Optimized Maintenance Decision-Making – A Simulation-supported Prescriptive Analytics Approach based on Probabilistic Cost-Benefit Analysis

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ABSTRACT

Prescriptive Maintenance strategies are emerging as potential next level of reliability and maintenance best practice. Likely outcomes of maintenance alternatives and their effects on e.g. cost and safety are comparatively evaluated by exploiting various sources of data, knowledge and models. By this means, optimized courses of actions are recommended to quickly resolve problems and to automate Maintenance, Repair and Overhaul (MRO) decisions. In this work, the key question is pursued as to how their dependability and potential business advantage can be assessed and improved in the presence of uncertainty and variability of various decision-influencing factors such as degradation and maintenance model parameters and cost sources. For this purpose, a step-by-step procedure to optimal solution prescription and potential / risk assessment is developed based on a probabilistic approach to cost-benefit analysis and on the definition of relevant metrics. By the help of a Wiener process degradation model capable of implementing random effects of imperfect repairs and a Monte Carlo simulation, its value is illustrated by a use case example – repair / replacement decision support in the aeronautical context. The probabilistic approach not only allows to determine, which decision option promises the higher profit and is thus preferred, but also with which risk and potential cost disadvantage it is associated. Furthermore, it uncovers, where higher-quality data or information, can gainfully reduce result uncertainty and hence be assigned a *monetary* value. It is argued that the presented approach could give industry practitioners directions for identifying and optimizing business cases for *Prescriptive Maintenance*, by pointing at which sources of data or information are particularly valuable and hence justify dedicated investments for acquiring it. The relevance of the results is discussed specifically with reference to emerging digitized and automated repair processes as well as more generally in the context of future data-trading schemes.

1. INTRODUCTION

The quest for continuous refinement of MRO strategies is driven by the increasing complexity of engineering systems and related MRO decisions as well as the large penalties arising for various stakeholders from unexpected maintenance needs, downtime and logistic effort. Adding to this is the growing importance of service-oriented business models and the need for competitive advantage. Examples include power-by-the-hour long-term service agreements between engine manufacturers and operators in the commercial aviation sector (Smith, 2013), which are based on a fixed price for the flown hour including all necessary MRO actions and possibly even the provision of the engine itself for the entire lifetime. The profitability of such business strategies strongly depends on the achievable level of performance and reliability. These demands for a high degree of predictability and decision quality in the advanced MRO business.

One of the general expectations of Prognostics and Health Management is the translation of raw data related to the health state of engineering systems into actionable information to facilitate rapid and informed maintenance decision-making. Here, the availability of more and more data and advanced analytics technologies fosters the progressive shift from time-based to demand-based maintenance concepts, which continuously adjust the maintenance strategy based on the needs and condition of monitored equipment. For instance, in the aviation industry, *Predictive Maintenance* approaches are increasingly adopted to detect early signatures of impending failures of monitored components or systems to allow for reduced downtime and timely MRO actions (cf. Saxena et al., 2014; Wagner, Saalmann, & Hellingrath, 2016; Koops, 2018 and references therein).

As a potential next level of reliability and maintenance best practice, *Prescriptive Maintenance* strategies are emerging (Bertsimas & Kallus, 2015; Sappelli et al., 2017; Diez-Olivana et al., 2018). Building on the knowledge, when and why failures are likely to occur, they aim at producing outcome-focused recommendations from *Prescriptive Analytics*. By comparing the chances of success of maintenance alternatives and their effects on e.g. cost and safety by using various sources of data, knowledge and models, optimized courses of actions are derived.

Besides reducing the susceptibility to human errors, this “more data-driven approach” allows for optimizing business value of various stakeholders by increasing service reliability, efficiency, uptime and capacity, lowering logistic effort and overall costs and finally by improving support offers and future engineering design based on derived insights. Furthermore, the increasing degree of automation allows for business innovation for instance in the context of remote maintenance, particularly interesting for surveillance, rescue or military operations.

However, maintenance model parameters are affected by uncertainties as well as variability. They arise from limited data, knowledge or contextual awareness, the stochastic nature of degradation and failure phenomena as well as from inherent heterogeneity or diversity such as due to environmental or operational factors (Compare, Martini & Zio, 2015; Pei et al., 2018). In the literature, different frameworks for uncertainty representation have been investigated such as probability distributions, fuzzy sets, and plausibility and belief functions (cf. Compare, Martini & Zio, 2015 and references therein).

Computational methods involving Monte Carlo tools and additional concepts have been developed to incorporate accordingly described imprecise parameters e.g. into Markov or semi-Markov multi-state (Hubbard, 2014) or continuous degradation models like the Wiener degradation process (Gorjian et al., 2010; Letot et al., 2017; Pei et al., 2018). The latter has attracted increasing attention in recent years due to its significance in *Predictive Maintenance*, e.g. for accurate Remaining Useful Life (RUL) prediction and the capability to consider both time-varying dynamics and unit-to-unit variability, the latter stemming from variations in operational conditions and initial degradation levels (Zhu, Zuo & Cai, 2013; Letot et al., 2017; Pei et al., 2018). For instance, RUL estimation of an aircraft engine has been performed based on lifecycle and performance-deteriorated parameter data without failures (Zhu et al., 2013).

Moreover, the Wiener Process has been applied to characterize degradation of mechanical components (Wang et al., 2018) and rotary machinery and its constituents including bearings as well as to gyroscopes in inertial navigation systems (cf. Zhang et al., 2018).

Letot et al. (2017) have related the Wiener degradation process to operational reliability and derived strategies for cost-optimized maintenance planning.

Regarding options for refurbishment, progress in repair technology and process automation offer increasingly (cost-) effective options for repairing equipment, instead of replacing it (Wang et al., 2015; Paquet et al., 2017; Guo & Brommesson, 2018; American Roller Bearing Company, 2020). However, in general, repair is imperfect, such that the post-maintenance life after “repair” is typically reduced as compared with “replacement” (Pham & Wang, 1996). The implications of imperfect repair on the degradation path have been analyzed by Pei et. al., 2018 and Zhao, He & Xie, 2018 considered random effects of imperfect repairs in the context of warranty cost optimization.

As prior research works have hence demonstrated, the degradation path and thus the life span of engineering assets and their components and implications for maintenance planning and refurbishment are influenced by various sources of uncertainty and variability. While in some of previous studies the maintenance effect has been modeled as random (Compare, Martini & Zio, 2015; Letot et al., 2017; Pei et. al., 2018; Zhao, He & Xie, 2018), resulting cost sources typically are considered as single-point values (Compare, Martini & Zio, 2015). Furthermore, to our best knowledge, the influence of random effects including sensible variations of cost factors on the quality of resulting MRO decisions and their business value has not been investigated before.

The aim of this study is hence to develop a probabilistic framework for determining “best-action” solutions within *Prescriptive Maintenance* and for assessing and subsequently deriving strategies for enhancing decision-reliability and business value on the example of repair / replacement decision support. By exploiting realistic degradation and maintenance models implementing random effects of imperfect repair as well as possible variations in cost factors, valuable data and information sources are identified that are relevant in the context of future (fully) digitized and automated maintenance processes and potential future data trading schemes.

For this purpose, the paper is structured as follows. In Section 2, Prescriptive Analytics is introduced. In Section 3 a step-by-step approach to prescribing “best action” solutions is presented on the example of repair / replacement decision support and the relevance of simulation-supported probabilistic cost-benefit analysis is discussed. Section 4 considers the Wiener degradation process and lays the basis for implementing the effects of imperfect repair. In Section 5, the considered maintenance scenario is outlined and assumptions and required inputs are elaborated on. In Section 6, key metrics are introduced that allow to assess reliability and economic value of *Prescriptive Maintenance* solutions. In Section 7, different use cases defined by particular sets of parameter variations are motivated. These are subsequently exploited for the probabilistic cost-benefit analysis singling out “best action” solutions by means of a Monte Carlo simulation and by the evaluation of key metrics. Based on the results, strategies for supporting and improving *Prescriptive Maintenance* business cases are discussed. Finally, in Section 8, we conclude and provide an outlook on future directions.

