a mean value of €69.3/MWh. By comparison, essentially the entire distribution of the higher risk SC 3 scenario is above the baseline value of LCOE, with the mean now at €77.5/MWh. This increase of around 12% is on the lower end of the reported 10-50% cost increases faced by offshore wind projects between 2021 - 2023 that directly led to cancellations of projects in Europe and the U.S. (and does not include effects from additional macroeconomic factors or the remaining uncertainty sources in Table 2) (Fuchs et al. (2024)). The contribution of supply chain risk outlined in this section has the potential to create a step change in project feasibility and delivery, and therefore represents a critical factor in project design and de-risking.

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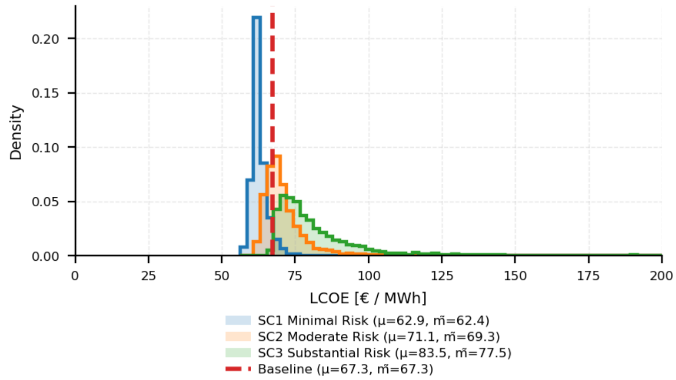


**Figure 5.** LCOE distributions for different scenarios.

### 4.2 Long-term asset viability - Through-life decision making

Wind turbines are typically designed for a nominal lifetime of 20 years for onshore installations and 25 years for offshore installations, in accordance with IEC standards (International Electrotechnical Commission (2019a, b)). In Europe, a large share of the installed onshore and offshore wind fleet is approaching or has reached its nominal design lifetime. Current estimates indicate that between approximately 60 GW (WindEurope (2025c)) and 80 GW (WindEurope (2025a)) of installed capacity will reach the end of design life in the coming years. The nominal design lifetime, however, does not necessarily define the actual end of operational life. In many cases, continued operation beyond the certified lifetime is technically feasible. Decisions on lifetime extension or decommissioning, therefore, depend on a combination of regulatory, technical, and economic considerations and constitute a complex, multidimensional decision problem under uncertainty. While this decision problem is most visible toward the end of the life time, the underlying uncertainties and risks are relevant throughout the lifetime of a wind energy asset.

Through-life decision-making is not a binary choice between continued operation and shutdown, but rather a set of interrelated technical, regulatory, and economic decisions that determine whether operation beyond the design lifetime is permissible and economically viable under uncertain future conditions. Depending on the outcome of this process, assets may be decommissioned, repowered, refurbished, or operated under a lifetime extension framework.

From a technical perspective, wind turbines are designed against standardized reference classes using conservative assumptions, while actual site-specific operating conditions are often less severe than those assumed in design. As a result, structural integrity frequently permits continued operation beyond the nominal design lifetime. Monitoring and evaluation of actual operational conditions and accumulated loads can reduce uncertainty in modeling assumptions and support the verification of safe continued operation (Nielsen et al. (2019)).

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If structural integrity can be ensured, the reliability of wind turbine components becomes a key determinant of continued operation. Many reliability modeling approaches assume increasing failure probabilities over time, commonly represented using Weibull-distributed failure models Carroll et al. (2016); Donnelly et al. (2024); Dinwoodie et al. (2013). This assumption reflects physical ageing mechanisms such as wear, corrosion, and fatigue. As reliability directly affects maintenance requirements, availability, and operational expenditure, estimating post-design-life reliability is critical for late-life phases, and epistemic uncertainty in reliability characteristics can substantially influence economic outcomes. In addition, aerodynamic performance may degrade due to blade erosion, which has been shown to cause non-negligible losses in annual energy production in ageing turbines (Malik and Bak (2025)).

Changing site conditions constitute an additional source of uncertainty in through-life decision-making, particularly due to climate-change-induced modifications of the wind climate and intra- and inter-farm wake effects. Climate projections based on ensembles of regional and global climate models indicate that, while annual mean wind speeds and capacity factors in Northern Europe are expected to change only modestly, the direction and magnitude of change vary across models and regions, introducing uncertainty in long-term yield estimates. Reported median changes in future hub-height wind speeds are typically on the order of $\pm$1–2%, corresponding to changes in wind power density and annual energy production (AEP) of approximately -2% to -5%, with substantially larger seasonal effects, particularly summer AEP reductions reaching -5% to -10% in parts of the North Sea, and a wide inter-model spread in projected outcomes (Hahmann et al. (2022)). Changes in wind direction distributions and extreme wind statistics have also been reported, although their implications for turbine class requirements remain uncertain (Larsén et al. (2024)).

Wake effects represent a site- and layout-dependent source of uncertainty that becomes increasingly relevant for ageing offshore wind farms embedded in dense clusters. Existing studies indicate that intra- and inter-farm wake losses can reduce AEP by approximately 5–10% for current offshore wind farms, with projected losses increasing to 10–18% or more under future high-deployment scenarios in regions such as the North Sea (van der Laan et al. (2023); Borgers et al. (2025)). Together, the non-stationarity of wind resources and the uncertainty in wake-induced production losses introduce variability in future revenues, increase downside risk in cash-flow projections, and therefore affect the economic viability of operations, especially when making decisions over long time horizons.

Regulatory conditions constitute a major source of uncertainty in through-life and end-of-life decision-making as permitting conditions may evolve over timescales comparable to project life cycles. Lifetime extension is not governed by a harmonized regulatory framework in Europe, and continued operation beyond original design assumptions is subject to national or regional regulations that differ in scope, stringency, and enforcement and may evolve over time (Ziegler et al. (2018)). Regulatory requirements directly affect the technical feasibility of lifetime extension through permitting, inspection, certification, and documentation obligations, and influence economic viability through additional compliance costs or operational constraints. Uncertainty regarding end-of-life obligations, including decommissioning and removal requirements, introduces further economic risk, particularly for offshore assets. Regulatory uncertainty, therefore, represents a regime-level risk that can materially influence lifetime extension decisions independently of the technical condition of the asset.

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Economic uncertainty in late-life phases is primarily driven by uncertainty in cost and revenue assumptions associated with refurbishment and continued operation. Refurbishment scope and associated costs are typically identified only after detailed inspections and condition assessments and vary widely across turbines, sites, and regulatory contexts (Ziegler et al. (2018)). The absence of standardized refurbishment pathways renders cost estimates highly project-specific and difficult to establish ex ante. Operational expenditure during extended operation is further subject to uncertainty arising from ageing-related reliability degradation, spare-part availability, and evolving maintenance and logistics conditions. Together, these factors introduce substantial variability in projected economic outcomes and limit the applicability of deterministic cost assumptions in lifetime extension assessments.

IEC 61400-28 (International Electrotechnical Commission (2025)) provides a technical framework for through-life asset assessment, with a primary focus on lifetime assessment, load and fatigue accumulation, inspection and monitoring strategies, and certification requirements. The standard identifies a set of technically relevant risk factors to be considered in through-life and end of life decision making, including changes to design requirements, local legislation, site and environmental conditions relative to the turbine class, previously tolerated design or equipment aspects, and modifications to control software. While IEC 61400-28 provides guidance on technical sufficiency and compliance, it does not prescribe an economic decision model, define cost or performance multipliers, or specify methods for risk quantification, leaving the assessment of economic implications and uncertainty largely to practitioners.

Several studies have addressed the quantification of risks associated with operation beyond the design life by focusing on individual or selected subsets of the underlying technical and economic uncertainties. Bayesian decision frameworks have been proposed to support lifetime extension (LTE) decisions by explicitly accounting for inspections, analysis, and the expected costs and benefits of continued operation (Nielsen et al. (2019)). While such approaches provide a structured decision logic and highlight the value of inspections and monitoring, they rely on simplified or implicit assumptions regarding the evolution of component reliability and do not fully quantify reliability-related uncertainty. Other studies combine probabilistic fatigue modeling with economic optimization to assess LTE feasibility using net present value criteria, explicitly accounting for failure probabilities and consequences (Nielsen and Sørensen (2021)). These approaches suggest that moderate reductions in target reliability may be economically acceptable for ageing assets, but remain focused on a limited set of technical risks. More comprehensive techno-economic frameworks integrate structural degradation modeling, inspection strategies, and economic evaluation under uncertainty, and acknowledge the strong sensitivity of LTE outcomes to assumptions on maintenance costs, refurbishment scope, future revenues, discount rates, and certification requirements Yeter et al. (2022). However, the resulting assessments remain highly project-specific and dependent on boundary conditions.

Overall, existing frameworks address important elements of through-life decision-making, but lack an integrated treatment of the full spectrum of uncertainties and their propagation to economic risk and decision variables. In particular, interactions between structural integrity, reliability and resulting O&M activities, energy yield, regulatory constraints, and market conditions are typically treated in isolation, and temporal aspects of uncertainty accumulation across the asset lifetime are only partially captured. Late-life decision-making, therefore, represents a complex problem spanning multiple uncertainty classes, aleatory, epistemic, and regulatory, and multiple time horizons, ranging from early-life design and fatigue accumulation to short-term

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operational decisions and long-term economic and financing risks. To support consistent and transparent decision-making, integrated decision-support approaches are required that jointly consider these dimensions. The key uncertainty domains, their
410 associated risks, and relevant time aspects are summarized in Table 5

**Table 5.** Key uncertainty dimensions in through-life decision-making, becoming most relevant in late-life phases, mapped to uncertainty type, decision risk, and time aspects. A: Aleatory, E: Epistemic, R: Regime.

| Dimension | Uncertainty source | Type | Risk | Time horizon |
|---|---|---|---|---|
| Structural integrity / remaining life | Remaining fatigue budget; crack growth; site-specific loads vs. design assumptions; effects of past operational strategies | E | Unsafe continued operation; unexpected life-limiting findings; unplanned refurbishment costs | through lifetime |
| Reliability and maintenance process | late-life phase failure rates; repair times (MTTR); logistics delays; spare-part availability | A, E | Higher downtime and O&M expenditure than expected; cascading failures; availability | Late-life phases |
| Energy yield during late-life operation | Performance degradation (e.g. blade erosion); availability-driven production loss; curtailment impacts | A, E, R | Revenue shortfall; inability to meet financial or contractual performance targets | Late-life phases |
| External conditions | Long-term wind resource shifts evolving wake interactions | A, E | Biased energy yield projections | Mid- to long-term |
| Regulatory and legal | Requirements for continued operation; inspection and certification scope; decommissioning and removal obligations; liability allocation | R, E | Project becomes non-permissible; unexpected compliance or decommissioning costs; schedule delays | Late-life decision and end-of-life |
| Market and cost environment | Electricity price and support-scheme changes; inflation; contract terms | A, R | Revenue volatility; adverse economics despite technical feasibility; inability to secure services or financing | Mid- to long-term |

### 4.2.1 Impact assessment

Building on the uncertainty dimensions identified in the literature review and summarized in Table 5, the impact assessment adopts a scenario-based approach to capture the aggregated uncertainty effects on energy yield, refurbishment effort, and system reliability during extended operation. Here, lifetime extension is chosen as one representative through-life decision-

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making challenge. The analysis is intended to demonstrate how plausible variations in key assumptions propagate to economic performance metrics such as net present value and levelized cost of electricity. The assessment aims to provide insights into the sensitivity of LTE economics to non-stationary operating conditions and ageing-related effects. To translate the identified uncertainty dimensions into parameters for the WINPACT toolchain, the risk drivers are aggregated at the scenario level, enabling assessment of their combined impact on production performance, refurbishment requirements, and system reliability during the lifetime extension period.

