On the importance of assessing the operational context impact on maintenance management for life cycle cost of wind energy projects

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Abstract

The increasing demand for energy from renewable sources is entailing the development of technologies oriented to increase the profitability of such projects and thus the attractiveness for potential investors. Wind power constitutes one of the most relevant renewable energy sources; however, the costs of the wind farms associated with Operations & Maintenance are prominent along the life-cycle. This paper proposes an approach intended to reduce these costs and lower the Levelized Cost of Energy. In this context, it is presented an opportunistic maintenance policy based on more accurate reliability estimates of the wind turbines components. The reliability of the components is estimated through a model based on Artificial Neural Networks that dynamically calculates the impact of operational conditions on the failures of the wind turbines. The approach has been validated through a case study based on real field data which proposes a multi-objective optimization of the maintenance strategy for the life-cycle of a wind farm. The obtained results provide interesting findings from the perspective of wind farms investors, operators, and owners.

Keywords: Wind energy, Maintenance management, Life-cycle, Artificial Neural Network, Operational context

1. Introduction

The deteriorating environment along with global warming and the shortage of fossil fuels is a current issue rising pressure levels in governments around the world (and in the European Union, EU) [1]. These concerns are propitiating policies like binding targets on greenhouse emissions and are urging a shift towards renewable energy sources [2, 3]. The attention drawn by renewable energy has increased over the recent years nurturing an important growth that has been especially prominent in the wind energy sector [4, 5]. For instance, in the EU, wind power installed more capacity than any other form of power generation in 2018, rising from 12% in 2017 to 14% of covered energy demand [6]. However, to keep up with the increasing demand for renewable and affordable energy, the profitability of wind energy projects should be guaranteed by reducing the Levelized Cost of Energy (LCoE) to its minimum [7]. In the literature, a considerable amount of works aimed at reducing the LCoE by addressing the Operations and Maintenance costs (O&M), see for instance [8–10] among other works which will be later on reviewed.

The costs associated with O&M are known to be prominent [11, 12]. They may account for 12-30% of onshore wind farms (WFs) rising up to 32% in offshore projects [13, 14]. These costs are uncertain and influence the economic feasibility of wind energy projects; a potential investor will rather allocate resources in a project not susceptible to risks [15]. In this context, to increase the cost-effectiveness of WFs it is necessary to reduce the cost derived from O&M activities [16, 17]. Nonetheless, the problem of the present objective of reducing the LCoE by cutting the O&M costs is a two-fold challenge [18]. If maintenance activities are insufficient, the failure rate will increase lowering system's reliability. Otherwise, if maintenance activities are performed too often, the system's maintenance costs increase to undesirable levels [16]. Besides, it is necessary to minimize the lost energy production at down-times caused by failures or maintenance activities for the entire life-cycle [19], which oscillates around 20 years [20].

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1.1. Related works

Considering the data provided by the International Renewable Energy Agency and other works [21–23], maintenance activities account for a considerable fraction of the LCoE. On these grounds, the optimization of the O&M strategy acquires an important role [24]. The evolution of the models and approaches to optimize the maintenance strategy have evolved along with the steady technological development of the wind turbines (WTs) [7]. The determination of WFs operators for maximizing the profitability of the investment drives the development of new techniques and decision-support tools for optimal maintenance strategies [18]. The maintenance management works are mainly focused on two main objectives, the minimization of the costs whilst maximizing the availability of the WTs [7, 25].

In this context, it is essential to consider and combine physical and statistical models with technical know-how [26, 27]. The WFs operators are compelled to implant new techniques and decision-support tools for optimal maintenance strategies if they seek to maximize the profitability of their investment [18]. However, the reality nowadays is that the most applied strategies are corrective maintenance (CM) and time-based minor preventive maintenance (PM) [28, 29]. Additionally, Condition Based Maintenance (CBM) is a popular method which has proven to be cost-effective [30, 31] and it has been widely researched [32, 33]. Notwithstanding the effectiveness of CBM methods, it is crucial to consider in the maintenance strategy that WTs are multi-components systems constituted by subsystems with dependencies among them conditioning the adequacy of the maintenance strategy [34, 35]. These dependencies have been classified as (i) structural, when to perform maintenance actions on one system some actions are required on others [36]; (ii) economic, when performing simultaneous activities entails different costs than performing them separately [37] ; and (iii) stochastic, for those systems whose failure rates are not independent [38].

The most studied maintenance policies dealing with the aforementioned dependencies of the WTs are the opportunistic maintenance and group maintenance [34]. In the case of wind energy, the opportunistic maintenance is especially interesting since it takes advantage of short-term circumstances performing maintenance actions on non-failed systems when failure happened in another one [25]. Traditionally, this policy has not been implemented in the wind energy sector [39], however, some recent works have demonstrated its potential for reaping important benefits due to economic dependencies among WTs, e.g. [40–43].

Among the reviewed publications, the work of Besnard et al. [40] focuses on reducing maintenance and opportunity costs jointly performing corrective and preventive actions at low wind speed periods. The work of Tian et al. [39] is a step forward in an opportunistic maintenance policy supported by condition monitoring indicators, the work proposes a reliability threshold based on systems' remaining useful life. Ding and Tian [35] consider perfect and imperfect maintenance actions in their work, these actions are triggered by an age indicator based on the Mean Time To Failure of the WTs systems. Another important contribution of the same authors is an extension of the previous work [28] where they consider different age thresholds for systems belonging to failed and running WTs. It is interesting to consider as well the work of Atashgar and Abdollahzadeh [44] in which they address the two-fold challenge previously mentioned of reducing the costs and maximizing the energy production by implementing a multi-objective optimization of the opportunistic policy. And the work of Abdollahzadeh et al. [41] determines the optimal maintenance activities according to reliability thresholds calculated for each component. Finally, the work of Zhu et al. [43] is based on the study of three different maintenance strategies consisting of periodic routines, reactive maintenance, and opportunistic maintenance.

