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Nielsen, Jannie Sønderkær; Sørensen, John Dalsgaard

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Risk-based derivation of target reliability levels for life extension of wind turbine structural components

Jannie S. Nielsen | John D. Sørensen

Department of the Built Environment, Aalborg University, Aalborg, Denmark

Correspondence
Jannie S. Nielsen, Department of the Built Environment, Aalborg University, Thomas Manns Vej 23, 9220 Aalborg, Denmark.
Email: jsn@build.aau.dk

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Abstract

The main wind turbine design standard IEC61400-1 ed. 4 includes an annual target reliability index for structural components of 3.3. Presently, no standards specify specific reliability requirements for existing wind turbines, to be used in relation to verification of structural integrity for life extension or continued operation. For existing structures in general, both economic and sustainability considerations support differentiation in reliability targets, as it is generally more expensive and requires more resources to improve the reliability. ISO2394 "General Principles on Reliability for Structures" includes tables with differentiated reliability targets depending on the consequences of failure and costs of improving reliability, which are derived using risk-based economic optimization. However, the assumptions behind these tables do not match the specific problem of life extension of wind turbines. In this paper, the risk-based approach is applied to derive specific target reliability levels for life extension of wind turbines, and a target annual reliability index around 3.1 is proposed.

KEYWORDS

fatigue, life extension, reliability analysis, risk-based decision making, target reliability, wind turbines

1 | INTRODUCTION

To facilitate decarbonization, the share of wind energy needs to increase continuously. Along with new sites being commissioned, there is a large existing fleet of wind turbines gradually reaching the end of their intended life. When wind turbines reach the end of the planned life, there are four options:

- Life extension without major component exchanges or repairs (also simply referred to as continued operation).
- Life extension with major component exchanges or repairs.
- Repowering: The wind turbines are taken down and new turbines are erected on the site.
- Decommissioning: The wind turbines are taken down and the site is decommissioned.

Several factors related to economy and local constraints affect the decision.[1] For some sites, repowering with new larger turbines is possible, which often contributes to increasing the capacity. In other cases, local constraints eliminate this possibility, and the options are to decommission the site or to continue operation with the existing turbines with or without component exchanges/refurbishments.[2] Also, if repowering is possible, it can be optimal to extend the life of existing turbines before going to repowering.[3]

When wind turbines are designed, they are expected to become obsolete after 20–25 years; thus, they are designed with a design fatigue life of 20–25 years. For components where fatigue is the design driver, this could mean that the end of the design fatigue life is reached, and the reliability of the structure is not proven sufficient any longer. Even if it can be shown to be sufficiently safe to operate for an extended lifetime, the profitability is not guaranteed and requires analysis.[4] Often, there is no debt in the wind farms unless the wind farm has been bought recently from another owner. But because there are generally no subsidies for life extension and continued operation, the electricity must be sold on the spot market, giving less income. The expenses relating to land rental and maintenance could be unchanged or even increasing, and with less revenue, the profit margins can be narrow. Rubert et al[5] developed a tool to assist with economic assessment and showed how the profitability would depend on the extent of required refurbishments. It was assumed that the updated fatigue calculations would show life extension to be sufficiently safe. Nielsen et al[6] presented a method for optimal decision making for life extension for wind turbines, by including the probability that the updated fatigue calculations would not find sufficient remaining fatigue life.

In some countries, specific rules are made to ensure that further operation will not lead to an unacceptable risk of failure. The rules in this relation differ between countries. In Denmark and Germany, there are specific regulations, whereas in many other countries, continued operation is allowed without any extra efforts. In both Denmark and Germany, a life extension inspection is necessary to assess the condition of turbines at the end of the planned life, and further efforts are needed to verify sufficient fatigue life. In Denmark, this is done indirectly through annual inspections of all load-transferring components. In Germany, sufficient fatigue life must be verified using updated fatigue calculations. Although not required in other countries, owners of large assets such as offshore wind farms need updated fatigue calculations for negotiations with insurance companies and banks. For smaller wind turbines, extra expenses to update fatigue calculations or additional inspections in the extended life could be the tipping factor making life extension infeasible.[7]

The DNVGL standards on lifetime extension[8,9] and the Dutch standard[10] NPR 8400 present various approaches for analytical assessment and allow for the utilization of site-specific measurements, monitoring, and SCADA data. They include both deterministic and probabilistic assessment methods but do not present details on how. The UL4143 standard[11] on life extension also presents an approach for semiquantitative risk assessment but also does not present details on how to utilize data for remaining fatigue life assessment. Therefore, the development of efficient and accurate methods for prediction of the remaining fatigue life is a research topic with large industry interest.

Most approaches are based on a semiprobabilistic (deterministic) assessment of the fatigue limit state, considering that the actual site conditions and operational history are different from the assumptions made in the design. For modern wind turbines, SCADA data are collected during the lifetime and can be utilized in the lifetime assessment. To this end, Ziegler and Muskulus[12] investigated which parameters mostly affect the fatigue life and argued that no general conclusions can be made. For example, for some turbines, less availability means lower loads, but for wave-dominated loading on large monopiles, the opposite might be the case, particularly where accumulated fatigue damage is dominated by non-operational periods, during which load cycles do not benefit from aerodynamic damping of the structure from the rotor. Kazemi Amiri et al[13] quantified the additional lifetime due to the wind not being unidirectional by considering the actual wind rose for the site. Dimitrov and Natarajan[14] used SCADA data for lifetime assessment and performance optimization and used machine learning to handle data limitations. Bouty et al[15] argue that it might not be economical to assess fatigue life for each turbine in a wind farm and propose an extrapolation method, when the conditions for several wind turbines are similar. Ziegler and Muskulus[16] compared a fracture mechanics model to the SN curve approach for jacket-supported offshore wind turbines and outlined the challenges and opportunities in the fracture mechanics approach. All of these approaches rely on data that are generally available and use better assessments of the wind conditions and the time in each operational state, compared to the assessments used in the design for new wind turbines.

Several studies also suggest using strain measurements in addition to the SCADA data. For example, Ziegler et al[17] developed a strain-based load extrapolation algorithm for lifetime extension of offshore wind monopiles using a deterministic approach. Mai et al[18] use a probabilistic approach and predict the remaining fatigue life of welded joints in wind turbine support structures by using strain measurement and oceanographic data. They use a Bayesian approach for updating the distribution for the oceanographic data and use the strain data to establish the relation between oceanographic parameters and stresses in critical locations. The use of strain measurements means that some of the uncertainty related to the assessment of stresses is reduced, but as these data are not available as standard, a measurement campaign is needed to obtain the data.

As a supplement to the analytical assessment, other researchers propose ways to physically increase the lifetime by changing the wind turbine control system logic. Zhang et al[19] find the optimal power dispatch in a wind farm with life extension of the wind turbine blades as the target. Pettas and Cheng[20] propose down-regulation and individual blade control as lifetime extension enablers, and Natarajan and Pedersen[21] propose curtailment in conditions with high loads to increase the lifetime. The result of these approaches is that less fatigue damage is accumulated during the original lifetime, but the energy production during the original lifetime is also slightly reduced.

All of the approaches implicitly assume that the structural components of wind turbines shall fulfill the same reliability requirements during the extended life, as during the original lifetime. Using the same requirement for existing structures does not necessarily lead to decisions that are optimal from a societal point of view when considering the economy, sustainability, and societal impacts. In standards for existing structures, it is often accepted to use lower target reliabilities than for new structures, because the costs of increasing the reliability are higher for existing structures, and it would lead to uneconomic and unsustainable decisions if the same reliability level was required.[22–24] The Dutch standard[10] NPR

8400 and the DNV GL standard[8] on lifetime extension and continued operation for wind turbines both mention the selection of target reliability level as the first step in the reliability analysis but give no guidance on the selection of target reliabilities.

The target reliability level used for calibration of material partial safety factors for structural components in new wind turbines[25] in IEC61400-1 ed. 4 was selected based on economic optimization, considering the relative consequence of failure and the relative cost of safety measures (i.e., how costly it is to increase the reliability).[26] A component annual probability of failure of $P_F = 5 \cdot 10^{-4}$ was selected, corresponding to a reliability index β = 3.3. (Within structural reliability, the annual reliability level β is related to the annual probability of failure P_F as $\beta = -\Phi^{-1}(P_F)$, where Φ is the standard normal distribution function).

