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Item-based Reliability-centred Life-Cycle Costing using Monte Carlo Simulation

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Abstract. This paper presents a time-sequential probabilistic simulation model for the detailed design of maintenance strategies for turbine critical items. The term *item* shall refer to any part, component, device, subsystem, or functional unit of a wind turbine that can be individually described and considered. The model enables wind farm operators and turbine manufactures to find the most cost-effective maintenance strategy for each turbine critical item. Cost optimizations are realized through a better adaptation of the maintenance strategy to the item-specific failure modes, degradation processes, failure detection capabilities and the given operational configuration of the wind farm. Based on a time-sequential Monte Carlo simulation technique, the maintenance activities at turbine level are simulated over the windfarm's operational lifetime, considering correlations between the stochastic variables. The results of the Monte Carlo simulation are evaluated using statistical means, thereby, determining the optimal maintenance strategy and associated parameters. The developed model is implemented as a Python application and equally applicable for onshore and offshore windfarms.

1. Introduction

In recent decades, wind energy has evolved from a niche to a mainstream energy source. This development has been made possible largely by reducing investment and operating costs while increasing the reliability and availability of wind farms. Further savings potential exists through better adaptation of the item-specific maintenance strategy to the item-specific failure behavior.

The objective of this paper is to develop a model to find the most cost-effective maintenance strategy for each turbine critical item without changing the operational configuration of the wind farm, i.e., the maritime logistic concept (type and number of vessels, service harbor, spare part supply) and crew rotation concept is assumed to be a constant framework condition. Therefore, the application of the model is particularly suitable for two use cases:

1. For operators to improve the maintenance strategy for turbine critical items of a wind farm in operation with established operational configuration
2. For turbine manufacturer to develop site-independent item-specific maintenance strategies for upcoming turbines



In both use cases, the result of the maintenance optimization could be a change in the maintenance type applied to the item (e.g., change from time-based to predictive maintenance or run-to-failure), an investment in additional condition monitoring systems or a change in the selected or preferred item supplier. Furthermore, due to the modelling of the interactions between item degradation, maintenance actions and failure occurrences, the model can assist in evaluating the cost-effectiveness of investments in predictive and non-predictive inspection technologies with associated probabilities of detection.

Considering these use cases, the purpose of the developed model differs strongly from operation and maintenance (O&M) simulation models, which aim to support estimating lifetime OPEX in the early development phase, forecasting asset availability, improving long-term logistic planning, and understanding interdependencies in any uncertainties. A list of these models can be found in [1-2] with concrete models described in [3-6] and commercially available models described in [7]. Instead, the developed model shall support the design of maintenance strategies for turbine critical items in more detail. Turbine critical items are items with a high criticality score when analyzed using a systematic failure mode effects and criticality analysis (FMECA) as described in [8].

The model contributes to closing the research gap described in [2] of maintenance optimization models incorporating all information regarding item reliability and failure behavior (e.g., modelling up to four failure modes per item with Weibull distributed time-to-failures, item degradations and failure detection capabilities) and clearly quantifying the item-specific net present value (NPV) and LCoE contribution on the overall performance of the windfarm. The results from [9] confirm the high importance of adequately incorporating failure distributions in addition to the absolute reliability figures in future research. Therefore, the developed model focuses on simulating the interactions between failure propagation, maintenance actions and failure occurrence in the time-domain while limiting other sources of uncertainty like weather dependent accessibility and logistics availability to stochastic input variables (e.g., lead time). These limitations imply, that wind farm specific system effects such as vessel, personnel and spare part logistics with limited and shared maintenance resources have been neglected, i.e., these resources are always considered available with stochastically distributed lead times.

Within the model, degradation is not explicitly modeled (degradation models to predict degradation of degradation variables such as length of cracks or thickness of brake pads based on CMB inspections as presented in [10]), but implicitly using detection functions and functions to adequately define the item-specific P-F interval and remaining useful life. To quantify the incremental net present value (NPV) on the total performance of the wind farm, the item-specific contribution to the lost revenues as well as the capital cost and cost item-specific cost escalation rates are considered.