According to the reviewed works, it is important to notice that the decision of whether to maintain or to not maintain a system is taken according to different thresholds regarding the system's age, reliability or health condition. It is therefore essential to estimate those indicators as accurately as possible [19]. In particular, reliability indicators are estimated with traditional models which involve assumptions and simplifications [45]; these are the reason underlying the inability of the reliability models to properly describe the true behaviour of the systems [46]. An important assumption that induces considerable uncertainty is the consideration that the operational conditions and external factors influencing the assets are constant [47]. It has been already stated in the literature that more realistic reliability estimates, through a model integrating operational context information, will enable more effective and better-customized maintenance strategies [48].

There have been several authors who have studied the affection that the operational context may have on reliability engineering and thus on maintenance management. The operational context is explicitly taken into account in the work of Tang et al. [49] for cable failures, and so it is in the work of Lin et al. [50] for traction transformers. More specifically in the wind energy sector, the operational context effect has been considered to model the failure rate in WTs components [51]. Besides, the work of Mazidi et al. [52] explores how different operational parameters affect the stress condition of the WTs.

Whilst reviewing relevant related works, it is inevitable to encounter with research making use of the Proportional Hazards Model to relate the reliability of the components with operational parameters, e.g. [53, 54]. Another recurrent approach, which has attracted considerable attention lately (see [55]), is the application of Artificial Neural Networks (ANN) due to their capabilities to represent non-linear relationships [56], and also due to the fact that no "a priori" assumption of the model is required [57]. Several authors present interesting research works in the application of ANN to determine components reliability according to operational context; Al-Garni et al. [58] compare their performance against traditional Weibull regression model, Fink et al. [59] provides a time-series perspective to predict reliability through ANN and in Beg et al. [60] several ANN-based models are compared. Besides, in the specific context of wind energy the ANN methods have also proven very useful predicting reliability [33, 61]. It is especially interesting for the scope of the present research the work of Izquierdo et al. [48] where statistical models are combined with ANN methods to provide a novel model with dynamic capabilities.

1.2. Motivation and scientific contribution

It has been already stated the role that O&M activities have on the costs associated with a wind energy project and therefore, the importance of optimizing the maintenance management in such scenarios. The literature review shows evidence that the opportunistic policy has the potential of minimizing maintenance costs whilst maximizing energy production. However, this policy should be supported by estimates which undoubtedly must be accurate in order to ensure the effectiveness of the maintenance actions. Nevertheless, the traditional reliability models, which render the estimates that trigger maintenance actions, involve assumptions and simplifications which may jeopardize the accuracy of the estimates. An important assumption often found in traditional reliability models is the operation under constant working conditions, but recent works have provided tools, technologies, and methods capable of overcoming the aforementioned simplification. These works show how their proposals render better estimates than traditional reliability models. However, to the best of authors' knowledge, the benefits of the proposed models have not been integrated with the benefits of advanced maintenance policies such as opportunistic maintenance. The integration of opportunistic maintenance with models integrating the effect of working conditions on assets' reliability is a novel proposition that should be compared with the same policy supported by traditional reliability models to see if it provides any improvement. The research herein presented provides considerable improvements that will set the foundations to explore the literature gap of combining reliability models integrating the operational context with advanced maintenance policies.

Accordingly, the research herein presented aims at unifying an operational-context aware reliability model with an opportunistic maintenance policy. The present work contributes by demonstrating, through a case study in the wind energy sector, that a maintenance policy should be supported by accurate reliability estimates considering operational context; and vice versa, an advanced reliability model, which takes into account the operational context, provides an important potential if it is integrated within an opportunistic maintenance policy. The link-up of an opportunistic maintenance policy with a reliability model considering operational context is a novel proposal intended to provide less uncertainty for potential investors in wind energy projects for two reasons:

- The opportunistic maintenance policy is optimized according to a multi-objective logic, i.e. the costs are not optimized regardless of other business objectives, organizational goals such as the maximization of energy production are considered as well. Such multi-objective logic entails a trade-off among the objectives since they often imply competing scenarios. In such a context, the multi-objective optimization of the opportunistic policy provides a wide spectrum of solutions so different trade-offs may be considered and the one more suitable for the business goals selected.

- Since the reliability model assesses the WTs failure probability considering the operational context and the changes happening in it, the estimates are more accurate and reflect better the real failure behaviour of the different components which may be influenced by different parameters. The influence of the operational context is considered in the estimates that will trigger the maintenance actions and this fact is remarkable because it provides a universality character to the maintenance plans guaranteeing that the output of certain maintenance plans will not differ for different operational contexts.

The research presented consist of theoretical and practical foundations which gather and combine state-of-the-art contributions of the authors to the fields of reliability engineering, asset management and O&M in the wind energy sector. The scientific contribution of the work is the novel conjoint consideration of a recent opportunistic maintenance policy with a recent reliability model making use of ANN to consider the operational context. This combination is validated through a case study in which it is opposed to the traditional approach based on the Weibull reliability model. In order to provide a solid validation, the case study is based on real-field data and consists of extensive experimentation.

1.3. Overview

In order to provide a holistic and comprehensive overview of the contribution here presented, the classification framework proposed by Shafiee and Sørensen [3] is utilized. In the framework five classification criteria are decomposed into several categories, Table 1 contains the information positioning the research here presented according to the framework's classification criteria.

Table 1: Positioning of the research according to criteria in Shafiee and Sørensen [3]

Criteria	**Description**	**Present research positioning**
System configuration	The type of wind power asset and the level of system modelling	WT at component level.
Decision-making attribute	Planning horizon, the decision-maker and the availability of field data	Finite time horizon considering time as continuous variable. The decision-maker are considered to be the WF owners and operators. The data for the case study comes from field failure data.
System failure modelling	Include the type of damage/failure and the failure modelling approach	Both, minor and major failures are considered with grey-box models.
Optimization model	Optimality criterion and the solution technique	Two optimally criteria are considered, the minimization of cost and the maximization of power output. The solution technique is a multi-objective model.
Maintenance strategy	The maintenance policy and the effectiveness of the repair actions	The opportunistic maintenance is the chosen policy considering both imperfect and perfect repair effectiveness.

The remaining of the paper consists of several sections that cover the theoretical aspects, the case study and the conclusions withdrawn from the obtained results. Section 2 depicts the theoretical aspects covering the maintenance strategy and the calculation of the life-cycle costs. This section explains the opportunistic logic contemplated under a life-cycle perspective as opposed to current practices of optimizing the first years of the maintenance of the WTs. Then section 3 introduces the reliability model which will support the maintenance strategy, in the section the strengths of the model are detailed. The case study is described in section 4 which comprehends the description of the data utilized and the adopted approach along with the obtained results. Finally, section 5 comprises the key conclusions obtained from the study and its results.

