Reduction of Operation and Maintenance Cost for Wind Turbine Blades – Cost Model and Decision Making

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1. Introduction

1.1 Background

As a pre-requisite of decision-making and cost estimation, a reliability model has been developed and documented in another separate report (Reduction of Operation and Maintenance Cost for Wind Turbine Blades – Reliability Model, referred to as ISSN 1901-726X DCE Technical Report No. 260 below). In the reliability model, the probabilistic damage propagation model can be used to predict and simulate the stochastic damage propagation process. With no loss of generality, a generic terminology, namely damage propagation, is used throughout this report, without differentiating different specific damage types. The probabilistic damage propagation model can be either of a data-driven model, a physics-based model (probabilistic crack propagation model) or a hybrid of the data-driven and physics-based models (simulation-based model). In Work Package1 (WP1), Discrete Markov Chain Model which is a type of simulation-based model is used to simulate the probabilistic damage propagation with in-history observations/records used to calibrate the model parameters. With the aim to keep consistent with the five-level damage categorization scheme in Guide2Defect (G2D), there are five damage states defined in Discrete Markov Chain Model. The damage severity levels can be abbreviated as *D*i (*i*=1, 2, 3, 4, 5) according to the five-level damage categorization. Besides the five damage states (damage severity levels), there are two more states needed in the Discrete Markov Chain model, namely an intact state (D0) and a collapse state (D6, the absorb state in the Discrete Markov Chain Model). The purpose of defining these two states is to satisfy the theoretical criteria in the Discrete Markov Chain Model, namely there must be an intact state from which a Markov Chain starts jumping, and an absorption state which represents the end of a Markov process.

Besides the established probabilistic damage propagation model, the information indicating the condition of the blades and the pre-defined maintenance strategy plays an important role in decision-making as well.

The collected information could be continuous and discontinuous, which depends upon the type of the condition-monitoring device. For wind turbine (WT) blades, the non-destructive testing (NDT) inspection outcome is a main resource of the discontinuous information. G2D is the focused database providing the discontinuous information based upon the in-history NDT inspections in the RATZ project. The in-history records in G2D database provide the prior information on the damage propagation. The prior information can be used to calibrate the transition probabilities. The information in G2 is renewed, when new NDT inspections are conducted. The latest non-destructive testing inspection information is uploaded into G2D to update the existing in-history records.

A maintenance strategy is usually composed of three fundamental aspects, namely the inspection method, the inspection interval and some pre-defined decision alternatives on actions (e.g. repairs) to be done after the inspections have been performed. These fundamental aspects, like some basic building blocks used to construct a system, constitutes the main framework of a maintenance strategy. There are some possible options of each of these fundamental aspects for a decision maker to choose from. Possible options for each fundamental aspect can be freely combined with the options of the other two fundamental aspects. For example, one of possible inspection methods is combined with one of inspection intervals and one decision alternative. This combination process is repeated until all the possible scenarios are covered. With the well-defined maintenance strategy, the decision maker can make decisions on the observed damage propagation process. A Discrete Markov Chain Model is used to generate the stochastic damage propagation process. The total expected maintenance costs can be calculated based upon different combinations of inspection methods, inspection intervals and decision alternatives. The decision maker can choose the cost-optimal maintenance strategy based upon the costs for different combinations. Of the common maintenance strategies, condition-based maintenance is the focused on in this WP.

Generally, a long/medium-term strategic maintenance planning should be developed by a decision maker, before a new wind farm starts operation. In the lifetime of a wind farm, an important consideration from a decision maker point of view is how to gain the maximum economic benefits, while minimizing the consequence of a total collapse or major repair of WT blades. On the one hand, frequent NDT inspections can provide a decision maker with much timely information on the operational condition of WT blades. On the other hand, plenty of maintenance costs are lost due to executing inspection and maintenance works too frequently. It is a trade-off between the tolerable risk undertaken by WT blades and the operation& maintenance (O&M) costs to ensure the structural integrity of WT blades. A cost-optimal maintenance strategy is needed to achieve such a trade-off, which recommends maintenance actions based on the information collected by a condition-monitoring device.

The primary objective of this report is to document the theoretical basis of pre-posterior Bayesian inference and describe the decision-making procedure, given the realizations of stochastic damage propagation process provided by the reliability model. The trade-off between safety and cost is expected to be achieved by means of condition-based maintenance.

1.2 Literature Review

The research regarding the O&M planning of WT blades has been a hot topic over the past two decades. Sørensen presented a general framework for rational and optimal planning of operation& maintenance (O&M), based upon a risk-based life cycle decision-making model [1]. Florian and Sørensen adopted the fundamental idea behind the model developed by Sørensen and presented the application of this model to a general cost-optimal planning for WT components [2- 4]. Toft and Sørensen discretized the damage evolution into some discrete damage categories, and used the least square algorithm to estimate the transition probabilities based upon the observations of those damage categories extracted from a database [5]. The model developed by Toft and Sørensen is a Discrete Markov Chain Model which probabilistically depicts how fast a crack/defect propagates from one damage state to a more severe state. Shafaiee et al. investigate an optimal opportunistic condition-based maintenance policy for a multi-bladed offshore wind turbine system subjected to stress corrosion cracking and environmental shocks [6].Typical methodologies of damage propagation simulation have been reviewed for the application of WT components.

Chan and Mo developed a Maintenance Aware Design Environment (MADe) model, which is based upon failure mode and effect analysis (FMEA) and bond graph modelling, to simulate the effects of maintenance strategies on the life-cycle costs of mechanical components of WTs [7]. Carlos et. al. used Monte Carlo simulation to generate random failure times to calculate the cost of corrective maintenance and the unavailability due to downtime, with the aim at maximizing the annual energy generation and minimizing the maintenance cost [8].

Yuan proposed a Gamma-process-based model to simulate the deterioration process of industrial devices, especially stochastic process of corrosion of power plant components and modeled the PM actions [9, 10]. Pandey et al. introduced a Gamma process to model an uncertain general degradation process which was used to simulate the probability distribution of repair/maintenance intervals, and estimated the expected maintenance cost, as well as the standard deviation of cost [11, 12]. The model proposed by Pandey et al. only considered a general type of damage and accordingly estimated the cost and downtime. The Gamma process model parameters were just extracted from a failure database.

1.3 Objectives

The general objective of cost modelling and decision making is to estimate the maintenance costs for all the possible combinations of inspection method, inspection intervals and decision alternatives based upon the Bayesian decision Tree. The realizations of the simulated damage propagation are the basic input data for decision making.

A detailed descriptions of the objectives are listed as follows:

- To present the Bayesian pre-posterior decision-making theory and the framework of the Bayesian decision tree developed based upon this theory;
- To detail the fundamental aspects of the decision-making process, e.g. inspection method, inspection intervals and decision alternatives, and document how these fundamental aspects are integrated into the Bayesian decision tree;
- To perform a case study by using a reference project depicted in a report issued by National Renewable Energy Laboratory (NREL) and briefly present the interface between reliability modelling and cost modelling (namely how the output in a reliability model can be integrated into a decision-making process).

1.4 Report Outline

The rest of this technical note is structured as:

- Section 2 – briefly reviews some typical maintenance strategies, and mainly presents the fundamental ideas of the condition-based maintenance strategy;
- Section 3 – details the decision-making and cost estimation for some maintenance strategies;
- Section 4 – demonstrates the case study (two examples, namely 'Transverse cracks' and 'Root Area & Transition Zone cracks').
- Section 5 – contains conclusions and recommendations.

1.5 Acronyms

CBM	Condition-based Maintenance
CM	Corrective Maintenance
G2D	Guide2Defect
NDT	Non-destructive Testing
O&M	Operation and Maintenance
WT	Wind Turbine

2. Maintenance Strategies

2.1 Overview

A maintenance strategy includes a set of policies and actions that are used to restore an infrastructure or a device. The detailed review of maintenance strategies is out of the work scope of this report. Therefore, some typical maintenance strategies will be only presented in this section. There are two typical types of maintenance strategies, namely corrective maintenance and preventive maintenance [13, 14]. The corrective maintenance is based upon a run-to-failure strategy, and will not be divided even further. The preventive maintenance can be further divided into time-based maintenance, predictive maintenance, condition-based maintenance and risk-based maintenance. The hierarchy structure of these typical maintenance strategies is illustrated in Figure 1. In the next sub-section, these typical maintenance strategies will be briefly presented, with the focus on the condition-based maintenance strategy.

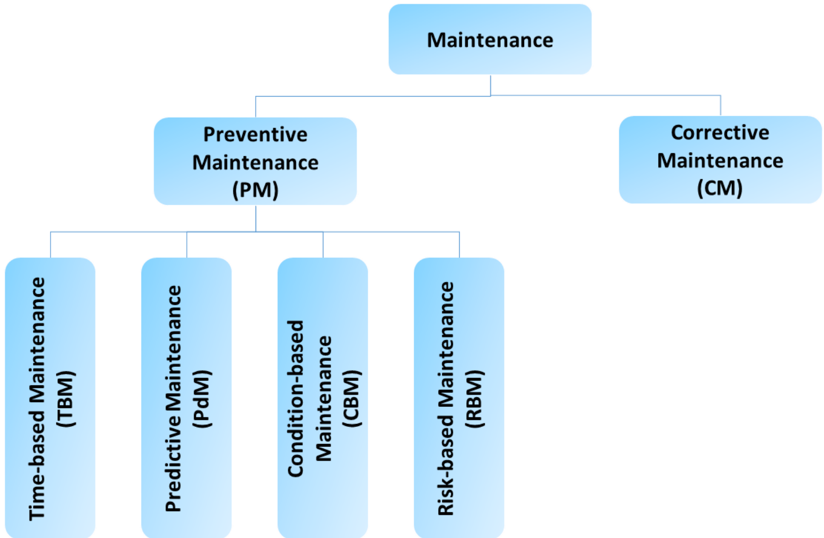


Figure 1 Typical Maintenance Strategies

2.2 Typical Maintenance Strategies

2.2.1 Fundamental Aspects of Maintenance Strategies

A maintenance strategy is usually composed of three fundamental aspects, namely the inspection method, preventive time interval (a generic term; could be also called inspection interval, if repair is not done), and some pre-defined decision alternatives to be done after the inspections have been performed. These fundamental aspects, like some basic building blocks used to construct a system, constitutes the main framework of a maintenance strategy. There are some possible options of each of these fundamental aspects for a decision maker to choose from. Possible options for each fundamental aspect can be freely combined with the options of the other two fundamental aspects. For example, one of possible inspection methods is combined with one of inspection intervals and one decision alternative.

The typical 'bath-tube' curve, as illustrated in Figure 2, is usually used to depict the failure rate as function of time, which can approximately characterize the damage evolution. A failure rate trend can be divided into three phases: burn-in, useful life, and wear-out. In either of these typical maintenance strategies, it is assumed that the decreasing failure rates are used for the 'burn-in' period, followed by a near constant failure rate for the 'useful life' period, and finally the increasing failure rates for the 'wear-out' period.