1.1. Model Requirements

The model aims to optimize the maintenance strategy of turbine critical items. Thus, advanced mixture Weibull and Weibull competing risk models shall be implemented to define failure characteristics of a specific item with several failure modes. The time between the potential failure detection and functional failure, defined as the P-F interval [8], shall be implemented as a stochastic variable per failure mode and under consideration of the used condition monitoring system, since the interval is even different from individual item to individual item within an item population with shared failure mode. All relevant maintenance types according to EN 13306 shall be included, i.e., immediate corrective maintenance (ICM) for corrective maintenance types and predetermined preventive maintenance (PPM) as well as condition-based maintenance (CBM) for preventive maintenance types. For condition-based maintenance the actions of CBM inspection (CBMI) and CBM replacement (CBMR) are distinguished as well as the CBM model as being either predictive or non-predictive. While a predictive CBM model uses current and prognostic information to plan the CBMR, a non-predictive CBM model uses only current information. The CBMI might either be executed as in-person or online condition monitoring. The CBMR shall be based on predictive or non-predictive capabilities. The costs per single replacement shall depend on response time, time in turbine, required number and workload of technicians, share of downtime caused, logistic overheads, material, consumables and lost revenue. As the operational configuration of the windfarm is not changed, marginal cost rates shall be assumed, i.e., the change in

the total cost on windfarm level that arises when the quantity of corrective or preventive maintenance actions is increased or reduced by one unit.

The model shall be able to accurately replicate reality in terms of maintenance execution, regardless of the combination and number of maintenance types included in one strategy. The execution of a CMBR shall depend on the success of the CBMI. The detection probability shall be a definable power function of the P-F interval. The start of the CBMR shall depend on a CBMR lead time under consideration of a life-margin to account for uncertainty in prediction. The term *life-margin* should be understood as the time interval between the planned replacement and the functional failure in case the component had not been replaced, expressed as a percentage of the P-F interval.

The calculation of strategy efficiency metrics is necessary to compare strategies and identify the optimal decision parameter. The calculation shall be based on the executed maintenance events as response to the failure events. To account for the time of the event occurrence, the LCC calculations must be stated in net present value (NPV) figures. Thus, general economic factors as discount factors, derived from Weighted Average Cost of Capital (WACC) and inflation rates need to be included [11]. Input parameters for which probability distributions are specified shall be treated as stochastic variables, where possible, throughout the simulation. The user must be able to select a sufficiently small time discretization to simulate fast failing elements such as UPS (uninterruptible power supply) batteries. Correlation between stochastic variables (described by a probability distribution) shall be specifiable. The simulation-based optimisation shall be based on altering decision variables (e.g., choice of maintenance type, predetermined replacement interval, inspection start, inspection interval) to assess the impact on the strategy efficiency metrics.

1.2. Life Cycle Cost

In the context of this paper, LCC is understood as the costs associated with maintaining a specific turbine function over the lifetime of the turbine, including initial investment and decommissioning costs. It is, therefore, possible that an item (e.g., hydraulic hose) is replaced several times over the lifetime of the turbine to guarantee the next higher system's functionality (e.g., hydraulic system).

1.3. Net Present Value

The LCCs of different maintenance strategies that aim to maintain an item's function are calculated as the net present value (NPV). Thus, maintenance strategies can be compared, and the time value of money is captured. The NPV is a single value and is calculated by adding the present values (PV) of expected future cash flows and the CAPEX as initial expenditure. Future cash flows can be negative (expenditure) or positive (revenue). Thus, the NPV can also be negative or positive [12]. The preferred maintenance strategies maximise a positive NPV (if the revenue share of the item under consideration is known) or minimize a negative NPV (which occurs when only an item's expenditure is considered as the contribution of this item might be unknown).

1.4. Model Conception

The design of the model concept is based on the model requirements. To account for the uncertain stochastic elements, such as item lifetimes, failure modes or P-F intervals, a time-sequential Monte Carlo simulation is implemented. The structure of the concept is illustrated in Figure 1. The user can enter all required input data through an GUI and select any of the program buttons to start a test run, full simulation, or a case handling activity.