2. Maintenance strategy

Considering the insights provided by the literature review, an opportunistic maintenance policy is proposed to make optimal maintenance decisions benefiting from the economic dependencies among the WTs' components. This maintenance strategy is intended to maximize the energy outcome of the WF whilst minimizing the costs not only for the first operating years but the whole life-cycle. The maintenance model has been adapted from recent literature, and while the interested readers are addressed to see the original model in [25], the essential aspects and characteristics of the proposed policy are hereunder presented.

The generic problem to be considered can be defined as a WF involving the maintenance of the WTs ($h = 1, 2, ..., H$) and their systems ($i = 1, 2, ..., N$) arranged in a serial disposition for failing purposes.

Each of the systems may fail in k different failure modes (FMs) entailing different consequences, and therefore requiring different CM actions ($k = 1, 2, ..., K$). A FM in this study is considered according to the definition introduced by Rausand and Høyland [62] and by Crespo [63] in which it is the manifestation of a failure entailing the termination of one or more functions. Besides, not only the WF managers can decide to preventively maintain the WTs' systems before failure occurs, but it is possible to perform PM at different levels ($j = 1, 2, ..., J$) depending on the restoration factor (q). If the preventive action restores the system to a state as-good-as-new it is considered as a perfect maintenance; on the contrary, if the PM action leaves the system in a better state than before but still worse than new, it is considered to be an imperfect maintenance being $j = 1$ for the present model the most imperfect maintenance and $j = J$ the perfect one (see [64] for further details).

The opportunistic maintenance is intended to address the previously described problem and it is optimized according to two main objectives, these objectives consider business implications and have a life-cycle perspective. For wind energy projects, it is essential to optimize the operational costs of the WF whilst also minimizing the lost energy production due to downtimes in the WTs. To mathematically describe these objectives it is important to define corrective and preventive costs, subject to the restoration effect (q). The corrective cost (CC) and the preventive cost (PC) can be seen in Equation 1 and Equation 2 respectively, they consider the materials and tools needed to perform the actions (c_{ik}^{c}, c_{ik}^{pr}), energy-production opportunity cost (c^{na}) and penalty cost (c^{p}) in case the supplied energy does not meet the committed level. Also, it is important to consider some binary decision variables associated to the model in order to understand the model: z_{hikt} determines if CM action k is performed in system i of WT h in period t, y_{hikjt} does the same with PM actions but the subindex j determines the type of preventive action, θ_t establishes if a maintenance team is correctively dispatched to the WF in period t and γ_t determines identical action but for a preventive dispatch.

$$CC = \sum_{h}\sum_{i}\sum_{k}\sum_{t} z_{hikt}\left[c_{ik}^{c}\left(q_{ik}^{c}\right)^{2} + m_{ik}^{c}\cdot GP_t\left(c^{na}+c^{p}\right)\right] \tag{1}$$

$$PC = \sum_{h}\sum_{i}\sum_{k}\sum_{j}\sum_{t} y_{hikjt}\left[c_{ik}^{pr}\left(q_{ikj}^{pr}\right)^{2} + m_{ikj}^{pr}\cdot GP_t\cdot c^{na}\right] \tag{2}$$

Another major cost element related to the costs-minimization objective is derived from the maintenance resources (MC) required to attend the WF, see Equation 3. They consider the number of maintenance teams (NT), their fixed costs (c^{team}), and the costs associated with their dispatches(c^{disp}) either preventively (γ_t) or correctively (θ_t).

$$MC = NT\cdot c^{team} + \sum_{t}(\gamma_t+\theta_t)\cdot c^{disp} \tag{3}$$

According to the second objective of the maintenance strategy optimization, the lost production (LP) is calculated as described in Equation 4. To calculate the lost in every period, the maintainability of CM and PM (m_{ik}^{c} and m_{ik}^{pr} respectively) are considered along with the power that would have been generated in that time (GP_t calculated as in [65]).

$$LP = \sum_{t} GP_t\left[\sum_{h}\sum_{i}\sum_{k} m_{ik}^{c}\cdot z_{hikt} + \sum_{h}\sum_{i}\sum_{k}\sum_{j} m_{ikj}^{pr}\cdot y_{hikjt}\right] \tag{4}$$

Having defined the components of the two objective functions of the optimization, it is vital to also define the constraints. The decision of whether preventively maintain or not a non-failed system is taken according to reliability thresholds: DRT_{ikt} is the threshold that compulsory dispatches a maintenance team to perform PM and SRT_{ikjt} is the threshold to determine certain PM action (according to j) once there is at least one maintenance team in the WF. Every SRT_j threshold must be higher than the DRT, and they should be sorted according to their level, being the lowest the most imperfect action threshold (see constraint in Equation 7). Another important constraint is the availability and working time of the maintenance teams defined as T^{wt} and regarded in Equation 8. Finally, it is important to consider in the model that only one maintenance action in the same WT is allowed for a single time period (see Equation

9). Therefore, having defined the terms comprising the objectives functions, as well as the ones in the constraints, the formulation of the model is expressed by the following equations, where k_a is the rate of the time value for money:

$$OF_{Opex} = min\left(([MC + CC + +PC] \cdot (1 + k_a)^{-t}\right) \tag{5}$$

$$OF_{LP} = min\,(LP) \tag{6}$$

S.T.

$$0 \leq DRT_{ikt} \leq SRT_{ik1t} \leq ... \leq SRT_{ikjt} \leq\leq ... \leq SRT_{ikJt} \leq 1 \; i\epsilon I, k\epsilon K, j\epsilon J; t\epsilon T \tag{7}$$

$$\sum_i \sum_k \sum_j m_{ikj}^{pr} \cdot y_{ikjt} + \sum_i \sum_k m_{ik}^{c} \cdot z_{ikt} \leq NT \cdot T^{wt} \quad \forall t\epsilon T \tag{8}$$

$$\sum_j y_{hikjt} + z_{hikt} \leq 1 \, h\epsilon H, i\epsilon I, k\epsilon K, t\epsilon T \tag{9}$$

$$z_{hikt}, y_{hikjt}\epsilon \{0, 1\} \; h\epsilon H, i\epsilon I, k\epsilon K, t\epsilon T, \forall j = 1, 2$$

