Cost-Benefit Analysis and Specification of Component-level PHM Systems in Aircrafts

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Abstract

Unplanned aircraft groundtimes caused by component failures create costs for the operator through delays and reduced aircraft availability. Unscheduled maintenance on the other hand also creates costs for Maintenance, Repair and Overhaul (MRO) companies. The use of PHM is considered to improve the planning of component-specific maintenance and thus reduces consequential costs of unscheduled events on both sides.

This study assesses the component-specific costs and characteristics of today's maintenance approach. A discrete event simulation represents all relevant aircraft maintenance processes and dependencies. For this purpose the Event-driven Process Chain (EPC) method and Matlab/SimEvents are used. The data input (process information, empirical data) is provided by a particular MRO company.

Whereas recent approaches deal with stochastically processed data only, e.g. failure probabilities, the proposed method mainly uses deterministic data. Empirical data, representing particular dependencies, describes all relevant stages in the component lifecycle. This includes operation, line and component maintenance, troubleshooting, planning and logistics.

By simulating different scenarios, various maintenance future states can be evaluated by analysing effects on costs. The obtained economical and technical constraints allow to specify component-level PHM design parameters, as minimum prognostic horizon or accuracy. Detailed process-specific information is provided as well, e.g. costs of non-productive MRO activities or no-fault-found (NFF) characteristics.

1. Introduction

Since the development in research fields as e.g. fuel efficiency has reached a point, where the savings potential is expected to advance incrementally only, the concept of PHM offers new opportunities to improve competitiveness, see (Sun, Shengkui Zeng, Kang, & Pecht, 2010) and (Feldman, Jazouli, & Sandborn, 2009). By converting unplanned aircraft groundtimes into planned maintenance tasks, it is considered to support the general objectives of aircraft maintenance. According to (Fromm, 2009) and (Knotts, 1999) these are:

- maximising aircraft availability and dispatch reliability
- minimising consequential costs of technical delays
- minimising direct maintenance costs (DMC)

The dispatch reliability (DR) describes the ratio of revenue departures without delays or cancellations compared to all flights. A higher DR results in a higher aircraft availability and thereby implies a reduction of delay compensation costs (e.g. rescheduling costs, payoffs) as well as lower opportunity costs through more revenue flights, see (Rodrigues, Balestrassi, Paiva, Garcia-Diaz, & Pontes, 2012) and (Sisk, 1993). According to (Eurocontrol, 2010) average costs of aircraft delays reach $113 per operating minute. Other results are given in (Rodrigues et al., 2012), (Cook, Tanner, & Anderson, 2004) and (Fritzsche & Lasch, 2012). In 2008 European airlines experienced 85 million delay minutes, creating estimated overall costs of $9.7 billion, see (Eurocontrol, 2011). According to (Eurocontrol, 2012) technically induced delays account for a large portion of all delays. Since PHM allows to perform maintenance tasks within planned maintenance events prior to a component failure, technical delay costs are one measured variable in this study. The scheduling is based on remaining useful life (RUL) prediction, e.g. see (Hölzel, Schilling, Neuheuser, Gollnick, & Lufthansa Technik AG, 2012). Within a prognostic horizon (PH) the future system state can be predicted with sufficient accuracy.

Reducing the DMC, being part of the direct operating costs (DOC), is another key factor in competition. According to (Fromm, 2009) DMC account for approximately 7% of the DOC of an airline. (Fritzsche & Lasch, 2012) state that PHM enables a MRO company to optimise the maintenance program's scheduling as well as structuring. This allows more efficient processes by converting unplanned into planned activities and preventing non-productive events. Therefore avoidable maintenance costs are another measured variable in this study.

Since a PHM system is not ideal, it is characterised by uncertainties and involves various risks:

- The PH is too short and allows no useful forecast.
- A low accuracy causes misinterpretation (NFF or undetected events).
- The PHM system itself fails (e.g. sensor failure).

In order to facilitate the planning of maintenance events, the PH has to allow forecasts for a certain number of flight cycles (FC) or flight hours (FH). For instance, if a component malfunction is indicated by a RUL prediction 5 minutes prior to failure, it may not be early enough in order to prevent a groundtime at the next station. On the other hand 5 minutes might be enough to significantly improve operation in some cases (Sun et al., 2010). If the PHM system's accuracy is not sufficient, false conclusions are possible. Non-productive NFF events may be generated by false alarms, or unscheduled events by undetected failures, see (Knotts, 1999) and (Hölzel et al., 2012). Furthermore, a PHM system involves requirements concerning its own maintainability.

In summary, the goals of this study can be defined as follows:

1. Evaluate the financial potential of a component-specific PHM system.
2. Specify component-based PHM parameters.

The required component-specific PHM performance parameters, as PH and accuracy, can be specified by the evaluated economic constraints. These are gained from the calculation of a component-specific PHM system's effect on

- delay compensation costs and
- direct maintenance costs

with respect to the different PHM design parameters. Studies analysing similar goals often use simulation models. (Hölzel et al., 2012) employ a model to carry out a cost-benefit analysis by using failure probabilities as input data and evaluating savings potentials of different PHM systems. An alternative to the data input approach will be discussed in sections 2.2.1 and 2.2.2. Another similar procedure is presented in (Feldman et al., 2009). Key of this study is the Return on Investment (ROI) calculation. Component failures are generated probabilistically as well in this case.

Compared to the other studies, this paper presents a PHM evaluation using mostly deterministic data to simulate maintenance events as close to reality as possible. This is enabled by available, adequate MRO data. The methodology, including assumptions and limitations, is discussed in the next chapter.

2. METHODOLOGY

This chapter provides an overview of the applied approach, illustrated in Figure 1. The major steps described in the next sections are indicated by the labeled arrows: Data preprocessing, modelling and simulation. The boxes represent the in- and outputs, further explained in the particular sections.

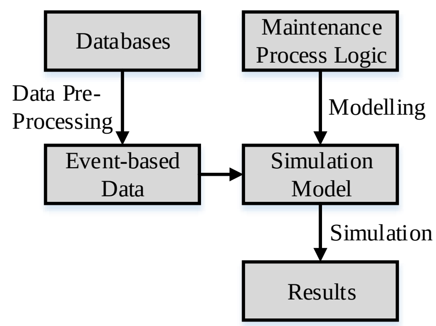

Figure 1. Description of the approach.

2.1. Component-Level Approach

The component-level approach used in this study is explained in the following.