The core calculation blocks are the 1. *Item Generation*, 2. *Maintenance Execution*, and 3. *LCC Calculation* blocks. Those three blocks are performed as separate functions. The Monte Carlo simulation (inner loop) and the loop over altering operational parameters (e.g., maintenance intervals) and multiple cases (outer loop) are implemented as further functions. The generation of the output graphs is performed in the postprocessing.

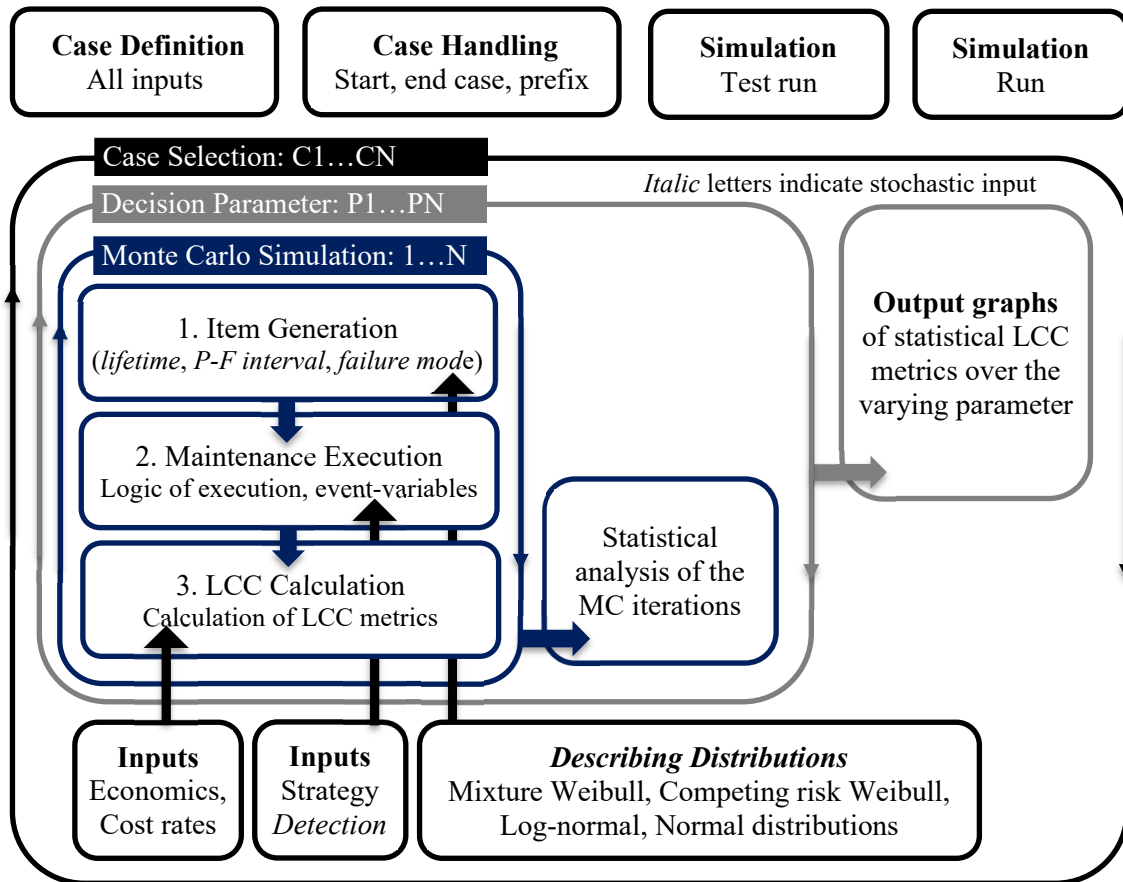


Figure 1: Structure of the LCC model with calculation steps and main in- and outputs

