

Advanced optimization of wind turbine gearbox gear train maintenance strategies incorporating oil filtration intervals and environmental costs

Abdou Aziz Dourfaye Najim^{1*} , Lahcen Mifdal^{1,2},
El Mehdi Guendouli^{1,2}, Sofiene Dellagi²

¹ Laboratoire InterDisciplinaire de Recherches Appliquées, LIDRA, Université Internationale d'Agadir-Universiapolis, Agadir, Morocco

² Laboratoire de Génie Informatique, de Production et de Maintenance, University of Lorraine, 3 rue Augustin Fresnel, BP 45112, CEDEX 03, 57073 METZ, France

* Corresponding author's e-mail: abdouaziz.dourfayenajim@e-polytechnique.ma

ABSTRACT

Wind turbine gearbox degradation driven by lubricating oil contamination represents one of the most environmentally and economically consequential challenges facing modern wind energy operations. This study proposes two optimized maintenance strategies designed to extend gear train service life, reduce hazardous waste generation, and lower the carbon footprint inherent to conventional intervention practices. The first strategy employs continuous oil contamination monitoring. When particulate concentrations exceed a predefined limit, production output is temporarily reduced to enable oil filtration, preserving lubricant integrity without full system shutdown. Repeated limit violations ultimately trigger a complete gear train overhaul. The second strategy introduces a non-ideal preventive maintenance framework (imperfect maintenance), initiated each time the contamination limit is surpassed. This strategy explicitly incorporates the environmental costs attributable to filtration operations. Each such intervention partially reduces the gearbox failure rate, reducing it to an intermediate level situated between the existing deteriorated state and that of a newly commissioned equipment. After N such interventions, full renewal is performed. This approach quantifies and minimizes the environmental costs embedded within each maintenance cycle. Two analytical models are developed. The first determines the economically optimal replacement periodicity and the second jointly optimizes the number of imperfect maintenance action and logistical scheduling. Numerical simulations and sensitivity analysis are conducted to compare both strategies. The results demonstrate that each maintenance strategy can be more advantageous depending on key criteria such as gearbox reliability, preventive maintenance costs and replacement expenses. From a practical standpoint, this work provides wind farm operators with clear, actionable decision rules. The imperfect maintenance strategy significantly reduces total costs compared to conventional periodic replacement. Sensitivity analysis reveals operational thresholds: when filtration costs are high, operators should reduce the number of imperfect interventions; when renewal costs dominate, increasing preventive interventions before full replacement becomes economically beneficial. The study provides wind farm operators with adaptable, optimized solutions tailored to their financial and operational specificities, contributing to more reliable and cost-effective wind energy production.

Keywords: maintenance strategies, optimization, wind turbine, gearbox, environmental costs.

INTRODUCTION

Decarbonizing the global electricity sector stands as one of the defining imperatives of the twenty-first century, and wind energy has emerged

as a cornerstone technology in this transition. From modest beginnings in the early 1980s, when individual turbines rarely exceeded 50–100 kW of installed capacity, the sector has undergone a transformation of extraordinary magnitude.

Driven by decades of interdisciplinary innovation spanning aerodynamic design, composite material engineering, power conversion electronics, and intelligent control architectures, contemporary turbines routinely deliver outputs measured in multiple megawatts, with cutting-edge offshore platforms now eclipsing the 15 MW threshold. This relentless upscaling has not only expanded energy yield per installation but has also profoundly improved the ecological credentials of wind generation by maximizing electricity output per unit of embedded material and land use [1,2]. The environmental dividends of this expansion are considerable. Global cumulative wind capacity surpassed 1,200 GW in 2025, displacing an estimated 2.3 billion tonnes of CO₂ annually — a quantity on par with the total yearly emissions of several major European industrial nations [3]. Beyond direct emissions avoidance, the proliferation of wind energy contributes to the structural decarbonization of energy-intensive industries, which historically depend on heterogeneous generation portfolios to balance cost volatility and supply continuity. Research by Guendouli [4] demonstrates that industrial operators under sustained energy price pressure increasingly pursue diversified procurement strategies, deliberately assimilating renewable generation to attenuate both carbon intensity and expenditure exposure [5]. This progressive transition towards an energy mix combining different energy sources ensures both energy security and reduced emissions in energy-intensive sectors. From a market perspective, the global wind electricity sector reached a valuation of USD 132 billion in 2025, expanding at a compound annual rate of 12% [6–8]. This trajectory is underpinned by the continued decline in the per-unit electricity cost of wind power generation, which now positions wind power as the most price-competitive non-hydroelectric renewable source globally [9]. Prospective analyses, particularly those conducted by Madvar and Golabek [10,11], anticipate a further 15% reduction in operational expenditures by 2030, attributable primarily to advances in maintenance engineering and asset management methodologies. Yet the ecological promise of wind energy is not unconditional. The gearbox (the mechanical interface coupling the slow-rotating rotor to the high-speed generator within the turbine drivetrain) [12,13], constitutes a persistent and environmentally significant vulnerability. Gearbox failures are among the most resource-intensive events in wind turbine

operation: they necessitate the deployment of heavy-lift crane systems, the mobilization of specialized personnel, the disposal of large volumes of contaminated lubricating oil, and ultimately the manufacturing of replacement components. All of which carry substantial carbon and material footprints. Prevailing maintenance paradigms, which condition intervention upon the observable deterioration of isolated components, consistently fail to anticipate failure cascades, resulting in unplanned outages that compound both economic losses and environmental costs through emergency logistics and accelerated waste generation. The present study introduces a novel analytical methodology focused on the systematic assessment of lubricating oil contamination, wherein the concentration of metallic particulates and water content functions as a dependable proxy for the degradation state of mechanical components [14]. Upon the detection of contamination levels exceeding critical thresholds, defined in accordance with the ISO 4406:2025 standard [15], the proposed model enables the optimization of gearbox replacement intervals by integrating both direct maintenance expenditures and indirect costs associated with production losses. In parallel, we develop an adaptive preventive maintenance strategy that, whenever contamination thresholds are breached, triggers targeted interventions aimed at progressively reducing the failure rate without requiring a complete turbine shutdown. The optimal frequency of these interventions is determined through a mathematical modelling framework that incorporates realistic operational constraints, including team mobilization lead times and the availability of specialized equipment. Both frameworks are grounded in mathematical models that explicitly incorporate environmental cost terms alongside conventional economic variables, establishing a rigorous basis for sustainability-oriented decision-making in wind farm operations. The remainder of this article is structured as follows.

BACKGROUND

The operational reliability of wind turbine gearboxes has attracted sustained scholarly attention, with large-scale field studies consistently identifying the gearbox as the component exerting the greatest influence on unplanned downtime per failure event [12,13]. This consequence

stems from the extraordinary logistical complexity and resource intensity inherent to gear train repair and replacement operations. Beyond their economic toll, such events carry measurable environmental externalities: each unplanned overhaul typically necessitates the disposal of several hundred to over one thousand liters of contaminated lubricating oil, the replacement of saturated filtration media, and the mobilization of carbon-intensive heavy-lift crane systems. Costs that conventional maintenance frameworks systematically fail to internalize.

Lubricating oil integrity has emerged as the primary determinant of gearbox longevity and a critical lever for both economic and environmental performance optimization. The progressive accumulation of metallic wear debris, principally iron particles released by deteriorating gear flanks and copper particles from bearing cage materials, engenders a self-reinforcing abrasive degradation cycle that exponentially accelerates surface deterioration. Foundational tribological research [16] has established that particulate concentrations exceeding 50 ppm for contaminants above 10 μm in diameter reduce rolling element bearing fatigue life by approximately 40%. Investigations by Martins and Pulikollu [17,18] attribute more than 75% of premature failures in contemporary wind farms to oil contamination, generating considerable maintenance expenditure. More recent studies conducted under the auspices of the National Renewable Energy Laboratory (NREL) confirm that particulate contamination constitutes one of the primary drivers of mechanical failure, accounting for approximately 40% of premature breakdowns [19,20].