2.1.1. Level of Detail

The introduced approach aims to evaluate the effects of a PHM system on component or line-replacable unit (LRU) level. LRUs are designed to be replaced quickly during turn around times between two flights. Hence, faulty LRUs are responsible for technical delays in many cases, because the replacement requires a prior diagnosis as well as spare parts and often takes place during flight operation time.

An evaluation on a more detailed level is not conducted, due to the fact that most available MRO data provides LRU specific data only. In most cases LRUs can be found within an ATA-6-digit chapter, specified as a subsystem. For further information on the ATA-numbering system see (Air Transport Association of America, 2012). If an LRU is supplied by different manufacturers or modified by minor updates, different partnumbers (PN) are applied.

2.1.2. Sample Component Selection

The assumptions made in this study require the evaluated LRUs to fulfill the following requirements:

- Standard LRU maintenance applies.
- LRU shows any sort of wear behaviour.
- LRU causes high costs through delays and cancellations.
- LRU causes high costs through NFF events.

It is assumed that all LRUs pass through a standardized LRU maintenance process, which is the focus of this study. The wear behaviour provides information about the technical feasibility of a prognosis application. In order to be able to perform prognosis an observable degradation process is necessary, whereas diagnosis requires the binary states ”functional” and ”not functional” only. LRUs can cause operational delays through time-consuming replacements or troubleshooting (TS) tasks. Costs through NFF events can result from insufficient fault interpretation and the conflicting goals of different maintenance departments. Line maintenance at an airport aims to assure an aircraft's availability by performing all tasks as quickly as possible, e.g. by simply replacing an LRU in case of a fault indication, even if a detailed TS was not conducted. The shop maintenance on the other hand overhauls all incoming LRUs. If a line maintenance replacement takes place without any exact finding, the subsequent shop maintenance event might be rated as NFF. This can be considered a non-productive maintenance action.

Besides the cost factors, the minimum equipment list (MEL) is considered for the LRU selection as well. A MEL category is specified by the corresponding rectification interval (RI) of a component or its function. The RI shows how urgently a problem has to be fixed in order to keep an aircraft realeased to service. Thus, a failure's priority and operational risk can be described. Examples for MEL RI are given in Table 1.

Table 1. MEL rectification intervals.

MEL RI	Time for rectification
A	instantly or failure-specific
B	within 3 days
C	within 10 days
D	within 30 days

In order to select adequate LRUs for the study, prior to the simulation all LRUs are ranked. Based on the available MRO data, a ranking as exemplarily shown in Table 2 for the LRU Air Data Inertial Reference Unit (ADIRU) is obtained. MRO component data from the years 2010 to 2013 is considered, providing estimated annual costs for delays and NFF events as well as the corresponding MEL RI categories for each LRU. At the end of this study the exemplary results for the ADIRU are discussed.

Table 2. Ranking of LRUs.

ATA	LRU	Delay costs	NFF costs	MEL RI
34-12-34	ADIRU 1	C_{Delay}	C_{NFF}	A
...	...	...	...	...

2.1.3. Component Maintenance

The LRU maintenance process can be described by the main modules shown in Figure 2. The interface between airline operation and the MRO involves the TS, the maintenance planning and the system maintenance. In the following the term system describes the aircraft, consisting of subsystems, the LRUs. The TS mainly derives supporting and maintenance actions from fault isolation, e.g. by interpretation of fault messages. The planning department concentrates on the time scheduling of maintenance tasks considering priority, required time as well as available ground times. The system maintenance consists of line and base maintenance. The subsystem (shop) maintenance, connected by the logistics, deals with the overhaul of LRUs. Repaired components are sent to and taken from the spare parts inventory. Since the impact of this study on the spares inventory is insignificant, it will not be subject in detail. Furthermore, information and material flows are illustrated.

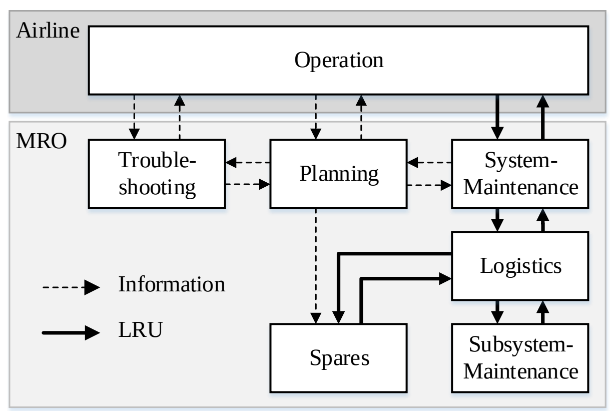

Figure 2. Modules of the component maintenance.

2.1.4. Non-routine Maintenance

The component maintenance can be subdivided into the fields routine and non-routine maintenance. Routine tasks deal with maintenance actions that are planned in advance. This applies for especially safety relevant items or consumables. Non-routine maintenance deals with unscheduled tasks, created by faults of components that are maintained on-condition. Since the earlier mentioned approach includes on-condition maintained LRUs only, this study focusses on non-routine maintenance. Furthermore, only maintenance events carried out at the homebase are analysed.

2.2. Discrete Event Approach

In a discrete event simulation (DES) state changes are only modelled at discrete time steps, called events. By skipping simulation times without any changes, the approach is very computing time-efficient. States are defined by objects, referred to as entities, and their attributes. Events are caused by attribute changes and the induced state transformations.

If a DES model uses non-probabilistic data only, it is called deterministic. Thus, all input variables are exactly defined and all states pre-determined. The use of a simulation model then primarily enables the computing of numerous operation steps. If input data is probabilistically specified, a simulation model allows to consider stochastic input by conducting a Monte Carlo simulation. A set of simulation runs then enables the representation of distributed variables.

DES allows to analyse interdependencies between particular events in detail, as described in (Rodrigues et al., 2012). For instance, information about failure message generation, LRU replacements and aircraft delays can exactly be represented and correlations described. Whereas pure probabilistic approaches mainly allow analysis concerning particular factors (consequence-wise analysis), an event-wise analysis provides information about specific causes and effects (see Figure 3). In this study both data input types, probabilistic distributions and deterministic data, are used.

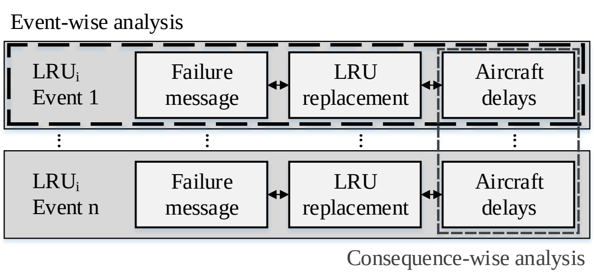

Figure 3. Different analysis approaches.