Each scenario defines:

- a stochastic production modifier applied uniformly across the LTE period,
- a stochastic refurbishment cost uplift applied as a one-off cost at the start of LTE,
- a deterministic shift in system reliability parameters during the extended lifetime.

Production and refurbishment uncertainties are modeled as aggregated normal distributions, representing scenario-level uncertainty rather than individual risk realizations. For a given scenario $s$:

$$X^{(s)}_{\text{AEP}} \sim \mathcal{N}\left(\mu^{\text{AEP}}_s, \sigma^{\text{AEP}}_s\right), \tag{1}$$

$$X^{(s)}_{\text{Ref}} \sim \mathcal{N}\left(\mu^{\text{Ref}}_s, \sigma^{\text{Ref}}_s\right). \tag{2}$$

The sampled modifiers are applied as:

$$\text{Production}_{\text{adj}} = \text{Production}_{\text{base}} \cdot \left(1 + X^{(s)}_{\text{AEP}}\right), \tag{3}$$

$$C_{\text{Ref}} = C_{\text{Ref, base}} + X^{(s)}_{\text{Ref}}. \tag{4}$$

In each Monte Carlo iteration, one random draw from $X^{(s)}_{\text{AEP}}$ and $X^{(s)}_{\text{Ref}}$ is applied uniformly across all LTE years, reflecting scenario-level uncertainty in energy yield and refurbishment costs. The corresponding assumptions for production loss, refurbishment uplift, and extension duration are summarized in Table 7.

Uncertainty in future reliability is captured through scenario-dependent shifts of component failure rates during the lifetime extension period. Failure rates during the original design life remain unchanged. Reliability degradation is implemented as a multiplicative factor on baseline component failure rates, applied only during the extended lifetime. This approach reflects the expectation that ageing-related mechanisms, such as wear of mechanical components, accumulated fatigue damage, corrosion, and blade erosion, become increasingly relevant beyond the original design life, while preserving the reliability characteristics of the asset during its initial operation. Reliability degradation is treated deterministically to reflect epistemic uncertainty regarding long-term ageing behavior. Table 6 summarizes the applied reliability modifications.

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**Table 6.** Scenario-dependent reliability parameter modifications applied during the lifetime extension period.

| Scenario | Interpretation | Failure-rate multiplier $\lambda_{\mathrm{LTE}}$ |
|---|---|---|
| Baseline (No LTE) | No lifetime extension; baseline reliability applies throughout project life | 1.00 |
| EOL 1 – Moderate degradation | Moderate ageing effects and increased corrective maintenance frequency during extended operation | 1.5 |
| EOL 2 – Substantial degradation | Pronounced ageing effects, higher failure intensity, and reduced reliability during extended operation | 2.0 |

**Table 7.** Lifetime extension scenarios and associated quantitative assumptions.

| Scenario | Interpretation | AEP modifier $(\mu, \sigma)$ [%] | Refurb uplift $(\mu, \sigma)$ [/€turbine] | Extension time [years] |
|---|---|---|---|---|
| Baseline (No LTE) | Operation limited to original design life; no additional uncertainty | (0.0, 0.0) | (0, 0) | 0 |
| EOL 1 – Moderate degradation | Conservative extension with moderate production degradation and limited refurbishment scope | (−2.0, 1.0) | (1.5M, 0.5M) | 8 |
| EOL 2 – Substantial degradation | Aggressive extension with pronounced production loss and major refurbishment effort | (−6.0, 2) | (5M, 2M) | 5 |

Figure 6 shows the distribution of total project NPV and LCOE for both the baseline case and the lifetime extension scenario. As expected, extending the operational lifetime of a wind farm is a powerful lever to increase project value and reduce the levelized cost of energy. Continued operation of an already depreciated asset allows additional production at comparatively low marginal cost, thereby lowering LCOE and increasing cumulative revenues. In addition, the postponement of typically substantial decommissioning costs further improves project economics. This should not be interpreted as an absence of through-life risk, but rather as an illustration of how late-life decisions can redistribute risk across time and uncertainty dimensions. The results indicate that the economic outcome of an LTE project can vary substantially, with a spread on the order of € 100 M in NPV or about € 4 /MWh in LCOE for the considered case. This shows that through life decisions can redistribute economic project outcome and associated risks. It should be noted that this illustrative experiment does not account for several important

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sources of uncertainty, including electricity price volatility, inflation, regulatory risk, or the risk of catastrophic failures. Future work should therefore focus on integrated methods that support through-life decision-making under the combined uncertainty dimensions summarized in Table 5.

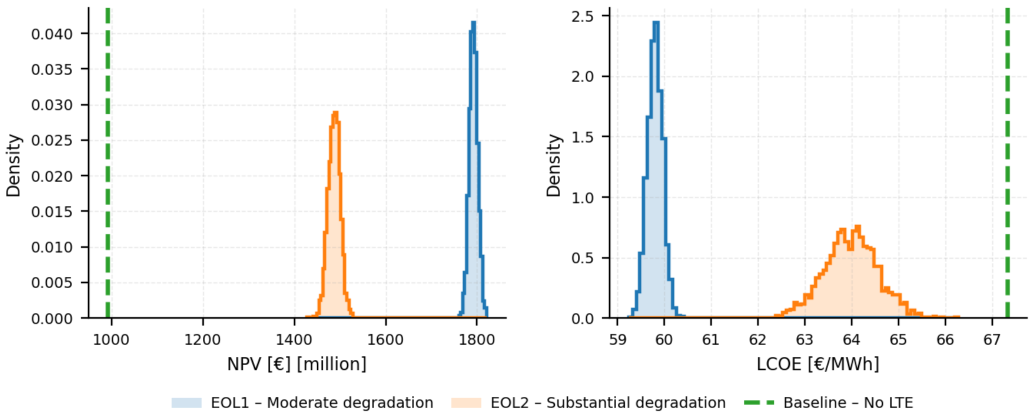


**Figure 6.** NPV and LCoE for different EOL Scenarios

### 4.3 Long-term asset viability - Curtailment

#### 4.3.1 Review

With the increasing share of variable renewable energy in power systems, production peaks occur more frequently, for instance during periods of high wind or/and sunny days (Global Wind Energy Council (GWEC) (2025)). These production peaks can have both local and system-wide impacts. At the system level, high VRE production tends to lower wholesale electricity prices, sometimes down to very low or even negative levels when production exceeds demand. In several European markets, the number of hours with negative prices has increased in the last years, reducing revenues and creating lost opportunities for wind farm operators who may have to curtail generation to avoid paying to inject power into the grid (Tselika (2022); Bird et al. (2016); Biber et al. (2022)).

At the local level, production peaks can create grid constraints when transmission infrastructure cannot accommodate the power flows required to match generation to demand, or when local generation exceeds the capacity of the grid (Agbonaye et al. (2022); EirGrid TSO and SONI TSO (2024)). In these cases, renewable generation must be curtailed to maintain system stability, leading to increasing volumes of constrained energy and, in many markets, constraint payments from system operators to affected wind or solar farms. Curtailment of excess wind and solar energy is therefore a growing concern in systems with high VRE penetration and limited demand flexibility or storage.

A further source of curtailment arises from constraints imposed to protect wildlife, particularly birds and bats. Indeed, wind turbines can create collisions and deaths due to pressure changes. Mitigation measures such as increased cut-in speeds or

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seasonal shutdowns can significantly reduce these risks but also reduce energy production and revenues for operators Hayes et al. (2023); Whitby et al. (2021); Behr et al. (2017).

We distinguish three main types of curtailment in our review: market-driven, grid-constraint, and wildlife-related.

**Transmission constraints**

As the penetration of renewable energy sources increases in Europe following the ambitious decarbonization targets, electricity grid design and capacity must develop accordingly. However, uncertainties in grid development and expansion remain a critical challenge. A recent study by the Joint Research Centre (Thomaßen et al. (2024)) explores uncertainties in redispatch volumes under different European grid expansion scenarios. The analysis considers three scenarios (Business-as-Usual, Ambitious Grid Expansion, and Extreme Grid Expansion) for 2030 and 2040, showing redispatch volumes increasing from 165 to 374 TWh by 2030 and from 274 to 809 TWh by 2040, depending on the level of grid reinforcement. These results highlight the growing risk of congestion and curtailment in the absence of targeted and timely grid investments. Such challenges are already growing in several European countries. In the Netherlands, grid congestion has increased in recent years, with most sections of the electricity grid considered congested since September 2024 (International Energy Agency (2025)). The resulting connection waiting list includes approximately 10,000 large consumers or battery projects and 7,500 large-scale generation projects, significantly constraining the country's electrification efforts and economic activity. Similarly, in Germany, high wind generation in the northern regions combined with concentrated industrial demand in the southern states frequently leads to north-to-south transfers that exceed transmission capacity, requiring redispatch and curtailment (c.f. SMARD – German Electricity Market Data (2024)).

According to data collected by the Irish TSO EirGrid (EirGrid TSO and SONI TSO (2024)), the percentage of wind generation curtailed due to grid constraints (i.e. local network capacity limits) varies significantly from one region to another. In 2023, wind energy production was reduced by only 0.3% in the South East of Ireland, while it was constrained by 11.4% in the North West. These differences may be explained by variations in renewable energy penetration, the presence or absence of energy-intensive industries, and the level of grid development in each region. Figure 7 displays the monthly variability of constraint levels across Ireland from 2016 to 2024, showing overall increasing curtailment levels and wider interannual spreads.

Constrained wind farms are often compensated by system operators for lost revenues. However, the exact compensation system varies by country. In Germany, for instance, curtailment compensation follows a cost-based approach, ensuring that wind farm operators receive the same income as if their generation had been fully dispatched. In contrast, countries such as Ireland, until recently, was providing limited or no compensation for curtailed renewable generation. To compensate the energy lost, gas-fired generators are paid to increase output at short notice, often charging a premium for this flexibility. While these mechanisms maintain financial stability for operators, frequent curtailment of wind energy can lead to high balancing costs for the system operator and threaten public perception of renewable energy, as it may be perceived as wasted or underutilized (Kerr (2025)).

**Market-driven curtailment** As the share of renewable power in the energy mix grows, careful planning of new renewable energy production sites becomes increasingly important. Highly centralized generation can lead to overlapping peaks, which are directly reflected in day-ahead markets as increased electricity price volatility. Negative price episodes are no longer rare

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events but a common mechanism in systems where inflexible supply and limited demand-side flexibility clash with high wind penetration. Global Wind Energy Council (GWEC) (2025) highlights, on top of acknowledging the recent drastic increase in the negative power prices, the potential impact on investor confidence if no de-risking approaches are suggested.

When prices turn negative, continuing to generate implies paying the system to take the electricity, making curtailment an economically rational, though value-reducing, decision. Negative prices typically occur during periods of high wind or solar generation, low demand, and limited flexibility from conventional plants or interconnectors, resulting in oversupply. In such conditions, wind farms are increasingly curtailed for economic rather than technical reasons. Over the years, the frequency of negative prices has increased in countries with high wind or solar PV penetration, such as Germany, Denmark, and the Netherlands. Figure Figure 7 shows the annual distribution of monthly negative electricity price hours for different European countries base on data extracted from Ember (2025).

