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 how these risks 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 (NPV) and levelized cost of energy (LCOE). The results demonstrate that different risks exhibit distinct economic signatures: some primarily shift mean outcomes, while others produce losses that are skewed toward worst-case outcomes, with rare but severe events dominating the overall risk profile. 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 starting point for developing integrated de-risking frameworks.

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 Global Wind Energy Council (GWEC) report highlights growing exposure to market and system-level risks, including a sharp increase in hours with negative electricity prices and 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, a structured survey of approximately 100 industry and academic experts, 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, i.e. a sequence of coupled computational models that together translate technical assumptions into economic performance metrics.

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

2 Methodology

The approach combines a structured expert survey, targeted literature review, and scenario-based quantitative impact assessment. 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. We use this term to denote industry-wide risk themes that are not specific to a single project, site, or technology. Regional differentiation of risk perceptions (e.g. across US and European markets) is not attempted here but would be a relevant direction for future work. Although the risk categories identified in this study are applicable to both onshore and offshore wind energy, the survey did not distinguish between the two contexts, and the quantitative case study is based on an offshore wind farm. The relative importance and specific manifestation of individual risks, particularly regarding maintenance logistics and access constraints, will differ for onshore projects.

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[1] (Gräfe et al. (2025); Gräfe et al. (2026); Pettas et al. (2026)). WINPACT is a modular, scenario-based framework that quantifies how uncertainties in wind energy projects propagate through the full project lifecycle to affect economic value. Alternative assumptions are introduced as scenario overrides and evaluated across all modules, enabling coupled effects (e.g. reliability changes influencing O&M costs, revenues, and ultimately LCOE or NPV) to be captured. Simulations are executed as scenario ensembles with stochastic replicates. Figure 1 provides a schematic overview of the module chain. The modules used in this study are:

- **Capital expenditure (CAPEX) module.** Assembles total capital expenditure from a bottom-up cost structure. Material-dependent costs are linked to stochastic commodity price models with configurable correlation, propagating supply-chain uncertainty into project cost.

- **WindFarm module.** Provides the baseline production time series. In this study, a fixed capacity factor is used, isolating economic risk drivers from wind-resource variability.

- **Operational expenditure (OPEX) module.** Links component reliability and maintenance processes to availability and operational cost using an analytic continuous-time Markov chain (CTMC) formulation. Captures failures, scheduled maintenance, weather-driven access constraints (i.e. inability to dispatch vessels and crews due to excessive wave heights or wind speeds), logistics delays, and repair activities. Uncertainty in failure rates and process parameters is sampled stochastically.

- **End-of-life module.** Represents continued operation beyond the nominal design life by modifying production, reliability, and cost assumptions for the extension period. Performance degradation during the design life is implicitly captured in the baseline capacity factor; this module applies additional modifiers for accelerated ageing beyond the design envelope.

[1] Full documentation: https://hipersim.pages.windenergy.dtu.dk/winpact/

– **Curtailment module.** Applies fractional production reductions to represent market-driven, grid-related, or externally imposed curtailment. Epistemic uncertainty in long-term curtailment regimes and aleatory variability in short-term conditions are represented separately.

– **FINEX and valuation modules.** Translate all upstream outputs into project-level financial metrics such as net present value (NPV), internal rate of return (IRR), debt service coverage ratio (DSCR), and levelized cost of energy (LCOE) via cash-flow construction over the full project horizon.

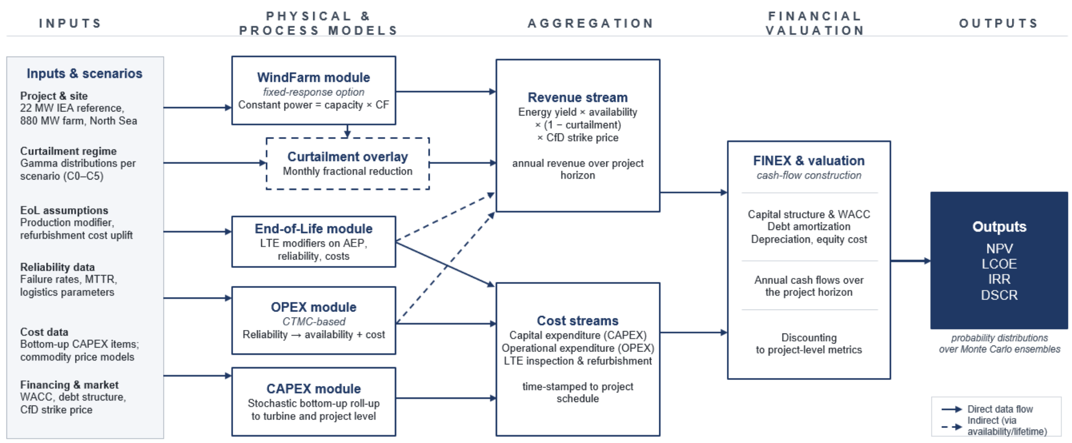

Figure 1. Schematic overview of the WINPACT module chain.

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_{farm}	748 MW
Turbine rating P_{unit}	22 MW
Number of turbines N_{turb}	34
Base design life t_0	25 years
Funding scheme	Contract for Difference
Strike price	86 €/MWh

The risk categories examined in this study affect different phases of the project lifecycle, from early development and financing through construction, operation, late-life assessment, and potential lifetime extension to end-of-life decisions. To establish a consistent terminology for these phases across all subsequent sections, Figure 2 provides a schematic overview of the project lifecycle as adopted in this study, together with the mapping of sector challenges introduced in Section 4 to the phases they predominantly affect.

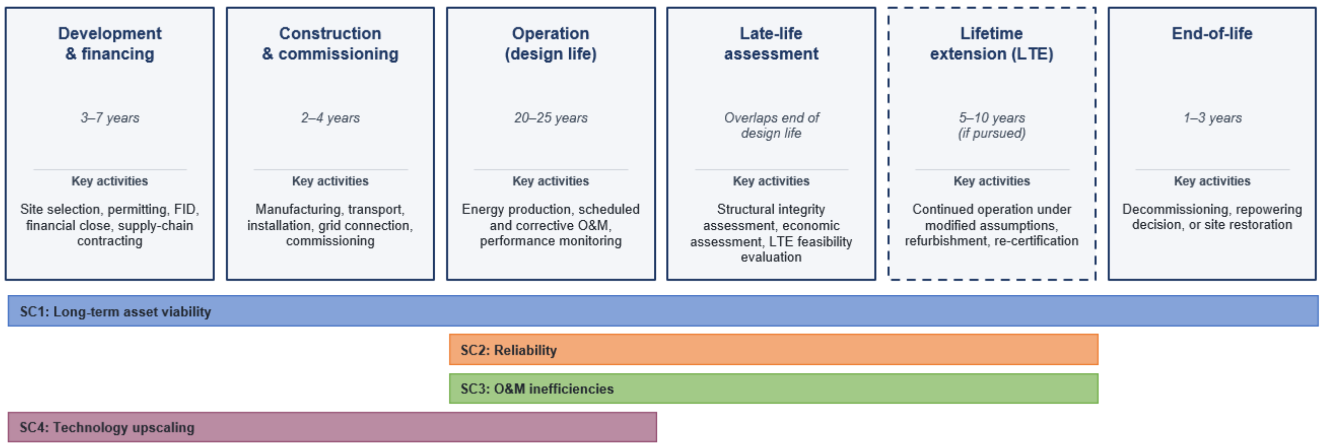

Figure 2. Schematic overview of the project lifecycle phases adopted in this study. Colored bars indicate the phases predominantly affected by each sector challenge defined in Section 4.

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 (34 turbines, 748 MW installed capacity, based on the 22 MW International Energy Agency (IEA) reference turbine) under deterministic assumptions for all cost, production, and financial parameters, without stochastic variation. 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 multiple 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.

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 3 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%).