Based on the same economic optimization model, the target reliability level for life extension could be determined using a different economic cost profile with increased relative costs for safety measures, which would imply that a lower reliability level could be accepted. However, the economic optimization model developed for new structures does not well represent the case for existing structures. Alternative economic optimization models can be set up for existing structures, as done by Steenbergen et al[27] who found reduced lifetime reliability targets for existing buildings and infrastructures by considering the costs in the remaining lifetime for upgrading or not upgrading, considering the remaining service life to be fixed. For the specific application of life extension decision making for wind turbines, a tailored economic optimization model can be established, providing a more rational basis for decision support.

The present study aims to investigate whether a reduction of the target reliability level can be justified for existing wind turbines when a tailored economic model is formulated and applied. This is done using a risk-based approach where economic optimization is performed and the consequences associated with the risk of structural failure are included directly. A reduced target reliability level can be used directly as a target when a probabilistic fatigue life assessment is made, and it can be used for calibration of reduced partial safety factors for semiprobabilistic assessment of existing wind turbines. In both cases, the result will be that the fatigue life is extended, even if the environmental conditions are equal to those assumed in the design; thus, they do not need to be more benign. Consequently, if reduced target reliability can be justified, most structural components of wind turbines will have sufficient estimated fatigue life for an extended lifetime, and it would not be necessary to use costly advanced methods in addition to a lifetime extension inspection to verify the fatigue life. However, a reduced target reliability level can also be used in combination with detailed approaches, where additional data are used to improve the estimates of loads and resistances.

Section 2 outlines the background for selection of reliability level based on economic optimization, and the optimization model used for selection of target reliability for new structures is briefly outlined. In Section 3, a novel economic optimization model is presented for life extension decision making for wind turbines, and a cost model is set up for a generic life extension project. In Section 4, results are presented for how the increased risk of structural failure can affect the economic feasibility, and feasible target reliability indices for the generic life extension project are found and discussed. In Section 5, conclusions and recommendations for standardization are given. Appendix A outlines the probabilistic model used for calibration of partial safety factors for IEC 61400-1 ed. 4, which is used for generating the results in Section 4.

2 | BACKGROUND FOR RELIABILITY REQUIREMENTS

Structural components of wind turbines are typically designed using the semiprobabilistic (deterministic) method used in the design standard IEC61400-1.[25] The semiprobabilistic method is the simplest of the methods of analysis outlined in the general standard for reliability of structures ISO2394,[28] where the more thorough methods of decision making are the probabilistic approach and the risk-informed approach. In the

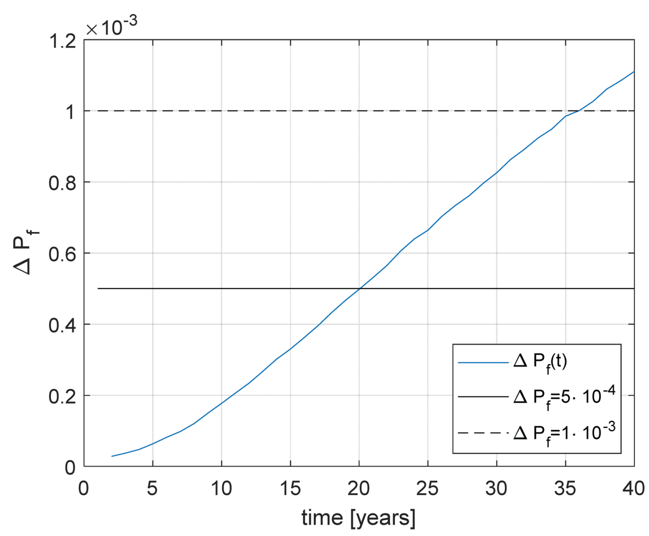

FIGURE 1 Annual probability of failure as function of time for a component designed to have a probability of failure equal to the limit

probabilistic approach, probabilistic models of loads and resistances are used to estimate the reliability using structural reliability methods, and this is compared to the target reliability. In the design situation, the optimal value of a design parameter z is found such that the annual probability of failure at the end of the design life reach the target value for new components $P_F = 5 \cdot 10^{-4}$ ($\beta = 3.3$). The annual probability of failure is shown in Figure 1 for a component designed for a lifetime of 20 years based on the probabilistic model used for calibration of partial safety factors for IEC61400-1.[25] Details of the model are given in Appendix A.

It is noted that the probability of failure increases almost linearly and will reach a value twice as high as the target value for new turbines after 35 years. Therefore, decreasing the target reliability for life extension to $P_F = 10^{-3}$ ($\beta = 3.1$) could allow for approximately 15 additional years of operation without further efforts to verify fatigue life.

In this section, the risk-based background for the selection of target reliability[25] in IEC61400-1 is outlined, to serve as background for the reader. The model is a general model for new structures, and the expressions are not derived specifically for wind turbines. This section is included to ease the understanding of the novel model presented in Section 3 and to highlight that the proposed method for life extension decision making is in line with the approaches currently used[25] in IEC61400-1 but with assumptions that more closely reflect the specific application. A more specific decision model could also be derived for new wind turbine structures, but this is beyond the scope of the present paper.

2.1 | Target reliability requirements for new structures

The general standard for reliability of structures[28] ISO2394 recommends that target reliability levels are set using the risk-informed approach, where economic optimization is performed by considering the utilities associated with all consequences, costs, and benefits directly and combining them with their probability of occurrence. The optimal decision is chosen as the one with the highest expected utility/profit. In case there is a risk of fatalities in case of structural failure, minimum acceptable reliabilities can be found using the marginal lifesaving cost principle. As wind turbines are generally erected in remote locations, the risk to human lives is neglected in IEC61400-1.[25,26] The approach for economic optimization for new structures was considered by Rackwitz,[29] and in Table 1, the derived target reliabilities are given.[30] The approach implies that the reliability is balanced against the consequences of failure and the relative cost of safety measures (costs of improving safety). The background for the table was elaborated by Fischer et al.[31]

Rules in standards influence decisions for a fleet of structures in an infinite time horizon or until the rules are updated due to new knowledge. When optimizing the target reliability in relation to standardization, it is assumed that a need for structures persists, whereas a specific structure will be demolished in case of failure, or if the structure does not meet the specific demands any longer, that is, it becomes obsolete. The rate of failures depends on the reliability of the structure, whereas the rate of obsolescence does not (it could depend on the flexibility, durability, and maintainability). In the model behind Table 1, failure events and obsolescence events are assumed to occur randomly in time with rates P_F and ω (following Poisson processes), and immediate systematic reconstruction after failure and obsolescence is assumed. Only costs to construction, obsolescence, and failure are included, as the other costs are assumed independent of the decision variables $\boldsymbol{p}$ which determine the reliability level. For new structures, the decision variables could be variables related to the geometry of the structure, cross-sectional parameters, material strengths, and for existing structures they could be related to various options for strengthening the structure. For repairable and exchangeable components, the operations and maintenance (O&M) costs would depend on the reliability, but for structural components as considered in the generic model described here, the O&M costs are assumed independent of the decision variables.

In the general model for new structures with systematic reconstruction after failure and obsolescence, the optimal values of the decision variables $\boldsymbol{p}$ are found by maximizing the present value of the benefit minus the costs for an infinite time horizon:

$$\boldsymbol{p}^* = \arg\max_{\boldsymbol{p}} \{Z(\boldsymbol{p})\}, \tag{1}$$

$$Z(\boldsymbol{p}) = B(\boldsymbol{p}) - C(\boldsymbol{p}) - A(\boldsymbol{p}) - D(\boldsymbol{p}), \tag{2}$$

TABLE 1 Optimal annual target reliabilities, β, and annual failure probabilities, P_F, in previous studies[28,30,31] found using economic optimization

	Consequence of failure		
Relative cost of safety measure	**Minor**	**Moderate**	**Large**
Large (A)	$\beta = 3.1$ ($P_F \approx 10^{-3}$)	$\beta = 3.3$ ($P_F \approx 5 \cdot 10^{-4}$)	$\beta = 3.7$ ($P_F \approx 10^{-4}$)
Normal (B)	$\beta = 3.7$ ($P_F \approx 10^{-4}$)	$\beta = 4.2$ ($P_F \approx 10^{-5}$)	$\beta = 4.4$ ($P_F \approx 5 \cdot 10^{-6}$)
Small (C)	$\beta = 4.2$ ($P_F \approx 10^{-5}$)	$\beta = 4.4$ ($P_F \approx 5 \cdot 10^{-6}$)	$\beta = 4.7$ ($P_F \approx 10^{-6}$)

where expected present values are used for

- $B(\boldsymbol{p})$: benefit from the existence of structure,
- $C(\boldsymbol{p})$: construction cost,
- $A(\boldsymbol{p})$: obsolescence cost, and
- $D(\boldsymbol{p})$: failure cost.