3. Reliability model

The ultimate goal of the optimization process is to find the values of the reliability thresholds (i.e. DRT_{ikt} and SRT_{ikjt}) that maximizes the energy production and minimizes the maintenance costs. As the optimized thresholds will launch maintenance activities, it is vital to ensure that the estimates of components' reliability are as accurate as possible. Therefore, as stated by several authors mentioned in the literature review, it is required to integrate operational context information in the reliability models. To such aim, a dynamic ANN-based reliability model is adopted from the work by Izquierdo et al. [48]. The present model is characterized by a failure rate decomposed in two terms, a baseline hazard dependent on time and an exponential part in which the operational context variables are considered as inputs of an ANN. The mathematical formulation of the hazard function can be seen in Equation 10; the $h_0(t)$ term corresponds to the baseline hazard; and the neural network is denoted as the function $G(\mathbf{X}, \mathbf{W}, \mathbf{B})$ where $\mathbf{X}$ is the input covariates vector, $\mathbf{W}$ are the weights of the connections between the nodes and $\mathbf{B}$ collects the bias parameters of the ANN.

$$h(t, \mathbf{X}) = h_0(t) \cdot exp\,(G(\mathbf{X}, \mathbf{W}, \mathbf{B})) \tag{10}$$

The ANN embedded in the hazard function employs as activation function the hyperbolic tangent described by Equation 11, and the input values of the operational context are normalized through Equation 12. As the ANN is integrated into a statistical model, the traditional training methods are of no use in this case; however, in order to obtain the optimal weights ($\mathbf{W}$) and bias ($\mathbf{B}$) values, the concept of maximum partial likelihood (introduced by Cox [66]) is employed. The optimization consists of finding the values that maximize the partial likelihood (L) described by Equation 13 in which p are all the historical failure data. As the complex architecture of ANN involves numerous parameters and thus considerably complicates the optimization process, a genetic algorithm is employed in order to find the optimal weights ($\mathbf{W}$) and bias ($\mathbf{B}$).

$$g(x) = \frac{exp(x) - exp(-x)}{exp(x) + exp(-x)} \tag{11}$$

$$x_{norm} = \frac{2(x - x_{min})}{(x_{max} - x_{min})} - 1 \tag{12}$$

$$L = \prod_{i=1}^{p} \frac{exp(G(\mathbf{X_i}, \mathbf{W}, \mathbf{B}))}{\sum_{l\,\epsilon\,\mathbf{R}_i} exp(G(\mathbf{X}_l, \mathbf{W}, \mathbf{B}))} \tag{13}$$

Once the optimal parameters of the ANN have been obtained, if the baseline hazard rate is considered to follow a Weibull distribution, the reliability may be expressed by Equation 14 in which α is the scale parameter and β is the shape parameter. If the integration is solved for an asset operating with changes in the operational parameters, the reliability model is expressed by Equation 15 in which $\mathcal{C}_i$ is the integration constant for the different i operational contexts in which the asset works.

$$R(t, X_i) = exp\left(-\int \frac{\beta}{\alpha}\left(\frac{t}{\alpha}\right)^{\beta-1} exp(G(\mathbf{X}, \mathbf{W}, \mathbf{B}))dt\right) \tag{14}$$

$$R(t, X_i) = exp\left(-\left(\frac{t}{\alpha}\right)^{\gamma} exp(G(\mathbf{X_i}, \mathbf{W}, \mathbf{B})) + \mathcal{C}_i\right) \tag{15}$$

Paying special attention at the integration constant $\mathcal{C}_i$ and assuming that the reliability is a continuous function with a value of 1 at $t = 0$, i.e. no failure probability before start operating, the value of the constant can be described by Equation 16. It is important to notice that the value of the constant $\mathcal{C}_i \forall i \neq 0$, can be decomposed into three terms:

- $\left(\frac{t_i}{\alpha}\right)^{\gamma}$. It is reasonable to reckon that the changes in the operational context do not affect the asset equally along the span of its operating time. This term explains such logic, the affection that a change may have on the asset depends on its technical characteristics, thus the scale (α) and shape (β) parameters, and on the moment at which the changes happen (t_i).

- $(exp(G(\mathbf{X_i}, \mathbf{W}, \mathbf{B})) - exp(G(\mathbf{X_{i-1}}, \mathbf{W}, \mathbf{B}))$. The impact that an operational context change may have on an asset is going to depend on how different the new conditions are from the previous, such information is integrated into this term.

- $\mathcal{C}_{i-1}$. By the recurrence of taking into account its previous value, the model is integrating information from previous operational context changes. It means that the system's current probability of failure is also affected by the operational changes suffered in its past operating time.

$$\mathcal{C}_i = \begin{cases} 0 & \forall i = 0 \\ \left(\frac{t_i}{\alpha}\right)^{\gamma} (exp(G(\mathbf{X_i}, \mathbf{W}, \mathbf{B})) - exp(G(\mathbf{X_{i-1}}, \mathbf{W}, \mathbf{B}))) + \mathcal{C}_{i-1} & \forall i \neq 0 \end{cases} \tag{16}$$