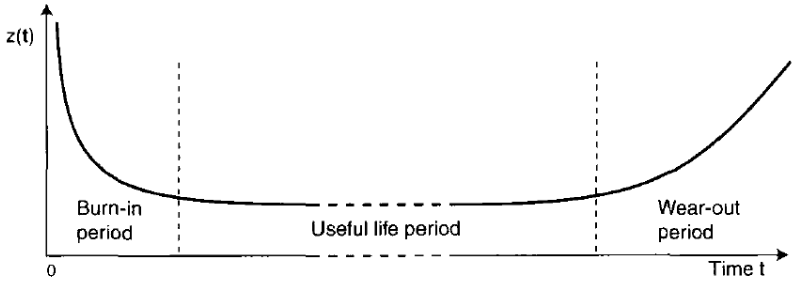


Figure 2 Bath-tube Curve [15]

2.2.2 Brief Description of Typical Maintenance Strategies

Time-based maintenance, also known as periodic-based/calendar maintenance, is a traditional maintenance strategy. In the framework of time-based maintenance, the preventive interval is pre-determined based upon the knowledge/ prior information on the damage evolution. Time-based maintenance could be an alternative maintenance strategy in the RATZ project.

Condition-based maintenance is a maintenance strategy that recommends maintenance actions based on the information depicting the current condition of a structure/ device. Generally, the information stems from two resources, namely G2D database and fracture mechanics analysis/ the laboratory test results. G2D database is the focused data resource in the RATZ project, while the laboratory test results provide some supplementary information. In light of the available information, condition-based maintenance is the focused maintenance strategy in the RATZ project.

Predictive maintenance is similar to condition-based maintenance in terms of the theoretical basis, but an advanced online monitoring data acquisition system is need to provide more data and artificial intelligence/ machine learning techniques (data-driven methods) are used to predict the damage indicator trend which indirectly indicate the physical damage evolution. The online monitoring data acquisition system for the application in WT blades is still pre-mature, and the data-driven methods are not well-established for the application in WT blades either. Therefore, predictive maintenance is not used for the RATZ project.

The primary objective of risk-based maintenance is to reduce the overall risk that may be caused as the consequence of unexpected failures of operating devices. The inspection and maintenance activities are prioritized on the basis of quantified risk caused due to failure of the components, so that the total risk can be minimized. For WT blades, there are two reasons that obstruct the application of the risk-based maintenance. On the one hand, the probabilistic damage propagation analysis is hard to be implemented due to the difficulty in obtaining a closed-form limit state function corresponding to a specific failure mode (e.g. 'Transverse cracks' or 'Root Area& Transition Zone cracks'). The failure probability cannot be easily quantified. On the other hand, the consequences of different damage categories are hardly quantified because of different assessment/evaluation criteria (e.g. the influences of economy, society and environment). Therefore, the risk-based maintenance is not used for the RATZ project.

Corrective maintenance is based upon the 'run-to-failure' principle. The estimation of corrective maintenance costs is only based upon the run-to-failure prediction. Usually, corrective maintenance is unplanned and results in a longer downtime which takes significantly long time for the maintenance team to restore the device in problem. As demonstrated in Section 3, the maintenance actions in decision alternative 5 are the same as the principle of corrective maintenance. Therefore, corrective maintenance will not be investigated separately in this report.

3. Condition-based Maintenance based upon Decision Tree Theory

3.1 Decision Tree based upon Classical Bayesian Pre-posterior Theory

The classical Bayesian pre-posterior Bayesian decision theory is used as a basis for the decision-making. The theoretical basis may be represented by a decision tree where some branches are defined to represent decisions made at some specific time, and other branches represent random outcomes, as illustrated in Figure 3. A decision tree is composed of decision nodes, chance nodes and consequence nodes, all of which are connected by directional links [16].

Since the design of a blade is not considered, the initial design (denoted by z in Figure 3) is not considered. The decision maker chooses an inspection strategy including inspection method and inspection time interval(s) (denoted by e in Figure 3). When the result (denoted by S in Figure 3) of an inspection is obtained and a damage has been detected, the decision maker needs to decide which type of maintenance/repair to be chosen (denoted by d(S) in Figure 3). Realizations of the damage growth process is denoted by X in Figure 3, and could represent total collapse. The costs associated with each branch are denoted by W in Figure 3.

The objective is to minimize the total expected value of W for the remaining lifetime with the inspection plan e and the maintenance /repair strategy d(s) as optimization parameters.

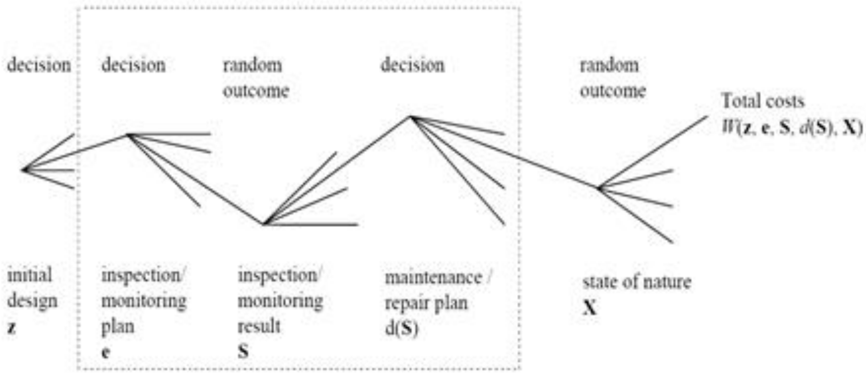


Figure 3 Generic Decision Tree for O&M Decision-making [1]

3.2 Framework of Condition-based Maintenance Strategy

3.2.1. Overview

A maintenance strategy is usually composed of three fundamental aspects, namely the inspection method, the inspection interval and some pre-defined decision alternatives regarding maintenance actions (e.g. repairs) to be done after the inspections have been performed. There are some possible options of each of these fundamental aspects for a decision maker to choose from. Possible options for each fundamental aspect can be freely combined with the options of the other two fundamental aspects. For example, one of possible inspection methods is combined with one of the inspection intervals and one decision alternative, as illustrated in Figure 4. This combination process is repeated until all the possible scenarios are covered. The Discrete Markov Chain Model is used to generate the stochastic damage propagation process. The total expected maintenance costs can be calculated based upon different combinations of inspection methods, inspection intervals and decision rules. The decision maker can choose the cost-optimal one and determine the inspection type, intervals and maintenance actions accordingly.

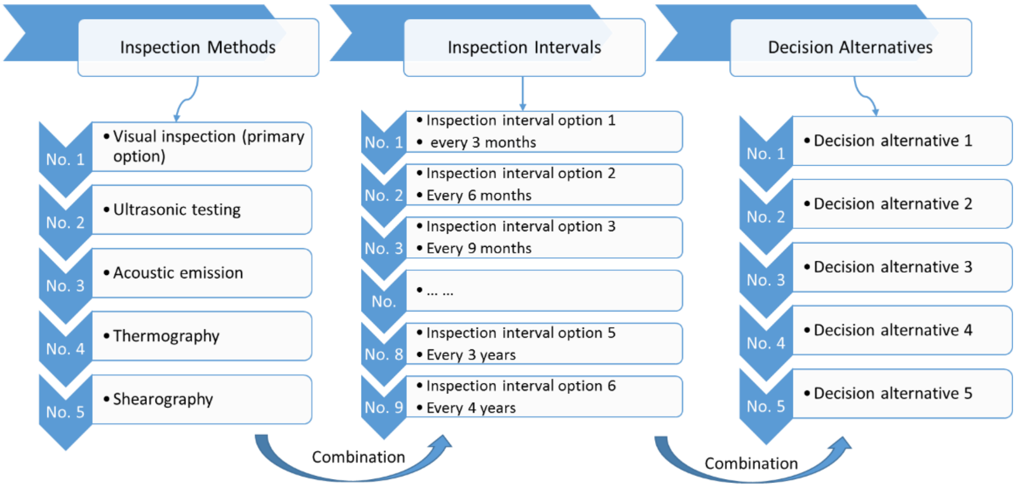


Figure 4 Illustration of Condition-based Maintenance Procedure

3.2.2. Inspection Methods

Nowadays, visual inspection is the most common non-destructive testing (NDT) method used in inspections of WT blades. However, there is little information on probability of detection (PoD) of visual inspection. Expert review meetings and tests should be performed to establish some discrete probabilities of detection for the five damage severity levels in the five-level damage severity scheme. Generally, PoD is related to the external environmental influences and the technicians' qualification. During the expert review meetings, the scenarios where the combination of these factors influencing PoD should be documented and discussed.

It is further noted that damages on the surface of a blade detected by visual inspection are only indicators of the more critical damages inside the blade. Advanced NDT inspections (e.g. ultrasonic testing) have the potential to give a more direct indication of the real damage size in the blade.

3.2.3. Inspection Intervals

With consideration of the practical engineering application in wind industry, the possible options for the inspection interval could be no shorter than 3 months and no longer than 4 years. In principle, any time interval between 3 months and 4 years should be used. However, with consideration of the computational efforts, nine inspection intervals used in the example below, namely 3 months, 6 months, 9 months, 1 year, 15 months, 1.5 years, 2 years, 3 years and 4 years, are only considered in this paper. In the sensitivity study (Section 4.4.2), the inspection intervals will be slightly adjusted.

In principle, the baseline inspection, as well as the inspection interval planning, should consider the influence of time window, especially for offshore WTs. Generally, the maintenance works are arranged under the benign weather conditions. The influences of time window will be presented in case study again.

3.2.4. Decision Alternatives

Decision alternatives, like d(s) in Figure 3, define the actual maintenance actions for a specific damage observed at an inspection, which is closely associated with the total maintenance costs. Based upon the aforementioned six-level damage category scheme, five decision alternatives are defined for illustration and are summarized, see below. It should be noted that for damage categories 5& 6 of offshore wind turbines, a heavy lifting vessel (HLV) should be chartered to carry the equipment for major repair or replacement, and a crew transfer vessel (CTV) can be deployed for the other damage categories.

- Decision Alternative 1
  - Action 1 – If a damage of damage category 1 is detected, no action will be taken;
  - Action 2 – If a damage of damage category 2 is detected, minor repair will be done;
  - Action 3 – If a damage of damage category 3 is detected, moderate repair will be done;
  - Action 4 – If a damage of damage category 4 is detected, moderate repair will be done;
  - Action 5 – If a damage of damage category 5 is detected, major repair will be done.
- Decision Alternative 2

  - Action 1 – If a damage of damage category 1 is detected, no action will be taken;
  - Action 2 – If a damage of damage category 2 is detected, no action will be taken;
  - Action 3 – If a damage of damage category 3 is detected, moderate repair will be done;
  - Action 4 – If a damage of damage category 4 is detected, moderate repair will be done;
  - Action 5 – If a damage of damage category 5 is detected, major repair will be done.
- Decision Alternative 3
  - Action 1 – If a damage of damage category 1 is detected, no action will be taken;
  - Action 2 – If a damage of damage category 2 is detected, no action will be taken;
  - Action 3 – If a damage of damage category 3 is detected, no action will be taken;
  - Action 4 – If a damage of damage category 4 is detected, moderate repair will be done;
  - Action 5 – If a damage of damage category 5 is detected, major repair will be done.
- Decision Alternative 4
  - Action 1 – If a damage of damage category 1 is detected, no action will be taken;
  - Action 2 – If a damage of damage category 2 is detected, no action will be taken;
  - Action 3 – If a damage of damage category 3 is detected, no action will be taken;
  - Action 4 – If a damage of damage category 4 is detected, no action will be taken;
  - Action 5 – If a damage of damage category 5 is detected, major repair will be done.
- Decision Alternative 5 (similar to corrective maintenance)
  - Action 1 – If a damage of damage category 1 is detected, no action will be taken;
  - Action 2 – If a damage of damage category 2 is detected, no action will be taken;
  - Action 3 – If a damage of damage category 3 is detected, no action will be taken;
  - Action 4 – If a damage of damage category 4 is detected, no action will be taken;
  - Action 5 – If a damage of damage category 5 is detected, no action will be taken.