The benefits from the existence of the structure are assumed independent of $\boldsymbol{p}$; thus, $B(\boldsymbol{p}) = B$. For wind turbines, this assumption implies that the production of energy is not affected by the reliability level of the structural components, and this is a direct result of the assumption of systematic immediate reconstruction after failure. With this assumption, the benefit needs not to be considered in the analysis, and instead, the minimum of the expected present value of the costs $T(\boldsymbol{p})$ is found; thus, the objective function becomes

$$T(\boldsymbol{p}) = C(\boldsymbol{p}) + A(\boldsymbol{p}) + D(\boldsymbol{p}). \quad (3)$$

Costs occurring in the future should be discounted. Continuous discounting is performed by multiplication by $\exp(-\gamma t)$, where γ is the interest rate.[29] The cost of first construction $C(\boldsymbol{p})$ occurs at time zero and should not be discounted. The expected present value of the obsolescence costs $A(\boldsymbol{p})$ is calculated from additional reconstructions occurring with constant obsolescence rate ω:

$$A(\boldsymbol{p}) = \int_0^\infty \exp(-\gamma t) \cdot \omega \cdot C(\boldsymbol{p}) dt = C(\boldsymbol{p}) \frac{\omega}{\gamma}. \quad (4)$$

The expected present value of the failure costs $D(\boldsymbol{p})$ is found by assuming that the annual probability of failure $P_F(\boldsymbol{p})$ is constant with respect to time and by accounting for additional failure costs H in addition to the reconstruction costs:

$$D(\boldsymbol{p}) = \int_0^\infty \exp(-\gamma t) \cdot P_F(\boldsymbol{p}) \cdot (C(\boldsymbol{p}) + H) dt = (C(\boldsymbol{p}) + H) \frac{P_F(\boldsymbol{p})}{\gamma}. \quad (5)$$

For fatigue, the annual probability of failure typically increases with time, but the constant annual probability of failure is used as an approximation in the general model.[29]

A single decision parameter p is defined to influence the resistance of the structure, and the annual probability of failure is found from $P_F(p) = P[R(p) - S < 0]$, where $R(p)$ is the resistance of the structure, and S is the load effect. For a given costs model, where the cost of the structure depends on the decision parameter, the optimal reliabilities can be derived by identifying the reliability corresponding to the optimal decision parameter, as illustrated in Figure 2. For very low reliability levels, the expected failure costs are large, and for very high reliability levels, the

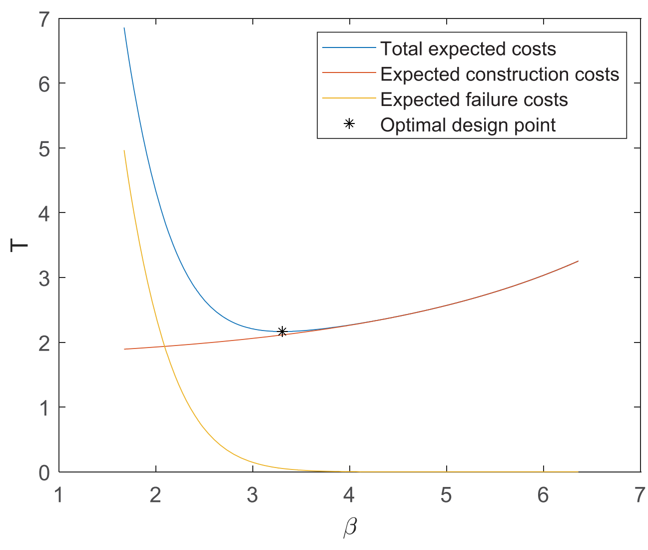

FIGURE 2 Illustration of the optimization of annual reliability index β to minimize the present value of total expected costs T

expected construction costs are high. The expected present value of the costs $T(p)$ also depends on the obsolescence rate ω, interest rate γ, and distribution types and coefficient of variation for resistance and load effect. As shown in Fischer et al,[31] Table 1 can be obtained using $\omega = 0.02$, $\gamma = 0.03$, and lognormal distributions for R and S with coefficients of variations equal to 0.3.

Based on Table 1, it can be argued that a lower reliability index is sufficient for existing structures, as the relative costs of improving safety are larger. However, for decision making for life extension for wind turbines, many of the conditions are different compared with the standard assumptions given here, and in Section 3, the optimization problem is set up for this specific problem.

3 | OPTIMAL DECISION MAKING FOR LIFE EXTENSION OF WIND TURBINES

For end-of-life decisions for sites, where repowering is not a viable option, the options are life extension (with or without component exchanges) or decommissioning. If the reliability of the major structural components is found to be lower than accepted, the only apparent option would be to decommission, if the costs of improving the reliability are too high. An alternative would be to accept the actual, low reliability of the structural components. If the expected profit is still found sufficient, when the risks related to a structural failure are included in the assessment, this could be the optimal solution.

3.1 | Economic optimization model

This section presents a novel optimization model for life extension, based on the same principles as the general model in Section 2.1 but tailored to the specific application. The model is set up for a finite life corresponding to the extended life, and therefore, obsolescence costs due to future reconstructions are not included here. Also, in case of failure of a single wind turbine in a wind farm, the owner will normally not erect a new wind turbine on the site. The benefits would depend on the end-of-life decision and need to be included in the economic assessment. The objective function is therefore the expected present value of the profit $Z(\boldsymbol{p})$, that is, the expected present value of the benefits minus the costs:

$$Z(\boldsymbol{p}) = B(\boldsymbol{p}) - C_{ext}(\boldsymbol{p}) - OM(\boldsymbol{p}) - D(\boldsymbol{p}), \tag{6}$$

with the following expected present values of

- $B(\boldsymbol{p})$: benefit (income from power production),
- $C_{ext}(\boldsymbol{p})$: life extension cost,
- $OM(\boldsymbol{p})$: costs of O&M including structural health monitoring (SHM) and inspections, and
- $D(\boldsymbol{p})$: cost of structural failure.

In a traditional feasibility assessment for life extension, the feasibility will typically be assessed considering only the first three terms, thus disregarding the risk of complete structural failure, although an insurance covering the loss could be included in the operational costs.[5] To limit the risk of structural failure, the structural integrity is typically verified using the same deterministic approach as used for the original site assessment but accounting for additional information obtained during the operating life. In a probabilistic approach, a target for the annual probability of failure is used.[8] In the following, we aim to find the optimal target, by including directly the costs related to a structural failure in the feasibility assessment. In case of a structural failure, the business case can be challenged by three contributions: the direct consequences of failure, the loss of benefit from power production after failure, and due to fixed operational costs that have to be paid also after failure in the remaining planned extended life.

The vector of decision variables $\boldsymbol{p}$ could include parameters for decisions on refurbishments, decisions on maintenance and control, and the length of the extended life. In practice, one of the decision options might encompass a spectrum of modifications to the wind turbine closed-loop and supervisory control functions to prolong the life of a damaged structural component, including wind direction sector management, curtailment, reduced electrical power, and explicit conditions for shutting the turbine down to reduce loading (at the expense of reduced revenue). Here, the focus is on the reliability of structural components. As the reliability decreases with time, the length of the life extension period T_{ext} is included as a decision variable. Additionally, the reliability depends on the fatigue loads and the initial design. The level of fatigue loading depends on the design variable z (see Appendix A for details), and the level of loading in the fatigue calculations can be scaled by adjusting the variable z. Here, z should not be interpreted as a decision variable; it is used to account for the original design and the actual fatigue loading on the site.

The life extension costs C_{ext} are the costs of analyses and refurbishments necessary for life extension to be performed at the end of the original lifetime T_{org}. The costs of life extension could depend on the planned life extension period. As the life extension costs occur at the time where life extension starts, this term is simply $C_{ext}(T_{ext})$. The other costs are distributed in the extended life and should be discounted with discount rate γ. As only costs occurring after the end of the original lifetime T_{org} are to be included, a shifted time scale is defined as $t' = t - T_{org}$, where the time life extension starts is denoted time zero on the time scale t'.