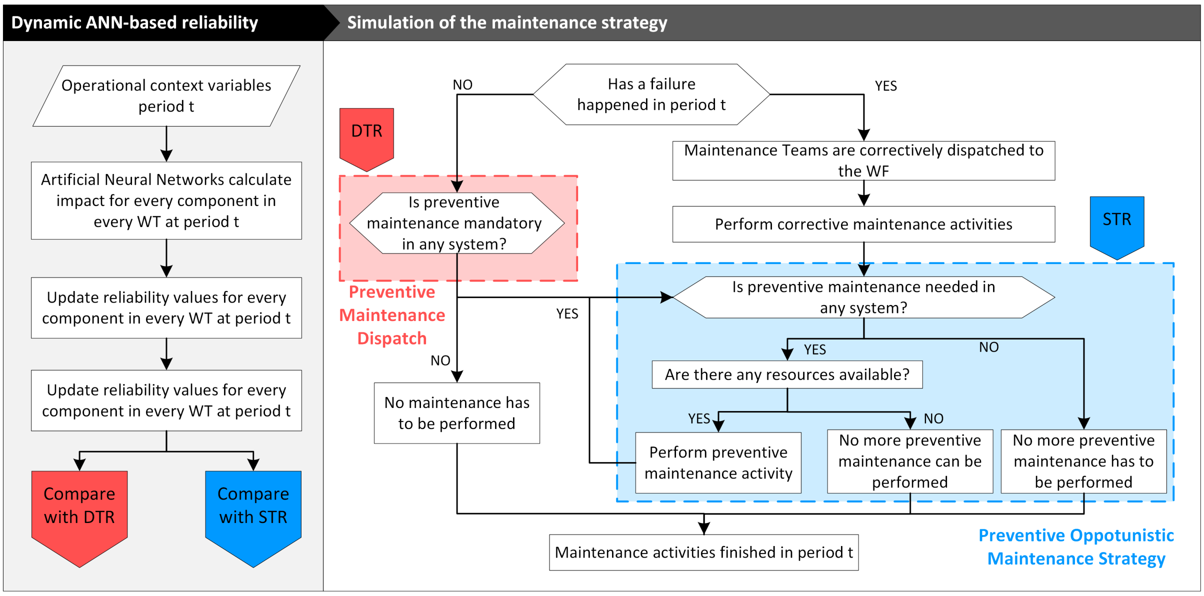
As can be seen, the model integrates the changes in the operational context, which are not specified but defined according to time periods allowing dynamic calculation of reliability in different time intervals, which don't have to be of the same length. Besides, by embedding into a statistical model the architecture of ANN it is possible to integrate information regarding interactions among operational context's variables and some other hidden phenomena without 'a priori' defining them.

4. Wind energy case study

To test if the integration of the operational context-aware reliability model with opportunistic maintenance policy provides a solid approach to maintenance management, a case study based on real field data is proposed. However, due to the stochastic processes entailed by maintenance management, it is difficult to adopt an analytical resolution method. Therefore a simulation-based is here presented since it has proven to effectively characterize the maintenance processes and its optimization [41, 42, 67]. The logic underlying the simulation is represented in the flowchart of Figure 1. It can be seen how the dynamic ANN-based reliability models calculate the reliability of the components in every period and then the values are compared with the opportunistic threshold to trigger maintenance actions if necessary.

Considering that the research pursues more than one objective, i.e. minimization of costs and lost energy production, a multi-objective algorithm must be implemented. To this aim, the Non-Sorted

Figure 1: Simulation chart



Genetic Algorithm II (NSGA-II) has been implemented as it has proven to be useful for providing high-quality non-dominated solutions on the Pareto front [19, 25, 68]. Accordingly, the optimal maintenance strategies will be obtained by the joint use of the simulation and the optimization. On the one hand, The simulation allows evaluating in every iteration of the NSGA-II algorithm the results of certain maintenance strategies in terms of cost key performance indicator (KPI) and energy lost KPI. Whilst, on the other hand, the optimization will guide the maintenance thresholds towards their optimal according to the NSGA-II logic.

Since the scope of this research is to demonstrate the added value provided by a reliability model with operational context information integrated into the maintenance policy, this scenario has been compared with one applying a traditional Weibull reliability model. Besides, this research is also intended to evidence that the optimization should be done considering the whole life-cycle of the project as opposed to current practices of optimizing the first 5-10 years of the project as a part of the warranty plans. Therefore, according to these aims the case study described in Figure 2 presents the optimization of 4 scenarios:

Scenario A - Weibull reliability model and 7 years optimization. In this scenario, a traditional two-parameter Weibull model is adjusted for the failure data of every FM of the WTs studied. Having the parameters of the Weibull models, the opportunistic policy is optimized for the first years of the WF operating time. Then it is evaluated how the optimal strategy for the 7 years behaves in a life-cycle, i.e. 20 years, perspective, obtaining several cost and energy lost KPIs for the different strategies which comprehend the Pareto-front.

Scenario B - Weibull reliability model and 20 years optimization. In this scenario, a Pareto front is obtained from the optimization of the maintenance strategy for 20 years. The reliability estimates triggering maintenance actions are calculated with the adjusted Weibull models for every FM.

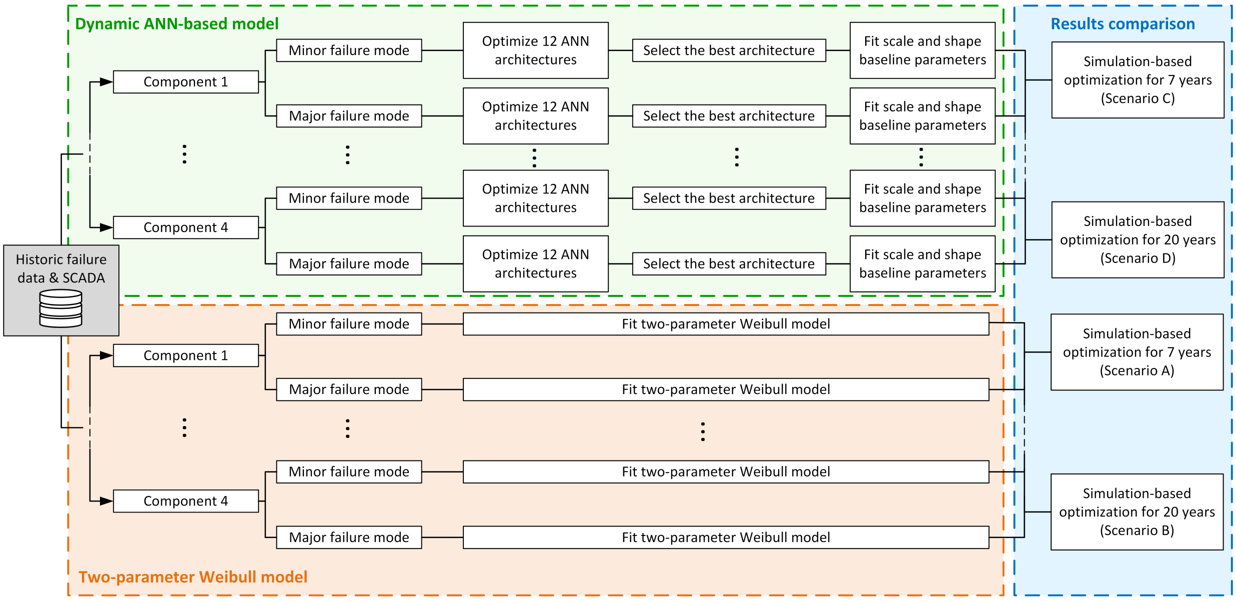
Scenario C - Dynamic ANN-based reliability model and 7 years optimization. In this scenario, a dynamic ANN-based reliability model is adjusted for every FM and then embedded in the simulation to optimize the maintenance for 7 years. Having optimized the reliability thresholds for 7 years, it is tested the output these thresholds render in a 20 years life period.