Market-driven curtailment can significantly impact a project's net present value, bankability, and operational reliability due to reduced availability. Gonzalez-Aparicio et al. (2022) analyzes the feasibility of offshore wind in the Dutch energy market by 2030 and conclude that new offshore wind farms may not always be profitable, particularly under low-electrification scenarios, mainly due to potential generation surpluses. The expected frequency of negative electricity prices should be considered during the design and planning phase of a wind farm, as they may affect the ability to secure PPAs, CfDs, or other contractual agreements.

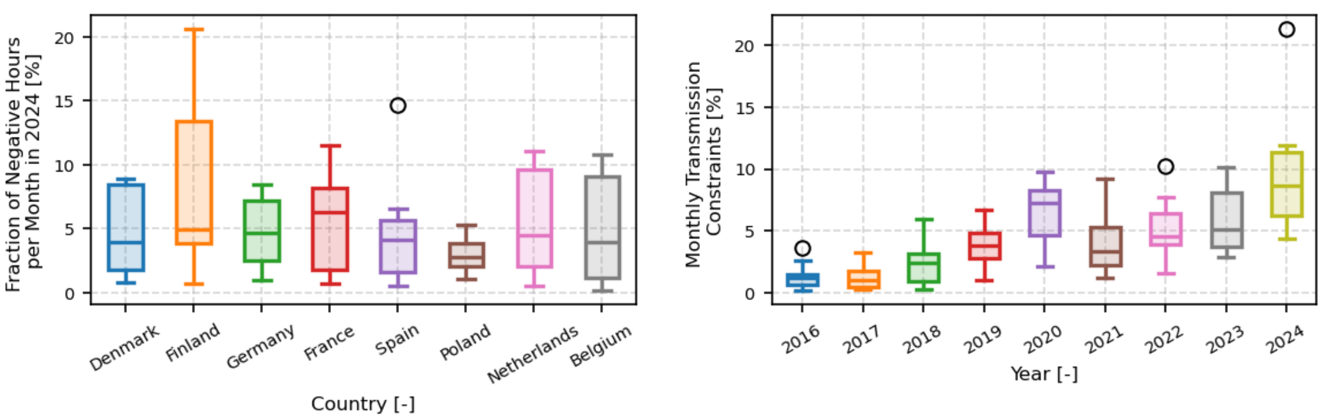


**Figure 7.** (Left) Distribution of monthly fraction of negative electricity prices per country (Ember (2025)); (Right) Distribution of monthly constraint levels in all Ireland (Republic of Ireland and Northern Ireland) per year.

**Curtailment - Wildlife Constraints** In some regions, wind energy development has been demonstrated to pose significant threats to bat populations (Cryan and Barclay (2009); Friedenberg and Frick (2021)), raising conservation concerns (Kunz et al. (2007); Rydell et al. (2010)). Fatalities are due to collision with turbine blades and barotrauma caused by air pressure changes near the rotating blades. These impacts are particularly evident during seasonal migration periods and under specific meteorological conditions such as low wind speeds and warm nights, when bats are the most active. As a mitigation measure, operators are often required to curtail turbines at night during low wind periods, a practice known as blanket curtailment. However, this approach directly conflicts with revenue optimization, since low wind speeds typically correspond to periods when turbines could still operate profitably without risk of being curtailed by the generation excess mentioned earlier.

To mitigate this problem and reduce the curtailed time, smart or dynamic curtailment strategies have been proposed (Hayes et al. (2023); Gottlieb et al. (2024)). These methods rely on real-time or forecast indicators of bat activity, meteorological data, and, sometimes, acoustic monitoring to identify when bats are likely to be present near turbines, enabling selective shutdowns only under high-risk conditions. Such approaches have shown promise in reducing bat mortality while minimizing energy loss (Hayes et al. (2023)), but their general applicability remains uncertain. Differences in local bat species behavior, habitat type, and atmospheric conditions mean that site-specific calibration is often necessary, and the effectiveness of smart curtailment may vary across geographic and climatic contexts.

EU regulations for bat conservation in new wind farm projects (European Commission, Directorate-General for Environment (2010)), mandate pre-construction surveys, avoidance of high-risk sites, operational curtailment (meaning higher cut-in speeds or shutdowns during peak bat activity), and post-construction monitoring, as detailed in the 2010 EU Guidance document and EUROBATS guidelines, with national implementations varying across Member States like Germany and Denmark. This ecologically driven curtailment contrasts with market-driven curtailment, where power output is reduced in response to negative electricity prices or grid congestion, typically occurring at higher wind speeds. Consequently, the two forms of curtailment affect different operational regimes, ecological curtailment emphasizing biodiversity protection, and market curtailment aligning with economic system integration, creating complex trade-offs for operators balancing conservation compliance with energy production and financial performance. Reported AEP losses due to bat curtailment are typically limited to the order of $< 1\%$–$3\%$, depending on turbine type, site conditions, and curtailment strategy, with smart curtailment consistently reducing losses relative to blanket shutdowns (Hayes et al. (2023); Whitby et al. (2021); Behr et al. (2017)). Table 8 shows an overview of curtailment uncertainty dimensions discussed.

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**Table 8.** Key uncertainty dimensions in wind energy curtailment, mapped to uncertainty type, decision risk, and time aspects. A: Aleatory, E: Epistemic, R: Regime.

| Dimension | Uncertainty source | Type | Risk | Time horizon |
|---|---|---|---|---|
| Transmission constraints | Grid capacity relative to renewable deployment; timing and scope of grid reinforcement; regional bottlenecks; interconnection availability | E, R | Loss of production; biased revenue projections; | Mid- to long-term |
| Market-driven curtailment | Frequency and duration of negative electricity prices; price volatility under high VRE penetration; demand flexibility and storage deployment | A, E | Revenue erosion; reduced project returns and bankability | Short- to mid-term |
| Short-term curtailment variability | Month-to-month or hour-to-hour variability in curtailment driven by weather conditions, and demand fluctuations | A | Cash-flow volatility; mismatch between expected and realized revenues; increased downside risk | Short-term |
| Regulatory and compensation schemes | Rules for redispatch compensation; cost-based versus market-based compensation; policy changes | R, E | Sudden revenue loss; stranded assets; increased regulatory risk premium | Policy cycles / lifetime |
| Wildlife-related curtailment | Seasonal shutdown requirements; cut-in speed constraints; effectiveness of smart curtailment strategies; site-specific ecological conditions | A, R, E | Systematic AEP reduction; uncertainty in compliance costs; | Seasonal to long-term |
| Spatial heterogeneity | Location-specific exposure to congestion, price zones, and ecological constraints; interaction with neighboring renewable projects | E | suboptimal siting and design of projects | Design and siting phase |

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### 4.3.2 Impact assessment

Curtailment is modeled as a system-level loss mechanism that reflects both persistent structural conditions of the power system and short-term operational variability.

Curtailment is represented through a multiplicative reduction of potential energy production. For a given month $m$, curtailed production $P_m^{\mathrm{curt}}$ is computed as

$$P_m^{\mathrm{curt}} = c_m P_m, \tag{5}$$

where $P_m$ is the uncurtailed production and $c_m \in [0,1]$ denotes the fraction of energy curtailed during month $m$. Depending on the case, $c_m$ either represents the transmission constraint level or the ratio of hours with negative electricity prices per month.

The curtailment fraction is modeled using a hierarchical stochastic formulation:

$$c_m \mid \alpha, \theta \sim \mathrm{Gamma}(\alpha, \theta), \tag{6}$$

$$\alpha, \theta \sim p(\alpha, \theta). \tag{7}$$

Two distinct sources of uncertainty are represented and mapped to different levels of the model. Epistemic uncertainty reflects limited knowledge about the long-term curtailment regime applicable to a given project and is represented through uncertainty in the Gamma distribution parameters. For each simulation, the shape parameter $\alpha$ and scale parameter $\theta$ are sampled from predefined ranges and remain fixed over the project lifetime. Variation ranges of 10% around the defined value are assumed to illustrate the uncertainty within the distribution. Conditional on this regime, aleatory uncertainty is represented by sampling monthly curtailment fractions $c_m$ from the resulting Gamma distribution, capturing irreducible month-to-month variability due to fluctuating system conditions.

The Gamma distribution is chosen for its ability to represent positively skewed loss processes. Variation in the parameters $(\alpha, \theta)$ across scenarios reflects uncertainty in system-level drivers such as transmission adequacy, system flexibility, market conditions, and regulatory constraints.

Five curtailment regimes are defined to represent epistemic uncertainty in system-level curtailment conditions. Within each regime, monthly curtailment fractions are generated according to Equation (6).

The definition of the regimes is informed by two empirical drivers observed in European power systems: (i) geographically heterogeneous transmission constraints and (ii) increasing frequency and variability of negative electricity prices under high renewable penetration. For the sake of simplicity, curtailment due to wildlife constraints has not been accounted for in the definition of the scenarios.

Transmission-driven curtailment regimes are derived from observed spatial variation in redispatch and constraint levels within Ireland, where regional differences in renewable penetration, demand location, and grid development lead to different curtailment outcomes. Monthly data reported by the Irish transmission system operators for the period 2021–2024 (EirGrid TSO and SONI TSO (2024)) indicate a wide spread of curtailment levels across zones, motivating the definition of three regimes representing low, medium, and high transmission constraints.

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Market-driven curtailment regimes are motivated by cross-country variability in the frequency of negative electricity prices observed across Europe. Monthly counts of negative-price hours in 2024 were converted to fractions of time and used to estimate representative ranges of Gamma distribution parameters based on their mean and variance. Two regimes are defined to reflect contrasting market conditions: one characterized by high variability and frequent negative prices, and one representing moderated price volatility under higher system flexibility and storage deployment.

Together, these five regimes span a plausible range of long-term curtailment conditions relevant for current and near-future wind energy projects. The resulting scenario definitions and corresponding parameter ranges are summarized in Table 9.