3.2.5. Procedures of Condition-based Maintenance

As detailed in Section 3.2.1, the inspection method, the inspection interval and the pre-defined decision alternatives constitute the basis of a maintenance strategy. In the framework of condition-based maintenance, the following major steps should be followed.

Step-1: Choose the inspection method(s) and the possible inspection intervals;
Step-2: Define decision alternatives;
Step-3: Generate stochastic damage propagation process based upon a Discrete Markov Chain Model;
A Discrete Markov Chain Model is used to generate *N* lifetime realizations of the propagation of the damage. For each of the *N* realizations, the maintenance costs, including wait time, inspection, technician, repair, vessel, downtime, replacement (if a total collapse occurs), are calculated, and the expected value of the total costs are estimated as the mean of the *N* realizations.
Step-4: To combine different options of inspection intervals and decision alternatives;
Inspection method, inspection intervals and decision rules can be freely combined, as illustrated in Figure 4.
Step-5: To choose the cost-optimal maintenance strategy, by comparing the expected costs corresponding to all the possible decision combinations.

3.2.6 Estimation of Maintenance Costs

Generally, the maintenance costs are composed of the wait time cost (waiting for an appropriate time window for the cases where the WT should be terminated for repair or replacement), the vessel cost, the technician cost, the repair cost, the downtime cost due to the repair and the blade replacement (if a total collapse occurs). For one specific combination as illustrated in Figure 4, the maintenance costs are calculated for the time when a repair is required based upon the chosen group of decision alternative, as given by Eqs. (1) and (2).

$$C_{CBM} = \sum_{i=1}^{N_{CBM}} C_{CBM}(t_i) \tag{1}$$

$$C_{CBM}(t_i) = C_{waittime,i} + C_{inspection,i} + C_{downtime,i} + C_{repair,i} + C_{vessel,i} + C_{technician,i} + C_{blade,i} \tag{2}$$

where N_{CBM} denotes the number of planned inspections. The chosen decision alternative defines the critical damage threshold for repair, which is independent of the inspection interval. At the inspection time, whether or not a repair is done depends upon the simulated damage. Therefore, $C_{repair,i}$ may be zero at some inspection time, if the simulated damage does not reach the critical damage threshold. If a total collapse occurs, $C_{repair,i}$ represents the replacement cost. $C_{blade,i}$ represents the blade cost, if a total collapse occurs. $C_{vessel,i}$ only refers to the daily rate of the employed vessel.

The estimated costs in the future should be discounted to present value when a decision maker makes decision on which combination of inspection method, inspection interval and decision rules is cost-optimal. The equivalent maintenance cost can be given by Eq. (3).

$$C_{CBM}(t_0) = \sum_{i=1}^{N_{CBM}} C_{CBM}(t_i) \frac{1}{(1+r)^{t_i}} \tag{3}$$

where $C_{CBM}(t_i)$ denotes the maintenance cost at a specific time t_i. r denotes the discounting rate. $C_{CBM}(t_0)$ denotes the equivalent cost for which $C_{CBM}(t_i)$ is calculated backwards.

4. Case Study

4.1 Principles for Case Selection

As mentioned in another separate report (ISSN 1901-726X DCE Technical Report No. 260), the Discrete Markov Chain Model is used to simulate the stochastic damage propagation. The essential input data for Discrete Markov Chain Model is the prior information which stems from two resources, namely G2D database and fracture mechanics/ the laboratory test results. G2D database is the focused data resource in the RATZ project, while the laboratory test results provide some supplementary information. In light of the complicated damage propagation paths, the application of the simplified crack propagation model is subjected to many limitations and can only provide a decision maker with quite general knowledge regarding the damage propagation rate.

The failure scenarios selected for the case study should reflect the primary concerns of 'Transverse cracks' and 'Root Area &Transition Zone cracks'. For 'Transverse cracks', there is one major source of information that is extracted from G2D database. The G2D database provides the in-history failure records each of which includes the failure mode, the time to the observed damage (with respect to the start-up of operation), the damaged position (the distance with respect to the blade root), damage category, and the other information. For 'Root Area& Transition Zone cracks', no data are available in Guide2Defect and therefore illustrative data are used. The failure scenario of 'Transverse cracks' is chosen as the major demonstration case, while the damages on 'Root area/ Transition zone cracks' may be qualitatively investigated.

The case study in another separate report (ISSN 1901-726X DCE Technical Report No. 260) is intended to mainly demonstrate how Discrete Markov Chain Model is used to simulate the stochastic damage propagation and how decisions are made based upon the realizations of the stochastic damage propagation to find out the optimal O&M inspection intervals. The case study in this report is intended to estimate the maintenance costs based upon the decision tree theory, with the realizations of the simulated damage propagation that has been presented in the aforementioned report as input.

4.2 Model Specifications

The basic WT design data are referred to a reference project detailed in a NREL-issued technical report. The design specifications of these WTs are based upon the offshore WTs with the average size installed in the United States. The basic technical design parameters are summarized in Table 1. It should be noted that one blade in a WT from the wind farm mentioned in [17] is considered in this case study. The other logistics data are summarized in Table 2. The time series of wind and wave are referred to the FINO3 database [18]. An empirical formula proposed in [19] is used to estimate the repair cost, as given in Eq. (4).

$$C_{repair} = 2000 + 4000 \times a \tag{4}$$

where a denotes the damage size in m. The unit of C_{repair} is Euro. For the six-level damage categorization scheme, a is taken as the upper limit for each damage category.

Visual inspection is the focused non-destructive testing method in the RATZ project, because it is the most commonly used technique in the wind industry. The discrete probabilities of detection for five damage categories are recommended by the experts, and summarized in Table 3. The environmental data, e.g. wind or wave time series, is referred to the FINO3 database, with the time series of wind and wave shown in Figure 5.

Table 1 Basic Technical Parameters of Hypothetical Off-shore Wind Turbines

Parameters	Unit	Value
Number of wind turbines	-	128
Rated power	MW	4.71
Water Depth	m	30/100
Design life	Year	20
Maximum Capacity Factor	-	0.47
Drivetrain design	-	Geared
Distance from Shore	km	30

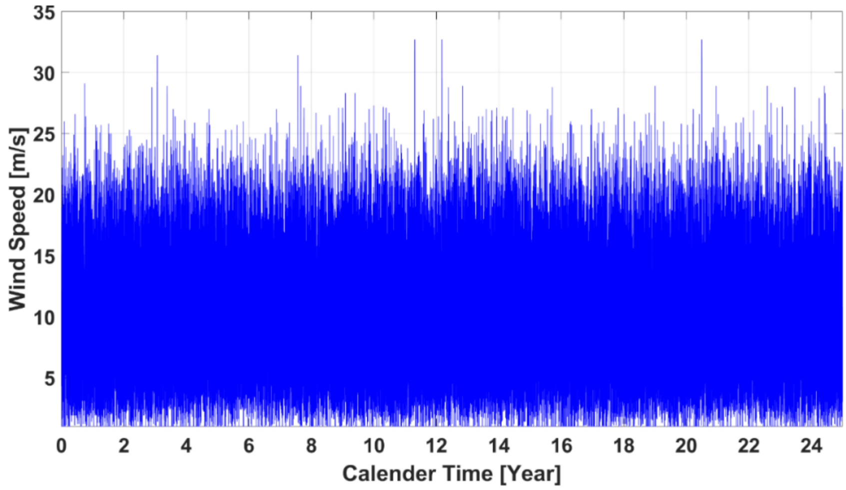
Parameters	Unit	Value
Cut-in Wind Speed	m/s	3
Cut-out Wind Speed	m/s	25

Table 2 Summary of Input Data – Weather data, Logistics and Finance

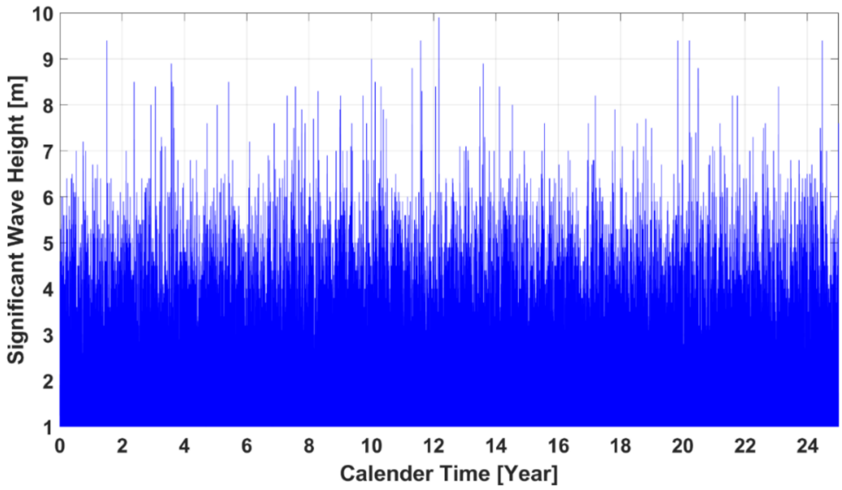
Parameter	Unit	Value	Description	Remark
C_{CTV}	Euro/day	1,000	CTV daily rate	Ref. [20]
C_{HLV}	Euro/day	100,000	HLV daily rate	Ref. [20]
C_{blade}	Euro	400,000	The blade cost	Ref. [20]
C_{mob}	Euro	250,000	The cost of mobilizing an HLV	assumed
$C_{inspection}$	Euro/time	22,000	The inspection cost	assumed
C_{repair}	Euro	-	The repair cost	Ref. [19]
$C_{technician}$	Euro/day	1,000	The technician daily rate	assumed
H_{max_CTV}	m	1.5	The maximum wave height for an CTV to operate safely	Ref. [20]
H_{max_HLV}	m	2	The maximum wave height for an HLV to operate safely	Ref. [20]
U_{max_CTV}	m/s	3	The maximum wind speed for an CTV to operate safely	Ref. [20]
U_{max_HLV}	m/s	10	The maximum wind speed for an HLV to operate safely	Ref. [20]
V_{CTV}	m/s	37.04	The CTV speed	Ref. [20]
V_{HLV}	m/s	1.852	The HLV speed	Ref. [20]
r	%	10	The discount rate	assumed
t_{insp}	hour	6	The inspection time	assumed
$t_{repair,D2}$	hour	10	The repair time for the damage category 2	Ref. [20]
$t_{repair,D3}$	hour	24	The repair time for the damage category 3	Ref. [20]
$t_{repair,D4}$	hour	40	The repair time for the damage category 4	Ref. [20]
$t_{repair,D5}$	hour	80	The repair time for the damage category 5	Ref. [20]
$t_{replace}$	hour	72	The time for replacing a blade	Ref. [19]