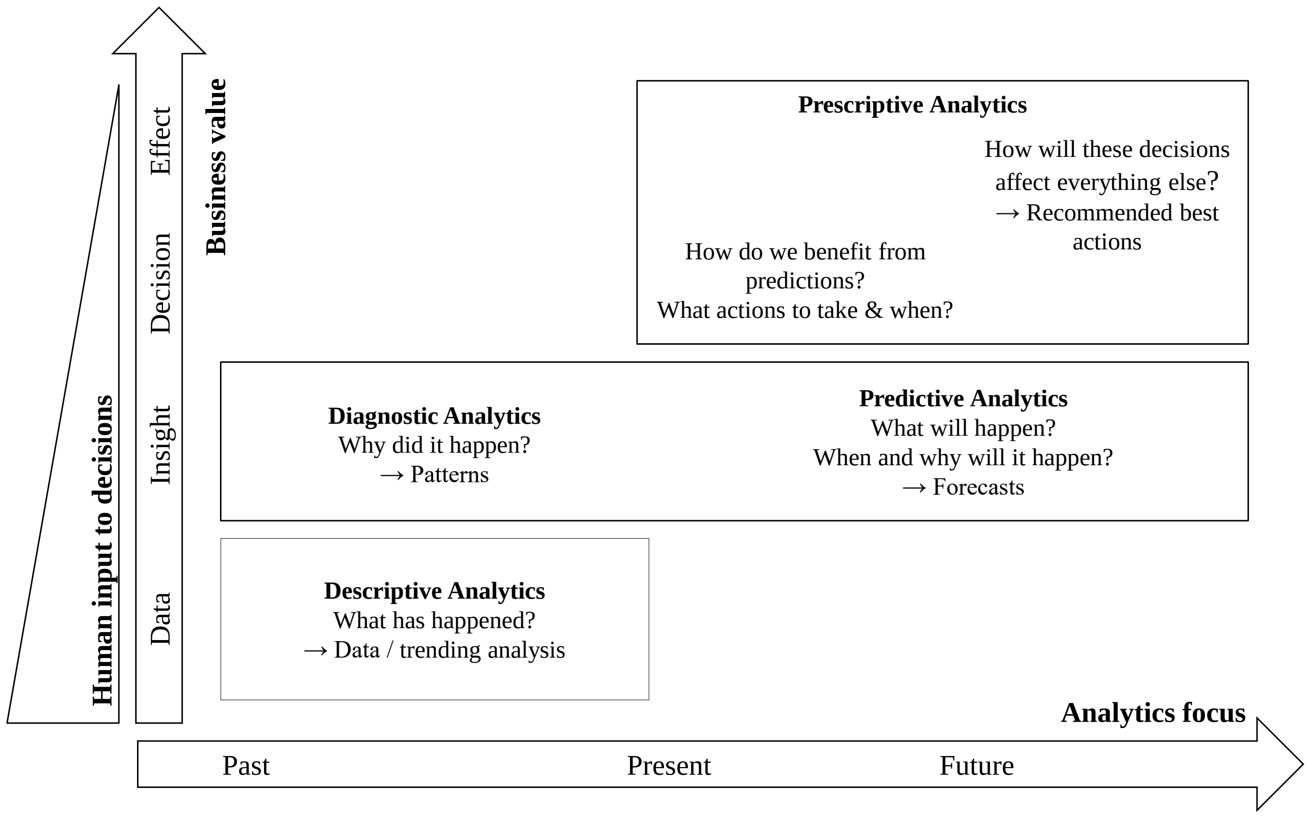

Figure 1: Characterization of various analytics techniques finding application within *Prescriptive Maintenance*.

2. PRESCRIPTIVE MAINTENANCE – DEFINITION, REQUIREMENTS, CAPABILITIES

In general, *Prescriptive Analytics* involves any combination of analytics, experiments, simulation, and / or artificial intelligence to improve the effectiveness of decision-making and to support new business models and opportunities (Bertsimas & Kallus, 2015; Sappelli et al., 2017; Diez-Olivana et al., 2018).

Typically, it provides enhanced business value by minimizing the amount of human input required for decision-making and builds on integrated knowledge gained from other analytics technologies (cf. Figure 1). These include descriptive and diagnostic analytics focusing on past (historical / test) and present (run-time) data in recognizing anomalies and identifying root causes for impending failures of monitored equipment. Furthermore, *Prescriptive Analytics* proactively makes use of insights gained from aforementioned data sources by means of predictive analytics that allows using the known status of monitored equipment, combined with physics-of-failure models and statistics for forecasting e.g. future behavior, trends and outcomes such as likely time of failure (cf. Figure 1). While diagnostic / prognostic approaches may be conceptualized regarding three levels with varying degrees of complexity, i.e., 1) existing, 2) future failure mode prognostics and 3) post-action prognostics with a focus in the literature on the first (Taheri, Kolmanovsky & Gusikhin, 2019), in a *Prescriptive Maintenance* setting, typically all three of them are exploited. Accordingly, additional business value is gained from analyzing the impact of predicted failures on operational and maintenance activities, to quantitatively compare decision options and their effects on Key Performance Indicators (KPIs). From a methodological point of view, it is the aim of *Prescriptive Analytics* to not only provide different action alternatives, but to single out the *optimal* set of actions. As becomes clear later on, here, the application of (multi-objective) stochastic optimization techniques is of paramount importance to incorporate measures of risk in the decision process. This provides the basis for recommending "best action" solutions and for automating decisions. Moreover, it allows tackling a broad range of questions within *Prescriptive Maintenance* placed at a system-oriented, business management level typically extending the decision support step in classical Prognostics and Health Management (PHM). Examples include optimized maintenance scheduling at fleet-level, planning of MRO work scope (e.g. order of execution of tasks or repair or replacement decision support, cf. the next section) as well as logistics / inventory management (e.g. spare parts ordering) under various constraints (cf. Koops, 2018 and references therein).