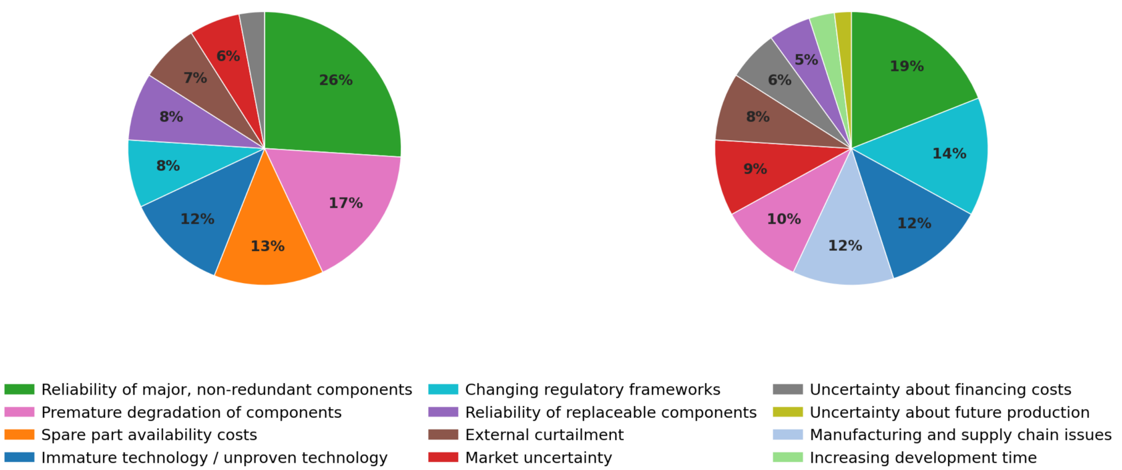

Figure 3. Survey results: What are the biggest risks for the economy of operational wind energy projects? (left) and What are the biggest risks for the economy of future wind energy projects? (right)

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.

Figure 3 (right) 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 operational projects, concerns about major component reliability, replaceable components, and premature degradation continue to dominate expert perceptions.

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 a temporal distinction: operational projects are primarily exposed to technical and O&M-related risks, while future projects are increasingly affected by system integration, market evolution, regulatory stability, and supply-chain robustness.

The responses to the third survey question, summarized in Figure 4, 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 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 consistent pattern: reliability emerges as the dominant risk driver across project phases, while the relative importance of external, system-level risks increases for future projects.

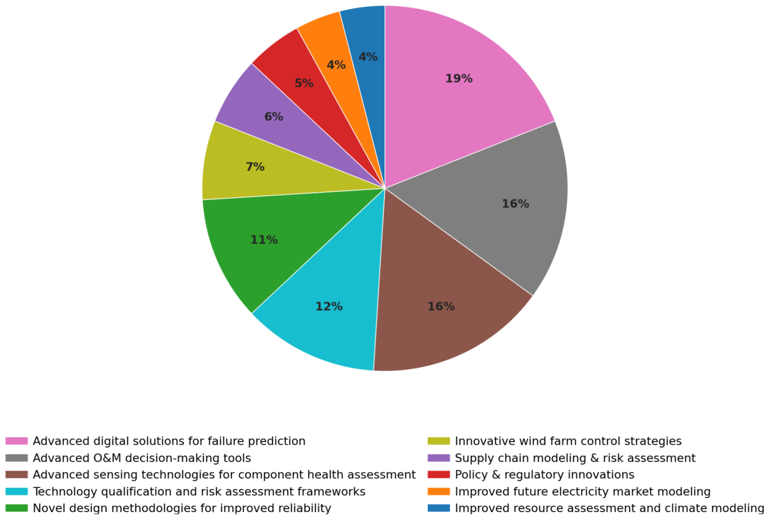

Figure 4. Survey results: What research areas or innovations could most effectively help mitigate risks in wind energy projects?

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 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)). Although many of these challenges could be mitigated by expanding networks of manufacturers, infrastructure, and skilled labor, investors remain cautious due to 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.

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	Development & financing
Cost volatility	Short- and long-term variations in key commodities, including shocks from externalities	E	Higher LCOE	Development & financing
Supply uncertainty	Component price equilibria attributed to supply / demand dynamics	E	Higher LCOE	Development & financing
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	Development & financing
Limited infrastructure	Uncertain availability of resources such as ports and vessels for offshore wind	E	Project delays, increased financing costs	Development & financing through operation
Technology evolution	Readiness level of current supply chain to produce new technologies	E	Higher LCOE	Development & financing

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 evaluate the impact of supply chain risks on the LCOE of representative wind projects through two coupled mechanisms: (i) stochastic uncertainty in key commodity prices, propagated through the CAPEX calculation, and (ii) variation in the cost of capital reflecting different levels of perceived geopolitical and supply chain risk. All other parameters, including OPEX, annual energy production, and project lifetime, are held at baseline values, so that the resulting LCOE variation is attributable solely to supply chain and financing risk. Because LCOE scales with the product of these factors, their combination can produce nonlinear impacts on project economics.

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)). Because steel and copper are globally traded commodities, these indices serve as proxies for global market dynamics. Although regional price levels may differ, it is assumed that volatility structure and jump behavior are broadly consistent across major markets. From the historical data we derive the following stochastic parameters:

- 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 produces heavy tails in the log returns that are poorly captured by Gaussian models. The linear correlations between the commodity price parameters are low (under 0.1) but are still included in the Monte Carlo simulation. The historical stochastic parameters for the three commodities are summarized in Table 3.

Financing risk is one of the most significant drivers of LCOE, although the causal relationship between supply chain disruptions and financial parameters is not well established in the public literature. We therefore select values of the weighted average cost of capital (WACC) that correspond to different levels of project risk, without attempting to draw a direct causal link with specific geopolitical or supply chain factors. Modeling these dependencies is a promising direction for future research.

WACC is calculated from the debt-equity ratio, tax rate, and cost of debt and equity, keeping the first two constant across scenarios. The cost of debt and equity are set relative to a risk-free rate using historical spreads from U.S. wind project data (Mirletz et al. (2024)). During 2017–2020, a period of relatively stable deployment (Wiser et al. (2024)), the debt premium over the risk-free rate was 1.73%; in 2023, amid global supply chain constraints, this premium rose to 3.5%. The cost of equity is estimated at approximately 5 percentage points above the cost of debt. A German 10-year bond yield of 2.7% serves as the risk-free baseline[2] (Deutsche Finanzagentur (2026)), with debt premiums increasing across scenarios to reflect rising risk profiles.

The scenario definitions, combining WACC assumptions with stochastic commodity price multipliers and exposure time horizons, are provided in Table 3. The time horizon represents the period over which stochastic cost pathways evolve, reflecting commodity price volatility exposure (Ury et al. (2024)).

Table 3. Supply chain risk scenarios and associated financial and commodity price parameters. Stochastic commodity parameters are expressed as multipliers on the historical values $(\mu_{\text{hist}}, \sigma_{\text{hist}}, \lambda_{\text{hist}})$ for steel (0.258, 0.288, 1.96), copper (0.422, 0.422, 0.915), and carbon fiber (0.521, 0.250, 1.05), derived from U.S. Bureau of Labor Statistics price indices (U.S. Bureau of Labor Statistics (2026c, b)).

Scenario	**Interpretation**	**WACC [%]**	**Drift α_s^μ**	**Volatility α_s^σ**	**Jump int. α_s^λ**	**Horizon t [yr]**
Baseline	Deterministic baseline assumptions	5.2	–	–	–	–
SC 1 – Min. risk	Risk-free rates on debt; lower bounds on stochastic commodity parameters	3.8	0.8	0.8	0.8	1
SC 2 – Mod. risk	Historic averages on debt and equity; historical commodity parameters	5.2	1.0	1.0	1.0	2
SC 3 – Subst. risk	Debt rates from supply chain shocks; upper bounds on commodity parameters	6.7	1.2	1.2	1.2	3

The NPV, total CAPEX, and LCOE simulation results for the scenarios in Table 3 are provided in Figs. 5 and 6, respectively. The effects of the commodity price volatility and increasing time exposure increase the tails of the distribution while slightly

[2]In reality, a wind project is unlikely to achieve a debt rate equal to a risk-free government bond rate. We use this value as a minimum threshold for supply chain risk-driven financing cost impacts on LCOE.

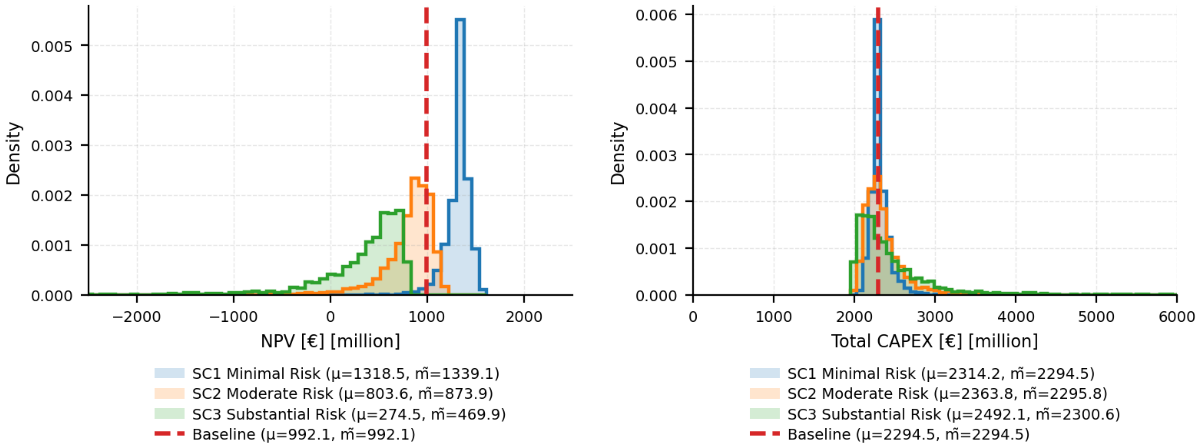

Figure 5. NPV (left) and total CAPEX (right) distributions for different scenarios.