2.2.1. Stochastic and Deterministic Data

If particular data is not described by a constant value, it is distributed. According to (Kohn, 2005) probability density functions (PDF) allow to describe the probability of a value to apply. An example for uncertain data used in this study is varying process time. Since in reality not every LRU replacement needs the same amount of time, an analysis of past process durations provides statistical information on the empirical distribution. Figure 4 shows different PDF types. Depending on how accurate the empirical data is available, one of the introduced approaches is used. If only one scalar value is available, the special case deterministic distribution applies. This is the case for most input data in this study.

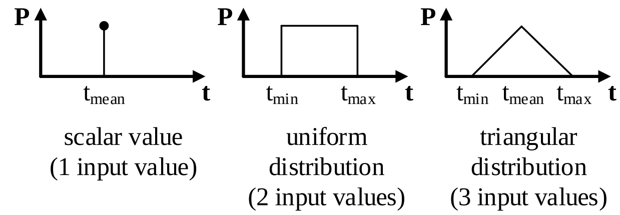

Figure 4. Used probability density functions.

2.2.2. Component Failure Generation

As opposed to many other studies, as (Hölzel et al., 2012) or (Feldman et al., 2009), the chosen approach defines component failures deterministically. Since empirical data regarding date and time of a component failure or replacement is available, all temporal information is inherited. Thereby different analysis scenarios all refer to the same initial failures as the root cause for replacements and allow exact comparisons.

2.2.3. Process Definition

In order to acquire knowledge about the overall maintenance process, a conducted process analysis provides information about the following process factors:

- work type (information-/LRU-processing)
- process time (minimum/average/maximum)
- number of required personnel
- qualification of required personnel
- required resources (e.g. hangar)

By mapping the process sequence including conjunctions, the process interdependencies are represented (see Section 2.4). Whereas the information on process sequence and personnel requirements is derived from MRO documents, the process times of LRU-specific processes are specified by maintenance experts and historical data. Concerning process resources only the demands are modelled as opposed to available capacities.

2.3. Data Acquisition and Preprocessing

The data preprocessing provides the event-based data input for the simulation. It is described in the following sections.

2.3.1. Input Data

Input data for the simulation is derived from various MRO databases. Flight log databases provide information about the flight schedule, ground events and operational irregularities. Fleet databases contain registration-specific information. A variety of technical logbooks provide data about failure messages, the maintenance history (reports and actions) and logistics. Experts contributed process-specific details.

All databases contain data sets that are exactly defined by the attributes aircraft registration, LRU part- and serialnumber, date, time and location. According to the logic introduced in the next section, corresponding data sets from different databases are connected to single events.

2.3.2. Event Definition

An LRU replacement event is specified by data from the aforementioned databases. In order to identify and extract data event-wise, the linking logic, shown in Figure 5, is applied. (Beynon-Davies, 2004) further discusses data models.

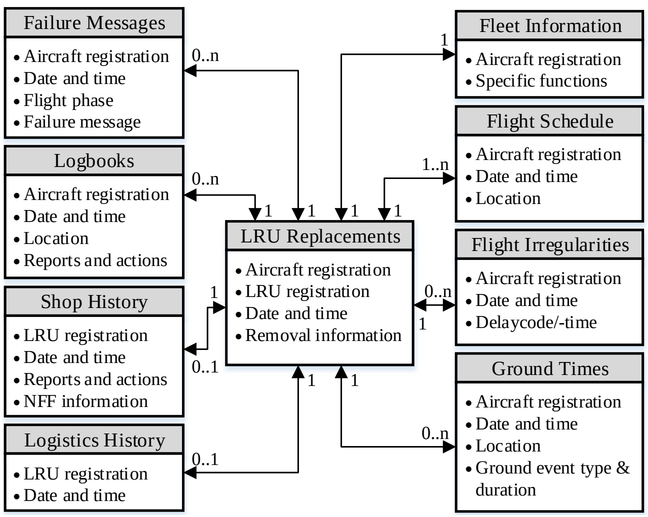

Figure 5. Relational object data model for an event definition.

As shown in the data model, an LRU replacement data set entry is the basis for an event definition. Based on the available attributes, all other databases are connected by linking parameters, e.g. aircraft registration and date. As indicated by the data model, several conjunction types are used. The connection of multiple data sets is possible (n) as well as single data entries or no data at all (1 or 0). By matching all relevant data, unique subsets specifying separate events are defined. Matching conflicts, redundancies or incomplete data is accounted for by robust merging, either correcting or skipping the particular data set. Insufficient data quality is a major limitation in this study. Therefore only reliably defined replacement events are considered for the evaluation.

The data is organised in the structure shown in Figure 6. Different hierarchy levels are used in order to classify similar information. Thereby results can later be analysed concerning particular characteristics, e.g. comparing all events of k different partnumbers for one LRU.

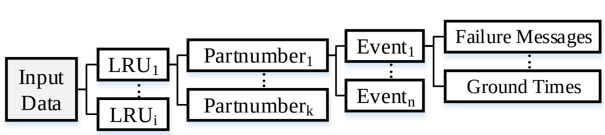

Figure 6. Hierarchy levels of the obtained data structure.

2.4. Modelling

The following sections explain the model building.

2.4.1. Process Modelling

The EPC method is used for the logical maintenance process modelling. It comprises the elements process, event and Boolean operators (AND, OR, XOR). A process, illustrated by a rectangle, is defined by the aforementioned process factors. An event, displayed as a hexagon, defines the state that is supposed to be reached after a process completion. The logical operators, illustrated by circles, enable the modelling of intersections by defining routing conditions. Information flow is indicated by dashed lines. Figure 7 shows an example:

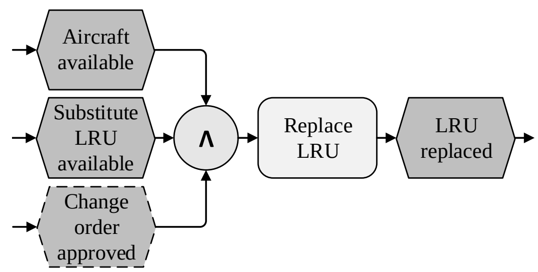

Figure 7. Example of EPC modelling.

By using the EPC method all modules of the component maintenance, shown in Figure 2, are described in detail. Due to intellectual property (IP) reasons, a detailed process map is not presented in this paper.

2.4.2. Simulation Model

The EPC model is transferred to a software model using Matlab SimEvents, as applied in (Gray, 2007) or (Bender, Pincombe, & Sherman, 2009). Matlab Stateflow is used to represent the system (aircraft) and subsystem (LRU) states. All defined states are shown in Table 3 and Table 4.