Table 3 Recommended Probabilities of Visual Inspection

Damage Category	Probability Mass Function [%]	Probability of Detection [%]
DC1	2	2
DC2	5	7
DC3	10	17
DC4	20	37
DC5	33	60
DC6	40	100



(a) Wind Time Series



(b) Wave Time Series

Figure 5 Time Series of Wind and Wave Extracted from FINO3 Database

4.3 Demonstration Case – Transverse Cracks

4.3.1 Damage Propagation Realizations

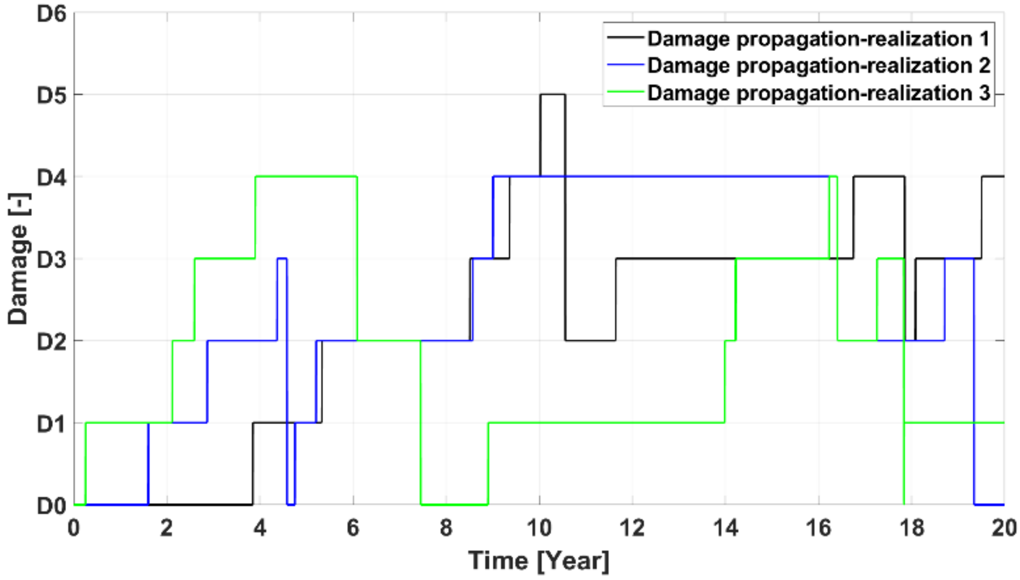
A total of *N* simulations (*N*=10000) are done based upon the sampling algorithm detailed in Section 2.4.3.2 and the maintenance strategies of another separate technical report (ISSN 1901-726X DCE Technical Report No. 260). Of the 45 combinations, namely visual inspection, 9 inspection intervals and 5 decision alternatives, three realizations corresponding to the cost-optimal maintenance strategy is only shown in Figure 6.

In Figure 6, each blue diamond represents the scheduled inspection time. Each red circle represents that an inspection is done and a damage is detected using the assumed PoDs for visual inspection as summarized in Table 3. The fact that a blue diamond and a red circle coincides indicates that visual inspection detects the damage at the scheduled inspection time. Otherwise, there is only one blue diamond at each scheduled inspection time. Each red cross represents that the detected damage is repaired, based upon a pre-defined decision alternative. There is a time lag between a diamond, a red circle and a red cross, which represents the repair time and also the wait time for an appropriate time window. The markers are overlapped in Figure 6, which is difficult to identify. An enlarged view is thus plotted for one inspection time in Figure 6 (b), where the time lag between the blue diamond and the red circle denotes the wait time for an appropriate time window and the time lag between the red circle and the red cross denotes the repair time and/ or the wait time for an appropriate time window (because the repair works may be interrupted by a harsh weather condition).

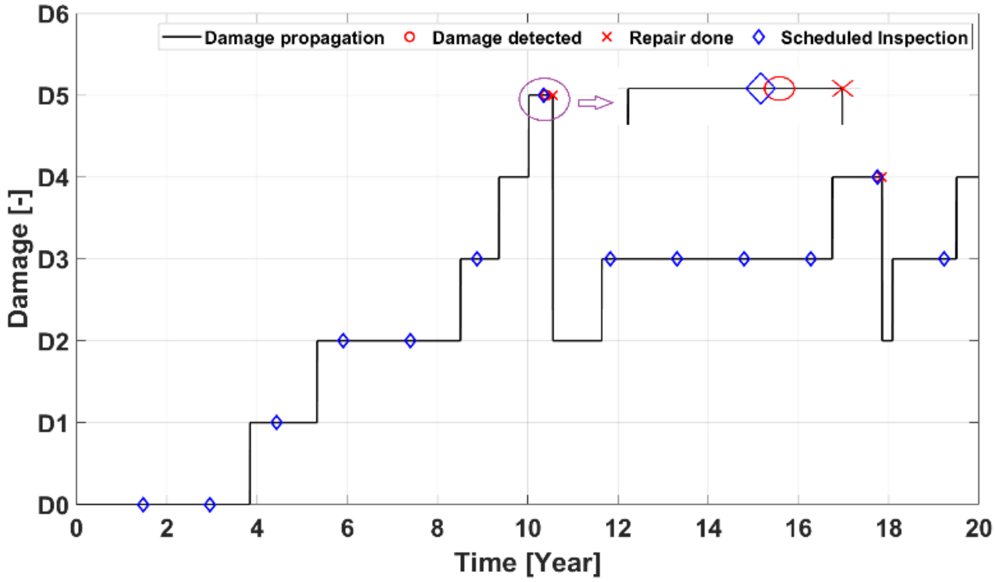
After the repair is done, each line drops down to the pre-defined post-repair condition based upon the assumptions as summarized below.

- For Damage Category 2& 3, the damaged portion of a blade recovers to the intact condition after repair;
- For Damage Category 4& 5, the damaged portion of a blade recovers to Damage Category 2 after repair;

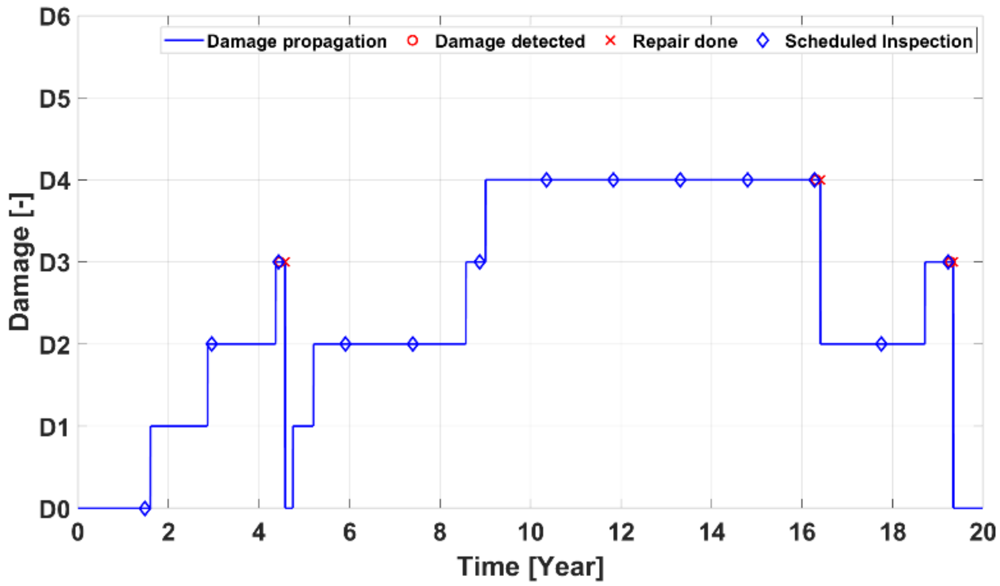
No repair is done for the detected damage that is less severe than this critical damage. For instance, it can be seen from Figure 6 (b)~(d) that at some inspections no damage is detected (no red circle) and at others a damage is detected and a repair is done. Based upon the assumptions regarding the post-damage condition as summarized in Table 1 in ISSN 1901-726X DCE Technical Report No. 260, the damage level drops to D0, if the damage is at D1, D2 or D3; or it drops to D2, if the damage is at D4 or D5. Figure 6 (b)~(d) also show that for most scheduled inspection times visual inspection cannot detect the damage, which indicates that the probability of detection for smaller damage sizes is relatively low.



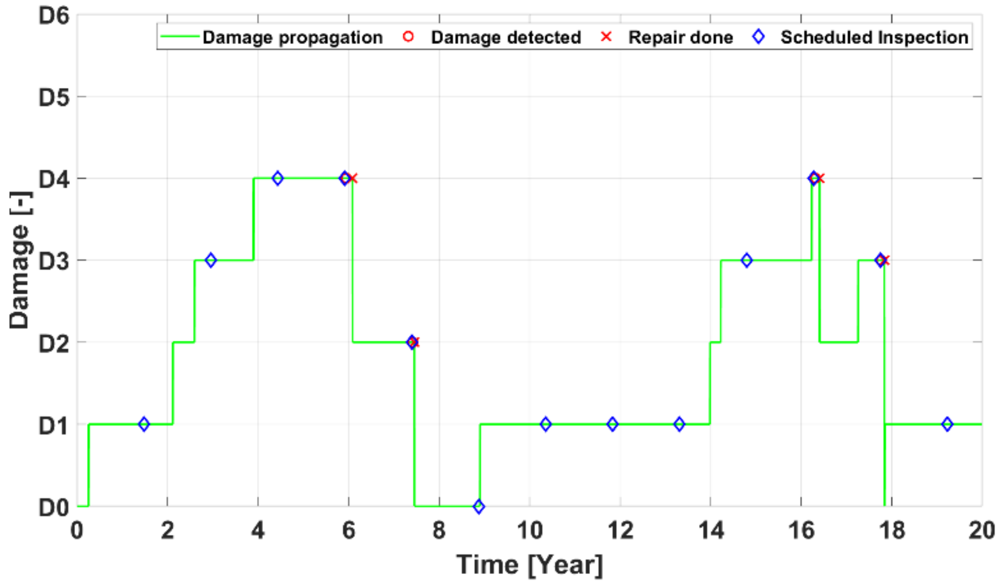
(a)



(b) Damage Propagation – Realization 1



(c) Damage Propagation – Realization 2



(d) Damage Propagation – Realization 3

Figure 6: Realizations of the Stochastic Damage Propagation

4.3.2 Decision-making and Cost Estimation

The theoretical model to calculate the maintenance costs for the different combinations of inspection intervals and decision alternatives is implemented to illustrate the procedure, see below [21].

Each bar in Figure 7 shows the minimum maintenance cost corresponding to one decision alternative. The cost-optimal inspection interval for each decision alternative is marked above each bar. The cost breakdown is plotted in Figure 7. The costs due to wait time, inspection and replacement account for most of the maintenance cost. Of the 45 possible combinations, the inspection interval of 1.5 years combined with Decision Alternative 2 is the most cost-optimal maintenance strategy. The trend of the total maintenance cost as function of inspection interval is shown for all decision alternatives in Figure 8~Figure 12. The 95% confidence intervals of the maintenance cost are only plotted for the cost-optimal case (the inspection interval of 1.5 years combined with Decision Alternative 2) to illustrate the uncertainty of the cost estimation, as shown in Figure 9. It is observed that the expected costs fluctuate between the inspection intervals of 1-year and 3-year in Figure 10~Figure 12, especially in Figure 11. This is caused by seasonal effects combined with the simulated failure events occurring during the harsh weather conditions requiring longer waiting time to obtain an appropriate time window.