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 fundamental 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)). Supply chain risk can therefore create a step change in project feasibility.

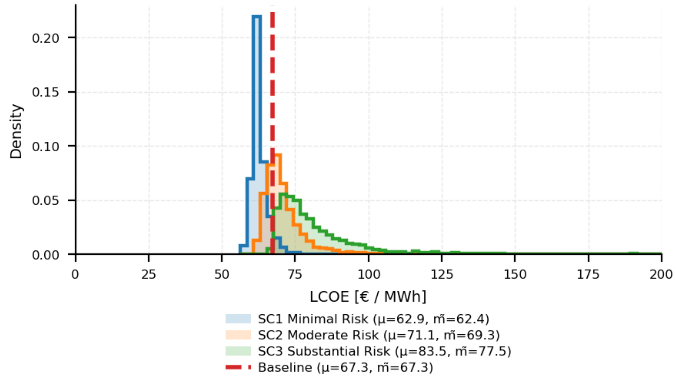

Figure 6. LCOE distributions for different scenarios.

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

4.2.1 Review

Wind turbines are typically designed for a nominal lifetime of 20 years for onshore installations and 25 years for offshore installations, in accordance with International Electrotechnical Commission (IEC) standards (International Electrotechnical Commission (2019a, b)). In Europe, 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. Through-life decision-making encompasses a set of interrelated technical, regulatory, and economic considerations that determine whether assets are decommissioned, repowered, refurbished, or operated under a lifetime extension (LTE) framework. The underlying uncertainties are relevant throughout the asset lifetime, even though they become most consequential in late-life phases.

From a technical perspective, structural integrity frequently permits continued operation beyond the design lifetime, because actual site-specific loads are often less severe than the conservative assumptions used in design. Monitoring of operational conditions and accumulated loads can reduce this uncertainty and support verification of safe continued operation (Nielsen et al. (2019)). If structural integrity can be ensured, component reliability becomes the key determinant: ageing mechanisms such as wear, corrosion, and fatigue lead to increasing failure probabilities (Carroll et al. (2016); Donnelly et al. (2024); Dinwoodie et al. (2013)), and epistemic uncertainty in post-design-life failure rates can substantially influence maintenance costs and availability. Aerodynamic performance may further degrade due to blade erosion (Malik and Bak (2025)). Beyond the asset itself, changing site conditions introduce additional uncertainty through climate-change-induced annual energy production (AEP) shifts of approximately -2% to -5% (Hahmann et al. (2022); Larsén et al. (2024)) and evolving wake effects that may reduce AEP by 5–18% under future high-deployment scenarios (van der Laan et al. (2023); Borgers et al. (2025)).

Regulatory conditions represent a regime-level uncertainty. Lifetime extension is not governed by a harmonized framework in Europe; national regulations differ in scope, stringency, and enforcement and may evolve over time (Ziegler et al. (2018)). Requirements for permitting, inspection, certification, and documentation directly affect technical feasibility, while decommissioning and removal obligations, particularly for offshore assets, introduce additional economic risk that can influence lifetime extension decisions independently of the technical condition of the asset.

Economic uncertainty in late-life phases is driven by refurbishment scope and costs, which are typically identified only after detailed inspections 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. During extended operation, OPEX is further subject to the ageing-related reliability and spare-part uncertainties described above, limiting the applicability of deterministic cost assumptions.

IEC 61400-28 (International Electrotechnical Commission (2025)) provides a technical framework covering load accumulation, inspection strategies, and certification, but does not prescribe an economic decision model. Several studies have addressed LTE risk quantification, including Bayesian decision frameworks (Nielsen et al. (2019)), probabilistic fatigue-economic optimization (Nielsen and Sørensen (2021)), and techno-economic frameworks integrating structural degradation with economic evaluation (Yeter et al. (2022)). These approaches demonstrate that moderate reductions in target reliability may be economically acceptable, but they typically address limited subsets of the relevant uncertainties.

Table 4 summarizes the key uncertainty domains, their associated risks, and relevant time horizons. Late-life decision-making spans aleatory, epistemic, and regulatory uncertainty across multiple time horizons, from early-life fatigue accumulation to short-term operational decisions and long-term financing risk, and existing frameworks typically address these dimensions in isolation rather than jointly.

Table 4. 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	Operation through lifetime extension
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 assessment & lifetime extension
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 assessment & lifetime extension
External conditions	Long-term wind resource shifts evolving wake interactions	A, E	Biased energy yield projections	Operation through lifetime extension
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 assessment & 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	Operation through lifetime extension

4.2.2 Impact assessment

Building on the uncertainty dimensions in Table 4, we adopt a scenario-based impact assessment using lifetime extension as a representative through-life decision-making challenge. The analysis demonstrates how plausible variations in energy yield, refurbishment effort, and system reliability during extended operation propagate to project-level NPV and LCOE.

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:

$$X_{\text{AEP}}^{(s)} \sim \mathcal{N}\left(\mu_s^{\text{AEP}}, \sigma_s^{\text{AEP}}\right), \tag{1}$$

$$X_{\text{Ref}}^{(s)} \sim \mathcal{N}\left(\mu_s^{\text{Ref}}, \sigma_s^{\text{Ref}}\right). \tag{2}$$

The sampled modifiers are applied as:

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

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

In each Monte Carlo iteration, one random draw from $X_{\text{AEP}}^{(s)}$ and $X_{\text{Ref}}^{(s)}$ 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 5.

Uncertainty in future reliability is captured through deterministic, scenario-dependent multipliers on baseline component failure rates, applied only during the LTE period. This reflects the expectation that ageing mechanisms (wear, fatigue, corrosion, blade erosion) become increasingly relevant beyond the design life. Failure rates during the original design life remain unchanged. The complete scenario definitions, including production, refurbishment, reliability, and extension duration assumptions, are summarized in Table 5.

Table 5. Lifetime extension scenarios and associated quantitative assumptions.

Scenario	**Interpretation**	**AEP modifier** (μ, σ) [%]	**Refurb uplift** (μ, σ) [€/turb.]	**Failure-rate mult.** λ_{LTE}	**Ext. [yr]**
Baseline (No LTE)	No lifetime extension; baseline reliability throughout	$(0.0, 0.0)$	$(0, 0)$	1.00	0
EOL 1 – Moderate	Conservative extension; moderate production degradation, limited refurbishment, increased maintenance frequency	$(-2.0, 1.0)$	(1.5M, 0.5M)	1.5	8
EOL 2 – Substantial	Aggressive extension; pronounced production loss, major refurbishment, higher failure intensity	$(-6.0, 2)$	(5M, 2M)	2.0	5

Figure 7 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 as an illustration of how late-life decisions can redistribute risk across time. The results indicate that LTE outcomes 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 illustrative experiment does not account for electricity price volatility, inflation, regulatory risk, or catastrophic failures; future work should therefore address through-life decision-making under the combined uncertainty dimensions summarized in Table 4.

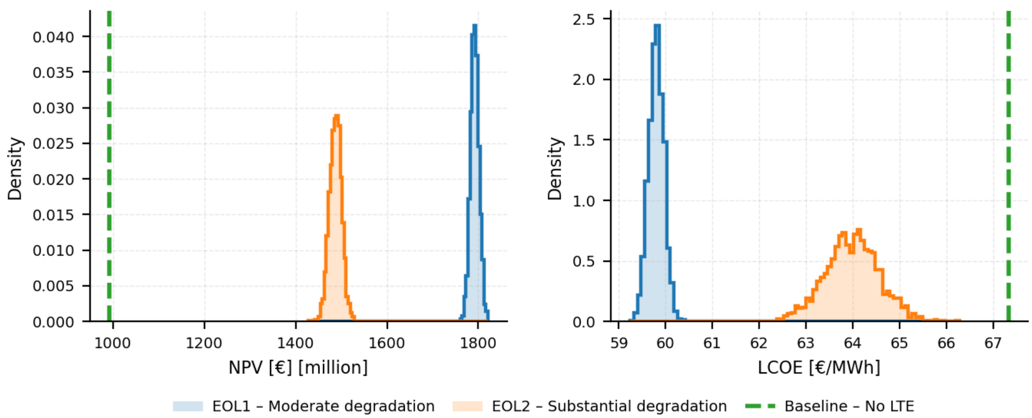

Figure 7. NPV and LCOE for different end-of-life scenarios

4.3 Long-term asset viability - Curtailment

4.3.1 Review

With the increasing share of variable renewable energy (VRE) in power systems, curtailment of wind and solar generation is a growing concern (Global Wind Energy Council (GWEC) (2025)). Curtailment reduces energy production, erodes revenues, and introduces uncertainty that is difficult to anticipate at the project level. We distinguish three main types: (i) transmission-constraint curtailment, arising from insufficient grid capacity; (ii) market-driven curtailment, triggered by negative electricity prices; and (iii) wildlife-related curtailment, imposed to protect birds and bats.