**Table 9.** Curtailment regimes representing epistemic uncertainty in system-level curtailment conditions. Distribution parameters were derived from data detailed on Figure 7, where monthly number of hours has been converted in monthly % of time, and monthly curtailment level is expressed in %.

| **Scenario** | **Interpretation** | **Shape parameter range** ($\alpha$) | **Scale parameter range** ($\theta$) |
|---|---|---|---|
| C0 – Reference | No curtailment. | [-,-] | [-,-] |
| C1 – Low transmission constraints | Successful grid development and high flexibility. | [0.4, 0.5] | [1.5, 1.8] |
| C2 – Medium transmission constraints | Successful grid development with important geographical mismatch between production and demand, which requires extensive transmission. | [0.7, 0.9] | [4.0, 4.9] |
| C3 – High transmission constraints | Renewable deployment outpaces grid reinforcement and flexibility. Geographical constraints. | [1.4, 1.7] | [6.0, 7.3] |
| C4 – High variability in market curtailment | Increasing renewable share causes weather-driven generation peaks, with no storage solutions. | [1.4, 1.8] | [4.6, 5.7] |
| C5 – Medium variability in market curtailment | Deployment of storage technologies reduces price volatility and the frequency of negative electricity prices. | [2.3, 2.9] | [1.6, 2.0] |

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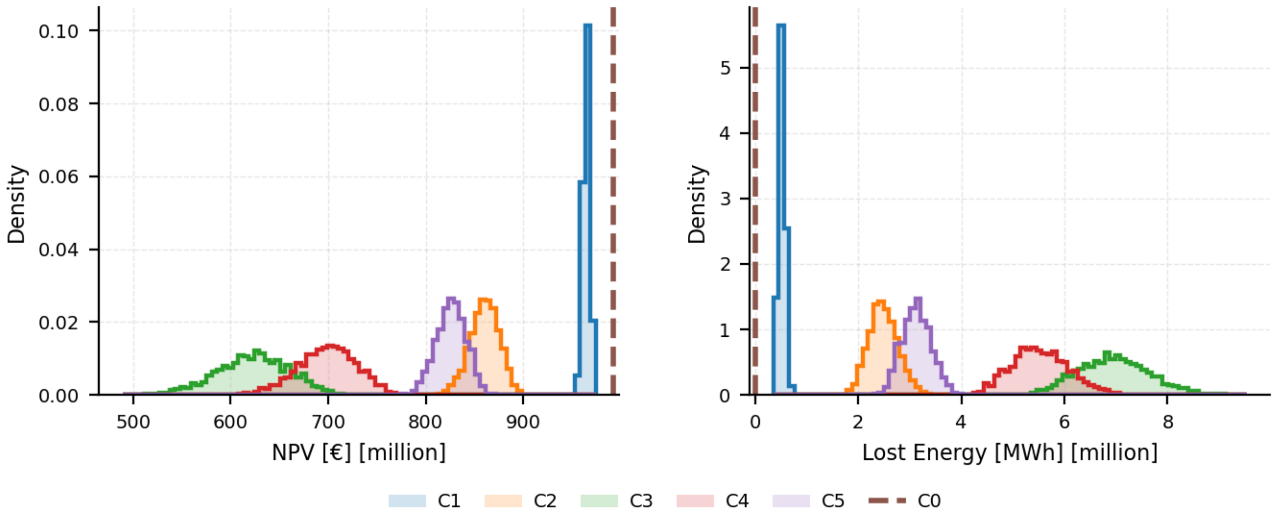


**Figure 8.** NPV (left) and Lost Energy (right) distributions for scenarios.

Figure 8 shows the distribution of project NPV and total lost energy for each curtailment scenario. The results are based on the assumption that curtailed energy leads to lost revenue for the project owner, with no compensation scheme considered. As such, the analysis primarily reflects the economic loss, which in practice would not necessarily be carried by the operator alone.

The results indicate that curtailment introduces substantial economic risk. Project NPVs are shifted by several hundred million euros across scenarios and exhibit a wide spread within individual scenarios. This confirms that curtailment represents a major threat to the economic value of wind energy projects and can, depending on the compensation mechanisms, render projects economically unviable. From an energy system perspective, curtailed production also represents a significant inefficiency, as this energy could have been generated at near-zero marginal cost and used productively. Future research should therefore aim to assess curtailment risk jointly from the perspectives of project operators, grid operators, and the broader energy system in order to identify effective mitigation measures.

### 4.4 Reliability gaps in major non-redundant components

#### 4.4.1 Review

The reliability of a turbine is defined as the probability that a turbine will function according to its intended purpose over its lifetime. Understanding wind turbine reliability is crucial to optimize performance and minimize operational costs. Various indicators are used in the literature to assess the reliability of both the system and its components (Walgern et al. (2025)). Despite efforts to develop consistent data collection practices, methodologies, and taxonomies (Hahn et al. (2017)), there is

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still no uniform standardization in the definition of reliability indicators, failure events, analysis of field data, or components failures that would apply across turbine types (van Kuik et al. (2016); Cevasco et al. (2021)).

Among the reliability indicators used in wind turbine studies, the average annual failure rate per turbine is the most widely reported, due to its simplicity and direct applicability in O&M analyzes. However, reliance on this parameter may hide substantial epistemic uncertainty associated with its estimation. Identical average failure rates can arise from datasets of different sizes. For example, an annual failure rate of 0.5 may be derived from 500 failures observed over 1,000 turbine-years or from 15,000 failures over 30,000 turbine-years. While the mean is the same in both cases, the statistical confidence in the estimate differs. Methods to quantify this uncertainty through confidence intervals or similar measures have been proposed in the literature (Fischer et al. (2018); Walgern et al. (2025), yet such information is rarely reported in publicly available reliability databases. As a result, failure rates are often treated as deterministic inputs in O&M models, despite being derived from limited or heterogeneous datasets. Table 12 summarizes the average failure rates (failures per turbine per year) reported in 12 publicly available databases. Most studies include both variable and fixed-speed turbines, as well as geared and gearless drive trains. The studies differ in turbine count, technology type, power rating, age, and observation period. Additional dataset characteristics, including observation time, wind farm location, and mean rating, are also provided. The reported failure rates span from 0.434 to 46.856 failures/WT/year, with the highest value likely representing an outlier due to SCADA alarm usage or a very short survey period. Following the approach of Dao et al. (2019), the datasets were clustered to highlight the variability of failure rates based on wind farm location, observation period, and mean rating. The resulting coefficients of variation are shown in Table 13, illustrating how differences in technology, location, and observation period contribute to variability (the value from University of Nanjing was excluded to avoid the influence of the high outlier). The impact of varying failure rates on operational expenditures has been shown in several studies (Gräfe et al. (2025); Donnelly et al. (2024)). This lack of uncertainty characterization introduces epistemic uncertainty into failure-rate assumptions, which can propagate into biased estimates of intervention frequency, downtime, and overall O&M costs.

Beyond statistical uncertainty in failure-rate estimation, a major source of epistemic uncertainty arises from heterogeneity across turbine fleets and study contexts. Reported failure behavior has been shown to depend systematically on turbine technology, drivetrain concept, rated power, manufacturer, and site conditions. Walgern et al. (2025) analyses large multi-fleet datasets and demonstrate OEM-specific differences in average annual failure frequencies normalized by installed capacity. Reported values range from approximately $\sim 1.5$ to $\sim 2.5$ failures/MW/yr for onshore turbines, and from $\sim 0.7$ to $\sim 1.6$ failures/MW/yr for offshore installations, highlighting substantial differences even after capacity normalization. These differences are attributed to a combination of design characteristics, component selection, operational environment, and maintenance strategy rather than random variation. Similarly, Reder et al. (2016) report systematic variations in failure rates at both system and component levels as a function of turbine power rating (Table 14), while Tavner et al. (2013) show that turbines of identical design installed at different sites can show different failure behavior. Despite this evidence, O&M modeling, especially in research contexts, in practice often relies on publicly available datasets that aggregate observations across manufacturers, sites, and operational contexts, due to the limited availability of homogeneous fleet-specific data. Due to the commercial sensitivity of reliability data, few recent large-scale datasets are publicly available, and many studies continue to rely on data collected prior to 2015,

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such as Carroll et al. (2016). The transfer of such aggregated failure-rate assumptions to a specific project therefore introduces epistemic uncertainty. This can lead to misaligned maintenance strategies and biased O&M cost estimates.

In addition to uncertainty in the overall frequency of failure events, substantial epistemic uncertainty exists in how failures are distributed across major wind turbine assemblies. Artigao et al. (2018) conducted a comparative analysis of 13 reliability studies and failure databases and developed a unified turbine taxonomy to enable consistent comparison across datasets. Large discrepancies were observed in the relative contribution of individual components to total failure counts. For example, the reported share of generator-related failures varies from approximately 3 % to 23 % across the analyzed studies. Similar variability is reported for other major assemblies, indicating that the component-level failure distribution is highly sensitive to dataset composition and study context. This uncertainty is particularly relevant for O&M decision-making, as different components are connected to different repair times, logistics requirements, and costs. Consequently, two systems with similar overall failure rates may exhibit substantially different OPEX and availability outcomes depending on how failures are distributed across components.

The bathtub curve is frequently used as a conceptual model for the temporal evolution of failure rates. This concept is motivated by theoretical considerations of degradation processes such as wear, fatigue, and ageing, which suggest that failure rates may decrease during an initial run-in phase, remain approximately constant during a useful-life period, and increase again as components approach wear-out. While this framework is well established in reliability theory (Kapur and Pecht (2014)), empirical observations from real wind fleets do not confirm a clearly defined bathtub-shaped evolution of failure rates.

Analyses of field data indicate that system-level failure rates rarely exhibit a pronounced bathtub shape. However, aspects of bathtub-like behavior can be observed for certain individual components or subsystems, particularly in the form of elevated early-life failure frequencies or age-dependent trends. Walgern et al. (2025), for example, demonstrate non-stationary failure behavior over turbine lifetime phases and report component-specific age dependencies. Similar conclusions can be drawn from Faulstich et al. (2011) and analyses of the Wind Network for Enhanced Reliability (WinNER) database (see Figure 9)(Electric Power Research Institute (EPRI) (2024)), where major assemblies exhibit component-specific trends that deviate from the idealized bathtub assumption and differ substantially between subsystems.

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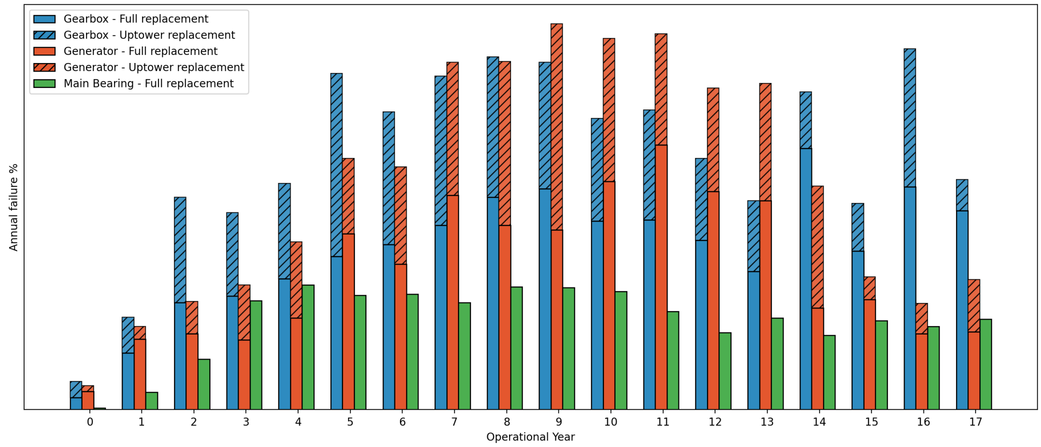


**Figure 9.** Key components failure rates from the WiNNER database (Pulikollu et al. (2023, 2024); Pulikollu and Han. (2021).

In O&M modeling, failure occurrence is typically represented using assumed statistical distributions, most commonly Weibull formulations, which implicitly impose assumptions on the temporal structure of failures. As shown by Scheu et al. (2017), these distributional choices can have a significant impact on model outcomes: even when average failure rates are identical, different failure-time distributions lead to substantial differences in simulated wind farm availability. This demonstrates that such models should be interpreted as simplifying representations under uncertainty rather than as empirically validated descriptions of failure mechanisms. Consequently, assumptions regarding the temporal distribution of failures constitute an important source of epistemic uncertainty in O&M simulations.

In addition to epistemic uncertainty, wind turbine operation is subject to aleatory variability in the occurrence of failure events. Even if the underlying failure-rate process were perfectly known, the number and timing of failures realized in a specific wind farm over a given period would remain stochastic. As a result, otherwise identical projects may experience substantially different maintenance histories, downtime, and O&M costs purely due to random variation in failure occurrences. Consequently, reliability-driven O&M assessments must be interpreted in probabilistic terms, rather than as deterministic forecasts of operational outcomes.