Table 3. System states.

z_{System}	**State description**
1	flight
0	on ground, other station
-1	maintenance, other station
-2	on ground, homebase
-3	unscheduled maintenance, homebase
-4	available for maintenance, homebase
-5	scheduled maintenance, homebase

An aircraft can only hold one particular system state at a time. Flight operation is represented by alternating system states $z_{System} \in \{-2, 0, 1\}$. Maintenance times are distinguished between scheduled $z_{System} \in \{-5, -4\}$ and unscheduled events $z_{System} \in \{-3, -1\}$.

Table 4. Subsystem states.

$z_{Subsystem}$	State description
1	regular operation
0	rectification in progress
-1	maintenance required
-2	deferred
-3	deferrable

An LRU holds the states functioning $z_{Subsystem} = 1$, in repair $z_{Subsystem} = 0$ or not properly functioning $z_{Subsystem} \in \{-3, -2, -1\}$, further described by the urgency accounted for by the MEL logic. Items that do not require immediate rectification, can be deferred. By defining discrete states and parameter dependent transitions, the toolbox allows to account for and evaluate different operating modes.

2.5. Simulation

The simulation characteristics are explained in the following sections.

2.5.1. Simulation Time Characteristics

One simulation cycle represents all events within the analysed time period for one aircraft at a time. This allows the evaluation of subsequent, interrelated events generated by different LRUs on the same aircraft. Due to computing time issues and the study objectives, only time frames of two weeks around an LRU replacement event are examined. Taking advantage of DES all dates without any relevant occurrences are skipped.

2.5.2. Scenario-based Analysis

If the degree of particular process transformations through PHM is supposed to be analysed, the definition of different simulation scenarios is useful. Defined scenarios are:

1. current state maintenance (data-based only)
2. best-case current state maintenance (data- / logic-based)
3. target state maintenance with PHM (data- / logic-based)

If the maintenance in its current state is to be analysed, the first scenario applies. In this case the simulation model directly uses the data input in order to represent all actions and queue times as they occurred in reality. The second scenario aims at the representation of a best-case evaluation of today's maintenance. The input data is used partially, e.g. date and time of first failure occurrence. The missing information is then generated by the modelled process logic. The third scenario is targeted on the evaluation of possible future states with PHM, by assessing the impacts of different prognosis parameters, as PH and accuracy. In this case only a small amount of the historical input data is used, e.g. first occurence of a failure message, in order to dissolve dependencies on today's procedure and to generate an ideal state case. The further rectification process is represented by the implemented process logic. By comparing the significant changes to possible maintenance characteristics with PHM, today's maintenance deficits can be analysed.

2.5.3. Monte Carlo Simulation

In order to account for input data provided as distribution functions, a Monte Carlo simulation carries out various simulation runs. Based on the in section 2.2.1 described distributions, at each cycle the stochastically provided input data is randomly assigned, creating slightly differing simulation results. This way especially the varying process times are accounted for. By defining and saving seed values - initial values for random number generators - all Monte Carlo simulation runs can be reproduced. The effects of the Monte Carlo simulation are considered in the model output interpretation by including the result's distributions and illustrating particular risks.

2.6. Target Values

The simulation results can be classified as process data and operational aircraft data. The results interpretation covers the statistical analysis of costs as well as raw, time-based simulation data. Cost values are obtained from calculation of time-based simulation data with available MRO cost rates. The simulations outputs are available on different levels of detail, allowing versatile result interpretation (see Figure 6). The different categories of target values are explained in the following sections. (Linser, 2005) e.g. gives an overview of other prevalent target values.

2.6.1. Costs

Cost analysis can be performed on all levels of detail. If desired, the IATA MRO cost structure, presented in (Fromm, 2009) or (Linser, 2005), can be considered. Primarily the approach determines costs for an event k according to the logic shown in eq. 1-3.

Event-based costs consist of process and operation irregularity expenses. Process costs are defined by labour, material and overhead expenses. Operational charges arise from flat rates defining compensation and opportunity costs of delays or Aircraft-on-Ground (AOG) times multiplied by the corresponding event duration.

$$C_{Event_k} = \sum_{i=1}^{m} C_{Proc_i} + \sum_{j=1}^{n} C_{Ops_j} \tag{1}$$

$$\begin{aligned} C_{Proc_i} &= t_{L_i} \cdot n_{L_i} \cdot c_{L_i} + n_{M_i} \cdot c_{M_i} + C_{O_i} && (2) \\ C_{Ops_j} &= t_{O_j} \cdot c_{O_j} && (3) \end{aligned}$$

C_{Event_k}	Total cost of event k
C_{Proc_i}	Cost of process i
C_{Ops_j}	Cost of operational irregularity j
t_{L_i}	Process time
n_{L_i}	Amount of labour
c_{L_i}	Labour cost rate
n_{M_i}	Amount of material
c_{M_i}	Material cost rate
C_{O_i}	Overhead costs
t_{O_j}	Irregularity duration
c_{O_j}	Compensation cost rate

Future model updates will include ROI calculation, as described in (Feldman et al., 2009). This will enable the comparison of different scenarios concerning PHM investments and avoided costs.

2.6.2. Process Characteristics

The simulation output directly provides process-specific information, as time distributions and process sequences. By evaluating the raw data, non-monetary target values can be analysed. Some examples are:

- response and wait times
- time savings through process transformations
- process loops
- bottlenecks

2.6.3. Additional Results

Examples for parameters, relevant for the MRO company and not expressed as costs or process times, are:

- aircraft dispatch reliability and availability
- delay characteristics
- NFF characteristics
- effectiveness of actions
- real-time data transmission benefit

Regarding a PHM design the following prognosis parameters are evaluated:

- minimum required PH
- minimum required prognosis accuracy

As explained in the introduction, these parameters will partially be based on cost factors. Statistical values as Mean Time Between Repair (MTBR) are not evaluated in this study, because the results will not have any impact on these parameters. For further information see e.g. (Saxena et al., 2008).

3. MODEL APPLICATION

In this section the results of an exemplary simulation model application are summarised. Due to IP reasons a detailed description of the maintenance process logic as well as particular process factors are not presented. Regarding the scenarios, introduced in section 2.5.2, the analysis represents data obtained from scenario 1. Results of the other scenarios are not presented in this paper due to IP reasons and model modifications not implemented yet.