Transmission-constraint curtailment occurs when local or regional generation exceeds the capacity of the grid (Agbonaye et al. (2022); EirGrid TSO and SONI TSO (2024)). Grid capacity must develop in pace with renewable deployment, yet uncertainties in the timing and scope of reinforcement remain a critical challenge: projected European redispatch volumes range from 165 to 809 TWh by 2040 depending on the expansion scenario (Thomaßen et al. (2024)), and congestion is already acute

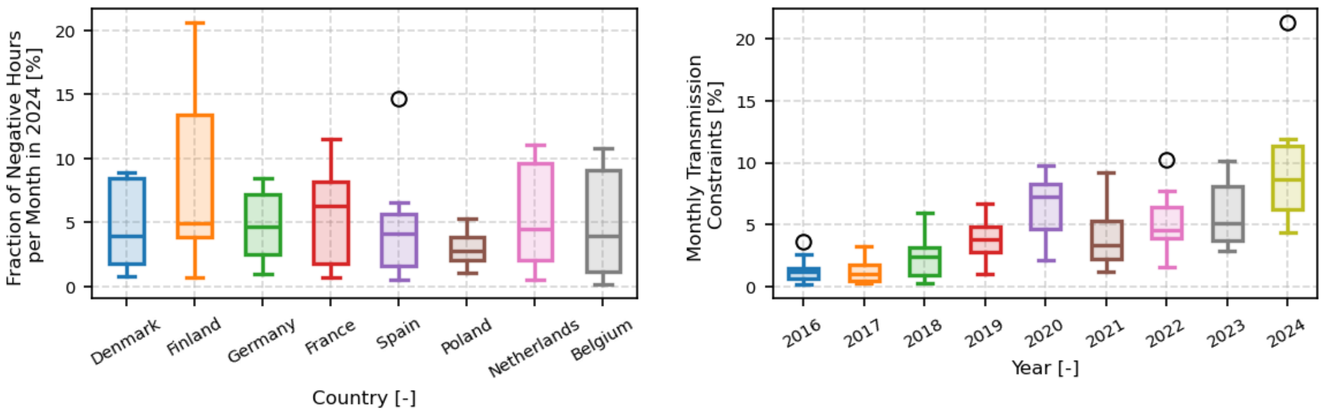

Figure 8. (Left) Distribution of monthly fraction of negative electricity prices per country (Ember (2025)); (Right) Distribution of monthly constraint levels in all Ireland (Republic of Ireland and Northern Ireland) per year.

in several countries (International Energy Agency (2025); SMARD – German Electricity Market Data (2024)). The spatial heterogeneity of constraint levels is illustrated by Irish transmission system operator (TSO) data (EirGrid TSO and SONI TSO (2024)): in 2023, grid-driven curtailment ranged from 0.3% in the South East to 11.4% in the North West (Figure 8, right). Compensation mechanisms vary by country, from full cost-based reimbursement (e.g. Germany) to limited or no compensation (e.g. Ireland until recently), and frequent curtailment can lead to high system balancing costs (Kerr (2025)).

Market-driven curtailment arises when high VRE production drives wholesale electricity prices to negative levels (Tselika (2022); Bird et al. (2016); Biber et al. (2022)). The frequency of negative prices has increased across high-penetration markets such as Germany, Denmark, and the Netherlands (Figure 8, left; Ember (2025)), making curtailment an economically rational response. Market-driven curtailment can significantly impact project NPV and bankability, and may affect the ability to secure power purchase agreements (PPAs) or contracts for difference (CfDs) (Gonzalez-Aparicio et al. (2022)).

Wildlife-related curtailment is imposed to mitigate bat and bird fatalities from blade collisions and barotrauma, particularly during seasonal migration and low-wind conditions (Cryan and Barclay (2009); Friedenberg and Frick (2021)). Regulatory frameworks mandate operational restrictions such as raised cut-in speeds or seasonal shutdowns (European Commission, Directorate-General for Environment (2010)), though smart curtailment strategies using real-time bat activity indicators can reduce AEP losses relative to blanket shutdowns (Hayes et al. (2023); Gottlieb et al. (2024)). Reported AEP losses are typically $< 1\%$–3% (Hayes et al. (2023); Whitby et al. (2021); Behr et al. (2017)). As wildlife curtailment affects a different operational regime (low wind speeds) than transmission or market curtailment (high wind speeds), it is not included in the quantitative assessment below.

Table 6 summarizes the curtailment uncertainty dimensions discussed.

Table 6. 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	Operation
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	Operation
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	Operation
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	Operation
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	Development & financing through operation
Spatial heterogeneity	Location-specific exposure to congestion, price zones, and ecological constraints; interaction with neighboring renewable projects	E	Suboptimal siting and design of projects	Development & financing

4.3.2 Impact assessment

Curtailment is modeled as a system-level loss mechanism reflecting both persistent structural conditions and short-term operational variability. For a given month m, curtailed production P_m^{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:

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

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

The model separates two uncertainty sources. Epistemic uncertainty in the long-term curtailment regime is represented through predefined ranges of the Gamma parameters (α,θ), sampled once per simulation and held fixed over the project lifetime (variation ranges of $\pm 10\%$ around scenario values). Conditional on this regime, aleatory uncertainty captures irreducible month-to-month variability through Equation (6). The Gamma distribution is chosen for its ability to represent positively skewed loss processes.

Five curtailment regimes are defined, informed by two empirical drivers: (i) spatially heterogeneous transmission constraints, derived from Irish TSO data for 2021–2024 (EirGrid TSO and SONI TSO (2024)), motivating three regimes of low, medium, and high grid constraints; and (ii) cross-country variability in negative electricity price frequency across Europe, motivating two market-driven regimes with contrasting price volatility. The resulting scenario definitions are summarized in Table 7.

Table 7. Curtailment regimes representing epistemic uncertainty in system-level curtailment conditions. Distribution parameters were derived from data detailed on Figure 8, where monthly number of hours has been converted in monthly % of time, and monthly curtailment level is expressed in %.

Scenario	Interpretation	Shape parameter range (α)	Scale parameter range (θ)
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]

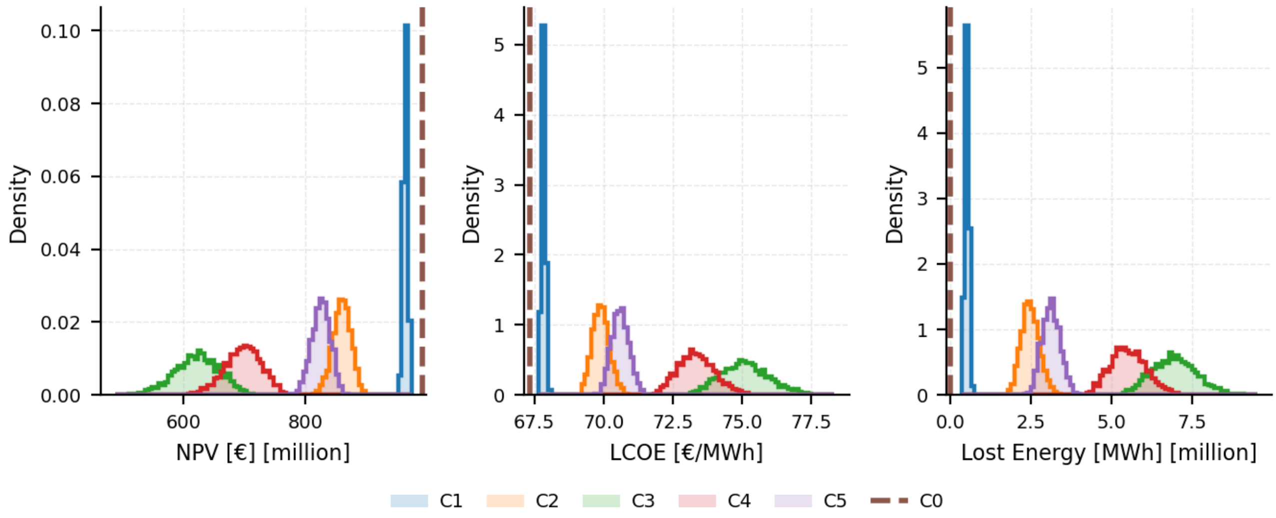

Figure 9. NPV (left), LCOE (middle) and Lost Energy (right) distributions for scenarios.