1.5. Correlated Random Numbers

All probability inputs can be correlated to each other to simulate the physics of the failure. At the current state, the item lifetimes (mixture Weibull distribution or competing risk Weibull model), P-F intervals (Normal distribution), repair times (lognormal distribution) and response times (two parameter Weibull) can be correlated using correlated random numbers. The generation of correlated random numbers is performed in the following steps [13]:

1. A set of standard normally distributed uncorrelated numbers is created (mean $\mu = 0$ and standard deviation $\sigma = 1$).
2. Cholesky decomposition is applied on the correlation matrix and the row vector of standard normally distributed uncorrelated random numbers is multiplied with the upper triangular matrix A^T to obtain a series of standard normally distributed correlated random numbers.
3. Uniformly distributed correlated random numbers between 0 and 1 are obtained by calculating the CDF of the standard normally distributed correlated random numbers.

1.6. Monte Carlo Simulation

As the inputs for the maintenance LCC analysis are also partly stochastic in nature (stochastic variables generated from describing probability distributions) and since a renewal process is considered and not a non-repairable population (with the chance of a single item failing several times over the lifetime of the turbine), a purely analytical solution is not possible. Instead, a stochastic solution is used by the application of the *Monte Carlo method*.

The advantage of the Monte Carlo (MC) method is its simple structure: in essence a deterministic computation with random variables as inputs is repeated N times, with each computation being performed independently of each other [14]. The discrete (lifetimes) and non-discrete (detectability) random variables are generated from probability distributions describing the variables. The results of all deterministic computations are thereafter evaluated using statistical means. Thus, the *Monte Carlo method* is particularly suitable for generating statistical mean values of statistically distributed quantities and for combining probability functions:

$$\bar{X} = \frac{1}{N} \sum_{i=1}^N X_i(x_{1i}, x_{2i} \dots x_{ni}) \quad (1)$$

with:

- N : Number of iterations
- x_{xi} : Discrete random variable for single iteration i
- X_i : Value of interest := {LCC, LCoE, Downtime, Lost Profit, Number of Activities}

2. Simulation Sequence

The Monte Carlo simulation process for the reliability-centred life-cycle costing is described in the following paragraphs for a single computation i .

2.1. Item Generation

Each simulation starts with the generation of a set of items, representing the initially installed item and those available for replacement. Three main characteristics are needed to be generated per item: failure mode, lifetime, and the corresponding P-F. For each characteristic, a random number is used. If correlation have been defined, correlated random numbers are used instead.

The failure mode is determined based on a correlated or uncorrelated random number and the mapped failure mode (mapped on intervals in the uniform distribution).

In the second step, the lifetime (also known as time-to-failure, TTF) is generated based on the inverse function of the cumulative distribution function (CDF) of the Weibull function. The cumulative distribution function (CDF) of the Weibull distribution describes the unreliability $F(t)$ of an item (i.e., the probability that an item will fail until time t) or – formulated strictly mathematically – the probability that the real-valued random variable T (here lifetimes) takes a value less than or equal to t and is given as [15]:

$$P(T < t) = F(t) = 1 - e^{-\left(\frac{t}{\eta}\right)^\beta}, \quad t > 0 \quad (2)$$

with t being any number larger than zero and P being the notation for probability. The random variable T is continuous (i.e., non-discrete) as the lifetime of an item has an infinite number of outcomes (any positive, real number).

The parameter β of the CDF describes the *physics of failure* (i.e., the failure pattern) and determines the shape of the distribution. It is also known as the slope parameter as the value of β is equal to the slope of the regressed line in a probability plot. To generate the lifetimes, the CDF is solved for the independent variable t and $F(t)$ is replaced by p as being the random or quasi random number:

$$t_i = \eta \left(-\ln(1 - p_i) \right)^{\frac{1}{\beta}}, \quad t > 0 \quad (3)$$

with:

- β : shape parameter
- η : scale parameter

The parameter η is called the *scale* parameter as it stretches or contracts the failure distribution along the age axis (i.e., determines *scale* of the distribution). Thus, the speed of the failure evolution in the field is described by the scale parameter. The larger the η , the slower the *Failure Rate*. Lastly, η is also known as the characteristic life as it is the point in time when 63.21% of the items have failed. The derivation of this property is simply given as $F(\eta) = 1 - e^{-1} = 63.21\%$ and can be read from the Figure 2 with shape parameters of 0.5 (Infant mortality), 1 (Random), 2 (Premature serial failure) and 3 (Wear-out).