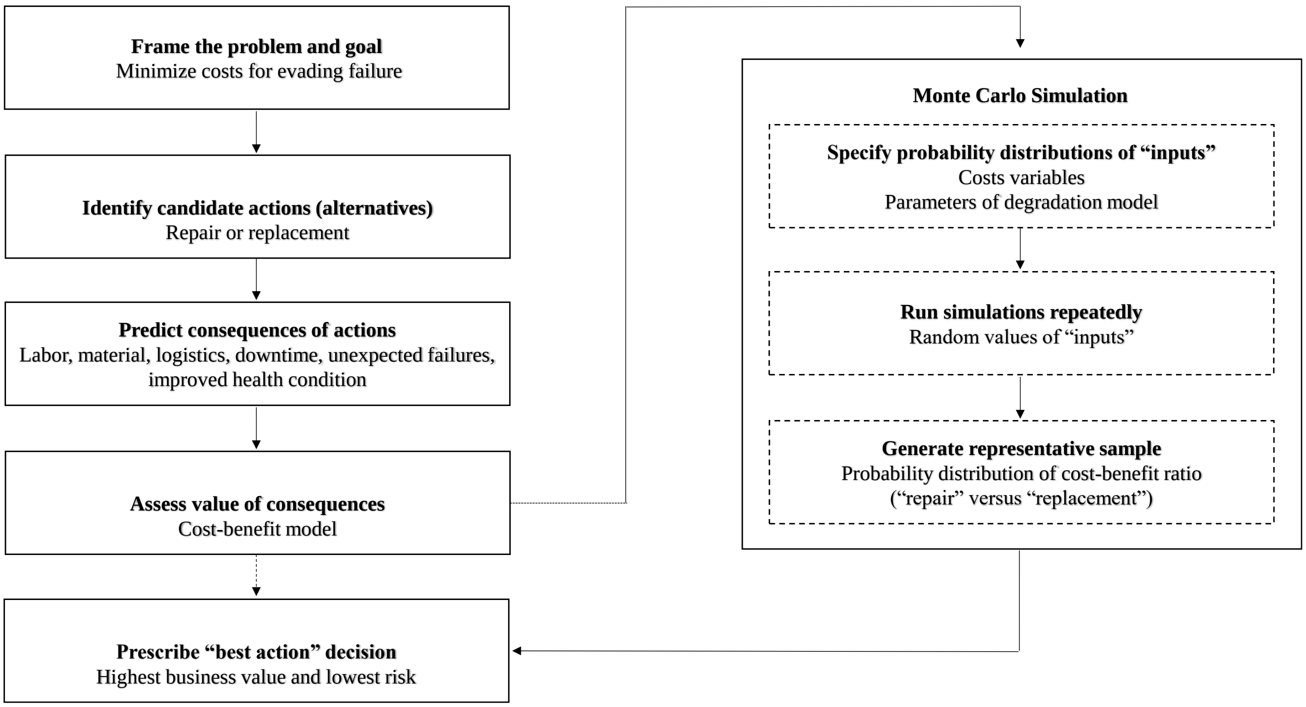

Figure 2: Step-by-step approach to solution prescription.

Requirements for making a *Prescriptive Analytics* approach sensible range from sufficient impact and complexity in terms of decision options for justifying the effort of the approach, over the presence of constraints limiting the decision space to the availability of data on possible actions, decisions and consequent situations (Sappelli et al., 2017). While in principle, in the MRO business, these requirements are typically fulfilled, the representativeness of results and hence the reliability of prescribed "best action" solutions can be strongly influenced by the quality of assumptions, data and models used, as will become apparent later on.

3. STEP-BY-STEP APPROACH TO SOLUTION PRESCRIPTION

The step-by-step approach to "best action" solution prescription outlined in the following provides a basis for identifying and optimizing business cases on an application-by-application basis.

As mentioned in the introduction, the approach is applied to the binary decision example "repair" or "replacement". While in the MRO context often multiple (competing) business objectives are sought to be optimized within multi-objective optimization schemes – like minimizing costs and simultaneously maximizing safety (Compare, Martini & Zio, 2015) – here, for simplicity, a focus is placed on economical aspects only. As shown in Figure 2, with the aim of minimizing costs for evading failure, the following steps are required for determining the "best action" solution, which is associated with highest business value and lowest decision risk. These include besides a proper problem statement, singling out alternative decision actions and determining their consequences within a maintenance model. Their value can be assessed by means of cost-benefit analysis. For this purpose, in maintenance modeling, in many cases, single point estimates are employed for model parameters such as costs or degradation model inputs. This deterministic approach leads to a constant output for the decision model. By this means, the influence of e.g. inherent stochastic effects, measurement errors, modeling inaccuracies or inherent parameter spread on decision-outcomes are neglected. As will become apparent in Section 7.2, this may compromise the representativeness of outputs and hence the reliability of as determined "best actions" decisions and potentially lead to financial penalties.

In this work, for properly dealing with various sources of uncertainty and variability in the context of *Prescriptive Maintenance*, a probabilistic approach to cost-benefit analysis based on a Monte Carlo simulation is pursued. It is outlined on the right hand side of Figure 2 and further described in the next section.

3.1. Simulation-supported Probabilistic Cost-Benefit Analysis

By means of a stochastic model, probability distributions of potential outcomes can be estimated by allowing for random variation in one or more inputs (Hubbard, 2014).

A Monte Carlo simulation is one example for a stochastic model that is applied to allow for dealing with certain degrees of unpredictability and randomness by determining a range of outcomes of the two different maintenance alternatives considered, “repair” or “replacement”. The right hand side of Figure 2 summarizes the corresponding steps typically involved in a Monte Carlo approach that can be adopted for a simulation-based cost-benefit and risk analysis. Namely, by simulating a large number of draws from the given distributions of input variables to the cost-benefit model, the resulting distribution of outcomes is established.

As indicated by Figure 2, first, the probability distributions of inputs have to be specified. In case real data is available, the underlying distributions can be fitted for each input variable and used as an input to the cost-benefit model (Hubbard, 2014).

A further description of the degradation model considered in this work is provided in the next section and an overview on relevant data sources and assumptions regarding maintenance costs and their distributions can be found respectively in Sections 5.1 and 5.2.

4. DEGRADATION MODEL BASED ON WIENER PROCESS

Degradation, in general, refers to the reduction in performance, reliability, and hence RUL of engineering assets. Many failure mechanisms can be traced to an underlying degradation process, which is stochastic in nature. Probabilistic models with continuous state are widely used to characterize the degradation process. Besides the gamma process (Gorjian, 2010), frequently used models from this process family include the Wiener process (Wang et al., 2018; Zhao, He & Xie, 2018), further considered in this study.

The Wiener process can be expressed as drifted Brownian motion (Szabados, 2010; Zhao, He & Xie, 2018). It is particularly suited to represent the evolution of a degradation process, which exhibits an increasing trend over time with random Gaussian noise, both being functions of elapsed time,

$$\mathrm{X(t)} = \eta\Lambda(t) + \sigma B\big(\Lambda(t)\big), \tag{1}$$

where initial degradation is assumed to be zero and $\Lambda(t) = t$ such that the degradation path is linear. Further, $\eta > 0$ and σ denote the drift and diffusion coefficients, respectively related with the expected rate of degradation and the magnitude of the Gaussian noise perturbing the trend. Moreover, B is the standard Brownian motion. Accordingly, the Wiener process is characterized by continuous sample paths, being a sequence of successive independent random, normally distributed increments (Szabados, 2010).

The importance of Brownian motion in probability theory amongst other things lies in a certain sense, in its constitution of a limit of rescaled simple random walk.

For degrading units one typically defines the hitting time $\mathrm{T_D}$ as the first passage time of X(t) with respect to a degradation threshold, D (Zhao, He & Xie, 2018; Pei et al., 2018). This corresponds to the failure time of the equipment, necessitating preventive / corrective maintenance actions somewhat before / thereafter. $\mathrm{T_D}$ exhibits an inverse Gaussian (IG) distribution with mean D/η and shape D^2/σ^2 (Zhao, He & Xie, 2018), i.e.,

$$T_{\mathrm{D}} \sim \mathrm{IG}\Big(\frac{D}{\eta}, \frac{D^2}{\sigma^2}\Big). \tag{2}$$

Hence, the Probability Density Function (PDF) of T_{D} reads

$$f_{T_D}(t; D, \eta, \sigma) = \Big(\frac{D^2}{2\pi\sigma^2 t^3}\Big)^{1/2} exp\Big(-\frac{(t\eta - D)^2}{2\sigma^2 \mathrm{t}}\Big). \tag{3}$$

For the case of “replacement”, Eq. (3) can be used to determine the reliability R(t), i.e. probability of zero failures in time t, as well as the failure function F(t), i.e. the probability of crossing the failure threshold at $\mathrm{T_D} \leq t$, according to (Letot et al., 2017)

$$R(t) = 1 - F(t), \tag{4}$$
$$F(t) = P(T_D \leq t) = P(X(t) \geq D) = \int_0^t f_{T_D}(T)dT.$$

In the case of “repair”, both R(t) and F(t) depend on the repair effectiveness, defining the degradation value after maintenance. Therefore, in the next section, random effects of imperfect repairs are implemented within the Wiener process model.