A comparative investigation encompassing 150 wind farms distributed across Europe demonstrates that the deployment of spectrometric oil analysis can yield a 30% reduction in maintenance expenditures while simultaneously enhancing turbine operational availability [21]. These conclusions are further substantiated by Zou et al. [13], who conducting continuous surveillance of iron and copper concentrations within lubricating oil of offshore wind turbines, which successfully enabled the anticipation of a significant proportion of bearing failure events.

Within the domain of maintenance optimization modelling, several frameworks have been proposed for wind turbine gearboxes. Aafif et al. [22] developed optimal preventive maintenance strategies grounded in periodic renewal

theory, demonstrating the sensitivity of optimal replacement intervals to Weibull shape parameters and renewal costs. Their subsequent work [23] extended this framework to integrate gearbox design decisions within the maintenance optimization problem, coupling reliability modelling with lifecycle cost analysis. Zheng et al. [24] incorporated wind speed effects into a preventive maintenance optimization model for wind turbines via a Cox proportional hazards formulation, establishing the methodological precedent that the present work extends. Gasmi et al. [25] proposed a general repair and proportional hazards framework for complex repairable systems, providing theoretical grounding for the imperfect maintenance modelling adopted here. Although this reference predates the wind energy context, its methodological contribution to proportional hazards modelling remains widely recognized and directly applicable. Moreover, recent case studies reinforce the relevance of our approach. Martins and Romão [26] show that wind turbine gearbox failures often cascade from lubrication issues, material voids, and heat treatment defects, problems that reactive maintenance fails to anticipate. Similarly, Frederiksen et al. [27] demonstrate that for offshore wind farms, the optimal maintenance cost is achieved not by preventing all downtime events, but by accepting a small residual risk (between 2 and 3%). However, neither study integrates explicit environmental costs (lubricant disposal, CO₂ emissions) into their optimization. The present work directly extends these recent findings by incorporating ecological criteria into a unified, mathematically rigorous maintenance framework.

Notwithstanding these advances, a critical structural gap pervades the extant literature. Table 1 presents a systematic comparison of the most relevant published works along four dimensions: (i) inclusion of a wind speed covariate in the failure rate model, (ii) imperfect preventive maintenance modelling, (iii) oil contamination threshold as the maintenance trigger, and (iv) explicit quantification of environmental costs within the objective function.

Table 1 reveals that, to the best of the authors' knowledge, no published study simultaneously integrates: (i) a wind speed-dependent failure rate modelled via the Cox proportional hazards framework, (ii) imperfect preventive maintenance triggered by oil contamination threshold exceedances, and (iii) quantified environmental

Table 1. Comparative analysis of related literature

Reference	Wind speed covariate	Imperfect PM	Oil contamination trigger	Environmental cost
Aaiff et al. [22], 2022	No	Yes	No	No
Aaiff et al. [23], 2024	No	Yes	No	No
Zheng et al. [24], 2020	Yes	No	No	No
Gasmi et al. [25], 2003	No	Yes	No	No
El-Naggar et al. [19], 2023	No	No	Yes	No
Present work	Yes	Yes	Yes	Yes

costs, encompassing lubricant disposal, filter waste, and logistical carbon footprint, within a unified optimization objective. This triple integration constitutes the primary scientific contribution of the present work. The environmental cost term is grounded in the EU27 Environmental Prices Handbook [28], which provides monetized unit costs for hazardous liquid waste disposal and associated CO₂ emissions, enabling rigorous and reproducible environmental cost quantification.

The present work responds directly to this gap by embedding environmental cost terms alongside conventional economic variables within mathematically rigorous optimization models, advancing a holistic and operationally applicable framework for wind turbine gearbox maintenance.

OPTIMAL RENEWAL STRATEGY

Analytical model

In this article, the following notation conventions are applied uniformly. Lowercase Latin subscripts (*i*, *j*) denote cumulative indices. The symbol ($\times$) denotes scalar multiplication and also dimensional products involving physical units. The baseline hazard rate is denoted $\lambda_0(t)$ when referring solely to the age-dependent Weibull component, and $\lambda(t, j)$ when referring to the complete failure rate conditioned by wind speed. All time variables are expressed in weeks unless otherwise stated.

Within this strategy, the expression for total cost per unit time depends on the renewal period *T*, serving as the primary decision variable of the optimization problem. Three cost components are integrated. The first pertains to the costs associated with oil filtration operations, comprising direct intervention expenditures, environmental costs incurred by the filtration process [28], and financial losses attributable to the transient

reduction in production output during filtration phases. The second component corresponds to the full average cost of gear train renewal, incorporating not only the price of the new equipment but also the substantial associated logistical expenses. These include the transportation of specialized technical teams, the rental of heavy equipment (large-capacity cranes, etc.), as well as commissioning and dismantling costs. Filtration operations, while temporarily restoring the lubricating properties of the oil and maintaining production at nominal capacity, have no effect on reducing the intrinsic wear rate of the gearbox's mechanical components. Therefore, in our mathematical model, we will systematically consider these filtration interventions as minimal repairs, preserving the immediate functional state but not influencing the progressive degradation of the system. This modelling convention faithfully reflects documented wind farm operational reality, wherein each contamination-filtration cycle represents a discrete stage in the progressive aging of the speed reducer until cumulative irreversible deterioration ultimately necessitates complete system renewal.

The gear train failure rate is represented through a Weibull distribution augmented by a wind speed covariate, introduced via the Cox Proportional Hazards (PH) model. This formulation yields a failure rate function that is both age-dependent and environmentally responsive, more accurately capturing the stochastic operational reality of wind turbines than conventional fixed-parameter approaches. The Cox PH model has been widely adopted in wind energy reliability analysis. Zheng et al. [24] used this approach to characterize risk functions of systems alternating between normal and severe operating environments, while Gasmi et al. [25] incorporated it into a maintenance optimization framework for hydro-electric turbines. The present work adopts this

modelling architecture to jointly capture the influence of turbine age and prevailing wind speed on gear train failure rate.

Wind speed characterization

Wind speed at a given site exhibits well-documented periodic variations driven by seasonal and meteorological cycles. For the purpose of analytical tractability within a maintenance optimization framework, and following the approach adopted by Zheng et al. [24]. This sinusoidal representation of wind speed was originally proposed by Zheng to capture seasonal wind variability in maintenance optimization models. The novelty of the present work lies in its integration with oil contamination thresholds, imperfect maintenance modeling, and explicit environmental cost accounting.

The equation for wind speed is given by the following expression:

$$V(t) = V_0 + A \times \sin \frac{2\pi t}{T_c} \quad (1)$$

where: V_0 is the mean wind speed (m/s), A is the amplitude of seasonal variation (m/s), t is the elapsed time (weeks), and T_c is the period of oscillation (weeks).

This formulation is not intended to replicate stochastic turbulence; rather, it captures the dominant periodic trend of wind resource variability at seasonal timescales, which is the primary driver of long-term fatigue loading on gearbox components. The sinusoidal representation of wind speed is a deliberate simplification for analytical tractability. Real wind speeds are stochastic and turbulent, exhibiting rapid fluctuations that are challenging to incorporate directly into a closed-form maintenance optimization model. However, for gearbox fatigue life assessment and long-term maintenance planning, the dominant driver is the seasonal variability of wind resource (e.g., higher average wind speeds in winter months, lower in summer) rather than short-term turbulence [24]. The sinusoidal model captures this seasonal trend while ignoring high-frequency stochastic variations, which have a second-order effect on the cumulative fatigue damage of gear train components. This approximation is standard in the wind energy maintenance literature [24,29] and its parameters (V_0 , A , T_c) are straightforwardly estimated from monthly or weekly wind speed averages recorded at the turbine site.