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**Table 10.** Key uncertainty dimensions in wind turbine reliability, mapped to uncertainty type, decision risk, and time aspects. A: Aleatory, E: Epistemic.

| Dimension | Uncertainty source | Type | Risk | Time horizon |
|---|---|---|---|---|
| Failure-rate estimation | Limited observation periods; small sample sizes; incomplete failure reporting; lack of confidence intervals in public datasets | E | Biased O&M cost estimates; under- or overestimation of intervention frequency | Throughout lifetime |
| Cross-study and fleet heterogeneity | Differences in turbine technology, OEM, drivetrain concept, power rating, site conditions, and maintenance strategies across datasets | E | Transferability errors when calibrating models to specific projects; misaligned O&M strategies | Throughout lifetime |
| Component-level failure distribution | Uncertain allocation of failures across major assemblies; variability in component contribution to total failures | E | Misidentification of cost- and downtime-critical components; inefficient spares and logistics planning | Throughout lifetime |
| Temporal evolution of reliability | Non-stationary failure behaviour (infant mortality, ageing, wear-out); unclear component-level trends over time | A, E | Mismatch between assumed and actual failure timing; distorted availability projections | Early and late life |
| Data taxonomy and definitions | Inconsistent definitions of failure events, components, and assemblies across databases | E | Systematic bias in model calibration; limited comparability of studies | At model calibration |
| Failure occurrence variability | Stochastic variability in the timing and number of failure events for a given project, even under identical failure-rate assumptions | A | Project-specific deviations in O&M costs and downtime; residual economic risk despite accurate parameter estimation | Throughout lifetime |

The review highlights that wind turbine reliability is affected by multiple, interrelated sources of uncertainty, as summarized in Table 10. A substantial share of these uncertainties is epistemic in nature, arising from limitations in available data, heterogeneity across fleets, and modeling assumptions regarding failure behavior.

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One key implication is that uncertainty in reliability assumptions directly propagates into economic risk: variations in failure rates, failure allocation across components, and temporal failure structure translate into uncertainty in intervention frequency, downtime, and O&M expenditures. Improved understanding, data quality, and uncertainty characterization can therefore reduce decision risk and improve the robustness of O&M planning.

Reliability itself remains a central driver of wind farm performance and cost, independent of how well it can be described. Even with perfect knowledge of failure processes, failure events still occur, resulting in downtime and costs. Consequently, technical solutions that increase component and system reliability are a complementary pathway to risk reduction. By lowering the underlying failure intensity, such improvements not only reduce expected O&M costs but also mitigate the impact of aleatory variability on project outcomes.

#### 4.4.2 Impact assessment

We model the impact of uncertainty around reliability of wind turbine components using the Markov chain based OPEX module of WINPACT. Failure occurrence is modeled using a two-level uncertainty framework that explicitly separates aleatory variability in the timing of failures from epistemic uncertainty in the underlying failure rates. Aleatory uncertainty reflects the inherently random nature of failure events given a fixed failure rate, while epistemic uncertainty captures imperfect knowledge of the true mean failure rate arising from limited observation periods, inconsistent failure definitions and reporting, and the transfer of reliability evidence across turbine generations, sites, and operational contexts. In the model, this epistemic uncertainty is represented by treating failure rates as random variables rather than fixed parameters, with uncertainty described using Gamma distributions, which provide a flexible and non-negative representation commonly used for rate parameters.

At the methodological level, epistemic uncertainty in failure rates is implemented through a structured decomposition of the coefficient of variation that distinguishes between system-level and component-level effects. A target coefficient of variation is first specified at the turbine level for each scenario, representing the intended overall uncertainty in the aggregate failure behavior. This uncertainty is then divided into a shared component and an independent component. The shared component represents coherent epistemic effects that affect all components simultaneously, such as systematic biases in data sources, modeling assumptions, or the limited transferability of evidence across fleets. It is implemented through a single multiplicative factor, sampled once per simulation realization and held constant over the simulated lifetime. The remaining portion of the uncertainty budget is allocated to independent, component-specific variability, representing residual heterogeneity between components beyond the shared effects. Through this construction, the combined effect of shared and independent terms reproduces the intended coefficient of variation at system level.

The scenarios presented in table 11 represent different levels of uncertainty about failure rate assumptions. Scenarios represent different assumptions about epistemic uncertainty, not properties of a specific turbine or project. We define three main scenarios based on evidence from literature:

- Scenario 1 [Low variability]: Mature wind turbine model with well-known weaknesses, deployed in a large and homogeneous fleet, supported by fully established O&M logistics and processes. The remaining variability reflects the heterogeneity typically observed within a fleet of identical technologies. The level of variability reported by Tavner et al. (2013) is adopted here to represent this low-variability scenario. In that study, the authors report differences in average failure rates (failures/WT/year) across three German wind farms operating Enercon E-33 and E-32/300 turbines, primarily stemming from weather variability.

– Scenario 2 [Medium variability]: Representative of analyses based on public or mixed-source reliability data. Variability arises from heterogeneous site conditions, differences in O&M contracting practices, and non-uniform failure definitions and reporting across studies. The coefficient of variation adopted for this scenario is informed by the variability observed in the CIRCE database (Reder et al. (2016)) and is reported in Table 14.

– Scenario 3 [High variability]: Representative of new wind turbine models in early deployment phases. At this stage, limited operational experience, rapidly evolving O&M practices, and incomplete harmonization of failure definitions and reporting lead to important variability across available studies. The coefficient of variation adopted for this scenario is informed by the spread observed in datasets with short observation periods (less than five years) and turbine ratings above 1 MW, as summarized in Table 12 and Table 13.

**Table 11.** Failure-rate uncertainty scenarios grounded in offshore wind reliability literature and implemented as Gamma uncertainty on $\lambda$.

| **Scenario** | **Interpretation** | **Failure rate $\lambda$ ($\alpha_\lambda$, CV$_\lambda$)** |
|---|---|---|
| Baseline | Baseline failure rates (no epistemic uncertainty) | $(1.00, 0.00)$ |
| R1 – Low epistemic uncertainty | Large homogeneous fleet with mature wind turbine model, and fully established O&M logistics and processes. | $(1.00, 0.30)$ |
| R2 – Mid epistemic uncertainty | Typical public-data with mixed-sources: epistemic spread reflects cross-study differences, reporting and taxonomy variation. | $(1.00, 0.50)$ |
| R3 – High epistemic uncertainty | Poorly observed turbines or contexts. Next-generation turbines without enough observation history or new technology. | $(1.00, 0.90)$ |

Figure 10 illustrates the distributions of net present value and operational expenditure obtained for the different failure-rate uncertainty scenarios. The results demonstrate that epistemic uncertainty in the specification of failure rates has a pronounced impact on project economics. Even under the low-uncertainty scenario (SC1), the spread of economic outcomes remains substantial, with a range on the order of €400 M. With increasing epistemic uncertainty, the spread of outcomes grows and the distributions exhibit pronounced long tails. Although such adverse outcomes are unlikely, they imply that unfavorable combinations of assumptions can lead to very low or even negative project values. Ignoring epistemic uncertainty would therefore lead to a systematic underestimation of downside risk in investment decision-making and an overly optimistic assessment of project robustness.

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**Table 12.** Failure rates of several previous studies compared (data from Reder (2018); Pfaffel et al. (2017); Ma et al. (2015)).

| Initiative | Location | Mean rating | Observation years | Failures per WT and year |
|---|---|---|---|---|
| WindstatsGermany | Germany | 1.3 | 9 | 1.796 |
| WindstatsDenmark | Denmark | 1.3 | 9 | 0.434 |
| LWK | Germany | 1.0125 | 13 | 1.855 |
| WMEP | Germany | 0.915 | 17 | 2.606 |
| VTT | Finland | 1.5375 | 12 | 1.45 |
| Vindstat | Sweden | 1.5275 | 8 | 0.403 |
| CIRCE | Spain | 1.65 | 3 | 0.481 |
| EPRI | USA | 0.32 | 2 | 10.195 |
| Muppandal | India | 0.225 | 5 | 1.013 |
| CWEA | China | 3.75 | 3 | 7.167 |
| Huandian | China | NA | 0.5 | 0.846 |
| University of Nanjing | China | 1.75 | 5 | 46.856 |

**Table 13.** Coefficient of variation of failure rates by category

| Category | Subgroup | CV |
|---|---|---|
| Location | Europe | 0.6 |
| | Outside Europe | 1.8 |
| Observation years | $\leq 5$ years | 1.0 |
| | $> 5$ years | 0.6 |
| Mean rating | $\leq 1$ MW | 0.9 |
| | $> 1$ MW | 1.2 |

Figure 11 shows the corresponding distributions of farm availability and the number of corrective maintenance activities. These results indicate that uncertainty in reliability assumptions propagates beyond economic metrics to technical performance indicators. In higher-uncertainty scenarios, availability may decrease substantially, while the number of corrective maintenance actions can increase sharply in extreme cases. This reflects a system-level impact, combining lost energy production with potentially stress on maintenance resources and supporting infrastructure.

Given the strong sensitivity of both economic and technical outcomes to reliability assumptions, uncertainty in component failure behavior emerges as a key driver of overall project risk. The presence of uncertainty-driven long-tail risks is particularly relevant for financing, insurance, and contractual risk allocation, for example in the context of O&M guarantees or availability-based contracts. Consequently, efforts to reduce epistemic uncertainty, for example through standardized failure classification

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**Table 14.** Data used for the SCADA Alarms and Failure Analysis (Reder et al. (2016))

| SCADA System | WT Make | Technology | Rated Capacity (kW) | Nb of Turbines | Failures per Turbine |
|---|---|---|---|---|---|
| 1 | A | Geared | 1500 | 55 | 0.709 |
| 2 | B, C | Dir. Drive | 2000 | 57 | 0.632 |
| 3 | D | Geared | 850 | 77 | 2.208 |
| 4 | E | Geared | 2000 | 168 | 1.780 |
| 5 | F, G | Geared | 1800–2000 | 83 | 1.313 |

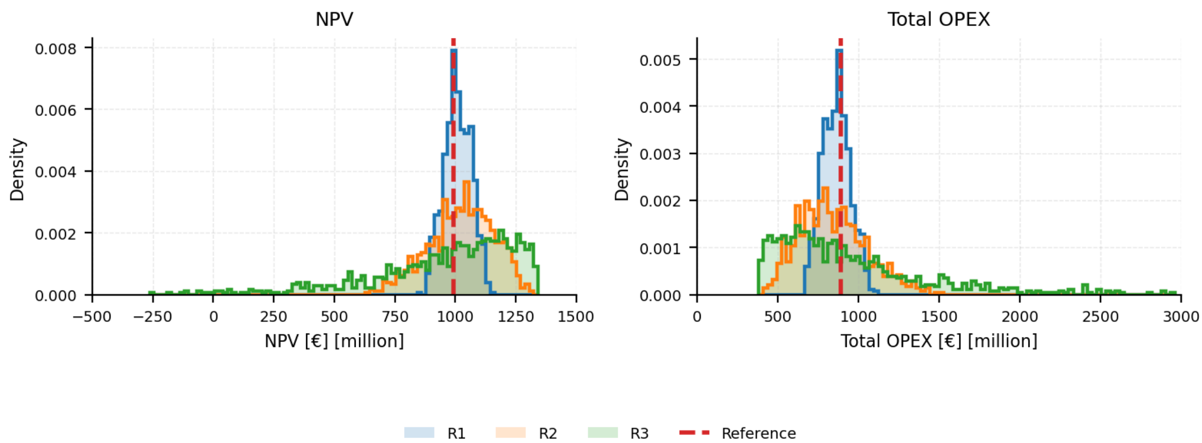


**Figure 10.** NPV (left) and total OPEX (right) distributions for scenarios

and reporting, longer and more representative datasets, and closer links between reliability parameters and actual operating and loading conditions, can reduce the perceived risk profile of projects. This may translate into lower risk premiums and reduced cost of capital, contributing to the overall de-risking of wind energy investments.