4.1. Imperfect Repair with Random Improvement Factor

While the repair of equipment is typically more cost-effective than replacing it, in general, it is imperfect and can hence only restore the health condition of the equipment to a state between “as good as new” and “as bad as old” (Pham & Wang, 1996). Hence, the post-maintenance life after “repair” before the next required maintenance activity is typically reduced as compared with “replacement”.

Assuming that the equipment exhibits no initial degradation, the respective degradation levels $\mathrm{X_k}$ and $\mathrm{X_k}^+$ before and after *k*th repair may be expressed in terms of the improvement factor α_k (Zhao, He & Xie, 2018),

$$X_{\mathrm{k}}{}^+ = (1 - \alpha_k)X_{\mathrm{k}}, \tag{5}$$

where $0 \leq \alpha_k \leq 1$. Here, the two limiting cases respectively correspond to minimal repair (“as bad as old”) and perfect repair (“as good as new”, i.e. resetting the degradation value to zero).

It is sensible to assume that the effect of repair is subject to potential randomness and that the improvement factor can be modeled by a univariate random distribution. Following Zhao, He and Xie (2018), we use independent and identical truncated normal distributions in the range [0,1] to model α_k, i.e. $\alpha_k \sim TN(u, v, 0,1)$ for $k = 1, 2, \ldots$ with PDFs given by

$$f_{\alpha_k}(\alpha_k; u, v, 0,1) = f_\alpha(\alpha; u, v, 0,1) = \frac{\phi\left(\frac{\alpha-u}{v}\right)}{\sigma\left(\Phi\left(\frac{1-u}{v}\right)-\Phi\left(\frac{0-u}{v}\right)\right)}, \tag{6}$$

where ϕ and Φ respectively denote the PDF and the Cumulative Distribution Function (CDF) of the standard normal distribution. As will be further discussed in Section 7.1, the higher / lower the parameters u / v, the larger is the average repair quality and the smaller its spread. Further, since α_k are independent and identically distributed, α is taken to represent α_k. Hence, the effect of repair is considered to be homogeneous and the kth hitting time T_{D_k} for $k \geq 1$ can be expressed as (Zhao, He & Xie, 2018),

$$T_{D_k} \sim \mathrm{IG}\left(\frac{D\{1+(k-1)\log[E(\exp(\alpha))]\}}{\eta}, \frac{\{D(1+(k-1)\log[E(\exp(\alpha))]\}^2}{\sigma^2}\right) \tag{7}$$

with

$$E\big(\exp(\alpha)\big) = \int_0^1 e^\alpha f_\alpha d\alpha, \tag{8}$$

being a constant for fixed u and v according to Eq. (6). Furthermore, the mean and variance of T_{D_k} are respectively given by $D\{1 + (k-1)\log[E(\exp(\alpha))]\}/\eta$ as well as $\{D(1 + (k-1)\log[E(\exp(\alpha))]\}^2/\sigma^2$. Note that for $k = 1$, Eq. (7) corresponds to Eq. (2) from the last section. The reason is that the evolution from zero degradation state up until 1st maintenance is independent of the improvement factor, which is used to describe the effect of repair on the degradation after the first maintenance event.

Moreover, the time between to maintenance events follows the distribution (Zhao, He & Xie, 2018),

$$\Delta T_k \sim \Delta T \sim \mathrm{IG}\left(\frac{D\log[E(\exp(\alpha))]}{\eta}, \frac{\{D\log[E(\exp(\alpha))]\}^2}{\sigma^2}\right), \tag{9}$$

which is independent of k.

Let us for comparison and for later reference define the mean of $\alpha, \mathrm{E}(\alpha)$, as constant improvement factor, where

$$\mathrm{E}(\alpha) = \int_0^1 \alpha f_\alpha d\alpha. \tag{10}$$

It is interesting to note that according to Jensen’s inequality, $E(\exp(\alpha)) \geq \exp(\mathrm{E}(\alpha))$, it follows that $\log[E(\exp(\alpha))] \geq \mathrm{E}(\alpha)$ such that the effect of randomness in the improvement factor is to increase the mean and also the variance of the kth hitting time. The effect on result uncertainty will be further investigated in Section 7.2.

5. CONSIDERED MAINTENANCE SCENARIO

In this study, it is assumed that one of the two maintenance alternatives “repair” or “replacement” is to be singled out by the *Prescriptive Maintenance* approach as “best action” solution for all successive maintenance events. In order to take the decision, the assessment time horizon is chosen to be long enough such that effects of imperfect repair become apparent. In general, with respect to replacement, these include a cost difference for maintenance as well as modifications in failure times as demonstrated by the comparison of Eqs. (3) and (8), which can enhance the number of required maintenance events. In this study, the following maintenance scenario is considered

- Preventive and Corrective Maintenance: fixed maintenance at time T_P that is chosen within a reliability-centered approach such that *replacement* costs are minimized (cf. approach below).

The cost-optimal time T_P for performing preventive maintenance is determined by the trade-off between lower preventive maintenance frequency / costs and increased unexpected failures in between that cause typically elevated costs related with corrective maintenance (cf. the discussion in Section 5.1). Accordingly, T_P optimizes the Expected Maintenance Cost Per Unit of Time (ECPUT) given by (Letot et al., 2017)

$$ECPUT = \frac{E(C)}{\int_0^{T_P} R(t)dt}, \text{ with} \tag{11}$$

$$E(C) = R(T_P) \cdot C_P + F(T_P) \cdot C_C, \tag{12}$$

where the denominator of Eq. (11) corresponds to the mean uptime and Eq. (12) corresponds to the expected maintenance costs, where C_P and C_C respectively denote preventive and corrective maintenance (i.e. failure) costs. Here, the degradation failure is assumed to be discovered and remedied immediately and that both repair and replacement time upon failure are negligible compared to the system lifespan.

In a sense, this problem corresponds to the case, where the optimal maintenance action is to be singled out under constraints, namely, that the maintenance time is fixed (e.g. to accommodate other necessary system’s refurbishment, simultaneously) and not chosen according to the economically most favorable time for the option "repair". As will become clear later on, this tends to increase corrective maintenance costs for imperfect repairs as compared with replacements.

In Section 7.2, the difference in expected maintenance costs between repair and replacement as preventive maintenance action is evaluated according to Eq. (12), using the respective distributions of hitting times specified in Eqs. (8) and (3).

Corrective maintenance costs are for simplicity assumed to be the same for both options as significant contributions other than for refurbishment arise for both options (cf. the discussion in Section 5.1).

It should be noted that the degradation model outlined in Section 4 could also be embedded into a *Predictive / Prescriptive Maintenance* setting with on-line monitoring of degradation indicators as is investigated in on-going work. This would allow for continuous update of the RUL as soon as new degradation data is available (Letot et al., 2017). In this case, maintenance events may be optimally planned in time to evade degradation failures and to optimize maintenance costs (i.e., here, corrective maintenance events could be evaded).

5.1. Assumptions on Maintenance Costs

For many applications such as for bearings or turbine blades, repair costs are reported to make up respectively only 20 to 70% and roughly 50% of replacement costs (American Roller Bearing Company, 2020; Wang et al., 2015). Effectively, they involve any costs related with required labor and material (e.g. spare parts, tools), logistics as well as (potential) monetary penalties resulting from downtime of the considered equipment during refurbishment (e.g. for the operator of an aircraft) (Letot et al., 2017). Costs are impacted by the local conditions such as material / labor costs of the repair shop location (region) and by the required turnaround-time. Furthermore, higher repair efficiency allowing for lower turnaround-time, is typically associated with higher repair costs (International Air Transport Association, 2015).