Wind speed discretization

To enable numerical computation of the failure rate integral, the continuous wind speed process $V(t)$ is discretized using a standard approach [24, 28] whereby wind speeds are grouped into intervals of width 2 m/s. Each interval $[V_i, V_f]$ is represented by its midpoint J . This discretization technique is conventional in wind energy reliability modeling and is employed here for computational tractability, not as a claimed novelty.

$$J = \frac{V_i + V_f}{2} \quad (2)$$

where: V_i and V_f denote the lower and upper bounds of the interval, respectively. For example, a wind speed within $[0, 2]$ m/s is assigned $J = 1$ m/s, and within $[3, 5]$ m/s, $J = 4$ m/s.

Failure rate model: Weibull baseline with Cox proportional hazards

The gear train failure rate is modelled by combining a Weibull baseline hazard function, capturing age-dependent wear progression, with a Cox proportional hazards term, capturing the multiplicative effect of the prevailing wind speed on that baseline rate. The failure rate function conditioned on wind speed class J is:

$$\lambda(t, j) dt = e^{\theta \times J} \times \lambda_0(t) dt \text{ with } \lambda_0(t) = \left(\frac{\beta}{\alpha}\right) \left(\frac{t}{\alpha}\right)^{\beta-1} \quad (3)$$

In this model, contamination threshold exceedances are assumed to occur according to a non-homogeneous Poisson process (NHPP) with intensity function $\lambda(t, j)$. A key property of an NHPP is that the expected number of events over the interval $[0, T]$ equals the integral of the intensity function over that interval. Hence, the expected number of contamination threshold exceedances over a renewal cycle $[0, T]$ is:

$$\int_0^T \lambda(t, j) dt = e^{\theta \times J} \times \int_0^T \lambda_0(t) dt = e^{\theta \times J} \times \left(\frac{T}{\alpha}\right)^{\beta} \quad (4)$$

where: $\alpha > 0$ is the Weibull scale parameter, $\beta > 0$ is the Weibull shape parameter, J is the representative wind speed of the current

interval, and θ is the Cox regression coefficient, quantifying the sensitivity of the failure rate to wind speed.

This formulation has been validated in wind energy reliability analysis by Zheng et al. [24] and in general repairable systems by Gasmi et al. [25]. The regression coefficient θ is estimated from operational failure data using maximum likelihood estimation. There are several methods for estimating θ , namely:

- An estimation from failure data using a graphical method or the maximum likelihood method.
- From the literature, such as [24] with $\theta \in [0.2, 0.6]$ for gears and bearings.

Notation and total expected cost per unit time (Strategy 1)

The objective is to minimize the long-run average cost per unit time, a standard criterion in renewal processes. For a renewal cycle of length T , the total expected cost consists of two parts:

- Variable costs: the expected number of filtration operations $\int_0^T \lambda(t, j) dt$ multiplied by the unit cost per filtration, Anf (Average nominal filtering time) ($Arl \times Anf + Afc + Ec$).
- Fixed renewal cost: ($Acr + Lc$), incurred once per cycle at time T .

Dividing the total expected cost per cycle by the cycle length T yields the average cost per unit time. This cost function $TEC(T)$ is convex in T , guaranteeing a unique global minimum. The optimal $\lambda(t)$ baseline hazard rate of the gear train (t denotes the elapsed time between consecutive exceedances of the critical oil contamination threshold) $AnfT^*$ is therefore obtained by minimizing $TEC(T)$.

The total expected cost per unit time $TEC(T)$, the objective function to be minimized with respect to the renewal period T – see Equation (5).

The first term of the numerator represents the product of the average unit cost per filtration operation encompassing, production losses and direct intervention expenditures and the expected number of contamination threshold exceedances occurring within a single renewal cycle. The

second term captures the total average renewal cost, comprising both the gear train acquisition price and the associated logistical expenditures.

Numerical example for the renewal strategy

All mathematical analyses underlying the present study were carried out using MATHEMATICA software, version 11.2, which made it possible to efficiently implement the optimization model thanks to its advanced symbolic computing capabilities to accurately process the anticipated total cost equation and manipulate the complex integral expressions necessary to solve the problem. The software was particularly useful for identifying the optimal replacement interval for each problem configuration using optimization algorithms. A key advantage of MATHEMATICA is its capacity to effectively manage this class of intricate problems by delivering high precision in computations with very stringent convergence tolerances.

Taking into account the characteristics of the wind turbine under study, the environmental cost $Ec = 50$ € per filtration event, derived from the CE Delft EU27 Environmental Prices Handbook [28]. Applying a cost of 0.35 €/kg CO₂-equivalent to the estimated emissions of a filtration operation (approximately 12 kg CO₂-eq. for energy consumption, filter disposal, and transport), plus a hazardous waste disposal cost of approximately 2 €/liter for 10–15 liters of contaminated filtrate, yields $Ec \approx 50$ €/event

All numerical parameters used in this study (except for environmental cost and wind speed) were collected from real onshore wind farm operations in Morocco [22]. These include gearbox reliability characteristics, economic parameters, and logistical lead times obtained from actual maintenance records. Our study is therefore grounded in real industrial practice. Our numerical input data are listed in Table 2.

As previously established, the logistical cost Lc exhibits a direct functional dependence on the preparation lead time Lp , reflecting the operational complexity inherent to mobilizing the specialized human and material resources required for gear train renewal. The duration of Lp thus evolves between two critical limits:

$$TEC(T) = \frac{\left(e^{\theta \times J} \times \left(\frac{T}{\alpha} \right)^\beta \right) \times (Arl \times Anf + Afc + Ec) + (Acr + Lc)}{T} \quad (5)$$

- Lp-min – minimum incompressible duration for optimal preparation,
- Lp-max – maximum economically viable threshold for the operator.

This modeling takes into account the constraints specific to wind farms, where the accessibility of the site and the weather conditions further complicate the planning of preventive maintenance operations.

Hence, a specific logistical cost L_c is defined by:

$$L_c = \begin{cases} L_{c1} & \text{if } L_p \in [L_{p-\min}, L_{p1}] \\ L_{c2} & \text{if } L_p \in]L_{p1}, L_{p2}] \\ L_{c3} & \text{if } L_p \in]L_{p2}, L_{p-\max}] \end{cases} \quad (6)$$

where: $L_{c1} > L_{c2} > L_{c3}$.

The following values of preparation period L_p and the costs L_c are considered in Table 2. The optimization problem consists of minimizing the total expected cost per unit time $TEC(T)$ defined in Equation 5 with respect to the renewal period T . For this first strategy, L_c is set to L_{c3} (800 €), corresponding to the least logistically constrained scenario in which the renewal date T is known sufficiently in advance to allow thorough preparation at

minimal cost. The associated preparation window L_p ranges between 13 and 20 hours. $TEC(T)$ is convex in T , ensuring a unique global minimum. The minimization is performed numerically using a golden-section search algorithm, a standard univariate optimization method for convex functions. The optimal renewal period T is identified as the argument that minimizes $TEC(T)$. Numerical computations were implemented in Mathematica 11.2 using the built-in FindMinimum function with the golden-section method. The results are summarized in Table 3 and illustrated in Figure 1. Figure 1 offers a complementary illustration that further specifies the results obtained.

The function is computed numerically from Equation 5 using the parameter values in Table 3. The global minimum at $T^* = 210$ weeks ≈ 4 years corresponds to $TEC^* = 479$ €/week. The convex shape of $TEC(T)$ confirms the existence and uniqueness of the optimum. Source: authors' numerical simulation (Mathematica 11.2). The symbol TEC in the figure stands for 'Total Expected Cost per unit time', as defined in Equation (5).

