Specification and Evaluation of Prediction Concepts in Aircraft Maintenance

Spezifikation und Evaluierung von Prädiktionskonzepten in der Flugzeuginstandhaltung

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Abstract

The goal of this thesis is to identify and quantify the potentials of predictive maintenance concepts in civil aviation. Fault prediction-based decision support is expected to optimise the effectiveness and efficiency of maintenance. Thus, it also enables further reduction of an airline's operating costs over the aircraft life cycle. Prediction aims to transform unscheduled maintenance events, often causing operational irregularities, into projectable preventive activities. Thereby, aircraft availability as well as maintenance processes are expected to be optimised. Because of low technology readiness levels in the industry as well as rather global scale scientific publications on predictive maintenance, the presented work aims to analyse its implementation's potentials in a more detailed manner. Thus, a decision-supporting tool for the cost-benefit assessment of predictive maintenance opposed to the initial state is to be developed.

The starting point is literature research with respect to today's standards and characteristics in civil aviation aircraft maintenance. This includes the applied maintenance strategies and cost structures in particular. Thereafter, the state-of-the-art concerning fault prediction and relevant performance metrics is presented.

Subsequently, the proposed evaluation concept is introduced. Two functions are to be covered: Firstly, based on information on today's maintenance, cost reduction potentials as well as minimum requirements with respect to prediction can be derived. Secondly, prediction concepts can be assessed concerning their specific cost-benefit characteristics. Whereas the evaluation focus lies on the effected costs, corresponding time- and ratio-based target values are analysed as well. A unique feature of the method is the use of mostly deterministic data enabling the derivation of more accurate and valid results than probabilistic approaches.

Thereafter, the proposed model's software implementation is described. Based on theoretically defined business process and data models, a simulation model is built. The proposed model accounts for prediction-induced modifications within the aircraft maintenance as well as the interdependencies of the aircraft operations. By means of Monte-Carlo simulation, input data uncertainties are accounted for and processed for a statistical results assessment.

In a case study, results of the method's application are presented. Firstly, the calibration of estimated process efforts by means of available real-world maintenance information is conducted. This enables the model validation as well. Thereafter, the analysis results concerning an exemplary aircraft component that is maintained correctively are presented. This real-world data is then counterposed to target values derived from the simulation of prediction-based maintenance approaches.

It can be concluded that a predictive maintenance strategy's benefit depends on the amount or the ratio of the interdependent prediction errors, the prediction forecast as well as the costs of implementation. Among the prediction errors, it is necessary to distinguish between errors negatively affecting aircraft operations and errors having negative impact on aircraft maintenance activities. A longer forecast increases the ability to plan in advance, while also leading to higher prediction error rates. It is shown how the overall cost-benefit is affected by investment and operating costs of a predictive strategy's implementation. Only when the derived break-even thresholds are underrun, will the cost-benefit turn out positive as compared to the initial-state maintenance. The overall optimum incorporates a prediction model with the least costly parameter setting.

Kurzfassung

Die vorliegende Dissertation identifiziert und quantifiziert die Potenziale prädiktiver Instandhaltungskonzepte in der Flugzeuginstandhaltung der zivilen Luftfahrt. Fehlerprädiktion wird in Industrie und Forschung als hilfreiches Werkzeug wahrgenommen, die Instandhaltung hinsichtlich Effektivität und Effizienz weiter zu optimieren und somit einen Beitrag zur Senkung der direkten Betriebskosten eines Flugzeugbetreibers im Flugzeuglebenszyklus zu leisten. Durch die Transformation von ungeplanten, den Flugbetrieb störenden Instandhaltungsereignissen hin zu präventiven, geplanten Maßnahmen wird erwartet, dass sowohl die Flugzeugverfügbarkeit als auch die Abläufe innerhalb des Instandhaltungsunternehmens optimiert werden können. Aufgrund der bislang in der Industrie geringen Verbreitung prädiktiver Instandhaltungsansätze sowie der nur wenigen, oberflächlichen Forschungsergebnisse auf diesem Gebiet wird als Ziel dieser Arbeit eine detaillierte Analyse der Potenziale einer Implementierung dieser neuartigen Ansätze definiert. Die Bewertungsmethode soll als entscheidungsunterstützendes Medium dienen, um das Aufwand-Nutzen-Verhältnis prädiktiver Ansätze gegenüber der heutigen Flugzeuginstandhaltung aufzuzeigen.
Den Beginn der Arbeit bildet eine Recherche zu den aktuell vorherrschenden Standards in der Flugzeuginstandhaltung der zivilen Luftfahrt. Hierbei werden sowohl die verschiedenen Instandhaltungsstrategien als auch die entsprechende Kostenstruktur zur wirtschaftlichen Bewertung der Instandhaltung berücksichtigt. Anschließend wird ein Überblick über die in der Wissenschaft verbreiteten Ansätze zur Fehlerprädiktion sowie Indikatoren zur Messung ihrer Performanz gegeben.
Nachfolgend wird die entwickelte Bewertungsmethode vorgestellt. Sie soll zwei grundlegende Funktionen erfüllen: Ausgehend vom Status Quo der heutigen Flugzeuginstandhaltung wird durch die Analyse von potenziellen Einsparungspotenzialen die Spezifikation von Mindestanforderungen an eine Fehlerprädiktion ermöglicht. Desweiteren können bereits vorhandene Prädiktionsmodelle hinsichtlich ihres Risikos und Nutzens im Falle einer Implementierung analysiert sowie bewertet werden. Hierbei stehen die beeinflussten Kostenarten im Fokus. Für eine umfassende Bewertung können zusätzlich zeitbasierte und dimensionslose Kenngrößen berücksichtigt werden. Ein Alleinstellungsmerkmal der vorgestellten Methode liegt hierbei auf der Verwendung von größtenteils deterministischen Eingangsdaten, welche eine hohe Genauigkeit und somit Validität der Analyseergebnisse ermöglichen.

Nachfolgend erfolgt die Beschreibung der softwaretechnischen Realisierung der Bewertungsmethode. Basierend auf zuvor definierten Geschäftsprozess- und Datenmodellen wird ein Simulationsmodell erstellt. Darin werden sowohl die Veränderungen innerhalb der Instandhaltung als auch die Wechselwirkungen mit dem Flugbetrieb abgebildet. Mithilfe einer Monte-Carlo Simulation können die Unsicherheiten bestimmter Eingangsgrößen berücksichtigt und die Analyseergebnisse mit Angabe entsprechender statistischer Größen aufbereitet werden.
In einer Fallstudie werden beispielhafte Ergebnisse der Bewertungsmethode in der Anwendung gezeigt. Dem voraus geht eine Kalibrierung der zunächst geschätzten Prozessaufwände mithilfe zur Verfügung stehender Informationen aus der heutigen Flugzeuginstandhaltung. In dem Zusammenhang erfolgt auch die Modellvalidierung. Nachfolgend werden die Resultate der Analyse einer heutigen korrektiven Instandhaltungsstrategie in Bezug auf eine Beispielkomponente präsentiert, gefolgt von Ergebnissen aus Prädiktionsmodellanalysen.

Aus den Ergebnissen kann abgeleitet werden, dass der Nutzen einer prädiktiven Instandhaltungsstrategie von der Häufigkeit bzw. der Anteile der Prädiktionsfehler, der Vorhersagedauer sowie den Entwicklungskosten abhängt. Dabei muss zwischen Prädiktionsfehlern, die eine Störung des Flugbetriebs zur Folge haben und Fehlern, die den Instandhaltungsbetrieb negativ beeinflussen, unterschieden werden. Ein längeres Vorhersagezeitfenster ermöglicht eine höhere Planbarkeit, bei gleichzeitig vergrößerten Fehlerraten. Desweiteren wird aufgezeigt, wie Entwicklungs- und Betriebskosten einer Einführung von prädiktiver Instandhaltung die Wirtschaftlichkeit des Vorhabens beeinflussen. Wenn die mithilfe des Modells spezifizierbaren Schwellwerte nicht überschritten werden, ergeben sich insgesamt geringere Kosten gegenüber dem heutigen Referenzfall. Die wirtschaftlichste Kombination der jeweiligen Parameter stellt dann das Gesamtoptimum dar.

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Darmstadt, Germany in October of 2016 *Alexander Kählert*

Contents

Nomenclature

Symbols

Variables

Symbol	Unit	Description
C	[€] [€ /a]	Costs overall/per year
FN	[ea]	Count of false negative predictions
FP	[ea]	Count of false positive predictions
FNR	[-]	False negative rate
K	[-]	Process calibration factor
N	[ea]	Number of simulation replications
$SFDR$	[-]	Specific false detection rate
TN	[ea]	Count of true negative predictions
TP	[ea]	Count of true positive predictions
X	[-]	Random variable
V	[-]	Halstead volume
c	[€ /min] [€ /a] [€ /ea]	Cost rate per minute/year/each
k	[-]	Maintenance event
m	[ea]	Processes per maintenance event
n	[ea]	General count
s	[min]	Empirical standard deviation (time-based)
t	[-]	Time instance
z	[-]	State indicator variable
$\vec{n}$	[ea]	Count vector
$\vec{q}$	[-]	Qualifications vector
α	[-]	Accuracy level
Δt	[min]	Temporal difference
μ	[min]	Expectancy value (time-based)
σ	[-]	Standard deviation

Subscripts

Symbol	Description
A	Autonomous process
AC	Aircraft-specific
ATA	Actual time of arrival
ATD	Actual time of departure
$Canc$	Flight cancellation
DC	Delay code
$Delay$	Flight delay
$Delay,40$	Primary flight delay
$Delay,90$	Reactionary flight delay
$Develop$	Development
$Diag$	Diagnosis-based
DI	Deferral interval
E	Event initiation
El	Modelling element
End	Termination/ending point
ET	Element type
$Failure$	Failure-specific
$Flightplan\ status$	Flight schedule information on flight/ground status
$Flightplan\ station$	Flight schedule information on stations
I	Fault indication
ID	Identification name/number
$Invest$	Investment
IP	Signal input port
L	Labour-specific process
Log	Logistics process
LRU	Line replaceable unit-specific
M	Material
$Maint$	Maintenance
MCS	Monte-Carlo simulation
$MTTR$	Mean time to repair
NFF	No-fault-found
NR	Non-recurring
OP	Signal output port
Ops	Operational impact
P	Prediction
PF	Prediction forecast
PM	Planned (scheduled) maintenance

Symbol	Description
$Proc$	Process-specific
Q	Labour qualification
R	Recurring
$Removal$	Component removal-specific
RW	Real-world
$Samples$	Sample data
STA	Scheduled time of arrival
STD	Scheduled time of departure
$SimTA$	Simulated time of arrival
$SimTD$	Simulated time of departure
$Start$	Initial/starting point
S/W	Software maintenance
$Train$	Personnel training
$Threshold$	Threshold-specific
TS	Troubleshooting
Y	Year
abr	Abroad-based
$average/avg$	Averaged value
$avoidable$	Characteristics classified as avoidable
cal	Calibration
d	Flight delay-specific
$expected$	Expected value
i	LRU
inl	Inland-based
k	Maintenance event
l	Process
min	Minimum value
mp	Most probable value
max	Maximum value
opt	Optimum value
$scheduled$	Scheduled maintenance event
$start$	Starting reference time instance
$train$	Training data
$unscheduled$	Unscheduled maintenance event
val	Validation data

Acronyms

ABC	Activity-based costing
AC	Aircraft
ACMS	Aircraft Condition Monitoring System
AD	Airworthiness directive
AEA	Association of European Airlines
AMM	Aircraft maintenance manual
ARIS	Architecture of integrated information systems
ATA	Air Transport Association/actual time of arrival
ATD	Actual time of departure
BITE	Built-in test equipment
BPM	Business process modelling
BPMN	Business process modelling notation
CBM	Condition-based maintenance
CI	Confidence interval
CLT	Central limit theorem
CM	Condition monitoring
CRS	Certificate of release to service
DC	Delay code
DCC	Delay and cancellation costs
DES	Discrete event simulation
DI	Deferred item
DMC	Direct maintenance costs
DOC	Direct operating costs
DT	Delay time
EASA	European Aviation Safety Agency
EoL	End of life
EPC	Event-driven process chain
EV	Expectancy value
FC	Functional check
FDR	False discovery rate
FN	False negative
FNR	False negative rate
FP	False positive
FPR	False positive rate
GUI	Graphical user interface
IATA	International Air Transport Association
ICAO	International Civil Aviation Organisation
IMC	Indirect maintenance costs

IOC	Indirect operating costs
KDD	Knowledge discovery in databases
LCC	Life cycle cost
LDG	Landing gear
LRU	Line replaceable unit
MCS	Monte-Carlo simulation
MEL	Minimum equipment list
MRO	Maintenance, repair and overhaul
MTTR	Mean time to repair
NFF	No-fault-found
NPV	Net present value
NRM	Non-routine maintenance
OEM	Original equipment manufacturer
OSA	Open systems architecture
PDF	Probability density function
PF	Prediction forecast
PH	Prognostic horizon
PHM	Prognostics and health management
PN	Part number
RI	Rectification interval
RNG	Random number generation
RW	Real-world
SB	Service bulletins
SFDR	Specific false discovery rate
SN	Serial number
STA	Scheduled time of arrival
STD	Scheduled time of departure
RM	Routine maintenance
ROC	Receiver operating curve
RUL	Remaining useful life
TDR	Technical dispatch reliability
TN	True negative
TOC	Total operating costs
TP	True positive
TPR	True positive rate
TS	Troubleshooting
TSM	Troubleshooting manual
TTF	Time to failure
UML	Unified modelling language
WT	Work type

1 Introduction

In the civil aviation market, airlines are faced with cost pressure exerted by various causes. For instance, so-called *low-cost carriers* enable public air transportation at low prices, forcing other airlines in the market to substantially lower their operating costs [But04, Dog10]. Efforts in reducing the fuel consumption or advanced aircraft financing concepts, e.g. leasing, have led to a state that is expected to enable incremental future improvements only. In contrast, the goal to reduce expenses on maintenance has drawn more attention recently [Sch03]. Depending on the particular aircraft type and age, maintenance costs can account for up to 20% of an airline's operating costs, estimated to be at US$ 40 billion per year and worldwide [Jen07, Hei02].

In civil aviation, aircraft maintenance is confronted with the conflict of equally optimising *quality*, *time* and *costs* [Grü02]. By means of maintenance, repair and overhaul (MRO) activities an aircraft's airworthiness and thus availability is assured (quality). To further increase the aircraft utilisation, the required ground times should be minimised (time), while being as economical as possible (costs). In [Lin05], further quality-related performance indices are introduced: *Safety*, *reliability* and *comfort*. "Safety and security are air transport's top priorities", primarily referring to the aircraft airworthiness [Int03]. Reliability includes the degree of punctuality influenced by maintenance activities [Pom01]. Opposed to the aforementioned criteria, comfort is not obligatory. It enables further improvement of competitiveness, e.g. through advanced cabin equipment [Sha11, Hol02, Pom01].

Concerning aircraft maintenance, the most important question is how to reduce costs while assuring the same or improved safety and quality requiring the least amount of time in order to optimise an aircraft's utilisation [Sch03, MR99]. One way to approach this problem is to adjust the applied maintenance strategy.

Figure 1.1 illustrates the classification of maintenance strategies with respect to the degree of preventive action ("*act before failure*") and their impact on costs. On the x-axis, the degree of preventive maintenance actions as part of all activities is shown. If no preventive maintenance is carried out at all (left), it is assumed that maintenance still has to be performed, but on a corrective basis resulting from system or component failure. Since these incidents often occur instantly, most of the time maintenance is unscheduled leading to increased efforts (e.g. ad-hoc troubleshooting) and operational interruptions (e.g. flight delays) resulting in so-called *breakdown costs*. Thus, the qualitative curve for repair and breakdown costs (thin

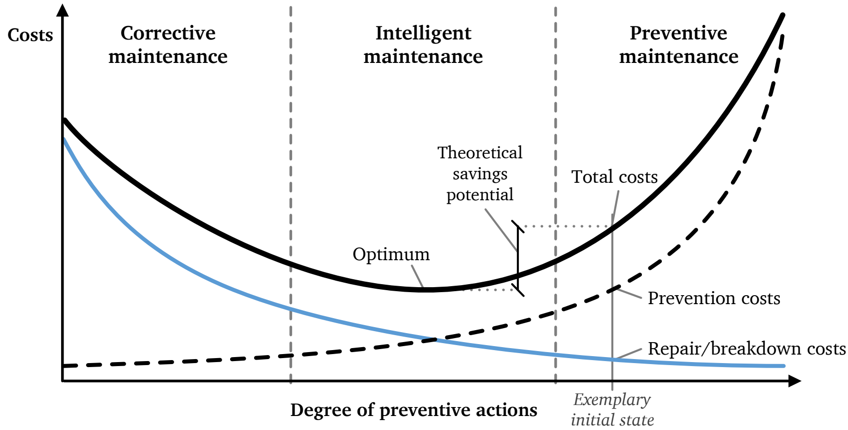


Figure 1.1.: Impact of maintenance strategies on costs. Based on [TWO+14, Lei14]

line) shows a decreasing behaviour for higher degrees of preventive actions. If all maintenance activities are preventive (right), it is assumed that almost no corrective actions apply, because most problems are fixed prior to any fault or failure. Then the applicable prevention costs (dashed line) are directly proportional to the frequency of actions, tending to infinity and thus showing uneconomical behaviour for the extreme case of preventing any corrective action. If both qualitative cost curves are added (thick line), the resulting qualitative relation shows an optimum in between the two traditional strategies. As discussed by [TWO+14], operating at this point is pursued by establishing *intelligent maintenance*, which [Lei14] refers to as *value-based maintenance*. The concept either refers to the combination of the traditional two concepts or the implementation of advanced maintenance strategies, such as *predictive* maintenance [Lei14].

The concept of prediction comprises continuously monitoring and assessing a system's current state in order to derive information for decision making, *whether* any maintenance action shall be taken (*diagnosis*), as well as scheduling *when* exactly an action shall be initiated (*prognosis*). It aims to overcome the disadvantages of the traditional maintenance concepts: On the one hand it is expected to improve the planning of today's correctively treated ad-hoc failures and thus to reduce the breakdown consequences. On the other hand it possibly reduces the amount of unnecessary preventive actions not adding any value or possibly even inducing additional failures [Cro99, And02]. However, the particular impact of predictive maintenance concepts on real-world maintenance operations still is controversially discussed. Since the stochastic nature of prediction-based maintenance recommendations typically involves statistical errors, the overall benefit opposed to the generation of additional risks is uncertain. Additionally, the particular savings potential (see Figure 1.1) is often unknown. Furthermore, in order to receive a positive business case in the end, the required investments should not exceed the realised savings [KBGB10].

1.1 Aim of the thesis

Based on the aforementioned insights, the need for an assessment method is identified, that firstly enables the identification of the cost savings potential of today's aircraft maintenance and secondly allows the counterposing of the variety of impacts of a prediction-based maintenance approach on the real-world initial state. For this reason, a component-level cost-benefit analysis of an exemplary aircraft maintenance in civil aviation is conducted. The description and analysis of the initial state maintenance characteristics shall enable the building of a generic process model and the identification of the cost saving potentials. An evaluation and subsequent comparison of prediction-based maintenance concepts eventually enables the determination of the exact impacts on costs as well as further performance indicators. Due to the impact on the airline as well as the MRO company, the bilateral effects shall be equally analysed. A detailed assessment of the particular prediction errors allows accounting for uncertainties and helps in conducting a generic assessment serving as the basis for future decision making on possible adjustments to real-world maintenance strategies. Based on the availability of deterministic real-world data, a detailed analysis considering particular causes and effects shall be conducted. Due to the fact that analytical approaches are not applicable to such complex optimisation problems, the evaluation shall be accomplished by means of simulation. This way, virtual future concepts can be broadly assessed without affecting the real-world operation.

This thesis is directed to persons involved in decision making concerning maintenance strategy planning as well as to developers actually designing prediction algorithms by providing minimum design specifications, as requested by [GV15].

1.2 Outline of the thesis

The thesis is divided into six chapters (see Figure 1.2). After the introductory section, Chapter 2 provides the relevant aspects of the state of the art to the reader. This includes an introduction of the civil aviation MRO and cost characteristics as well as the fault prediction fundamentals. Chapter 3 describes the proposed evaluation concept. After the definition of requirements, the particular design steps are presented, including specific model building procedures, the simulation method setting, the post-processing procedure as well as verification and validation. Chapter 4 briefly explains the applied software selection as well as the software implementation and its verification. Furthermore, the graphical user interface that was built is introduced. In Chapter 5, results of a case study are presented. On the one hand the proposed case study is defined; on the other hand its application and results are discussed in detail. Eventually, an overall cost-benefit assessment is conducted. Lastly, Chapter 6 summarises the perceptions and provides an outlook into the future of related research.

Chapter	Central research questions	Methodology
Chaper 1 Introduction	• What are current research questions in the field of aircraft maintenance in civil aviation? • What is the aim of this thesis?	
Chaper 2 State of the art	• What is the state of the art considering aircraft maintenance, cost aspects and fault prediction? • What lack of conducted research is identified?	➢ Literature research ➢ Conclusion
Chaper 3 Conception of an evaluation method for predictive maintenance	• What are the demands/assumptions on the proposed method? • What shall the proposed concept evaluate? • How can the real-world problem be abstracted and transferred to an evaluation tool? • How can the results be obtained?	➢ Requirements definition ➢ Target value definition ➢ Model building, deterministic approach ➢ Postprocessing procedure, results assessment
Chaper 4 Software implementation of the concept	• Which software is adequate? • How is the concept implemented into a software environment? • Can the implementation be trusted? • How can the results be assessed?	➢ Software selection ➢ Simulation model building ➢ Verification ➢ Graphical user interface
Chaper 5 Application of the evaluation method	• What case study shall be analysed? • How can the results accuracy be assessed? • What costs characteristics apply for the initial state vs. prediction-based maintenance cases?	➢ Design of experiments ➢ Calibration and validation ➢ Cost-benefit analysis
Chaper 6 Summary and conclusions	• Is the shift to predictive maintenance useful? • What recommendations can be formulated? • What future research work should be conducted?	➢ Case study assessment ➢ Stakeholder-specific advice ➢ Outlook

Figure 1.2.: Overview of chapters and research questions

2 State of the art in aircraft maintenance

In this chapter, the research state of the art relevant for this work is discussed. Firstly, an introduction of the aircraft maintenance characteristics (Section 2.1) and relevant costs (Section 2.2) in civil aviation is provided. In Section 2.3, the fundamentals of fault prediction are presented, followed by a conclusion of identified areas with need for action in Section 2.4.

2.1 Maintenance, repair and overhaul in civil aviation

The MRO business in civil aviation is affected by safety standards to a large extend. Regulatory authorities, e.g. the *International Civil Aviation Organisation* (ICAO) or the *European Aviation Safety Agency* (EASA), define the safety requirements that are to be followed by the aviation industry. These standards are permanently reviewed and constantly evolving. The EASA defines the following basic rules, see Figure 2.1:

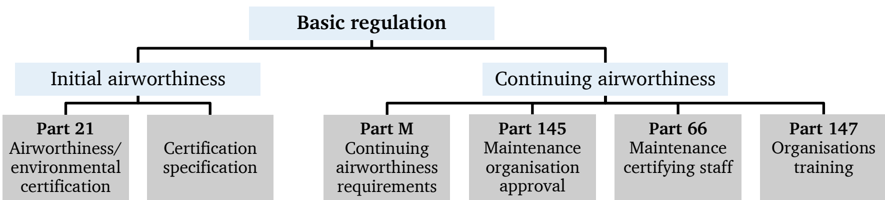


Figure 2.1.: EASA basic rules in civil aviation. Based on [Hin10, Eur03]

Aspects concerned with the *initial airworthiness* e.g. refer to the initial aircraft approval (*Part 21*). *Continuing airworthiness* rules incorporate to constantly preserve an aircraft airworthiness by means of maintenance (*Part M*), conducted by approved maintenance organisations (*Part 145*). Furthermore, personnel certification (*Part 66*) and training (*Part 147*) rules are defined.

Maintenance tasks have to be carried out in accordance with the currently effective manuals and directives by means of approved tools and parts. The legal maintenance program is created by the particular airframe manufacturer and possibly adjusted by the airline or certified MRO companies. Logbooks assure the recording of accomplished maintenance work. Subsequent to task completion, a *certificate of release-to-service* documents an aircraft's airworthiness [Eur03].

MRO companies in civil aviation create their organisation and infrastructure independently, while being certified and supervised by the dedicated authorities. The latter is enabled by a detailed documentation on the MRO side, that is supposed to cover the following aspects [Lin05]:

- Organisation's scope of work
- Infrastructure description
- Responsible persons and their competences
- Approval eligible persons
- Maintenance quality assurance
- Customers of the MRO company
- Subcontractors and suppliers
- Remote stations of the MRO

The documentation primarily assures transparency of the on-going work for authorities. Additionally, it provides a data history for internal purposes as well as for the airlines as customers.

2.1.1 Assignments and goals of aircraft maintenance

According to [Jac92] maintenance assures the sustainment and improvement of the functionality of a production facility, while its nominal condition is expected to deteriorate over time. A system's nominal condition is defined by fulfilment of all functional requirements [Deu12]. If functionally essential requirements are not met, the system or component operates outside its specification and is considered inoperative. The difference between nominal and minimum condition is called reserve of wear-out (discussed in Section 2.1.2). Its degree determines the remaining useful life of a system or component. Thus the primary maintenance goal is to decelerate or stop the wear-out process and restore the nominal condition [Bie85, Lin05]. Different maintenance approaches are introduced in Section 2.1.2.

In the particular case of aircraft maintenance the aforementioned production facility is the aircraft and the nominal condition equals the aircraft's airworthiness [Eur03]. After the initial approval of airworthiness, aircraft maintenance has to continuously sustain the airworthiness status by performing required maintenance tasks. According to [Eur03] this includes "all processes assuring that the aircraft meets all requirements concerning the airworthiness and that it can be operated safely."

From a macroscopic point of view aircraft maintenance can be described by the following processes (Figure 2.2, within box) [Lin05]:

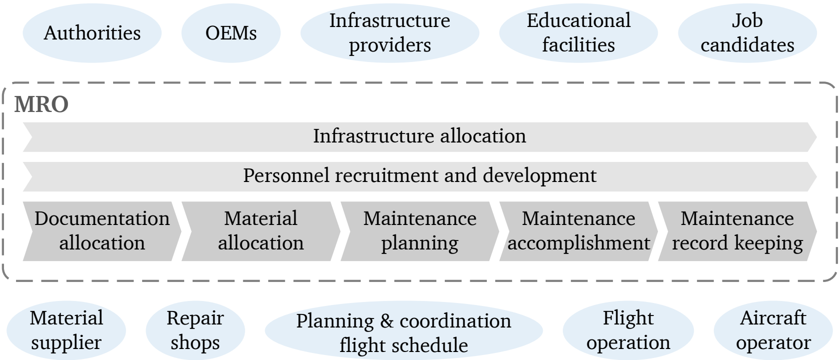


Figure 2.2.: Aircraft maintenance global process. Based on [Lin05]

According to [Lin05] the processes *maintenance planning*, *accomplishment* and *record keeping* are considered to be the core assignments. Support functions are the allocation of infrastructure, personnel, documents and material. Significant stakeholders involved at particular interfaces to the MRO are also illustrated. In the following only the documentation and material functions as well as the three core processes will be described in more detail.

2.1.1.1 Documentation allocation

The documentation allocation deals with all maintenance documents edited by authorities, original equipment manufacturers (OEM), aircraft operators and MRO companies. The original information is processed with respect to the particular target persons and eventually provided on-time. The following maintenance documents can be distinguished [Eur03, Lin05]:

- Maintenance manuals for aircraft, engines and components
- Maintenance program
- Reliability program
- *Airworthiness Directives* (ADs)
- *Service Bulletins* (SBs)
- Modifications
- Authority-based information

The *maintenance manuals* are edited by the particular OEM. They provide detailed testing or rectification instructions on task- and step-level for all aircraft components. The *maintenance* and *reliability programs* are also created by the OEM and possibly modified by the aircraft operator, requiring authority certification a priori. The maintenance program is transferred into so-called *jobcards*. These job descriptions provide detailed information about a job's content (steps, tasks), objects (aircraft, component), time, location, required personnel and tools. *Airworthiness Directives* (ADs) are issued by local authorities and have to be followed accordingly. *Service Bulletins* (SBs) are published by OEMs and include supplementary instructions. *Modifications* arise from operational experience and can be edited by all involved parties [Eur03, Hin10].

2.1.1.2 Material allocation

In this case, material includes spare parts, consumables and operating supplies. The input for the material allocation process is the amount, destination and delivery time for a requested parts delivery. The allocation tasks include the request, receipt, test, storage and delivery of parts. The process output can be defined as the supply of the requested material at the required location on-time [Lin05].

A large spare parts inventory together with an effective supply chain guarantees a high aircraft availability by provisioning required components without any delay. Due to the expected savings potential, spare parts inventory optimisation plays an important role in research (see e.g. [KSY96],[SH00] or [Wan12]). According to [McD02], the value of aircraft spares world-wide was estimated to be larger than US$ 50 billion in 2002.

2.1.1.3 Maintenance planning

The planning process involves the scheduling of maintenance tasks as well as the coordination and allocation of required resources. For this reason, the availability of aircraft, spare parts and resources (e.g. hangar, personnel, tools) has to be considered with respect to relevant due dates. Thus the planning department operates at several interfaces and it is often confronted with conflicts, which arise from differing goals of airline operations and maintenance. It receives various maintenance documents as input and provides the scheduling information as output, for the material allocation for instance. Additionally, the planning department possibly influences the flight schedule as well. The actual maintenance department receives work orders from the planning and possibly returns deferred jobs for future planning.

Aircraft maintenance planning can be divided into three categories [Lin05]:

- Long-range planning: Many months in advance, approximate scheduling and resources allocation
- Mid-range planning: A few days in advance, exact scheduling and final resources allocation
- Short-range planning: Within one day, assignment and scheduling of mostly ad-hoc tasks

The main goal of the maintenance planning is to assure the completion of mandatory tasks, as part of the maintenance program, within a given deadline (long- and mid-range). In case a task is not completed before the deadline, airworthiness can only be approved if the item is deferred by authorised bodies. Firstly this requires the item to be deferrable concerning the particular safety requirements and secondly a documentation for the deferred item (DI), including a due-date as well as the required resources. Therefore, an unscheduled item can eventually become scheduled. The planning system of an MRO company has to be certified by local authorities. Furthermore, activities outside the maintenance program, e.g. ad-hoc component failures, have to be considered for planning as well (short-range) [Eur03, Hin10].

2.1.1.4 Maintenance accomplishment

The general subjects of aircraft maintenance can be classified as aircraft, engines and components. An engine can be considered an assembly, built up of components [Lin05]. It is usually listed separately due to its complexity and particular maintenance requirements. Components can be identified by their particular part and serial number.

Maintenance work can further be classified by its cause or coverage:

- Cause [Zek00, Hin10]
  - *Routine maintenance* (RM): The RM is defined by the maintenance program (edited by the manufacturer, adjusted by the operator, approved by the authorities). RM is always scheduled, e.g. *checks* or *overhauls*.
  - *Non-routine maintenance* (NRM): In NRM, the maintenance program is not applied. Component faults and failures result in troubleshooting. Troubleshooting manuals (TSM) then allow to define the necessary tasks that are unscheduled. NRM also considers ADs, SBs and modifications, classified as scheduled maintenance.

- Coverage [Lin05]
  - *Maintenance and repair*: This usually covers tasks with low complexity or duration being conducted during flight operations. RM and NRM equally apply.
  - *Overhaul*: This includes more complex maintenance tasks, which are carried out outside flight operations. Primarily RM is applied, possibly leading to NRM in case of any findings.

Table A.1 in Appx. A.1 gives some examples for the classification of RM (e.g. checks) and NRM (e.g. airworthiness directives) maintenance events. An alternate approach to classify maintenance jobs is given in Section 2.1.2.

2.1.1.5 Maintenance record keeping

Goal of the documentation function is to gather and save information about maintenance tasks in order to assure the approval of airworthiness. According to [Eur03, Lin05], examples for relevant documents required by the authorities are:

- Certificate of release-to-service for the aircraft: Approval for the accomplishment of all aircraft-related airworthiness affecting maintenance tasks.
- Certificate of release-to-service for engine/components: Approval for the accomplishment of all component-related airworthiness affecting maintenance tasks.
- Airworthiness tag: Proves the applicability of an engine or component to be installed in an aircraft. Hereby lifetime control and record keeping of a removal- and installation-history are enabled.
- Check documents: In case of condition-based maintenance these records allow the tracking of particular parameters under investigation.