Replacement of components or systems is often more time-effective than repair with subsequent quality inspection, in particular when (a chain of) manual processes are involved (International Air Transport Association, 2015). This is why significant research efforts go into approaches for automating respective repair actions to save valuable (down)time and hence costs (Gardiner, 2011; Paquet et al., 2017). This also provides means to decrease the dependence of the repair costs on local conditions, like labor costs of the repair shop region. As will be discussed in Sec. 7.1, this can influence the variability of future repair costs.

In addition, in the maintenance scenario described in the last section, unexpected failures can occur before the next scheduled maintenance event that are typically related with higher costs than for preventive maintenance. For instance, they comprise contingency damage and potential labor and logistic costs associated with component or system restoration as well as downtime-related costs (cf. Koops, 2018 and references therein). Since in general, after imperfect repair, the component is not "as good as new", the failure probability after maintenance action is larger than after replacement.

For simplicity, in this study repair, replacement and unexpected failure costs are assumed to exhibit a normal distribution. Valuable data and information sources are discussed in the next section and meaningful parameter ranges are specified in Section 7.1.

5.2. Valuable Data and Information Sources

Financial data / information may be gained from

- Financial reports
- Cost models
- Expert knowledge

Technical data and information as needed to quantify the degradation model and repair efficiency by means of probabilistic modeling and inference includes

- Degradation and usage data from equipment monitoring (historic, "on-line")
- Failure / maintenance / repair history
- Repair process and quality control data
- Expert knowledge

Degradation data often provide more information than failure time data for assessing reliability and predicting the RUL of systems (Gorijan et al., 2010) and are easier to acquire in high-risk sectors like aviation. For instance, within *Predictive maintenance* approaches, prognostics may be based on a degradation process through available degradation data.

More precisely, for instance prior degradation information can be used to determine prior distributions of Wiener process parameters. By means of on-line monitoring of degradation indicators and Bayesian methods, these can be updated to posterior distributions for accurate assessment of performance reliability and RUL, whenever new degradation data is available (Zhu, Zuo &,Cai, 2014; Zhao, He & Xie, 2018).

6. KEY METRICS FOR EVALUATING BUSINESS VALUE AND RISK

In this study, various metrics originating from business analytics (Hubbard, 2014) are adopted to assess the impact of different sources of uncertainties generally arising e.g. from data measurement, modeling and costs, within the described framework of probabilistic cost-benefit analysis used to prescribe "best action" solutions by means of a Monte Carlo simulation. These include

- Mean cost difference $\mathrm{E}(\Delta C)$ between both maintenance alternatives (i.e. profit or loss), determined from the cost difference ΔC and its PDF $f_{\Delta C}$ according to $\mathrm{E}(\Delta C) = \int_{-\infty}^{\infty} \Delta C f_{\Delta C} d\Delta C$. Without loss of generality, we define $\mathrm{E}(\Delta C)$ to be the expectation value of the cost difference between repair and replacement.
- Risk of taking the wrong decision, i.e. the cumulative probability that the dismissed maintenance alternative leads to a higher benefit, i.e. $\int_{0}^{\infty} f_{\Delta C} d\Delta C$ for repair and $\int_{-\infty}^{0} f_{\Delta C} d\Delta C$ for replacement, respectively
- Expected Opportunity Loss (EOL), i.e. the cost of taking the wrong decision, determined as $\int_{0}^{\infty} \Delta C f_{\Delta C} d\Delta C$ and $\int_{-\infty}^{0} \Delta C f_{\Delta C} d\Delta C$, respectively for repair and replacement
- Expected Value of Information (EVI), i.e. the difference in EOL before and after the information is available

Note that the "best action" solution is singled out as the one with highest benefit, i.e. repair for $\mathrm{E}(\Delta C)$<0 and replacement for $\mathrm{E}(\Delta C)$>0, and with smallest potential cost penalty, EOL. Clearly, the confidence in the prescribed solution increases with decreasing risk of taking the wrong decision and with decreasing EOL. Finally, the EVI is an important metric for assessing how gainfully specific sets of data or information can reduce result uncertainty. By assigning them a *monetary* value, this gives important indication as to how much investment effort is justified for acquiring them.

7. MONTE CARLO ANALYSIS

In this section, a Monte Carlo analysis is performed. It allows to determine input parameters, whose variation exhibits a large impact on output values, hence, indicating, which sources of data and information are particularly valuable for lowering decision-risk and enhancing benefit. As a prerequisite, in the next section, use case scenarios are defined with meaningful parameter ranges to be investigated. The results of the simulation can be found in Section 7.2.

7.1. Definition of Use Cases

In the following, a motivation is provided for considering particular sets of parameter variations defining different use case scenarios for the subsequent Monte Carlo analysis.

As long as in the repair process (a series of) manual actions are involved, the quality of the repair is still largely dependent on the individual repair technician's experience and skills (Gardiner, 2011). Accordingly, this translates into a source of spread in the resulting repair quality, or equivalently the lifetime of the repaired component after repair. In the last decade, emphasis is put on improving the automation level of repairing processes, e.g. for aero engine blades (Wang et al., 2015).

Here, the reconstruction of a digital model of the damaged blade together with overlay welding and machining the welded excess are the three key technologies, positively affecting the automation level of repairing (Wang et al., 2015). More generally speaking, automated (robotic) repair technologies are gaining momentum, e.g. in the context of composite structures inspection and repairs (Gardiner, 2011; Paquet et al., 2017; Guo & Brommesson, 2018).

Further approaches for enhancing repair quality and decreasing its spread include the increasing number of new technologies now in development with the goal of improving process control and excluding for instance damage done during repair (Gardiner, 2011; Guo & Brommesson, 2018). They aim at both reducing cost of labor as well as risk of human error. Hence, they provide a handle for decreasing a) repair - and hence downtime and repair costs, b), variability of repair costs (cf. the discussion in Section 7.1) and for increasing c) repair quality.

While a (more) digitally controlled repair process offers exciting possibilities to capture and exploit sources of accurate data for *Prescriptive Maintenance* purposes, an evaluation of the effects on maintenance model KPIs is important to justify associated investment effort / costs. Moreover, in some cases, there are alternative repair technologies that are associated with different repair effectiveness / variability and costs. Typically, there exists a trade-off between them, i.e. higher repair quality is associated with larger costs (International Air Transport Association, 2015; Zhao, He & Xie, 2018).

Hence, in this context, the probabilistic approach to cost-benefit analysis can give valuable insights into what controls the output of corresponding MRO decisions. With this information at hand, it may be determined, where best to spend time and money for improving both engineering and data quality and reducing uncertainty and properly characterizing inherent spread in parameter values, e.g. arising from political, environmental or operational factors.

Based on this motivation, the influence of average repair quality and its spread is investigated for different ratios between and variability of various maintenance costs. Meaningful parameter ranges are summarized in Table 1. By this means, 12 use case scenarios are defined (cf. Table 2) that are investigated within Monte Carlo analysis in the next section.

In Figure 3, the PDF of the improvement factor is shown according to Eq. (6) for different choices of the parameters u and v defined in Table 1.

Table 1: Parameter ranges chosen to investigate the impact of various sources of uncertainty and variability on the confidence and business value of "best action" solutions determined in Section 7.2.