The annual benefits are denoted $c_B(t')$. In case of failure, the benefit will discontinue, and the expected present value of the benefits is calculated as

$$B(T_{ext};z) = \int_0^{T_{ext}} \int_0^{t'} \exp(-\gamma\tau')\, c_B(\tau')\, d\tau' f_{T'}(t';z)\, dt' + \int_0^{T_{ext}} \exp(-\gamma t')\, c_B(t')\, dt' (1 - F_{T'}(T_{ext};z)). \tag{7}$$

The first term in Equation 7 calculates the expected benefits in case failure happens in the extended life, and the second term calculates the expected benefits in case there is no structural failure in the extended life. Continuous discounting is performed using $\exp(-\gamma t')$, and τ' is used as an integration variable as a substitute for time t'. The probability of failure enters through the probability density function of the time to failure $f_{T'}(t';z)$ and the associated cumulative distribution function for the time to failure $F_{T'}(t';z)$, both conditioned on survival up until the end of the original lifetime. The distributions depend on the design parameter z and are evaluated using Equations 8 and 9 based on the models presented in Appendix A for $t' > 0$ (which imply that $t > T_{org}$ as $t' = t - T_{org}$):

$$F_{T'}(t'z) = F_T(t|g(z,T_{org}) > 0) = \frac{F_T(t;z)}{1 - F_T(T_{org};z)}, \tag{8}$$

$$f_{T'}(t';z) = f_T(t|g(z,T_{org}) > 0) = \frac{f_T(t;z)}{1 - F_T(T_{org};z)}. \tag{9}$$

For the O&M costs that will discontinue in case of failure, the expected present value is found similarly, with annual O&M costs $c_{OM1}(t')$:

$$\begin{aligned} OM_1(T_{ext};z) = {} & \int_0^{T_{ext}} \int_0^{t'} \exp(-\gamma\tau')\, c_{OM1}(\tau')\, d\tau' f_{T'}(t';z)\, dt' + \\ & \int_0^{T_{ext}} \exp(-\gamma t')\, c_{OM1}(t')\, dt' (1 - F_{T'}(T_{ext};z)). \end{aligned} \tag{10}$$

For O&M costs $c_{OM2}(t')$ that will continue for the duration of the planned extended life also in case of failure, the expected present value is found as

$$OM_2(T_{ext}) = \int_0^{T_{ext}} \exp(-\gamma t')\, c_{OM2}(t')\, dt'. \tag{11}$$

The expected present value of the failure costs is

$$D(T_{ext};z) = \int_0^{T_{ext}} \exp(-\gamma t') H(t')\, f_{T'}(t';z)\, dt', \tag{12}$$

where the monetary value of the failure consequences are $H(t')$. These should include all consequences in relation to a structural failure, both economic losses and other consequences for the owner. As this term may include consequences that are not directly associated with a monetary value, a translation to monetary value needs to be made using a utility function, a function that translates any nonmonetary value into monetary value based on the preferences of the decision maker.[32] In the following, we will denote the expected present value of the profit as the expected present value of the utility, as nonmonetary values could be included.

The expected present value of the utility is a function of the life extension period and the design parameter and can therefore be written as

$$Z(T_{ext};z) = B(T_{ext};z) - C_{ext}(T_{ext}) - OM_1(T_{ext};z) - OM_2(T_{ext}) - D(T_{ext};z). \tag{13}$$

It depends on the costs, the interest rate γ, and the probability distribution for the time to failure. Life extension is feasible if Z is positive.

3.2 | Cost model for a generic life extension project

In this section, a cost model is formulated for a generic life extension project. For a specific case, the benefits and costs to be included in the model presented in Section 3.1 are

- $c_B(t')$: expected annual benefit depends on expected power production and expected selling price of electricity;
- $C_{ext}(T_{ext})$: costs of life extension (life extension CAPEX), for example, costs of analyses, inspection, and component exchanges;
- $c_{OM1}(t')$: annual OPEX in extended life that will discontinue in case of failure, for example, direct variable maintenance costs relating to spare parts;
- $c_{OM2}(t')$: annual OPEX in extended life that will continue in case of failure, for example, land lease and other fixed expenses; and
- $H(t')$: consequence of failure in monetary value.

For decision making, the ratio between costs is important, not the absolute value of the costs. For generic modeling, the costs are assumed constant with time, and the number of input parameters can therefore be reduced. First, the annual profit P_a (considering annual costs and benefits but excluding life extension costs) is defined as a scaling parameter by $P_a = c_B - c_{OM1} - c_{OM2}$, and all costs are defined relative to P_a. The annual profit then appears as a scaling factor, and the expected present value of the utility $Z(T_{ext}; z)$ (Equation 13) will scale with this factor. We will require that P_a is always positive, as life extension cannot be feasible if it is negative. The values of T_{ext} resulting in maxima and zero crossings for the expected present value of the utility are invariant with respect to P_a, and therefore, optimal values and ranges of feasible values can be determined without defining P_a.

The costs to be defined are then the costs of life extension C_{ext}, the operational costs that will continue in case of failure c_{OM2}, and the consequence of failure H. (The individual values of c_B and c_{OM1} are not important; only the difference between them is of importance, which is fully defined when P_a and c_{OM2} are defined.) The proportion of operational costs that are fixed $c_{OM2,rel}$ and the consequence of failure H_{rel} are defined directly as a proportion of the annual profit:

$$c_{OM2,rel} = \frac{c_{OM2}}{P_a}, \tag{14}$$

$$H_{rel} = \frac{H}{P_a}. \tag{15}$$

The costs of life extension could be defined similarly. However, as the annual profit is distributed in time, whereas the cost of life extension is not, the annual profit should be discounted for a meaningful comparison, and thus, the life extension period and discount rate should also be accounted for when defining C_{ext}. Most important is the profit margin or the expected internal rate of return (IRR). The IRR is defined as the discount rate which causes the net present value of all costs and benefits to be equal to 0, that is, $Z = 0$. Although profit margins for life extension projects are often narrow, the opposite could also be the case. For life extension projects with only minor investments, the IRR could in principle be very high—much higher than the interest rate.

The initial IRR when failures are not considered is denoted γ_0, and the cost of life extension is calculated based on this value from:

$$C_{ext}(T_{ext}) = \int_0^{T_{ext}} P_a \exp(-\gamma_0 t')\, dt'. \tag{16}$$

Figure 3A shows γ_0 as function of the relative life extension costs C_{ext}/P_a for various life extension periods. For a rate of return equal to 0, the life extension costs correspond to the sum of the annual profits, which is the length of the life extension period times the annual profit P_a. Positive rates of return are obtained when the costs of life extension are less than the sum of the annual profits. Generally, a rational investor will not make investments if the IRR is lower than the interest rate.

Figure 3B shows γ_0 as function of the relative life extension costs per year of life extension $C_{ext}(p)/(P_a \cdot T_{ext})$. When the relative life extension costs per year are equal to 1, the IRR is equal to 0 for all life extension periods. For different life extension periods, the same change in relative life extension costs per year will give the highest change in the IRR for smaller life extension periods, as the rate has a higher effect when benefits

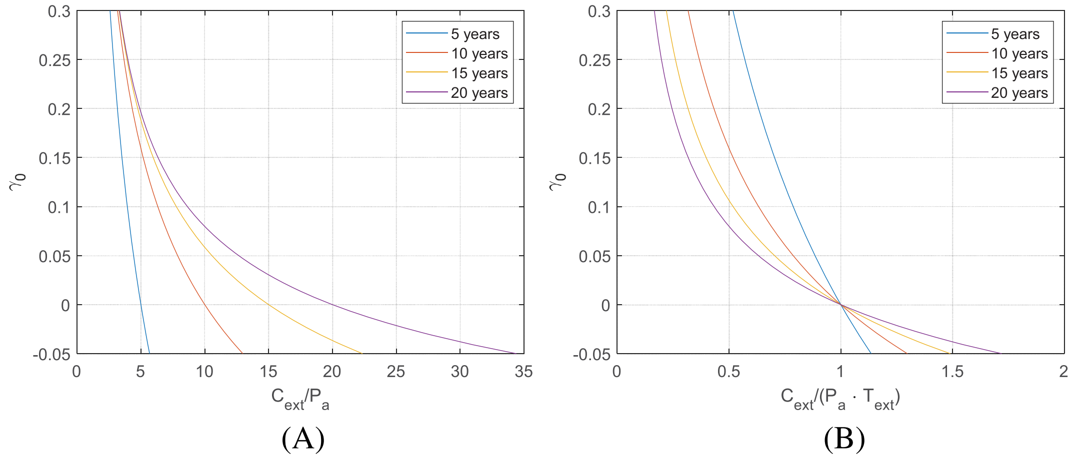

FIGURE 3 Initial internal rate of return (when not considering failures) as a function of relative costs of life extension (A, total and B, per year) for life extension periods T_{ext} = 5, 10, 15, and 20 years

and costs are distributed over a longer period. Thus, a unit change in rate gives a higher change in cost for a longer life extension period. This relation should be kept in mind when analyzing the results.