2.1.1.6 Additional maintenance assignments

Among other additional maintenance assignments, a quality assurance system is mandatory. It comprises random checks according to the safety requirements. Its primary goal is to check, ensure and enforce the correct accomplishment of all activities. An exemplary quality assurance tool is a global process system.

2.1.2 Traditional maintenance concepts

Depending on the extend to which an aircraft's airworthiness is affected by usage or failure and depending on which strategy is pursued, three traditional maintenance strategies can be applied (see Figure 2.3) [Zer00]. Other classifications of maintenance strategies can be found in [Men13] or [Vac06] for instance.

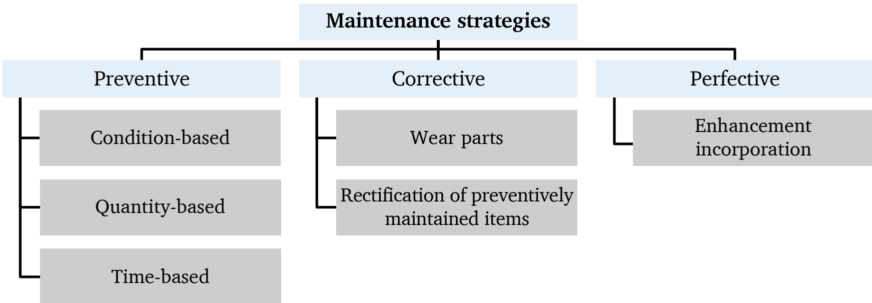


Figure 2.3.: Overview of the conventional maintenance strategies. Based on [AM15, Zer00]

Preventive (or preventative) maintenance implies to proactively preserve a system's or component's nominal condition prior to failure (also see Figure 2.4). This applies for safety-critical aircraft systems in particular. Additionally, preventive maintenance is conducted if a failure is projectable. The maintenance program serves as the basis for preventive tasks. Condition-based maintenance (CBM) is triggered by the exceeding of predefined thresholds of relevant performance parameters that are constantly observed through inspections. An example is the measurement of tire profile depth. Generally, CBM is only applicable, if the reserve of wear-out is measurable [Ach10]. Quantity-based maintenance is defined by tasks that become mandatory by the exceeding of particular usage counts, e.g. number of landings. Time-based preventive tasks are defined by temporal thresholds, independent of the actual wear behaviour of a component. An example is the flap actuator removal every 144 months [AM15, Lin05, Air15].

Corrective (or curative) maintenance is based on failure rectification. Failures can either result from components not maintained preventively (wear parts), because they are not safety relevant or redundancies are provided, or from unexpected failures of preventively maintained parts occurring prior to the next planned task. As shown in Figure 2.4, corrective maintenance restores the nominal condition of a component and is only triggered if the reserve of wear-out is low or at minimum condition. A benefit of this approach is the maximum exploitation of a component's reserve of wear-out [AM15, Lin05, Jac92, Ach10].

The perfective maintenance strategy is considered optional, e.g. see [Vac06, Deu10]. If particular technical enhancements have been developed, perfective maintenance tries to not only restore nominal condition, but to reach an even higher safety or performance level compared to the original one [Lin05]. Examples are ADs, SBs or modifications, e.g. computer firmware updates.

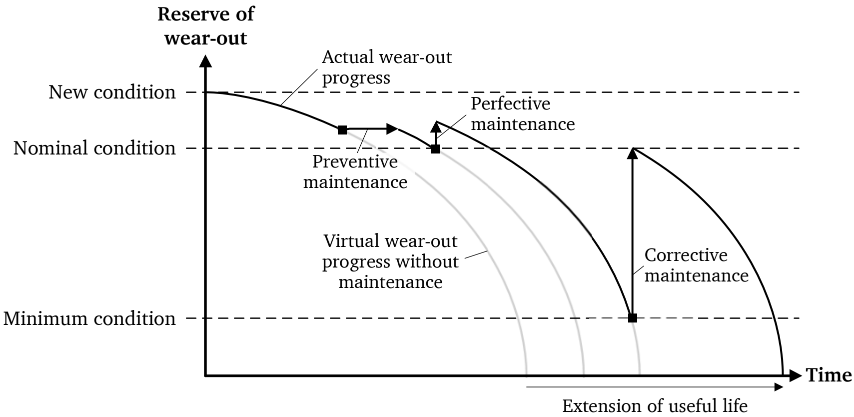


Figure 2.4.: Impact of maintenance concepts on reserve of wear-out (idealised). Based on [Lin05]

Figure 2.4 illustrates the aforementioned maintenance concepts with respect to the reserve of wear-out over time. It is shown that each type of maintenance supports the extension of a component's useful life by restoring or improving its condition. Whereas preventive and perfective maintenance usually apply for system states above or equal to normal condition, corrective maintenance takes place if deterioration has led to a wear-out state below nominal condition.

2.1.3 Predictive maintenance concepts

Although MRO companies have lots of experience and statistical data concerning the above mentioned maintenance strategies, they recently started considering new approaches, because the conventional approaches also incorporate drawbacks. In case of the preventive concepts, maintenance is usually not carried out at the optimum point in time. As depicted in Figure 2.4, this would be at the undercut of the nominal condition. If a time-based check does not result in any findings (above nominal condition), the task could also have been performed at a later point in time, thus reducing maintenance efforts. On the other hand by performing preventive component replacements, remaining useful life of a component is possibly wasted, if the reserve of wear-out still is large enough.

Since corrective maintenance tasks are unscheduled, ad-hoc servicing often causes profound operational irregularities [Hei02]. These can appear on the airline operations side, e.g. an airline not being able to follow the flight schedule, or on the MRO side by instantly requiring actions that were not scheduled resource-wise. Additionally, time pressure can lead to misinterpretations, so that wrong actions are taken subsequently (maintenance induced failures) [Ach10]. These in turn can result in unnecessary, additional MRO activities. Furthermore, there is a higher risk of secondary failures further reducing the overall safety [MS13].

Predictive maintenance concepts, dealing with the prediction of faults and failures (see detailed introduction in Section 2.3), are expected to overcome the aforementioned drawbacks by improving operational and resource planning, while focussing on the essential tasks. This strategy is expected to reduce costs and make maintenance more beneficial. Predictive maintenance aims to operate in between nominal and minimum condition [KM12]. Any action too far above the nominal condition would result in additional, non-essential efforts (similar to preventive maintenance). Any activity below minimum condition possibly leads to operational impacts through instant failures (similar to corrective maintenance) [Mik15].

In literature, the classification of predictive maintenance within the traditional approaches varies. One common approach is to understand prediction-based maintenance as a preventive action prior to failure (see Figure 2.5 as a complement to Figure 2.3). Thus it is often associated with CBM, involving to constantly observe a system's condition [BL04]. On-condition then refers to the original preventive strategy comprising inspections [Men13]. The predictive approaches can be further divided into *diagnostics* and *prognostics*, explained in detail in Section 2.3:

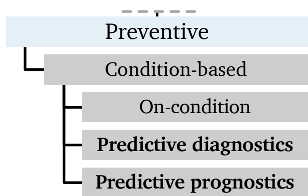


Figure 2.5.: Classification of predictive maintenance strategies. Based on [Deu10]

The impact of a predictive maintenance approach compared to the traditional strategies can be versatile. As shown in Figure 2.6, its influence can be divided into aircraft operations- (above time line) and maintenance-related (below time line) effects:

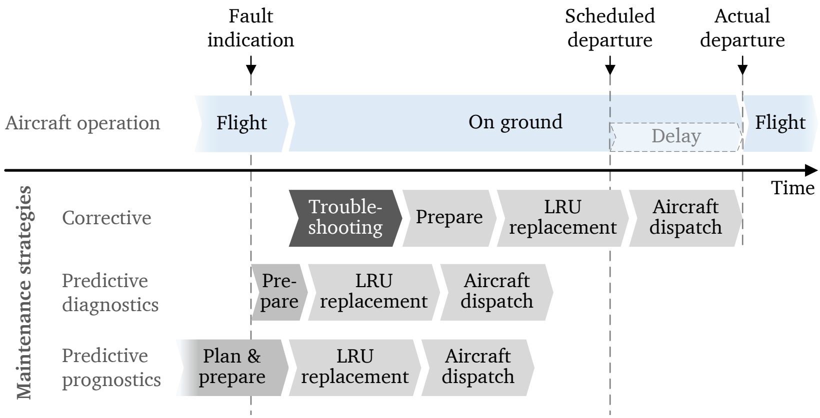


Figure 2.6.: Visualisation of impacts of predictive maintenance (exemplary)

In the upper section of Figure 2.6, the aircraft operations is described by the two repetitive states *flight* and *on ground*. In case of corrective maintenance, a fault indication, that needs to be accounted for, requires maintenance to carry out *troubleshooting*. As this can often not be done before landing, the subsequent maintenance processes (*prepare*, *LRU replacement* in case of component issues and *aircraft dispatch*) are postponed even further. If the aircraft release to service is accomplished after the time of scheduled departure, a delay is generated.

As can be derived from Figure 2.6, maintenance processes are influenced by predictive approaches. Firstly, processes can be modified. In Figure 2.6, the *prepare* activity can be shortened or advanced in case of the predictive strategies. This can be explained by the increased a priori knowledge the maintainer has in advance to an upcoming fault or failure [Ach10]. Either preparation time can simply be reduced (*diagnostics* in Figure 2.6) or improved by a longer time frame for planning and preparing (*prognostics* in Figure 2.6). Additionally, processes can become obsolete (*troubleshooting* in Figure 2.6). Whereas corrective maintenance prerequisites fault isolation in order to determine the required actions, a predictive approach possibly enables to automatically identify the faulty component a priori. It is expected to minimise misinterpretations and thus false decision making through further automation of troubleshooting [Fro09].

Although simplified, the difference between diagnostic and prognostic strategies is depicted in Figure 2.6 as well. Ideally, prognostic approaches gather information on the degradation progress. Whereas diagnostics still rely on the detection of current fault states, the prognostic determination of the remaining useful life (RUL) allows to plan ahead before critical fault states occur. Depending on how particular thresholds are defined and data interpretation is conducted, diagnostics can also be used for prediction. Opposed to the expected benefits of transforming unscheduled into scheduled maintenance, additional uncertainties are generated as well. Depending on the sensitivity of a prediction model, the generation of false statements can possibly create higher efforts, for example through the initiation of more maintenance events as compared to a corrective approach [Mik15].

In order to give insights into the potential of predictive maintenance with respect to components, in the following the component-specific maintenance is described.

2.1.4 Component-specific maintenance

According to [Ver14] a component is the smallest item in a system, with a system being defined as "a distinguishable arrangement of components building a functional entity". Many aircraft components are often referred to as *line replaceable units* (*LRU*). In other words, these components are designed to be quickly replaced in the aircraft line maintenance, taking place at maintenance stations during regular flight operations [Men13].

In most cases LRUs can be found within an ATA-6-digit chapter (see Figure 2.7). The numbering system from aircraft level down to section level is defined by the *Air Transport Association* (ATA). The subsystem and LRU levels below are defined by the particular OEM. An LRU is defined by its part number (PN), that identifies a particular component model, as well as a unique serial number (SN). [KGK14, Men13, Hin10] For further information on the ATA-numbering system see [Air09]. In the following the terms LRU and component are used synonymously.

Whether a particular LRU requires immediate maintenance subsequent to a fault indication, depends on the particular fault's criticality. For this reason, the airline-specific *Minimum equipment list* (MEL) was developed (see Table 2.1). It provides information about components required to be operative in order to keep an aircraft airworthy and is based on the *Master*-MEL, published by the aircraft manufacturer. The MEL only applies for LRUs that are safety relevant [Hol11, Hin10, Int13, Sah12, Men13]. A MEL category is specified by the corresponding rectification interval (RI) of an LRU or a function. The RI defines, how urgently a fault has to be fixed in order to keep an aircraft released to service.

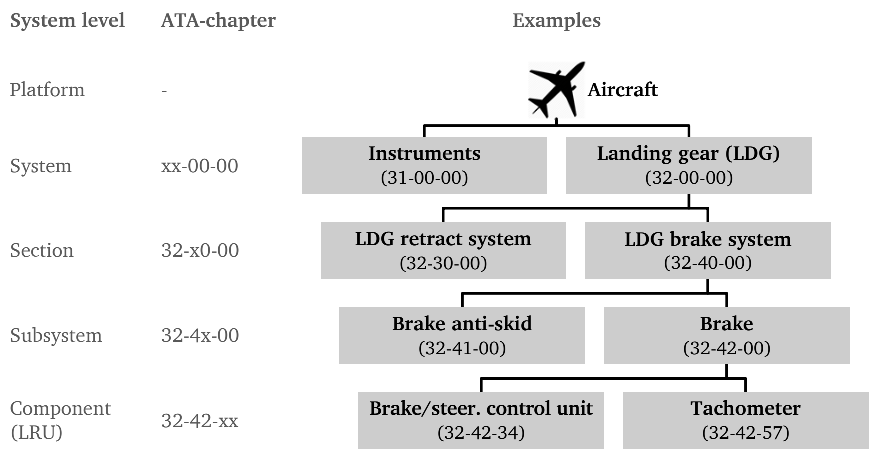


Figure 2.7.: System levels and ATA numbering for the Airbus A320 family. Based on [Air09]

Thus, a fault's priority and operational risk can be described, see the example in Table 2.1:

Table 2.1.: MEL rectification intervals [Air05]

MEL RI	Time for rectification
A	Instantly or component-specific
B	Within 3 days
C	Within 10 days
D	Within 30 days

How the component-specific maintenance activities are integrated into the general aircraft maintenance process, is abstracted in Figure 2.8. The LRU-based maintenance process is illustrated from a macroscopic point of view. In the upper section of Figure 2.8 the normal operations state represents regular flight operations. In case an LRU fault or failure is indicated, maintenance performs on-aircraft system function tests according to the applied TSMs. If a fault cannot be reproduced, the complaint is marked as fixed and the LRU goes back into service. This test outcome is called *no-fault-found* (NFF), which can eventually be considered an unnecessary

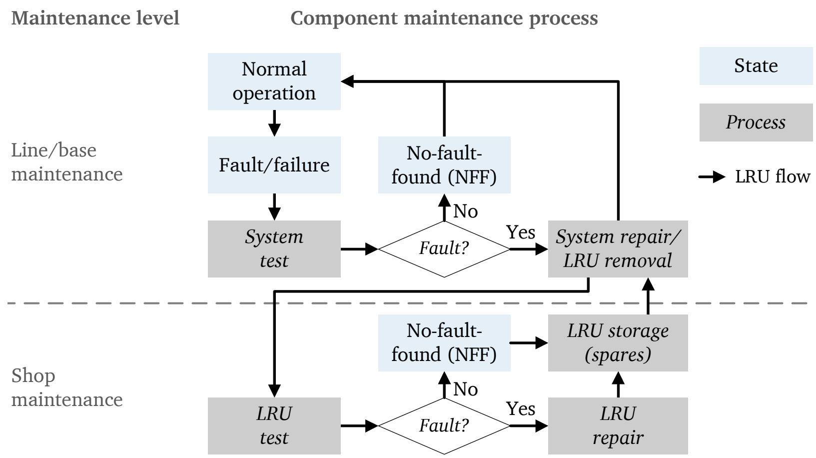


Figure 2.8.: Component-based maintenance process. Based on [ZZZJ14, KPHJ15]

maintenance event [Söd05, KPHJ15]. Thus NFF events should be prevented to keep costs low, also because of further affected divisions, e.g. the spare parts inventory [Men13, KMPD10]. If a fault is found, the system is fixed by immediate replacement of the faulty LRU [ZZZJ14, Fro09].

If not planned in advance, repair activities often cause operational interruptions and additional stress to maintenance personnel given the time constraints. In comparison with pre-planned preventive maintenance tasks, experience in performing unscheduled repair actions is usually lower. That leads to the assumption that maintenance-induced failures are more likely for unplanned maintenance activities (repair, corrective maintenance) than for planned, preventive maintenance [Ach10]. After replacement, the LRU is shipped to the shop maintenance, where it is repaired or overhauled off-aircraft. LRU tests by means of particular test equipment allow to conduct more specific tests than line or base maintenance are able to perform. Once again, the testing can result in NFF if the initial fault is not reproducible. In case a deterioration is identified, the LRU is either scrapped or repaired and handed over to the spares inventory [ZZZJ14, Fro09].

It is important to note that, the further downstream (shop after line/base maintenance) an event is declared NFF and the related LRU marked as serviceable without any further action, the more costs have been generated up to that point.

The following section is supposed to provide more information on maintenance related costs in civil aviation and their assessment.

2.2 Cost aspects in civil aviation

The current market situation significantly affects the way aircraft maintenance is conducted. Competitive constraints the airlines are confronted with are usually passed on to the MRO providers [Lin05, Dog10]. In order to identify possible starting points for cost-benefit calculations, the next sections provide an overview of operating and maintenance costs within civil aviation as well as cost accounting methods and performance indicators for profitability assessment.

2.2.1 Operating costs

Airline operating costs can be classified in various ways. A cost type-based approach is the classification by the *International Civil Aviation Organisation* (ICAO), also used by the *International Air Transport Association* (IATA) and *Association of European Airlines* (AEA) [Dog10].

Generally, airline costs can be split into operating and non-operating costs, as taxes for example. Within the total operating costs (TOC) it can be distinguished between aircraft type-specific direct operating costs (DOC) and indirect operating costs (IOC), see the example in Figure 2.9:

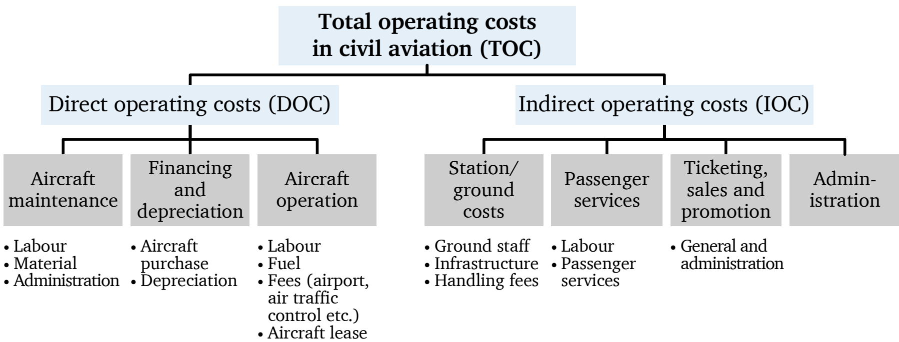


Figure 2.9.: Operating costs structure in civil aviation. Based on [Dog10, Ass03, Int03, Mar06]

DOC can be considered variable unit costs directly dependent on flight operations. The use of *costs per block hour/minute* as a time-based relation is widely spread. According to [Eat11], in 2009 the ATA estimated an airline DOC per block minute, representing the aircraft utilising time off-block (taxiing, in-flight), to US$ 60.99. DOC include costs for the divisions *aircraft maintenance*, *financing* and *depreciation* as well as *operational* costs. Within the particular divisions it can further be distinguished between different *direct* costs, as labour- or material-based expenses, for instance.

IOC on the other hand are fixed costs usually independent of flight operations. These include expenses for ground operations, passenger services, marketing as well as general administration [Dog10, Pou89]. Depending on how airlines define their cost structure, there are further ways of classification, as discussed in [Fro09, Kro96, Dog10, Hor03].

The importance of maintenance expenses as part of the DOC is illustrated in Figure 2.10:

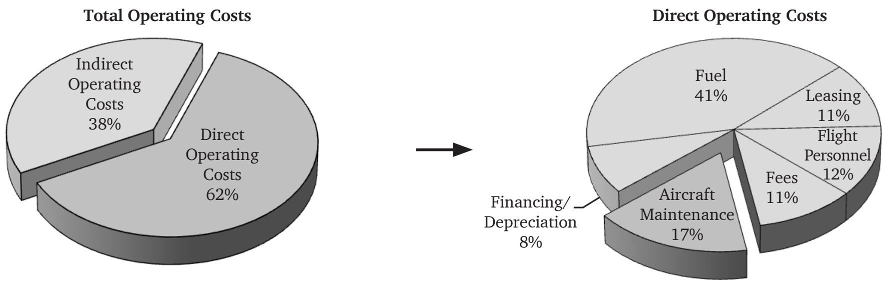


Figure 2.10.: Exemplary distribution of TOC and DOC. Based on [Dog10, Gen99]

For the example shown, comprising averaged airline data, aircraft maintenance costs account for approximately 17% of the DOC [Dog10]. For this reason, a reduction of maintenance costs can significantly affect an airline's profitability. A detailed discussion of maintenance costs is presented in the next section.

2.2.2 Maintenance costs

Similar to the TOC, expenses on maintenance can be split into direct (DMC) and indirect maintenance costs (IMC), see Figure 2.11.

DMC are variable costs depending on the particular flight operations, e.g. on the amount of an aircraft's flight hours [Lin05]. According to [Fro09], over an aircraft life cycle the DMC can reach the level of the aircraft purchase costs. They arise from line or base maintenance (on-aircraft) and shop maintenance (off-aircraft) activities (*cost centre* view). Those activities can be related to the specific aircraft components (*cost object* view). Structural maintenance is usually carried out on-aircraft, whereas engines and components are maintained off-aircraft. At the lowest

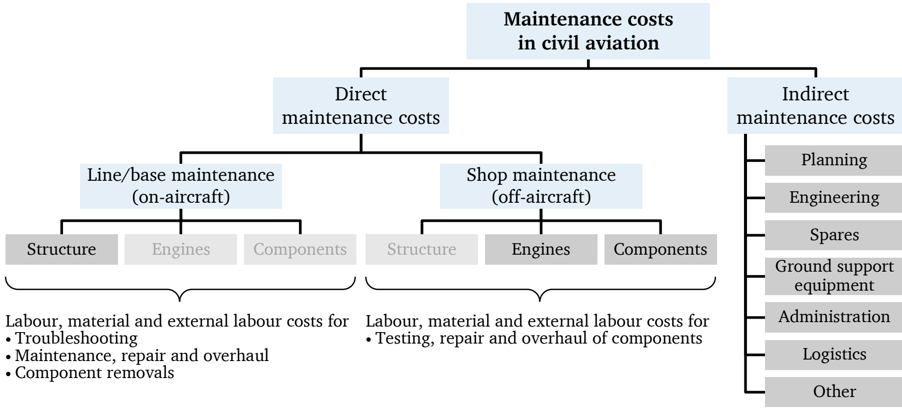


Figure 2.11.: Classification of maintenance costs. Based on [Fro09]

level it is distinguished between direct labour, material and external labour costs (*cost type* view) [Air92, Fri92]. As mentioned before, line or base maintenance deal with troubleshooting, maintenance, repair and overhaul as well as component removals. Shop maintenance rather focusses on testing, repair and overhaul of LRUs [Pou89, Sch03]. Costs on the lowest level can be associated with particular activities. Although not depicted in Figure 2.11, it is possible to further distinguish between scheduled and unscheduled activities as well [Fro09, Hei02]. Figure 2.12 gives an example for a DMC distribution with respect to different criteria:

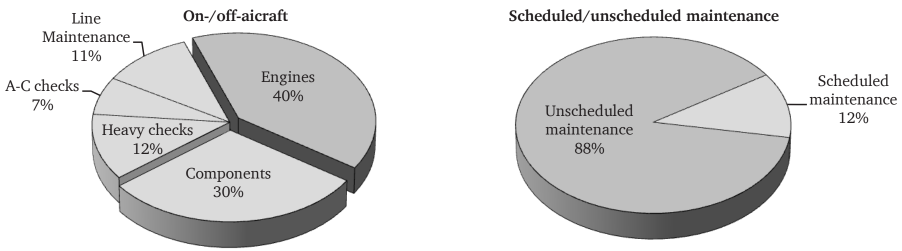


Figure 2.12.: DMC distributions with respect to classification and scheduling ability

The data in Figure 2.12 is based on Boeing 737-300 and Airbus A320-200 operating costs for an average flight length of 500 nautical miles [Fro09, Hei02, Hor03, Kro96, Mas97, MK96, RM00, Rut97, She16, SH96, Wil04]. From the distribution concerning on- and off-aircraft activities it can be derived that engines and components, both maintained off-aircraft, have a significant impact on DMC [Gen99, Pou89, She16]. The second diagram shows that unscheduled maintenance has the most significant impact on DMC by far [Hei02].

The IMC are overhead costs resulting from support functions within the maintenance process. Usually they are not assignable to any particular maintenance activity [Gen99]. IMC are proportional to the DMC and partially influenced by an airline's strategy [Fro09]. The costs arise from planning, engineering, spares inventory management and logistics activities, for example.

2.2.3 Delay and cancellation costs

In the following, costs shall be discussed, that are dependent on the interaction of aircraft operations and maintenance. As for every production resource, the availability is targeted to be maximised, since it is proportional to the amount or duration of revenue flights [Fro09]. Maintenance is considered non-utilisation time. Whereas scheduled maintenance is carried out during planned aircraft non-utilisation time, unscheduled maintenance, e.g. as a reaction to unexpected wear-out behaviour, causes the availability to decrease even further. Figure 2.13 illustrates the negative impact of component wear-out and its consequences on costs:

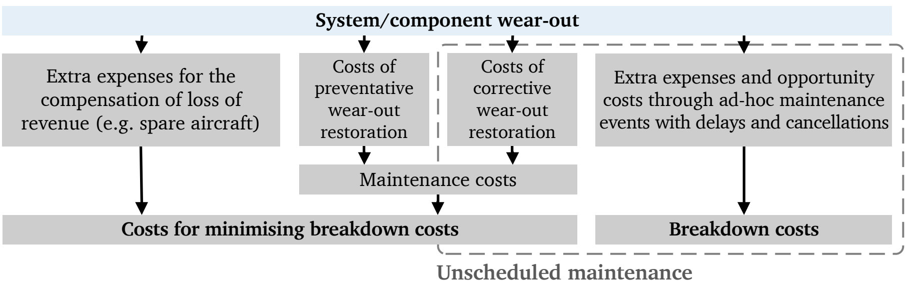


Figure 2.13.: Wear-out effects on maintenance and economics. Based on [War92]

Generally, it is aimed to minimise the impact of unexpected maintenance events on aircraft availability by providing spare aircraft or spare parts available at hand. Preventive or corrective wear-out restoration directly affects maintenance costs. Since these activities primarily aim to instantly restore an aircraft's airworthiness, they try to minimise breakdown costs, in the following referred to as *delay and cancellation costs* (DCC). These expenses arise from ad-hoc events (due to maintenance, weather etc.) that result in extra costs (passenger compensation costs, additional fees) and opportunity costs (loss of revenue) [RBP+12, Sis93]. As the naming implies, within DCC delay and cancellation compensations can be distinguished. They are described in the following.

According to [Eur12, Eur15, Uni11], flight delay costs are defined as average costs per minute, that an airline has to bear in case of an airborne- or ground-based aircraft delay. These costs are calculated by multiplying an average time-dependent delay cost rate ($c_{\text{Delay, average}}(t)$, see Eq. 2.1) with the duration of a particular delay Δt_d, defined as the temporal difference between actual (t_{ATD}) to scheduled time of departure (t_{STD}), if the focus lies on ground-based delays.

$$C_{\text{Delay}}(t) = c_{\text{Delay, average}}(t) \cdot \sum_{d=1}^{n} \Delta t_d \tag{2.1}$$

$$\text{with} \quad \Delta t_d = t_{\text{ATD}} - t_{\text{STD}} \tag{2.2}$$

The particular delay cost rate depends on various factors, e.g. time, and thus accounts for real-world, economical effects, e.g. price changes. It distinguishes between different aircraft types, e.g. short-haul vs. long-haul, as well as flight routes, e.g. continental vs. intercontinental flights. For more details on its composition see *Eurocontrol* [Eur10]. Besides the so-called *primary* initial delay, subsequent *reactionary* delays are considered as well. [Eur15] further differentiates between strategic and tactical effects. Strategic effects cover the additional direct costs to an airline, such as fuel, crew and ownership costs that apply for a delay. Tactical effects also include passenger compensations and opportunity costs as well as maintenance costs. Examples for compensations are passenger vouchers, hotel costs or rebooking expenses. Most of these costs can be assigned to elements in the common cost structure in Figure 2.9 [Eur15].

A data-based analysis of technically induced aircraft delays is enabled through the *IATA delay codes*. Among airline-, airport-, ground handling- or weather-specific delay causes, technically-caused delays are identified as well (IATA-code 41-49) [Eur12]. According to [Eur10], average costs of aircraft delays reach up to US$ 113 per operating minute for long-haul aircraft (see also [RBP+12, CTA04, FL12]). In the year 2008 European airlines accumluated 85 million delay minutes [Eur11]. According to [Eur11], technically induced delays account for approximately 10% of all delays, creating estimated US$ 970 million of delay costs per year.

Cancellation costs apply, if a commercial scheduled flight is cancelled on the day of operations [Eur15]. They are defined as average costs per cancellation ($c_{\text{Canc, average}}(t)$, see Eq. 2.3) times the number of cancelled flights (n_{Canc}). Similar to delay costs, they are dependent on the particular boundary conditions (aircraft, flight, range of effect).

$$C_{\text{Canc}}(t) = c_{\text{Canc, average}}(t) \cdot n_{\text{Canc}} \tag{2.3}$$

The cancellation cost rate accounts for passenger compensation costs (vouchers, hotels etc.), loss of revenues (opportunity costs) as well as operational savings, because unit costs could be saved (fuel, crew costs, fees etc.). Furthermore it is assumed that only part of the revenue is lost, due to the fact that some passengers can possibly be rebooked to other flights [Eur15].

In Figure 2.13 the role of unscheduled maintenance is emphasised as well. It is shown that the costs on the right side (corrective maintenance, DCC) arise from unscheduled maintenance events. They are directly related to a system's or component's so-called *technical dispatch reliability* (TDR) [Fro09]. The TDR describes the ratio of revenue departures without delays or cancellations compared to all flights. The expenses on the left side of Figure 2.13 (spare aircraft, preventive maintenance) are considered to be independent of the particular amount of unscheduled maintenance events.

There are many alternate ways to merge and abstract maintenance costs, concerning different hierarchy levels of cost types, cost centres or cost objects [HB08]. Independent of which cost structure is applied, the problem of ambiguity becomes obvious: Sometimes it can be difficult to clearly assign costs of an activity. For instance, how is a component classified that operates at the interface of engines and other components, e.g. the *engine driven pump* [Fro09]? For this reason, cost accounting and costs-by-cause assessments are discussed in the following.

2.2.4 Cost accounting aspects

This section deals with the aspects of cost accounting that are relevant to this work. A brief introduction to cost accounting and its basic elements is presented, followed by a discussion of the applied methods.

According to the *American Accounting Association* accounting is "the process of identifying, measuring and communicating economic information to permit informed judgements and decisions by users of the information." [Dru92] It can be distinguished between *management accounting* and *financial accounting*. Among many distinctions, they differ with respect to their target groups: Management accounting serves as an internal knowledge base, whereas financial accounting is concerned with the provision of information to external parties [Dru12]. Furthermore it can be differentiated between the terms *management accounting* and *cost accounting*, with the latter only focussing on cost accumulation for internal profit measurement. [Dru12] concludes to use these terms synonymously, as done in this work. The general functions of a cost accounting system can be summarised firstly as allocation of costs and secondly as provision of relevant information for decision making, planning, control and performance measurement [Dru12].

As mentioned before, operating costs and maintenance costs can be distinguished by cost types: There are direct, variable costs (e.g. labour and material expenses) and indirect, fixed costs. The question important for this work is, how to assign direct and indirect costs to cost objects, e.g. aircraft or components? [Dru12] outlines the general cost allocation procedure as shown in Figure 2.14:

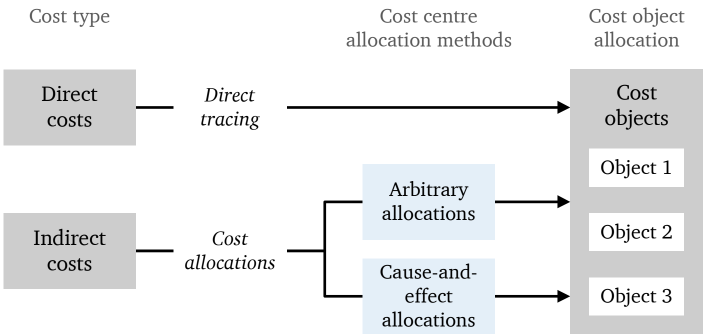


Figure 2.14.: General cost allocation procedure. Based on [Dru12]

Direct costs are observable and easily attributable to particular cost objects (*direct tracing*). For example, time sheets or job cards provide information for a time-based allocation of labour costs of a particular activity, whereas a logistics handling request document allows to cover material-based fixed price activities. This information can then be associated with cost objects by means of a *direct costing system* (also referred to as *marginal* or *variable costing system*).