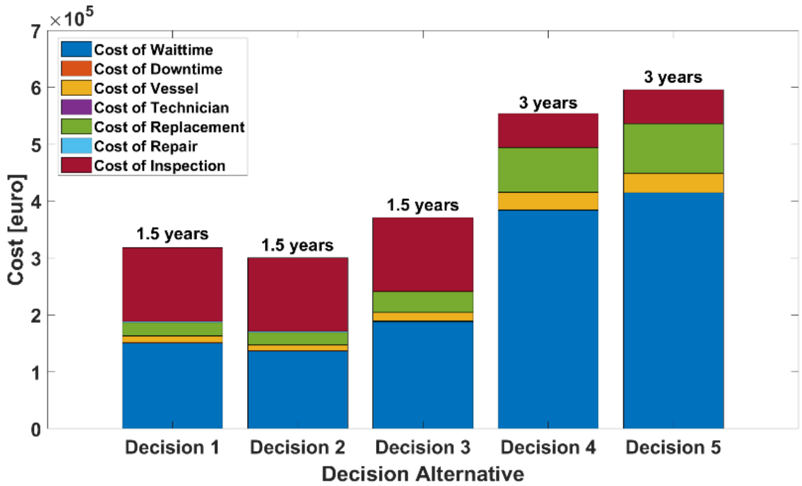
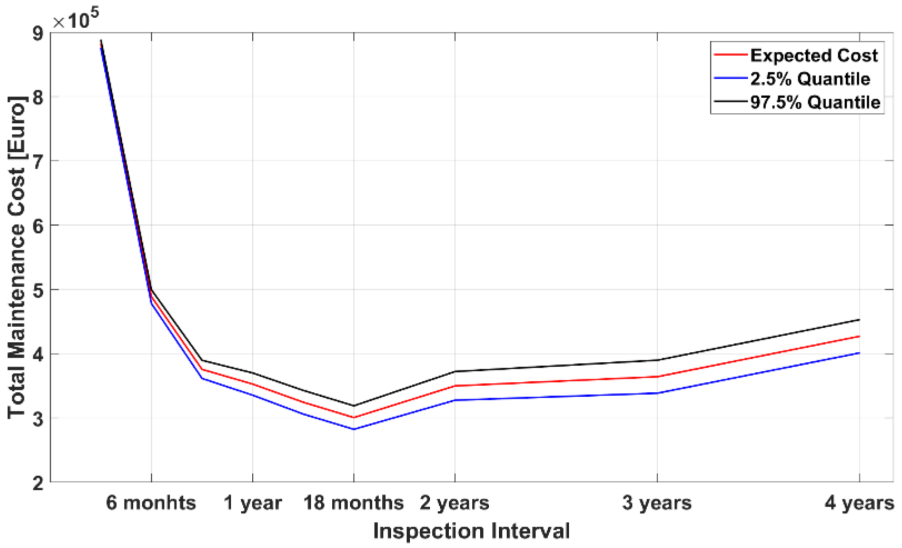


Figure 7: The Total Maintenance Cost for Different Decision Alternatives

Figure 8 Cost Trend as Function of Inspection Interval – Decision Alternative 1

(a) Decision Alternative 2– with the expected cost trend only



(b) Decision Alternative 2 – with 95% confidence intervals

Figure 9 Cost Trend as Function of Inspection Interval – Decision Alternative 2

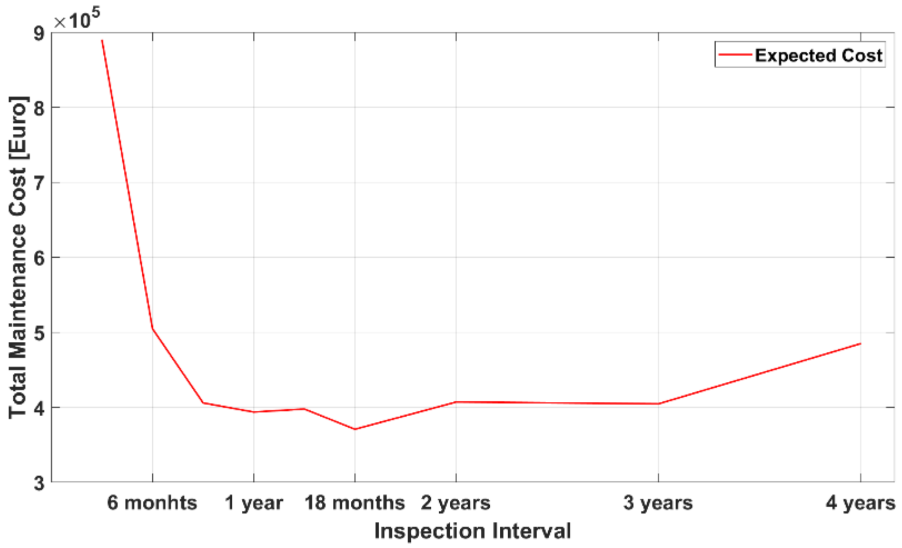


Figure 10 Cost Trend as Function of Inspection Interval – Decision Alternative 3

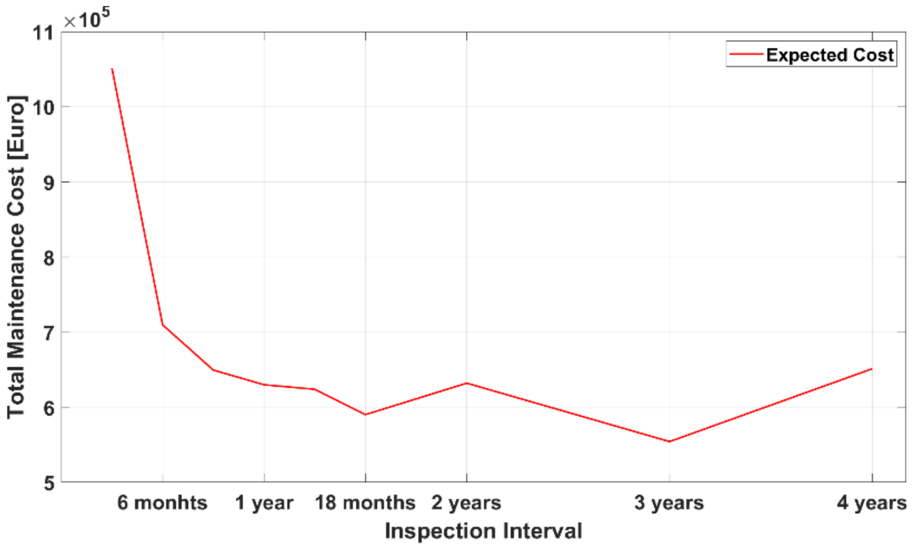


Figure 11 Cost Trend as Function of Inspection Interval – Decision Alternative 4

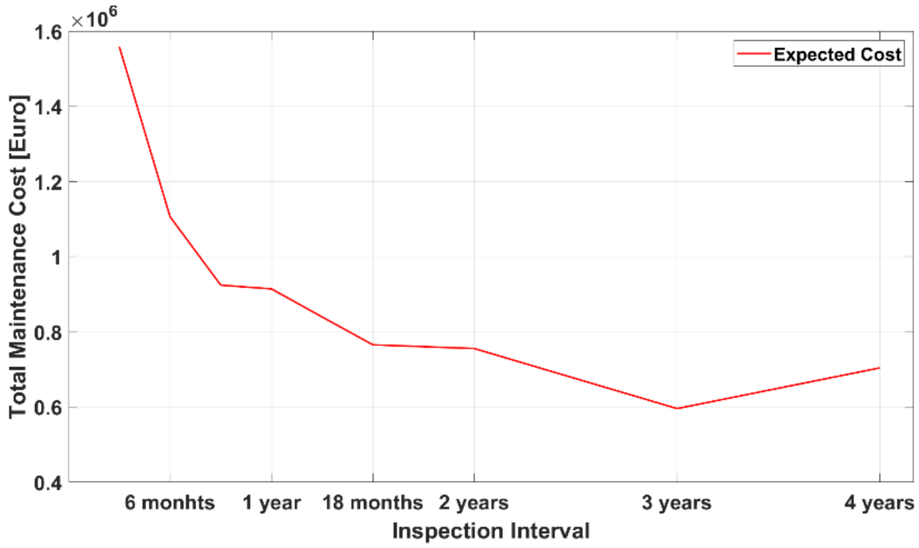


Figure 12 Cost Trend as Function of Inspection Interval – Decision Alternative 5

4.4 Demonstration Case – Root Area& Transition Zone Cracks

4.4.1 Damage Propagation Realizations

As explained in another separate technical report (ISSN 1901-726X DCE Technical Report No. 260), the decision alternative 5 combined with a 2-year inspection interval is used to demonstrate the damage propagation. With the assumed transition probabilities, *N* simulations (*N*=10000) are done for the two manners of the damage propagation, namely the almost linear damage propagation as illustrated in Figure 13 and the nonlinear (a hybrid of exponential and polynomial) damage propagation as illustrated in Figure 15. Figure 14 shows one realization of all *N* simulations for the case where a crack/defect propagates approximately linearly. Figure 16 shows one realization of all *N* simulations for the case where a crack/defect propagates nonlinearly. The meanings of the markers in Figure 14 and Figure 16 can be referred to Section 4.3.1.