Defining the life extension costs C_{ext} through γ_0 (the initial IRR when failures are not considered) is useful as the reduction of IRR due to the risk of failure can then be estimated without defining the interest rate as an additional input parameter. Instead, the interest rate will appear as an acceptance criterion; the minimum acceptable IRR, when a reduction of utility due to the probability of failures is considered. As acceptance criterion, an interest rate γ equal to 3% is used as also used by Fischer et al.[31]

With these definitions, the only cost model input parameters to be defined are γ_0, $c_{OM2,rel}$, and H_{rel}, and the reduction to these values has been made without loss of generality if the annual costs and benefits are constant with time. The base case values are set to γ_0 = 0.05, $c_{OM2,rel}$ = 1, and H_{rel} = 10. The values for γ_0 and $c_{OM2,rel}$ are selected with a view to Rubert et al.[5] From their data, a value of the relative fixed operational costs $c_{OM2,rel}$ of around 1 can be derived for their base case and around 2 for their most pessimistic case. Rubert et al[5] showed that the feasibility of life extension heavily depends on the extent of refurbishments necessary. The IRR was above 10% in the optimistic cases with low refurbishment costs, and the IRR could be much lower in the more pessimistic cases with large costs. Therefore, γ_0 = 0.05 is selected to represent a life extension project with a relatively low margin. The direct costs of failure should also include the additional costs of decommissioning a single failed turbine compared to the normal case of decommissioning of a single turbine as part of a complete wind farm. The reason for using a high value is that the unit costs of decommissioning one turbine will be larger, when only one turbine is decommissioned. Also, there could be difficulties in dismantling components, when it is not safe to access the turbine. As the costs will vary between projects, each cost parameter is varied one at a time, while the others are fixed.

3.3 | Calculation procedure

The main aim of this paper is to derive target reliabilities for life extension. In this section, a calculation procedure is set up, with that objective. The procedure combines the economic optimization model presented in Section 3.1, the generic cost model presented in Section 3.2, and the probabilistic fatigue model outlined in Appendix A.

The approach is to generate values of the expected present value of the utility Z as a function of ranges of values of life extension periods $\boldsymbol{T_{ext}}$, design parameters $\boldsymbol{z}$ (used to scale fatigue loads), and discount rates $\boldsymbol{\gamma}$, for various combinations of cost parameters. The procedure for generating $Z(\boldsymbol{T_{ext}}; \boldsymbol{z}, \boldsymbol{\gamma}, \gamma_0, c_{OM2,rel}, H_{rel})$ is as follows:

- For a range of values of the design parameter $\boldsymbol{z}$, the probability density function $f_{T'}(t'; \boldsymbol{z})$ and cumulative distribution function $F_{T'}(t'; \boldsymbol{z})$ for the time to failure given survival in the original design life (20 years) are found using Equations 8 and 9, and tables of the annual reliability index are found after 20 years of operation ($\beta_{20}(\boldsymbol{z})$) and in the last year of the extended life ($\beta_{ext}(\boldsymbol{z}, \boldsymbol{T_{ext}})$).
- The expected present value of the utility, $Z(\boldsymbol{T_{ext}}; \boldsymbol{z}, \boldsymbol{\gamma}, \gamma_0, c_{OM2,rel}, H_{rel})$, is calculated by numerical integration using Equation 13 for all combinations of input values.

Results are extracted from the generated tables $Z(\boldsymbol{T_{ext}}; \boldsymbol{z}, \boldsymbol{\gamma}, \gamma_0, c_{OM2,rel}, H_{rel})$, $\beta_{20}(\boldsymbol{z})$, and $\beta_{ext}(\boldsymbol{z}, \boldsymbol{T_{ext}})$ as follows:

- First, the relation between the annual reliability index in the last year of the extended life $\beta_{ext}(\mathbf{z}, \mathbf{T_{ext}})$ and the expected present value of the utility and IRR is investigated for the base case values of the costs. (Results are presented in Section 4.1.)
  - The expected present value of the utility is found for a discount rate equal to the interest rate γ: $Z(\mathbf{T_{ext}}; \mathbf{z}, \gamma, \gamma_0, c_{OM2,rel}, H_{rel})$
  - The IRR, when accounting for the risk of failure, is found by interpolation to identify the values of γ which fulfill: $Z(\mathbf{T_{ext}}; \mathbf{z}, \boldsymbol{\gamma}, \gamma_0, c_{OM2,rel}, H_{rel}) = 0$
- It is then assumed that the structure is designed according to current codes to reach the target reliability 3.3 at the end of the original lifetime of 20 years. The corresponding design parameter is denoted $z_{\beta_{20}=3.3}$, and is found by interpolation in the table $\beta_{20}(\mathbf{z})$.
  - The expected present value of the utility is found for a discount rate equal to the interest rate γ by interpolation in the table: $Z\left(\mathbf{T_{ext}}; z = z_{\beta_{20}=3.3}, \gamma, \gamma_0, c_{OM2,rel}, H_{rel}\right)$. (Results are presented in Section 4.2.1.)
  - The IRR, when accounting for the risk of failure, is found by interpolation to identify the values of γ which fulfill: $Z\left(\mathbf{T_{ext}}; z = z_{\beta_{20}=3.3}, \boldsymbol{\gamma}, \gamma_0, c_{OM2,rel}, H_{rel}\right) = 0$. (Results are presented in Section 4.2.2.)
- Feasible target reliability indices for life extension projects are identified by requiring that life extension should be feasible; Z should not be less than 0, when costs are discounted with a factor γ equal to the interest rate.
  - The design parameters z are identified by interpolation in the table: $Z(\mathbf{T_{ext}}; \mathbf{z}, \gamma, \gamma_0, c_{OM2,rel}, H_{rel}) = 0$, and the associated reliability index in the last year of the extended life is found from $\beta_{ext}(\mathbf{z}, \mathbf{T_{ext}})$. (Results are presented in Section 4.3.)

4 | RESULTS AND DISCUSSION

This section presents and discusses the results of the model presented in Section 3. Figures are shown for life extension periods T_{ext} equal to 5, 10, 15, and 20 years. The expected present value of the utility Z is generally shown as relative values, that is, for $P_a = 1$.

4.1 | Base case

Initially, the influence of the annual reliability index in the last year of the extended life β is investigated for the base case values of the costs. Figure 4A shows the expected present value of the utility Z as a function of the reliability β for a discount rate equal to the interest rate. The curves are flat for high values of the reliability (larger than 3.5), and Z reduces with an increasing rate as the reliability drops. A project with a life extension period of 5 years is infeasible, if the reliability index β is below approximately 2.7, and for a life extension period of 20 years, if the reliability index β is below approximately 2.5.

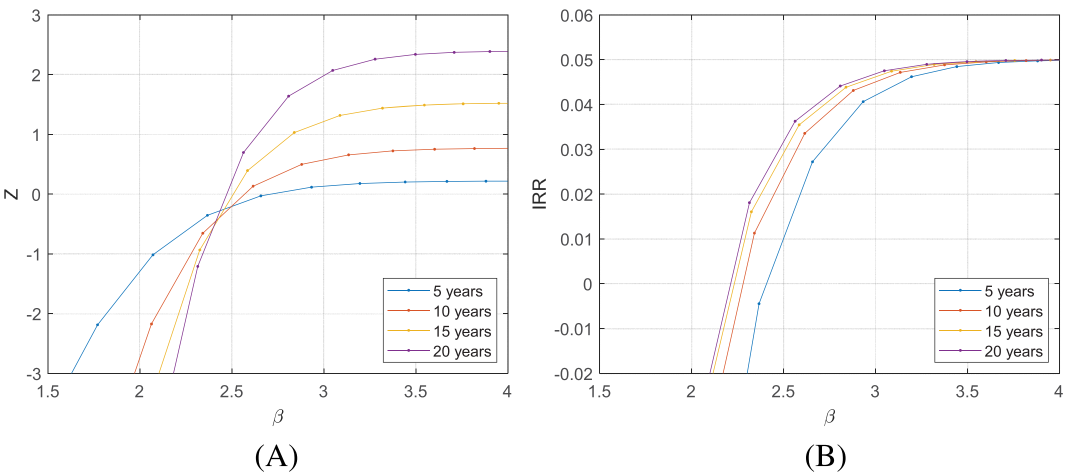

FIGURE 4 The expected present value of the (A) utility Z and (B) internal rate of return as a function of annual reliability index in the last year of the extended life for life extension periods T_{ext} = 5, 10, 15, and 20 years