MODELING OF THE IMPERFECT PREVENTIVE MAINTENANCE STRATEGY

Presentation of the proposed IPM strategy

The first strategy is the most commonly used by wind farm operators. However, using filtration to temporarily restore the oil's properties without addressing the underlying cause of its progressive degradation is not only ineffective but can also be harmful to the environment in the long run. Indeed, it generates waste and consumes energy over time without tackling the root cause of the contamination. The exceedance of critical contamination thresholds constitutes irrefutable evidence of advancing wear within the gearbox's mechanical constituents. A process that inevitably engenders the production of metallic debris and accelerated physicochemical degradation of the lubricant, dynamics that collectively amplify the overall environmental burden associated with turbine operation.

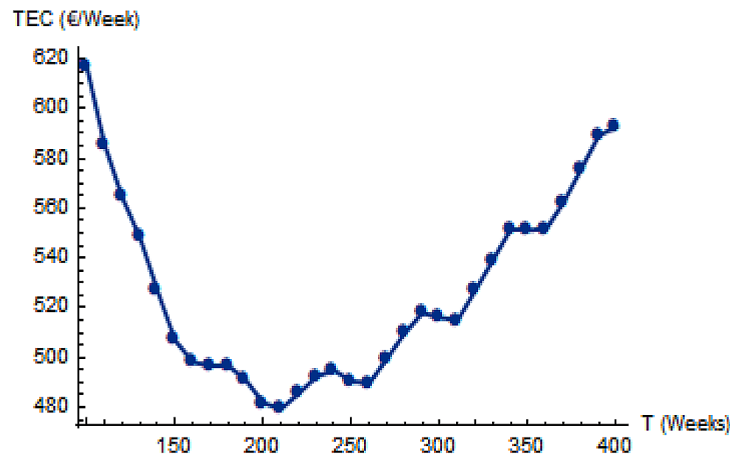
In response to these shortcomings, the present work proposes an innovative preventive maintenance framework that synergistically combines targeted corrective interventions with logistical optimization, while explicitly incorporating ecological considerations into the decision-making

Table 2. Input data used in the optimization

Parameters	Data	Source
β	2	Aaif et al. [22]; Zheng et al. [24]
α	200	Aaif et al. [22]
A_{rl}	1100 € / hour	Aaif et al. [22]
A_{cr}	50 000 €	Aaif et al. [22]
A_{fc}	2000 €	Aaif et al. [22]
E_c	50 €	Environmental Prices Handbook [1]
A_{nf}	11 hours	Aaif et al. [22]
θ	0.2	Zheng et al. [24]
V_0	6 m/s	Onshore Wind [5]
A	2 m/s	Onshore Wind [5]
T_c	52 Weeks	Onshore Wind [5]
L_{c1}	7000 €	Aaif et al. [22]
L_{c2}	1600 €	Aaif et al. [22]
L_{c3}	800 €	Aaif et al. [22]
$L_{p-\min}$	3 hours	Aaif et al. [22]
L_{p1}	10 hours	Aaif et al. [22]
L_{p2}	13 hours	Aaif et al. [22]
$L_{p-\max}$	20 hours	Aaif et al. [22]

Table 3. The optimal replacement cycle length and the related minimal total cost per week

Logistical scenario	Lp interval (h)	Lc (€)	T* (Weeks)	T* (Years)	TEC*(€/Weeks)
Long preparation	[13, 20]	800	210	4	479


Figure 1. Total expected cost per unit time TEC (T) as a function of the gear train renewal period T
(Source: Mathematica 11.2)

process. Each instance of contamination threshold exceedance simultaneously triggers an oil filtration cycle and an imperfect preventive maintenance (PM) action, thereby attenuating the system's failure rate to an intermediate value situated between its current degraded condition and that of a newly commissioned gearbox, while concurrently decelerating the progression of wear across gear stages and bearing assemblies. This dual action not only limits the frequency of costly and polluting complete gearbox replacements but also reduces the consumption of new lubricating oil and the volume of hazardous waste (used oil, contaminated filters). This approach integrates a crucial logistical dimension where responsiveness (duration L_p) considers the operational constraints of mobilizing specialized teams and equipment, while establishing an optimal economic trade-off between the additional cost of a rapid intervention and the losses linked to the immobilization of the wind turbine. The model developed thus makes it possible to determine the optimal number of preventive interventions before complete renewal and the ideal implementation duration, with the aim of minimizing the sum of direct economic costs and environmental impacts while guaranteeing the reliability of the system [23].

Analytical model

The mathematical model expressing the total expected cost per unit time as a function of the two decision variables N and L_p is presented hereafter. By definition the renewal cycle is the period starting, immediately after the installation of a new gearbox and ending when this gearbox gear train is renewed. The notation adopted throughout this model is summarized in Table 4.

Figure 2 illustrates the sequence of maintenance operations performed within a representative renewal cycle, depicting the cumulative effect of successive imperfect PM actions on the gear train hazard function. The total expected cost (TEC) is expressed in Equation (7).

The total expected cost TEC integrates four principal components. The loss of income linked to technical shutdowns, the expenses of emergency filtrations, the costs of planned preventive interventions and finally the budget allocated to the replacement of the system which offers an exhaustive vision of the financial implications over the entire operating cycle [22].

It is worth noting that upon the $(N+1)$ -th contamination threshold exceedance, following N imperfect PM actions, a renewal operation is

$$TEC(N, P) = \frac{\text{The expected total cost over a cycle } [TC(\text{Cycle})]}{\text{Average duration of a renewal cycle } [D(\text{Cycle})]} \quad (7)$$

Table 4. Second strategy notations

Parameters	Data
N	Number of imperfect preventive maintenance actions carried out prior to replacement (Decision variable)
Lp	Preparation or logistical lead time for maintenance or replacement operations
γ_1	Time interval before the initial exceedance of the contamination limit
f1	Distribution function of the stochastic variable γ_1
γ_i	Time span separating the (i-1)th non-ideal preventive intervention ($i = 1, N+1$) from the ith occurrence of threshold contamination exceedance
V(t)	Instantaneous wind speed as a function of time t
Vo	Average wind speed
A	Average amplitude of variations
Tc	Period of oscillations
Afc	Average filtering operation cost per time unit
Ec	Environmental cost related to the filtering operation
Acm	Average unit cost of the imperfect preventive maintenance action
Acr	Mean replacement cost
Arl	Average revenue loss per time unit occurring during oil filtration
Lc	Logistical expenditure related to replacement actions (dependent on the lead time L_p)
D (Cycle)	The average duration of a renewal cycle
TC (Cycle)	The total expected cost over a cycle
TEC (N, P)	Total expected cost per time unit
MTBFi	Average elapsed time between consecutive crossings of the critical contamination threshold

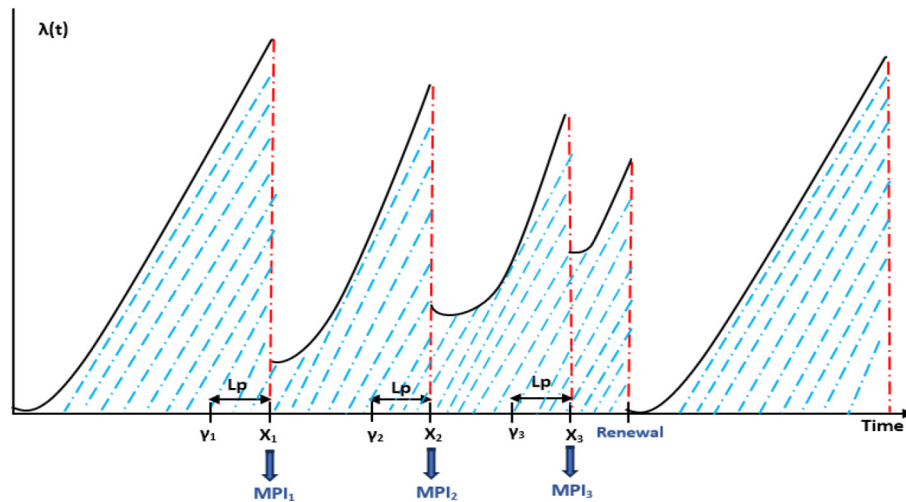


Figure 2. The failure rate of the gearbox gear train evolution during a renewal cycle

initiated after a logistical preparation period of L_p time units. The final term of the cost equation accordingly incorporates production loss during this preparation window ($Arl \times L_p$), the associated

filtration cost Afc , and the renewal cost Acr . Since Lc is a discrete function of L_p as defined in Equation (6), the total cost expression of Equation (8) is reformulated accordingly.