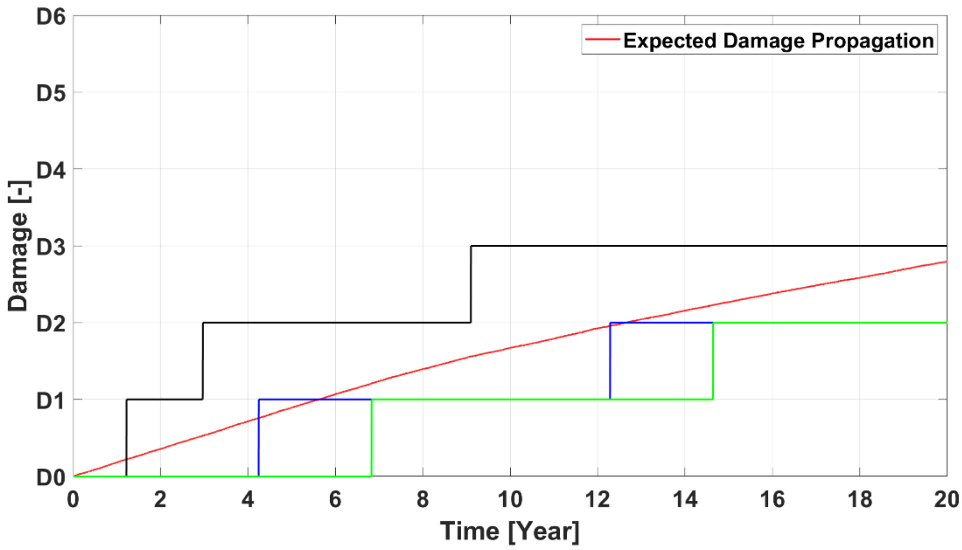


Figure 13: Illustration of Expected Damage Propagation – Approximately linear damage propagation

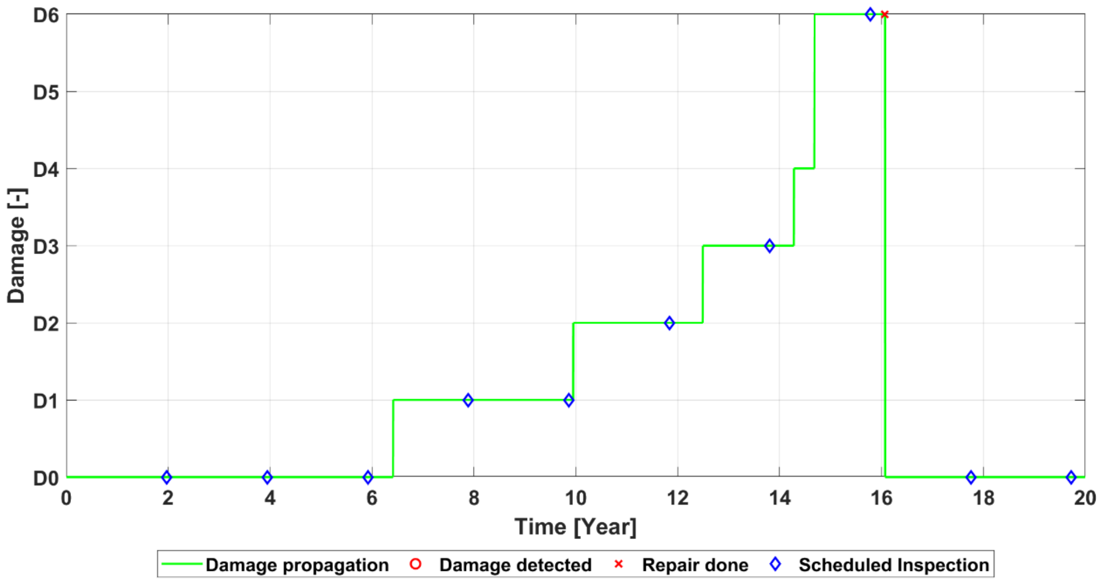


Figure 14: A Realization of the Stochastic Damage Propagation – Approximately linear damage propagation

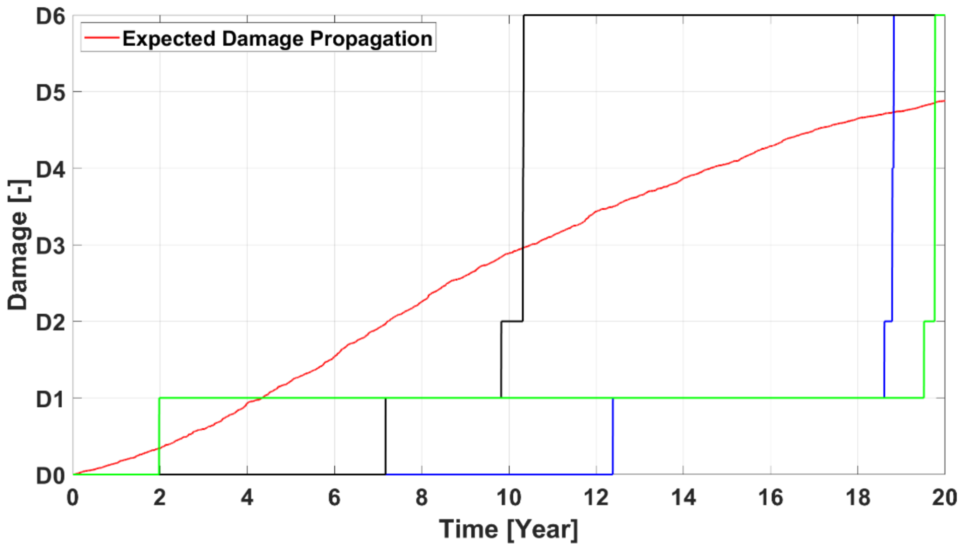


Figure 15: Illustration of Expected Damage Propagation – Nonlinear (a hybrid of exponential and polynomial) damage propagation

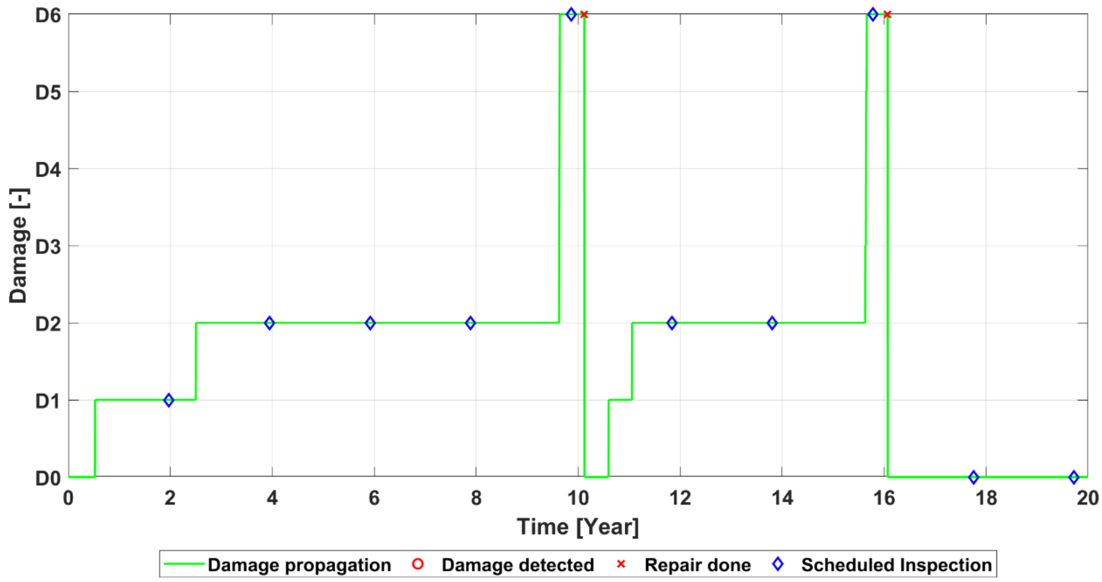


Figure 16: A Realization of the Stochastic Damage Propagation – Nonlinear (a hybrid of exponential and polynomial) damage propagation

4.4.2 Decision-making and Cost Estimation

The theoretical model to calculate the maintenance costs for the different combinations of inspection intervals and decision alternatives is implemented to illustrate the procedure, see below [21]. The results for the two cases are illustrated separately and discussed as follows.

The case of Almost Linear Damage Propagation

Each bar in Figure 17 shows the minimum maintenance cost corresponding to one decision alternative. The cost-optimal inspection interval for each decision alternative is marked above each bar. The cost breakdown is plotted in Figure 17. The costs due to wait time, inspection and replacement account for most of the maintenance cost. Of the 45 possible combinations, the inspection interval of 3 years combined with Decision Alternative 1 is the most cost-optimal maintenance strategy. The trend of the total maintenance cost as function of inspection interval is shown for all decision alternatives in Figure 18~ Figure 20. The 95% confidence intervals of the maintenance cost are only plotted for the cost-optimal case (the inspection interval of 3 years combined with Decision Alternative 1) to illustrate the uncertainty of the cost estimation, as shown in Figure 18. It is observed that the expected costs fluctuate between the inspection intervals of 1-year and 3-year in Figure 19~Figure 22. This is caused by seasonal effects combined with the simulated failure events occurring during the harsh weather conditions requiring longer waiting time to obtain an appropriate time window.

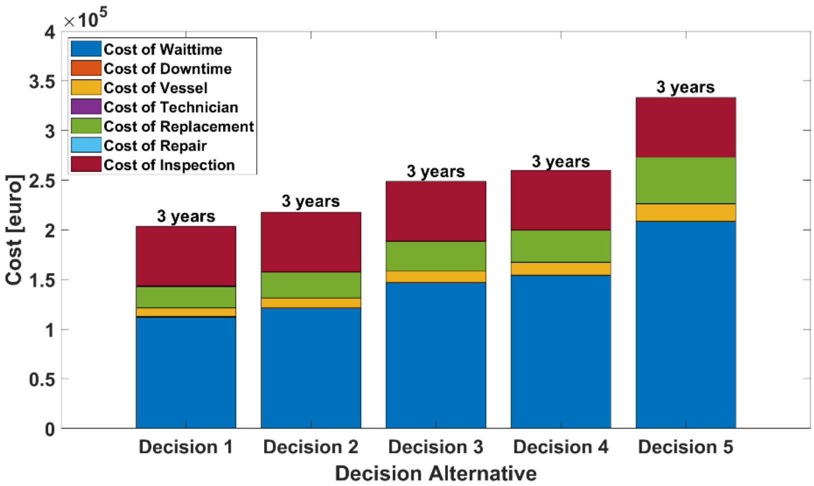
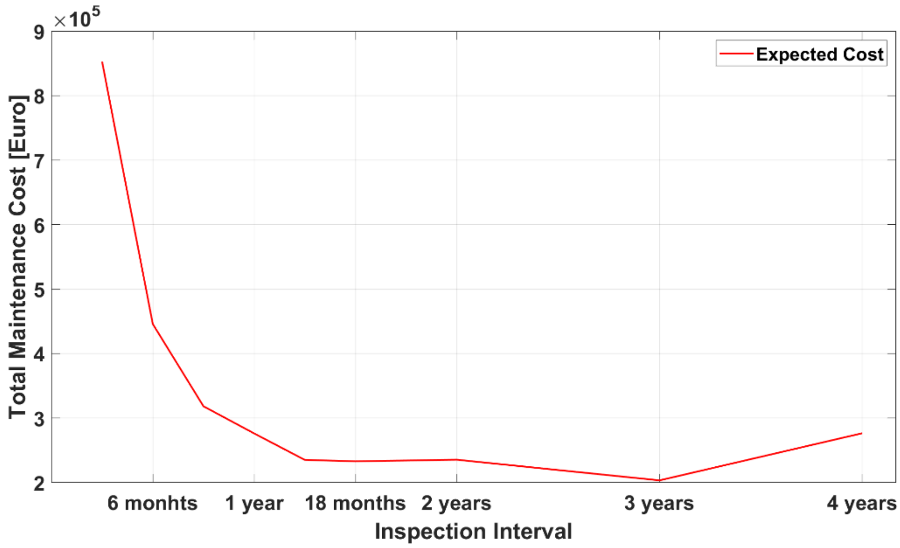
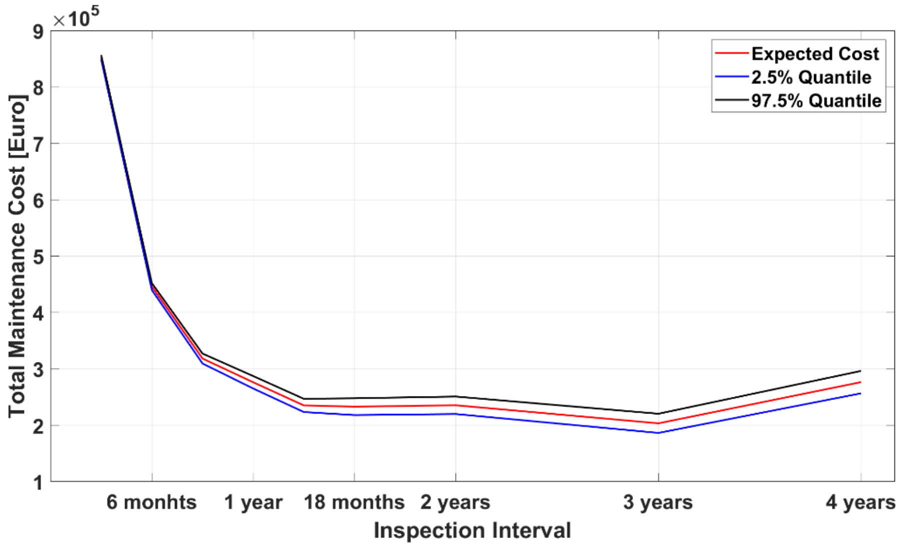