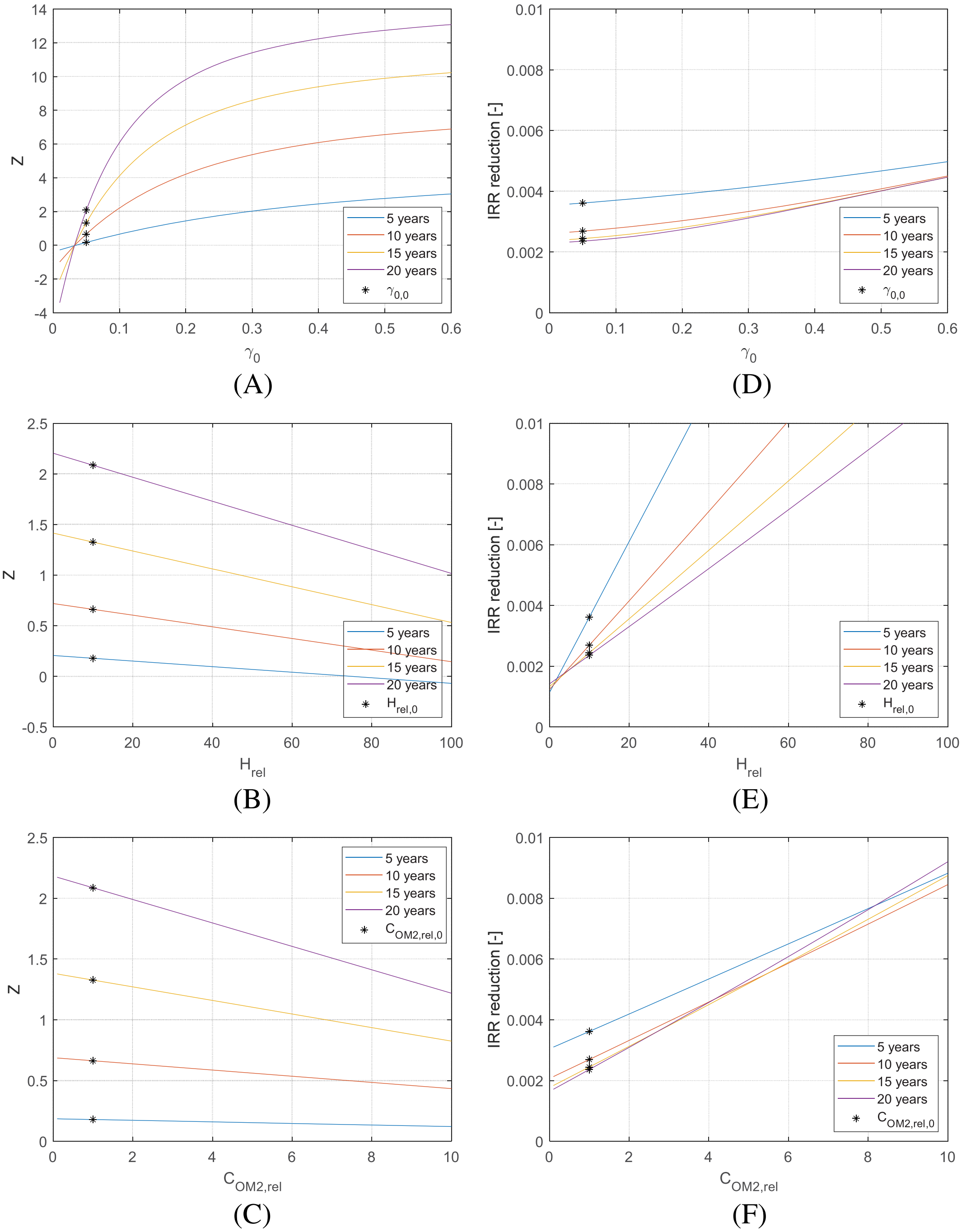

FIGURE 5 The expected present value of the (A–C) utility Z and (D–F) reduction of IRR due to the risk of structural failure. Both are shown for various values of initial internal rate of return γ_0, proportion of operational costs that are fixed $c_{OM2,rel}$ and the consequence of failure H_{rel}. The base case value are marked with stars

Figure 4B shows the IRR as a function of reliability β. The IRR approaches γ_0, as the reliability increases, and drops with increasing rate, when the reliability index is reduced. A rational decision maker should not accept reliability levels leading to IRR values lower than the interest rate.

4.2 | Original fatigue lifetime of 20 years

Here, the feasibility is investigated for various values of the cost input parameters, for a component designed for a fatigue lifetime of 20 years.

4.2.1 | Expected present value of utility

In Figure 5A–C, the expected present value of the utility Z is shown, when the interest rate γ is applied as the discount rate. Changes in cost parameters which give a decrease in Z result in the largest decrease for longer life extension periods. This is due to the costs generally being higher for larger life extension periods, as could be seen in Figure 3A.

The expected present value of the utility Z decreases linearly with increasing relative failure costs H_{rel} and with increasing relative fixed O&M costs $c_{OM2,rel}$. The most important cost parameter in terms of reduced Z is the initial IRR γ_0. A reduction in the initial IRR gives a decrease in Z, and the rate of change is higher for lower initial IRR.

4.2.2 | Reduction of IRR

Figure 5D–F shows the absolute reduction of IRR when failures are included. The reduction is higher for higher initial IRR, but as there is also more "margin to reduce," a life extension project with a higher IRR will also have a higher "adjusted" IRR. For low IRR (the potentially critical values), the absolute reduction is almost constant for an IRR between 0 and 0.1. As expected, the IRR reduction increases with increasing relative failure costs and with increasing relative fixed O&M costs.

In most cases, the IRR reductions are largest for shorter life extension periods, which might be surprising, as the utility reduction is lowest. However, this can be explained by Figure 3B: for a shorter life extension period, a larger change in IRR arises from the same reduction in annual profit. An exception is the situation with high fixed operational costs, where long life extension periods become critical. The explanation is that a structural failure in the beginning of the extended life will imply that large annual costs need to be paid for many years, without having any income.

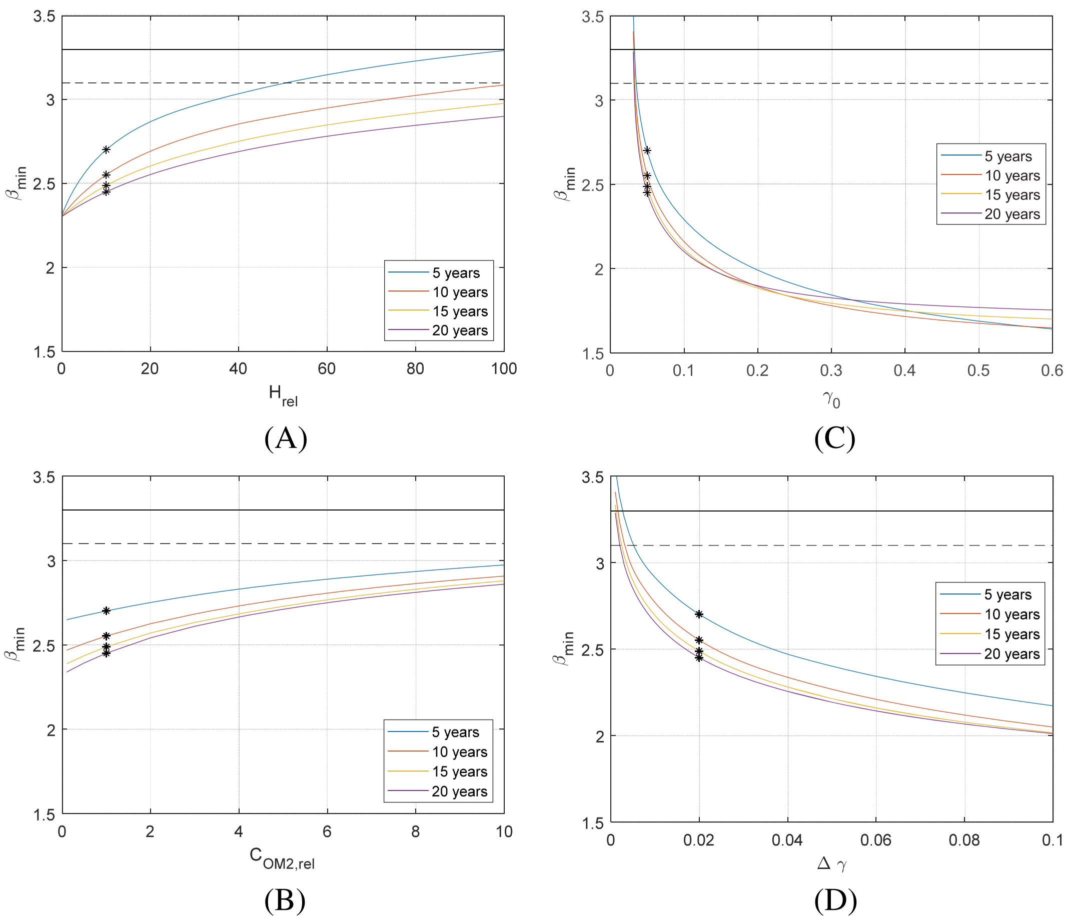

FIGURE 6 Minimum target reliabilities for life extension as a function of (A) the consequence of failure H_{rel}, (B) proportion of operational costs that are fixed $c_{OM2,rel}$, (C) initial internal rate of return γ_0, and (D) initial IRR margin $\Delta\gamma_0$. The horizontal black lines correspond to reliability indices 3.3 (full) and 3.1 (dashed). The base case values are marked with stars