Indirect costs cannot be related to cost objects, because the quantity of resources consumed by a particular cost driver usually is not measurable. Examples for such indirect costs are joint resources, as the maintenance engineering or planning departments (see Figure 2.11), demanded by various products. These services are provided for all aircraft fleets and components. Since their activities might be relevant for a cost-benefit analysis as well, *cost allocation* is a method to assign indirect costs to cost objects. [Dru12] points out two common strategies (see Figure 2.14): Since the early 20th century, *arbitrary allocations* have been used. Here, particular distribution keys represent the estimated share of overhead costs on unit costs. Although widely spread due to its simplicity, this method is known to be inaccurate in allocating indirect costs to cost objects. *Cause-and-effect* allocation is preferred, if particular cost drivers are well-known and allow to quantify the ratio of overhead costs on unit costs. This method is known to be more accurate than arbitrary allocation. An example that has emerged since the late 1980s is the *activity-based costing*

(ABC) system. In an ABC system indirect costs are aggregated to activity-based cost centres and thereafter assigned to cost objects (see Figure 2.15) [Dru12, Lin05]:

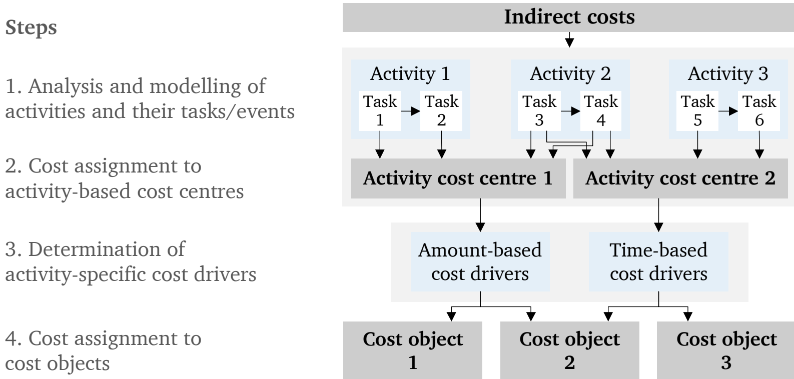


Figure 2.15.: Activity-based costing method. Based on [Dru12, Hor10]

Starting point of the ABC procedure is the analysis of relevant business activities [HSS96]. Their defined names typically consist of actions associated with objects, e.g. *replace LRU*. Activities consist of the aggregation of many tasks or events that cause the consumption of resources. Whereas activities can clearly be separated, tasks can be associated with different main activities, or cost centres. Tasks need to be exactly defined in terms of resource consumption (time, personnel) based on interviews, job descriptions or flow charts. Thereafter task-specific costs can be determined. The consolidation of task- and activity-based costs to cost-centres is the next step. Opposed to arbitrary cost allocation, ABC allows to create service department-based cost-centres as well. The third step involves the definition of adequate cost-drivers, measures that quantify the frequency or the amount of an activity or task. In case of so-called *activity quantity induced* tasks this can be e.g. the number of LRU-specific maintenance events per time period (amount-based/transaction drivers). If time consumption seems more adequate for cost allocation, so-called *duration drivers*, e.g. set-up time, account for a task's resource consumption. Lastly, the cost driver rates are applied to cost objects. Because cost driver rates need to be measurable, the efforts of obtaining data on cost driver consumption is a factor that must be considered during the third stage, when appropriate cost drivers are being selected [Dru12, Hor10].

In literature the ABC method is still controversially discussed, see [CFG16, FFHP99, Gla92, KPV12]. Further advancements can be found as well, e.g. the *resource-oriented approach* in [Kös06]. Advantages of the ABC method comprise its accuracy and the support of cost-centre-independent business thinking. It primarily provides information for mid-/long-term business decisions and enables to identify particularly cost-intensive activities [Wun02]. The ABC method's disadvantages include high efforts for implementation and wrong assumptions concerning proportionality between activity frequency and resource consumptions (economies of scale). The application of ABC is reasonable, if the particular activities are repetitive and standardised. Departments that are not representable by standardised activities, still have to be covered by arbitrary approaches [Hor10].

2.3 Fault prediction

In this section the state of the art concerning fault prediction is introduced. Firstly, the particular definitions and terminologies are provided in Section 2.3.1, followed by a summary of the goals and areas of application (Section 2.3.2). In Section 2.3.3 classification concepts are discussed, followed by a summary of common performance metrics (Section 2.3.4).

2.3.1 Definitions and terminologies

In order to introduce the relevant terms, a distinction between a component *fault* and *failure* shall be made first. According to [Deu10] a fault is the "state of an item characterized by the inability to perform a required function." In Figure 2.4 (Section 2.1.2) a wear-out state below nominal condition refers to a fault occurrence. The functionality of the overall system consisting of a faulty item (component) does not necessarily need to be affected. According to [Sau15] "aircraft components are robust and capable of flying with faults." [KM12] uses the term *minor defect* for a fault not having any operational or economic impact. *Errors* are manifestations of faults, with error logs providing information on the particular fault history [LS90]. As long as the component operates above minimum condition and no notable malfunction occurs, there is no failure [ST08]. The definition of a failure according to [NH78] is "the inability of an item (or the equipment containing it) to meet a specified performance standard", referred to as minimum condition in this work. A fault can lead to a failure, if certain conditions are met [KPHJ15]. Then the system does not work within the given specifications and is considered inoperative (below minimum condition, see Figure 2.4). According to [KM12], a failure leads to unacceptable operational or economical penalties. A potential failure is "an identifiable physical condition which indicates a functional failure is imminent" [NH78].

Prediction concepts usually focus on the detection, isolation and forecast of faults prior to any failure. Especially in aviation, the existing systems architecture is built in such a way to prevent momentous failures by allowing to react to relevant fault states a priori, e.g. through so-called *built-in test equipment* (BITE) [SMM09]. Different ways of classifying predictive maintenance are applicable. In order to provide a common framework for information exchange concerning fault prediction, in 2001 a joint venture by the US Navy and the industry established the *Open Systems Architecture - Condition Based Maintenance* (OSA-CBM) standard, see Figure 2.16 [Ach10]:

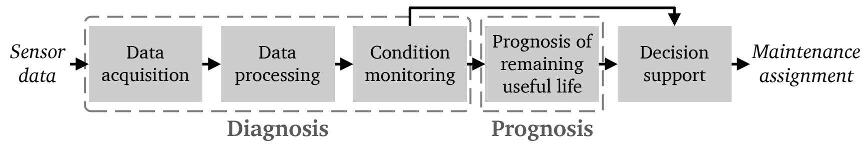


Figure 2.16.: OSA-CBM Standard. Based on [Ach10]

The steps *data acquisition* (data transmission and storage issues), *data processing* (de-noising and filtering issues) and *condition monitoring* (observe predefined features), also referred to as *diagnosis*, eventually enable to assess sensor data during the occurrence of an event. They incorporate all processes to detect and isolate a fault, followed by a severity assessment [GV15]. Furthermore, the finding of a particular problem's root cause is enabled [LWZ+14]. Additionally, diagnosis builds the basis for the *prognosis* of a component's *RUL*. Then not only a component's current state is considered for a health assessment, but also the information of reference cases (e.g. run-to-failure data or model-based failure rate information, see Section 2.3.3) is used to predict the future health state *before* an event occurs [GV15]. Both principles serve as *decision support* for maintenance assignments. The expected benefits and drawbacks have been discussed before in Section 2.1.3.

Opposed to the OSA-CBM standard, there are further ways of classifying prediction-based approaches. [MS13] distinguish between traditional maintenance concepts and *predictive* as well as *proactive* maintenance. Predictive then refers to the traditional concept of CBM (see Section 2.1.2), if represented by an automatised procedure also referred to as diagnosis, proactive maintenance then is associated with prognosis-based decision making. Whereas [GV15] draw a similar picture, where diagnosis refers to CBM that builds the basis for prognostics, referred to as *prognostics and health management* (PHM), they also sensitise the reader to further ways of distinction concerning prediction: Prognosis primarily enables the estimation of a component's RUL. On the other hand, *trending* refers to the linear projection or regression of measurements as forecasting. Furthermore, *predictive diagnostics* aims at finding precursors to failure and allows a priori planning by predictive means as well.

2.3.2 Goals and area of application

The goal to improve scheduling and effectiveness of maintenance by an increased availability of real-time health information of a particular component and the effects on costs has been discussed before. With respect to an LRU's reserve of wear-out, the operating point of predictive maintenance is depicted in Figure 2.17:

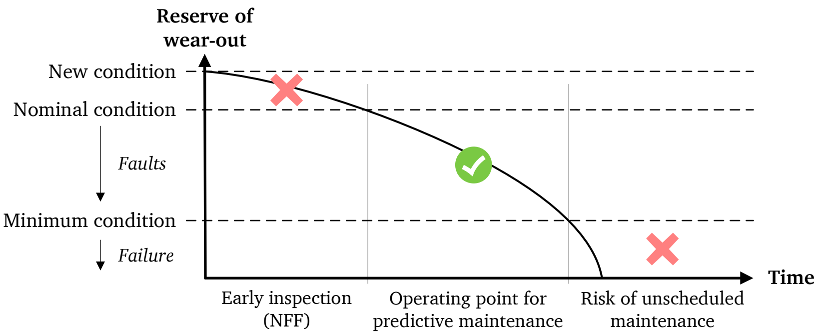


Figure 2.17.: Application of predictive maintenance with respect to component wear-out. Based on [KM12]

The optimum point of operations for predictive maintenance is defined by a component state below nominal condition (faults possibly indicated already) and above minimum condition (no failure yet). Any action above nominal condition (similar to preventive maintenance) possibly results in NFF events, because a particular degradation cannot be measured and confirmed [KM12, Mik15]. Thus, an early prediction-based indication should be prevented. On the other hand, predictions applied after failure (below minimum condition) are considered late predictions leading to unscheduled maintenance and breakdown costs. Depending on the particular boundary conditions, it might be desired to apply predictions more conservatively by preventing any faults at all (prediction around nominal condition) or to operate close to failure (prediction around minimum condition). Generally, it is desired to apply prediction not too early (risk of NFF) as well as not too late (risk of unscheduled maintenance).

For the application of predictive maintenance two requirements should be met:

- The wear-out behaviour is measurable [Ach10]
- The degradation progress is steady

As Figure 2.17 implies, a component's wear-out must be observable in order to provide evidence for any change in condition. Additionally, if it is desired to not only classify a component as *operative* and *non-operative*, but also to determine any states in between, a steady degradation progress is essential. Figure 2.18 illustrates the two basic cases *step failure* (left) and *drift failure* (right), that are often superimposed in reality (center):

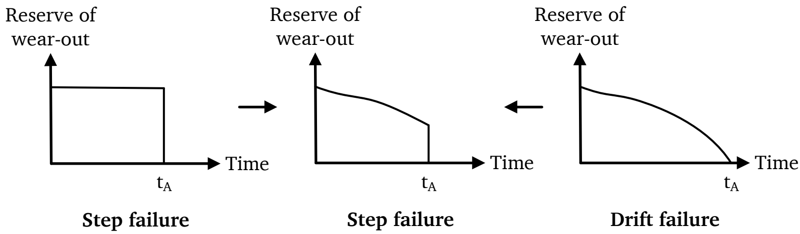


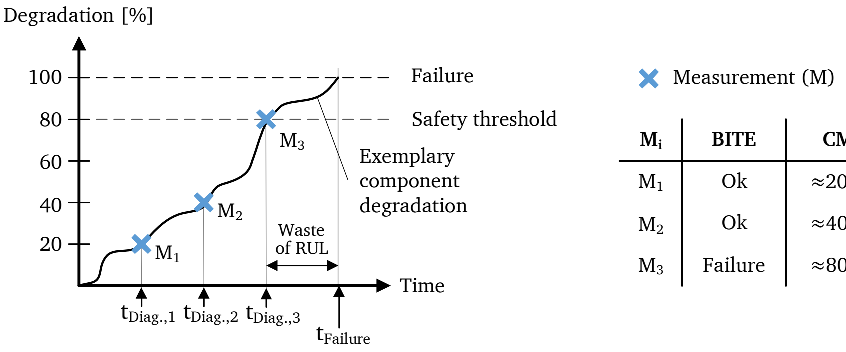
Figure 2.18.: Failure velocities. Based on [Eic90]

A drift failure mechanism allows to qualitatively assess a wear-out behaviour as shown in Figure 2.17, whereas a step failure allows a binary classification only, possibly not enabling any prognosis. As can be derived from Figure 2.18, the determination of adequate features allowing to represent a component's steady degradation process is essential. In the following the concepts of diagnosis and prognosis shall be clearly distinguished.

2.3.2.1 Diagnosis

The goal of diagnosis is to constantly monitor and assess a system's or component's health in order to identify critical states by comparison to predefined thresholds and thus to enable early enough maintenance [Mik15]. Diagnosis examples are *usage monitoring* for aircraft structures [HH98] or *engine trend monitoring* [KP11]. Concerning diagnosis abilities, there is a clear distinction between a simple *BITE* system and a continuous *condition monitoring* (CM), as illustrated in Figure 2.19.

Whereas a BITE system only allows a binary assessment of a component's condition (*healthy* vs. *failure*), a continuous CM enables to quantitatively assess any state changes prior to failure. Since diagnosis systems are always imperfect, the diagnosis performance is a key factor in minimising the interval between the identification of a critical state and the actual failure. If the diagnosis leads to a preventive LRU replacement at $t_{\text{Diag.},3}$, this interval is equal to the waste of component life (RUL). Depending on the diagnosis performance and the predefined thresholds, in case of



M_i	BITE	CM
M_1	Ok	≈20%
M_2	Ok	≈40%
M_3	Failure	≈80%

Figure 2.19.: Diagnosis: Distinction between BITE and CM. Based on [Mik15]

the BITE system it is also possible that a failure is not indicated before t_{Failure} at all. Furthermore, threshold violations do not account for time periods with possible decreasing degradation (regeneration). In order to account for imperfect diagnosis performance, a safety threshold usually leads to conservative assessments. Metrics for the assessment of diagnosis performance are discussed in Section 2.3.4.

Since the particular diagnosis model building and algorithm development is not part of this work, it is not discussed in more detail. For further reading, [Ekl13, Mik15] is recommended.

2.3.2.2 Prognosis

According to [Mik15], the application of prognosis requires a CM-based diagnosis as the basis. It also covers the assessment of a component's health by means of measurements, but additionally aims at projecting the future degradation progress including the RUL determination in order to enable time-optimised maintenance, see Figure 2.20 [GV15].

Represented by the dashed lines are the predicted degradation progresses (minimum bound, most probable value, maximum bound) at a measurement point in time $t_{\text{Prognosis}}$. In order to account for uncertainty, different predictions are conducted eventually generating a distribution of possible RUL values. If it is desired to act more conservatively, the minimum RUL is accounted for and vice versa. As shown in the example in Figure 2.20, the real degradation progress is slower than all prediction outcomes estimated, resulting in a longer RUL than predicted. If maintenance planning were based on one of the predictions, the prognosis would lead to a waste of RUL. As can be derived from Figure 2.20 as well, the earlier a

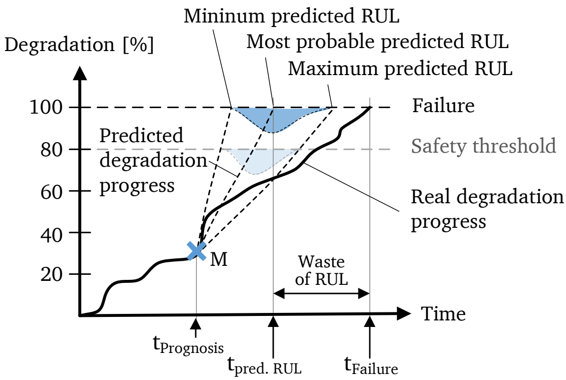


Figure 2.20.: Prognosis characteristics. Based on [GV15]

prediction is applied, the larger the generated uncertainty of the RUL estimation is (wider distribution over time). This trade-off has to be considered, when bringing together prediction model characteristics and maintenance requirements, preferring larger RUL values for planning purposes. Again, a safety threshold (also *safety margin*) accounts for prognosis inaccuracy. The exact assessment of prognosis performance is discussed in Section 2.3.4.

Similar to diagnosis, prognosis algorithm development is not part of this work. For further reading, [Ekl13, Mik15] are recommended.

2.3.3 Classification of prediction concepts

The exact procedure concerning diagnostic approaches depends on the particular method. Figure 2.21 gives an overview of applicable diagnosis-based CM procedures, divided into data-driven and model-based methods.

Qualitative data-driven approaches are considered to be robust and easy to implement. With no complex algorithms required, the focus lies on the determination of adequate thresholds. Implementation examples are given in [Mün06]. Quantitative methods utilise extensive datasets in order to identify and distinguish nominal and faulty behaviours. The health assessment is based on pattern recognition algorithms by analysing selected features from the collected data [VRYK03]. Examples for common classification methods are neural networks (e.g. see [Ypm01]) and support vector machines (e.g. see [SHK07]) [MSB14].

Model-based methods use a mathematical or logical description of the monitored process to compare the expected behaviour to measurements. The results allow to

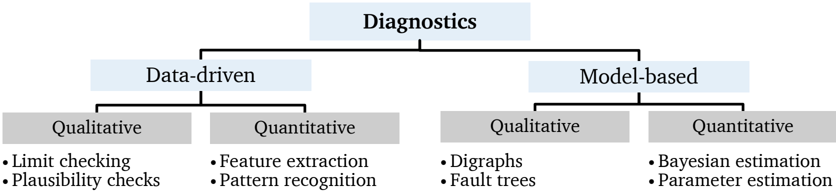


Figure 2.21.: Classification of diagnostic approaches. Based on [MSB14, Sch11, VRYK03]

derive estimates of the actual health status. Qualitative models are abstract process representations without detailed physical modelling. For example, logical graphs include information about causes and effects of failure modes and enable fault detection and isolation [CY90]. Quantitative methods apply a mathematical model in order to "represent a virtual redundancy of the monitored process" [MSB14]. A model enables to derive a residual describing the difference between nominal and faulty behaviour. Examples are recursive Bayesian estimations (e.g. see [CK00]) and parameter estimation techniques (e.g. see [Ise92]). The advantages and drawbacks of the particular methods are discussed in [MSB14].

A classification of prognosis-based methods, also divided into data-driven and model-based approaches, is given in Figure 2.22. A classification in reliability-, stress- and condition-based methods is proposed by [GV15], for instance.

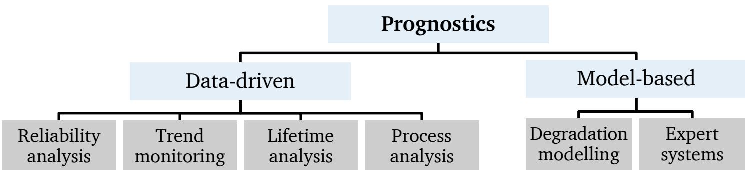


Figure 2.22.: Classification of prognostic approaches. Based on [MSB14, Sch05, MZB13, GSS08]

Among the data-driven methods, a reliability analysis incorporates the statistical evaluation of collected failure modes and the correlation with recorded operating conditions for the RUL estimation. It is important to note, that no real-time status information is used in this case. A common example is the Weibull analysis, e.g. see [Gro00]. Trend monitoring applies time series regression of selected features for the extrapolation of a trend to a predefined threshold. Auto-regression methods are one example of applicable procedures, e.g. see [PA09]. The lifetime analysis relates the current condition to the monitored component's RUL, without consideration of the real degradation process, e.g. see [GL08]. Process analysis approaches use degradation path and operating condition information in order to identify an adequate damage propagation model, which is then applied to predict the future degradation trend. Common methods are neural networks (e.g. see [RPN12]), support vector machines (e.g. see [KM12]) and Gaussian process (e.g. see [LPZ+13]) [MSB14].

An example for a model-based approach is the degradation modelling using functional or physical models in order to identify and predict model parameters [DSG12]. Examples are extended or unscented Kalman filter methods, see [CKB+11, Bec08, ZP12]. Expert systems rely on a detailed technical understanding of the relationship between a condition indicator and the RUL, see e.g. [BJJW00].

In [AC15], a procedure is introduced that helps choosing the adequate prognosis method depending on the particular requirements and boundary conditions. A summary of the particular advantages and disadvantages is given in [AC15, GV15].

2.3.4 Performance metrics

Because a prediction method always incorporates uncertainties, the use of statistical measures allows to assess an algorithm's performance [GV15]. In the following common diagnosis (Section 2.3.4.1) as well as prognosis (Section 2.3.4.2) metrics are discussed.

2.3.4.1 Diagnosis metrics

According to [KNP+09], "metrics for evaluating diagnostic algorithms depend on the particular use of the diagnostic system, the users involved, and their objectives". They further introduce the classes of *temporal*, *technical* and *computational* performance metrics. Whereas temporal and computational indicators are concerned with the speed of diagnosis results and the efficiency of computational resource usage, technical indicators, as detection rates, are relevant for the maintenance impact assessment and thus further discussed in the following. Additional metrics can be found in [KNP+09, Ekl13].

The technical performance of diagnostic systems is often analysed by means of a *confusion matrix*, see Table 2.2 [Ekl13]:

Table 2.2.: Confusion matrix for binary classification

True outcome	Prediction outcome: **Positive** (Fault)	**Negative** (No fault)
Positive (Fault)	True positive (TP)	False negative (FN)
Negative (No fault)	False positive (FP)	True negative (TN)

For a two-class problem, e.g. *anomaly detection*, the four possible outcomes resulting from two prediction classes and two true results are shown. If a diagnosis correctly predicts a fault, a *true positive* (TP) or *hit* applies. If the prediction falsely indicates a fault, a *false positive* (FP) or *false alarm* error occurs. When the predicted negative class matches the actual positive case, a *false negative* (FN) or *missed alarm* error applies. Lastly, a correct prediction of the negative case leads to a *true negative* (TN) or *correct rejection*. In case more than two classes apply, the confusion matrix can simply be scaled up [Ekl13].

The confusion matrix enables various types of analyses. If numerous diagnosis outcomes are collected, the particular counts allow to qualitatively and quantitatively assess the diagnosis performance. Qualitatively it can easily be identified, which prediction error (FP vs. FN) is more frequent. This can be relevant, if one misclassification type is more expensive, for instance [Ekl13]. By means of quantification, particular classification ratios, representing relative behaviour, can be derived. Table 2.3 provides a summary of common relationships:

Table 2.3.: Diagnosis metrics overview. Based on [Pow11, SJS06]

Metric	**Formula**	**Description: Rate of**
Accuracy	$Acc. = \frac{TP+TN}{TP+TN+FP+FN}$	Correct predictions to all predictions
Precision (confidence)	$Prec. = \frac{TP}{TP+FP}$	Correct hits to positive predictions
Sensitivity (true pos. rate)	$TPR = \frac{TP}{TP+FN}$	Correct hits to real positive cases
F1 score	$F1 = \frac{2TP}{2TP+FP+FN}$	Precision and sensitivity (harmonic mean)
False positive rate	$FPR = \frac{FP}{TN+FP}$	False alarms to real negative cases
False negative rate	$FNR = \frac{FN}{TP+FN}$	Missed alarms to real positive cases
False discovery rate	$FDR = \frac{FP}{TP+FP}$	False alarms to positive predictions
Specific false discovery rate	$SFDR = \frac{FP}{TP+FP+FN}$	False alarms to all predictions except TN
Jaccard coefficient	$Jac. = \frac{TP}{TP+FP+FN}$	Correct hits to all predictions except TN

The shown metrics allow to evaluate particular prediction fault-specific behaviour. For instance, in medicine the ability to correctly identify positive cases of disease plays an important role, thus reducing FN is important with the sensitivity being an adequate measure [Pow11]. Using the basic four classifiers, it is obvious that the shown ratios are interdependent. For example, an increase in false positive (false alarm) rate usually leads to a higher sensitivity and vice versa. This particular relationship is often visualised by means of the so-called *Receiver Operating Curve* (ROC), explained in more detail in [Ekl13]. An increased precision normally leads to a decreased sensitivity, induced by a shift of prediction errors.

Detecting faults with as much lead time as possible for maintenance scheduling purposes requires to define temporal performance indicators as well [Ekl13]. [XEHY10] defines the *time to failure* (TTF) as the time between the classifier first exceeding an alerting threshold and the actual fault occurrence, see Figure 2.23:

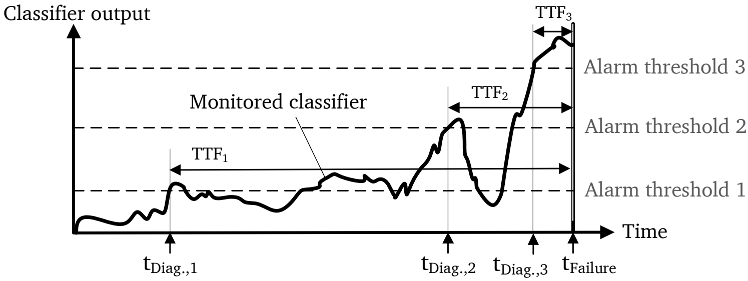


Figure 2.23.: *Time to failure* (TTF) metric. Based on [XEHY10]

In the figure three different exemplary alarm thresholds and classifier exceeding time instances are shown. Qualitatively it can be derived, that higher threshold lead to shorter TTFs and thus less waste of RUL in case of related maintenance actions. If the threshold is too low, the TTF can possibly be very long, resulting in too early alarm respectively maintenance (e.g. TTF_1). On the other hand, if the threshold is too high, the TTF might be too short as opposed to temporal maintenance requirements (e.g. TTF_3). If maintenance requires longer lead times, alarm threshold 2 might be the best choice. A general problem of diagnosis-based decision making is shown in Figure 2.23 as well: The regeneration occurring after $t_{\text{Diag.,2}}$ cannot be accounted for, if the diagnosis-based is based on single threshold violation trigger conditions. Thus, more sophisticated threshold violation rules should be pursued.

2.3.4.2 Prognosis metrics

In [SCB+08], prognostics metrics are divided into *algorithm performance-*, *computational performance-* and *cost-benefit*-based metrics. A relevant temporal algorithm performance indicator is the *Prognostic horizon* (PH, see Figure 2.24). It indicates the time between the prediction ($t_{\text{first pred.}}$) to the actual *End of life* (EoL, time index for the actual end of life according to the particular failure threshold) that the algorithm's prediction stays within a specified error margin α, a statistical confidence parameter [SCS+09]. For example, a PH with error bound of $\alpha = 0.05$ identifies when a given algorithm start predicting estimates within 5% of the actual EoL. Similar to the TTF in diagnostics, it enables to assess whether an algorithm yields a sufficient lead time for subsequent maintenance actions [Jen11].

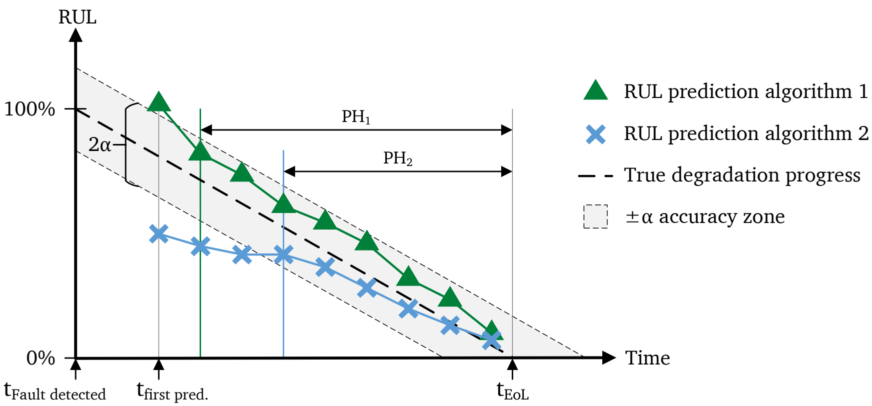


Figure 2.24.: Prognostic horizon definition. Based on [SCS+09]

The earlier a prediction stays within the particular accuracy zone, the longer the resulting PH is, enabling extended maintenance-related lead times. Thus, in the example of Figure 2.24, algorithm 1 is superior to algorithm 2. Similar to the TTF, a minimum lead time specified by maintenance requirements restricts the amount of adequate algorithms. From Figure 2.24 it can also be derived that for higher confidence values α, meaning increased error bounds or lower required accuracy, a larger PH is enabled. This results in the same conflict of goals as for diagnostics: A higher accuracy usually decreases lead time and vice versa. The error bound α is also used for the so-called *α-λ performance*, which identifies whether the particular algorithm performs within desired error margins α of the actual RUL at any given point in time λ. In this case, a converging error margin cone towards EoL represents a more stringent performance indicator over time (see Figure 2.25). $\lambda = 0$ represents the point in time of the initial fault identification, $\lambda = 1$ is equal to the EoL [Jen11].

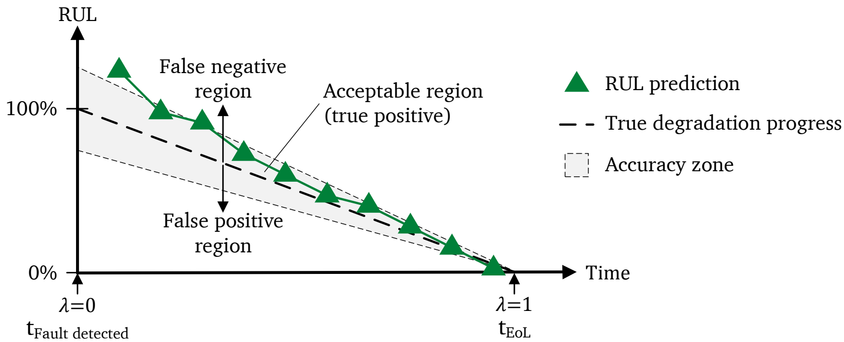


Figure 2.25.: False positives and false negative in prognostics. Based on [SCB+08]

Figure 2.25 shows the common prediction errors FP and FN. In case of prognosis, a FP refers to an early prediction, meaning the predicted RUL is smaller than the true RUL. Opposed to that, a FN is concerned with late predictions at specified time instances. In this case, user-defined thresholds (t_{FP} and t_{FN}) set the acceptable error range. This way maintenance lead time requirements can be accounted for. [SCB+08] Additional prognosis metrics and their classification are not relevant for this work and are extensively discussed in [SCB+08, SCS+09].

2.4 Conclusions

From the introduction of today's aircraft maintenance characteristics it can be derived, that the need for intelligent maintenance has already been identified in the aviation industry (e.g. see discussion of *maintenance value* in [San15a] or the potential of digitalisation with respect to safety and economics in [Int03]). Still, innovative approaches as predictive maintenance incorporate particular risks with their likelihood and microscopic as well as macroscopic impact unknown to a large extend. An example is the initiation of additional, unnecessary maintenance events. Thus, the need for a method is identified, which allows to cover the particular benefits and drawbacks of a shift towards predictive maintenance for the MRO as well as the customer (airline) through a predictive maintenance approach in detail.

Concerning costs, the significance of maintenance costs as well as breakdown costs with respect to a predictive maintenance strategy's expected impact has been identified. In order to not only cover global economic impacts, a process-based cost assessment allows to quantify bottom-level changes as well, exposing detailed causes and effects. To consider indirect cost-related departments, an allocation of the expenses by means of activity-based costing has been identified as adequate.

The section on fault prediction provides the fundamentals on prediction-based algorithms including their performance assessment by means of the introduced metrics. Hereby adequate specification parameters are defined, eventually required by algorithm developers as discussed in [GV15]. Since all prediction algorithms are imperfect, a statistical analysis of the dependencies and effects is required. The conflict of gaining accuracy while losing lead time (and vice versa) shows, that a detailed assessment of maintenance requirements concerning the effects of advanced warning time opposed to probabilities of wrong decisions through prediction errors is essential. Thus, a definition of break-even settings concerning relevant (interdependent) prediction metrics in order to oppose added value to risk accounting is desirable.