Figure 17: The Total Maintenance Cost for Different Decision Alternatives – Almost Linear Damage Propagation



(a) Decision Alternative 1– with the expected cost trend only



(b) Decision Alternative 1 – with 95% confidence intervals

Figure 18 Cost Trend as Function of Inspection Interval for the Case of Almost Linear Damage Propagation – Decision Alternative 1

Figure 19 Cost Trend as Function of Inspection Interval for the Case of Almost Linear Damage Propagation – Decision Alternative 2

Figure 20 Cost Trend as Function of Inspection Interval for the Case of Almost Linear Damage Propagation – Decision Alternative 3

Figure 21 Cost Trend as Function of Inspection Interval for the Case of Almost Linear Damage Propagation – Decision Alternative 4

Figure 22 Cost Trend as Function of Inspection Interval for the Case of Almost Linear Damage Propagation – Decision Alternative 5

The case of Nonlinear (a hybrid of exponential and polynomial) Damage Propagation

Of the 45 possible combinations, the inspection interval of 4 years combined with Decision Alternative 2 is the most cost-optimal maintenance strategy. The trend of the total maintenance cost as function of inspection interval is shown for all decision alternatives in Figure 23~ Figure 27. The 95% confidence intervals of the maintenance cost are only plotted for the cost-optimal case (the inspection interval of 4 years combined with Decision Alternative 2) to illustrate the uncertainty of the cost estimation, as shown in Figure 23. It is observed that the expected costs fluctuate in these figures. This is caused by seasonal effects combined with the simulated failure events occurring during the harsh weather conditions requiring longer waiting time to obtain an appropriate time window. Beside the fluctuations, it is also seen from these figures that the cost-optimal inspection interval is 4-year for all decision alternatives. The minimum total maintenance cost is slightly different between the five decision alternatives as seen from these figures. This may be caused by the higher assumed transition probabilities compared with the case of almost linear damage propagation. A damage propagates very fast to higher levels of damage severity (D5 or D6) which cost much in maintenance. For example, D5 or D6 occurs more times than the of almost linear damage propagation within a short period of time. The frequent inspection cannot provide some benefits for preventing the occurrence of D5 or D6. Therefore, the advantage of preventive maintenance is not very apparent. This may be the reason that a longer inspection interval can lead to less total maintenance costs.

In light of the aforementioned observations, the bar plot illustrating the maintenance costs for the decision alternatives is not plotted in this sub-section.

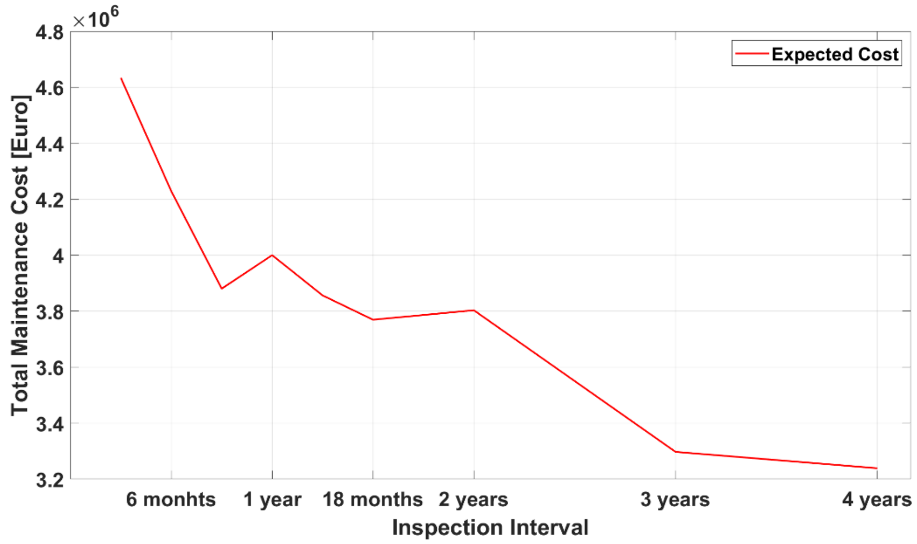
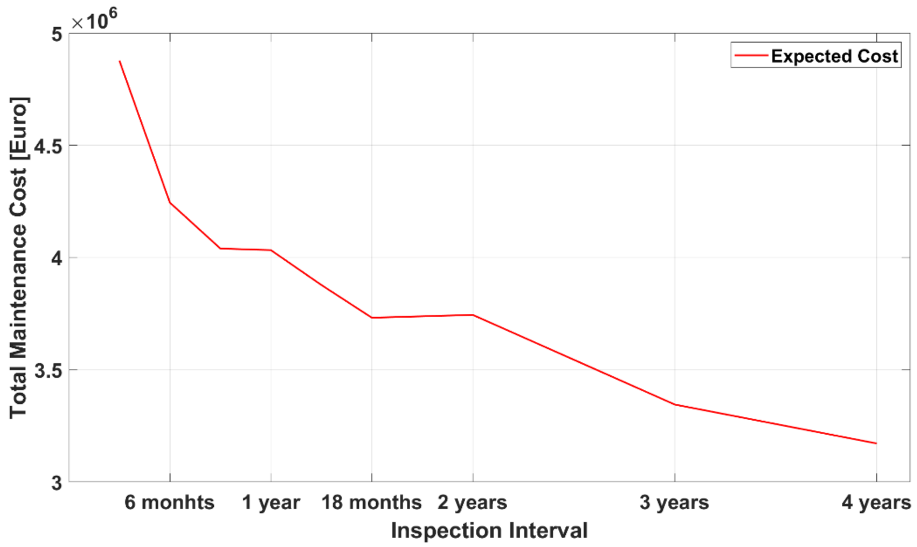
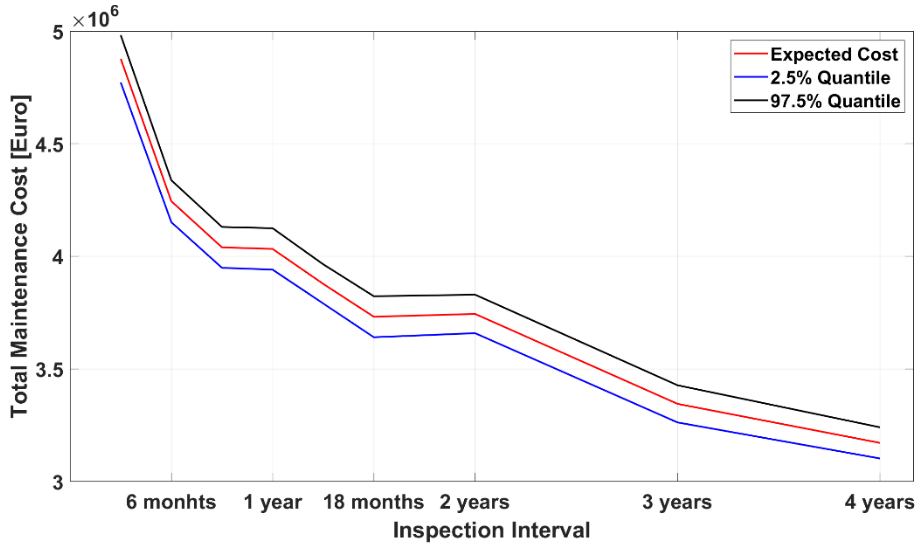


Figure 23 Cost Trend as Function of Inspection Interval for the Case of Nonlinear Damage Propagation (a hybrid of exponential and polynomial) – Decision Alternative 1



(a) Decision Alternative 2– with the expected cost trend only



(b) Decision Alternative 2 – with 95% confidence intervals

Figure 24 Cost Trend as Function of Inspection Interval for the Case of Nonlinear Damage Propagation (a hybrid of exponential and polynomial) – Decision Alternative 2

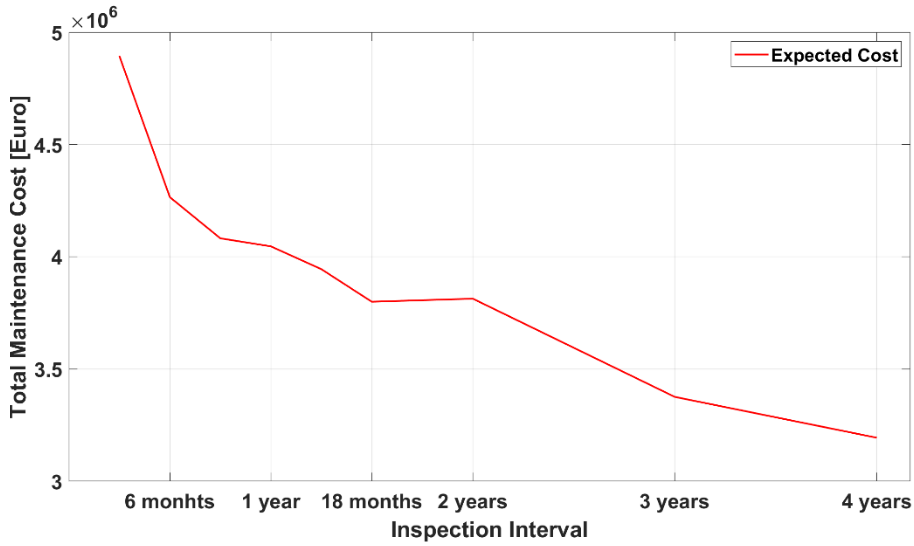


Figure 25 Cost Trend as Function of Inspection Interval for the Case of Nonlinear Damage Propagation (a hybrid of exponential and polynomial) – Decision Alternative 3