$$\begin{aligned}
 TC(\text{cycle}) = & \left(\int_0^{X_1} Arl \times (X_1 - \gamma_1) \times An f_1(\gamma_1) d\gamma_1 + \int_0^{X_2} Arl \times (X_2 - \gamma_2) \times An f_2(\gamma_2) d\gamma_2 \right. \\
 & + \dots + \int_0^{X_N} Arl \times (X_N - \gamma_N) \times An f_N(\gamma_N) d\gamma_N \Big) + N(Acm + Afc + Ec + Lc) \\
 & + ((Arl \times L_p) + Afc + Ec + Acr + Lc)
 \end{aligned} \quad (8)$$

$$TC \text{ (cycle)} = Arl \times Lp \times \sum_{i=1}^N (f_i(\gamma_i) d\gamma_i) + N(Acm + Afc + Ec + Lc) + ((Arl \times Lp) + Afc + Ec + Acr + Lc) \quad (9)$$

Thus, the expression of the TEC is given by:

$$TEC(N, P) = \frac{Arl \times Lp \times \sum_{i=1}^N (f_i(\gamma_i) d\gamma_i) + N(Acm + Afc + Ec + Lc) + ((Arl \times Lp) + Afc + Ec + Acr + Lc)}{(N + 1) \times Lp + \sum_{i=1}^{N+1} (MTBF_i)} \quad (10)$$

As previously mentioned, imperfect PM interventions partially lower the gearbox hazard rate are triggered each time the oil contamination limit is exceeded. Based on the Gertsbakh framework, the failure rate function associated with the random variable γ_i (defined as the duration needed to reach the critical contamination threshold following each non-ideal maintenance action) evolves in the following manner [30].

$$\lambda_{i+1}(t) = e^\delta \times \lambda_i(t) \quad (11)$$

where: $\lambda_1(t)$ denotes the failure rate function prior to the first imperfect preventive maintenance intervention (corresponding to a system that began operating in a brand-new condition).

The term e^δ is considered as a “deterioration acceleration” factor that is strictly positive. δ can be found empirically using linear regression. Hence, considering this failure rate function:

$$f_i(t) = \lambda_i(t) \times e^{-\int_0^t \lambda_i(t) dt} \quad (12)$$

Lastly, the time points X_i ($i = 1, 2, \dots, N$) at which preventive maintenance actions are carried out will be determined as follows:

$$X_i = MTBF_i + L_p \quad (13)$$

Noting that:

$$MTBF_i = \int_0^{+\infty} \gamma_i f_i(\gamma_i) d\gamma_i + L_p \quad (14)$$

Numerical results

The numerical configuration, including gearbox reliability characteristics, operational parameters, Weibull inter-threshold time distribution, and logistical preparation periods from Table 1, is retained here for consistency. Supplementary input parameters are provided in Table 5. The

objective is to simultaneously determine the optimal number N^* of preventive maintenance actions to be performed before renewal and the optimal logistical or preparation period L_p^* , which minimize the total expected cost per unit of time.

The logistical cost, in the Table 6, depends on the logistical or preparation period L_p . The variation in these costs is the same as that considered for the renewal strategy in the previous section.

Using the proposed strategy, we obtained, in Table 7, the results. In addition, Figure 3 offers a complementary illustration of the result obtained.

The proposed optimization yields an optimal maintenance policy comprising $N^* = 6$ imperfect preventive maintenance interventions prior to complete gear train renewal or equivalent as new overhaul. With respect to the logistical dimension, the optimal preparation lead time is determined to lie within the interval $L_p^* \in [10, 13]$ hours. A configuration that establishes the most economically advantageous balance between intervention responsiveness and mobilization cost across the full renewal cycle.

Table 5. Input data used for the second strategy

Parameters	Data	Source
β	2	Aafif et al. [22]
α	200	Aafif et al. [22]
Arl	1100 € / hour	Aafif et al. [22]
Acr	50000 €	Aafif et al. [22]
Afc	2000 €	Aafif et al. [22]
Ec	50 €	Environmental Prices Handbook [1]
Acm	2500 €	Aafif et al. [22]
θ	0.2	Zheng et al. [24]
V_0	6 m/s	Onshore Wind [5]
A	2 m/s	Onshore Wind [5]
Tc	52 Weeks	Onshore Wind [5]
δ	0.223	Gertsbakh [29]

Table 6. LC cost corresponding to preparation or logistical lead time for maintenance

Parameter	Lp ∈ [2–10 h]	Lp ∈ [10–13 h]	Lp ∈ [13–20 h]
Lc1	7000 €	–	–
Lc2	–	1600 €	–
Lc3	–	–	800 €

Analysis of model sensitivity to key parameters

In this section, we will analyze the effect of varying the main input parameters on the optimal strategy (N^* , Lp^*).

Initially, the influence of modifying gearbox dependability through the Weibull shape parameter β is examined. Keeping the remaining input parameters unchanged, the outcomes are shown in Table 8:

When gearbox reliability is reduced through an increase in the Weibull shape parameter β , the optimization responds by prescribing a greater number of imperfect PM interventions within each renewal cycle, reflecting the heightened degradation rate and the consequent economic benefit of more frequent corrective action prior to full renewal. The optimal preparation lead time Lp^* , however, remains insensitive to this parameter variation. This behaviour is illustrated in Figure 4.

Next, the impact of changing the average cost per filtration cycle Afc is analyzed. With all other parameters unchanged, Table 9 summarizes the obtained results:

As the unit filtration cost Acf increases, the optimal strategy advocates earlier gear train renewal by reducing the number of PM interventions. For instance, when Acf reaches 8.000 €, the optimal policy contracts from $N^* = 6$ to $N^* = 5$ interventions prior to renewal, reflecting the diminishing economic justification for repeated filtration cycles as their unit cost escalates. Concurrently, a significant increase in Acf reduces the optimal preparation lead time Lp^* , thus promoting more responsive intervention scheduling. These trends are depicted in Figure 5.

Then the effect of the change in renewal cost Acr and using the same input data, the following results are obtained in Table 10.

As the gear train renewal cost increases, the optimization predictably defers complete overhaul by prescribing a larger number of preventive interventions. Notably, doubling the renewal cost from 50,000€ to 100,000€ shifts the optimal policy from $N^* = 6$ to $N^* = 9$ interventions. A substantive adjustment that reflects the growing economic incentive to extend component service life through imperfect maintenance rather than incur premature full replacement expenditure. The corresponding results are illustrated in Figure 6. Impact of changing the mean revenue loss per time unit Arl . With all other inputs held constant, the outcomes are displayed below in Table 11:

When the revenue loss rate Arl rises, the optimal imperfect preventive maintenance approach leads to earlier replacement of the gear train. This translates into a lower number of preventive maintenance interventions and a reduced logistical lead time per action (a decrease in Lp^*). As shown in Figure 7, the impact of this parameter variation is clearly visible. Influence of modifying the effectiveness of imperfect preventive maintenance actions on the gear train failure rate (δ). With all other inputs kept unchanged, the outcomes are reported in Table 12.