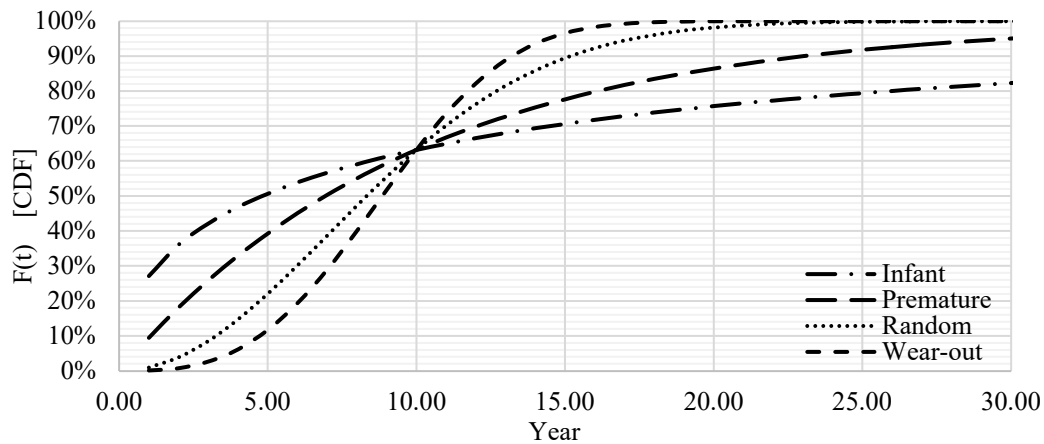


Figure 2: CDF of the Weibull distribution for differently shaped parameters¹

Lastly, the third item property, the P-F interval is generated from the P-F interval distribution that belongs to the specific failure mode. The number of generated items in each iteration step of the Monte Carlo simulation equals the number of time steps and is thus dependent on the chosen time discretization (year vs. month) and lifetime of the turbine.

2.2. Maintenance Execution

After the items are generated in the first block, maintenance activities are executed according to the chosen maintenance strategy and the occurring failures. Up to four different maintenance strategies can be chosen and tested. All four strategies are explained separately below:

2.2.1 PPM & ICM. An interval-based predetermined preventive maintenance strategy (PPM) is still applied frequently for items with a rapid wear-out failure mode ($\beta > 3$). Once the interval is reached, the item is replaced, regardless of its age or history. If a generated item has a lifetime that is less than the specified interval length, an immediate corrective maintenance (ICM) activity is performed as soon as the item fails. Still, at the next fixed interval, the item will be replaced again, independent of its age. Thus, if a PPM interval of 7 years is defined and the initial item installed only has a lifetime of 5 years, a ICM activity will be executed in year 5 and additionally a PPM activity in year 7. This shall reflect reality, as for wear-out parts such as hydraulic hoses or UPS batteries, often no age-based differentiation is performed, or no item-individual age tracking is used.

2.2.2 CBM & ICM. The CBM strategy can either be predictive or non-predictive. If a non-predictive CBM is chosen, an ok/not-ok check is performed during the CBM inspection. The item is replaced immediately if the condition is found to be not-ok (i.e., if the asset condition is found to be within the P-F interval). If no inspection takes place during the P-F interval or if the failure is not detected

(according to the evaluation of the detectability function), an ICM activity is performed as soon as the functional failure appears.

For Predictive CBM, the CBMR could be performed latest possible, i.e., if a potential failure is detected, a CBMR is scheduled just a life-margin + lead time before the failure would occur. Alternatively, the CBMR could be performed annually, i.e., if a potential failure is detected during an annual service, a CBMR could be either performed directly or in the latest annual service possible.