Figure 9 shows the distribution of project NPV, LCOE 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. Depending on the compensation mechanism, curtailment at these levels can 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.

4.4 Reliability gaps in major non-redundant components

4.4.1 Review

Wind turbine reliability is central to performance optimization and cost control, yet various indicators are used in the literature to assess it at both system and component level (Walgern et al. (2025)). Despite efforts to develop consistent data collection practices and taxonomies (Hahn et al. (2017)), there is still no uniform standardization in the definition of reliability indicators, failure events, or component classifications 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 analyses. 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. A compilation of average failure rates reported in 12 publicly available databases (Table A1) shows values spanning from 0.434 to 46.856 failures/WT/year, with the highest value likely an outlier due to supervisory control and data acquisition (SCADA) alarm usage. Following the approach of Dao et al. (2019), the datasets were clustered by location, observation period, and mean rating; the resulting coefficients of variation (Table 10) illustrate how these factors contribute to variability. This lack of uncertainty characterization introduces epistemic uncertainty that can propagate into biased estimates of intervention frequency, downtime, and O&M costs (Gräfe et al. (2025); Donnelly et al. (2024)).

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 original equipment manufacturer (OEM)-specific differences in average annual failure frequencies normalized by installed capacity. Reported values range from approximately ~ 1.5 to ~ 2.5 failures/MW/yr for onshore turbines, and from ~ 0.7 to ~ 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 11), 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, 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 failure-rate evolution (Kapur and Pecht (2014)), but empirical data from wind fleets do not confirm a clearly defined bathtub shape at the system level. Component-specific analyses reveal non-stationary behavior, including elevated early-life failure frequencies and age-dependent trends, that differs substantially between subsystems (Walgern et al. (2025); Faulstich et al. (2011)), as illustrated by the WinNER database (Figure 10; Electric Power Research Institute (EPRI) (2024)).

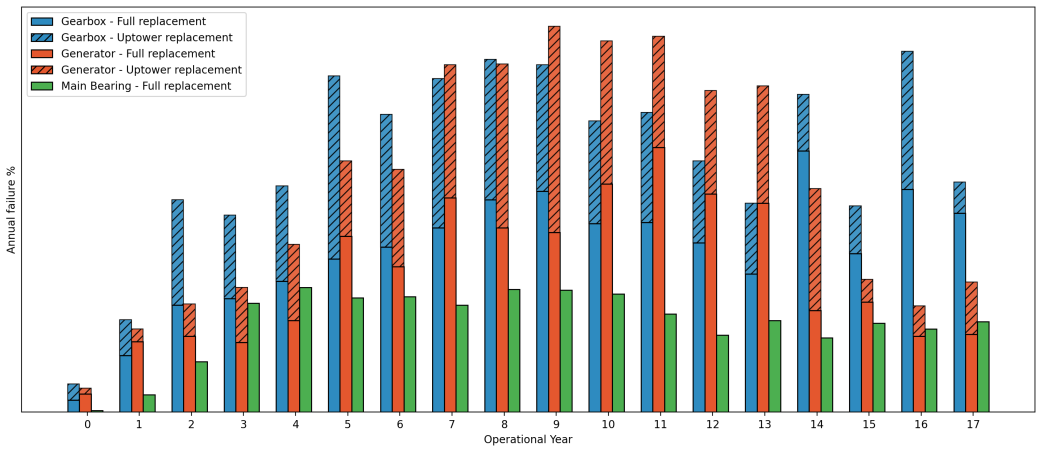

Figure 10. Key components failure rates from the WiNNER database (Pulikollu et al. (2023, 2024); Pulikollu and Han. (2021)).

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, aleatory variability in failure occurrence means that otherwise identical projects may experience substantially different maintenance histories and costs purely due to random variation. Reliability-driven O&M assessments must therefore be interpreted in probabilistic terms.

Table 8. 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	Operation through lifetime extension
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	Operation through lifetime extension
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	Operation through lifetime extension
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	Operation through lifetime extension
Data taxonomy and definitions	Inconsistent definitions of failure events, components, and assemblies across databases	E	Systematic bias in model calibration; limited comparability of studies	Development & financing
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	Operation through lifetime extension

As summarized in Table 8, wind turbine reliability is affected by multiple interrelated sources of uncertainty, predominantly epistemic in nature. Uncertainty in failure rates, their allocation across components, and their temporal structure propagates directly into intervention frequency, downtime, and O&M expenditures.

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. The scope is limited to turbine-level components (drivetrain, blades, electrical systems, etc.); substructure and cable system failures are not included in the current model, which is acknowledged as a limitation. 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.

Epistemic uncertainty in failure rates is implemented through a structured decomposition of the coefficient of variation (CV) into a shared and an independent component. The shared component captures coherent effects — systematic biases in data sources, modeling assumptions, or limited transferability — through a single multiplicative factor sampled once per simulation and held constant over the lifetime. The independent component captures residual component-specific heterogeneity. A target CV is specified at the turbine level for each scenario, and the combined effect of shared and independent terms reproduces this target at system level.

The scenarios presented in Table 9 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 R1 [Low variability]: Mature turbine model in a large homogeneous fleet with established O&M processes. The CV reflects within-fleet heterogeneity, informed by site-to-site differences reported by Tavner et al. (2013) for Enercon turbines across three German wind farms.

- Scenario R2 [Medium variability]: Representative of public or mixed-source reliability data, where variability arises from heterogeneous sites, contracting practices, and non-uniform failure definitions. The CV is informed by the CIRCE database (Reder et al. (2016); Table 11).

- Scenario R3 [High variability]: Representative of new turbine models in early deployment with limited operational experience. The CV is informed by the spread observed in datasets with short observation periods (< 5 years) and ratings above 1 MW (Table A1; Table 10).

Table 9. Failure-rate uncertainty scenarios grounded in offshore wind reliability literature and implemented as Gamma uncertainty on λ.

Scenario	**Interpretation**	**Failure rate** λ **(**α_λ**,** CV_λ**)**
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.	$(1.00, 0.90)$

Table 10. Coefficient of variation of failure rates by category

Category	**Subgroup**	**CV**
Location	Europe	0.6
	Outside Europe	1.8
Observation years	≤ 5 years	1.0
	> 5 years	0.6
Mean rating	≤ 1 MW	0.9
	> 1 MW	1.2

Table 11. 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 11 illustrates the distributions of NPV, LCOE, 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 (R1), 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.

Figure 12 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 potential stress on maintenance resources and supporting infrastructure.

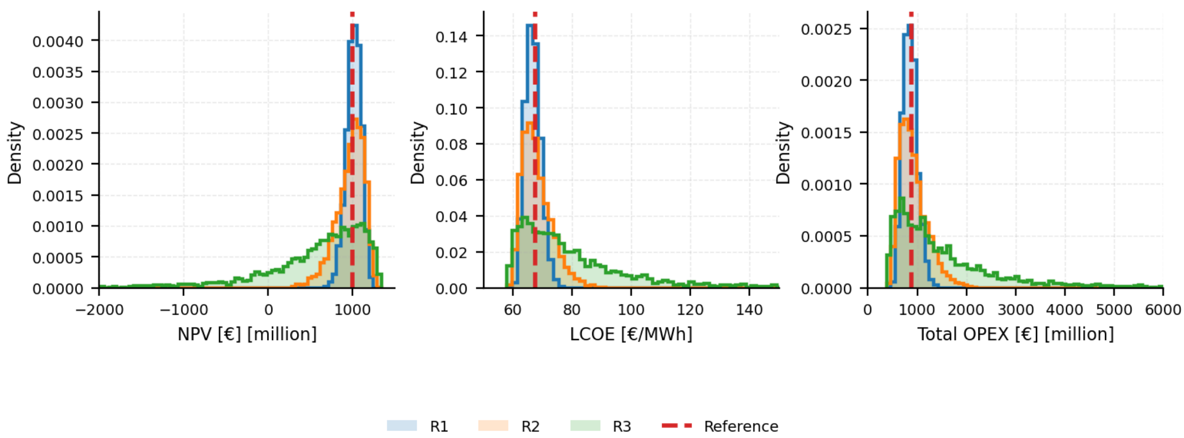

Figure 11. NPV (left), LCOE (middle) and total OPEX (right) distributions for scenarios

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.