Recall that e^δ represents the factor governing the evolution of the hazard rate following each non-ideal preventive intervention. Accordingly, a lower value of e^δ indicates greater effectiveness of the preventive maintenance action, while a higher value implies reduced effectiveness. In this context,

Table 8. Effect of the variation of β

Beta β	N^*	Lp^*	TEC*
2	6	[10–13 h]	221
4	9	[10–13 h]	152
6	11	[10–13 h]	131

Table 7. The optimal IPM strategy obtained with the corresponding minimum TEC

Logistical scenario	Lp interval (h)	Lc (€)	N^*	TEC*(€/Weeks)
Medium preparation	[10, 13]	1600	6	221

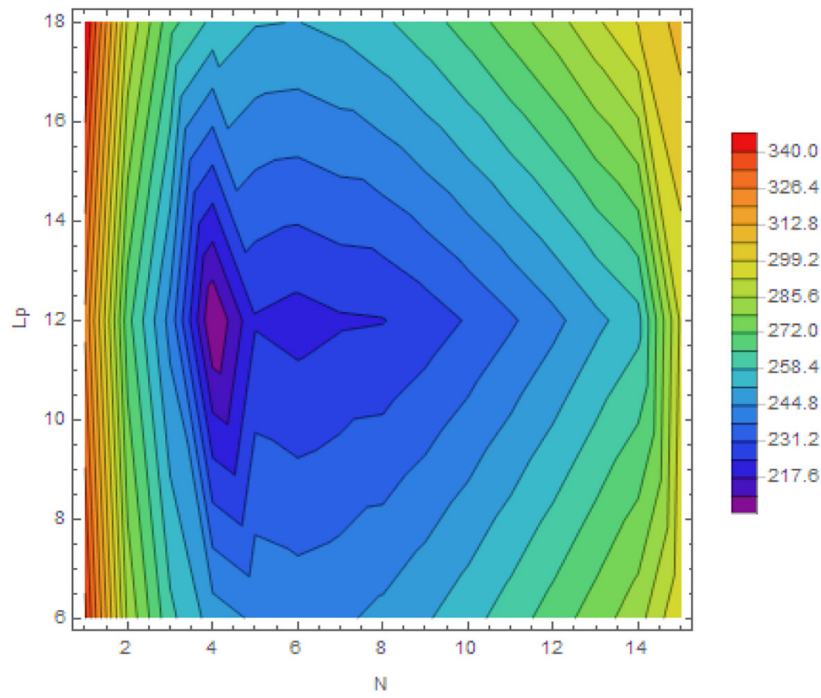


Figure 3. TEC optimization, visualization of N and P combinations

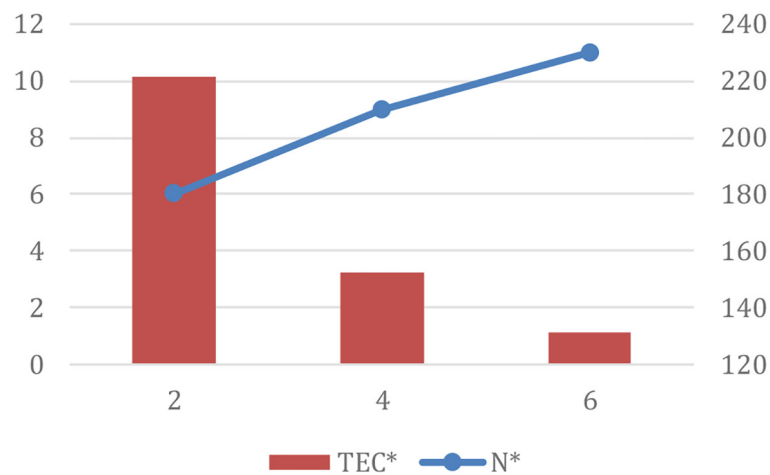


Figure 4. Effect of β variation on TEC and N

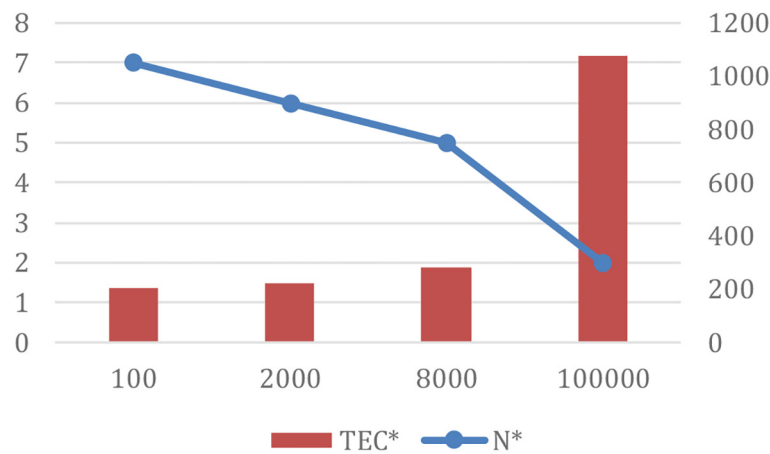


Figure 5. Effect of Afc variation on TEC and N

Table 9. Effect of the variation of Afc

Afc	N*	Lp*	TEC*
100	7	[10–13 h]	202
2000	6	[10–13 h]	221
8000	5	[10–13 h]	281
100000	2	[13–20 h]	1077

Table 10. Effect of Acr variation

Acr	N*	Lp*	TEC*
10000	3	[10–13 h]	153
20000	4	[10–13 h]	174
50000	6	[10–13 h]	221
100000	9	[10–13 h]	284

Table 11. Effect of the variation of Arl

Arl	N*	Lp*	TEC*
500	8	[10–13 h]	169
1100	6	[10–13 h]	221
2000	5	[2–10 h]	279
3000	5	[2–10 h]	320

Table 12. Effect of the variation of δ

δ	N*	Lp*	TEC*
0.095	11	[10–13 h]	179
0.223	6	[10–13 h]	221
0.40	4	[10–13 h]	263
0.80	3	[10–13 h]	330

the findings indicate that as e^δ increases (meaning preventive interventions become less efficient), the optimal policy consists of reducing the number of preventive maintenance operations and performing gearbox replacement sooner. Figure 8 illustrates the consequences of this parameter variation.

Lastly, the impact of varying the regression coefficient θ is examined. Maintaining the same

values for the remaining input parameters, the results are presented in Table 13.

Recall that this coefficient quantifies the impact of wind speed on the failure rate of wind turbines. The more it increases, the more significant the impact and vice versa. In this sense, Table 13 shows that when θ increases, the optimal strategy is to increase the number of preventive