3 Conceptual design of an evaluation method for predictive maintenance

Based on the insights in Section 2, in this chapter, an evaluation method for the cost-benefit assessment of predictive maintenance's operationalisation is proposed. Since today's research has not come up with detailed cost-benefit-analysis approaches that take into account today's misinterpretations of maintenance activities and the resulting costs, an adequate evaluation methodology is introduced in the following sections. In Section 3.1, the particular requirements and functions for this approach are discussed, followed by a description of the concept design in Section 3.2. Subsequent sections explain particular model building procedures in detail: Section 3.3 covers the representation of aircraft operations, Section 3.4 the MRO process modelling and Section 3.5 the chosen concept of maintenance event initiation. Thereafter, Section 3.6 addresses the simulation set-up, accompanied by explanations concerning the data post-processing in Section 3.7 and followed by a conclusion in Section 3.8.

3.1 Applications, functions and requirements of the method

The primary goal of the introduced approach is to assess predictive maintenance concepts (see Figure 3.1). By considering the existing (*status quo*) maintenance and prediction model design concepts, an evaluation of their impact on particular target values is conducted. If there is evidence of unconditional improvement, the concept's application (*prediction model implementation*) is advised. In case the enhancement is limited, the specification of modified prediction model design requirements and its consideration in the design process can possibly improve the performance. If the assessment does not show any benefit at all, the investigated approach is advised to be rejected.

On a global scale, the evaluation method shall incorporate more general functions as well, as proposed by [Fro09]: *Decision support*, *influence* and *monitoring*. As mentioned above, the main goal is to support entrepreneurial strategic decisions, e.g. whether a new maintenance approach should be applied or if any further research investments should be made. *Influence* means to consider analysis results in early model design. By modifying the initial model parameters,

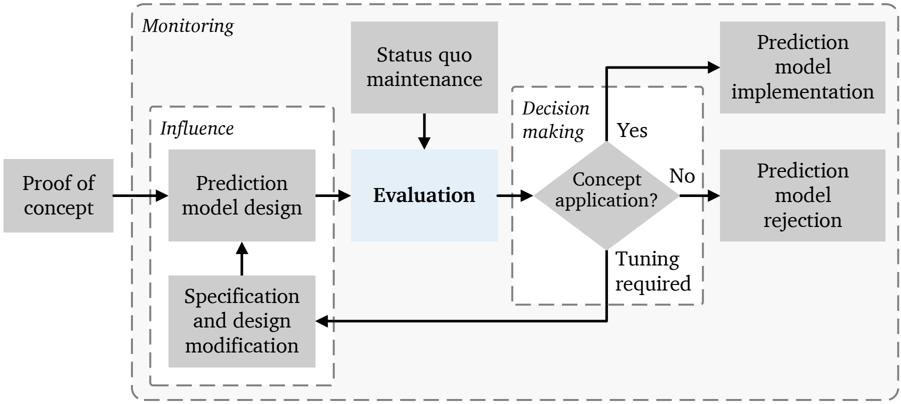


Figure 3.1.: General functions of the method

the design process and thus the overall assessment can be optimised in an iterative manner [AT15, ASSB16]. *Monitoring* allows to continuously observe changes in design, evaluation or decision making processes and assures the actuality and validity of the results.

Concerning the *evaluation*, the method is supposed to fulfil two major functions, dependent on the field of application (see Figure 3.2):

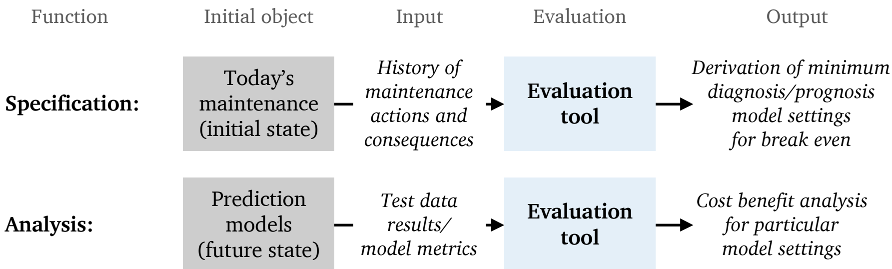


Figure 3.2.: Main evaluation functions of the method

Firstly, the evaluation enables a *specification* of future diagnosis or prognosis algorithms if only today's maintenance is analysed. By varying specific prediction parameters a global solution space is created, representing all possible outcomes. Parameter combinations that create the same results as today's maintenance, e.g. costs or other performance metrics, define the break even data set and thus the minimum requirements for a prediction model design. This retrospective approach is applicable if predictive models have not been developed yet. A disadvantage of this procedure is that it cannot be distinguished between realistic and unrealistic results within the virtual solution space.

If any prediction models have been developed, the method can determine the target values for particular algorithm settings (*analysis*). In this case, the aforementioned solution space is created partially, leaving out inapplicable settings. The results eventually allow to determine the economical potentials as well as the optimum cost-benefit setting. If the analysis of today's maintenance is carried out contiguously, the model results can be compared to the target values of the status quo, combining the steps *specification* and *analysis* to a global assessment.

Taking into account the described main functions, the requirements for the evaluation method are defined in Table 3.1:

Table 3.1.: Overview of defined requirements

Category	Requirement
General requirements	Analysis and specification of prediction (diagnosis/prognosis) models
	Consideration and evaluation of different prediction model settings
	Comparison of predictive (future) maintenance to the initial state
	Consideration of impact on aircraft operations and maintenance
Specific requirements	Analysis of component-specific maintenance
	Modelling of flight operations and maintenance as well as their interface
	Evaluation of costs concerning aircraft operations and maintenance with respect to the common cost structure (see Sections 2.2.1 and 2.2.2)
	Declaration of avoidable costs
	Evaluation of cost- and time-based target values
	Evaluation of prediction-specific indicators
	Aggregation of target values on different levels of detail
Risk assessment	Consideration of input data uncertainties
	Risk representation of output data uncertainties by means of statistics
Usability	Low complexity of evaluation method usage, extension and results assessment
	User acceptability through simplicity, comprehensibility and transparency
	Graphical user interface (GUI)
Non-Requirements	Development of prediction algorithms
	Simultaneous assessment of all aircraft systems
	Modelling of maintenance processes not affecting the target values
	Aircraft or component *life cycle cost* (LCC) evaluation
	Real-time decision support

Whereas *general requirements*, *specific requirements*, *risk assessment* and *usability* comprise requirements that shall be fulfilled, the *non-requirements* explicitly show functions outside the scope of this work. The collection of requirements is inspired by [Fro09, Lin05, Nef02]. Based on the defined functions and requirements, the following section explains the developed evaluation concept in detail.

3.2 Design of the evaluation concept

This section deals with the definition of the evaluation scope (Section 3.2.1) and the relevant target values (Section 3.2.2). Thereafter, the evaluation elements (Section 3.2.3), an assessment of applicable state-of-the-art methods (Section 3.2.4) as well as the proposed design steps (Section 3.2.5) are discussed.

3.2.1 Scope of this work

So far the general evaluation purpose has been introduced. In this section, the scope of this work shall be further narrowed.

Concerning the defined requirements, maintenance shall be analysed on component-level (ATA-6-digit, see Section 2.1.4). An evaluation on a more detailed level is not conducted, due to the fact that most available MRO data provides system- or LRU-specific data only. On the other hand a more global evaluation, e.g. on system level (ATA-2-digit), possibly dilutes particular LRU-related effects. This way, important information on causes and effects would be lost.

Because of the aircraft system architecture's complexity, a simultaneous assessment of all systems and subsystems including their interdependencies is not part of this work. Additionally, not every component provides the economical potential for a detailed analysis. As a result, only LRUs fulfilling the following requirements are in the focus of the investigations:

- Component is maintained correctively
- Component failure has negative impact on aircraft operations
- Component-related maintenance costs are significant
- Component is responsible for NFF events
- Component shows observable wear-out behaviour

LRUs maintained correctively as wear-parts, and thus often subject to unscheduled component replacements, are in the scope of this study. The potential for improvement in the field of preventive maintenance largely depends on scheduled maintenance fixed interval optimisation (e.g. see [SW07, San15b, WHVH04]). Furthermore, preventively maintained LRUs are usually safety-relevant and incorporate higher certification requirements, in case of changes to the current maintenance strategy. Thus, it is expected that a possible shift from corrective to predictive maintenance would be easier to accomplish in the future. Most importantly, corrective maintenance provides more historical information on faults and failures available, eventually providing the data-based foundation for fault prediction.

The aircraft operations impact is related to the aforementioned aspect, as correctively maintained components are often responsible for technically induced flight delays and cancellations (see Section 2.2.3). Because these costs are considered to be avoidable, LRUs that are responsible for operational irregularities are the focus of this work. So are components that affect the maintenance costs significantly. This can be caused either by the amount or complexity (e.g. labour-intensive tasks) of the related maintenance events. Another issue is the amount of LRU-specific NFF events, which can be considered unnecessary maintenance activities (see Section 2.1.4).

Lastly, in order to be able to conduct any predictive approach, a component's wear-out behaviour must be observable (see Section 2.3.2). The integration of an LRU into the on-board maintenance system, e.g. the *Aircraft Condition Monitoring System* (ACMS) in case of *Airbus Industries* aircraft automatically triggers the generation and transmission of fault messages, possibly enabling predictive diagnostics, for example.

3.2.2 Definition of target values

Based on the expectations of a predictive maintenance strategy application (discussed in Section 2.1.3), the impact on maintenance and aircraft operations is the focus of these investigations. It is assumed that different amounts of maintenance events are initiated, and that particular maintenance activities are modified. Thus, maintenance costs (DMC and IMC) are directly affected. Similarly, flight operations are expected to be influenced in a different manner, becoming apparent in change of costs (DCC). The overall assessment is supposed to provide information as to whether the total costs are increased or lowered by a predictive maintenance approach.

In this section, adequate target values are proposed. In order to compare different component-specific maintenance strategies, the use of measures for quantification is necessary. According to the requirements definition in Section 3.1, only target values that measure the expected changes in performance (see insights from Section 2.1.3), are considered. In the following, a distinction between financial and non-financial measures, as proposed by [Lin05], is applied.

3.2.2.1 Financial performance indicators

In the first instance, Table 3.2 summarises the different areas of influence and the proposed global cost-based measures:

Table 3.2.: Derivation of global cost-based target values from scope of study

Scope	Global cost-based measure
1. Aircraft operations effects	Impact on delay and cancellation costs (DCC)
2. Maintenance effects	Impact on affected maintenance costs (DMC/IMC)
3. NFF effects	
4. Troubleshooting effects	
5. Prediction efforts	

Whereas the effects of maintenance on aircraft operations can be quantified by the DCC (see Section 2.2.3), the effects within an MRO company, concerning all maintenance activities, NFF and troubleshooting effects as well as prediction efforts are best described by DMC and IMC. Figure 3.3 qualitatively illustrates the relationships between the considered cost types:

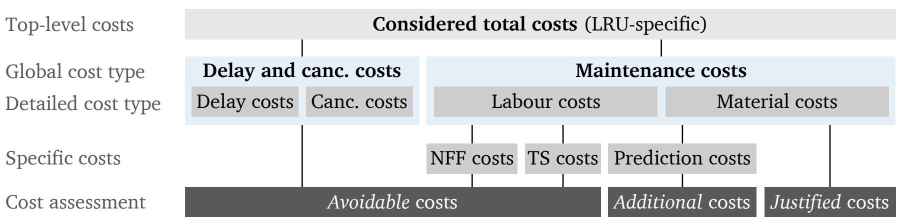


Figure 3.3.: Relations and assessment of considered LRU-specific costs

Based on an LRU-specific assessment, the considered total costs are composed of delay and cancellation costs (occurring on the airline side) as well as maintenance costs (occurring on the MRO side). Within the maintenance costs, direct cost types are distinguished between labour and material costs. The NFF and troubleshooting (TS) costs are considered as part of the maintenance costs caused by tasks declared NFF or fault isolation-related. The prediction costs refer to costs occurring through the new strategy's introduction and operation [MS13]. At the bottom of Figure 3.3, the expenses are assessed with respect to justification. For a corrective maintenance strategy, it is proposed that all maintenance costs not classified as NFF, not related to TS tasks and not concerned with prediction management, thus involving actual wear-out restoration activities, are justified. On the other hand DCC, NFF and TS maintenance expenses are declared unjustified. Since these expenses should ideally by prevented, they are labelled as *avoidable costs* and identified as the potential for cost reduction through predictive maintenance. Prediction costs are labelled as *additional costs* with respect to the initial state.

The calculation of the proposed cost-based target values is introduced in the following.

Evaluation of total costs

The total costs related to a particular LRU$_i$ (C_{LRU_i}) are defined as the sum of DCC, in the following referred to as *costs of operational impact* (C_{Ops}), process-based maintenance costs (C_{Proc}) as well as prediction costs (C_P):

$$C_{LRU_i}(t) = C_{Ops_{LRU_i}}(t) + C_{Proc_{LRU_i}}(t) + C_{P_{LRU_i}}(t) \tag{3.1}$$

In the following, the composition of these particular cost types is discussed.

Evaluation of costs of operational impact

Based on the insights in Section 2.2.3, the LRU-specific costs of operational impact shall be evaluated. *LRU-specific* refers to only cover delay and cancellation costs that are caused by the particular component, leaving out all other breakdown events. These costs are defined as the sum of delay-related (C_{Delay}) and cancellation-related (C_{Canc}) costs over all events k, according to Eq. 3.2:

$$C_{Ops_{LRU_i}}(t) = \sum_{k=1}^{n} C_{Delay_{LRU_i,k}}(t) + \sum_{k=1}^{n} C_{Canc_{LRU_i,k}}(t) \tag{3.2}$$

Evaluation of process-based maintenance costs

For the evaluation of impact on the maintenance side, direct and indirect maintenance costs affected by a particular LRU shall be equally considered. For the allocation of indirect costs to particular LRUs (cost objects), the ABC method is applied (see Section 2.2.4). A process-based evaluation covers only activities and costs of interest. In the following, the terms *process* and *activity* are used synonymously. The particular affected cost centres will be discussed in Section 3.3.1. A detailed description of the process-based approach is given in Section 3.4. The ABC application is introduced in Section 3.7.3.2.

Because costs are calculated on an activity-level, the process costs ($C_{Proc_{LRU_i,k,m}}$) for LRU$_i$, event k and process l can be described by the sum of labour (C_L) and material (C_M) expenses, according to Eq. 3.3-3.5:

$$\begin{aligned} C_{Proc_{LRU_i,k,l}}(t) &= C_{L_{LRU_i,k,l}}(t) + C_{M_{LRU_i,k,l}}(t) && (3.3) \\ \text{with} \quad C_{L_{LRU_i,k,l}}(t) &= c_{L_{k,l}}(t) \cdot \Delta t_{L_{LRU_i,k,l}} \cdot n_{L_{LRU_i,k,l}} && (3.4) \\ C_{M_{LRU_i,k,l}}(t) &= c_{M_{LRU_i,k,l}}(t) \cdot n_{M_{LRU_i,k,l}} && (3.5) \end{aligned}$$

In Eq. 3.4, the composition of labour-based process costs (C_L) is shown. Their calculation is based on particular process factors: The time-dependent labour cost rate (c_L) specifies the LRU-independent costs per man-hour. Since wages vary with different qualifications, the cost rate does depend on the specific process with its particular labour requirements. For example, engineering processes usually involve higher wages than mechanic activities. Furthermore, the duration of labour consuming time (Δt_L) as well as the amount of required labour (n_L) is required. Both factors are LRU-specific, because these particular maintenance task characteristics vary with different components. In this work, a linear dependency between costs and duration of a particular process is defined, as proposed in [ZB06], opposed to a fixed cost factor association by building the mean average, e.g. discussed in [LZY01]. LRU-specific material costs (C_M) are derived by multiplying time-dependent unit costs per material (c_M) by the required material count (n_M).

As shown in Eq. 3.6, LRU-specific maintenance costs ($C_{Proc_{LRU_i,k,l}}$) for event k and process l can be aggregated to LRU-specific overall maintenance process costs ($C_{Proc_{LRU_i}}$) by summarising over all processes and events.

$$C_{Proc_{LRU_i}}(t) = \sum_{k=1}^{n} \sum_{l=1}^{m} C_{Proc_{LRU_i,k,l}}(t) \qquad (3.6)$$

Evaluation of prediction costs

The additional costs of an LRU-specific predictive maintenance strategy's introduction (C_P) are composed of non-recurring ($C_{P,NR}$) and recurring ($C_{P,R}$) costs, as suggested by [FSJ08]:

$$\begin{aligned} C_{P_{LRU_i}}(t) &= C_{P,NR_{LRU_i}} + C_{P,R_{LRU_i}}(t) && (3.7)\\ \text{with} \quad C_{P,NR_{LRU_i}} &= C_{P,\text{ Invest}_{LRU_i}} + C_{P,\text{ Develop}_{LRU_i}} && (3.8)\\ C_{P,R_{LRU_i}}(t) &= C_{P,\text{ S/W}}(t) + C_{P,\text{ Train}}(t) + \sum_{k=1}^{n} c_{P,L_{LRU_i,k}}(t) \cdot \Delta t_{P,L_{LRU_i,k}} && (3.9) \end{aligned}$$

The non-recurring costs arise from investments ($C_{P,\text{ Invest}}$) in prediction tools, e.g. product acquisitions, or prediction tool development expenses ($C_{P,\text{ Develop}}$). By taking into account particular component-specific model efforts, these costs are calculated LRU-wise. The recurring costs comprise software maintenance costs ($C_{P,\text{ S/W}}$), personnel training costs ($C_{P,\text{ Train}}$) as well as process-based usage costs ($c_{P,L}$, $\Delta t_{P,L}$). The first two cost types are considered to be fixed, LRU-independent costs. The usage costs are assessed by means of the aforementioned process-based maintenance costs. It is assumed that only positive prediction indications (TP, FP) lead to a prediction tool's usage and thus generate costs for interpretation tasks carried out by analysts. Thus, these costs are treated as labour costs, derived by multiplying the labour cost rate (c_P) with analysis process duration (Δt_P) cumulated over all applicable events k.

The characteristics of prediction outcomes in comparison to real-world information, including a general cost assessment, are illustrated in Figure 3.4. As described in Section 2.3.4, the relation between a diagnosis-based prediction outcome and the actual class can be depicted in a confusion matrix. The four applicable classifications are shown in Figure 3.4. A correct indication is performed if an event that actually requires maintenance is correctly predicted (TP), or if insignificant information is correctly classified as such (TN). TP event costs are justified because a necessary rectification is conducted a posteriori. The actions based on prediction are expected to be even more efficient than the real-world ones, due to an increased planning ability. For TN predictions, no costs apply.

In case a positive prediction outcome advises to perform maintenance that is not necessary (no fault indication in real-world), a false alarm (FP) applies. For prognostics, the term *early alarm* is used. If a prediction classifies an event as insignificant, when in real-world maintenance was necessary, a missed alarm (FN) applies – in prognostics referred to as *late alarm*. For both fault types, not all of the generated costs are justified. FP predictions create additional maintenance events

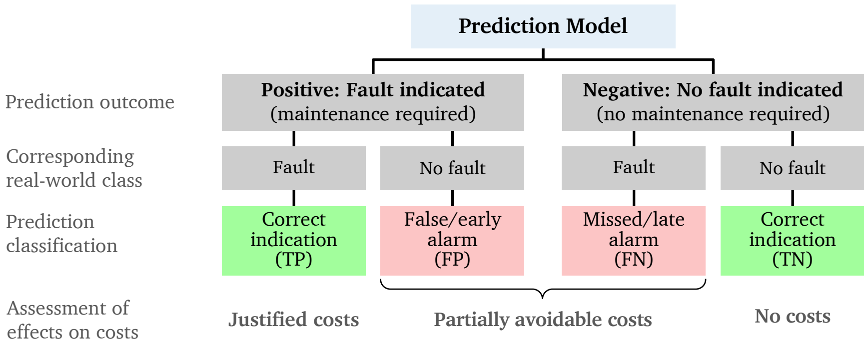


Figure 3.4.: Cost assessment of prediction outcomes

as opposed to real-world, further increasing costs. As these misinterpretations also occur in real-world, the extent of this particular prediction error's impact depends on the initial costs of the real-world errors. FP predictions are expected to mainly create additional NFF maintenance costs, because predictions are assumed not to affect the aircraft operations through the ability to plan in advance. FN predictions lead to unscheduled ad-hoc maintenance. It is expected that this prediction error mainly generates avoidable costs through the impact on aircraft operations. Except for extra efforts due to ad-hoc requirements, maintenance costs are justified, because the required actions are inevitable.

Based on the aforementioned perceptions, prediction errors are expected to have a significant impact on the avoidable costs in Eq. 3.12. Thus, they are in the scope of this thesis as relevant for a prediction model's performance assessment.

Evaluation of NFF-, TS-based and avoidable costs

Concerning the quantification of effects of NFF-events and TS tasks on maintenance costs, a distinct analysis of corresponding processes (l_{NFF} or l_{TS}) is proposed:

$$C_{Proc_{LRU_i,NFF}}(t) = \sum_{k=1}^{n} \sum_{l=1}^{m} C_{Proc_{LRU_i,k,l_{NFF}}}(t) \tag{3.10}$$

$$C_{Proc_{LRU_i,TS}}(t) = \sum_{k=1}^{n} \sum_{l=1}^{m} C_{Proc_{LRU_i,k,l_{TS}}}(t) \tag{3.11}$$

According to [Dru12], avoidable costs are particularly relevant for decision making purposes. They are defined as follows:

$$C_{\text{avoidable}_{LRU_i}}(t) = C_{Ops_{LRU_i}}(t) + C_{Proc_{LRU_i,NFF}}(t) + C_{Proc_{LRU_i,TS}}(t) \tag{3.12}$$

Figure B.1 in Appx. B.1 provides information on the classification of the aforementioned costs with respect to the previously introduced cost structures. The assessment procedure is discussed in Section 3.7.3.2.

3.2.2.2 Non-financial performance indicators

As discussed before, most cost-based target-values require temporal information as input. According to [Dru12], in *activity-based performance measurement*, time-based target values, e.g. cycle time, become more important nowadays. In the following, time-based indicators based on non-financial parameters are introduced.

Evaluation of time-based target values

In Table 3.3, particular temporal indicators are proposed:

Table 3.3.: Proposed LRU-specific time-based target values

Time-based target value	Formula
Duration of all flight delays	$\Delta t_{Delay} = \sum_{d=1}^{n} \Delta t_d \quad (3.13)$
Cumulated labour process time	$\Delta t_L = \sum_{k=1}^{n} \sum_{l=1}^{m} \Delta t_{L_l,k} \quad (3.14)$
Mean time to repair (mean average)	$\Delta\bar{t}_{MTTR} = \frac{\sum_{k=1}^{n} \sum_{l=1}^{m} \Delta t_{l_{Repair},k}}{n} \quad (3.15)$

An assessment of the delay duration is required to determine delay costs which can also be investigated discretely (Eq. 3.13). Similarly, labour-based process costs require information on the duration of the particular activities (Eq. 3.14). The labour process times per LRU per maintenance event are a key indicator in order to determine labour-based unit costs, e.g. annual costs per man hour.

Mean time to repair (MTTR), also *maintenance repair time* (see [BL04]), can be defined in various ways. In the case of overhauling, the MTTR comprises the mean time of all tasks to have a faulty system or component repaired (Eq. 3.15) [Lin05]. With respect to an LRU, it can also be interpreted as the time required to release an aircraft into service again, not including off-aircraft tasks taking place subsequently. Then the MTTR represents the lead time (or cycle time) of on-aircraft tasks. In addition to processing activities, the MTTR then also comprises move, wait and inspection time. Only processing time (in the case of aircraft maintenance, the restoration of reserve of wear-out) actually adds value to the product. The remaining activities are considered *non-value added* processes and should be prevented [Dru12].

In the next section, the main elements of the evaluation method are introduced.

3.2.3 Elements of the evaluation method

Now that the desired evaluation output is defined, an overview of the available input data as well as the proposed evaluation elements is provided in Figure 3.5:

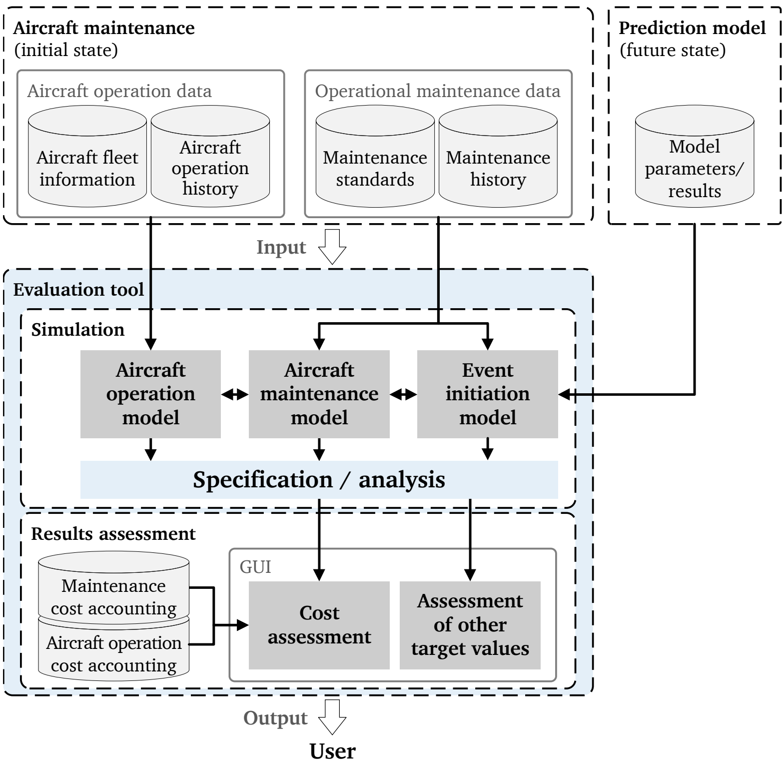


Figure 3.5.: Elements of the evaluation method

In order to adequately describe the initial situation, aircraft operations data as well as operational maintenance data is required. With respect to the aircraft operations, general information on the fleet composition describes particular aircraft characteristics. Historical aircraft operations data provides records of flights and operational irregularities.

Information on component-specific maintenance standards characterises the particular MRO activities and requirements. For example, by means of documents such as maintenance manuals or the MEL, real-world behaviour is described. Historical maintenance records, e.g. logbook data, provide information about the completion of past maintenance events.

In case a prediction model is analysed (future state analysis), its particular characteristics, e.g. error rates, or discrete test data results are required. This information provides an alternate input for the initiation of maintenance events.

The aforementioned sources of information provide the data input for the evaluation tool. The tool itself comprises a simulation environment, based on the interconnected models *aircraft operations*, *aircraft maintenance* as well as *event initiation*, described in detail in the following sections. The models account for the specification and analysis function by means of simulation.

As part of the results assessment, a graphical user interface (GUI) enables an analysis of the simulation results with respect to the aforementioned target values, such as costs and non-financial indicators. The cost calculation is based on maintenance- and aircraft operations-specific cost accounting data.

3.2.4 Maintenance modelling literature review

In the following, the proposed method is discussed with respect to the state-of-the-art in modelling of maintenance. Figure 3.6 (also see details in Table B.1 in Appx. B.2) provides an overview of reviewed published works on this topic concerning their stochastic nature and analysis level.

As discussed in [BL04], many maintenance modelling approaches deal with probabilistic failure representations, e.g. *Weibull analysis*, defined by specific reliability measures that usually require large amounts of data samples in order to derive valid data distributions. As can be derived from Figure 3.6, most reviewed publications deal with probabilistic methods for the analysis of maintenance characteristics. They either incorporate maintenance activities and impacts in a generalised, macroscopic manner by means of long-term analysis (e.g. life cycle analysis, see [El 06, FJS09, Fro09, HSNG12, Van15]) or from a more microscopic point of view (e.g. [Ach10, El 06, Fro09]), focusing on specific maintenance processes, e.g. logistics. Specific assumptions allow maintenance data to be rep-

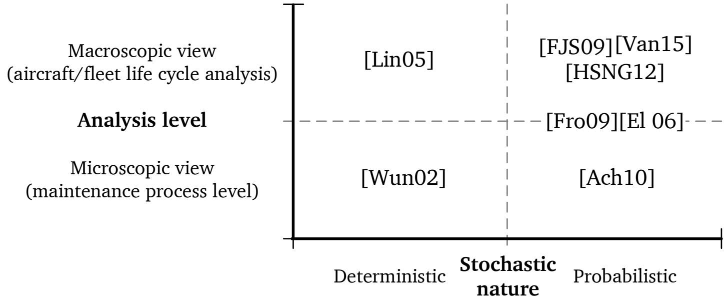


Figure 3.6.: Classification of reviewed publications

resented generically. For instance, distributions initiate component failures, often intentionally excluding particular outliers [BL04]. The application of probabilistic approaches for the assessment of future maintenance concepts is convenient, when using available parametric models that can easily be adjusted by means of parameter variation. It is the only way to describe complex maintenance characteristics if there is no detailed input data at hand to describe particular events more specifically [Bad13].

The downside of probabilistic approaches is that they also exclude valuable information that would possibly represent the real-world characteristics more accurately. Additionally, the formulation of probabilistic distributions usually requires the assessment of statistical reliability measures. Especially in cases, where the data sample size is low, the definition of general distributions can lead to inaccurate abstractions. Furthermore, system immanent dependencies between particular LRUs are often not covered by more general approaches, possibly ignoring real-world causes and effects.

The opposite of a probabilistic assessment is represented by a deterministic approach. Again, macroscopic (e.g. [Lin05]) and microscopic (e.g. [Wun02]) analyses are distinguished. The use of deterministic historical data overcomes the aforementioned disadvantages. However, it is essential to have adequate data available [MSB14]. Most of the input data shown in Figure 3.5 is deterministic in nature. This way, all sorts of real-world consequences between LRU-specific maintenance characteristics and the aircraft operations are implicitly included, meaning that some relations have to be analysed and represented first in order to derive cause-and-effect information. Additionally, validation is facilitated by using input data that can directly be compared to the simulation output.

The downsides of a deterministic approach include demanding requirements concerning data quality, often related to a costly data preprocessing, as well as the limitation to retrofit approaches, since valid deterministic data can be derived from historical records only.

Based on the aforementioned insights, this work operates between the lower two quadrants in Figure 3.6. Concerning stochastic behaviour, in this work a hybrid approach is applied, using deterministic data – if available and applicable – and applying probabilistic data, where there is a lack of adequate deterministic information. An example for deterministic data is the flight schedule. An example for probabilistically defined information is data on maintenance process durations. The advantage of this approach lies within the retrospective representation of maintenance events close to real-world as well as the ability to validate the derived model by means of specific examples. Since maintenance processes are analysed in a detailed manner, the analysis level is considered to be microscopic.

The application of ABC as a method for the allocation of indirect costs is regarded as state-of-the-art. For this reason, a process-based modelling approach is chosen in order to enable an activity-based performance measurement, as proposed by [Dru12]. This way, a framework is provided that enables the representation of various aircraft components based on the same generic process model. The model's modular composition aims at decreasing the overall complexity, important for process modelling steps [Bad13]. The approach can be easily transferred to similar problem statements in different industry fields concerned with maintenance.

3.2.5 Steps of the evaluation method design

As can be derived from the requirements, the evaluation method has to account for various relationships, measures and usability issues. Under these circumstances the use of a standardised procedure, such as model building, is recommended [Bro99, Len93, PS96]. In order to represent real-world problems as accurate as possible, the use of an abstract model seems adequate to handle a system's complexity. In [Win99], a model is defined as "a schematic description of a system, theory, or phenomenon that accounts for its known or inferred properties and may be used for further study of its characteristics." Instead of being a copy of a real-world situation, a model focusses on the important aspects of the system under investigation only (*abstraction*). Besides the modeller's preferences, the degree of abstraction largely depends on the following two aspects [Ach10]:

- Problem statement ("What are the processes or costs of interest?")
- Available resources (e.g. time, money, manpower or computational power)

The problem statement exactly specifies the objects to be modelled and defines adequate system boundaries and levels of detail. On the other hand, available resources limit the feasible abstraction level, creating conflicting modelling goals. As a general guideline, it is often stated that a model should only be as detailed as necessary, while being as abstract as possible (*principle of efficiency*) [Buc06]. An example of a general model building procedure is shown in Figure B.2 in Appx. B.3.