2.2.3 PPM & CBM & ICM. This strategy combines the PPM and CBM strategy. As example, an item might be inspected every second year and replaced if a failure is detected by the CMBI. Additionally, independent of the condition, the item is replaced every tenth year. The constant replacement after ten years could be necessary due to regulatory requirements or might be economical beneficial due to a rapid wear-out pattern arising.

2.2.4 RTF only. This strategy reflects a replace-on-failure strategy, also known as run-to-failure (RTF). No preventive maintenance is performed. Instead, the item is only replaced on a corrective basis if it fails. This strategy might be the most cost-effective strategy for many reliable items. ICM is the natural default if no other strategy is defined. For items with a dominant random failure mode (P-F Interval towards zero), a preventive maintenance strategy could become unsuitable as well. ICM could also be the best solution for many items with early wear-out pattern and mechanism-related expensive condition assessments.

2.3. LCC-Calculation

In the third step of the simulation sequence, five different *strategy-efficiency metrics* (*Life-cycle costs, LCoE, Downtime, Lost profit, Number of Activities*) are calculated based on the executed maintenance events. After completion of the simulation for one decision parameter (e.g. $PDM_{Interval} = 7 \text{ years}$), the statistical metrics of the five *strategy-efficiency metrics* are calculated and plotted. Once the set of decision parameters (e.g., 7 to 13 step 1) of a single case has been calculated, associated graphs illustrating the strategy-efficiency metrics over the varying decision parameter (x-axis) are generated.

2.3.1 LCC [NPV in €]. The LCC of the specific maintenance strategy is given as net present value (NPV) figure. The NPV is the sum of all predicted discounted nominal cash flows (i.e., inflated) of maintenance actions associated with this item over the lifetime of the turbine (e.g., 25/30 years). Through the net present value, it is possible to take a holistic view of the cost of a maintenance strategy and compare strategies. The LCC can be calculated in two ways:

1. $LCC_i(MC)$: Only the direct maintenance costs (MC) are included
2. $LCC_i(TC)$: Total costs (TC) as the sum of MC and lost profit (LP) to account for downtime induced lost profit by the considered item.

The LCC for a single Monte Carlo iteration i is defined in this paper as:

$$\begin{aligned}
 LCC_i(CR) = & \underbrace{\frac{CAPEX_0}{CAPEX}}_{CAPEX} + \underbrace{CR_{ICM_0} \sum_{t=1}^n e_{ICM}(t, x_1) R^t}_{LCC_{ICM}} + \underbrace{CR_{PDM_0} \sum_{t=1}^{n-1} e_{PPM}(t, x_1) R^t}_{LCC_{PDM}} \\
 & + \underbrace{CR_{CBMR_0} \sum_{t=1}^n e_{CBMR}(t, x_1, x_2, x_3) R^t}_{LCC_{CBMR}} + \underbrace{CR_{CBMI_0} \sum_{t=1}^{n-1} e_{CBMI}(t) R^t}_{LCC_{CBMI}} + \underbrace{DECEX_0 R^n}_{DECEX}
 \end{aligned} \quad (4)$$

with:

- n : Windfarm's lifetime (usually 20, 25, or 30 years)
- $R = (1 + \Pi) \cdot (1 + DR)^{-1}$
- DR : Discount rate (measured in percent)
- Π : Rate of inflation (measured in percent)
- x_1 : Item lifetime (stochastic variable)
- x_2 : P-F interval (stochastic variable)
- x_3 : Detection probability (function of x_{2i} .)
- e : Binary event-variable with $e = \{0,1\}$, here single outcomes
- CR : Cost rate per event with $CR = \{MC, TC\}$
 - MC : Maintenance costs
 - TC : Total costs with $TC = MC + LP$, LP : Lost profit

As PPM and CBMI are not performed in the last year of a windfarm's life, the summation ends at $t = (n - 1)$ for these maintenance types. If, for an installed item, the maintenance strategy shall be optimised, CAPEX and DECEX could be set to zero (unless there are strategy-specific CAPEX). The binary event-variables e_i have the states $\{0,1\}$ with the state $\{1\}$ indicating that a maintenance activity (i.e. event or outcome) occurs.