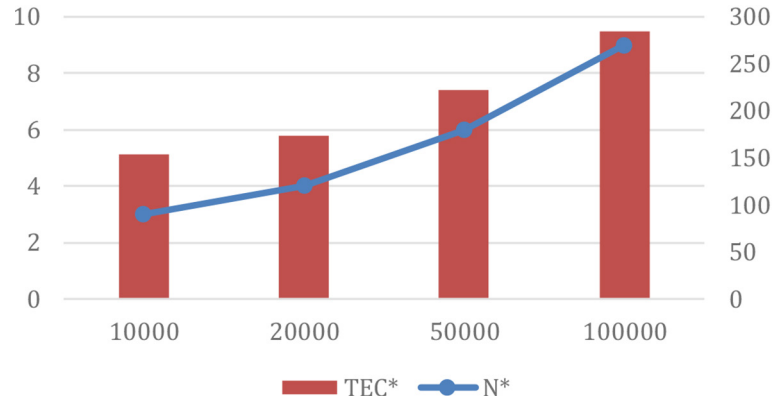


Figure 6. Effect of Acr variation on TEC and N

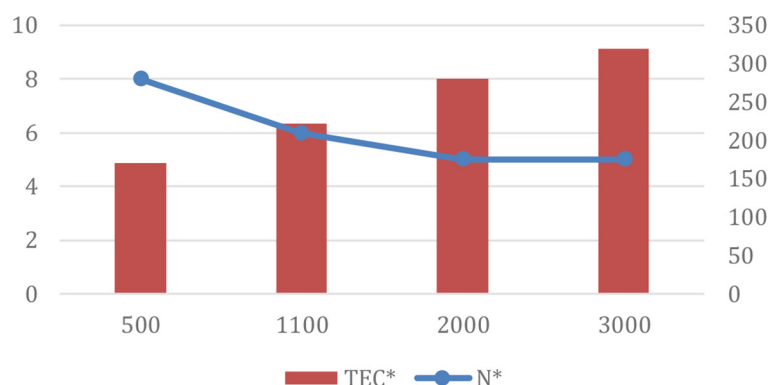


Figure 7. Effect of Arl variation on TEC and N

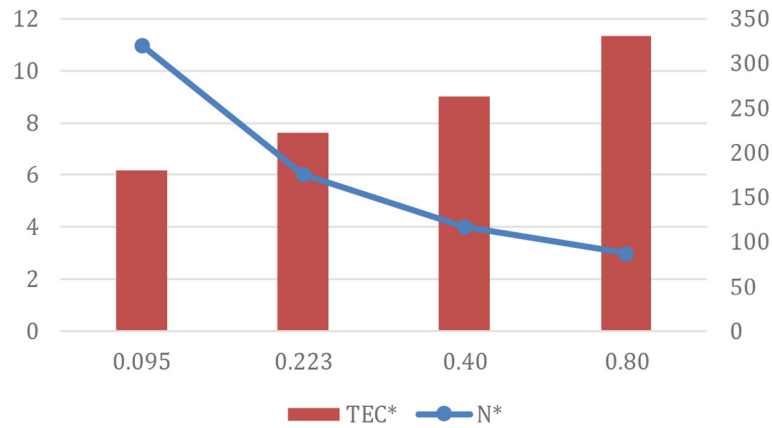


Figure 8. Effect of δ variation on TEC and N

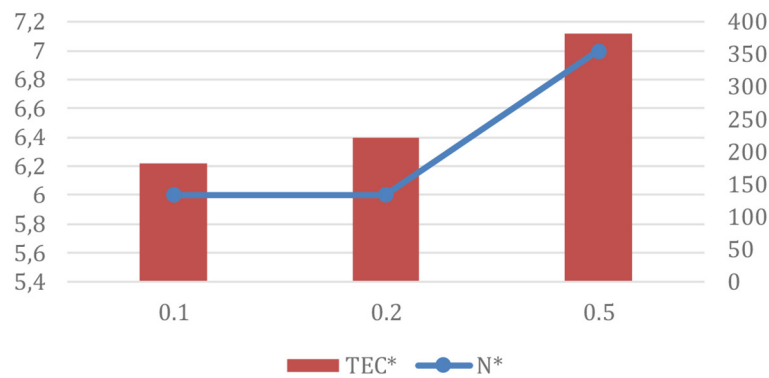


Figure 9. Effect of θ variation on TEC and N

Table 13. Effect of the variation of θ

θ	N*	Lp*	TEC*
0.1	6	[2–10 h]	181
0.2	6	[10–13 h]	221
0.5	7	[10–13 h]	380

maintenance actions because the impact of wind is significant. Figure 9 allows us to see the effect of this variation.

COMPARISONS

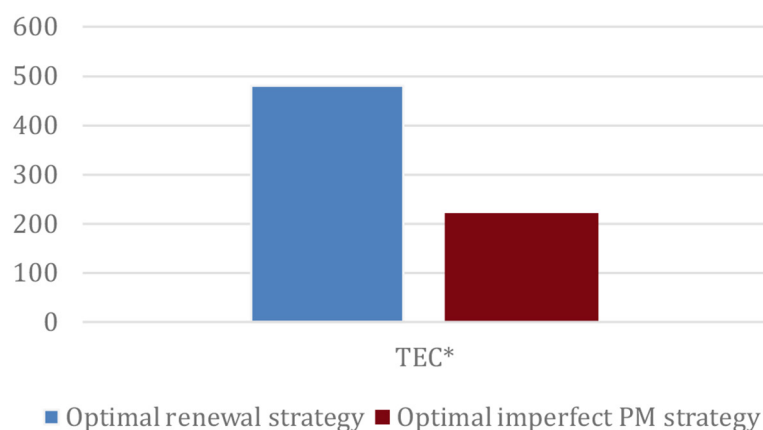
With both maintenance strategies having been formally modelled and independently optimized, wind farm operators are now equipped to select the most economically advantageous approach in accordance with their specific operational context and the governing values of key parameters (covering gearbox renewal outlays, imperfect preventive interventions, filtration costs, environmental charges, logistics expenses, production downtime losses, and the probability law governing the time to reach the critical contamination threshold).

To illustrate this comparison, we analyze below the numerical cases previously studied for each strategy. Following this comparative analysis, the findings are summarized in Table 14. Notably, under these specific conditions, the imperfect preventive maintenance strategy yields lower costs than the periodic replacement approach. As illustrated in Figure 10, the savings achieved relative to the renewal-based strategy reach 53%. $\text{Gain} = (479 - 221) / 479 = 53\%$.

Although developed specifically for wind turbine gearbox maintenance, the proposed optimization framework is methodologically general. The core components, Weibull-based degradation modeling, threshold-triggered interventions, imperfect preventive maintenance, can be adapted to other energy systems where gradual deterioration threatens operational integrity. For instance, in cryogenic gas storage facilities, the underground ice ring that forms during operation undergoes progressive degradation due to thermal and mechanical cycling, ultimately compromising containment [31]. In such a context, the ice ring's integrity could be monitored via a measurable indicator

Table 14. Comparative assessment of both approaches

Strategies	T*	N*	Lp*	TEC*
1 st Strategy: Optimal renewal	210 weeks	***	****	479
2 nd strategy: Optimal imperfect PM	****	6	[10–13 h]	221


Figure 10. Cost performance comparison

(e.g., crack density or thermal gradient), and interventions analogous to the filtration actions in our model could be scheduled when a critical threshold is reached. The same mathematical framework would then apply, enabling the joint optimization of intervention frequency, logistical lead times, and environmental costs. More broadly, any infrastructure asset with a quantifiable degradation signal and discrete maintenance opportunities could benefit from this approach.

CONCLUSIONS

Our study was motivated by a pervasive and operationally consequential challenge in wind turbine asset management: gearbox lubricating oil contamination arising from progressive mechanical wear, which precipitates accelerated component degradation, elevated operating expenditures, and substantial environmental impacts stemming from the generation of hazardous waste alongside unnecessary resource consumption. Conventional practice has historically confined operator intervention to the moment at which contamination attains a critical threshold, thereby triggering emergency filtration cycles or complete gear train replacement. The inherent limitations of this reactive paradigm manifest as significant production losses, sub-optimal maintenance expenditure profiles, and an amplified environmental footprint,

particularly due to logistical costs and prolonged downtime, frequent disposal of oil and filters, and premature replacement of mechanical components. Two maintenance strategies were developed and analytically modelled. The first is based on a planned replacement of the gearbox gear train after a fixed duration T , determined to minimize the total cost per unit of time while also reducing the environmental impact by limiting unplanned interventions and associated waste. The second strategy introduces imperfect preventive maintenance actions each time the contamination threshold is surpassed, thereby extending component service life prior to complete renewal. This approach offers pronounced ecological benefits, as it reduces the frequency of full gearbox overhauls, curtails lubricating oil consumption, minimizes filtration waste generation, and diminishes the cumulative carbon footprint associated with the manufacturing of replacement components and the disposal of end-of-life assemblies. A comprehensive mathematical model was developed to jointly optimize both the number of interventions N and the logistical preparation period L_p , integrating maintenance costs, production shutdown penalties, logistical expenditures, and environmental costs attributable to filtration operations, waste management, and component replacement. A sensitivity analysis then confirmed the robustness of the proposed models, demonstrating that the choice between the two strategies depends

heavily on operational conditions, the reliability of the gearbox gear train, and the specific costs and environmental priorities of each wind farm. Operators can now economically compare these two approaches and assess their respective environmental performances to adopt the most sustainable and cost-effective one for their context.