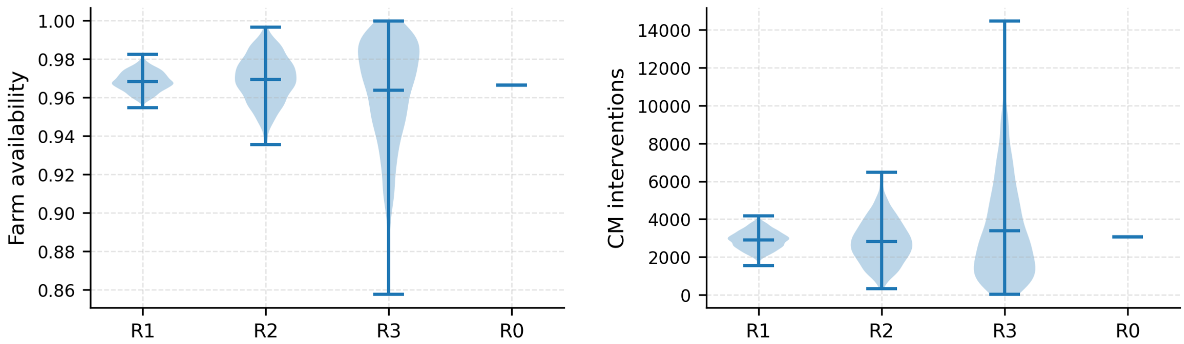

Figure 12. Availability (left) and absolute number of corrective maintenance interventions (right) across scenarios. Shaded areas represent kernel density estimates of the simulated distributions; wider regions indicate higher probability density.

4.5 Inefficiencies in operations & maintenance

4.5.1 Review

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 12 provides an overview of these risks.

Multiple monitoring and diagnostic systems, including SCADA-based condition inference (Tautz-Weinert and Watson (2017); Wang et al. (2026); Chesterman et al. (2023)), dedicated vibration and oil-condition CMS (Kestel et al. (2025)), and structural health monitoring (Haseeb and Krawczuk (2025)), aim to represent the true health state of turbine components. Their practical value depends not only on diagnostic accuracy but on how uncertainty propagates from data collection to decision-making and operational actions.

Uncertainty arises at sensing, modeling, and integration levels: sensor noise, limited coverage, and partial observability (Haseeb and Krawczuk (2025)); data gaps and reliance on aggregated 10-minute SCADA statistics that may miss transient faults (Wang et al. (2026); Kestel et al. (2025)); and sensor degradation over time if models are not actively maintained.

Model-based and data-driven approaches introduce additional uncertainty through modeling simplifications, limited fidelity, and poor transferability across turbines, sites, and control configurations (Gräfe et al. (2024)). At the operational level, algorithmic detection latency compounds with system-level latency from weather, vessel, and contractual delays, so that faster diagnostics do not translate linearly into reduced downtime.

Failure detection uncertainty affects process performance in two ways: false positives trigger unnecessary interventions and availability losses, whereas false negatives enable secondary damage or catastrophic failures. Because logistics and access constraints continue to dominate total downtime, diagnostics constitute a necessary but not sufficient condition for reducing O&M risk.

Diagnostic outputs are typically provided as alarms, health indices, or remaining useful life (RUL) estimates rather than as decision-relevant risk metrics linking fault probabilities to consequence severity. Confidence bounds are rarely propagated into the decision layer, so maintenance planning continues to rely on static thresholds and heuristic rules (Borsotti et al. (2026)). Decision-theoretic frameworks, notably Bayesian pre-posterior models (Nielsen and Sørensen (2011)), address this gap in principle but have been demonstrated only for idealized single-component cases; their extension to full wind farms with realistic logistics and organizational boundaries remains an open challenge.

Maintenance execution and weather-dependent accessibility introduce aleatory uncertainty. Empirical studies show strongly right-skewed repair-duration distributions (Dao et al. (2019)), where rare events (weather lock-in, vessel unavailability, campaign interference) dominate cumulative downtime (Faulstich et al. (2011)). Vessel mobilization ranges from days to months, and waiting-for-access frequently exceeds actual repair time (Kolios et al. (2023)). These interactions produce heavy-tailed downtime distributions that cannot be captured by mean process parameters. Process maturity and advanced access concepts can compress but not eliminate these tails, implying that modeling approaches must explicitly represent this stochasticity.

Organizational coordination is a significant source of epistemic uncertainty. Fragmented responsibilities among owners, OEMs, and service providers lead to coordination delays, repeated site visits, and prolonged diagnosis-to-fix cycles (Borsotti et al. (2026); Hadjoudj and Pandit (2023)). Contractual misalignment of incentives and separate management of turbines, balance-of-plant, and marine operations further increase system-level downtime (Hawker and McMillan (2015)).

The absence of widely adopted failure taxonomies and maintenance standards, a limitation already noted for reliability data in Appendix A, restricts cross-farm learning and benchmarking (Hahn et al. (2017)). Information asymmetries between OEMs, owners, and service providers further limit the availability of integrated failure, operational, and cost datasets (Paquette et al. (2024); Shafiee and Sørensen (2019)), so that epistemic process uncertainty persists across projects.

Finally, the adoption of advanced O&M technologies itself introduces uncertainty. Despite promising results in research settings, many condition monitoring, predictive maintenance, and digital twin concepts face a persistent gap between demonstrated technology readiness and operational deployment (Paquette et al. (2024)). Integration with legacy SCADA and control infrastructure, limited field validation data, and emerging cybersecurity risks from increased connectivity represent additional barriers that can delay or diminish the expected benefits of digitalisation in O&M practice.

Table 12. 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	Operation
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	Operation
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	Operation
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	Operation
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	Operation
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	Operation through lifetime extension

4.5.2 Impact assessment

To evaluate the uncertainty arising from inefficiencies in O&M processes, we use the OPEX module of 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 mean time to repair (MTTR), (ii) mean time to wait for logistics and spare parts (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 α and a lognormal uncertainty term with standard deviation σ:

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

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

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

Table 13. Process-focused O&M inefficiency scenarios. Failure rates are fixed at baseline values.

Scenario	Interpretation	MTTR (α, σ)	MTTW$_L$ (α, σ)	Access factor α_p
Reference	Deterministic baseline (mean values only)	$(1.00, 0.00)$	$(1.00, 0.00)$	1.00
P1 – High process uncertainty	Volatile offshore execution, immature logistics, conservative access strategy	$(1.00, 0.55)$	$(1.00, 0.85)$	0.90
P2 – Typical offshore operations	Industry-average execution with stochastic delays	$(1.00, 0.35)$	$(1.00, 0.50)$	1.00
P3 – Mature O&M processes	Learning effects, framework contracts, improved planning and access	$(0.95, 0.25)$	$(0.90, 0.30)$	1.05
P4 – Best practice O&M	Optimized logistics, campaign planning, condition-based maintenance, advanced access	$(0.80, 0.18)$	$(0.75, 0.25)$	1.10

Scenario assumptions are summarized in Table 13. The Reference scenario represents the baseline 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 crew transfer vessel (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.

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 field service vessel (FSV) or jack-up supported strategies 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)).

Figure 13 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. Variance reduction in O&M processes is therefore at least as important as reducing mean repair or logistics times.

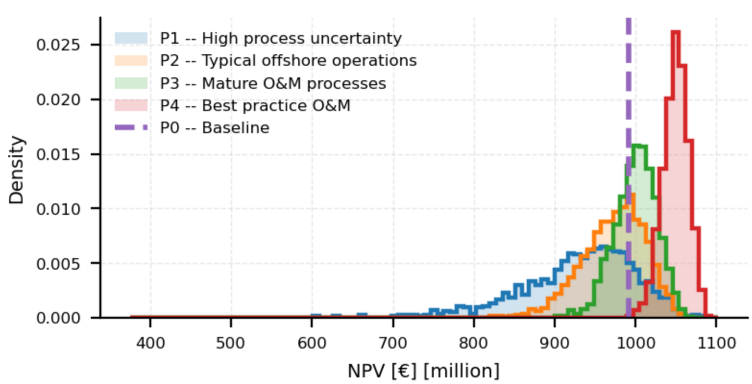

Figure 13. NPV distributions for scenarios

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 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.

Even with identical component failure rates across scenarios, differences in O&M process uncertainty result in substantial differences in NPV. Improving component reliability alone is therefore insufficient to stabilize project economics unless accompanied by parallel improvements in organizational coordination, logistics planning, and access strategies.