Ranges (90% confidence interval)	Replacement costs [k$ per unit]	Repair costs [k$ per unit]		Failure costs [k$ per unit]		Repair quality			
		"medium / small spread"	"high / large spread"	"small spread"	"large spread"	"medium / small spread" (u=0.7, v=0.1)	"Constant medium"	"high / small spread" (u=0.9, v=0.1)	"high / large spread" (u=0.9, v=0.3)
Upper bound	18.00	12.00	16.00	40.00	60.00	1.00	0.70	1.00	1.00
Mean	17.00	10.50	13.50	35.00	30.00	0.70	0.70	0.87	0.72
Lower bound	16.00	9.00	11.00	30.00	10.00	0.00	0.70	0.00	0.00

Table 2: Assumptions for different case studies

Case Study	Failure costs (spread)	Repair costs (average)	Spread in repair costs	Repair quality	Spread in repair quality
1a)	Small	Medium	Small	Medium (on average)	Low
1b)	Large				
2a)	Small	Medium	Small	Medium (constant)	None
2b)	Large				
3a)	Small	High	High	High (on average)	High
3b)	Large				
4a)	Small	Medium	Small	High (on average)	High
4b)	Large				
5a)	Small	Medium	Small	High (on average)	Low
5b)	Large				
6a)	Small	High	High	High (on average)	Low
6b)	Large				

Accordingly, the higher / lower the parameters u / v, the larger is the average repair quality and the lower is its variability.

7.2. Results of Monte Carlo Simulation

In this section, the step-by-step approach to prescribing "best action" decisions outlined in Section 3 is applied for the action alternatives "repair" and "replacement", considering the maintenance scenario outlined in Section 5 and the respective use cases defined in Section 7.1.

Furthermore, the parameters defining the Wiener degradation path defined in Eq. (1) in Section 4 are taken to be

$$\eta = 1, \sigma = 0.3, D = 5. \tag{13}$$

According to Eqs. (11) – (12) and (3), this results in an optimal time for replacement after $T_P = 3.7$. The results are evaluated considering an assessment horizon of $2 \cdot T_P$ such that effects of imperfect repair come into play (cf. the discussion in Section 5).

A spreadsheet example for use case 1a) is shown in Table 3, where the difference in expected maintenance costs for "repair" versus "replacement", $E(\Delta C)$, is determined from Eq. (12) in Section 5.

For each of the 12 use cases, the cost difference between "repair" and "replacement" is calculated for a representative sample of 10^4 possible combinations according to the statistics of all parameters considered to be variable.

In Table 4, key metrics introduced in Section 6 are evaluated that allow to assess the impact of various sources of uncertainty and variability on the prescription of the "best action" solution either constituted by "repair" or "replacement". These are determined by means of the bin frequency / cumulative bin frequency of occurrence in the respective spreadsheets for the 12 case studies performed.

A selection of the corresponding results for the PDFs / CDFs of the cost difference of both decision alternatives is presented in Figures 4 – 7.

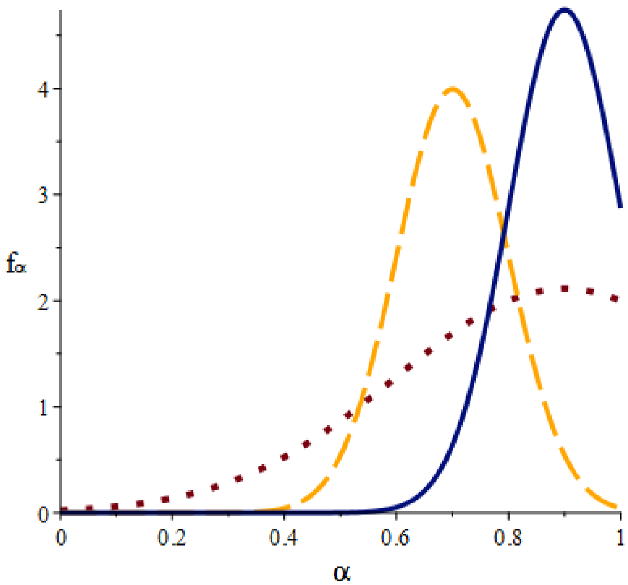

Figure 3: PDF of the improvement factor, $f_{\alpha}(\alpha; u, v, 0, 1)$, for u=0.9, v=0.1 (solid), u=0.9, v=0.3 (dotted) and u=0.7, v=0.1 (dashed).

The "best action" solution is singled out as the one with the largest profit and the lowest EOL. Accordingly, a negative / positive mean cost difference between "repair" and "replacement" indicates respectively that "repair" / "replacement" is the preferred alternative (cf. the fourth column of Table 4 and the definition in Section 6).

The following general key results can be deduced

- While in most cases "repair" is prescribed as more profitable solution, in some cases "replacement" is slightly preferred
- In some cases, the risk of taking the wrong decision and the associated EOL are strongly increased in the presence of various sources of uncertainties / variability.

More specifically, the lower the average repair quality and the higher the ratio of repair to replacement costs, the more important become variations in repair quality and uncertainties regarding failure and / or replacement costs.

For instance, the comparison of case studies 1a) and 1b) demonstrates that choosing "repair" for a varying, but on average medium repair quality, a large spread in expected failures costs significantly enhances the risk of taking the wrong decision from merely 3 to 29% (cf. Figures 4-5) with associated strong increase of EOL from 30 to 660$ per unit.

So here, basing the cost ranges e.g. on a set of historic data rather than for instance a less-informed, conservative expert estimate leading to a large cost spread, would allow to considerably reduce the amount of uncertainty in the risk-based decision. Possibly, beyond that one may infer the best fit probability distribution function from the data, which does not necessarily have to be a normal one as assumed here for simplicity. This approach directly translates into a higher confidence associated with the prescriptive approach and a lower potential loss. Hence, this information can be assigned a monetary value. It is with 630$ per unit equivalent to the difference in EVI for the two use cases, if repair is chosen.

Table 3**:** Excerpt from Monte Carlo Layout for use case 1a).

Scenario #	Repair costs [k$ per unit]	Replace-ment costs [k$ per unit]	Failure costs [k$ per unit]	$E(\Delta C)$ "repair" vs. "replacement"
1	10.18	17.17	37.99	-2.41
2	9.60	17.22	31.91	-2.21
3	96.38	17.72	34.31	-1.99
4	10.02	16.86	34.59	-1.92
5	96.88	15.78	31.74	-0.15
6	99.32	15.98	33.60	-2.50
7	93.41	16.68	39.95	-4.26
8	10.47	17.03	30.77	-2.96
9	96.0	17.11	33.23	-2.52
10	85.89	17.56	33.64	-0.65
…	…	…	…	…
9,997	10.77	16.50	41.33	+0.51
9,998	10.10	17.03	36.94	-1.34
9,999	9.45	16.58	35.54	-1.68
10,000	10.42	16.72	30.78	-2.01

It is particularly interesting to note that in case for imperfect repair of medium quality instead of a randomly varying α as in use case 1), its mean is taken as *constant* improvement factor as in use case 2), the prescribed "best action" solution changes from "repair" to "replacement". Moreover, the risk of taking the wrong decision significantly increases from merely 3 / 29 % to 28 / 39% (respectively for low / high spread in failure costs, cf, Figures 6-7).

As mentioned in Section 4.1, the randomness in improvement factor α increases the mean time until the kth failure for k≥2, while also increasing its variability. The first effect beneficially reduces the failure probability within the predefined time horizon for assessment (i.e. $2 \cdot T_P$) and hence in comparison leads to lower costs for corrective maintenance.

This example hence demonstrates that gaining knowledge on the actual distribution of the improvement factor such as by means of test / operational (life time) degradation data instead of assuming a reasonable average value could prevent taking a sub-optimal decision. Namely, in other words, if the decision for replacement is placed on the premise of a constant improvement factor α, while actually, imperfect repair is best described by a randomly varying α, instead, repair would be more cost-effective. Accordingly, this would on average lead to a loss of 1270 / 1330 $ per unit, namely the mean cost difference between "repair" and "replacement" in case studies 1a) and b), respectively.