2.3.2 LCoE [€/MWh]. The levelized cost of energy (LCoE) describes the mean net present cost of electricity production (e.g., in €/MWh) for a windfarm over its lifetime. The LCoE can be calculated by dividing the net present value of all cash flows (i.e., sum of discounted costs over the lifetime) by the net present value of energy produced over the lifetime [16]. The numerator, therefore, equals the LCC(MC), as derived in equation(4). By calculating LCC(MC) instead LCC(TC), lost profits due to downtime are not considered in the LCC. Instead, the denominator includes the induced downtime as the induced downtime directly effects the associated AEP. The LCoE (in €/MWh) can then be calculated for a single Monte Carlo iteration i as:

$$LCoE_i = \frac{LCC_i(MC)}{\sum_{t=1}^n \frac{AEP_t}{(1 + DR)^t}} \quad (5)$$

with:

- $LCC(MC)$: Life-cycle costs with maintenance costs as cost rate, see equation (4)
- AEP : Annual energy production for the year t in MWh

The annual energy production AEP_t for a specific year t is calculated approximately as constant baseline AEP ($AEP_{Baseline}$) less the lost production (i.e., downtime induced by the item's maintenance strategy for the year t). Let the lost production over the total lifetime of the turbine be called *lost energy production* (LEP). If expressed in terms of NPV in MWh, the LEP can be defined as:

$$LEP_i = P_R C_F \left(\underbrace{DT_{ICM_0} \sum_{t=1}^n \frac{e_{ICM}(t, x_1)}{(1 + DR)^t}}_{\text{Downtime ICM}} + \underbrace{DT_{PDM_0} \sum_{t=1}^{n-1} \frac{e_{PPM}(t, x_1)}{(1 + DR)^t}}_{\text{Downtime PDM}} + \underbrace{DT_{CBMR_0} \sum_{t=1}^n \frac{e_{CBMR}(t, x_1, x_2, x_3)}{(1 + DR)^t}}_{\text{Downtime CBMR}} + \underbrace{DT_{CBMI_0} \sum_{t=1}^{n-1} \frac{e_{CBMI}(t)}{(1 + DR)^t}}_{\text{Downtime CBMI}} \right) \quad (6)$$

with:

- LEP : Lost energy production as NPV in MWh
- P_R : Rated power of turbine in MW
- C_F : Capacity factor of turbine in percent (for offshore between 40-60%)
- DT : Downtime in h as a proportion to be allocated to the item

It should be noted that only the downtime proportion (factor DT) that is caused by the considered item, is used. If, for example, a preventive replacement would be performed during annual service from one out of four technicians, also only 25% of the downtime is allocated to the item. Using the LEP , the $LCoE$ can now be expressed for a single Monte Carlo iteration i as:

$$LCoE_i = \frac{LCC_i(MC)}{\sum_{t=1}^n \frac{AEP_{Baseline}}{(1+DR)^t} - LEP} \quad (7)$$

Equation (7) represents the formula that is integrated in the model.

2.3.3 Downtime [h]. The downtime describes the total downtime over the lifetime of the turbine induced by maintenance activities of the considered item. Equation (8) states the calculation for a single Monte Carlo iteration i .

$$DT_i = \underbrace{DT_{ICM_0} \sum_{t=1}^n e_{ICM}(t, x_1)}_{\text{Downtime ICM}} + \underbrace{DT_{PDM_0} \sum_{t=1}^{n-1} e_{PPM}(t, x_1)}_{\text{Downtime PDM}} + \underbrace{DT_{CBMR_0} \sum_{t=1}^n e_{CBMR}(t, x_1, x_2, x_3)}_{\text{Downtime CBMR}} + \underbrace{DT_{CBMI_0} \sum_{t=1}^{n-1} e_{CBMI}(t)}_{\text{Downtime CBMI}} \quad (8)$$

The downtime can be caused by all maintenance types applied to maintain the item of interest. Terms of maintenance types that are not included into current strategy are zero for all time steps and iterations.