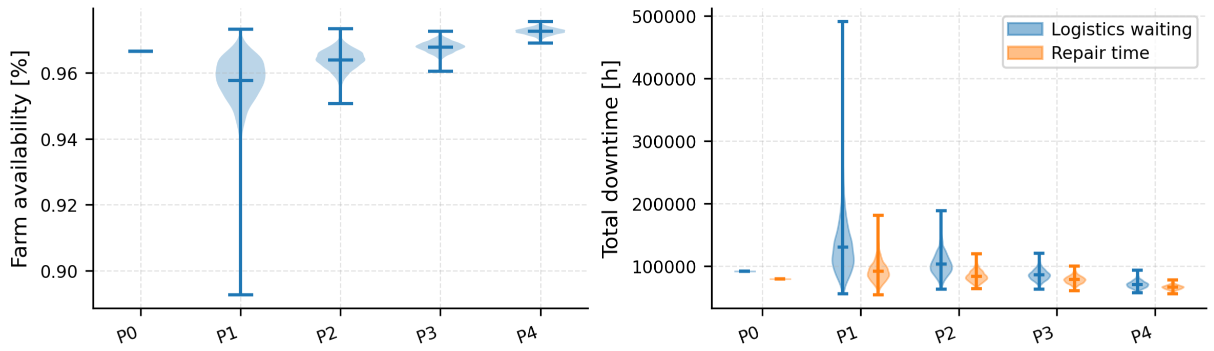

Figure 14. Availability (left) and downtime (right) distributions across O&M scenarios. Shaded areas represent density estimates; wider regions indicate higher probability density.

Figure 14 illustrates the corresponding technical effects: increased process uncertainty directly reduces farm availability and increases downtime hours, translating into economic risk through lost production and increased OPEX.

4.6 Operational risk from rapid technology upscaling

4.6.1 Review

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 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 empirical operating experience (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. A primary concern is reliability: newer turbine generations exhibit elevated early-life failure rates in blades, main bearings, power electronics, and cable systems (Mishnaevsky (2022); Pelka and Fischer (2023); Strang-Moran (2020)). Critically, such failures tend to be systemic: design or manufacturing deficiencies may affect entire fleets, triggering serial failures and large-scale retrofit campaigns (Veers et al. (2023)). This challenges the stationarity and independence assumptions underlying conventional reliability models discussed above.

Upscaling also amplifies the O&M logistics uncertainties discussed in the preceding section. Larger turbines require heavier lifting equipment and specialized vessels with limited availability, prolonging corrective maintenance waiting times (Stålhane et al. (2019)). Because fewer turbines represent a larger fraction of farm capacity, single-turbine outages have a disproportionate impact on revenue (Mehta et al. (2024)).

Supply-chain risks, discussed in the context of commodity and financing uncertainty above, are further compounded by upscaling (Carrara et al. (2023)). Manufacturing concentration among few suppliers (Shields et al. (2023)), nonlinear quality-control challenges at extreme component scales (Kong et al. (2023)), and long lead times for bespoke replacement parts amplify both delivery risk and operational downtime.

Financial and insurance dimensions reflect the systemic nature of upscaling risk. Higher repair costs per event (Mikindani et al. (2025)) and increased single-loss exposure lead insurers to raise premiums and tighten coverage for first-of-a-kind platforms (Ioannou et al. (2019)). OEM warranty provisions have risen to 5–6 % of revenues (Vestas Wind Systems A/S (2024)), and technology novelty affects bankability and financing terms during due diligence (Guillet (2022)).

Table 14 summarizes the key uncertainty dimensions associated with rapid technology upscaling, their dominant uncertainty types, principal operational risk implications, and relevant time horizons.

Table 14. 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	Construction & commissioning, operation
Manufacturing and supply	Quality control at extreme component scale; concentrated supplier base	E, R	Delivery delays, defects, project cost and schedule overruns	Development & financing, construction & commissioning
Reliability and performance	Limited field data for new turbine models; non-stationary failure behaviour	A, E	Elevated downtime, serial failures, availability losses	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 & financing through operation
Regulatory and standards	Evolving certification and grid compliance requirements	R, E	Redesign, additional testing, permitting or curtailment risk	Construction & commissioning through end-of-life

4.6.2 Impact assessment

Traditional quantitative risk models rely on historical failure statistics from mature fleets and are not readily transferable to novel turbine designs operating outside established envelopes (Dao et al. (2019)). Because upscaling-related risks are epistemic, path-dependent, and coupled across the domains discussed above (Dao et al. (2020)), a fully quantitative impact assessment is currently not feasible without speculative assumptions. This risk category is therefore best addressed through structured qualitative analysis and scenario-based reasoning (Scheu et al. (2019); Lopez and Kolios (2022)). Closing the gap between technology upscaling and its propagation to economic risk is identified as a research priority.

5 Discussion

5.1 Combined-risk experiment

The impact assessments in Sections 4.1 through 4.5 each activate one risk category while holding all others at baseline values. To test whether individually moderate risks compound into jointly severe outcomes, we simultaneously activate moderate-level scenarios from four categories: supply-chain uncertainty (SC2), transmission-constraint curtailment (C2), epistemic reliability uncertainty (R2), and O&M process uncertainty (P2). The scenario parameters are identical to those used in the isolated assessments. Critically, in the isolated experiments, reliability (R2) and O&M process (P2) uncertainties were activated with mutually exclusive flags on the same OPEX module. In the Combined scenario, both are simultaneously active, so that epistemic failure-rate uncertainty compounds with stochastic repair and waiting times.

Figure 15 shows the results of the combined experiment. At the level of expected values, losses are roughly additive: the combined mean NPV loss ($\Delta = -381\,\mathrm{M€}$) is close to the sum of individual deltas ($-356\,\mathrm{M€}$), with an interaction term of only $-25\,\mathrm{M€}$ ($\sim 7\,\%$). However, tail risk is *super-additive*: the combined P10–P90 band (867 M€) exceeds the quadrature-sum expectation under independence (696 M€) by 170 M€, or $\sim 24\,\%$. The probability of negative NPV is nearly a property of combination: individually, only SC2 produces non-negligible $P(\mathrm{NPV} < 0)$ (2.3 %); the Combined scenario yields 7.0 %. The likely driver of super-additivity is the intra-module coupling between reliability and O&M process uncertainty: higher-than-expected failure frequency (R2) compounds with longer-than-expected repair campaigns (P2), amplifying downside outcomes beyond what either risk produces alone.

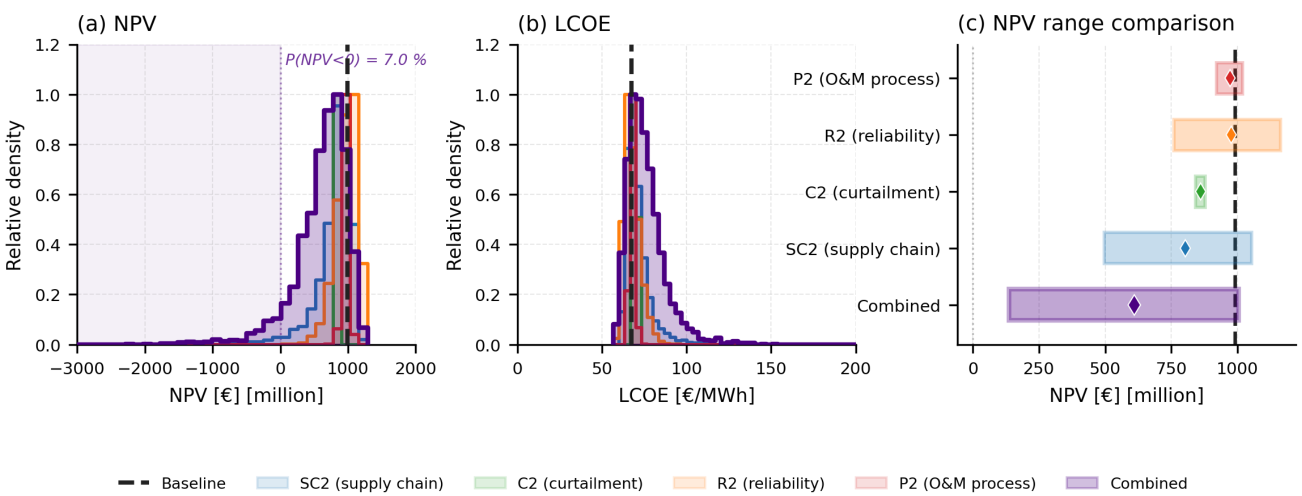

Figure 15. Combined adverse-alignment experiment. (a) NPV distributions for individual moderate-risk scenarios and the Combined scenario, with the deterministic baseline marked. (b) Corresponding LCOE distributions. (c) P10–P90 range bars comparing individual scenarios and the Combined scenario.

5.2 Cross-category synthesis

Table 15 brings together the individual and combined results. Under the scenario parameterizations adopted in this study, the six risk categories produce qualitatively distinct economic signatures. Supply-chain and curtailment risk primarily shift mean outcomes downward, while reliability and O&M process uncertainty predominantly widen outcome distributions and generate pronounced downside tails. Through-life decisions act as a value lever with large upside potential. These signatures are not intrinsic properties of the risk categories; they depend on the input assumptions and scenario design chosen for each assessment. Nevertheless, the distinction matters for management strategy. Mean-shifting risks are driven by systematic market factors that can be hedged or contracted against (e.g. locking commodity prices, securing grid access). Tail-widening risks, by contrast, are largely epistemic: the wide spread reflects insufficient knowledge of failure rates or repair times, and would narrow as better fleet data and monitoring reduce that uncertainty. These findings motivate the integration gaps and research priorities examined in section 6.