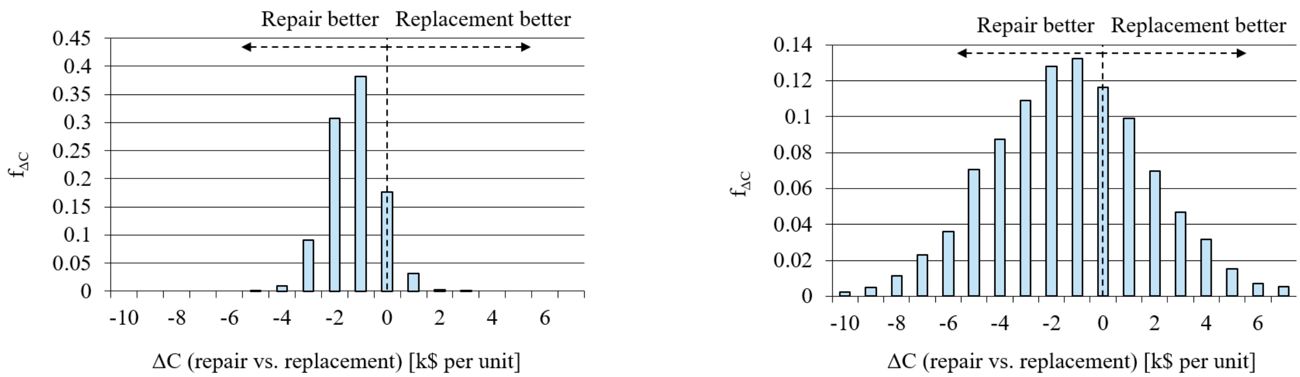

Figure 4: *Left* PDF of use case 1a) and *right* of use case 1b) with respectively small and large spread in failure costs.

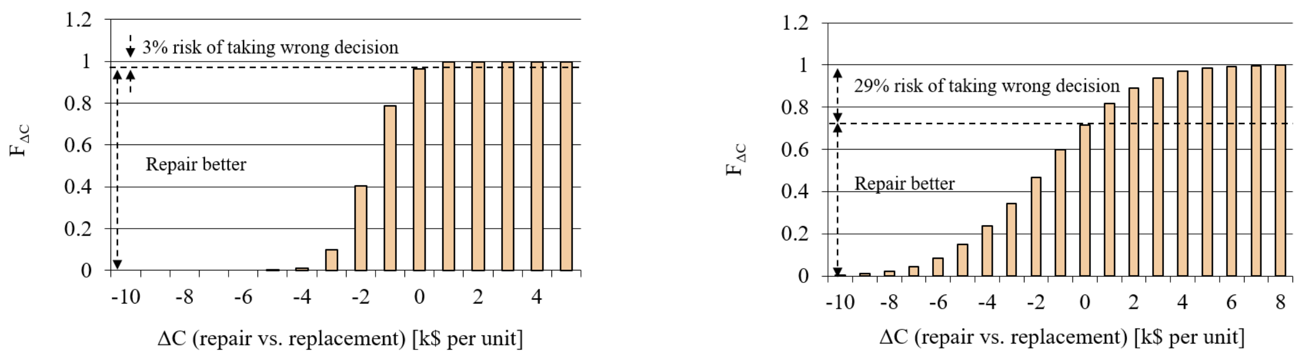

Figure 5: *Left* CDF of use case 1a) and *right* of use case 1b) with respectively small and large spread in failure costs.

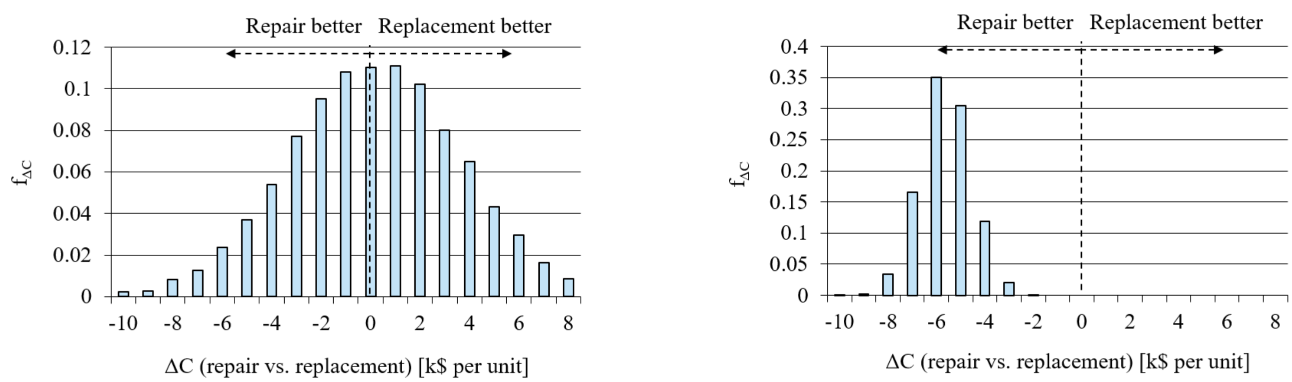

Figure 6**:** *Left* PDF of use case 2b) and *right* of use case 5b) with respectively large spread in failure costs.

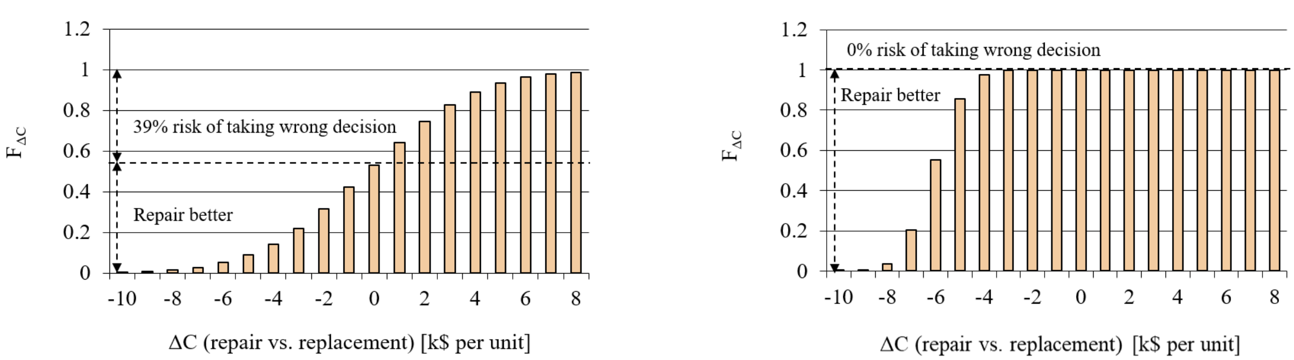

Figure 7: *Left* CDF of use case 2b) and *right* of use case 5b) with respectively large spread in failure costs.

Table 4. Results from the Monte Carlo simulation for the different case studies specified in Table 2 in Section 7.1.