As described before, the proposed evaluation tool uses information about today's maintenance and aircraft operations as well as possible prediction models as input. On this basis, Figure 3.7 illustrates the evaluation method design steps:

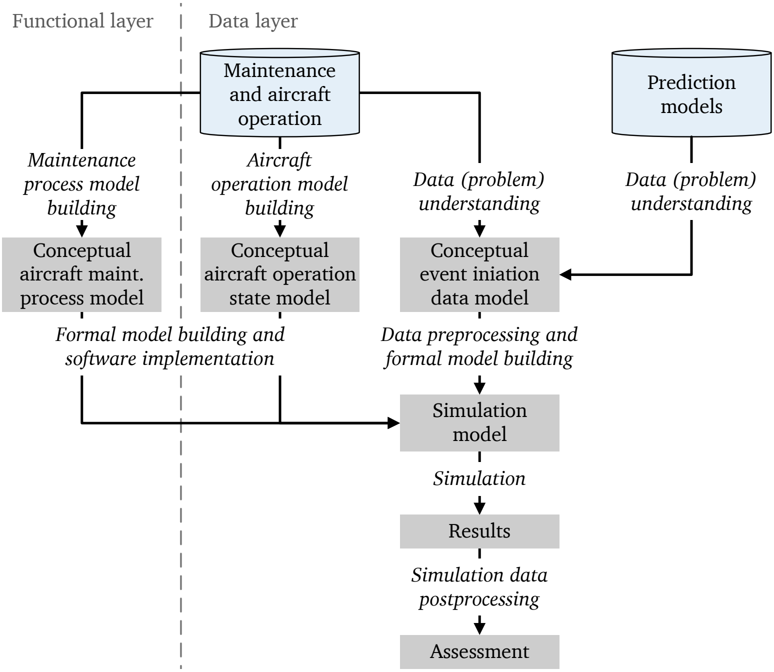


Figure 3.7.: Steps of the evaluation method design

As described by [Sch01], the *architecture of integrated information systems* (ARIS) concept provides a framework for the representation of business processes based on different modelling techniques. It distinguishes between function- (process-) and data-based information, represented by the dashed line in Figure 3.7. In the upper section of the Figure, the different sources of information are shown. Maintenance and aircraft operations data is required to describe the initial state. If available, a prediction model provides data as well. The prediction model development itself is not part of this work.

Concerning the functional layer (left in Figure 3.7), the maintenance process model building is represented. According to the general model building procedure, the real-world information needs to be transferred to an abstract model first. In order to obtain a general maintenance model, a business process model (BPM) building procedure is applied (Section 3.4). The derived model serves as the basis for a simulation model implementation and verification.

Similarly, the aircraft operations model building is conducted as part of the data layer, introduced in Section 3.3. It comprises the generation of a state chart model as well as its simulation model integration and verification.

Thirdly, the event initiation data model building is represented. This includes the generation of maintenance events either based on real-world records or prediction model data (right in Figure 3.7). Its building procedure is described in Section 3.5.

Additional data further qualifies and quantifies the maintenance and aircraft operation characteristics. The data modelling process – not depicted in Figure 3.7 – can be understood as a complementary process to business process modelling, providing the required data for the model-based analysis. One way to define the data analysis procedure is the *Knowledge discovery in databases* (KDD) process (see Figure 3.8), an overview of which is given in [KM06]:

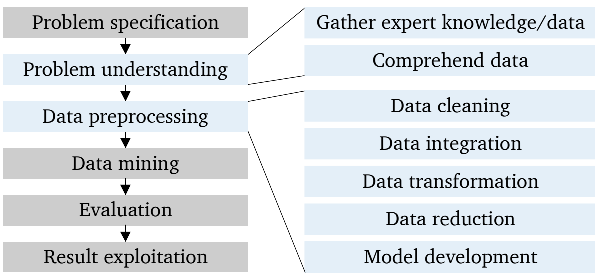


Figure 3.8.: Knowledge Discovery in Databases (KDD) procedure. Based on [BGK14, GLH15]

Besides providing a framework for *Data Mining* tasks, e.g. see [GLH15], it also serves as a guideline for *Data Warehousing*, concerning the collection and cleaning of data to make it available for analysis and decision support [FPSS96, Sta06].

The KDD process application is discussed in Section 3.5. Concerning the procedure shown in Figure 3.8, the steps *problem understanding* and *data preprocessing* are conducted in this work.

The simulation characteristics are discussed in Section 3.6. The subsequent data post-processing enables results interpretation and is discussed in Section 3.7.

The next sections explain the aforementioned steps in detail. Despite the sequential manner of the following introductions, it is important to note that the real modelling process often consists of parallel actions and involves various iterations as well as adjustments at interfaces, as discussed in [Lar11].

3.3 Aircraft operations model building

In this section, the real-world aircraft operations representation by means of model building is presented in order to fulfil the following requirements:

- Account for the impact of maintenance on flight operations and vice versa
- Represent the real-world flight schedule

In Section 3.3.1, the method's system boundary is defined. Thereby the general model elements as well as their relevant interfaces are specified. Section 3.3.2 addresses the flight schedule representation, followed by a description of the adjustments made (Section 3.3.3).

3.3.1 Aircraft operations and maintenance system

For the purpose of model building, it is required to abstract a real-world system like aircraft operations and maintenance. As one prerequisite to define a system, the definition of its boundary is essential. As formulated in the requirements, the component-based aircraft maintenance as well as the aircraft operations and their interface are supposed to be analysed. Furthermore, only corrective component-based maintenance is considered. Based on these claims, and a typical MRO company's structure, Figure 3.9 illustrates the system boundary as well as the global system elements in the focus of this work.

Within the system boundary, it is distinguished between an airline's aircraft operations and the MRO provider's company-level processes. The aircraft operations primarily incorporate to follow the flight schedule as well as to account for component wear-out and failures. Airworthiness is supposed to be assured by the MRO company. At the interface, three supervising MRO departments exist: *Troubleshooting*, *planning* and on-aircraft *system maintenance*.

The troubleshooting is responsible for fault isolation concerning technical issues occurring during operations. An example is the interpretation of automatically

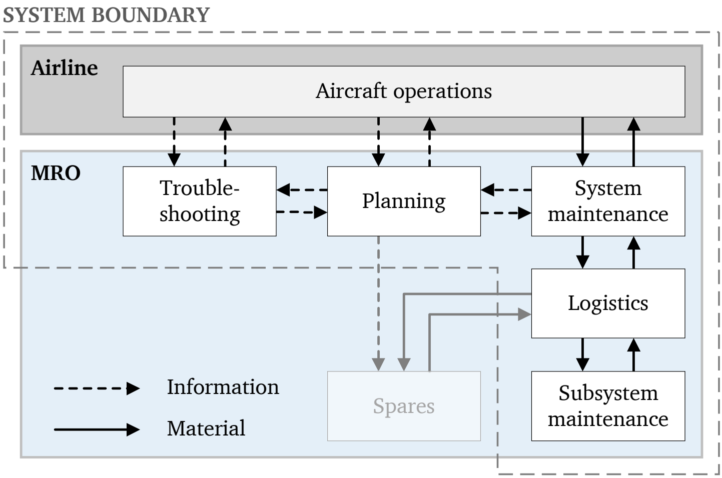


Figure 3.9.: System boundary and relevant system elements. Based on [Bad13]

generated, in-flight fault messages. Its output is the decision, whether a particular job should be performed based on the available information, and secondly what exactly this job should include. This information is then passed on to the maintenance planning department, involving the scheduling of jobs with respect to criticality as well as aircraft and MRO resources availability. Its output is the job's scheduling with respect to its deadline, which is constantly revised concerning modified boundary conditions, such as criticality or resource availability. Additionally, the planning department is responsible for requesting spare part deliveries.

The system maintenance performs all on-aircraft maintenance tasks at the interface of aircraft operations and the MRO company. With respect to Section 2.1.1.4, it is further divided into routine (RM) and non-routine (NRM) maintenance. The output is a *released-to-service* aircraft. Additionally, this department represents the transition from system-based to subsystem-based (shop) LRU maintenance. Connected by the logistics, the subsystem maintenance deals with the off-aircraft overhaul of LRUs. Repaired components are sent to and taken from the spare parts inventory, which is outside of the scope of this work. Spare parts inventory optimisation is subject to specific research, e.g. see [Ach10, RY12, KSY96].

As indicated by the dashed and continuous arrows in Figure 3.9, it is differentiated between information and material flow. Whereas the system maintenance and the subsequent LRU-based processes are represented by material flows, the troubleshooting and planning activities are information-based. Since predictive maintenance is expected to improve automated information provision, this classification eventually allows a more specific analysis of a prediction strategy's impact.

In order to correctly model the interface of aircraft operations and maintenance, its characteristics have to be defined. In general, the interaction is bilateral: if necessary, the MRO can request an aircraft to become available for maintenance. On the other hand, a given flight schedule restricts the earliest point of availability. Inspired by [BL04], in the following, *state indicators* are defined to describe distinct interaction rules between the flight schedule, the aircraft and its components. An overview of introduced flight schedule-based state variables is given in Table 3.4:

Table 3.4.: Flight schedule-specific state variables

State variable	Value	State description
$z_{\text{Flightplan status}}(t)$	1	In flight
	0	On ground
$z_{\text{Flightplan station}}(t)$	1	Service station
	0	Non-service station
$z_{\text{PM}}(t)$	1	On going scheduled maintenance
	0	No scheduled maintenance

The shown variables account for the flight plan input data concerning information on *status*, *station* and *planned maintenance* (PM). This discrete information represents boundary conditions for maintenance opportunities. In order to account for maintenance requests and their urgency, a component state indicator z_{LRU} is introduced, see Table 3.5:

Table 3.5.: Defined LRU states. Based on [KGK14, Bad13]

$z_{LRU}(t)$	State description
1	Regular operations
0	Serviceable
−1	Rectification in progress
−2	Rectification required
−3	Rectification deferred
−4	Rectification deferrable
−5	Unserviceable

An LRU can hold the states *serviceable* ($z_{LRU} \in \{0,1\}$), *in repair* ($z_{LRU} = -1$), *rectification required* ($-4 \leq z_{LRU} \leq -2$) or *unserviceable* ($z_{LRU} = -5$). For the representation of priorities, the criticality of the required maintenance is accounted for by means of the MEL logic (see Table 2.1 and Table B.11 in Appx. B.7). Items not requiring immediate rectification are deferrable. If the maximum allowable defer time is reached, immediate rectification is required. Depending on the criticality of an LRU status, the aircraft status can be affected by LRU-based maintenance requirements, possibly declaring ground times at non-service stations as available maintenance time as well [KGK14].

Based on the aforementioned information, a global aircraft-specific state indicator z_{AC} is defined, see Table 3.6:

Table 3.6.: Defined aircraft operations states. Based on [KGK14, Bad13]

$z_{AC}(t)$	**State description**	**Available for maintenance?**
1	Flight	
0	On ground, non-service station	(✓)
−1	Unscheduled maintenance, non-service station	(✓)
−2	On ground, service station	(✓)
−3	Available for maintenance, service station	✓
−4	Unscheduled maintenance, service station	(✓)
−5	Scheduled maintenance, service station	(✓)

Within the investigated interval $t \in [t_{Start};\ t_{End}]$, at each point in time one particular aircraft state applies. Flight operations without any maintenance is represented by alternating system states ($z_{AC} \in \{-3,-2,0,1\}$). Maintenance times are distinguished between scheduled ($z_{AC} = -5$) and unscheduled events ($z_{AC} \in \{-4,-1\}$). The ground times ($-5 \leq z_{AC} \leq 0$) are further distinguished by the station. It is preferred to conduct maintenance at so-called *service stations*, where the required maintenance infrastructure is available. Maintenance at *non-service stations* is always considered unscheduled.

Furthermore, Table 3.6 shows which aircraft states imply availability for additional maintenance. Potentially, all ground times are available for maintenance, but not all states are appropriate, as illustrated by the brackets on the right in Table 3.6. Only an aircraft located at a service station with no actions planned for a defined period of time, e.g. a night stop, is available for maintenance ($z_{AC} = -3$). For the other on-ground cases, the aircraft has limited availability for maintenance. Only in urgent cases do these states allow maintenance to be conducted.

The dependency of z_{AC} on an LRU's state z_{LRU} and the flight schedule's state variables can be interpreted as a general system reliability characteristic that can be written as (and illustrated in Figure B.12 in Appx. B.7)

$$z_{AC} = f(z_{LRU}, z_{\text{Flightplan status}}, z_{\text{Flightplan station}}, z_{\text{PM}}, t) \tag{3.16}$$

The definition of interdependent states has two objectives:

1. Represent the interdependency between flight operations and maintenance as well as the aircraft and its components

2. Provide a mathematical formulation for the target value calculations

The first aspect has been discussed before (see Figure 2.7): the system *aircraft* directly interacts with its subordinate LRUs, as a system failure is always caused by failure of one or more subsystems or components. The specific interaction between z_{AC} and z_{LRU} is represented by a *state chart model* (also *finite state machine*) by means of *Boolean algebra*. The resulting state model is introduced in Section 4.2.1 as part of the software implementation. Concerning the second issue, for the derivation of aircraft operations-specific target values, a mathematical formulation is required. For instance, a delay applies if the following state condition is met:

$$(z_{\text{Flightplan status}} = 1) \cap ((z_{AC} = -1) \cup (z_{AC} = -4) \cup (z_{AC} = -5)) \tag{3.17}$$

The derivation of flight schedule-based state indicators is discussed subsequently.

3.3.2 Flight schedule representation

For the representation of real-world flight operations, available historical flight schedule data is considered, formatted as shown in the example in Table 3.7.

For each completed flight, information on the particular aircraft registration and the city-pairs is given. The schedule data is comprised of four fields: Scheduled ($t_{\text{STD,RW}}$) and actual time of departure ($t_{\text{ATD,RW}}$), and scheduled ($t_{\text{STA,RW}}$) and actual time of arrival ($t_{\text{ATA,RW}}$). As opposed to simulation-based data, introduced later in this study, real-world data is indicated by *RW* in this thesis.

These timestamps also build the basis for flight delay information. Delays are defined by the delay code (DC) and the corresponding delay time ($\Delta t_{\text{d,RW}}$). As discussed in Section 2.2.3, a DC of 41-49 indicates technically caused delays, possibly involving maintenance activities. A DC of 93 represents reactionary delays due

Table 3.7.: Exemplary real-world flight schedule information

Airc. reg.	From/ To	Sched. time of departure $t_{\text{STD,RW}}$	Actual time of departure $t_{\text{ATD,RW}}$	Sched. time of arrival $t_{\text{STA,RW}}$	Actual time of arrival $t_{\text{ATA,RW}}$	DC	DT [min] $\Delta t_{\text{d,RW}}$	Canc.
D-ABCD	LHR-CDG	01.01.2009 12:15	01.01.2009 12:14	01.01.2009 13:20	01.01.2009 13:25	-	-	N
D-ABCD	CDG-MUC	01.01.2009 13:55	01.01.2009 14:45	01.01.2009 15:10	01.01.2009 15:45	41	50	N
D-ABCD	MUC-LHR	01.01.2009 15:45	01.01.2009 16:10	01.01.2009 16:30	01.01.2009 16:45	93	25	N

to any previous deferrals. As described in [Uni11], delays in civil aviation usually refer to a deferred departure as opposed to a deferred arrival. Thus, a delay Δt_d results from the temporal difference $\Delta t_d = t_{\text{ATD}} - t_{\text{STD}}$ for $t_{\text{ATD}} > t_{\text{STD}}$. In the last column of Table 3.7, a boolean flag indicates, whether any flight cancellations (canc.) occurred.

As shown in the example in Table 3.7, the real-world (actual) flight schedule data already accounts for any impacts of maintenance on the aircraft operations. In order to be able to provide valid flight schedule data for further evaluation and identify a particular LRU's impact on aircraft operations, the information requires further preprocessing.

3.3.3 Flight schedule modification

As discussed in [Ber14], three ways to incorporate the historical flight schedule in the evaluation tool can be considered:

1. Actual flight schedule ($t_{\text{ATD,RW}}$, $t_{\text{ATA,RW}}$)
2. Original flight plan ($t_{\text{STD,RW}}$, $t_{\text{STA,RW}}$)
3. Actual flight schedule without LRU effects ($t_{\text{STD,RW}}$, $t_{\text{ATD,RW}}$, $t_{\text{STA,RW}}$, $t_{\text{ATA,RW}}$)

Firstly, the flight schedule can be represented by taking into account the actual times of departure and arrival only. Since the data is explicitly available, this approach would be easy to implement, not requiring any further preprocessing. A disadvantage is that any maintenance-induced delays or cancellations are already incorporated in the represented flight schedule. If further analyses were based on this flight plan, at these particular points in time, any simulated maintenance would have more time available than in reality, not having any negative impact on flight operations. Within the simulation, a delay would then only be generated if the simulated maintenance consumed more time than the real-world data states, ending up in an unrealistic representation of delay generation.

The second approach, applying the original flight plan to the simulation, is easy to implement as well, as the data is explicitly available. It provides information that does not incorporate any delays at all, enabling the simulation to realistically represent any impact of the simulated maintenance on aircraft operations. The downside of this approach is that a representation of flight operations based on this schedule does not refer to real-world boundary conditions any more. Not only LRU-related delays are removed this way, but all other interruptions as well, e.g. any air traffic- or weather-related impacts. If the general question throughout this study, how the real-world aircraft operations were affected by predictive maintenance, shall be answered, the use of the third approach – a combination of both aforementioned schedule types – seems more adequate.

It is proposed that a flight schedule, which is based on the actual flight history with any specific LRU-related effects on the flight plan removed, represents maintenance effects on the real-world behaviour best. Such a flight plan would represent the operations as it would have occurred, had no maintenance occurred on the investigated LRU. This approach involves two disadvantages: firstly, which operational irregularities were caused by a particular LRU must be analysed. Secondly, the flight schedule has to undergo additional preprocessing, before being provided to the simulation as input data. Therefore, these steps are conducted and explained in detail hereafter:

1. Identify LRU-related flight irregularities (Section 3.3.3.1)

2. Remove LRU-related effects on the flight plan (Section 3.3.3.2)

3.3.3.1 Identify LRU-related flight irregularities

Assuming the available input data identifying technical flight delays related to a particular component is accurate, two types of information are associated with each other:

- Technically caused flight delays with DC 41-49 and related DC 93

- Historical records of LRU-specific maintenance events

As shown in Table 3.7, the given flight schedule provides information on technically caused delays. On the other hand, LRU-specific records, by means of logbook data, identify points in time of accomplished maintenance activities, as shown in the example in Table 3.8:

Table 3.8.: Exemplary LRU removal logbook entry

Airc. reg.	Station	Date/time	Action	PN	SN	...
D-ABCD	CDG	01.01.2009 14:33	Component A replaced	PN001	SN001	...

This way, the corresponding aircraft, station and point in time can be uniquely identified. If the logbook entry refers to a component removal, the LRU is identified by its part number (PN) and serial number (SN). As stated in Section 3.2.1, only components known to have negative impact on flight operations are considered. Thus, a high degree of conformity between the two record types, flight plan and logbook, is expected. By associating LRU-specific maintenance events with flight irregularities, the points in time of LRU-related impact are identified, modifying the flight schedule data, as described in the following.

3.3.3.2 Remove LRU-related impact

Figure 3.10 illustrates the procedure of adjusting the actual flight plan with respect to the aforementioned logbook information, as described in [Ber14]:

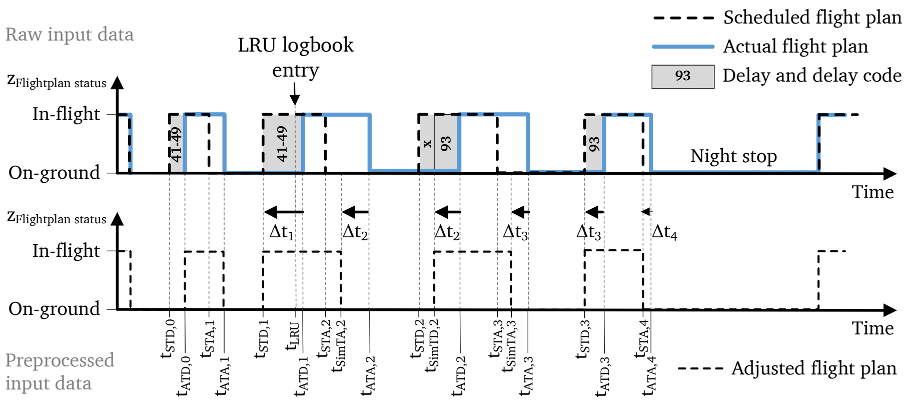


Figure 3.10.: Flight plan adjustment procedure

In the upper section of Figure 3.10, the data input providing the scheduled (dashed line) and actual (solid line) flight plan is shown. The two states *in-flight* and *on-ground* are drawn over time. The example shows a discrepancy (delays) between the scheduled and the actual flight plan, including the declaration of the related DCs. There is only one relevant LRU logbook entry, referring to a technical delay (41-49). Reactionary delays (93) occurred among others (x).

In the lower section of Figure 3.10, the resulting output flight plan is shown, with arrows indicating the particular adjustments. The first technical delay ($\Delta\ t_{d,0} = t_{\text{ATD},0} - t_{\text{STD},0}$) is not accounted for, because it does not refer to the investigated LRU. The actual flight plan is simply adopted ($t_{\text{SimTD},0} = t_{\text{ATD},0}$), with *SimTD* being the simulation input time of departure. The next technical delay referring to the LRU ($\Delta t_{d,1} = t_{\text{ATD},1} - t_{\text{STD},1}$) is removed from the flight plan, resulting in the original (planned) schedule ($t_{\text{SimTD},0} = t_{\text{ATD},1} - \Delta t_1$). The adjustment of the subsequent arrival time follows two rules: Primarily, it equals the next departure delay adjustment Δt_2, assuming that deferrals are made up for airborne and not on-ground. Second, it is not brought forward earlier than the original flight plan states ($t_{\text{SimTA},2} \geq t_{\text{STA},2}$). In case there are any further related technical or reactionary delays, these are removed as well. As shown in Figure 3.10, the next delay includes a reactionary (93) as well as an irrelevant part (x). Thus, only the associated reactionary part is removed ($\Delta t_2 = \Delta t_{\text{d},2,93}$), leading to a departure timestamp independent of the real-world data ($t_{\text{STD},2} < t_{\text{SimTD},2} < t_{\text{ATD},2}$). As a rule, at a night stop (a time longer than a regular turn around time where the aircraft is not operated) any delay removal calculations are cancelled, assuming that all tasks are able to be accomplished before the night stop end, not leading to any further delays. In the case of short-range single-aisle aircraft, this assumption is justifiable. The procedure's verification is discussed in Section 4.3.1.

3.4 Aircraft maintenance process model building

The building of the aircraft maintenance process model has four main objectives:

- Abstract the real-world maintenance process
- Provide the required input for the simulation model in order to derive the defined target values by means of simulation
- Gather more detailed process-based information than the available historical input data provides
- Allocate indirect costs to cost objects (LRUs)

Whereas the first two goals are considered obligatory, the last two aspects point out the need for a detailed process-based approach. In order to account for the bottom-level effects of a modified maintenance strategy as well as to quantify LRU-specific indirect costs, a process model approach is chosen, as e.g. proposed in [Fro09].

Furthermore, the following simplifications are made:

- A standardised maintenance process applies for all service stations
- Resources and spare parts availability are not represented

Concerning the missing representation of resource availability, the proposed method does not attempt to simulate all aircraft and subordinate systems simultaneously. For this reason, an extensive fleet-wise assessment is not conducted, making a partial coverage of resource availability obsolete. Spare parts availability is assumed not to be limited, due to lack of adequate information on real-world, component-specific service levels.

First of all, the introduced method's level of detail is explained in Section 3.4.1. The top-level system elements have been described before in Section 3.3.1. The definition of a business process in the context of this work is given in Section 3.4.2. Thereafter, Section 3.4.3 addresses the process mapping, the visual modelling by means of a chosen modelling language, as well as the definition of descriptive process factors. Lastly, the areas of impact concerning a predictive maintenance approach are discussed in Section 3.4.4.

3.4.1 Level of detail

In this section, the degree of abstraction concerning the maintenance process levels is defined. To further improve the standardisation, and thus the transferability of model building, [BPV12] defines general principles (see summary in Table B.2 in Appx. B.3). According to the modelling principle of *relevance*, it is reasonable to only go into as much detail as necessary. Figure 3.11 a) shows exemplary different levels of abstraction.

The company level refers to the aforementioned global system, shown in Figure 3.9. An example for a maintenance event level process is *replace LRU*. A more detailed view than on maintenance task level, e.g. *perform functional check on LRU*, is not conducted. In this work, it is defined that maintenance processes are only modelled to the degree that covers process-specific changes occurring through a new maintenance approach. Additionally, only processes are covered that are essential for the generation of the aforementioned target values.

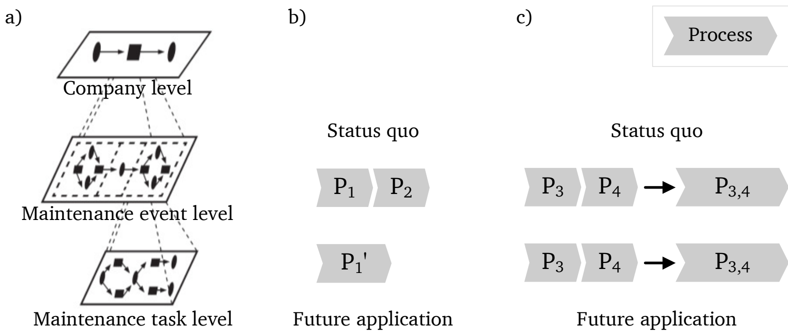


Figure 3.11.: a) Hierarchical process levels based on [Wag12, LLH], b) Process transformation and elimination, c) Process integration

In the example in Figure 3.11 b), it is shown that future applications can imply process transformations (P_1' instead of P_1) as well as eliminations (P_2 becomes obsolete). Furthermore, it is presumed that processes not affected by alternate maintenance strategies can be combined to one higher-level process. In Figure 3.11 c), P_3 and P_4 can be modelled as $P_{3,4}$. A more detailed view would increase modelling efforts, but not the informational value of the evaluation [Sta06].

3.4.2 Process definition

In order to provide the basis for the simulation, the definition of a process in the context of this work is required. On a global level, a process can be described as a system entity of sequentially interacting procedures, which consume resources (e.g. labour, time, money) to convert inputs (e.g. data, material) into outputs [Dav93]. For other definitions, see [AS04, FL97], for instance. More specifically, a business process is defined as "a procedure relevant for adding value to an organisation" [Sch01, vDO00]. Further definitions are given in [Sta06, Ros06, Gül04].

As defined in the target value definition section, maintenance costs shall be evaluated on the process-level. More precisely, the process costs are based on *labour count* (n_L), *labour cost rate* (c_L) as well as the *process duration* (Δt_L) in order to enable a quantification of the labour-based resource consumption. Based on these requirements, the following process factors are considered to uniquely describe a specific maintenance activity l [KGK14]:

- Process identification (l_{name}, l_{ID})
- Work type (l_{WT}): Labour-based processing (L) vs. autonomous (A)
- Process duration ($\Delta t_{L/A_l}$)
- Number of required labour ($\vec{n}_{L_l}$)
- Qualification of required labour ($\vec{q}_{L_l}$)

The *ID* uniquely identifies a particular process, essential for the further processing of corresponding data. The name is supposed to be self-explanatory, the process ID refers to the aforementioned hierarchy levels. The global processes in Figure 3.9 are named with letters, e.g. *Troubleshooting* is denoted TS. Subordinate activities are separated by underscores, indicating the amount of hierarchy levels below, e.g. *Gather additional information* is denoted *TS_2_2* being two levels below the global troubleshooting process [Bad13]. The work type defines whether an activity requires labour for information- or material-processing, or if it represents labour-autonomous actions, such as data transmission. The additional process factors include the process time as well as the amount and qualification of required personnel, whose specification is described in detail in Section 3.4.3.2.

3.4.3 Process model building

The maintenance process model building comprises two steps: firstly, the mapping of relevant activities provides information about the sequence of considered processes. Secondly, the specification of process factors further describes the specific activities. In the following, the modelling of today's processes is described, thereafter the particular changes of a predictive approach are accounted for.

3.4.3.1 Process mapping

The process mapping aims to logically and graphically represent the particular activities of the aircraft maintenance process at an exemplary maintenance service station. Firstly, it is required to determine all relevant processes in the desired level of detail. For this purpose, [ZSZM10] suggests to apply a top-down approach, incrementally increasing the analysis level of detail. Secondly, it is essential to model the correct process sequence including particular conjunctions accounting for process chain intersections [KGK14]. The information on processes and their sequence is mainly derived from available MRO documents, because every maintenance company is required to operate process quality assurance systems and provide a so-called *maintenance organisation exposition* [Eur08] in civil aviation. Partially, expert input is obtained by means of workshops and interviews (see applied methods in [BW09]), gathering complementary information that describes non-standardised maintenance activities. In order to enable an automatised and objective assessment, the use of document-based information is always preferred.

Since today's company structures have become very complex, business process modelling (BPM) as a modelling technique is useful to abstract, comprehend, visualise, document and analyse processes in the real-world business environment [FG08]. Additionally, it provides the models required for simulation-based studies [Sta06]. BPM can be divided into graphic- and script-based methods, the latter not applied in this work [Gad08, Sta06]. An overview of graphic-based approaches is given in Figure B.3 in Appx. B.4.

Among common control flow- and object-based methods, [Gad08, FG08] state that the *(extended) event-driven process chain* method (*eEPC/EPC*), the *business process modelling notation* (*BPMN*) as well as the *unified modelling language* (*UML*) approach are the most established. Table B.3 in Appx. B.4 gives an overview of these methods, including their particular advantages.

According to the modelling principles, the following questions affect the decision process for which method should be applied [Gad08]:

1. How long does it take to model a business process with the given notation?

2. How many elements are needed to describe a business process?

3. How clear, complete and accurate is the resulting business process model?

It can be summarised that the applicability of the described methods depends on the intended purpose [AS04]. If it is desired to obtain a comprehensible model that is easy to build and based on an established standard, the EPC method is most convenient. The BPMN language on the other hand can be characterised by its high level of detail and customising capabilities, due to its versatile element library. A UML modelling approach seems reasonable if a software developer is involved during all modelling processes, because of its link to software implementation issues. On the other hand, [HM08] states that UML is "not suitable for analysing business requirements". For further reading on the characteristics and advantages of the different BPM methods, [AR12, Koc11, AS04, SHG, Sch10, HM08] are recommended.

Based on these insights, the EPC method is applied for the mapping procedure. It is considered the most adequate modelling technique for the defined purpose, due to its manageable element library allowing to develop a model that is accurate enough, while being manageable to build. The EPC approach is considered to be intuitive and thus appropriate for the visualisation of process analysis results that serve as the basis for the subsequent simulation model implementation. A disadvantage is the lack of explicit material- or information-flow indicating elements, which is overcome through a model extension by modifying the standard elements, discussed below.

Figure 3.12 shows an example of the EPC-based process model:

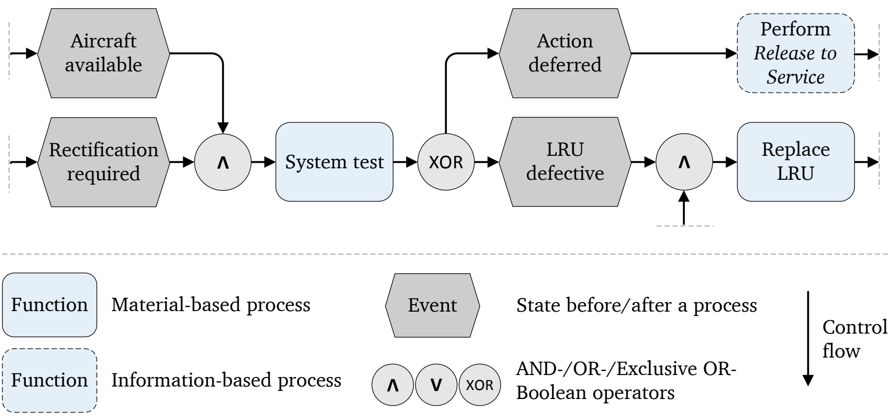


Figure 3.12.: Example of an EPC model concerning a system test

It comprises the elements *function* (process), *event*, *Boolean operators* (AND, OR, XOR) and *control flow*, represented by the arrows. A process, illustrated by a rounded rectangle, is characterised by its duration and the consumed resources, both provided by the aforementioned process factors. Additionally, it is characterised by the initial and preceding events [Sch01]. An event, displayed as a hexagon, defines the state that is reached after a process is completed or before a process starts. Because processes can cause different events and vice versa, logical operators, illustrated by circles, enable the modelling of intersections by defining routing conditions. Information-based processes are indicated by dashed lines, introduced as a model language extension in [Bad13]. The control flow, illustrated by directed edges, represents the connections between the particular elements [BPV12, Sta06].