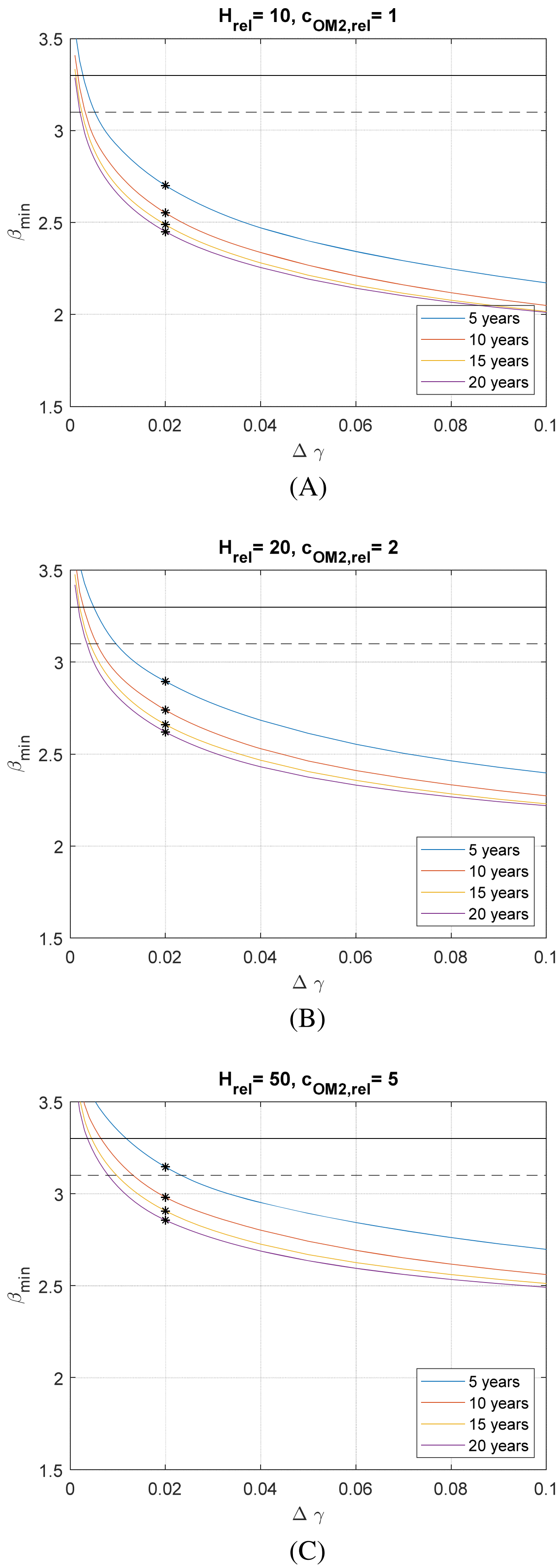

FIGURE 7 Minimum target reliabilities for life extension as function of $\Delta\gamma$ for values of relative failure costs H_{rel} = 10, 20, 50 and relative fixed operational costs $c_{OM2,rel}$ = 1, 2, 5. The horizontal black lines correspond to reliability indices 3.3 (full) and 3.1 (dashed). The reliability indices for the base case value of $\Delta\gamma$ are marked with stars

From a decision making perspective, the initial IRR reduced by the IRR reduction should be larger than the interest rate to be profitable. If comparing different projects, the projects with the highest IRR should be chosen.

4.3 | Minimum target reliabilities

Figure 6A–C shows the minimum target reliabilities for life extension, which are identified by requiring that life extension should be feasible; Z should not be less than 0, when costs are discounted with a factor γ equal to the interest rate. For the base case values of costs, it is seen that the target reliability is around 2.5 for life extension periods of 10 years or more. For increasing failure costs and increasing fixed operational costs, the required minimum target reliability index is seen to increase steadily. For failure consequences less than 100 times the annual profit, a minimum reliability index of 3.3 is sufficient, and for failure consequences less than 50 times the annual profit, 3.1 is sufficient. The fixed O&M costs can be 10 times the annual profit, and still, a reliability index of 3.1 is sufficient. When the initial IRR is increased, lower target reliability can be tolerated. When the initial IRR is reduced towards the interest rate, an aggressive increase of the required reliability level is seen. The reason for this is that life extension is always infeasible when the initial IRR is smaller than the interest rate.

A more generic result can be obtained by plotting the minimum target reliability as a function of the difference between the initial IRR and actual interest rate: $\Delta\gamma = \gamma_0 - \gamma$, which is done in Figure 6D, for values of $\Delta\gamma$ less than 0.1. As $\Delta\gamma$ is a measure for the initial IRR margin before the risk of failure is accounted for, the required reliability becomes lower when $\Delta\gamma$ is larger. If the same figure is made with other values of the interest rate, only very small changes to the figure are seen, and it can be considered approximately valid for interest rates up to 20%. (It was found that the change of reliability index due to increased interest rate was less than 2% in the critical range with high required reliability indices.) This is in line with the observations in Figure 5D that the IRR reduction was almost constant for small values of IRR.

It can be observed that the target reliability depends mainly on the difference between the IRR and interest rate, on the failure costs, and on the fixed operational costs. Figure 7 shows the variation with $\Delta\gamma$ for other values of relative failure costs and relative fixed operational costs. It is seen that for a given $\Delta\gamma$, the minimum reliability would need to be increased if relative failure costs increase or if relative fixed operational costs increase; for the base case values, an annual reliability level of 3.1 is sufficient if the $\Delta\gamma$ is larger than 0.5%. If both costs are twice as high, an annual reliability level of 3.1 is sufficient if the $\Delta\gamma$ is larger than 1%, and a reliability level of 3.3 is needed if $\Delta\gamma$ is between 0.5% and 1%. If the costs are five times as high, an annual reliability level of 3.1 is sufficient if the $\Delta\gamma$ is larger than 2.5%, and a reliability level of 3.3 is needed if $\Delta\gamma$ is between 1.2% and 2.4%. Regardless of the relative failure costs and relative fixed operational costs, the required reliability becomes very low if the initial IRR margin $\Delta\gamma$ is higher than 5%.

The curves for different life extension periods T_{ext} should not be compared directly. For a specific life extension project, other factors than those related to the structural reliability (e.g., the condition of the mechanical components) could influence the desired life extension period, and if various options are investigated (e.g., where more mechanical components are exchanged for longer life extension periods), they would most likely lead to different initial IRR.

5 | CONCLUSIONS

This paper aimed to evaluate if the target reliability level for existing wind turbines could be reduced compared to the target for new wind turbines and to suggest a viable target.

For new assets where the expected revenue is relied on to pay back the investment, the economic consequences in case of failure are large. However, in relation to decisions on life extension or continued operation for old assets, the failure consequences can be much smaller. The risk of structural failure could be critical for the feasibility of a life extension project if the direct relative consequence of failure is high, if the relative fixed operational costs are high, or if the life extension costs are so high that the IRR is close to the interest rate.

It was found that when the initial IRR was high compared to the interest rate, which could be the case for continued operation without any component exchanges, the target annual reliability level could be very low, that is, below $\beta = 2.5$. In many cases, an economic assessment would conclude this to be acceptable, but it might still be unacceptable for other reasons. In addition to the economic consequences for the owner, also consequences for the society such as loss of reputation, pollution, and lack of energy production capacity should be considered. For the collapse of a wind turbine, there can be a lack of reputation not only for the owner, if is it a large developer, but also for the wind industry in general. Therefore, the societal consequences should set a minimum level for the acceptable reliability index. Decreasing the reliability level to $\beta = 2.5$ would result in a probability of failure in the last year of operation that is increased by a factor of almost 13 compared to the requirement for new wind turbines. Instead, a more moderate change of target annual reliability level is suggested, namely, from $\beta = 3.3$ ($P_F = 5 \cdot 10^{-4}$) to a value in the interval from $\beta = 3.0$ to $\beta = 3.2$ with $\beta = 3.1$ ($P_F = 10^{-3}$) as the recommended value balancing economic and societal consequences. This would lead to less than a factor 2 increase in the number of collapses seen over the fleet of wind turbines, which is within the same order of magnitude and should not lead to a loss of reputation.