3.1. Numerical Example

The conducted test run presents LRU-specific data for the ADIRU using the Lufthansa Airbus A320 fleet. The MRO data provides complete information for the ADIRU from the years 2010 to 2013. 294 exemplary replacement events at the homebase are generated. Since the LRU is not maintained periodically, all replacements are unscheduled.

According to redundancy requirements each aircraft has three ADIRUs. ADIRU 1 is classified as particularly critical (MEL RI A). Regarding the examined fleet, four modifications (partnumbers) of the ADIRU are currently in service (see Table 5).

Table 5. ADIRU-specific model input values.

Parameter	Value
number of events	294
installed ADIRUs per aircraft	3
MEL RI$_{ADIRU\ 1}$	A
MEL RI$_{ADIRU\ 2,3}$	C
different ADIRU modifications (PNs)	4

General simulation input parameters are defined in Table 6. The labour cost rate is an average value for different employee qualifications. In reality, different qualifications with varying cost rates apply. An ADIRU replacement does not require any extra materials, thus not creating additional material costs. Logistics are considered as overhead costs.

Table 6. Simulation input values.

Parameter	Value
$n_{Monte\ Carlo\ Runs}$	250
c_L	\$200 per man hour
$c_{Ops_{Delay}}$	\$82 per delay minute
$c_{O_{Logistics}}$	\$100 per component

3.2. Input Data Analysis

Analysing the preprocessed data input without any simulation, provides information about LRU-specific maintenance characteristics, made available through the event-wise data clustering. A target value, supposed to be reduced by PHM, is the component's NFF rate. The influence of particular event characteristics on the NFF ratio is illustrated in Table 7. The NFF rate provides information about the diagnosis accuracy. An ideal 100% accuracy is not realistic, since the aim of lowering risks of false positive statements (NFF), falsely assuming an LRU is defective, is opposed to the aim to reduce false negative statements, falsely assuming an LRU is functioning.

It is shown that 35% of all replacement events are classified as NFF. Replacements involving AOG times (7%) show a slightly higher NFF ratio. As expected, cost-intensive groundtimes as AOGs mainly cause quick part removals even without exact findings. Subsequent NFF findings in the subsystem maintenance then often occur. However, the sample size is low in this case and a direct correlation cannot reliably be stated. Replacements, that were deferred in the past (22%), show a higher NFF ratio as well. This behaviour is not expected. A deferral should leave more time for troubleshooting, thus improving diagnosis quality resulting in less NFF cases. The ability of an aircraft to provide fault messages in real-time (RTS) (72% of the events) has no influence on the NFF ratio. Regarding the mounting location, the evaluation shows that the replacements are equally distributed over the different ADIRU positions. If the ADIRU 1 is affected, the NFF rate is lower. Since the ADIRU 1 is more critical (MEL RI A), this behaviour is contrary to the AOG results. On the other hand a higher components priority can lead to more precise troubleshooting, eventually creating less NFF events.

Table 7. NFF analysis w.r.t. event characteristics.

Event characteristic	n_{events}	n_{NFF}	$\frac{n_{NFF}}{n_{events}}[\%]$
1. all events	294	103	35.0
2.a) AOG	21	13	61.9
2.b) no AOG	273	90	32.9
3.a) deferred	66	40	60.6
3.b) non-deferred	228	63	27.6
4.a) with RTS	211	74	35.1
4.b) without RTS	83	29	34.9
5.a) ADIRU 1	94	13	13.8
5.b) ADIRU 2	91	46	50.5
5.c) ADIRU 3	109	44	40.4

By analysing LRU-specific delay characteristics the effects of a PHM system introduction can exactly be quantified. A delay analysis, concerning technically caused delays only, provides the results shown in Table 8. 20.4% of the events generated technically caused (primary) delays. The average delay duration is 18.1 minutes. Within subsequent flights further delays (secondary) were generated. Their accumulated average duration is 19.6 minutes. The results are relevant for the cost calculation in Section 3.3.3.

Analysing LRU data on an aircraft-based level provides information about correlations between events (see Figure 8). For three exemplary aircrafts it is shown that ADIRU replacements occur w.r.t. all mounting positions. Table 7 also illustrates the nearly equal distribution over all positions. A further analysis shows that within the period of examination 131 consecutive ADIRU replacements occur. Out of 131 events, 59 replacements (45%) occur at the same mounting position as the prior one, being slightly higher than the probability of an equally distributed behaviour (33% for 3 mounting positions). Probably not all replacements actually solved the root cause of the problem.

Table 8. Analysis of initial (primary) and subsequent (secondary) delays.

Delay type	n_{delay}	$\frac{n_{delay}}{n_{events}}[\%]$	$t_{O,mean}[min]$
primary delay	60	20.4	18.1
secondary delay	53	18.0	19.6

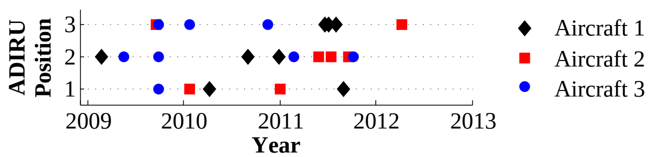

Figure 8. Aircaft-specific failure sequence analysis w.r.t. the ADIRU mounting positions.

3.3. Simulation Results

The following subsections deal with results obtained from the simulation.

3.3.1. Simulation States

The system states (see Table 3 and 4) of an exemplary event are illustrated in Figure 9. The subsystem state illustrates the point of time of failure ($t_{Simulation} = 0$) and the further processing. The failure rectification, starting after the aircraft has landed, is represented by $z_{Subsystem} = 0$.

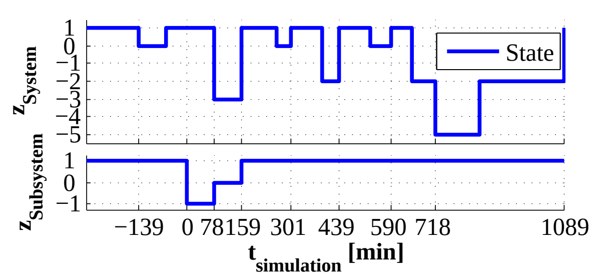

Figure 9. System and subsystem states of an exemplary event.

The plot primarily enables model validation by visualisation of the system states. It shows available maintenance times as well as generated delays and rectification process characteristics. z_{System} is a result of the flight plan and particular boundary conditions generated by maintenance actions. The effects on aircraft availability can be represented, if the entire flight operation is considered.