The example in Figure 3.12 shows, only if an aircraft is available (e.g. $z_{AC} = -3$) and at the same time an LRU requires immediate rectification ($z_{LRU} = -2$), a system test is carried out. Depending on z_{LRU} the *Exclusive OR*-Boolean operator allows the transition to one subsequent system state only. If the exemplary LRU is non-deferrable ($z_{LRU} \neq -4$), an immediate rectification is required and the LRU will be replaced. An overview of all applicable EPC modelling elements and syntax rules is provided in [Bad13, Ber14].

It is important to note that the degree of automation of the proposed approach is supposed to be as high as possible in order to provide the basis for an assessment of various aircraft components. For this reason, the created process model is built as generic as possible, defining standard processes that all components have in common. The only process model parts that require LRU-specific information and thus possible manual modification, include the actual material flow-based LRU processes, as testing or rectification tasks within the system maintenance and subsystem maintenance departments.

Given the introduced EPC modelling language and information on an exemplary MRO company, all processes identified to be relevant are analysed and mapped according to the available documents. The classification of relevant processes opposed to insignificant activities is conducted under supervision of MRO process experts with respect to the aspects discussed in Section 3.4.1. The derived process maps are implemented in *Microsoft Visio* and provided in Figures B.4-B.9 in Appendix B.4.

3.4.3.2 Process factor definition

Since the EPC method is not capable of modelling or handling process factors, their management has to be accounted for separately, as illustrated in Figure 3.13:

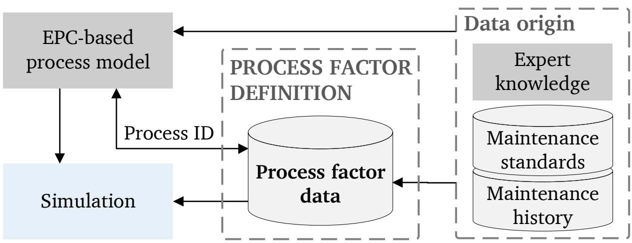


Figure 3.13.: Process factor data management. Based on [Bad13]

The process ID is used to allocate factor data to the corresponding processes. Concerning the process factor specification, the gathered data is of different types. The process ID, the work type as well as the qualification of required labour is descriptive data. The process duration as well as the number of required personnel comprise numerical values. If numerical data is not described by a constant value, it is distributed. A *probability density function* (PDF) then allows to describe the probability P of a time-dependent value $x(t)$ to apply. Thereby data uncertainty can be accounted for [Koh05].

An example for uncertain input data used in this study is the duration of a process. Since in reality not every LRU replacement consumes the same amount of time, and thus any available planning data providing constant estimates is not useful, it is assumed that the duration of particular activities is best represented by data distributions. If detailed data for every maintenance event were available, a discrete PDF could be derived. In case the number of samples is very low, particular outliers can influence the PDF significantly. This way abnormal one-time-effects are eventually reproduced by a discrete PDF, which is not desired. If it is preferred to use distributions that represent a more general probability of occurrence, continuous PDFs should be applied.

Concerning particular process times, in this study exact empirical data is not available. For this reason, as also proposed by [Fro09, Bad13], process time definitions are gathered from estimated planning data as well as expert knowledge. Whereas some maintenance documents provide information on estimates for particular maintenance tasks, other activity durations are derived from interviews conducted with maintenance experts. For the definition of process times in this study the simplified PDFs in Figure 3.14 are applied, as suggested by [Gal89]:

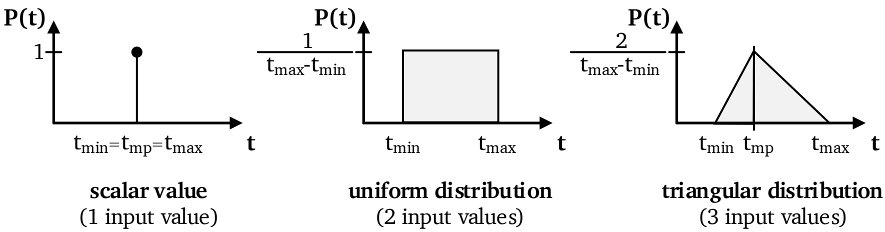


Figure 3.14.: Applied probability density functions

Depending on how accurate the planning data or the expert defines the process duration, one of the approaches is used. An exemplary application, based on the procedure described in [Vos08, Wun02], is shown in Table 3.9:

Table 3.9.: Exemplary records of process times and other factors

Process name	Proc. ID	Process time $\Delta t_{L/A}$			Type	Count	Qual.
		t_{min} [min]	t_{mp} [min]	t_{max} [min]	WT	$\vec{n}_L$	$\vec{q}_L$
Check spare parts availability	*L_1*		1		A		
Check criticality	*P_1_5*	2		5	L	1	Q2
Functional check	*I_1_7_TS*	5	100	300	L	2	Q3

If a process duration is considered to be constant, a single scalar value defines the (deterministic) PDF. As for process *L_1* in Table 3.9, this applies for highly automated processes only, assumed not to be subject to any variance. If the process duration is considered to be equally probable over a certain range, see process *P_1_5*, a uniform PDF is applied by defining the minimum and maximum possible duration values. If the complexity of an activity varies, see *I_1_7_TS* for instance, it is described by the triangular PDF (also *simpsons distribution*) by defining the minimum (optimistic guess), mode (most probable guess) and maximum (pessimistic guess) duration (see Eq. B.1 in Appx. B.4).

The process duration definition by means of non-parametric PDFs accounts for imprecise input data quality as well as the variation of actual real-world activity durations, while being intuitive for the guessing person [Gal89, Vos08]. Although more sophisticated parametric PDF types, such as normal or binomial distributions, possibly provide more accurate representations of real-world operations, they are not considered, because their definition requires the assignment of less intuitive statistical measures, such as standard deviations.

Furthermore, Table 3.9 provides information about the process-specific work type (WT). Whereas the durations of autonomous (A) processes (Δt_A) are considered to be cycle times (generating lags, but no labour costs), labour-based (L) processing activities (duration Δt_L) actually consume labour-based resources. For the purpose of cost accounting, the amount and qualification of required labour are defined. This way, the applicable counts and cost-rates with respect to Eq. 3.4 are provided. In the example, the qualifications *Q2* and *Q3* are shown. The results of the process factor definitions are presented in Tables B.4 and B.5 in Appendix B.4.

3.4.4 Impacts on the system through predictive maintenance

Concerning the impacts of a predictive strategy, maintenance process experts are consulted as well. It is assumed that the existing processes are altered by providing different information. The described system is modified in two ways:

- Modified troubleshooting because of advanced, automated fault isolation
- Modified planning through shift from unscheduled to scheduled maintenance

In Figure 3.15, all possible causes for the initiation of LRU-related maintenance events are illustrated. It is distinguished between typical corrective maintenance (grey) and predictive maintenance (blue) influence:

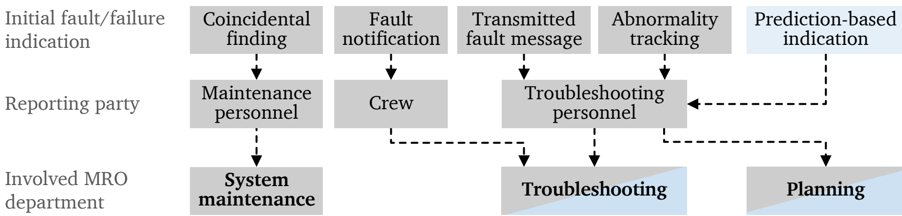


Figure 3.15.: Corrective (grey) and predictive (blue) initiation of fault rectification

In corrective maintenance, fault rectification either results from maintenance personnel findings, crew findings or general troubleshooting (TS) activities. The TS usually is confronted with in-flight transmitted fault messages or generates additional complaints by investigating a particular fault history. Whereas findings by maintenance personnel occur at the system maintenance department, all other fault identifications usually end up at the TS department, before being processed within the planning or system maintenance departments.

Prediction-based information is assumed to be processed by TS personnel. Either the analyst further processes the information within the TS department or directly passes orders on to the planning department if no further fault isolation is required.

Additionally, it is proposed that particular troubleshooting activities are modified, due to the fact that prediction improves the prior knowledge of an LRU's health. Whereas all other activities remain the same, those system and subsystem maintenance processes dealing with fault isolation procedures are assumed to become obsolete (see process maps in Figure B.4 in Appendix B.4).

3.5 Modelling of the maintenance event initiation

This section deals with the model building procedure concerning the data-based initiation of maintenance events, based on the *Knowledge discovery in databases* (KDD, see Figure 3.8) process. Similar to the general modelling procedure, KDD first requires a problem specification. Concerning the data model building, the two subsequent steps *problem understanding* and *data preprocessing* are the most important ones to transform raw input data into information usable for analysis. According to [KM06], these two steps also consume the most time. Problem understanding includes the gathering of expert information and data in order to comprehend the available information. Data preprocessing is comprised of cleaning, integration, transformation and reduction of data as well as model building. Cleaning means looking for and removing inconsistent data as well as deleting insignificant outliers. By bringing the data into the appropriate environment, combining different data sources and making it accessible for analysis, the data integration and transformation tasks are conducted. The data reduction is dependent on the goal of the particular KDD task. It mainly focusses on the selection and extraction of useful tables, records and attributes, thus reducing the number of model variables. Eventually, the semantic data model is set up [GLH15, BKK+96, FPSS96, TLCV15].

The event initial model accounts for two objectives:

- Management of maintenance event initiation based on historical data
- Accounting for prediction-based event initiation

Historical data provides information for the representation of the initial state aircraft maintenance. This requires adequate understanding and preprocessing of the input data. For this reason, the conducted procedure (Sections 3.5.1-3.5.4) follows the general KDD process. Lastly, the characteristics of a prediction-based event initiation are described in Section 3.5.5.

3.5.1 Data acquisition and understanding

According to [GLH15], the KDD *data acquisition and understanding* step includes "the comprehension of both the selected data to approach and the expert knowledge associated in order to achieve high degree of reliability." In Table 3.10, the applied data sources are provided in condensed form. Only databases providing information on the system elements defined in Figure 3.9 are considered.

The relevance of the MEL as a document concerning maintenance standards was discussed earlier. The maintenance history is described by various documents: logbook data provides historical information on aircraft- or LRU-specific

Table 3.10.: Overview of input data sources

	Context	Database	Description
Maintenance operations data	Maintenance standards	MEL	Information on LRU-specific fault or failure criticality
	Maintenance history	Logbook data	History of aircraft- and LRU-specific reports and maintenance events
		Shop maintenance data	History of LRU-specific reports and maintenance events
		Fault message data	History of aircraft- and LRU-specific in-flight fault messages
		Logistics data	History of LRU-specific logistics tasks
	Maintenance cost accounting	Maintenance-specific cost rates	Information on LRU-, process-, and labour-specific cost rates
Aircraft operations data	Fleet overview	Fleet information	Information on aircraft types and characteristics
	Operations history	Flight schedule	History of accomplished flights
		Flight irregularities	History of flight irregularities (delays, cancellations)
		Sched. maintenance program	History of scheduled (planned) maintenance
	Aircraft operations cost accounting	Airline-specific cost rates	Information on delay and cancellation costs

reports and actions. The same applies for the shop maintenance history, providing component-specific information only. Additionally, a history of all generated in-flight fault messages is provided. Logistics data can trace back LRU requests and deliveries. Maintenance cost accounting information provides labour-specific annual cost rates.

As part of aircraft operations-related data, fleet information is concerned with the utilised aircraft types and their characteristics. For instance, depending on the particular modification status, only some aircraft allow real-time fault message transmission. Aircraft operations are described by historical data concerning the flight schedule, flight irregularities as well as the accomplished planned maintenance program. Airline-specific cost rates provide cost accounting information for the quantification of delay and cancellation costs.

Process factor data is not included in Table 3.10, since it has already been covered and is considered to be part of the maintenance process model building procedure.

3.5.2 Data cleaning

Prior to the data model building and as part of the preprocessing input, *data cleaning* has to be conducted. According to [GLH15], this includes removal of noise and inconsistent data in the first place.

Concerning the aforementioned databases, data cleaning is carried out in order to provide the input data in the required form. An exemplary task is the removal of data sets containing empty fields and thus no information. Additionally, data sets containing conflicting information, e.g. misspellings of LRU registrations (part/serial numbers), are deleted. Since the data cleaning is considered a standard procedure, it is not discussed in greater detail.

3.5.3 Data integration

Data integration is the process of combining multiple data sources into one. An essential part of data integration is to build a data model map that shows the structure of the relations between the particular data sources [GLH15]. In order to efficiently organise large amounts of data in models, the concept of *classes*, *entities* (*objects*) and *attributes* is applied. It provides the framework for the formulation of relational data models. They illustrate related data by means of so-called *keys*. As it is typically mistaken, a data model does not represent activities or processes, but static characteristics, as entities and their relationships to one another [Sta05].

Figure 3.16 illustrates the hierarchy between the particular elements:

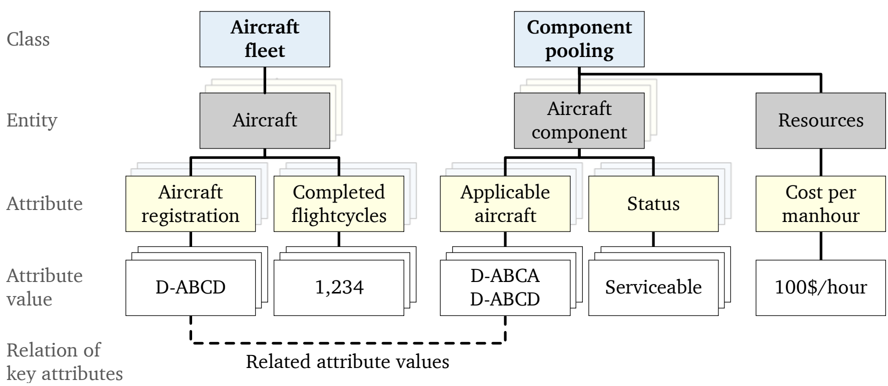


Figure 3.16.: Examples for classes, entities and attributes

On the highest level, classes are defined. A class, for example an aircraft fleet, consists of several entities, in this case different aircraft, each having the same properties (attributes). In Figure 3.16, this is depicted by the different layers. Attributes can be of different kind, defined by their values: *name*, *qualitative* or *quantitative attributes*. A name, e.g. the aircraft registration *D-ABCD*, has an identifying function. It can serve as a key attribute, particular attributes that are unique to an entity (marked with #), relating different attributes or entities to each other [Sta05]. As shown in Figure 3.16, this allows to associate a component with the applicable aircraft. Qualitative attributes are non-numerical and provide information to differentiate between objects of the same class. An example is the component status *serviceable*. Quantitative attributes are numerical and allow to compare or calculate entity's properties. For instance, an aircraft's number of completed flight cycles can exactly be quantified. Qualitative and quantitative attributes are also called *descriptive* [Sta05].

By means of the introduced concept, the real-world problem is transferred to an abstract *relational* data model. Among other data model types (e.g. *hierarchical*, *object-oriented*, *semantic* or *network database-related*), a relational data model is – in particular – applicable to independent data in the form of tables, as provided in this study [GLH15]. In Figure 3.17, the data model is illustrated by means of a UML class diagram.

LRU removal data, derived from component replacement logbook entries, builds the basis. By relating all corresponding data, unique records specifying separate LRU-based maintenance events are defined. For clarity reasons – opposed to the common way of illustration – the arrows are not directed to one key attribute. Instead, each dataset is uniquely defined by the combination of numerous #-marked key attributes (*linkings fields*) of the particular database. For instance, each LRU removal is uniquely identifiable through the corresponding aircraft (registration), the date and time as well as the particular component registration, comprising part number (PN) and serial number (SN). The shown cardinalities (see explanations in Table B.7 in Appx. B.5) represent the applicable relationships. An LRU removal can be associated with 0 to n fault messages, depending on how many related fault message datasets can be found for the particular aircraft registration at the given point in time. On the other hand, for each removal there will be exactly one related dataset within the fleet information database, referring to the corresponding aircraft registration. Concerning the temporal relationship, a time window of 14 days around an LRU removal ($[t_{\text{LRU,Removal}} - 14d; t_{\text{LRU,Removal}} + 14d]$) is defined, covering only related data within this time frame.

Process factor- and cost-related data is not shown in the relational data model. As mentioned before, the process factor definition is considered as part of mainte-

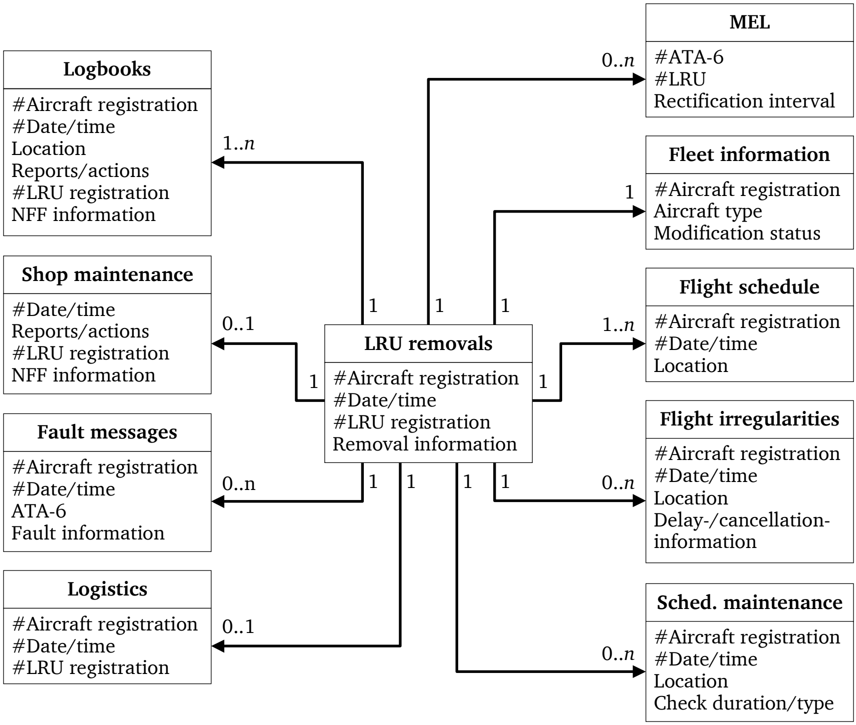


Figure 3.17.: Relational database model in UML notation

nance process model. According to the concept proposal (see Figure 3.5), the cost assessment is carried out a posteriori and discussed in Section 3.7.

3.5.4 Data transformation and reduction

The steps *data transformation* and *data reduction* deal with the actual consolidation, selection and extraction of data examples relevant for the subsequent analysis tasks [GLH15]. Based on the aforementioned relational database model, all data examples are extracted and consolidated to LRU-specific event-wise data. Only data of LRUs fulfilling the requirements in Section 3.2.1 are considered. Concerning the data structure, a tree format (see Figure 3.18) as suggested by [SWW11] is applied:

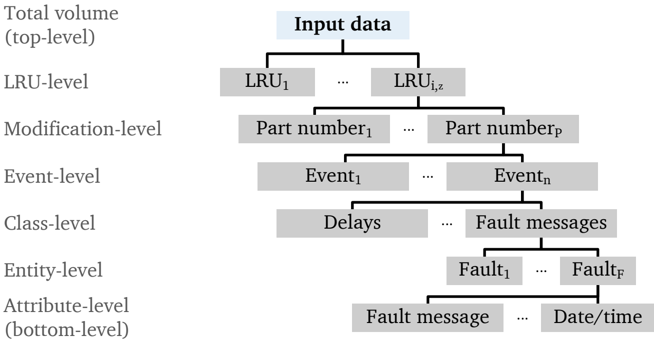


Figure 3.18.: Data structure of the event initiation model

For data consolidation purposes, different hierarchy levels are used in order to integrate similar information. With the total input data as the top-level, firstly it is distinguished between the particular LRUs. If an LRU is supplied by different manufacturers or modified by minor updates, different PNs apply. Thereby results can later be analysed concerning particular modification characteristics. For each PN, it is differentiated between the part removal events. Within an event, all related data is then consolidated, as shown in the relational data model in Figure 3.17. At the bottom-level, the particular entity attributes, e.g. a fault message text or a timestamp, are included.

The derived formal event initiation data model is based on discrete historical information. In case the LRU-specific maintenance event initiation is supposed to be based on prediction, the data model is not exclusively based on historical information any more, but also on virtual prediction-based data. The applied procedure is discussed in the following.

3.5.5 Prediction-based event initiation

For the maintenance process model building, the model adjustments accounting for prediction-based approaches have been described. Concerning the data model building, the characteristics of the prediction model data representation are introduced in this section.

Depending on the availability of preliminary work, two types of prediction model data can be considered in the evaluation tool (also illustrated in Figure 3.19):

1. Discrete analysis results of prediction model application to historical data
2. Metrics describing a particular prediction model (e.g. FNR, FDR etc.)

Concerning the first case, existing prediction models are applied to historical test data, eventually generating discrete time-based results. These can be handled as virtual historical data, being subject to the same preprocessing procedure as the real-world data. In the second case, prediction metrics are given. Then the representation of historical events is modified so that the given metrics are accounted for. The impact on the data model building procedure is shown in Figure 3.19:

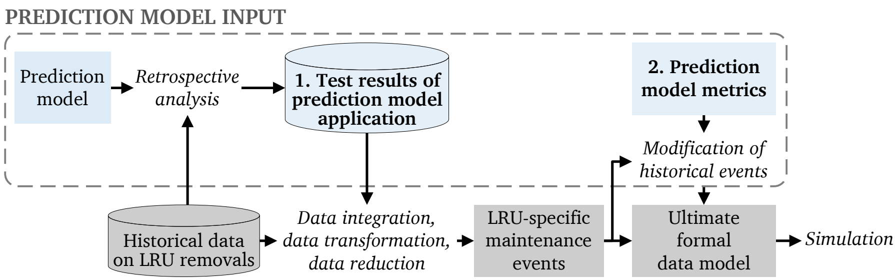


Figure 3.19.: Data preprocessing of the two prediction model data types

At the bottom line in Figure 3.19, the standard data preprocessing approach is shown if the evaluation tool is supposed to analyse the initial state maintenance only. Based on historical records, the LRU-specific event data is generated that is equal to the simulation input data. The two types of prediction model considerations (within dashed line in Figure 3.19) are discussed in detail in the following.

3.5.5.1 Test data-based prediction model specification

The first type of prediction model data is derived from test results of a retrospective analysis that is based on the initial real-world maintenance data. If a prediction model is applied to this test data, for each time step Δt that needs to be defined a priori, predictions are applied. This way, discrete time-based prediction results are provided, allowing to eventually simulate a virtual initiation of maintenance events based on prediction. The derived maintenance events possibly differ from the historical data-based event initiation. The four applicable cases are illustrated in Figure 3.20. The behaviour according to real-world (RW) data of a corrective maintenance approach (above time line), in comparison with the behaviour based on prediction (below time line) is shown:

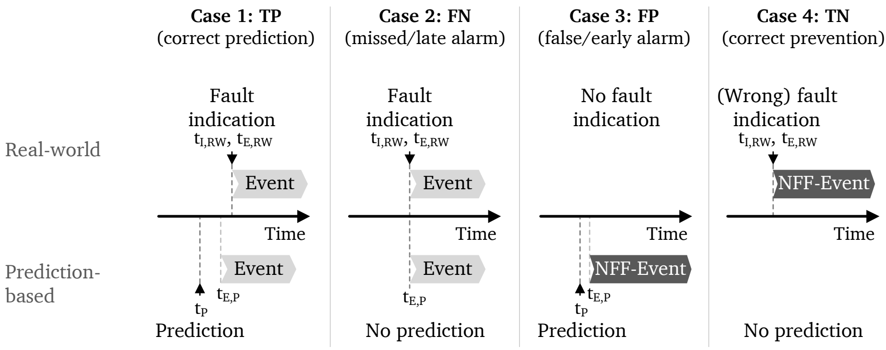


Figure 3.20.: Four cases of prediction-based event initiation

In case 1 in Figure 3.20, a TP prediction at time t_P applies, correctly indicating an event classified as justified based on the real-world data. For the real-world case, it is assumed that the point in time of fault indication $t_{I,RW}$ is equal to the point in time of event initiation $t_{E,RW}$, referring to the first maintenance process execution. A prediction is expected to indicate faults prior to the real-world corrective ad-hoc procedure. Thus, the point in time of initiating maintenance $t_{E,P}$ possibly is preponed as opposed to the real-world information ($t_{E,P} \leq t_{E,RW}$). The temporal difference of prediction-based and real-world data ($\Delta t_{PF} = t_{E,RW} - t_P$) depends on the particular prediction setting, concerning TTF for diagnosis or PH for prognosis, in the following more generally referred to as *Prediction forecast* (PF).

In case an FN prediction does not indicate a significant event (case 2 in Figure 3.20), a missed alarm applies. If, according to the real-world data, the maintenance event was declared justified, the missed alarm results in a behaviour that is equal to the real-world corrective approach. It is assumed that for safety-relevant components the fault is still indicated and maintenance is performed the same way as in reality. Thus, the point in time for the event initiation is the same as described in the historical real-world data ($t_{E,P} = t_{E,RW}$).

An FP prediction (case 3 in Figure 3.20) leads to the generation of unnecessary maintenance events (false alarms), classified as NFF. If in real-world no maintenance was performed, the prediction model generates additional maintenance. Then the prediction time is not related to any real-world maintenance event.

Case 4 in Figure 3.20 shows a TN outcome, meaning that the prediction model correctly identifies a non-significant state as such. No further maintenance events are generated in this case. If in real-world unnecessary maintenance was conducted (NFF), for the predictive approach it becomes obsolete. As can be derived from Figure 3.20 as well, the amount of maintenance events based on prediction can vary from the amount in real-world, dependent on the ratio of FN and TN predictions.

For the prediction-based cases, the LRU removals are not based on real-world historical information any more, but instead initiated by the virtual prediction results. This procedure comprises the advantage of providing data directly applicable for the evaluation tool. Particular causes and effects referring to real-world events are directly accounted for. On the other hand this approach requires a validated prediction model to be developed a priori as well as to be applicable to available historical test data.

The particular temporal characteristics of the event initiation are comprised of two variables:

- Prediction point in time (t_P)
- *Deferral interval* between prediction and event initiation ($\Delta t_{DI} = t_{E,P} - t_P$)

Firstly, the prediction point in time (t_P) is variable, depending on the particular prediction model setting, in particular the PF. The more sensitive a prediction algorithm is tuned, the earlier it leads to positive predictions. As the PF is a characteristic that is immanent to a particular prediction model, it cannot be varied arbitrarily and needs to be adjusted by variation of training data and prediction model tuning and separate test data applications.

The second factor, the deferral interval between the points in time of prediction and actual event initiation (t_{DI}), does not depend on the retrospective analysis results. Thus, it is not an input data characteristic, but its definition is incorporated in the event initiation model. Depending on how urgently a prediction-based recommendation is supposed to be accounted for within the aircraft maintenance, an immediate processing is possible as well as a processing subject to optimal planning purposes, further postponing a prediction-based rectification. For this reason, the following variables are considered for the dynamic, prediction-based event initiation:

- Aircraft state z_{AC}
- Component state z_{LRU}
- Planned maintenance z_{PM}
- Airline-specific preferences

As mentioned before, the definition of aircraft operations and LRU states accounts for criticality issues with respect to maintenance availability. Furthermore, the time schedule concerning planned maintenance times is accounted for. Additionally, particular planning preferences can be considered that distinguish between different airline-specific risk profiles. In Figure 3.21, the three applicable cases of event initiation based on prediction are illustrated:

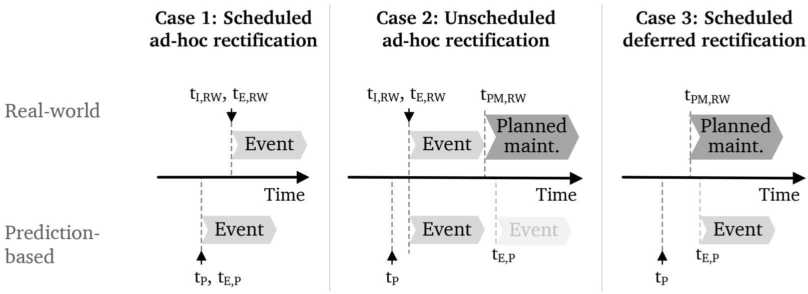


Figure 3.21.: Prediction-based event initiation with respect to criticality

If the prediction indicates a critical fault requiring immediate rectification ($z_{LRU} = -2$), case 1 in Figure 3.21 applies. Then the prediction initiates ad-hoc rectification ($\Delta t_{DI} = 0$), possibly prior to a real-world event. Due to the advanced planning, these events are considered to be scheduled.

In cases 2 and 3 in Figure 3.21, the prediction indicates faults involving a deferrable rectification ($z_{LRU} = -4$, $\Delta t_{DI} \geq 0$). Then the next planned maintenance times ahead ($t_{PM,RW,t_P..t_P+14d}$) are considered for the prediction-based event initiation ($t_{E,P} \geq t_{PM,RW}$) with respect to optimal planning. If in the real-world for the particular component, a justified rectification was conducted in the meantime, the deferral is overruled by an ad-hoc rectification (case 2), similar to an FN prediction. It is assumed that the particular fault becomes critical prior to the planned rectification. Then the event is initiated at the point in time of the real-world event ($t_{E,RW}$). If there is no evidence for a critical fault in the meantime, the event is initiated within the targeted maintenance ground time (case 3, $t_{E,P}$).

The introduced procedure accounts for optimal prediction-based planning as well as the overruling of predictive planning by ad-hoc operational requirements. More sophisticated scheduling strategies are subject to particular research studies, e.g. [VRY15, PPX$^+$10, SH03], and not considered.

3.5.5.2 Metrics-based prediction model specification

The second type of prediction model input (see 2. in Figure 3.19) is based on the definition of prediction metrics. In this case, the input data does not provide any discrete temporal information that can directly be accounted for. Instead, the input data has the format shown in the example in Table 3.11:

Table 3.11.: Exemplary prediction model metrics

Metric	**Value**
False negative rate (FNR)	0.25
Specific false discovery rate (SFDR)	0.17
Prediction forecast (PF, Δt_{PF})	5 days

The first two metrics (FNR, SFDR) refer to the ratio of prediction errors, including FP and FN predictions. The meaning of PF has been discussed before, providing information on the prediction algorithm's temporal performance.

In the example in Table 3.11, an FNR of 25% implies that in one fourth of the predictions, a significant event is not classified as such early enough. Concerning the event initiation model, this is accounted for by representing one fourth of the predictions to real-world maintenance events as missed alarms (FN) that are not predicted in advance. More specifically, in this case the same event initiation is applied as in the real-world case (corrective, $t_{E,RW}$).

In the example of an SFDR of 17%, this leads to the representation of this particular ratio of false alarm events, initiated by FP predictions. Thus, at random points in time, additional predictions (t_P) and maintenance events ($t_{E,P}$) are generated with respect to the given ratio and the particular deferral interval (Δt_{DI}).

The remaining predictions represent true negative and true positive cases. If TN predictions apply, where unnecessary maintenance has been conducted in the real-world (NFF), the event will not be considered for the evaluation and is simply removed from the data samples. For the representation of true positive predictions, only the PF is of relevance. The generation of each significant real-world event is then preponed by this particular temporal interval. By means of simplification, the PF is assumed to be constant.

Because for this approach it is uncertain which prediction result applies at which point in time in a particular test case (maintenance event), the analysis is restricted to enabling a general assessment by covering all possible results. In order to account for the randomness of a true or false prediction on the various events, Monte-Carlo simulation is carried out (see Section 3.6.4). All events are randomly assigned one of the prediction results, so that eventually the given metrics are represented by the particular prediction fault cases as part of all events. Depending on the particular PF (Δt_{PF}), the prediction point in time (t_P) varies. For this reason, it is reasonable to conduct additional analyses by means of parameter variation of the PF. Thereby different prediction points in time can be accounted for and later be analysed concerning the impact on prediction errors and costs.

Since this approach provides a global solution space of all possible outcomes containing realistic and non-realistic results at the same time, it is considered less useful than the prediction data approach based on test data results. On the other hand, this approach provides information on the economical potential without prior prediction model development. Furthermore, it serves as a basis to conduct simulation runs that eventually define minimum specifications for the development of prediction algorithms.