Although this change is relatively moderate, this alone corresponds to increasing the fatigue life by around 75% (from 20 to 35 years), as shown in Figure 1. In addition to the economic benefit for owners, the main reason for reducing the minimum reliability level to around β = 3.1 would be the positive consequences for society in terms of avoidance of unnecessary decommissioning of wind turbines, which support sustainability and sustain the renewable energy production capacity. It would thereby become possible to extend the life of more wind turbines, as the remaining fatigue life will be adequate for more wind turbines. For smaller wind turbines, where the costs of extensive analytical assessment would make life extension infeasible, much more simple assessment methods could be sufficient to verify sufficient fatigue life if allowed by authorities.

For major wind farm owners with a large portfolio of assets, it could be feasible to assess structures in relation to life extension using an economic optimization model directly. They could apply the economic optimization model presented in Section 3.1 in combination with their specific cost models and specific probabilistic fatigue models, instead of relying on a target reliability index found using generic models. The specific probabilistic fatigue models could be updated using all relevant operational information.

The analysis only considers wind turbines located in remote areas, where the probability of personal injury or fatality in case of structural failure is negligible. This is in line with the assumptions behind the reliability target for new wind turbines in the design standard IEC61400-1 ed. 4.[25] For wind turbines located close to buildings or infrastructural facilities, a separate risk assessment should be performed.

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PEER REVIEW

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ORCID

Jannie S. Nielsen https://orcid.org/0000-0003-2752-7673
John D. Sørensen https://orcid.org/0000-0001-6987-6877

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APPENDIX A.: PROBABILISTIC SN MODEL FOR FATIGUE FAILURE

The probabilistic SN model outlined here is based on the model applied for the calibration of the partial safety factors for welded steel details[25] in IEC61400-1 ed. 4 as presented in Sørensen and Toft.[26] The probabilistic model is based on bilinear SN curves in combination with Miner's rule for linear damage accumulation. The stress cycles for a specific mean wind speed and turbulence intensity are assumed Weibull distributed with standard deviation proportional to the wind turbulence standard deviation, and the joint distribution of wind speed and turbulence is used to find the stress range distribution.

The number of cycles N to failure for constant amplitude loading with stress range $\Delta\sigma$ is for a bilinear SN curve with slope change from $m_1 = 3$ to $m_2 = 5$ at $N_D = 5 \cdot 10^6$ given by

$$N = K_1\, \Delta\sigma^{-m_1} \text{ for } \Delta\sigma \geq \Delta\sigma_D, \tag{A1}$$

$$N = K_2\, \Delta\sigma^{-m_2} \text{ for } \Delta\sigma < \Delta\sigma_D. \tag{A2}$$

The mean value of the SN curve parameter K_1 can be found from the characteristic (mean minus two standard deviations) fatigue strength $\Delta\sigma_F = 71$ MPa at $N_F = 2 \cdot 10^6$ cycles using Equation A1. Then $\Delta\sigma_D$ can be found using Equation A1, and finally the mean value of K_2 is found using Equation A2.

Using Miner's rule, the limit state equation for fatigue failure before time t is written as

$$g(z,t) = \Delta - \nu \cdot t \left(\frac{(X_{\text{Wind}} X_{\text{SCF}})^{m_1}}{K_1} D_{BL1,tot}(z) + \frac{(X_{\text{Wind}} X_{\text{SCF}})^{m_2}}{K_2} D_{BL2,tot}(z) \right), \tag{A3}$$

where

- Δ is the model uncertainty related to the use of Miner's rule for damage accumulation.
- $\nu = 10^7$ is the number of load cycles per year.
- X_{Wind} and X_{SCF} are the model uncertainty of the wind load and stress concentration factor, respectively.
- $D_{BL1,tot}(z)$ and $D_{BL2,tot}(z)$ are the mean values of s^m for each part of the SN curve divided by the proportion of cycles on the respective parts of the curve. These are calculated by

$$D_{BL1,tot}(z) = \int_{U_{in}}^{U_{out}} \int_0^{\infty} D_{BL1}(U,\sigma_u,z) f_{\sigma_u}(\sigma_u \mid U) f_U(U) d\sigma_u dU,$$

$$D_{BL2,tot}(z) = \int_{U_{in}}^{U_{out}} \int_0^{\infty} D_{BL2}(U,\sigma_u,z) f_{\sigma_u}(\sigma_u \mid U) f_U(U) d\sigma_u dU,$$

where

- $f_U(U)$ is the Weibull probability density function for the mean wind speed with assumed shape parameter $k = 2.3$ and scale parameter $A = 9.0$ m/s.[26]
- $f_{\sigma_u}(\sigma_u \mid U)$ is the lognormal density function for the standard deviation of turbulence modeled with a standard deviation equal to $\sigma_{\sigma_u} = I_{ref} \cdot 1.4\,[\mathrm{m/s}]$, with turbulence intensity $I_{ref} = 0.14$ and mean value $\mu_{\sigma_u} = I_{ref}(0.75\,U + 3.3\,\mathrm{m/s})$.[26]
- $D_{BL1}(U, \sigma_u)$ and $D_{BL2}(U, \sigma_u)$ are found from

$$D_{BL1}(U,\sigma_u,z) = \int_{\Delta\sigma_D}^{\infty} s^{m_1} f_{\Delta\sigma}(s|\sigma_{\Delta\sigma}(U,\sigma_u,z))ds, \tag{A4}$$

$$D_{BL2}(U,\sigma_u,z) = \int_0^{\Delta\sigma_D} s^{m_2} f_{\Delta\sigma}(s|\sigma_{\Delta\sigma}(U,\sigma_u,z))ds, \tag{A5}$$

where $f_{\Delta\sigma}$ is the Weibull density function for stress ranges with shape parameter assumed to be 0.8 and standard deviation $\sigma_{\Delta\sigma}(U, \sigma_u)$ proportional to the wind turbulence[26]:

$$\sigma_{\Delta\sigma}(U,\sigma_u,z) = \alpha_{\Delta\sigma}(U)\frac{\sigma_u(U)}{z}. \tag{A6}$$

Here, z is a design parameter (proportional to a cross-sectional parameter). The factor $\alpha_{\Delta\sigma}(U)$ relates the standard deviation of the turbulence to the standard deviation of the response. Due to the control system, the ratio has a nonlinear relation with wind speed. For example, $\alpha_{\Delta\sigma}(U)$ for the mudline bending moment is taken from Sørensen and Toft.[26]

Although the mean wind speed, turbulence standard deviation, and stress ranges are modeled by their distributions, numerical integration is performed over these to get the contributions to fatigue damage, and only the five stochastic variables given in Table 2 are to be treated as stochastic variables in the reliability analysis. The coefficient of variation of the product $X_{Wind}X_{SCF}$ is set to the typical value $COV_{\mathrm{load}} = \sqrt{COV_{\mathrm{Wind}}^2 + COV_{\mathrm{SCF}}^2} = 0.2$ in accordance with Sørensen and Toft.[26]

TABLE 2 Stochastic model

Variable	Distribution	Expected value	Standard deviation/coefficient of variation
Δ	Normal	1	$COV_{\Delta} = 0.3$
X_{Wind}	Lognormal	1	COV_{Wind}
X_{SCF}	Lognormal	1	COV_{SCF}
$\log K_1$	Normal	Found from $\Delta\sigma_F$	$\sigma_{\log K_1} = 0.2$
$\log K_2$	Normal	Found from $\Delta\sigma_F$	$\sigma_{\log K_2} = 0.2$

Note: $\log K_1$ and $\log K_2$ are fully correlated.

Structural reliability methods can be applied to evaluate the reliability index. First, the cumulative distribution function for the time to failure from the beginning of the lifetime is calculated for 1-year steps using 10^8 crude Monte Carlo simulations from limit state equation A3 as follows:

$$F_T(t;z) = P(g(z,t) \leq 0). \tag{A7}$$

The density function for the time to failure is then found using numerical differentiation:

$$f_T(t;z) = F_T(t;z) - F_T(t-1;z). \tag{A8}$$

The annual probability of failure in year t given survival in all years before t is found as

$$P_F(t) = \frac{f_T(t;z)}{1 - F_T(t-1;z)}. \tag{A9}$$