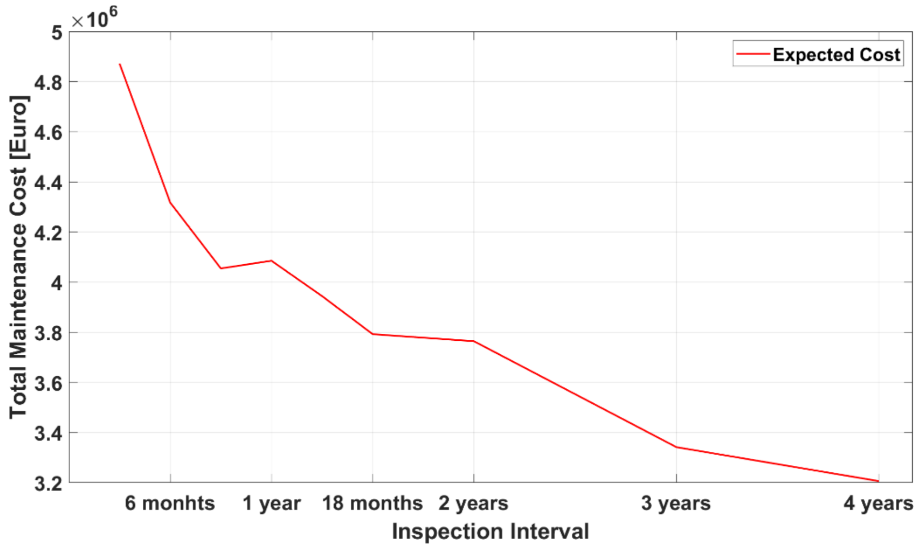


Figure 26 Cost Trend as Function of Inspection Interval for the Case of Nonlinear Damage Propagation (a hybrid of exponential and polynomial) – Decision Alternative 4

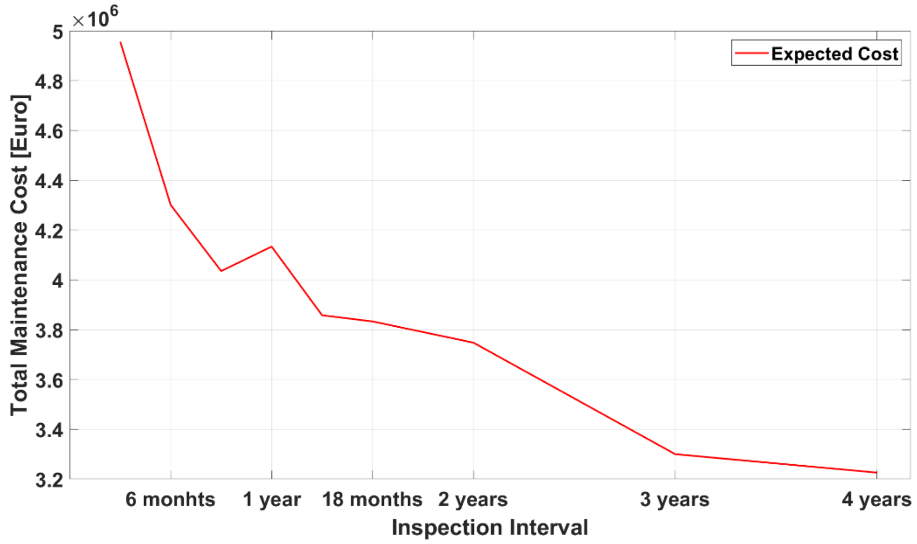


Figure 27 Cost Trend as Function of Inspection Interval for the Case of Nonlinear Damage Propagation (a hybrid of exponential and polynomial) – Decision Alternative 5

Sensitivity Study – the Case of Nonlinear Damage Propagation (a hybrid of exponential and polynomial)

The sensitivity study is performed to demonstrate how the inspection and/or maintenance expenses influence the maintenance strategies. Two key parameters, namely inspection cost and inspection duration, related to the inspection and/or maintenance expenses are chosen.

With the updated two input parameters, the expected maintenance costs as function of inspection intervals are illustrated in Figure 28 for the five decision alternatives. Based upon the experience obtained in the previous sections, the relatively shorter inspection intervals correspond to higher maintenance costs. Therefore, the inspection intervals, such as 3-month, 6-month, 9-month and 1-year, are not considered in the sensitivity study.

The 95% confidence intervals of the maintenance cost are only plotted for the cost-optimal case (the inspection interval of 3.5 years combined with Decision Alternative 1) to illustrate the uncertainty of the cost estimation, as shown in Figure 29.

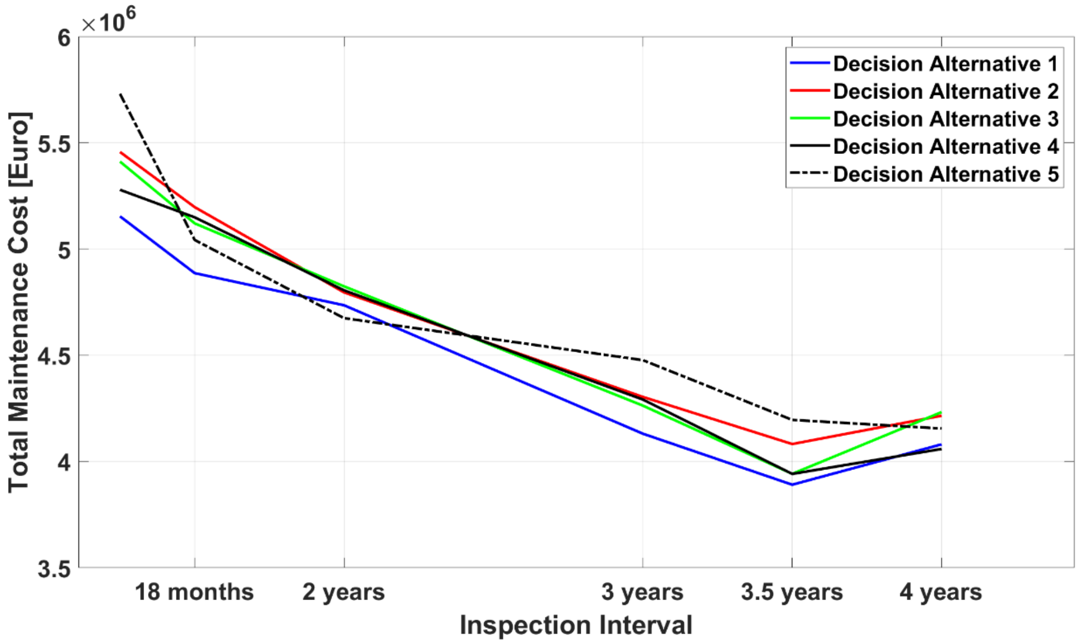


Figure 28 Cost Trend as Function of Inspection Interval for the Case of Nonlinear Damage Propagation (with the updated inspection cost and inspection duration)

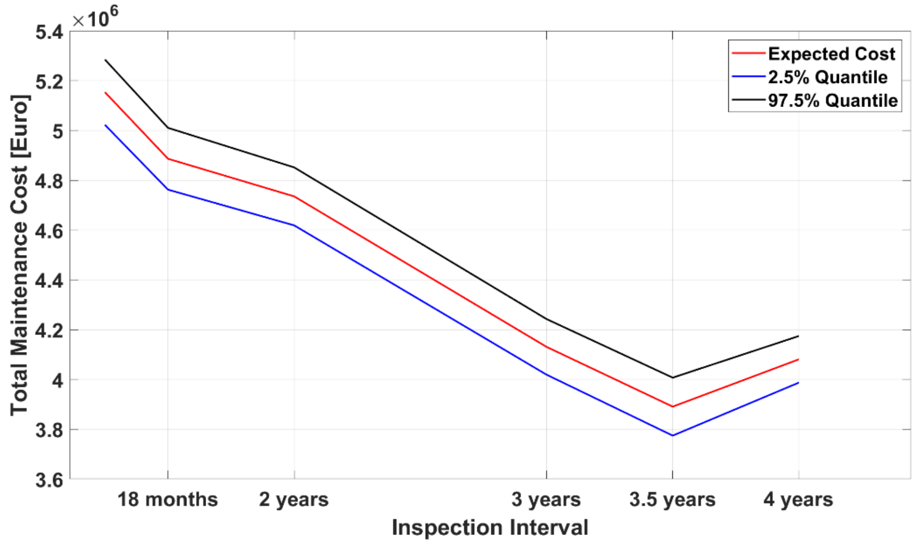


Figure 29 95% Confidential Interval for the Case of Nonlinear Damage Propagation (with the updated inspection cost and inspection duration) – Decision Alternative 1

5. Conclusions and Recommendations

A simulation-based method, namely combining a Discrete Markov Chain model with Bayesian decision tree theory, is primarily investigated in this WP in order to identify cost-optimal condition-based maintenance strategies where the cost-optimal inspection method and interval, and the corresponding decision alternative are identified. Based upon the Discrete Markov Chain model detailed in ISSN 1901-726X DCE Technical Report No. 260, the way Bayesian Decision Tree is integrated into the Discrete Markov Chain model and how the maintenance costs are estimated are demonstrated in a case study of this report.

The simulation of the probabilistic damage propagation is the basic input to the cost modelling and decision-making. The accuracy of the simulated realizations of the probabilistic damage propagation depends upon the calibrated transition probabilities which are closely associated with the in-history failure records. As mentioned in ISSN 1901-726X DCE Technical Report No. 260, there are two demonstration cases, namely 'Transverse Cracks' and 'Root Area & Transition Zone Cracks' investigated in this WP. 'Transverse Cracks' is the focused demonstration case with the actual failure records extracted from the G2D database, while 'Root Area & Transition Zone Cracks' can only be qualitatively investigated with the assumed transition probabilities. Therefore, the cost-optimal maintenance strategy for the case of 'Transverse Cracks' can be used as guidance for decision-making. However, the cost-optimal maintenance strategy for the case of 'Root Area & Transition Zone Cracks' can only be used for decision-making together with the engineering judgement.

Generally, the Discrete Markov Chain model can be applied to the failure modes mentioned in the demonstration cases, as long as a large amount of records for different damage severities (preferably to obtain the records for one damage on the same blade) can be obtained. It can be concluded from the case study in this report that:

- The crack/ defect propagation rate is highly related to the transition probabilities. The crack/defect propagation route/path (either almost linear or nonlinear propagation) can be qualitatively estimated, namely whether it propagates linearly or nonlinearly, based upon the calibrated transition probabilities. It is noted that not all uncertainties can be accurately represented by the Discrete Markov Chain model, e.g. model uncertainties related to the crack growth process.
- The greater transition probabilities indicate that a crack/ defect propagates and reaches to the collapse state much faster than the lower transition probabilities; in addition, the number of the blade collapse for the case where a crack/ defect propagates nonlinearly (corresponding to higher transition probabilities) is higher than that for the case where a crack/ defect propagates almost linearly (corresponding to lower transition probabilities);
- The assumptions regarding the post-repair conditions are made based upon the engineering considerations. These assumptions indirectly influence the rate of a damage propagating to the state corresponding to either major repair or collapse; With the limited knowledge of the effectiveness of repair, the post-repair conditions assumed in this WP are used as a default set-up;
- The frequent inspection cannot provide some benefits for preventing the occurrence of the severe damage categories D5 or D6, if the transition probabilities are very high (e.g. the assumed probabilities for the case of nonlinear damage propagation). The advantage of preventive maintenance is not very apparent. This may be the reason that a longer inspection interval can lead to less total maintenance costs.

The Discrete Markov Chain Model developed for the RATZ project is a simplified methodology that characterizes the crack/ defect propagation from the probabilistic point of view. This model can be easily implemented in a computer code, however, it is unable to interpret the failure mechanisms for 'Transverse Cracks' and 'Root Area & Transition Zone Cracks'. Therefore, it is recommended that a quantitative fracture mechanics model be developed from the perspective of failure mechanism, and be used together with the Bayesian decision tree to do cost-optimal inspection planning.

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