Case Study	Mean cost difference $E(\Delta C)$“repair” vs. “replacement”) [k$ per unit]	EOL (“repair” / “replacement”) [k$ per unit]	Prescribed “best action” solution	Risk of taking wrong decision [%]	Difference in EVI [k$ per unit]
1a)	-1.27	0.03 / 1.30	Repair	3	0.63
1b)	-1.33	0.66 / 1.98	Repair	29	
2a)	+0.20	0.49 / 0.29	Replacement	28	0.98
2b)	+0.17	1.47 / 1.30	Replacement	39	
3a)	+0.03	0.58 / 0.55	Replacement	37	0.38
3b)	+0.05	0.96 / 0.92	Replacement	42	
4a)	-2.81	0.00 / 2.81	Repair	0	0.09
4b)	-2.52	0.09 / 2.62	Repair	7	
5a)	-5.61	0.00 / 5.61	Repair	0	0.00
5b)	-5.59	0.00 / 5.59	Repair	0	
6a)	-2.79	0.02 / 2.81	Repair	2	0.00
6b)	-2.79	0.02 / 2.81	Repair	2	

Importantly, the example hence demonstrates that the quality of assumptions, data or information used for prescribing “best action” solutions influences the representativeness of the result and hence the reliability of these prescriptions .

Further, if on the one hand, the repair quality is on average high, but on the other hand subject to a fairly large variation like in use case 3a) and 3b), respectively, then this leads to a highly uncertain decision for “replacement” in case repair costs are comparatively high. The risk of taking the wrong decision is further increased from 37 % in use case 3a) to 42% in use case 3b), since here, in addition, failure costs are rather uncertain. If, however, the cost difference between “repair” and “replacement” is more pronounced like in use case 4), then – only in combination with uncertain failure costs – the variation in repair quality results in a slightly negative impact on decision risk (cf. use case 5b) in Figures 6-7).

While in general, variability stemming e.g. from environmental or operational factors, can hardly be reduced, one may imagine that the spread in repair quality could be controlled by more effective process / quality control technologies. Moreover, fully digitizing the repair process itself bears promise with respect to achieving higher repair quality (cf. the discussion in the last section). As demonstrated by the above example, this is particularly valuable, if the cost difference between repair and replacement is less pronounced. Since enhanced repair quality typically is associated with higher repair costs, the presented analysis can be used to quantitatively analyze this trade-off on an application-by-application basis.

It should finally be noted that for on average high repair quality with comparatively low spread, both medium and even high repair costs (cf. use cases 5) and 6)) respectively lead to a vanishing or very low risk of just 2% for taking the wrong decision, when option “repair” is selected. This is the case, even if failure costs are rather uncertain like in use cases 5b) (cf. Figures 6-7) and 6b), respectively. Here, the ratio of repair to replacement costs determines the mean profit, which increases with decreasing cost ratio from roughly 3k$ to about 6k$ per unit for use cases 5) and 6), respectively.

This again underlines the above argument that investing in technology for decreasing variations in repair quality can make repair / replacement decisions much more predictable, less risky and promises higher gains as the comparison of e.g. use cases 3) and 6) or 1b) and 5b) demonstrates (of course, provided the exploited data is accurate).

Hence, the last two examples show that enhancing average repair quality and reducing its inherent spread can support *Prescriptive Maintenance* business cases, as solutions with lower associated decision risk can be deduced and be implemented e.g. in future automated maintenance settings.

In summary, strategies for mitigating risk and enhancing business value of MRO decisions include

- Identifying risk variables within sensitivity analysis i.e. input parameters, whose variation exhibits a large impact on output values; this points at which sources of data are particularly valuable for lowering decision-risk and enhancing benefit
- Clearly characterizing inherent variability in decision model factors that cannot be reduced per se
- Properly dealing with incomplete data e.g. by means of Machine Learning techniques (Paluszek & Thomas, 2017)
- Evaluating the EVI in order to specify, which additional data to acquire and how much to invest into doing so

Regarding the last point, it is important to note that in a situation with large uncertainty, even little data can help to reduce the latter significantly (as e.g. the comparison of use cases 1a) and 1b) indicates). However, in a situation with low uncertainty, a large amount of data is needed to reduce it even further (Hubbard, 2014).

8. CONCLUSIONS AND OUTLOOK

In this work, a probabilistic framework for determining “best-action” solutions within *Prescriptive Maintenance* and for assessing and subsequently deriving strategies for enhancing decision-reliability and business value has been presented on the example of repair / replacement decision support.

Using realistic degradation / maintenance models that implement random effects of imperfect repair, the approach was shown to identify input parameters, whose variation exhibits a large influence on resulting decision quality.

For example, an increase in average repair effectiveness and reduction of inherent spread, possibly achievable by digitizing and automating repair and quality control processes, was demonstrated to bear potential for making repair / replacement decisions much more predictable, less risky and potentially more profitable. For example, lowering the spread of on average high repair quality was shown to change the “best action” solution from “replacement” to “repair” at the same time lowering the risk of taking the wrong decision from as much as 42% to merely 2%. This was the case, even though the mean cost ratio assumed between repair and replacement was with 80% above the current “Beyond Economic Repair” rule of thumb of 60-70% (International Air Transport Association, 2015) and in addition exhibited a large spread, i.e. uncertainty.

As a further key result, it was demonstrated that the appropriateness and quality of assumptions, data or information determines the representativeness of the distribution of outcomes and hence directly relates with decision quality. An example showed that gaining knowledge on the actual distribution of the improvement factor for imperfect repair – such as by means of test / operational (life time) degradation data – instead of assuming a reasonable average value could prevent taking sub-optimal decisions related with significant cost penalties.

Importantly, the Expected Value of Information was shown to give a quantitative measure for determining, where and how much to invest for improving engineering quality as well as for acquiring accurate, high-value data to reduce decision-influencing uncertainty and enhance business value.

The relevance of the presented approach hence also lies in providing a quantitative way for assigning data / information sources a *monetary* value in the maintenance business. This seems particularly valuable in the context of novel business models such as Data-as-a-Service, or specifically, possible new forms of service contracts between Original Equipment Manufacturers (OEMs) and operators, i.e. “OEMs selling efficiencies, operators selling operational data”.

In summary, the probabilistic approach may hence give industry practitioners directions for designing and improving business cases for *Prescriptive Maintenance* on an application-by-application basis, e.g. by fully exploiting available high-quality data sources and models, by appropriate, dedicated measurements, by further digitizing and automating (repair) processes, and by investing in high-value data, possibly within future data trading schemes. In the context of service-oriented business model innovation like power-by-the-hour service agreements for aero engines, this seems particularly valuable for enhancing MRO decision quality and predictability of related costs.

In the same line of thinking, acquiring and connecting data within *Prescriptive Maintenance* from different areas such as maintenance, operations, planning and logistics could be key for optimizing data-enabled decisions with respect to e.g. MRO efficiency, fleet availability and supply chain agility.

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BIOGRAPHIES

Lily Koops received her diploma and PhD in physics from the University of Hamburg, Germany, respectively in 2005 and 2008. In addition, she holds an MSc-equivalent in Applied Mathematics from the University of Cambridge, UK. Before joining Bauhaus Luftfahrt in 2011 as a Research Associate, she has been a Postdoctoral Research Fellow in Theoretical Physics at the University of Heidelberg, Germany for 3 years. At Bauhaus Luftfahrt, she is Deputy Head of the Department of Future Technologies and Ecology of Aviation and Lead of the institution-wide Technology Radar. It aims at collaboratively identifying future technologies and methodologies for aviation with high innovation potential. Furthermore, she leads and contributes to several industry and research projects, in which technology potentials are quantitatively assessed within different aeronautical use cases. Her current research interests include the development of (probabilistic) frameworks for identifying and optimizing business cases within Predictive and Prescriptive Maintenance, the quantitative assessment of performance benefits arising from Artificial Intelligence / Machine Learning as well as hybrid approaches and the development and techno-economic evaluation of Structural Health Monitoring concepts. Her research has led to a number of publications in recognized journals and conference proceedings. Furthermore, she has received the Best Paper Award at the European Conference of the Prognostics and Health Management Society in 2018.