3.3.2. Time-based Analysis

Analysing processes w.r.t. temporal data, provides information about particularly time-consuming or delay-causing processes and modules. Concerning the ADIRU, the overall process time from failure identification to rectification is represented in Figure 10. The plot shows two distributions caused by different rectification procedures. If a failure occurs during flight operation and is classified as urgent, the rectification usually takes place at the ramp immediately (left distribution, short duration). If the complaint is deferred, the rectification is carried out in a hangar at the next planned plug (right distribution, long duration). This usually involves higher maintenance efforts, e.g. through detailed planning and repeated troubleshooting tasks and thus is more time-consuming. For the ADIRU the mean average is $t_{rectification} = 71.7min$.

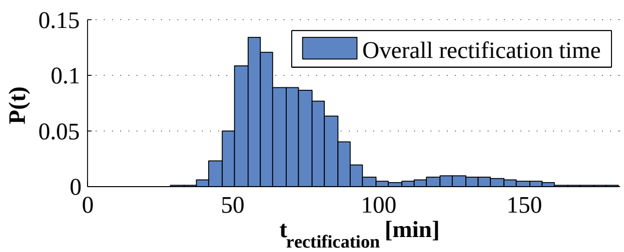

Figure 10. Overall processing time of ADIRU replacements.

Figure 11 shows ADIRU diagnosis process times. The mean average time is $t_{diagnosis} = 37.6min$. One aim of PHM is to consistently carry out system diagnosis prior to failures in order to reduce replacement durations. Since the average diagnosis time is almost half the average total rectification time, the effects on unscheduled groundtimes and delays are expected to be significant.

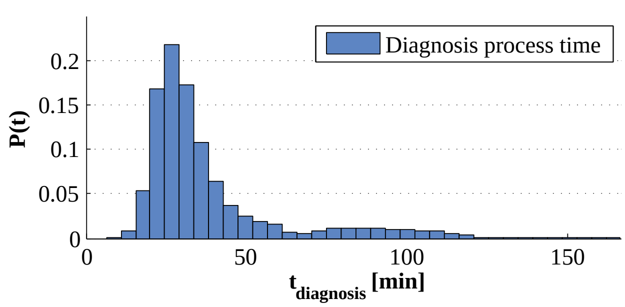

Figure 11. ADIRU diagnosis process time.

If a failure requires specific action, the TS creates an Action Order (AO), a detailed task manual. The completion of replacements with an AO requires more time in most cases, as confirmed by the results shown in Figure 12. Since events involving AOs can be classified as special case treatment, the use of PHM is expected to standardize the rectification and to reduce the number of AO processes.

Based on a detailed delay analysis w.r.t. process times, all

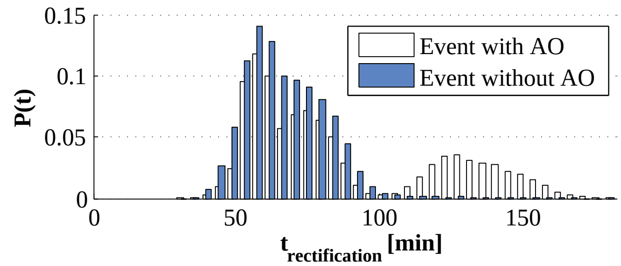

Figure 12. ADIRU processing time w.r.t. AO characteristics.

events are categorized into four classes. 79.6% of the ADIRU replacements do not generate any delays. 6.6% of the events cause delays, but could have been prevented, if the diagnosis processes were carried out prior to the unscheduled groundtime. 13.6% of the events generated delays that could only be prevented by planning the replacement into a prior groundtime. 0.2% of the events would always cause delays, because a unique ADIRU problem occured.

Based on the event characteristics of the second and third category (events with avoidable delays) the results shown in Figure 13 and 14 can be obtained.

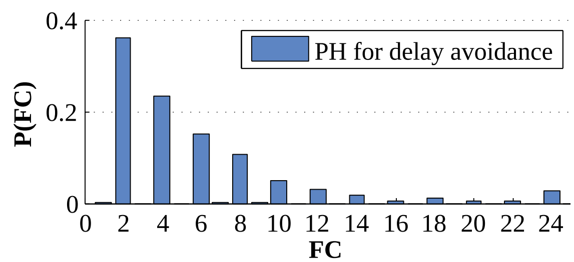

Figure 13. Required prognostic horizon for delay avoidance as a function of flight cycles.

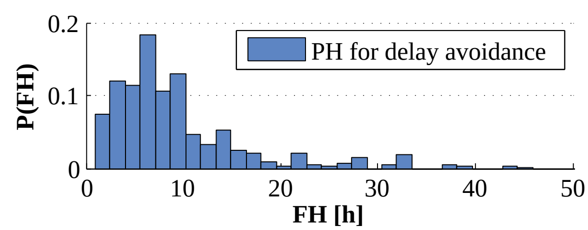

Figure 14. Required prognostic horizon for delay avoidance as a function of flight hours.

By means of the flight schedule and the calculated process times, the prior groundtime for every event, not generating a delay, can be identified. The necessary time-shift to that particular groudtime can be specified in terms of FC or FH, illustrated as a PDF. Since only replacements at the homebase are analysed in the first place, the FC analysis shows the expected behaviour that only every second flight is accounted for (groundtimes at the homebase). For instance, if an ideally working PHM system with a PH of 4 FC or 9 FH is used, 60% of the delays could have been avoided completely. Additionally the delays of other events could partially be reduced by scheduling them into more adequate groundtimes than the actual ones.

3.3.3. Cost-based Analysis

A cost-based analysis provides information about specific cost distributions. Table 9 gives an overview of the calculated ADIRU replacement costs. The average value for the annual costs as well as the lower and upper boundaries of the confidence interval (CI), including 95% of the values, are given. Due to deterministic input data, for logistics overhead costs no CI applies.

The average overall costs for ADIRU replacements sum up to \$125,365 per year. One event generates average total costs of \$1,706. The uncertainty is described by the given CI, ranging from \$269 to \$4,419. Two thirds of the costs of an ordinary replacement event are generated by MRO processes, one third by operational irregularities. The module-wise analysis shows that especially the maintenance modules and the logistics account for a large portion of the costs. A further analysis determines the costs of NFF events ($C_{Subsys.M._{NFF}}$) as a fraction of the subsystem maintenance costs. The subsystem maintenance process is the costliest process, due to the fact that all on-aircraft ADIRU tasks are performed quickly, whereas a detailed component maintenance - the ADIRU is a computer - is time-consuming. Furthermore, the costs of diagnosis tasks ($C_{Diagnosis}$) are analysed, being part of troubleshooting (C_{TS}), system maintenance ($C_{Sys.M.}$) and subsystem maintenance costs ($C_{Subsys.M.}$).