3.6 Simulation

Based on the defined requirements, the evaluation tool has to account for the following aspects:

- Stochastic or deterministic representation of the input data
- Interaction of aircraft operations and aircraft maintenance processes
- Provision of the required data for the calculation of the defined target values

These functions are supposed to be accounted for by means of simulation that is most convenient with respect to the formulated goals. In [Ver14], a simulation is defined as the emulation of a dynamic system process by means of an experiment-ready model to obtain information transferable to a real-world problem. It requires a verified model as input and provides simulation results as the output. Generally, simulation can assess problems that cannot be investigated in the real world or would be too costly. It enables the evaluation of numerous experiments by means of parameter variation and time compression. Disadvantages of simulation include high efforts for model building as well as verification and validation (V&V) [Ban10]. A summary of *simulation* characteristics is given in Table B.9 in Appx. B.6.

Based on the aforementioned models, defined logic- and data-wise, a simulation model is built. In Sect. 3.6.1, the basic simulation elements are explained. Sect. 3.6.2 introduces the applied scenario-based approach, followed by a description of the selection process (Sect. 3.6.3) and the simulation method (Sect. 3.6.4).

3.6.1 Elements of the simulation

In Figure 3.22, the basic simulation steps are illustrated:

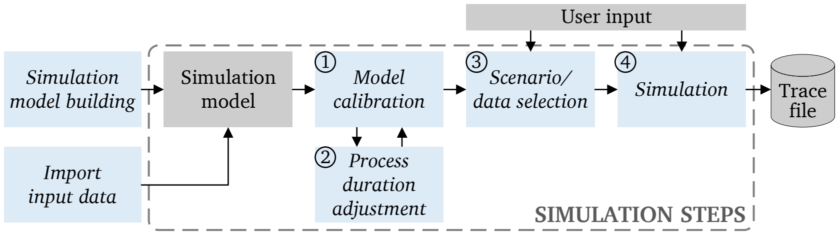


Figure 3.22.: Basic elements of the simulation

After completion of the simulation model building and integration, as well as the import of all input data, the model calibration (see Section 3.6.2) is conducted. For every newly imported dataset or adjusted simulation model, the calibration has to be performed once. It entails the modification of the initially estimated process durations. As part of the simulation preparations, the user is required to define which evaluation scenario is supposed to be performed (*analysis* vs. *specification*) as well as which data shall be considered for the simulation. Concerning the *discrete event simulation* (DES, see Section 3.6.4), the user has to determine further parameters. The derived results, saved in a so-called *trace file*, provide the data for the post-processing procedure (see Section 3.7) to obtain the desired target values.

3.6.2 Scenario-based analysis and model calibration

The scenario-based approach accounts for the specification and analysis functions. For the evaluation of the initial state maintenance (specification), observational studies by means of a retrospective simulation of historical real-world events are conducted (see Figure 3.23, above time line). A retrospective approach incorporates the analysis of the past, from a present point of view [BSG07]. The simulation then aims to represent these past events as close to reality as possible in order to observe and reproduce the real-world event characteristics. According to [Pom14], this approach is adequate for the cost-benefit-analysis of predictive maintenance strategies as well.

In the second case, the analysis of prediction-based maintenance is conducted by means of a pseudo-retrospective analysis. It is based on the simulation of modified maintenance events that refer to the original real-world occurrences (see Figure

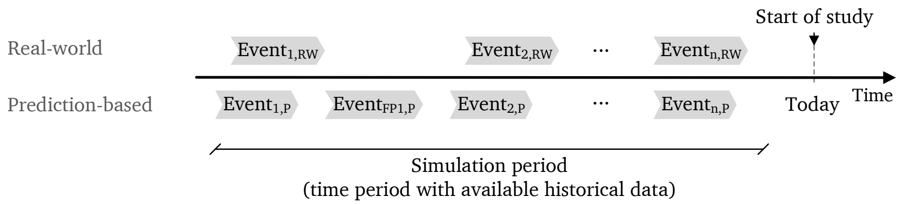


Figure 3.23.: Retrospective approach

3.23, below time line). The discrepancy between the events based on prediction opposed to real-world can range from complete, to over partial, to no difference at all, depending on a particular prediction model's impact. The event modification procedure refers to the four cases of prediction-based event initiation as part of the event initiation model, discussed previously in Section 3.5.5.

A retrospective approach has several advantages: it conducts a more representative evaluation by comparing maintenance events under exact, real-world boundary conditions (real flight schedule, real fault indication etc.) as opposed to a plain stochastic prospective approach based on virtual events. Disadvantages of a retrospective approach include the lack of provision of recognised proofs for the results validity and the relational direction of causes and effects [Put87]. For the representation of the two retrospective procedures described above, particular simulation scenarios are defined, see Table 3.12:

Table 3.12.: Defined simulation scenarios

Scenario	Scenario description
1	Model calibration
2	Calibrated model-based representation of real-world events (*specification*)
3	Calibrated model-based representation of prediction-based events (*analysis*)

The first scenario enables the selection of a valid model [Jam13]. In this case, the estimated process factors are calibrated based on exact historical information on the real-world maintenance events. Figure 3.24 illustrates the calibration procedure:

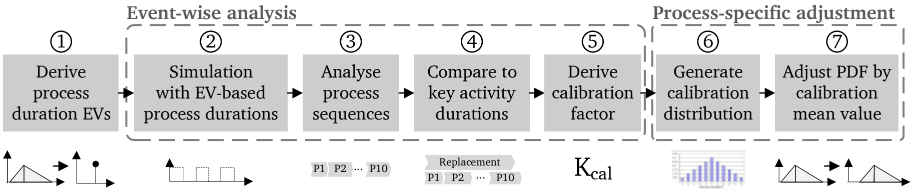


Figure 3.24.: Model calibration with respect to process duration

In the first instance, the process duration is not yet represented by the PDFs defined in Section 3.4.3.2, but by the particular distribution's *expectancy values* (EVs, μ), equal to the arithmetic mean, see ① in Figure 3.24 and Eq. 3.18-3.20:

$$\text{Scalar value:} \quad \mu_l = t_{l,mp} \tag{3.18}$$

$$\text{Uniform distribution:} \quad \mu_l = \frac{t_{l,min} + t_{l,max}}{2} \tag{3.19}$$

$$\text{Triangular distribution:} \quad \mu_l = \frac{t_{l,min} + t_{l,mp} + t_{l,max}}{3} \tag{3.20}$$

Based on these abstract values, the simulation of all maintenance events defined by the real-world input data is conducted (② in Fig. 3.24). Subsequently, the process sequences, resulting from the particular process map and the real-world event characteristics, are derived (③ in Fig. 3.24). Thereafter, these are compared to specific *key activity* durations (④ in Fig. 3.24 and Fig. 3.25) derived from real-world input data. For instance, *spare part requested* or *replacement accomplished* are available time stamps of significant process completion states, see Figure 3.25:

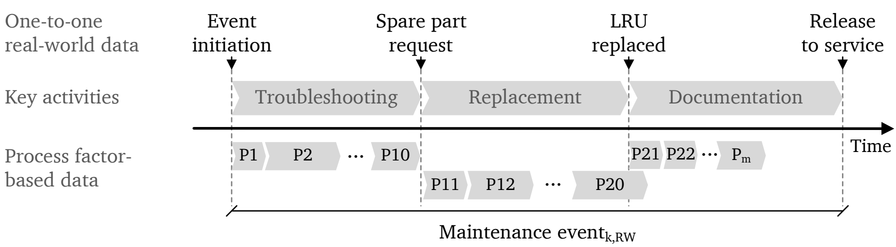


Figure 3.25.: Calibration examples

Above the time line in Figure 3.25, the available real-world information is depicted. Only discrete points in time of the LRU maintenance process are addressed, leaving the particular process durations on a more detailed level, as defined in Section 3.4, unknown. This way, training data is provided that calibrates the particular EVs, as control variables, in order to derive a more accurate model, rather than based on the estimated process durations alone.

In case the cumulative process factor-based durations exactly match the real-world overall process length, no changes to the process factor data are required (see *Troubleshooting* in Figure 3.25: $\sum_{l=1}^{10} \Delta t_l = \Delta t_{\mathrm{TS}}$). If the sum of particular durations is greater than the real-world data states, scaling down the particular process factors eventually leads to a more accurate representation (see *Replacement* in Figure 3.25: $\sum_{l=11}^{20} \Delta t_l > \Delta t_{\mathrm{Repl}}$). The opposite case, the cumulative process durations are shorter than in real-world, requires an up-scaling of the control variables (see *Documentation* in Figure 3.25: $\sum_{l=21}^{30} \Delta t_l < \Delta t_{\mathrm{Doc}}$).

Based on these insights, over all simulated events k a specific calibration factor $K_{cal,LRU_i,\bar{l}}$, uniquely assessed for each LRU_i and process chain $\bar{l}$ is derived (⑤ in Figure 3.24). It is calculated according to Eq. 3.21:

$$K_{cal,LRU_i,\bar{l}} = \frac{1}{\sum_{l_{start}}^{l_{end}} \mu_l} \cdot \frac{1}{n} \cdot \sum_{k=1}^{n} \Delta t_{k,\bar{l},RW} \tag{3.21}$$

Associated calibration factors are then combined to discrete distributions (⑥ in Fig. 3.24) in order to account for real-world process duration variation. Furthermore, a process-specific l_i *empirical standard deviation* s_{cal,LRU_i,l_i} can be calculated to give insight into the variance of the real-world variations, see Eq. 3.22 [Pap11]:

$$s_{cal,LRU_i,l_i} = \frac{\mu_{l_i}}{\sum_{l_{start}}^{l_{end}} \mu_l} \cdot \sqrt{\frac{1}{n-1}\left[\sum_{k=1}^{n}\left(\Delta t_{k,\bar{l},RW} - \frac{1}{n}\sum_{k=1}^{n} \Delta t_{k,\bar{l},RW}\right)^2\right]} \tag{3.22}$$

As the last step, the particular process duration PDFs from Section 3.4.3.2 are multiplied with the corresponding distribution's mean values (⑦, as depicted in in Fig. 3.24), thus carrying out an average calibration of the original PDF estimates. This way, the process duration parameters, generating the least errors concerning the match to the real-world data, are selected for the further evaluation.

All PDF parameters are equally, linearly re-scaled by means of the calibration factor. The original quantitative ratios between the parameters are preserved, although the absolute differences are modified. It is assumed that during the process duration specification procedure, the relative relation between the intuitively defined parameters, e.g. $t_{l,max} = 2t_{l,min}$, is more significant than the absolute relation, e.g. $t_{l,max} = t_{l,min} + 10\mathrm{min}$.

Given the calibrated process duration factors, in the second scenario (see Table 3.12), simulation experiments are conducted that are based on the analysis of the maintenance in its initial state (specification). In this case, the event initiation is based on real-world data exclusively. The third scenario aims to assess prediction-based maintenance event initiation. The differences of scenario 3 as opposed to scenario 2 concerning the simulation are summarised in Table B.8 in Appendix B.6. The discrepancies refer to the model adjustments concerning a prediction-based approach, as discussed in Sections 3.3-3.5, not further discussed at this point.

3.6.3 Scenario and data selection

Before the simulation is started, user input is required, as described in Figure 3.26:

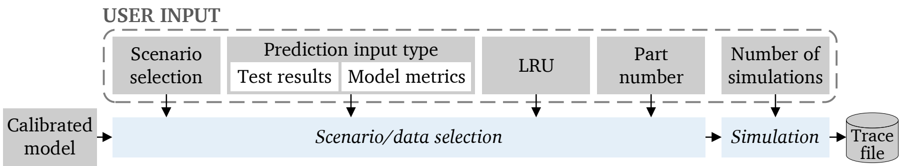


Figure 3.26.: User input related to the simulation procedure

Firstly, the user is required to select the desired scenarios, in case of future case analysis also the applied prediction input type according to Section 3.5.5. In order to narrow the relevant maintenance event data samples, the user can select particular LRUs or part numbers. Concerning the simulation, the number of simulation runs (see *Monte-Carlo simulation* in the next section) has to be specified.

3.6.4 Simulation method

In this work, the applied simulation method is *discrete event simulation* (DES). If a simulation model is discrete, mathematically formalised and dynamic, it is a DES model (see Figure B.11 in Appx. B.3). Generally, a DES can be conducted without a computer. Since in most cases a simulation involves the processing and saving of large data amounts, the use of a software tool is recommended [Law07].

In a DES, state changes are only modelled at discrete time steps, called *events*. Time periods without any changes are skipped. The time step size can vary with different events. System states are defined by objects, referred to as *entities*, and their properties (*attributes*). Entities can be enduring and stay in the system (e.g.

an aircraft) or they can be temporal and move through the system (e.g. a work order). Events cause interaction of entities and their attributes, generating state transitions. *Lists* ensure the correct sequence of events. Business processes can be represented by *activities*, or *servers*. A *clock* element enables the synchronisation of different simulation events. Furthermore *routing* elements and *queues* ensure a correct mapping of the different model elements. This way, supply chains can be modelled, for instance as in [Law07, Ban10]. Table B.10 in Appx. B.7 gives an overview of the basic elements.

In scientific research on maintenance, DES is widely spread. It allows one to skip time periods without any changes as well as to handle large amounts of data that can also be stochastically defined. According to [VHI+11, Ban10], BPM, in combination with DES, is a common instrument for economic analysis nowadays. They further state that it is "becoming increasingly difficult to rely on static solution techniques to optimise maintenance systems and ignore the dynamic and stochastic nature of current business environments". For further reading, the review given in [TR12, AT15], together with a variety of assessed DES modelling examples (see [AA14, CSW15, JS11, San15c, WCS15, WJD+02]) is recommended.

The composition of the DES applied in this work is illustrated in Figure 3.27:

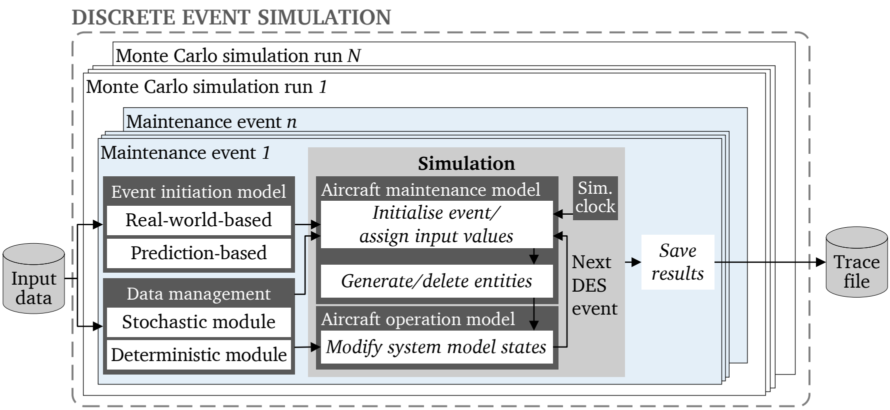


Figure 3.27.: Elements of the cascaded discrete event simulation

Concerning the term *event*, two perspectives are distinguished: from a macroscopic point of view, 1..*n* particular maintenance events are investigated, each referring to one LRU replacement. However, the original notion of a *DES event* refers to particular simulation steps that incorporate the management of entities and the modification of system model states.

As shown in Figure 3.27, the simulation procedure comprises three cascades: Repetitive *Monte-Carlo simulation* (MCS) runs, maintenance events as well as microscopic DES events. In the outer cascade, $1..N$ MCS runs are conducted. As a heuristic approach, MCS is applied due to the stochastic nature of some input parameters, as the process duration PDFs. For this reason, as part of the data management, a stochastic module initialises appropriate input values, based on *random number generation* (RNG), see details in [Koh05, Wag12]. At each MCS run, different values are defined in order to eventually represent the original distributions. By definition, and saving of *seed values* – controllable initial values for the RNG – all MCS runs can be reproduced with respect to the subsequent comparisons of different scenario's simulation results. The deterministic module assigns input values that are constant over all MCS runs for one maintenance event. An example is the process-specific labour count. The heuristic MCS approach is based on the *sample path optimisation* principle, as discussed by [GOR].

Within the event initiation model, at particular time-instances, the maintenance event generation is triggered. The input data's temporal discretisation interval is $\Delta t = 1\text{min}$. If only deterministic data were used, the minimum simulation time step size would be the same. As the input PDFs are continuous functions, creating floating point-based data in case of RNG, the actual simulation step size can vary and possibly be lower.

Within one particular MCS run, the maintenance events are evaluated sequentially, each consisting of various DES steps. In the lower section of Figure 3.28, the exemplary actions for two DES events are shown. The tasks are performed in the shown sequence, but at the same simulation time instance. The event steps refer to tasks concerning *entity management* (enter/exit process, generate/delete entity), *input value generation* and *allocation* (RNG, process duration initialisation), *data output management* (save simulation data to trace file) as well as *system model state modification* (adjust system states).

With respect to *Design of Experiments* principles, it is necessary to define the number of replications per simulation experiment as well as the length of a replication. Since the simulation time instances are pre-defined, the simulation run length is pre-defined, leaving only the number of replications undetermined. The requirement, defining the number of simulation runs to be conducted, can be derived from the simulation goals. To achieve better statistical performance, e.g. less variance in the computed values, more measurements have to be collected [And98]. Depending on how accurate the output values are supposed to be, thus directly affecting the results quality, the minimum number of simulation runs can be quantified. A plot showing variance convergence over number of simulation runs specifies the

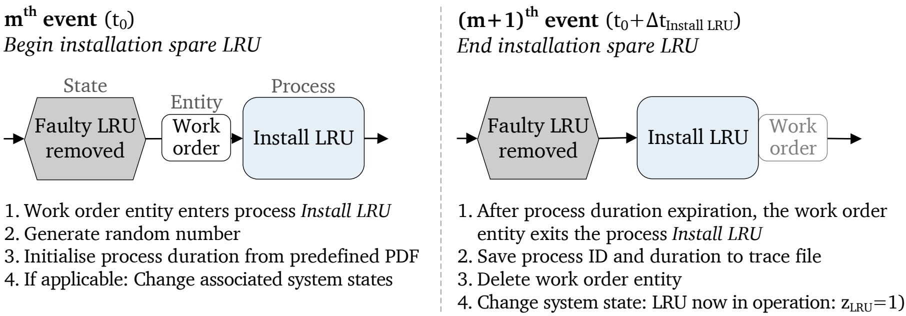


Figure 3.28.: Examples for two microscopic events

desired results data set size with respect to accuracy, as applied in Chapter 5 as part of the case study analysis.

The simulation output is saved to a trace file, which comprises two types of information: Process-based and aircraft operations-based data. An example for process data simulation output is given in Table 3.13:

Table 3.13.: Exemplary process-based simulation output

Item l	**Process ID** l_{ID}	**Simulation clock** $t_{l,start}$ [min]	**Process duration** Δt_l [min]	**NFF** z_{NFF}
1	*TS_1_1*	1623.00	1.00	N
2	*TS_2_1*	1624.00	1.28	N
3	*TS_2_2*	1625.28	4.12	N

The item number and the corresponding process ID provide information on the sequence of accomplished activities. The simulation clock records the absolute value (in minutes) of the activity initiation point in time with respect to the pre-defined reference date t_{Start} = 01/12/2010 00:00. The process duration is equal to the temporal difference between the start times of two subsequent activities. It builds the basis for the subsequent process cost calculation (see Section 3.7) and helps to identify especially time-consuming activities. Lastly, an NFF boolean flag ($z_{NFF} \in \{Y,N\}$) provides information on possible non-value added tasks in combination with NFF events. Not shown in Table 3.13, but essential for the further data post-processing, is the detailed description of the particular data sample concerning the related LRU, the corresponding part number, the scenario, a possible prediction model setting, the MCS run count as well as the event count.

Additionally, the impact on aircraft operations is recorded, as shown in the example in Table 3.14:

Table 3.14.: Exemplary aircraft operations-based simulation output

Item d_n	**Airc. reg.** AC_{ID}	**Flight ID** $AC_{FlightID}$	**Schedule**	**DC** d_{DC}	**DT** Δt_d [min]	**Cancellation** z_{Canc}
1	D-ABCD	XY0001	...	-	-	Y
2	D-ABCD	XY0002	...	40	31.13	N
3	D-ABCD	XY0003	...	90	13.09	N

The item number, the particular aircraft registration and the flight ID describe the sequence of accomplished flights. Also included in the data, but not shown in Table 3.14, is detailed temporal information on the scheduled times of departure and arrival as well as the actual times, as introduced in Table 3.7 before. Based on this data, delay information including the delay code (DC) and the delay time (DT) is derived. In this work, the generalised DC 40, indicating a primary delay, as well as 90, a reactionary delay subsequent to and caused by a primary delay, are used. The DT is derived as described in Eq. 2.2 and 3.17. Lastly, a boolean cancellation flag indicates, whether a flight is cancelled. Again, the LRU, PN, scenario, prediction setting as well as event and MCS run IDs are recorded and not shown in Table 3.14.

In the following, the simulation output data post-processing is discussed.

3.7 Post-processing of simulation data

This section introduces the processing of the simulation data provided by means of the trace file. In Section 3.7.1, the goals and elements of the post-processing procedure are introduced, Sections 3.7.2-3.7.5 discuss the conducted steps in detail.

3.7.1 Post-processing procedure

The general post-processing goals can be summarised as follows:

- Prepare simulation output data in order to derive the desired target values
- Account for distributed data
- Allow assessment on various levels of detail

Figure 3.29 illustrates the post-processing procedure's elements, including the interfaces to the input data and the user:

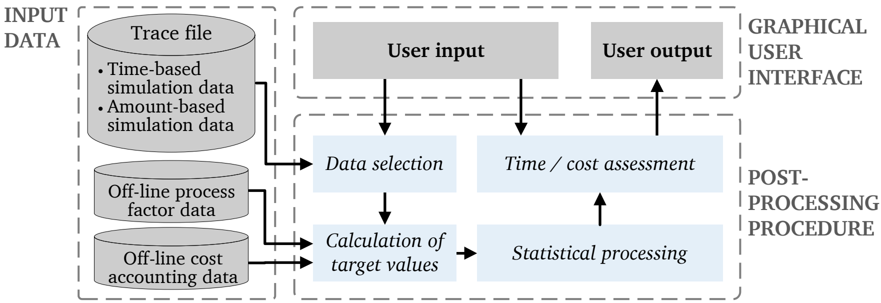


Figure 3.29.: Elements of the data post-processing procedure

The central element concerning the user interaction with the post-processing procedure is provided by the graphical user interface (GUI, see Section 4.4). On the input side, it allows the user to select the favoured data, e.g. only specific LRUs or aircraft registrations, as well as particular output options, e.g. plot types. On the output side, it graphically represents the evaluation results.

The post-processing procedure itself is comprised of four steps: *Data selection* (Section 3.7.2) accounts for only that part of the simulation data that refers to the user input. The *calculation of target values* (Section 3.7.3) includes the actual computation of time- and cost-based target value distributions. *Statistical processing* (Section 3.7.4) describes the large amounts of data by specific statistical values, being more comprehensible for the user. Lastly, the *assessment* (Section 3.7.5) accomplishes data clustering and other preparation tasks, eventually providing the data to the GUI for the graphical results assessment.

3.7.2 Data selection

The data selection includes the creation of subsets from the simulation output trace file. This way, only essential results are considered for the target value calculation. The trace file contains time-based, amount-based as well as descriptive information. In order to give insight into the applicable data selection options, the trace file data structure is illustrated in Figure 3.30:

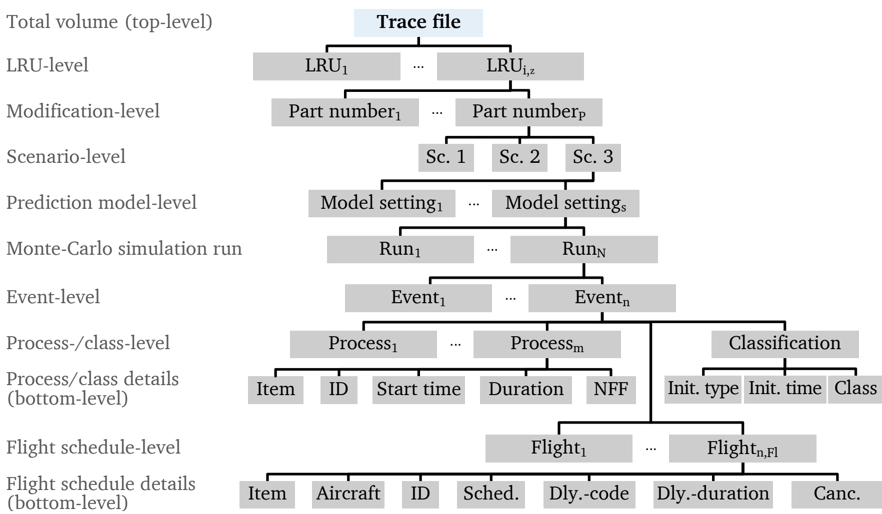


Figure 3.30.: Trace file data structure

The shown data structure is similar to the input data structure in Figure 3.18. Additionally, for a particular LRU and part number, it is differentiated between the three scenarios, in case of prediction also between particular model settings, as well as between the MCS runs. At the bottom-level, within a maintenance event, it is differentiated between process data, flight delay or cancellation data as well as classification information. As previously shown in Table 3.13, process data provides descriptive information on the sequence (item, ID), the temporal occurrence (start time, duration) as well as the NFF status. Referring to Table 3.14, information on flight irregularities provides descriptive data (item, aircraft registration, ID, delay code, cancellation) as well as temporal data (flight schedule, delay duration). The classification data describes, how the particular event is initiated (real-world- vs. prediction-based) and when it is initiated ($t_{I,RW}$,$t_{E,RW}$ vs. t_P,$t_{E,P}$). It also includes a classification assessment with respect to the confusion matrix (TP, TN, FP, FN). Only selected data samples are considered for the further post-processing.

3.7.3 Calculation of target values

With the relevant data selected, the general procedure concerning the transformation of event-specific simulation data to target value-specific information is introduced. Generally, the simulation output data can be combined on any of the data levels shown in Figure 3.30, depending on the particular evaluation goal. For instance, if the impact of prediction on a particular LRU part number is of interest, the results of scenario 2 (real-world) need to be compared to the scenario 3 (prediction-based) results on modification-level. All corresponding data below the particular reference level then needs to be combined. The number of output values to account for depends on the particular reference level as well as the amount of samples per data level. Given a particular LRU_i, PN_j, scenario and model setting, the number of process-based values to consider is represented by Eq. 3.23, with N as the number of MCS runs, $n_{Removal,RW}$ as the average amount of maintenance events and m as the average number of accomplished processes per MCS run event:

$$n_{Samples} = N \cdot n_{Removal,RW} \cdot m \tag{3.23}$$

The number of samples concerning flight operations impact is expected to be significantly lower and thus neglected in this estimate.

The actual target value calculation is based on the selected event-specific simulation data as well as simulation-independent data (see *off-line data* in Figure 3.29). The latter includes descriptive as well as quantifying content. An example for descriptive data is the process work type or the qualification of required labour, enabling to evaluate specific process characteristics. Quantifying information is essential for the target value calculation. On the process factor side, this includes the amount of process-specific required labour. Cost accounting data provides information on particular labour- and aircraft operations-specific cost rates.

3.7.3.1 Time-based target values

Figure 3.31 gives an overview of the applied calculations in order to transform the simulation output data into the time-based target values defined in Section 3.2.2.2.

It is shown that the simulation output consists of different temporal information: Labour-based process duration data ($\Delta t_{L,l}$), autonomous process duration data

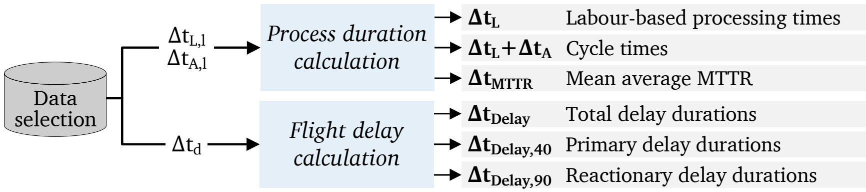


Figure 3.31.: Overview of time-based target value generation procedures

($\Delta t_{A,l}$) as well as aircraft delay durations (Δt_d). By means of the two shown procedures (*process duration*- and *flight delay*-calculation), the target values on the right of Figure 3.31 are computed according to the calculation formulas given in Section 3.2.2.2. The process duration calculation module differentiates between labour-based and autonomous processes. The flight delay calculation distinguishes between primary and reactionary delays. For a total delay assessment, the derived discrete target value distributions of primary and reactionary delays can simply be cumulated.

3.7.3.2 Cost-based target values

Concerning the calculation of cost-based target values, three aspects are discussed:

- Target value calculation and classification according to Section 3.2.2.1
- Application of activity-based costing (ABC) according to Section 2.2.4.
- Applicable cost rate types

The derivation of cost-based target values is dependent on the calculation of time-based indicators, e.g. labour-based process times or delay durations, as well as amount-based data, e.g. number of cancelled flights. Additionally, simulation-independent data, such as process factor or cost accounting information, is required. As proposed in [Ver01, Wun02], the calculation procedure is conducted independent of and subsequent to the simulation. Figure 3.32 gives an overview of the cost calculation. It is based on the formulas introduced in Section 3.2.2.1. The calculation procedures are illustrated in Figures B.13-B.18 in Appendix B.9.

The additional, specific cost-based target values (NFF-based or avoidable costs) are derived by further narrowing the selected data with respect to the corresponding event characteristics.

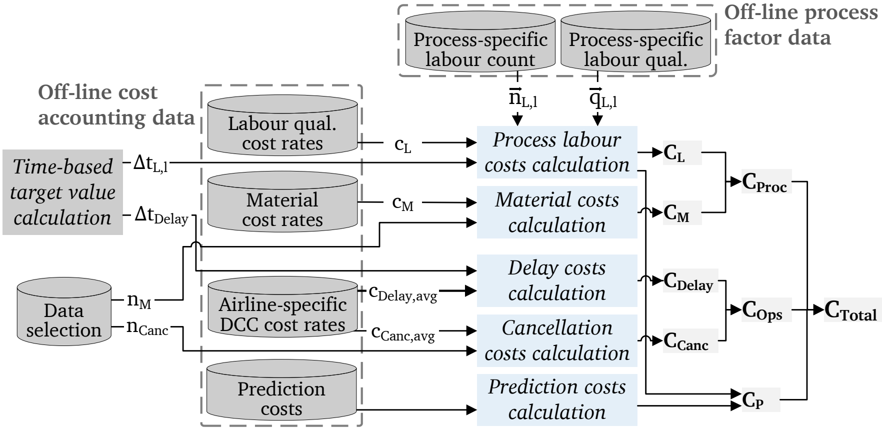


Figure 3.32.: Overview of cost-based target value generation procedures

As it can be derived from the requirements, the intent is not to calculate all operating and maintenance costs. Instead, the aim is to analyse affected costs only. The actual applied cost structure with respect to the calculated cost values is illustrated in Figure B.1 in Appx. B.1. It is shown that aircraft maintenance costs (DMC and IMC) are accounted for by means of a bottom-up approach, considering labour-based and material-based (direct) costs, as proposed in [GS98]. Since costs of supportive MRO departments (e.g. planning) are typically concerned with overhead cost accounting, the activity-based costing (ABC) method is applied. Similar to [Men13], components are defined as cost objects, which the investigated expenses are allocated to. It is assumed that a shift in maintenance strategy affects the considered components and the costs of associated activities only. The process model approach enables the activity-based quantification of maintenance costs for typical direct cost-based as well as typical overhead cost-based activities.

The proposed cause-and-effect allocation approach follows the ABC procedure, introduced in Section 2.2.4. The relevant business activities are provided by the aircraft maintenance model. The specification of labour-related process factors (count and qualification of labour) quantifies the activity-based resource consumption. The definition of activity-based cost centres is described by the global MRO processes in Figure 3.9, including typical overhead departments such as troubleshooting, planning and logistics. The determination of the particular cost-drivers is conducted by means of simulation. This way, the amount (or frequency) and duration of particular activities are obtained. These amount- and time-based cost-drivers are then used to quantify the LRU-specific labour process costs. Although the general ABC procedure is followed, one distinct difference exists: in this study, no total department-based overhead costs are given; instead labour qualification-based cost rates per hour are provided.