In conclusion, this study provides wind farm operators with a holistic decision-making methodology to optimize the maintenance of gearboxes, simultaneously reducing costs, improving the reliability of installations, and minimizing the environmental costs associated with maintenance operations. The developed models enable the advancement of more sustainable and environmentally responsible wind energy production.

Acknowledgments

The authors would like to acknowledge the International University of Agadir and the University of Lorraine.

REFERENCES

- Kadriu K, Kabashi G, Gjukaj A, Kabashi Q. Challenges of renewable integration in Kosovo: A technical study of balancing reserve needs. *Ecological Engineering & Environmental Technology* 2025;26:166–76. <https://doi.org/10.12912/27197050/204180>
- Batu T, Lemu HG, Sirhabizuh B. Study of the performance of natural fiber reinforced composites for wind turbine blade applications. *Advances in Science and Technology Research Journal* 2020;14:67–75. <https://doi.org/10.12913/22998624/118201>
- GWEC. Global Wind Report 2023| GWEC. Gwec 2023.
- Guendouli EM, Mifdal L, Dellagi S, Kibbou EM, Moufki A. Integrated production-maintenance strategy considering energy consumption and recycling constraints in dry machining. *The International Journal of Advanced Manufacturing Technology* 2024;133:3335–53. <https://doi.org/10.1007/S00170-024-13954-5>
- Mifdal L, Guendouli EM, Dellagi S, Chelbi A. Production planning for sustainable dry machining production systems. *Management of Environmental Quality* 2025:1–21. <https://doi.org/10.1108/MEQ-03-2025-0200/1276506>
- Naqash MT, Aburamadan MH, Harireche O, Alkassem A, Farooq QU. The Potential of wind energy and design implications on wind farms in Saudi Arabia. *International Journal of Renewable Energy Development* 2021;10:839–56. <https://doi.org/10.14710/IJRED.2021.38238>
- Kaloi GS, Wang J, Baloch MH, Tahir S. Wind energy potential at Badin and Pasni Costal Line of Pakistan. *International Journal of Renewable Energy Development* 2017;6:103–10. <https://doi.org/10.14710/IJRED.6.2.103-110>
- Batablinlè L, Yessou-Gnouyarou K, Latévi L, Lorimpo K, Bazyomo S, Kpéli Easo-Ehanam T, et al. Future wind speed and energy potential in Togo for the period 2021-2040: Projections from CORDEX-Africa models. *International Journal of Renewable Energy Development* 2026;15:16–28. <https://doi.org/10.61435/IJRED.2026.61680>
- Renewable capacity statistics 2025 <https://www.irena.org/Publications/2025/Mar/Renewable-capacity-statistics-2025> (accessed May 30, 2025).
- Madvar MD, Ahmadi F, Shirmohammadi R, Aslani A. Forecasting of wind energy technology domains based on the technology life cycle approach. *Energy Reports* 2019;5:1236–48. <https://doi.org/10.1016/J.EGYR.2019.08.069>
- Gołębek M, Stefaniak B, Wójcik D, Rymarczyk T, Kłosowski G, Kulisz M. Ultrasonic beam-forming for enhanced wind turbine inspection and safety. *Advances in Science and Technology Research Journal* 2026;20:389–401. <https://doi.org/10.12913/22998624/215387>
- Kr Singh D, Kurien J, Villayamore A. Study and analysis of wind turbine gearbox lubrication failure and its mitigation process. *Mater Today Proc* 2021;44:3976–83. <https://doi.org/10.1016/J.MATPR.2020.10.047>
- Zou X, Zhang J, Chen J, Orozovic O, Xie X, Li J. Oil monitoring and fault pre-warning of wind turbine gearbox based on combined predicting method. *Sustainability* 2023;15. <https://doi.org/10.3390/su15043802>
- Najim AAD, Mifdal L, Dellagi S, Guendouli EM. Maintenance strategies integrating environmental impact for wind turbine gear trains. *AIP Conf Proc* 2026;3486:840001. <https://doi.org/10.1063/12.0042917>
- Transactions on Sustainable Energy - IEEE PES <https://ieeepes.org/publications/transactions-on-sustainable-energy/> (accessed May 30, 2025).
- Martinez et al 2022 https://www.researchgate.net/publication/364150328_Martinez_et_al_2022 (accessed May 30, 2025).
- Pulikollu R V, Erdman W, McLaughlin J, Alewine K, Sheng S, Bezner J. Wind turbine generator reliability analysis to reduce operations and maintenance (O&M) Costs 2023.
- Martins RC, Fernandes CMCG, Evaluation of

- bearing, gears and gearboxes performance with different wind turbine gear oils. *Friction* 2015 3:4 2015;3:275–86. <https://doi.org/10.1007/S40544-015-0094-2>
19. El-Naggar M, Sayed A, Elshahed M, EL-Shimy M. Optimal maintenance strategy of wind turbine subassemblies to improve the overall availability. *Ain Shams Engineering Journal* 2023;14. <https://doi.org/10.1016/j.asej.2023.102177>
20. Sheng S. Wind Turbine Gearbox Oil Filtration and Condition Monitoring (Presentation), NREL (National Renewable Energy Laboratory) 2015.
21. Executive summary – Renewables 2023 – Analysis – IEA. <https://www.iea.org/reports/renewables-2023/executive-summary> (accessed May 30, 2025).
22. Aafif Y, Chelbi A, Mifdal L, Dellagi S, Majdouline I. Optimal preventive maintenance strategies for a wind turbine gearbox. *Energy Reports* 2022;8:803–14. <https://doi.org/10.1016/J.EGYR.2022.07.084>
23. Aafif Y, Schutz J, Dellagi S, Chelbi A, Mifdal L. Integrated design and maintenance strategies for wind turbine gearboxes. *J Qual Maint Eng* 2024;30:521–39. <https://doi.org/10.1108/JQME-01-2024-0009>
24. Zheng R, Zhou Y, Zhang Y. Optimal preventive maintenance for wind turbines considering the effects of wind speed. *Wind Energy* 2020;23:1987–2003. <https://doi.org/10.1002/WE.2541>
25. Gasmi S, Love CE, Kahle W. A general repair, proportional-hazards, framework to model complex repairable systems. *IEEE Trans Reliab* 2003;52:26–32. <https://doi.org/10.1109/TR.2002.807850>
26. Martins JA, Romão EC. Catastrophic failure analysis of a wind turbine gearbox by the finite element method and fracture analysis. *Designs* 2025;9:4. <https://doi.org/10.3390/DESIGNS9010004>
27. Frederiksen RD, Bocewicz G, Nielsen P, Radzki G, Banaszak Z. A reference modelling approach for cost optimal maintenance for offshore wind farms. *Sustainability* 2024;16:8352. <https://doi.org/10.3390/SU16198352>
28. Environmental Prices Handbook 2024: EU27 version - CE Delft – EN. <https://cedelft.eu/publications/environmental-prices-handbook-2024-eu27-version/> (accessed February 17, 2026).
29. Onshore Wind - European Energy. <https://europeanenergy.com/green-solutions/onshore-wind/> (accessed May 22, 2026).
30. Gertsbakh I. Reliability theory: with applications to preventive maintenance 2000.
31. Turkyilmazoglu M, Alotaibi A. Prolonging the life time of underground ice ring formed in the period of the cryogenic gas storage. *European Journal of Mechanics - B/Fluids* 2026;115:204395. <https://doi.org/10.1016/J.EUROMECHFLU.2025.204395>