Scenario D - Dynamic ANN-based reliability model and 20 years optimization. In this scenario, the simulation is with the same models of Scenario C but optimizing the thresholds for 20 years ensuring that the maintenance policy is not optimal for first years of operating time but for the life-cycle of the project.

The comparison of the four scenarios will be later on presented. Firstly, the optimizations for the 7 years are compared (scenarios A and C) to see if in the short term the model integrating the operational context provides better solutions than the Weibull model. The strategies provided by these two optimizations then are projected in the long term to see their performance in spite of not being optimal. Then, the optimizations for 20 years (scenarios B and D) are compared among them and with the 20 years projections of the previous 7-years optimizations.

It is done so it can be seen how a life-cycle perspective provides better solutions even with a traditional reliability model (scenario B compared with scenario A). Then both are compared with a maintenance plan optimized for the early years but with a model integrating operational context information (scenario C compared with B and A). Finally, scenario D will be compared with the previous to see how the dynamic ANN-based model in a life-cycle perspective provides the best results in terms of costs and energy loss.

Figure 2: Case study procedure chart



4.1. Case description and data considerations

The case study presented in Figure 2 is based on real field data provided by a wind energy OEM and comes from over 300 onshore WTs of 1.67 megawatts(MW) which are operating in different locations in the north of Spain, and therefore they are exposed to multiple operational conditions. The field data comprises a period of over 12 years and includes two databases coming from the historic maintenance records and the SCADA information. The SCADA data contained information regarding the alarms and states of the WTs along with sensors information, and the maintenance records contained the carried maintenance activities with the corresponding associated costs. Both databases were combined by identifying the patterns of the failures in the alarms and states and linking them with the corresponding maintenance actions in order to build a single RAM (Reliability, Availability, and Maintainability) database containing the different Times Between Failure (TBFs), the associated costs and the operational conditions. The obtained RAM database was validated and contrasted with the know-how and opinion of experts in WTs operators and WTs OEM, and it is nowadays used to support data-driven decision-making processes.

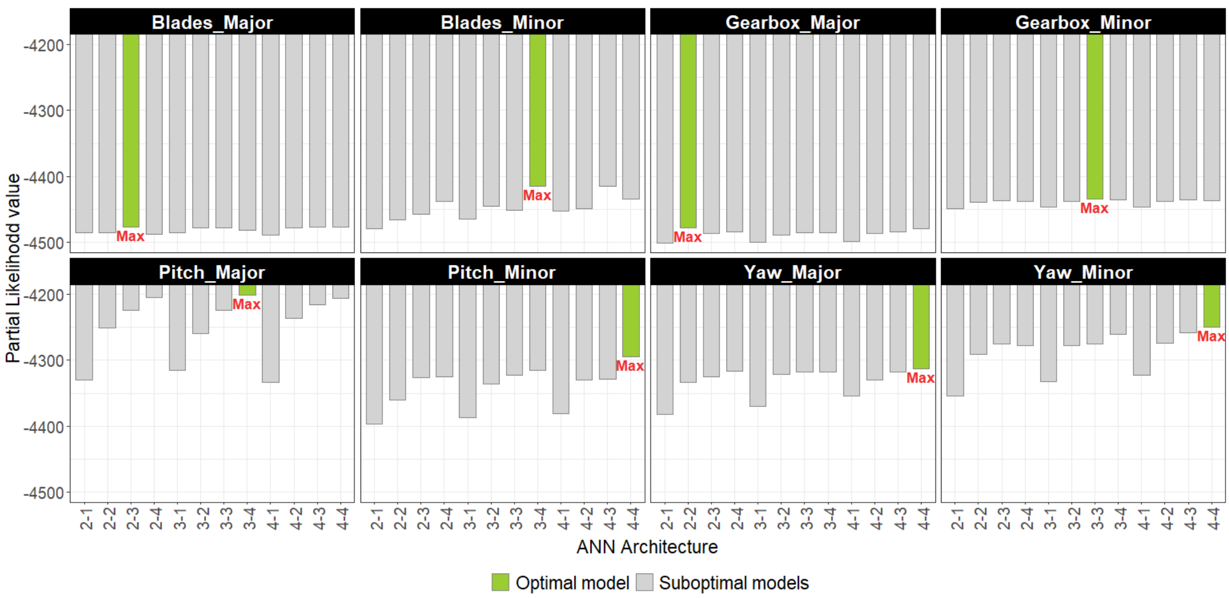
For the simulation, a WF consisting of 62 WTs is considered. Every WT consist of four main components (N=4) and each one of the components has minor and major failures (K=2). The considered components correspond to four critical systems from the maintenance perspective: gearbox, blades, yaw, and pitch. Therefore there are two FMs for every component, and for every of them it is considered perfect and imperfect maintenance levels with corresponding restoration factors of $q_{ik2}^{pr} = 1$ and $q_{ik1}^{pr} = 0.75$ respectively.

Regarding the cost structure, the costs considered in the simulation are those regarded as relevant to analyse the maintenance management from a life-cycle perspective. The cost of a maintenance team consisting of 2 workers is considered to be 800€/day, 105€/MWh as an opportunity cost and 35€/MWh as the penalization cost. Likewise, each component has its corresponding material cost for which the interested readers are addressed to [69]. The cost of PM is considered to be 30% lower than CM and a discount rate of 5% is considered for the annualized life-cycle cost analysis.