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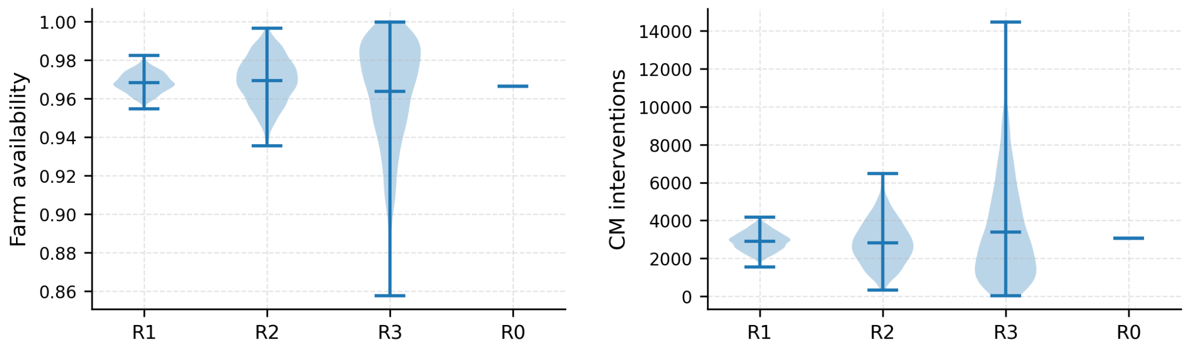


**Figure 11.** Availability (left) and absolute number of corrective maintenance interventions for scenarios.

### 4.5 Inefficiencies in operations & maintenance

O&M costs and downtime are fundamentally driven by two coupled factors: the reliability and maintenance requirements of the physical asset, and the effectiveness of the organizational processes responsible for detecting failures, planning interventions, and restoring operation. The reliability characteristics of wind turbine components and their associated uncertainties were introduced in the previous section. In the following, we focus on inefficiencies within the O&M process itself and the uncertainties that arise from them.

For offshore wind turbines, a generic corrective maintenance process can be described as a sequence of partly overlapping steps. Following the occurrence of a failure, the turbine transitions from normal operation to a down state. This event initiates a chain of activities including fault detection and diagnosis (performed remotely or manually), identification and procurement of spare parts and specialized equipment, waiting for suitable weather windows, mobilization of crews and logistics, transport to site, execution of the repair, and finally the return of the turbine to normal operation. Each step introduces delays and uncertainty, and the overall downtime is typically dominated by access, logistics, and organizational constraints rather than by the repair action itself.

Technological and process-oriented advances have been developed to reduce the time between failure and return to operation. These include advanced monitoring, diagnostics, prognostics, and, more recently, preventive and prescriptive maintenance concepts. While such approaches have the potential to improve O&M performance (Jardine et al. (2006)), their impact is not uniform across the maintenance process. We therefore review the uncertainties and risks associated with these approaches from a system-level O&M perspective. Table 15 provides an overview of these risks.

Several types of monitoring and diagnostic systems are used to assess the condition of wind turbine components or the turbine as a whole. These include SCADA-based approaches, which infer system health from supervisory and operational data (Tautz-

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Weinert and Watson (2017); Wang et al. (2026); Chesterman et al. (2023)), as well as dedicated condition monitoring systems (CMS) that rely on high-frequency measurements. CMS typically include vibration-based drivetrain monitoring, oil debris and oil condition monitoring, and electrical signature analysis (Kestel et al. (2025)). In addition, blade and structural health monitoring (SHM) methods aim to detect damage using load-based, modal-based, acoustic, or strain-based measurements (Haseeb and Krawczuk (2025)). Across all these system types, the main goal is to represent the true health state of the turbine or its components, either in real time through monitoring and diagnostics or in advance through prognostics. The practical value of these systems depends not only on diagnostic accuracy but also on how uncertainty propagates from data collection and modeling to decision-making and operational actions.

Uncertainty in monitoring and diagnostic systems arises at several levels, including sensing, modeling, and operational integration. Measurement-related uncertainties stem from sensor noise, calibration errors, and environmental effects, while limited sensor coverage leads to partial observability of turbine components (Haseeb and Krawczuk (2025)). Additional uncertainty is caused by data availability and synchronization issues, such as missing data and the use of aggregated measurements like 10-minute SCADA data (Wang et al. (2026)), which may not capture transient events or rapidly developing faults (Kestel et al. (2025)). Furthermore, sensor degradation, system ageing, and control software updates can reduce diagnostic performance over time if models are not actively maintained.

Model-based approaches, including digital twin concepts, may introduce uncertainty through modeling simplifications, threshold definitions, and limited model fidelity. Data-driven and machine-learning approaches are typically trained on data representing specific turbines, sites, or control configurations, which makes transferability across fleets and technologies challenging (Gräfe et al. (2024)). Turbine- and technology-agnostic models, therefore, remain an active area of research. At the operational level, algorithmic detection latency arising from data processing and conservative thresholds compounds with system-level latency driven by weather windows, vessel availability, spare-part lead times, and contractual decision delays, so that improvements in information timeliness do not translate linearly into reduced downtime.

Failure Detection uncertainty affects process performance in two ways: false positives lead to unnecessary inspections, stoppages, or technician dispatch, and thus immediate availability losses, whereas false negatives or delayed detections increase risk by enabling secondary damage or catastrophic failures. Overall, economically relevant risk arises not only from residual uncertainty in monitoring and prognostic systems but also from misalignment with decision-making processes and the continued dominance of logistics and access constraints. Consequently, diagnostics constitute a necessary but not sufficient condition for reducing O&M downtime. Effective impact requires decision layers that integrate diagnostic information across models, logistics, and operational planning.

Despite substantial advances in monitoring, diagnostics, and prognostics, diagnostic information is often not expressed in a form that directly supports economically optimal maintenance decisions. Outputs are typically provided as alarms, health indices, degradation states, or remaining useful life (RUL) estimates, rather than as decision-relevant risk metrics that explicitly link fault probabilities to consequence severity and optimal actions. Consequently, uncertainty associated with diagnostic outputs is frequently implicit, with confidence bounds rarely propagated into the decision layer, leading decision-making to rely on static thresholds and heuristic rules. Recent reviews of offshore wind O&M decision-making emphasize that diagnostic

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and prognostic information remains largely confined to the operational horizon, while strategic and tactical planning continues to rely on aggregated failure assumptions and fixed maintenance rules, with limited feedback between decision layers (Borsotti et al. (2026)). Decision-theoretic frameworks that address this translation gap have been proposed. Risk-based O&M models grounded in Bayesian pre-posterior decision theory, which formally link probabilistic descriptions of component condition, inspection reliability, repair decisions, and life-cycle cost through explicit decision rules and have been demonstrated for offshore wind turbine components in simplified settings (Nielsen and Sørensen (2011)). However, these approaches are typically applied to idealized cases, often considering single components or turbines with known damage models and near-perfect information integration, and their extension to full wind farms, multiple interacting components, realistic logistics constraints, and organizational decision boundaries remains challenging, limiting their direct applicability in operational O&M practice despite their strong conceptual foundations.

Beyond monitoring and decision-making, maintenance execution and weather-dependent accessibility are sources of aleatory uncertainty in offshore wind O&M and determine actual downtimes and costs. Empirical studies show that offshore repair durations exhibit strongly right-skewed, heavy-tailed distributions (Dao et al. (2019)), in which a small number of events dominated by weather lock-in, vessel unavailability, and campaign interference account for a disproportionate share of total downtime (Faulstich et al. (2011)). Logistics and accessibility delays behave as stochastic, state-dependent processes rather than fixed lead times, with vessel mobilization periods ranging from days to several months depending on market situation, seasonality, and concurrent fleet demand. Weather accessibility further acts as a gating mechanism. Waiting-for-access frequently exceeds actual repair time (Kolios et al. (2023)). Repair duration and waiting times interact nonlinearly with weather windows, vessel availability, and concurrent campaign scheduling. This results in heavy-tailed downtime distributions that cannot be captured by mean process parameters, such as mean time to repair. Process maturity, standardization, and advanced access concepts can reduce mean delays and partially compress the tails of downtime distributions. Nevertheless, residual variability remains due to the inherent stochasticity of weather conditions and maintenance execution, implying that even best-practice O&M strategies cannot fully eliminate execution, and access-related uncertainty (Kolios et al. (2023)). Consequently, modeling approaches that explicitly represent this stochasticity and translate it into economically relevant risk indicators are required.

Organizational coordination constitutes a significant source of epistemic uncertainty in offshore wind O&M, as it determines how diagnostic information is translated into operational action across multiple actors, including owners/operators, OEMs, and service providers. Even when technical fault detection and diagnosis are correct, fragmented responsibilities, unclear decision authority, and restricted data access can lead to coordination delays, repeated site visits, and prolonged diagnosis-to-fix cycles. Multi-party interfaces introduce handover and coordination efforts (Borsotti et al. (2026); Hadjoudj and Pandit (2023)). Contractual arrangements may misalign incentives through availability guarantees, warranty risk allocation, or fixed-price service agreements. Organizational fragmentation can additionally increase system-level downtime when turbines, balance-of-plant components, and marine operations are managed by different contractors operating under separate schedules and priorities (Hawker and McMillan (2015)). Thus, operational performance is not only a question of technical performance but is strongly influenced by organizational efficiency.

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The absence of widely adopted industry standards and taxonomies for documenting failure behavior and maintenance processes limits cross-farm learning and benchmarking (Hahn et al. (2017)). This limitation is further exacerbated by restricted data access and information asymmetries between OEMs, owners, and service providers, as diagnostic data and analytical insights are often contractually constrained and not shared across organizational boundaries (Paquette et al. (2024)). As highlighted by Shafiee and Sørensen (2019), effective maintenance management requires comprehensive failure databases complemented by supplementary operational and cost data, yet such integrated datasets are rarely available in practice. Consequently, epistemic process uncertainty persists, as empirical evidence on best-practice O&M strategies cannot be systematically consolidated or transferred across projects.

#### 4.5.1 Impact assessment

To evaluate the uncertainty arising from inefficiencies in O&M processes, we use the OPEX module of the WINPACT.

This Experiment isolates inefficiencies in wind farm O&M execution while holding component reliability constant. The aim is to quantify how operational processes, rather than failure behavior, drive availability, OPEX and thus the economic project performance. The scenarios represent (i) variability in repair execution (MTTR), (ii) logistics and spare-part delays (MTTW), and (iii) access limitations driven by sea-state operability and weather-window decision making. Failure rates are fixed at baseline values across all scenarios. In the model these parameters determine the transition rates between the states of the underlying Markov model.