2.3.4 Lost Profit [NPV in €]. The lost profit (LP) represents the downtime-related lost profit of the windfarm operator. The lost profit is stated as NPV in € over the full lifetime. Equation (9) states the calculation for a single Monte Carlo iteration i .

$$LP_i = P_R C_F CM \left(\underbrace{DT_{ICM_0} \sum_{t=1}^n e_{ICM}(t, x_1) R^t}_{\text{Downtime ICM}} + \underbrace{DT_{PDM_0} \sum_{t=1}^{n-1} e_{PPM}(t, x_1) R^t}_{\text{Downtime PDM}} + \underbrace{DT_{CBMR_0} \sum_{t=1}^n e_{CBMR}(t, x_1, x_2, x_3) R^t}_{\text{Downtime CBMR}} + \underbrace{DT_{CBMI_0} \sum_{t=1}^{n-1} e_{CBMI}(t) R^t}_{\text{Downtime CBMI}} \right) \quad (9)$$

with:

- LP : Lost profit as NPV in €
- CM : Contribution Margin [€/MWh]

The LP calculation differs from the LEP calculation, equation (6), not only by the constant factor CM but also by the time- and maintenance type dependent inflation factor $(1+I)^t$ within R . The contribution

margin (CM) is defined as difference between revenues generated (sales revenue per MWh) and variable costs per MWh produced.

2.3.5 Number of Activities. The number of maintenance activities for a single Monte Carlo iteration i can be derived by simply summing the values of the binary event-variables over all time sequences (years or month):

$$N_A = \underbrace{\sum_{t=1}^n e_{ICM}(t, x_1)}_{\text{Activities ICM}} + \underbrace{\sum_{t=1}^{n-1} e_{PDM}(t, x_1)}_{\text{Activities PDM}} + \underbrace{\sum_{t=1}^n e_{CBMR}(t, x_1, x_2, x_3)}_{\text{Activities CBMR}} + \underbrace{\sum_{t=1}^{n-1} e_{CBMI}(t)}_{\text{Activities CBMI}} \quad (10)$$

While the number of PPM activities can be derived from the strategy setup directly, the number of CBMRs and IMCs is of particular interest.

3. Conclusion

3.1. Summary

Within this paper an LCC model was developed to design the maintenance strategies of turbine critical items in detail. The core element of the model is the reliability module. The user can define different time-dependent failure mechanisms and associated P-F intervals for an item. For each iteration step, item life data are generated. Depending on the chosen maintenance strategy, predetermined, condition-based or corrective maintenance activities are executed to react to the generated item lifetimes. Based on the executed maintenance activity, different LCC metrics are calculated.

Each iteration of the MC simulation corresponds to a single wind turbine being considered over its operational life. Thus, the LCC metric for a single turbine represents the costs needed to maintain the item function over the turbine's lifetime. If there are no CAPEX and DECEX and an ICM maintenance strategy is chosen for a highly reliability item, then the item-specific LCC costs per turbine could be zero for a large part of the fleet. The operator of a windfarm, however, is interested in the costs to maintain the considered item function in the total fleet. Thus, the results are not presented as histograms estimating probability distributions with constructed confidence intervals but as statistical means. Thereby it is assumed that the number of wind turbines is sufficiently large. As enhancement of the model, LCC metrics could be averaged over a number of iterations equal to the number of turbines in the considered windfarms. In this case it would be meaningful to present the results as histograms estimating probability distributions of the total LCC needed to maintain the considered function in the fleet.

3.2. Limitations

The reliability model as a core element of the LCC model presupposes that the failure mechanisms of the considered item can be adequately determined. However, this is only the case if the item is used in other industry sectors with a comparable operating environment or if the item is maintenance intensive and therefore a significant number of failures in the offshore wind sector can be evaluated. To determine the Weibull parameters for a single failure mechanism, at least a dozen items that failed due to the specific failure mechanism must be evaluated. A third option to obtain the necessary reliability data would be to perform accelerated life testing. For some components, reasonable estimates can also be achieved through theoretical calculations (Gearbox, Bearings) or by using available handbooks.

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