Table 15. Synthesis of risk categories examined in this study. The four quantified categories are shown with moderate-scenario results (3 000 replicates each; deterministic baseline NPV = 992 M€). The Combined row activates all four moderate scenarios simultaneously. The last row shows the sum of individual Δ NPV values for comparison.

Risk category	**Economic signature**	**Δ NPV [M€]**	**P10–P90 [M€]**	**P(NPV<0) [%]**	**Primary industry lever**
Supply chain & financing (§ 4.1)	Mean shift + wide tail	−189	558	2.3	De-risking instruments; lock material prices
Curtailment (§ 4.3)	Near-deterministic mean shift	−132	38	0.0	Grid reinforcement; storage; market design
Reliability (§ 4.4)	Long downside tail	−16	403	0.0	Failure data; design for reliability; insurance
O&M inefficiencies (§ 4.5)	Asymmetric tail	−20	100	0.0	Logistics standardization; condition-based maintenance (CBM); advanced access
Through-life (§ 4.2)	Value redistribution (upside)	*not included in combined experiment*			Inspection-informed LTE; refurbishment
Upscaling (§ 4.6)	Risk multiplier (qualitative)	*not quantified*			Prototype validation; phased deployment
Combined	**All four above**	**−381**	**867**	**7.0**	—
Sum of Δs	(independence)	−356	696[a]	—	—

[a] Quadrature sum of individual P10–P90 bands.

6 Toward integrated risk treatment

The combined-risk experiment in subsection 5.1 demonstrates empirically that individually moderate risks produce tail-coupled outcomes exceeding what isolated assessment predicts: mean losses are roughly additive, but the P10–P90 band widens by 24 % beyond the independence assumption, and the probability of negative NPV triples. This compounding behavior is a direct consequence of integration deficits in the assessment framework. A useful distinction can be drawn between two classes of such deficit: *interface gaps* between model components, and *injection gaps* between external drivers and the model chain.

Interface gaps arise at boundaries between coupled sub-models within the assessment framework, where both sides are internal to the model chain. Three principal interface gaps are identified:

1. **Loads → reliability.** Structural loading models and reliability models are developed and calibrated independently. The translation from site-specific, operation-dependent loading to component-level failure rates is not formalized, so that the effect of design choices, operating strategies, or environmental conditions on failure behavior cannot be assessed within the model chain.

2. **Reliability → O&M.** O&M simulation relies on stationary failure-rate assumptions and predefined maintenance rules. Load-dependent and condition-dependent failure behavior from structural or monitoring models is not fed back into maintenance scheduling, preventing realistic assessment of how site conditions and operational strategies influence maintenance outcomes.

3. **O&M → revenue.** Operational decisions (maintenance campaigns, access strategies) affect production timing and volume, but revenue models treat production loss as a simple annual deduction rather than resolving the interaction with time-varying electricity prices and market conditions.

Injection gaps arise where external drivers originating outside the project boundary need to enter the model chain but lack formalized interfaces. Five principal injection gaps are identified:

1. **Wind resource and wake evolution.** Long-term changes in wind climate and evolving wake interactions due to increasing wind farm density are not systematically propagated into energy yield and revenue projections.

2. **Commodity and supply-chain conditions.** Geopolitical developments, commodity price dynamics, and industrial policy changes affect both CAPEX (material costs) and financing terms (cost of capital), but typically enter models as static assumptions rather than as scenario-dependent parameter distributions linked to the cost and financing modules.

3. **Grid and curtailment regime.** Transmission infrastructure trajectories, renewable deployment, and system flexibility investments jointly determine curtailment exposure but are not endogenously modeled within the assessment chain.

4. **Market design and policy regime.** Electricity market structures, support-scheme evolution, and compensation mechanisms affect project revenue risk but enter models as exogenous assumptions rather than uncertain parameters.

5. **Technology maturity and model transferability.** Reliability, O&M, and cost parameters are calibrated from mature-fleet operational data. For next-generation turbine platforms with limited field history, validated transfer functions from design parameters to operational failure behavior do not exist, so that all downstream model outputs inherit unquantified epistemic uncertainty.

Figure 16 illustrates these gaps schematically, mapping both interface gaps and injection gaps onto a generalized impact assessment model chain.

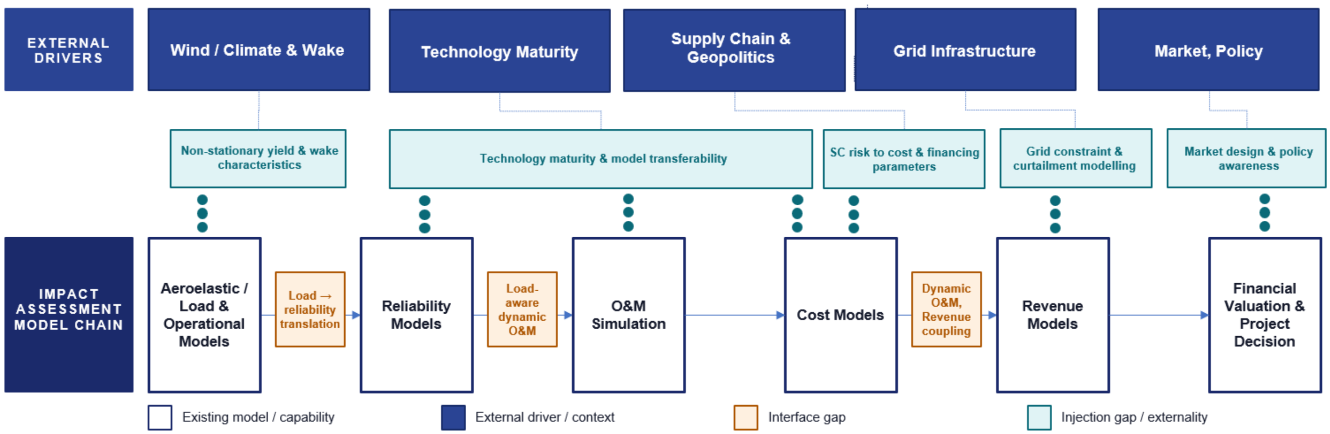

Figure 16. Integration gaps in the impact assessment model chain. Interface gaps arise at boundaries between coupled sub-models. Injection gaps arise where external drivers lack formalized interfaces to the model chain. Existing model capabilities are shown in dark blue.

Closing these gaps requires progress on several fronts. Reliability and O&M data with consistent component taxonomies, documented uncertainty bounds, and reproducible benchmarks remain a binding prerequisite; without them, even well-coupled models propagate poorly constrained inputs. Some of the integration deficits identified above demand new methods that do not yet exist: translating site-specific loading histories into failure-rate distributions requires physics-informed reliability models beyond fleet-average statistics, and coupling reliability with O&M requires condition-dependent maintenance formulations in which failure behavior evolves with operational state. Other deficits are primarily coupling tasks, connecting models that exist independently but are not yet linked: project-level techno-economic assessments need to be coupled with electricity system models to endogenize curtailment exposure and price formation, and with supply-chain and macroeconomic models to propagate commodity dynamics and financing conditions as scenario-dependent inputs.

7 Conclusion

This paper reviewed and quantified six major risk categories affecting wind energy projects across development and operational phases, combining expert elicitation, literature review, and scenario-based impact assessments using the WINPACT toolchain. The illustrative case studies show that different risk categories, under the scenario assumptions adopted here, produce qualitatively distinct economic signatures, from near-deterministic mean shifts (curtailment) to pronounced downside tails (reliability, O&M process uncertainty), and that these signatures call for different management responses: mean-shifting risks are addressable through hedging and contracting, while tail-widening risks require reducing the underlying epistemic uncertainty through better data and monitoring.

The combined-risk experiment demonstrates that individually moderate risks can compound into jointly severe outcomes: while mean NPV losses are roughly additive across categories, tail risk is super-additive, and the probability of negative NPV emerges as a property of combination rather than of any single risk in isolation. This finding underscores that siloed risk assessment, however detailed, systematically underestimates downside exposure.

The study does not claim to resolve these integration challenges. Rather, it maps the gap between current fragmented practice and the integrated treatment that project-level risk management requires. Eight specific integration deficits (three interface gaps between coupled sub-models and five injection gaps between external drivers and the model chain) are identified as priorities for future research. Progress will depend on shared data infrastructure with consistent taxonomies and documented uncertainty bounds, physics-informed methods to couple loads with reliability and O&M, and integration of project-level assessments with electricity system and supply-chain models.

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

Appendix A: Supplementary reliability data

Table A1. 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

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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