Baseline process parameters are read from the O&M input data and modified per scenario using a multiplicative mean-shift factor $\alpha$ and a lognormal uncertainty term with standard deviation $\sigma$:

$$\theta = \theta_0 \cdot \alpha_\theta \cdot X_\theta, \qquad X_\theta \sim \mathrm{Lognormal}(0, \sigma_\theta), \tag{8}$$

where $\theta \in \{\mathrm{MTTR}, \mathrm{MTTW}_L\}$. Accessibility is represented by an hourly access probability $p_{\text{access}}$ and modified via a scenario factor $\alpha_p$:

$$p_{\text{access}} = p_{\text{access},0} \cdot \alpha_p. \tag{9}$$

Scenario assumptions are summarized in Table 16. The P0 scenario represents the baseline scenario without variation of O&M process parameters.

The P1 (High process uncertainty) scenario reflects immature or highly volatile offshore operations where repair execution and logistics are strongly weather- and market-driven. Empirical downtime data show highly right-skewed distributions with many short repairs but a small number of very long events that dominate average downtime (Faulstich et al. (2011)), while vessel mobilization times of 30–60 days for offshore support and jack-up vessels indicate that logistics waiting can be extremely variable (Donnelly et al. (2024)). The reduced access factor in P1 represents conservative access strategies dominated by CTV limits (1.5 m significant wave height), which constrain operability to these conditions.

The P2 (Typical offshore operations) scenario reflects industry-average practice in which mean repair and logistics times remain unchanged but stochastic variability persists due to weather, coordination delays and campaign interference.

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**Table 15.** Sources of inefficiency in wind farm O&M processes, mapped to dominant uncertainty types and economic impacts. A: Aleatory, E: Epistemic.

| Dimension | Uncertainty source | Type | Risk | Time horizon |
|---|---|---|---|---|
| Monitoring and diagnostics | Limited sensor coverage, data quality degradation, false alarms, missed detections, model transferability across fleets | E | Unnecessary interventions, delayed fault detection, increased diagnostic effort | Short-term to medium-term |
| Decision-making and planning | Uncertainty in failure prediction and RUL estimates, conservative thresholds, misalignment between diagnostics and maintenance planning | E | Suboptimal maintenance timing, increased corrective maintenance, reduced availability | Medium-term |
| Maintenance execution | Variability in repair duration (MTTR), spare-part availability, vessel mobilization delays, campaign interference | A | Long-tail downtime distributions, high OPEX variability, revenue loss | Short-term |
| Weather and accessibility | Uncertain weather windows, conservative access limits, imperfect decision rules for go/no-go conditions | A | Extended waiting times, lost production during outages | Short-term |
| Organizational coordination | Fragmented responsibilities between operators, OEMs, and service providers; limited learning and benchmarking | E | Prolonged diagnosis-to-fix cycles, repeated site visits, balance-of-plant downtime | Medium-term to long-term |
| Technology adoption | TRL-to-field gap, integration challenges with legacy systems, limited validation data, cybersecurity and compliance constraints | E | Sunk costs, stranded digital tools, operational friction, insurance and warranty impacts | Long-term |

The P3 (Mature O&M processes) scenario represents learning effects, standardization and contractual maturity, leading to modest reductions in mean repair and logistics delays and lower variability. Such improvements are consistent with the gap identified by Carroll et al. (2016) between conservative expert-assumed repair times and more efficient data-informed practices, and with reduced exposure to high mobilization delays.

Finally, the P4 (Best practice O&M) scenario reflects optimized logistics, campaign planning, condition-based maintenance and advanced access concepts. Literature shows that moving from CTV-based access to FSV or jack-up supported strategies

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**Table 16.** Process-focused O&M inefficiency scenarios. Failure rates are fixed at baseline values.

| Scenario | Interpretation | MTTR ($\alpha, \sigma$) | MTTW$_L$ ($\alpha, \sigma$) | Access factor $\alpha_p$ |
|---|---|---|---|---|
| Reference | Deterministic baseline (mean values only) | $(1.00, 0.00)$ | $(1.00, 0.00)$ | 1.00 |
| I1 – High process uncertainty | Volatile offshore execution, immature logistics, conservative access strategy | $(1.00, 0.55)$ | $(1.00, 0.85)$ | 0.90 |
| I2 – Typical offshore operations | Industry-average execution with stochastic delays | $(1.00, 0.35)$ | $(1.00, 0.50)$ | 1.00 |
| I3 – Mature O&M processes | Learning effects, framework contracts, improved planning and access | $(0.95, 0.25)$ | $(0.90, 0.30)$ | 1.05 |
| I4 – Best practice O&M | Optimized logistics, campaign planning, condition-based maintenance, advanced access | $(0.80, 0.18)$ | $(0.75, 0.25)$ | 1.10 |

expands the operability envelope through higher allowable wave heights (3–4 m versus 1.5 m), justifying a moderate increase in access probability (Donnelly et al. (2024)).

875 Figure 12 shows the NPV distributions for the different O&M efficiency scenarios and demonstrates that economic risk is driven not only by mean O&M performance but, to a large extent, by variability in operational execution. Projects with similar expected repair and waiting times can exhibit markedly different risk profiles when downtime distributions differ in shape. In particular, heavier-tailed distributions lead to substantially higher downside risk, even if mean performance is comparable. This highlights that variance reduction in O&M processes is at least as important as reducing mean repair or logistics times.

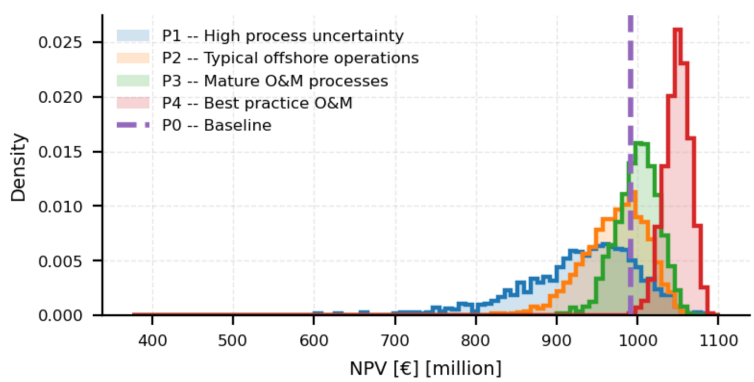


**Figure 12.** NPV distributions for scenarios

880 Scenarios characterized by high process uncertainty display pronounced right-skewed NPV distributions with long downside tails. These tails arise from rare but severe events such as extended logistics delays, prolonged weather inaccessibility, or coordination failures, which dominate cumulative downtime and revenue loss. While such events are infrequent, their economic

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impact is large and not symmetrically compensated by shorter-than-average interventions. As a result, downside deviations are not offset by upside outcomes to the same degree, leading to an asymmetry in economic risk.

885 The results show that operational execution risk can dominate technical reliability risk. Even with identical component failure rates across scenarios, differences in O&M process uncertainty result in substantial differences in NPV. This implies that improving component reliability alone is insufficient to stabilize project economics unless accompanied by parallel improvements in organizational coordination, logistics planning, and access strategies.

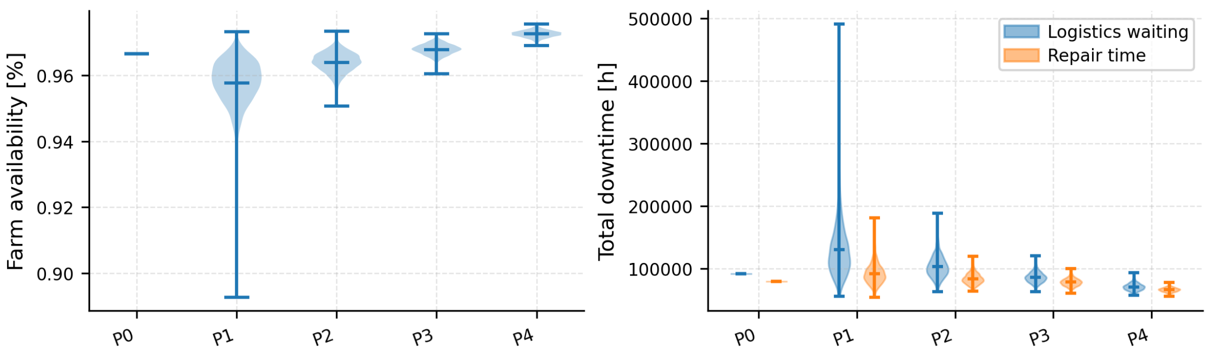


**Figure 13.** Availability (left), and downtime (right) distribution.

Figure 13 illustrates the corresponding technical effects. Increased process uncertainty directly reduces farm availability and

890 increases downtime hours. These technical impacts translate directly into economic risk through lost production and increased OPEX. Finally, the results underline the limits of digitalisation and advanced diagnostics when not embedded in end-to-end O&M processes. Improved monitoring, fault detection, and remaining useful lifetime estimation reduce informational uncertainty but, by themselves, do not eliminate economic risk unless they translate into faster, more predictable repair execution. Effective risk reduction, therefore, requires coupling technologies with process integration and formalized decision-making.

### 895 4.6 Operational risk from rapid technology upscaling

The wind energy sector is undergoing a period of rapid technology upscaling, characterized by unprecedented increases in turbine rated power, rotor diameter, hub height, and system complexity. Offshore wind has been at the forefront of this trend, with commercial turbines exceeding 15 MW and rotor diameters approaching or surpassing 230 m, while onshore turbines have also seen steady increases in size and complexity. Upscaling is primarily driven by the objective of reducing LCOE, as

900 larger turbines increase energy capture per unit and reduce the number of turbines required for a given plant capacity, lowering balance-of-system costs such as substructures/foundations and electrical infrastructure (Shields et al. (2021)). However, the acceleration of turbine scaling has introduced a distinct class of operational risk, rooted in technology novelty and limited

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empirical operating experience. These uncertainties are increasingly surfaced during technical due diligence, where turbine novelty, compressed development cycles, and limited operational track record are identified as key threats to asset reliability, investment security, and long-term project viability (Moverley Smith et al. (2022)).

Rapid upscaling differs from incremental technological evolution in that multiple design parameters are pushed simultaneously beyond previously validated ranges. These include structural dimensions, drivetrain torque levels, blade flexibility, power electronic ratings, and control-system complexity. New materials (e.g. high-modulus composites), drivetrain concepts (e.g. direct-drive or hybrid medium-speed systems), and advanced grid-support functionalities are often introduced concurrently. As a result, new turbine platforms enter service with limited field data, compressed prototype testing cycles, and restricted opportunities for iterative design refinement (Siddiqui et al. (2023)). This creates a dominance of epistemic uncertainty, as the true long-term behavior of critical components and systems is not yet well understood.

Operational risk from rapid upscaling propagates through several interconnected pathways, and a primary concern is reliability. Industry surveys and field observations indicate that newer turbine generations frequently exhibit elevated early-life failure rates and unexpected failure modes, particularly in blades, main bearings, power electronics, and auxiliary systems (Mishnaevsky (2022); Pelka and Fischer (2023)). This also includes high-voltage export and array cable systems and associated joints, where scaling effects and installation tolerances have led to technically complex and high-consequence failure modes (Strang-Moran (2020)). The interaction between increased structural loads, higher component utilization, and tighter design margins can lead to failure mechanisms that are not well represented in historical reliability datasets. Importantly, such failures tend to be systemic rather than isolated, as design or manufacturing deficiencies may affect entire turbine fleets, leading to serial failures and large-scale retrofit or replacement campaigns (Veers et al. (2023)). This challenges conventional reliability modeling approaches, which typically assume stationarity and independence of failures calibrated from mature fleets.