4.2. Dynamic ANN-based reliability models fitting

According to the reliability model description in Section 3, before embedding the models in the simulation it is necessary to select the optimal ANN architecture for the different FMs. To this aim, several architectures have been proposed and optimized, up to twelve different models have been fitted for every one of the FMs, each one of the models consisting of two hidden layers from 1 up to 4 neurons in each layer. The maximization of the value obtained for the partial likelihood has been the criterion adopted as a basis to choose the most appropriate configuration of hidden layers and nodes. In Figure 3, it can be seen for every FM the obtained values of the partial likelihood in every model with a specific ANN architecture. As it can be seen in Figure 3, in most of the cases, even the simpler models of ANN are able to consider the impact the operational context considering that in most of the failure modes every configuration reaches similar values of the partial likelihood value and being that the reason for not increasing the complexity of the neural networks. Nonetheless, from these values, the optimal dynamic ANN-based models are selected to be embedded in every WT of the simulation.

Figure 3: Partial likelihood values for all ANN models



Once the best architectures of the ANNs in the models have been selected for every FM, with their corresponding parameters optimized, the following step is to fit the baseline parameters. Therefore for every FM, there is one dynamic ANN-based reliability model with a specific ANN architecture and specific shape parameters, this information is detailed in Table 2. These will be the models that are embedded in the simulation, for every agent corresponding to a WT eight ANNs are calculating the daily impact of operational context on each FM's probability of failure.

Table 2: Optimal Dynamic ANN-based models details for every FM

Failure Mode	ANN Architecture	ANN Number of parameters	Partial Likelihood	Shape parameter	Scale Parameter
Blades Major	2-3	21	-4476.486	6.27	3259.3
Blades Minor	3-4	30	-4414.759	3.28	3410.4
Gearbox Major	2-2	15	-4477.709	7.53	3122.8
Gearbox Minor	3-3	28	-4434.685	5.42	1148.4
Pitch Major	3-4	33	-4201.663	8.41	604.4
Pitch Minor	4-4	37	-4294.931	4.99	408.9
Yaw Major	4-4	41	-4313.041	8.11	1707.6
Yaw Minor	4-4	37	-4250.076	5.30	1750.8

4.3. Simulation results

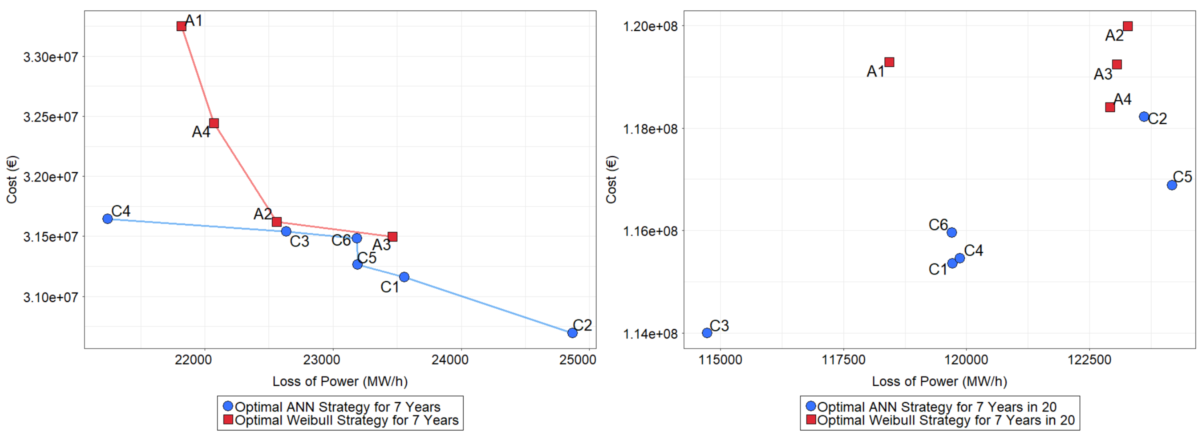
With the dynamic ANN-based reliability models adjusted, it is possible to optimize the opportunistic maintenance strategies according to the two previously defined objectives, minimization of costs and lost energy production. The optimization for each of the scenarios previously defined will provide a set of solutions consisting of maintenance thresholds which lead to a Pareto front of the solutions trade-off among the two competing objectives. These two competing objectives, as it can be seen in Figures 4 and 5, are the Cost (in €) and the Loss of Power (in Mw/h). The costs considered are the ones stated before in subsection 4.1 and the Loss of Power indicator measures the production of energy lost due to downtime in the WTs caused by failures or maintenance activities. The Loss of Power is calculated according to the average wind speed in each period following the method proposed in [25, 65]. Accordingly, Figures 4 and 5 represent the possible trade-off of these objectives as a Pareto front of the maintenance strategy optimization for 7 and 20 years correspondingly.

Firstly, the scenarios for 7 years have been optimized and represented in Figure 4, in that period the traditional Weibull reliability and the dynamic ANN-based reliability provide sets of 4 and 6 optimal solutions respectively as it can be seen in Figure 4. As it was expected, in a 7 years projection of the optimal strategies using both reliability models, the dynamic ANN-based model provides better results (see Figure 4a). Besides, not only the results are better, but the model integrating the operational context allows to offer levels in terms of costs and lost energy levels otherwise unreachable for traditional reliability models (see strategies C2 and C4 in Figure 4a).

However, to explore how the strategies optimized for 7 years perform in a life-cycle scenario, they have been projected to 20 years (see Figure 4b). The obtained results for the 20 years projections have been surprising, yet they provide enlightening findings. As it can be observed in Figure 4b, the strategies following a Weibull model still provide worse results in general than the ones of the dynamic ANN-based reliability, but for certain strategies the results are quite similar (see strategies A4 and C2 in Figure 4b). The remarkable fact underlying this finding is that an optimal strategy for a different span misbehaves in a different time scenario in spite of relying on better the reliability estimates.