Table 9. ADIRU replacement cost analysis.

Cost type	mean costs [per event]	95% CI [per event] min - max	mean costs [per year]
C_{Event}	\$1,706	\$269 - \$4,419	\$125,365
C_{Ops}	\$593	\$0 - \$2,291	\$43,558
C_{Proc}	\$1,113	\$269 - \$2,524	\$81,807
C_{TS}	\$35	\$11 - \$127	\$2,597
$C_{Planning}$	\$13	\$8 - \$22	\$948
$C_{Sys.M.}$	\$164	\$112 - \$207	\$12,039
$C_{Subsys.M.}$	\$801	\$0.4 - \$1,859	\$58,873
$C_{Logistics}$	\$100		\$7,350
$C_{Subsys.M._{NFF}}$	\$183	\$26 - \$432	\$11,282
$C_{Logistics_{NFF}}$	\$35		\$2,573
$C_{Diagnosis}$	\$125	\$59 - \$348	\$9,212

Out of the listed costs only some are avoidable (eq. 4). These are delay costs C_{Ops}, costs of NFF events $C_{Subsys.M._{NFF}}$, logistics costs of NFF events $C_{Logistics_{NFF}}$ and costs of diagnosis processes $C_{Diagnosis}$. The avoidable, annual costs reach $C_{avoidable} = \$66,625$ or 53.1% of the average overall costs per year.

$$C_{avoidable} = C_{Ops} + C_{Subs._{NFF}} + C_{Log._{NFF}} + C_{Diag.} \quad (4)$$

3.3.4. Derivation of PHM Design Parameters

Based on the calculated operational and economic constraints, the benefit of particular PHM design parameters can be evaluated. Figure 15 shows the impact of different PHM system prognosis horizons, specified by the numbers of FH, and different prognosis accuracies on the costs of operational irregularities (C_{Ops}). An imperfect system is accounted for by a confidence value, representing a simplified accuracy. A confidence of 0.25 implies that 25% of the delay causing events could have been prevented by performing proactive maintenance. It is shown that an effective cost reduction requires a reliable prognosis (high confidence) as well as a sufficient PH (high number of FH). A full reduction of delay costs is not feasible because of few unavoidable major events within the evaluation period.

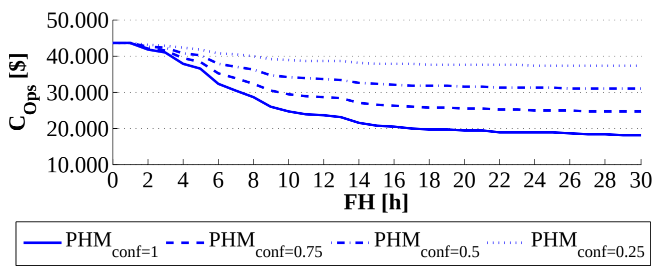

Figure 15. Impact of different inaccurate PHM systems with varying PH on costs of operational irregularities.

Some potential cost reductions are quantified in Table 10. The reductions for realistic PHM systems (confidence < 1, short PH) appear to be low. If the parameters of an exemplary PHM system are set to $PHM_{conf} = 0.5$ and $PH = 2$ FH, the potential savings reach \$987 per year only. If investment costs of PHM systems are considered, the cost-benefit might turn out negative in the end.

Table 10. Impact on costs of operational irregularities w.r.t. prognosis accuracy and horizon.

PHM_{conf}	2 FH	5 FH	10 FH	20 FH
0.25	-\$494	-\$1,756	-\$4,768	-\$6,038
0.5	-\$987	-\$3,513	-\$9,536	-\$12,076
0.75	-\$1,481	-\$5,269	-\$14,304	-\$18,114
1.0	-\$1,974	-\$7,025	-\$19,072	-\$24,152

Besides the impact on delay costs, the influence on MRO process costs is evaluated as well. Table 11 gives an overview of potential savings concerning the aforementioned avoidable cost categories. It is assumed that the PHM system's confidence allows to avoid the calculated costs proportionally. For instance, a PHM system with 50% accuracy enables the reduction of 50% avoidable costs, generating savings of \$11,534 per year in this case.

Table 11. Impact of different inaccurate PHM systems on avoidable MRO process costs.

PHM_{conf}	$C_{Sub.NFF}$	$C_{Log.NFF}$	$C_{Diag.}$	$\sum$
0.25	-\$2,821	-\$643	-\$2,303	-\$5,767
0.5	-\$5,641	-\$1,287	-\$4,606	-\$11,534
0.75	-\$8,462	-\$1,930	-\$6,909	-\$17,300
1.0	-\$11,282	-\$2,573	-\$9,212	-\$23,067

The overall savings potential is illustrated in Figure 16. It depends on accuracy and PH of the PHM system. Whereas the accuracy reduces costs in both categories, operational and MRO costs, a longer PH primarily allows to prevent more delays. So the effects on process costs only depend on the accuracy. For instance, a realistic PHM system for the ADIRU with 50% accuracy and $PH = 2FH$ reduces the avoidable costs to $C_{avoidable} = \$54,104$ per year, an annual reduction of \$12,521 or 18.8%. Since no investment costs are considered in this study, the savings potentials specify a boundary for reasonable PHM investment costs.

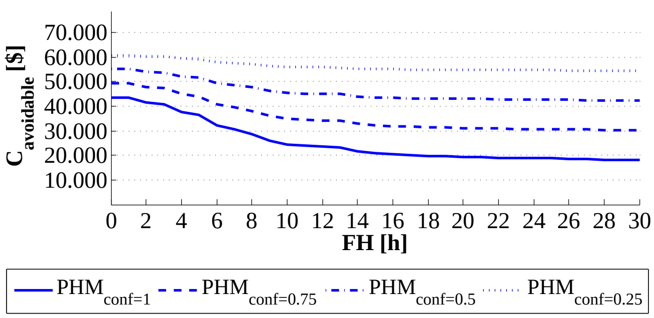

Figure 16. Impact of different inaccurate PHM systems with varying PH on avoidable costs.

Since no prognosis algorithm performance data is available for this study, the effects of correlations between PH and accuracy are not represented. It is assumed that a shorter PH will result in a higher prediction accuracy. By quantification of the exact correlations, the analysis quality and the conclusions could be described more detailed in the future.

3.4. Model Validation

The model validation is carried out by conducting plausibility checks. By comparing the simulated process sequences with the process analysis EPC model, the model logic is validated. A comparison of the simulated process time distributions to the input distributions verifies correct data usage. The system state diagram enables the validation of the interaction between flight operation and MRO processes. This way also the generation and recording of delay data can be confirmed. Further methods for model validation include Gantt charts for visualisation as well as process route marking for plausibility checking.