Upscaling also amplifies operational risk through its impact on O&M logistics. Larger turbines require heavier lifting equipment, specialized vessels, and extended weather windows for offshore interventions (Stålhane et al. (2019)). For next-generation offshore turbines, the availability of suitable jack-up vessels and heavy-lift cranes is limited, and competition for these assets is increasing. Consequently, corrective maintenance actions for major components may experience prolonged waiting times, significantly increasing downtime and revenue loss. The operational consequence of a single turbine outage also increases with turbine size, as fewer turbines represent a larger fraction of farm capacity (Mehta et al. (2024)). These effects introduce heavy-tailed downtime distributions and increase the sensitivity of project economics to rare but high-impact events, which are difficult to capture with standard O&M process models.

Supply-chain considerations further compound upscaling-related operational risk (Carrara et al. (2023)). Manufacturing and transporting ultra-large blades, nacelles, towers, and subsea cables requires specialized facilities, infrastructure, and skilled labor, often concentrated among a small number of suppliers and regions (Shields et al. (2023)). Quality control challenges scale nonlinearly with component size, and latent manufacturing defects may only become apparent after extended operation or under extreme loading conditions (Kong et al. (2023)). The limited redundancy in supplier networks increases the likelihood that defects or bottlenecks propagate across multiple projects. From an operational perspective, long lead times for replacement components can substantially extend repair durations, particularly for bespoke or first-of-a-kind designs.

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Financial and insurance dimensions reflect the systemic nature of upscaling risk. Larger turbines imply higher repair and replacement costs per failure event, increasing the potential severity of losses (Mikindani et al. (2025)). From an insurer's perspective, larger turbine ratings and novel technology increase single-loss exposure. As a result, insurers raise premiums, increase deductibles, and tighten coverage conditions for projects deploying first-of-a-kind or early-generation turbine platforms (Ioannou et al. (2019)). OEMs, in turn, have reported increasing warranty provisions associated with quality issues and performance uncertainty in recent turbine generations. Recent financial disclosures indicate that warranty-related costs for major OEMs have risen to the order of 5–6% of revenues, underscoring the economic materiality of technology novelty and early-life performance risk (Vestas Wind Systems A/S (2024)). For project developers and financiers, technology novelty translates into higher perceived risk during due diligence, potentially affecting bankability, financing terms, and required contingencies (Guillet (2022)). These financial responses do not directly reduce operational risk but represent its monetization under uncertainty.

Table 17 summarizes the key uncertainty dimensions associated with rapid technology upscaling, their dominant uncertainty types, principal operational risk implications, and relevant time horizons.

**Table 17.** Key uncertainty domains introduced by rapid turbine upscaling, mapped to uncertainty type (A: aleatory, E: epistemic, R: regulatory/external).

| Dimension | Uncertainty source | Type | Risk implication | Time horizon |
|---|---|---|---|---|
| Design and engineering | Load scaling beyond validated ranges; novel blade and drivetrain concepts | E | Design deficiencies, early failures, retrofit needs | Design and early operation |
| Manufacturing and supply | Quality control at extreme component scale; concentrated supplier base | E, R | Delivery delays, defects, project cost and schedule overruns | Development and construction |
| Reliability and performance | Limited field data for new turbine models; non-stationary failure behaviour | A, E | Elevated downtime, serial failures, availability losses | Early–mid operation |
| O&M logistics | Limited availability of vessels and lifting assets; weather sensitivity | E,R | Prolonged repairs, extended outages, revenue loss | Operation |
| Financial and insurance | Lack of actuarial data; increased loss severity per failure | E, R | Higher premiums and deductibles; reduced bankability | Development and operation |
| Regulatory and standards | Evolving certification and grid compliance requirements | R, E | Redesign, additional testing, permitting or curtailment risk | Design, commissioning, EoL |

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#### 4.6.1 Impact assessment

A key challenge in addressing operational risk from rapid upscaling is the limited applicability of traditional quantitative risk models. Reliability and O&M frameworks commonly rely on historical failure statistics and calibrated stochastic processes, which are not readily transferable to novel turbine designs operating outside established envelopes (Dao et al. (2019)). Many upscaling-related risks are epistemic and path-dependent, influenced by design choices, manufacturing quality, learning effects, and organizational maturity. While several aspects of upscaling risk are implicitly reflected in other sections of this paper, their coupled and reinforcing nature is not fully captured when these risks are treated independently (Dao et al. (2020)). Rapid technology upscaling acts as a risk multiplier, simultaneously increasing uncertainty across multiple domains.

Given these limitations, a fully quantitative impact assessment of upscaling risk is currently not feasible without introducing speculative assumptions. Instead, this risk category is best addressed through structured qualitative analysis and scenario-based reasoning (Scheu et al. (2019); Lopez and Kolios (2022)). Addressing the gaps in modeling capabilities and causal relationships between aspects of technology, up scaling operational performance parameters, and their propagation to economic risk is identified as a research priority area.

## 5 Discussion and conclusions

This study reviewed, structured, and quantified major risks affecting wind energy projects across development and operational phases, with a focus on how these risks propagate into project-level economic performance. By combining expert elicitation, structured survey results, targeted literature review, and scenario-based techno-economic impact assessments, the analysis moves beyond risk identification and illustrates how different classes of uncertainty translate into distinct economic signatures in terms of net present value and levelized cost of energy. Across all risk categories, a central finding is that wind energy projects are increasingly exposed not to isolated uncertainties, but to interacting risk dimensions spanning technical performance, operational processes, market conditions, and system-level constraints.

The scenario-based impact assessments show that many economically consequential risks exhibit long-tailed and asymmetric loss distributions rather than symmetric uncertainty around a mean outcome. This is particularly evident for supply chain impacts, component reliability, and inefficiencies in O&M processes. Such characteristics are poorly captured by deterministic or narrowly scoped sensitivity analyses and help explain why projects that appear robust under conventional assumptions may nevertheless experience severe value erosion under adverse conditions.

The scenario-based impact assessments demonstrate that many economically consequential risks in wind energy projects exhibit long-tailed and asymmetric loss distributions, rather than symmetric uncertainty around a mean outcome. This behavior is particularly evident for supply-chain disruptions, component reliability, and inefficiencies in O&M processes. Such risk characteristics are poorly captured by deterministic assessments or narrowly scoped sensitivity analyses and help explain why projects that appear robust under conventional assumptions may nevertheless experience severe value erosion under adverse conditions.

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Across impact categories, risks do not affect economic outcomes uniformly. Some risks, such as financing conditions driven by supply-chain uncertainty, primarily induce a systematic shift in mean outcomes, while others predominantly widen outcome distributions and generate pronounced downside tails, as observed for reliability- and O&M-related risks. Comparison of risk categories, therefore, requires evaluating how they distort the range of possible economic outcomes, rather than focusing on changes in expected values.

Supply-chain risk, including increased financing costs, produces a substantial downward shift in project value. In the assessed scenarios, the mean net present value decreases by approximately 70% between the baseline and the substantial-risk case. This effect reflects a structural cost inflation driven by a higher weighted average cost of capital, rather than increased variability alone. As a result, supply-chain and financing risks are among the most severe, as they directly threaten project feasibility.

Curtailment risk introduces large downside exposure at the scenario level. The investigated curtailment regimes result in a 35% change in mean NPV between the baseline and high transmission-constraint scenarios. While compensation mechanisms may redistribute these losses among system stakeholders, they do not eliminate the underlying economic and energy-system inefficiencies. Curtailment, therefore, represents a severe risk for both project operators and the broader power system, combining significant economic losses with lost electricity production.

Uncertainty in component reliability and O&M process parameters primarily manifests as tail risk rather than mean shifts. Elevated failure rates of individual non-redundant components, prolonged repair times, or logistical inefficiencies can lead to extreme increases in downtime and costs, resulting in availability-driven revenue losses. Although reliability and O&M risks exhibit a smaller impact on average economic indicators than system-level risks, they are critical contributors to long-tailed downside outcomes that can threaten the profitability of individual projects.

Through-life decision-making, exemplified by a lifetime extension experiment in our study, acts as a powerful value lever but redistributes risk across time. The assessment shows substantial potential for cumulative NPV gains relative to the baseline, but also highlights large variability between scenarios. The observed spread in the order of € 100 M in NPV and approximately € 4 /MWh in LCOE underscores the sensitivity of outcomes to assumptions regarding degradation, refurbishment effort, and reliability evolution. Through-life risk is therefore less about loss avoidance and more about managing uncertainty in value creation.

Overall, the results indicate that supply-chain, financing, and curtailment risks are the dominant systematic drivers of project feasibility, while reliability and O&M inefficiencies are the primary drivers of downside tail risk affecting project profitability. Through-life decisions represent a high-impact but uncertain value lever.

The results also highlight the limitations of fragmented risk treatment. Many risk categories span multiple interdependent dimensions and involve different types of uncertainty. For example, end-of-life decisions interact strongly with reliability and O&M process uncertainty, which in turn includes both epistemic and aleatory elements. Treating these dimensions in isolation risks systematic underestimation of economic exposure and may lead to suboptimal decisions.

The findings point to several directions for further research and methodological development to support risk-informed decision-making in wind energy. There is a need for integrated decision-support frameworks that capture interacting uncertainties across the full project lifecycle. Such frameworks should reflect feedback among technical performance, O&M strategies,

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market conditions, financing terms, and regulatory constraints, rather than treating these elements independently. The ability to represent correlated risk dimensions and regime shifts is particularly important. Improved data availability and transparency are critical, especially for reliability and ageing-related processes. Publicly available failure databases often lack uncertainty quantification, consistent definitions, and sufficient detail to support probabilistic modeling of major component reliability and post-design-life behavior. Enhanced sharing of reliability data and insights into the relationship between operating conditions and failure occurrence would significantly improve the robustness of reliability-driven economic assessments. Curtailment risk requires further investigation from a system-integrated perspective. Future work should assess curtailment jointly from the viewpoints of project owners, grid operators, and the wider energy system, accounting for compensation schemes, market design, and system flexibility. This is essential to distinguish between risks specific to individual projects and inefficiencies at the system level. Lifetime extension and end-of-life decision-making will become increasingly important as a growing share of the wind fleet approaches nominal design life. Integrated approaches are needed that combine structural integrity assessment, reliability modeling, inspection and monitoring strategies, regulatory compliance, and economic evaluation under uncertainty. Finally, ongoing trends toward larger turbines, accelerated deployment, and higher renewable penetration underscore the importance of risk-aware design and qualification processes.

Overall, this work does not propose a complete solution for capturing the full complexity of wind energy risks. Instead, it demonstrates the limitations of fragmented risk treatment and provides a structured starting point for developing integrated, quantitative de-risking and decision-support tools. Such tools will be essential for supporting robust investment, design, and operational decisions in an increasingly constrained and risk-exposed wind energy sector.

*Code availability.* The WINPACT toolchain, including the experiment implementation used in this study, is available under: https://gitlab.windenergy.dtu.dk/HiperSim/winpact.

*Author contributions.* MG: Conceptualization, code implementation, scenario development, drafting. AL: Review on curtailment, reliability, MS: Review on supply chain, AK: Review on technology upscaling, RP: Survey execution, ND: Ideation, Survey design, formulation of sector challenges, and conceptualization and review of the paper.

*Competing interests.* At least one of the (co-)authors is a member of the editorial board of Wind Energy Science.

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