Figure 4: Optimal Strategies for 7 years

(a) 7years projection (b) 20 years projection*



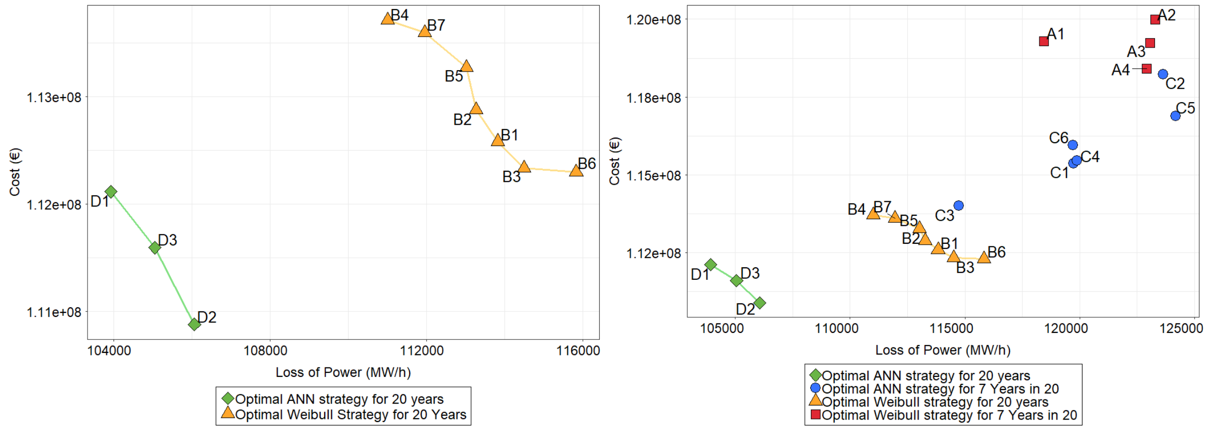
* It is important to note that in Figure 4b the dots are not connected because as the optimal strategies have been projected to a 20 years scenario they are not optimal and thus, they do not conform a Pareto front.

Turning now to scenarios B and D represented in Figure 5, where the optimization of the opportunistic maintenance strategy for 20 years is considered with both reliability models, Weibull model and dynamic ANN-based model respectively. It can be seen how the optimization for the Weibull model provides a set of 7 solutions whilst the optimization for the dynamic ANN-based model provides a set of 3 solutions. It is important to observe the results in Figure 5a, as it happened in the 7 years scenarios, the solutions of the dynamic ANN-based model reach levels of costs and lost energy production which are unreachable for the Weibull model. In Figure 5b it can be seen that the optimization for 20 years performs considerably better.

As it can be seen in both scenarios, 7 years and 20 years, the model based on ANN renders better reliability estimates resulting in improved strategies in term of costs and loss of power. By further exploration of the reliability estimates of both models, the Weibull model and the dynamic reliability based on ANN, the better results of the latter model can be explained by two reasons. In the first place, as the model based on ANN considers the operational conditions, it takes into account both, low and high-stress periods and influences the calculation of the reliability accordingly ensuring that the maintenance

Figure 5: Optimal Strategies for 20 years

(a) Pareto fronts for 20 years (b) All scenarios comparison for 20 years*



* It is important to note that in Figure 5b the dots of strategies C and A are not connected because as the optimal strategies have been projected to a 20 years scenario they are not optimal and thus, they do not conform a Pareto front.

actions are actually performed in the optimal threshold, however, the Weibull model only considers the operational time rendering less accurate estimates. The second reason behind the better performance of the ANN model is derived from the first reason and the effect of imperfect maintenance since the Weibull model provides inaccurate estimates, the effect of the imperfect maintenance action cannot be properly addressed (i.e. if the state before the maintenance is not properly assessed, the state after will hardly be) and this provokes the error in the estimates to widen and propagate over time.

Besides, a remarkable finding is how the optimal strategies for dynamic ANN-model yield substantially better results in a 20 years scenario in comparison with the Pareto front in the 7 years (see Figure 4a). The reason leading to these differences to be more significant in a 20 years scenario is the fact that inaccurate estimates accumulate undue costs for a longer span. The conjoint application of opportunistic maintenance and the dynamic ANN-based model ensures that the maintenance actions are performed in the most suitable moment. Besides, Figure 5b shows evidence of the importance of optimizing the maintenance strategy for the life-cycle since the 20-years optimized strategy based on a Weibull model outperforms the 7-years optimal strategies based on the dynamic ANN-based model.

5. Concluding remarks

The research presented in the paper was intended to provide an approach to reduce not only the O&M costs of wind energy projects but the associated uncertainty as well, in order to increase the attractiveness of wind energy projects for possible investors. The approach proposes to optimize the maintenance strategy according to several objectives by means of two state-of-the-art technologies: i) an opportunistic maintenance policy which allows considering the economic dependencies of the WTs performing maintenance actions in the most suitable moments; and ii) more accurate reliability estimates of the WTs' components through a dynamic model considering operational context through the capabilities of ANN. Besides, the research also intended to provide a scientific basis to confirm that maintenance optimizations for the early years of the WFs are misaligned with the best strategies for the life-cycle.

The proposed approach has been validated with a case study that is based on real-field data and consists of intensive experimentation. Thought the case-study validation, interesting results have been presented, these results entail relevant conclusions from the research and the practical perspectives. It has been seen how the integration of the opportunistic maintenance with the dynamic ANN-based model provides the best results in the long term when the strategy has been optimized for the life-cycle. Not merely does it provide the best results, but this conjunction of technologies enables to reach a wider solutions space and therefore offers in terms of costs and availability otherwise unreachable. Besides, the importance of optimizing the strategy for a life-cycle span has been also proven, since 20-years optimized strategy based on traditional reliability estimates shows better results than the one optimized for a shorter period but with better estimates. And more importantly, by considering the operational context in the reliability estimates the definition of the optimal maintenance strategy is disentangled of the working environment and therefore acquires a more universal character whilst maintaining its optimality nature.

Nonetheless, the work and the case study give rise to interesting questions and thus promising lines to further develop the research. The current application comprises a WF in which every turbine is identical to each other; however in practice, this is not always true, so it would be interesting to explore the problem when several WT models are considered. Moreover, it would be appealing to study the performance of optimal maintenance strategies for different sizes of WFs. The future research lines show evidence that there is still margin to keep increasing profitability not only of wind energy projects but other energy sources as well if these technologies are extrapolated.

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