4. CONCLUSION AND OUTLOOK

This study presents a new approach for the assessment of PHM relevant components concerning avoidable costs of unscheduled events. The aim is to evaluate the characteristics of today's maintenance on LRU level and to derive design information for future PHM systems. Therefore, a DES model is built up in order to represent the MRO process logic using empirical maintenance data. After a data preprocessing is carried out, a Monte Carlo simulation enables the representation of uncertain parameters. Process times and costs of exemplary LRUs are calculated and analysed. Unique features of this study are the use of mostly deterministic data and the event-discrete approach. Both procedures allow to evaluate dependencies, causes and effects within replacements events.

The results of an exemplary LRU, the ADIRU, show a decent savings potential. Operational irregularities and non-productive MRO processes cause \$66,625 avoidable costs per year. A sensitivity analysis of the impact of imperfect PHM systems on the aforementioned costs reveals that the benefit largely depends on the prediction accuracy as well as the PH. Whereas the PH allows to facilitate planning processes and thereby reduces delay costs, a PHM system's accuracy mostly saves costs of non-productive MRO processes through improved diagnosis. Not considering PHM investment costs, a realistic PHM system allows to save approximately 20% of the annual costs for the entire fleet.

A final specification of a PHM system is enabled by a ROI calculation, considering avoidable as well as investment costs, and an analysis of the correlation between prognosis accuracy and horizon, providing prognosis algorithm performance characteristics. Future work will focus on the simulation of target state scenarios in order to evaluate the effects of different diagnosis and prognosis approaches in detail. Influential parameters will be considered by performing further sensitivity analysis. The analysis of a large number of LRUs will further improve the understanding.

It is assumed that there is a standardized LRU maintenance process and that the analysed LRUs show an observable wear behaviour. LRUs that do not meet these requirements, are not applicable for the simulation. Furthermore, the quality of the simulation results largely depends on the input data quality, as inaccurate or conflicting data degrades the conclusions.

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ABBREVIATIONS

ADIRU	Air Data Inertial Reference Unit
AO	Action Order
AOG	Aircraft on Ground
ATA	Air Transport Association
CI	Confidence Interval
DES	Discrete Event Simulation
DMC	Direct Maintenance Costs
DOC	Direct Operating Costs
DR	Dispatch Reliability
EPC	Event-driven Process Chain
FC	Flight Cycle
FH	Flight Hour
IP	Intellectual Property
LRU	Line replacable Unit
MEL	Minimum Equipment List
MRO	Maintenance, Repair and Overhaul
MTBR	Mean Time Between Repair
NFF	No-Fault-Found
PDF	Probability Density Function
PH	Prognostic Horizon
PHM	Prognostics and Health Management
PN	Partnumber
RI	Rectification Interval
ROI	Return on Investment
RTS	Real-Time-Sending
RUL	Remaining Useful Life
TS	Troubleshooting

REFERENCES

Air Transport Association of America. (2012). *ATA iSpec 2200 - Information Standards for Aviation Maintenance.*

Bender, A., Pincombe, A. H., & Sherman, G. D. (2009). Effects of decay uncertainty in the prediction of life-cycle costing for large scale military capability projects. In *18th World IMACS/MODSIM Congress, Cairns, Australia.* (Vol. 1).

Beynon-Davies, P. (2004). *Database systems* (3rd ed.). Basingstoke: Macmillan.

Cook, A. J., Tanner, G., & Anderson, S. (2004). *Evaluating the true cost to airlines of one minute of airborne or ground delay: final report.* Eurocontrol.

Eurocontrol. (2010). Eurocontrol Performance Review Commission: An Assessment of Air Traffic Management in Europe during the Calendar Year 2009.

Eurocontrol. (2011). Planning for Delay: Influence of Flight Scheduling on Airline Punctuality. *EUROCONTROL Trends in Air Traffic*(Volume 7).

Eurocontrol. (2012). Eurocontrol Central Office for Delay Analysis: CODA Digest - Delays to Air Transport in Europe November 2011.

Feldman, K., Jazouli, T., & Sandborn, P. A. (2009). A methodology for determining the return on investment associated with prognostics and health management. *IEEE Transactions on Reliability*, *58*(2), 305–316.

Fritzsche, R., & Lasch, R. (2012). An Integrated Logistics Model of Spare Parts Maintenance Planning within the Aviation Industry. *Proceedings of world academy of science, engineering and technology*, *Volume 68*.

Fromm, H. B. (2009). *Bewertung innovativer Instandhaltungsszenarien in den frühen Phasen des Innovationsprozesses in der Luftfahrt*. Aachen: Shaker.

Gray, M. A. (2007). Discrete event simulation: A review of SimEvents. *Computing in Science & Engineering*, *9*(6), 62–66.

Hölzel, N. B., Schilling, T., Neuheuser, T., Gollnick, V., & Lufthansa Technik AG. (2012). System Analysis of Prognostics and Health Management Systems for Future Transport Aircraft. In *28th International Congress of the Aeronautical Sciences (ICAS), Brisbane, Australia.*

Knotts, R. M. (1999). Civil aircraft maintenance and support Fault diagnosis from a business perspective. *Journal of Quality in Maintenance Engineering*, *5*(4), 335–348.

Kohn, W. (2005). *Statistik: Datenanalyse und Wahrscheinlichkeitsrechnung*. Berlin: Springer.

Linser, A. (2005). *Performance Measurement in der Flugzeuginstandhaltung* (Unpublished doctoral dissertation). Hochschule für Wirtschafts-, Rechts-und Sozialwissenschaften, St. Gallen.

Rodrigues, R. S., Balestrassi, P. P., Paiva, A. P., Garcia-Diaz, A., & Pontes, F. J. (2012). Aircraft interior failure pattern recognition utilizing text mining and neural networks. *Journal of Intelligent Information Systems*, *38*(3), 741–766.

Saxena, A., Celaya, J., Balaban, E., Goebel, K., Saha, B., Saha, S., & Schwabacher, M. (2008). Metrics for evaluating performance of prognostic techniques. In *2008 International Conference on Prognostics and Health Management* (pp. 1–17). IEEE.

Sisk, L. (1993). Analysing the value of maintenance in terms of despatch reliability. *Cost Effectiveness Maintenance Conference*.

Sun, B., Shengkui Zeng, Kang, R., & Pecht, M. (2010). Benefits analysis of prognostics in systems. In *2010 Prognostics and System Health Management Conference* (pp. 1–8). IEEE.