Concerning the used cost rates, their composition and origin is briefly discussed in the following. The given hourly labour rates are based on *historical costs* accounting for actual price-adjustments within the reference time period. A general assessment of different cost rate types, including *normal costs* and *planned costs*, is provided in Table B.12 in Appx. B.8. An advantage of historical costs is the applicability for retrospective analyses, in particular. Any historical, economical impact is accounted for within the cost data. An example for such typical impact is the *interest rate* that could be considered by means of the *net present value* (NPV) method, when normal costs were applied (e.g. see [Ach10, Swa00]).

As abstracted in Figure B.1 and discussed in [Eur15], the delay and cancellation cost rates account for various effects. On the one hand, these costs consider the saving of expenses on flight crews, fuel as well as airport and air traffic control fees. On the other hand, additional expenditures on handling fees, passenger service costs or lost future revenues (opportunity costs) are considered as well.

3.7.4 Statistical processing

The simulation output (e.g. Figure 3.31, left) consists of event-wise data samples described by scalar values. After conducting the calculation procedures, the derived target values (e.g. Figure 3.31, right) are handed over to the statistical processing module as one-dimensional array data, as proposed in [BBK11]. In order to evaluate the data, the application of descriptive statistics methods is required [Pos15]. Figure 3.33 gives an overview of the methods and measures applied in this work:

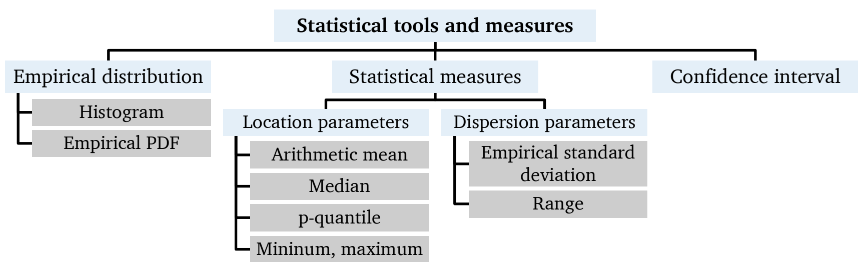


Figure 3.33.: Statistical tools and measures for the evaluation of one-dimensional arrays

If discretisation intervals are applied, the vector-based data can be transformed to class-based distributed data and empirical (discrete) PDFs. The procedure is illustrated in Figure 3.34:

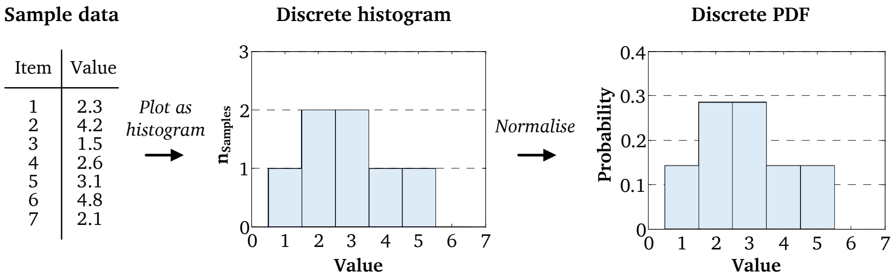


Figure 3.34.: Derivation of discrete histograms and PDFs from array data

Whereas the histogram visualises the plain quantity of target values within particular intervals, from a PDF, a value's probability to apply can be derived [BBK11].

An analysis based on statistical measures evaluates data by means of single scalar values [GH12]. Generally, location parameters enable the derivation of intuitive, exactly assessable measures. Dispersion parameters describe a given distribution's uncertainty. Often, the expectancy value μ and the empirical standard deviation s are used as estimates if the simulation results are considered as samples of a universal distribution with unknown arithmetic mean and variance σ^2.

The formulation of a *confidence interval* (CI) is based on the approximation of the empirical, discrete distribution by means of a continuous, steady distribution. Therefore, the application of the *Central limit theorem* (CLT) is required. The CLT states that the sum of n independent, identically distributed random variables X_n converges to a normal (*Gaussian*) distribution for large n. It leads to the assumption that a sample's mean value distribution can be approximated by a normal distribution N with the expectancy value μ and the standard deviation σ for large enough sample sizes, see Eq. 3.24 [Kuc10, Mit11]:

$$\overline{X}_n \sim N(\mu, \frac{\sigma}{\sqrt{n}}) \tag{3.24}$$

The CLT's application calculates a sample's CI. This way, the range can be determined that contains the sample's unknown expectancy value for a given probability (*interval approximation*) [Kuc10]: For a mean value $\overline{x}$ and an empirical standard deviation s of an exemplary sample out of n sets, the universal set's expectancy value μ with probability $1-\alpha$ is given by the interval defined in Eq. 3.25 [Eck14]:

$$[\overline{x}-z_{1-\frac{\alpha}{2}}\frac{s}{\sqrt{n}}\ ;\ \overline{x}+z_{1-\frac{\alpha}{2}}\frac{s}{\sqrt{n}}] \tag{3.25}$$

$1-\alpha$ is the so-called *confidence level*, $z_{1-\frac{\alpha}{2}}$ is the corresponding standard deviation's quantile. From the CI, intuitive statements are derived, e.g. "the costs are expected to be in the range of $C \in [C_{CI,min}; C_{CI,max}]$ with a probability of 95% ($\alpha = 0.05$)", as applied later in this work.

3.7.5 Assessment

As discussed before, the assessment procedure requires user input. The details are shown in Figure 3.35:

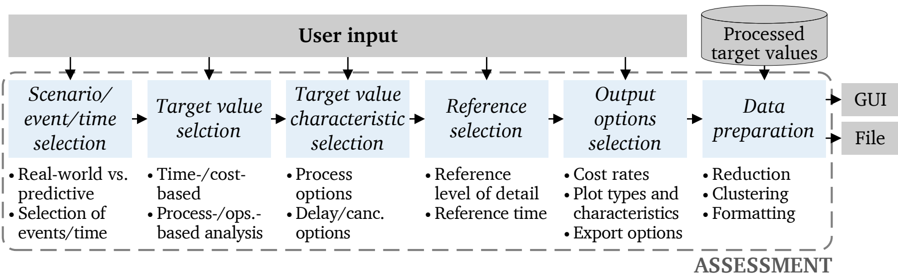


Figure 3.35.: Assessment function as part of the post-processing procedure

The user is required to select various types of assessment characteristics. Firstly, the selection of scenarios (real-world- and/or prediction-based) and the evaluation time period is obligatory (step 1 in Figure 3.35). The selection of particular maintenance events (e.g. NFF events only) is optional. The subsequent selection of target values of interest and their characteristics (step 2 and 3) involves several options. On a top-level, the user chooses the relevant time- or cost-based, process- or flight operations-specific target values. Then, on a bottom-level, for each particular target value, more detailed analysis options are selectable. For instance, this includes the selection of module-specific results (e.g. only troubleshooting process costs) or flight interruption-specific values (e.g. only duration of reactionary flight delays). In the next step, particular reference selections can be made (step 4). This includes the level of detail the target values shall be consolidated on, e.g. LRU- or PN-level, as well as temporal scales, e.g. duration per quarter or costs per year. Lastly, the user is required to select options for further specifying the assessment output (step 5). This refers to the selection of particular cost rates, different plot types (histogram, box plot etc.) as well as export tasks (e.g. spreadsheet file export). Figure 3.36 summarises the applicable user selection options:

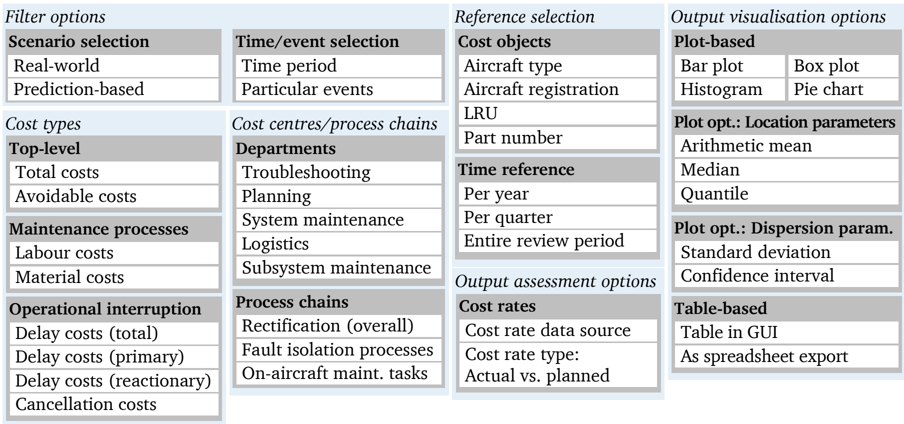


Figure 3.36.: User selection options for target value assessment

Based on the user input selections, subsequently the actual data preparation is conducted (step 6 in Figure 3.35). With respect to the defined boundary conditions, the processed target values are reduced (only selected samples), clustered according to the defined levels of detail and formatted in order to derive the desired output GUI visualisations and export files.

3.8 Concept summary and conclusions

In this chapter, the proposed concept has been described in detail. The introduced evaluation method accounts for the demand formulated in Chapter 2 and the requirements defined in Section 3.1. Due to the necessity of a simulation-based evaluation procedure (complexity of the real-world problem, evaluation of future states, accounting for uncertainties), adequate model building procedures are proposed in Sections 3.2-3.5. This way, aircraft and maintenance operations are represented with respect to appropriate levels of detail. The introduced state indicators account for the interdependency between flight and maintenance operations. The initiation of maintenance events can either be triggered by real-world or prediction model data. Hereby, different prediction model settings can be represented. Based on *discrete event simulation* (Section 3.6) and data post-processing procedures (Section 3.7), the pre-defined target values are to be derived. The transfer of the theoretically defined conceptual models to a software simulation model is described in the following chapter.

The novelty of this approach lies in the mostly deterministic, microscopic view on aircraft maintenance events. The proposed method represents all relevant characteristics of aircraft operations and MRO processes by means of real-world information. This way, particular causes and effects are exactly represented.

As discussed in Section 2.2.4, decision making by means of cost-benefit analysis requires cost accounting in order to have the economical information adequately provided. With the built conceptual process model as the basis, ABC considers typical supportive MRO departments as well. This way, all affected costs within the aircraft operations and maintenance system are accounted for.

The proposed user interface enables analyses on various levels of detail with respect to specific criteria. Thereby, a framework for the comparison of the initial state maintenance with respect to predictive future concepts is created.

4 Prototypic software implementation of the concept

This chapter briefly describes the concept's software implementation. Based on the defined requirements in Section 4.1, the selection of an adequate software environment, in particular for DES, is discussed. Thereafter, the particular model implementation steps are described (Section 4.2), followed by a discussion of the software verification (Section 4.3), the designed graphical user interface (Section 4.4) and a brief conclusion (Section 4.5).

4.1 Requirements and software selection

Firstly, the requirements concerning the concept's software implementation are discussed (Section 4.1.1). In Section 4.1.2, the selection of an adequate software environment is described.

4.1.1 Requirements

Concerning the selection of applicable software, in [Law07] six general requirements are defined:

- General capabilities
- Animation
- Statistic functions
- Customer support, documentation
- Reports and visualisation
- Hardware/software prerequisites

Among general capability requirements, in particular the factors *flexibility*, *usability*, *execution speed* and *economics* are relevant. Flexibility includes the ability to hierarchically, module-wise represent complex systems. Furthermore, a library enables the creation of model element extensions. Entities and their attributes should be definable, adjustable and readable without restrictions. Usability can be characterised by the *ease of learning/application*, referring to the same requirements as defined in Section 3.1. The execution speed is also relevant: if simulation runs can be conducted in days instead of weeks, the economical benefit can be tremendous, compensating for possibly higher acquisition and licensing costs [Ban10, Law07].

Animation requirements primarily cover *communication* as well as *debugging* capabilities. If used as a decision making tool, animated simulation intuitively visualises particular model changes, for instance. Furthermore, V&V and debugging are facilitated, in case troubleshooting has to be carried out subsequent to any unexpected model behaviour [Ban10, Law07].

Statistic functions refer to the issues discussed in Section 3.7.4 and the ability to generate random numbers. Reports and visualisation requirements are concerned with the characteristics discussed in Section 3.7.5 (e.g. GUI-based assessment). Hardware and software requirements are assumed to be met without any restrictions in this work. For details on the requirements, see [Ban10, Law07].

4.1.2 Software selection

As discussed in [AT15], DES is a common instrument for simulating maintenance systems. Taking this into consideration, a variety of applicable software is available, such as *Arena*, *Plant Simulation* or *MATLAB SimEvents* [Ach10, AT15, Wag12]. Concerning these software packages, a detailed assessment, including the building of prototype models in each program, has been conducted. Based on [Bad13, NW91] and the previously described requirements (req.), more specific criteria are defined. The assessment results are provided in Table C.1 in Appx. C.1. For instance, *hierarchical structuring* (req. 1.1) and *visualisation management* (req. 5.1) are key factors concerning the concept's objectives.

For this work, the software environment *MathWorks Inc. MATLAB* is applied. It includes the extensions (*toolboxes*) *Simulink* (block diagram modelling), *SimEvents* (DES capability) as well as *Stateflow* (finite state machine capability). MATLAB as the basis provides an established, numerically operating software environment. *Simulink* can be used to graphically represent and solve linear and non-linear non-differential equations time-continuously [Rhe07]. For the enabling of non-continuous DES, the *Simulink* extensions *SimEvents* and *Stateflow* are used [CL08]. For detailed documentation of the particular characteristics and applicable model elements see [The11, The13, The03].

4.2 Simulation model

Concerning the implementation of the models introduced in chapter 3, in this section the realisation of a software-based simulation model integration, as shown in Figure 4.1, is described:

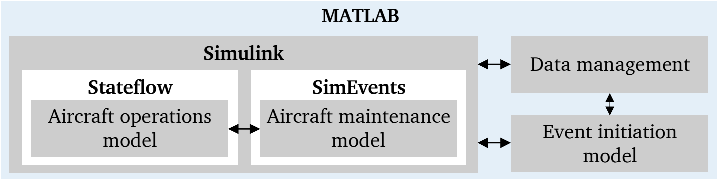


Figure 4.1.: Model interdependencies with respect to MATLAB toolboxes

The particular model implementations are discussed in the following.

4.2.1 Aircraft operations model

The aircraft operations model building procedure refers to the creation of a state chart model within the MATLAB Stateflow environment with respect to the design concept introduced in Section 3.3. Figure 4.2 shows the implemented model:

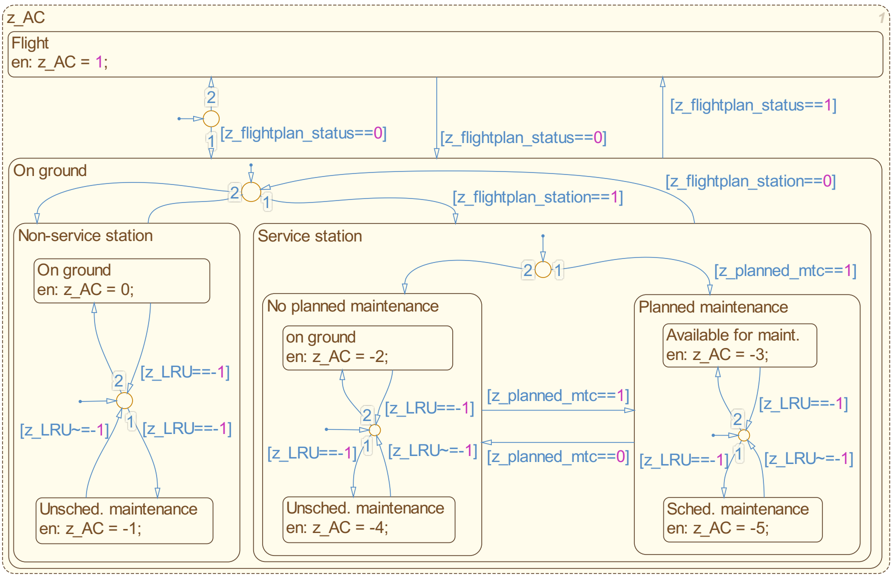


Figure 4.2.: Implemented *MATLAB Stateflow* state chart model

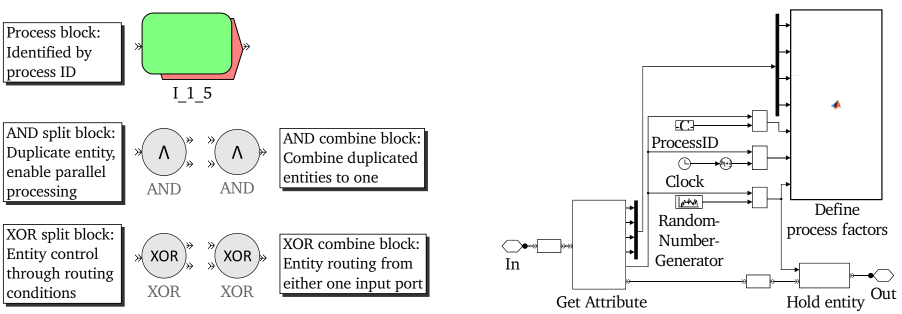
The particular states are represented by boxes, with different hierarchy levels between top-level- and sub-states as nested boxes. For instance, the top-level state on-ground is defined by general flight schedule information ($z_{\text{flightplan, status}}$). One level further down the station-specific flight schedule information is accounted for ($z_{\text{flightplan, station}}$). The arrows and the corresponding formulas represent so-called *transitions*: mathematically defined state change conditions. In case multiple transitions apply for a particular state change, an additional node (circle element) and an execution order (see number at a node) have to be defined. For instance, if the aircraft has landed ($z_{\text{flightplan, status}} = 0$), firstly it is checked, whether it has landed at a service station ($z_{\text{flightplan, station}} = 1$). If this equation is not true, the non-service station state automatically applies and z_{AC} can be defined depending on z_{LRU}. The variable names within the transition condition formulas refer to global simulation model variables accessible from all MATLAB toolboxes simultaneously.

4.2.2 Aircraft maintenance model

The maintenance process model's software implementation, referring to the procedure described in Section 3.4, incorporates the following steps:

1. Generation of reusable, library-administered EPC model elements
2. Software implementation of the conceptual EPC-based process model
3. Management of the corresponding process factor data

For re-usability purposes, in MATLAB SimEvents model element library is set up, as shown on the left in Figure 4.3 (a):



(a) Masked library elements (b) Unmasked process block

Figure 4.3.: Implemented library of EPC modelling elements in *MATLAB SimEvents*

The library contains all basic EPC elements introduced in Section 3.4.3. Since the element *state* does not provide any added value, it is omitted. The shown items consist of so-called *masks*, covering the more complex model structure made up of numerous basic Simulink and SimEvents modelling elements. In the example in Figure 4.3 (b), the DES-based representation of the *process block* element is shown. The *Get attribute*-element identifies which particular LRU actually initiates the process by reading out the entity's attributes, referring to the particular component identification. The derived information is required in order to define the adequate process duration factor by means of random number generation in the next step. At the same time, the process ID and the simulation clock record all relevant data for the results assessment.

For the selection of the most adequate library element modelling solutions, the following metrics, introduced in [Int01], are applied: *functionality*, *reliability*, *usability*, *efficiency*, *maintainability* and *portability*. Functionality and reliability are considered mandatory, implying that the desired data operation tasks are fulfilled without restrictions. Usability refers to the requirements discussed earlier. Concerning the efficiency, two temporal measures are introduced: *model loading time* and *computation time*, that are recorded for exemplary, particularly complex test cases. With respect to maintainability, the *Halstead volume* (V) metric is applied, as proposed in [SPR10]. Taking into account the amounts of signal input ports n_{IP}, signal output ports n_{OP}, modelling elements n_{El} and different element types n_{ET}, it is a measure for a model's complexity. It is calculated as shown in Eq. 4.1:

$$V = (n_{IP} + n_{El}) \cdot \log_2(n_{OP} + n_{ET}) \tag{4.1}$$

The model with the lowest Halstead metric indicates the least complex solution. Portability is accounted for by means of the library per se.

The process model software implementation is comprised of two steps: firstly, the offline process model is transferred to MATLAB SimEvents using the pre-defined library elements (mapping). Secondly, the variable element parameters have to be defined, see Figure 4.4:

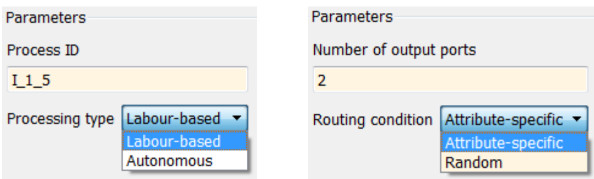


Figure 4.4.: Library element properties: Process (left) and XOR (right) options

Concerning a process (Fig. 4.4, left), its *ID* and *processing type* (labour-based vs. autonomous) have to be defined. By using the uniquely identifying ID, the corresponding process durations are assigned. For the Boolean operators (Fig. 4.4, right), the amount of input or output ports has to be defined as well as the port selection routine. In case distinct routing information is available, the corresponding attribute or variable is defined, otherwise a random-based routing is applied.

The process factor data management is implemented in the top-level MATLAB software environment. The original information, stored in spreadsheet data files, is transferred to MATLAB variables using two-dimensional arrays. These again are accessed by the *Define process factors* block in Figure 4.3 (b), automatically defining the applicable process duration for each process during a simulation run.

4.2.3 Data management and event initiation model

For the data management integration, the MATLAB data format *struct* (see [The11]) is applied in order to hierarchically organise the event-wise data samples, as shown in Figure 3.18. One distinctive feature of the provision of time-based information in MATLAB SimEvents is that additional data preprocessing is required, because temporal data has to be described as time differences (see discussion in [Bad13]). For the generation of random numbers, MATLAB internal tools are applied. As proposed previously, by defining seed values, the random numbers are reproducible in order to make simulation results comparable.

The event initial model implementation, according to the procedure described in Section 3.5, is mainly concerned with the management of the particular input data. Depending on which event initiation type (real-world vs. prediction-based) is supposed to be considered, the different time instances are passed on to the simulation routine in order to trigger the generation of maintenance events.

4.3 Software implementation verification

Verification and validation (*V&V*, see Figure C.1 in Appx. C.2) are essential to guarantee credibility of model building, simulation and the obtained results [Rab08]. According to [OR10], the *Society of Computer Simulation* defines *model qualification* as the "determination of adequacy of the conceptual model to provide an acceptable level of agreement for the domain of the intended application". Based on expert feedback and plausibility checks, the underlying conceptual models were qualified. For instance, the created process maps were shown to personnel actually involved in the particular tasks. Any ambiguities were directly accounted for accordingly. This way, the derived conceptual models are declared adequate.

In [OR10], *model verification* is defined as the "substantiation that a computerised model represents a conceptual model within specified limits of accuracy". It provides quality assurance and ensures that the subsequently derived results are based on a correct model. Examples for verification methods are computer code verification (*Do the algorithms work as intended?*) or solution verification (*Is the solution accurate enough in order to represent the conceptual logic?*) [OR10, Rab08]. In this section, the applied verification techniques concerning the particular model building procedures are briefly discussed. A general overview of verification techniques can be found in [Ban10, OR10, Rab08].

Validation, concerned with the results assessment in comparison to the real-world problem, is discussed in Section 5.3.1 as part of the case study application.

4.3.1 Aircraft operations model verification

Concerning the state chart model, monitoring of state variables for each simulation point in time allows to check the model for logical behaviour, as proposed in [Ban10]. Since the simulation input flight schedule does not equal the original planned or executed schedule, a verification of the schedule adjustment concept (Section 3.3.3) is obligatory as well. The conducted verification tasks are mainly comprised of plausibility checks on the input and output values compared to the expected range of values. Concerning the conducted plausibility checks, it is investigated if all of the criteria summarised in Table C.2 in Appx. C.2 are simultaneously met, while adjusting the input flight schedule according to the procedure proposed in Section 3.3.3.

According to the criteria, the analysis of the results applied on virtual input data as well as the real flight schedule has not shown any incorrect behaviour, except for one case: if a night stop is particularly short, its identification within the data is inaccurate, possibly not allowing to cancel any subsequent flight plan adjustments. Thus, the definition of a night stop has been refined so that the modified flight schedule is correctly represented within the simulation model.

4.3.2 Aircraft maintenance process model verification

The aircraft maintenance process model can be verified concerning its syntactic and semantic correctness. A graphical modelling language's syntax exactly defines the visual appearance, e.g. the correct use of notion symbols [BPV12]. If the syntax is strictly followed during the building process, the model is syntactically correct, which has been checked during and after the process mapping procedure. A model is semantically correct if the transfer of a conceptual system model to a formal model (see Figure C.1 in Appx. C.2) is correct, meaning without any logical discrepancy [BPV12]. As suggested by [Bad13], the derived process model, including the process maps and the related process factors, is presented to the consulted process experts. Their selective feedback eventually optimised and confirmed the implemented model.

Concerning the interaction of the particular maintenance processes, the *trace analysis* method (see Figure 4.5) is applied. Hereby, the conducted process steps are visualised, allowing to check the particular maintenance event processing for logical behaviour.

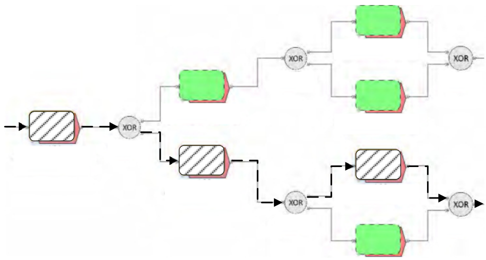


Figure 4.5.: Trace analysis example. Based on [Hof13]

The logic of the process factor determination, assignment and recording has undergone plausibility checks with respect to *monitoring* and *cause-effect analyses* (see detailed descriptions in [OR10]). By means of monitoring, the assigned process duration values are observed. It is checked if the desired distributions are represented correctly. Cause-effect analysis implies to vary input parameters, e.g. doubling all process factor input parameters, and to check if the resulting target values are doubled as well. The MATLAB internal debugging tools further support the verification by automatically indicating any data conflicts and erroneous model behaviour through automated code and solution verification.

4.3.3 Data model and event initiation verification

With respect to the data model generation, the criteria in Table C.3 in Appx. C.2 are considered for plausibility checks, enabling model verification.

For the event initiation procedure, the criteria in Table C.4 in Appx. C.2 are checked. A detailed analysis of exemplary data model building test runs with respect to the aforementioned criteria has shown that the proposed implemented procedure meets the defined requirements.

4.3.4 Simulation model integration verification

Verification of the integrated simulation model has been conducted through a module-wise assessment in order to reduce verification complexity. By means of *extreme condition tests*, all relevant parameters are set to zero. Then it is observed, whether the associated target values become zero as well. Additionally, it is checked if the same results can be derived from alternate calculation procedures, for instance arithmetic mean of the process-specific duration input data should equal the process-specific average output data for large enough amounts of MCS runs. Because any occurring model inconsistencies could be overcome, the implemented simulation model is considered to be verified.

4.4 Graphical user interface

As part of the post-processing routine (see Figure 3.29), the GUI represents the interface between the simulation results with the user. It is designed in *GUIDE*, the MATLAB GUI design environment. In the following only the results assessment GUI is discussed, see Figure 4.6:

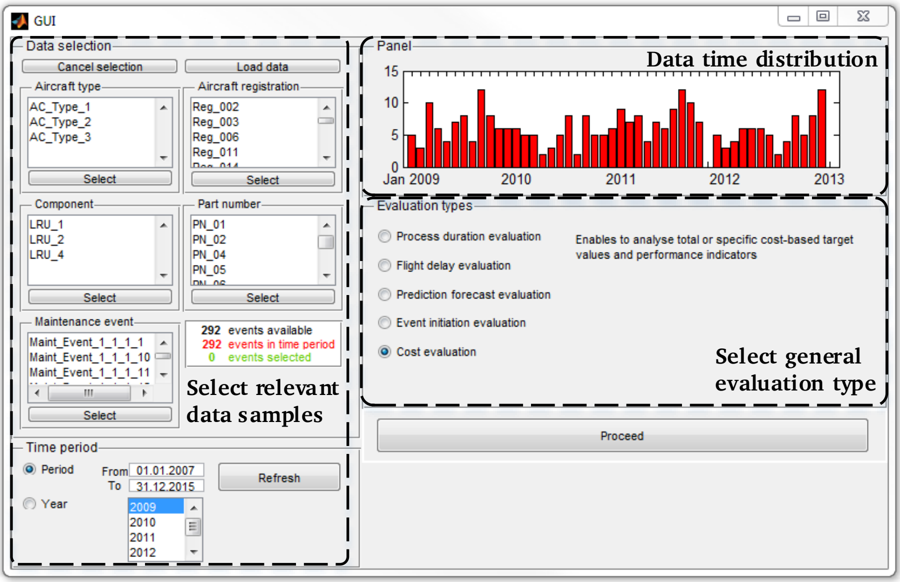


Figure 4.6.: Global results assessment GUI

The shown interface refers to the data selection step. The functional areas are highlighted by the dashed-line boxes. On the left of Figure 4.6, the user is enabled to narrow the desired data samples within the simulation output data, e.g. by choosing only specific aircraft or LRUs. On the right of Figure 4.6, general time distribution information is provided as well as the selection of general evaluation types, referring to Section 3.7.3.1 for time-based analyses and Section 3.7.3.2 for cost-based analyses.

More specific evaluation options are provided in an additional GUI window, see Figure 4.7:

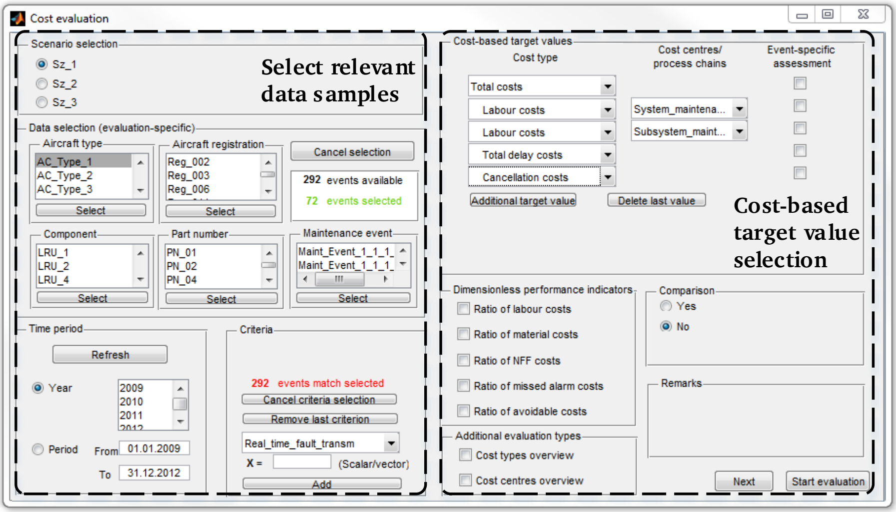


Figure 4.7.: Cost evaluation GUI

In case the results of varying data samples or analysis settings are supposed to be compared, separate windows allow the selection of distinct samples. They can be switched by specific toggle buttons. Again, on the left of Figure 4.7, the data selection can be further narrowed. For the cost evaluation example on the right of Figure 4.7, the particular cost assessment options are available.

The next step includes selecting general output options, implemented as shown in Figure 4.8. The content follows the description in Section 3.7.5 and is not discussed in more detail.

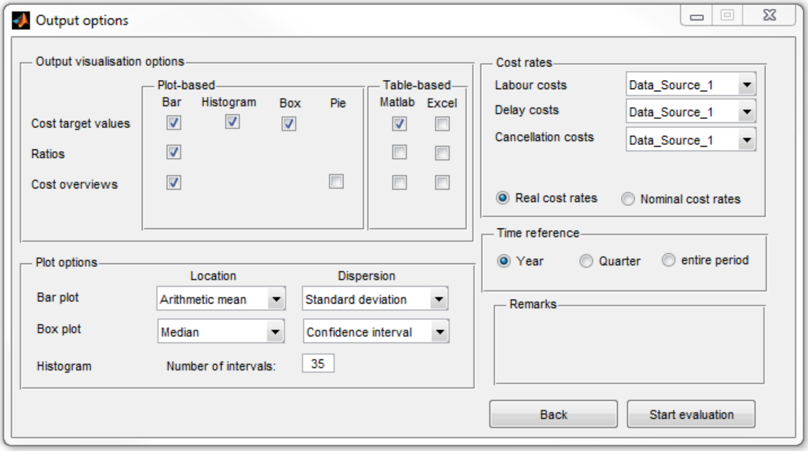


Figure 4.8.: GUI output options

With all output options chosen, the evaluation assessment can be started, immediately providing the analyses results to the user after each completed calculation procedure. The applicable visualisation types (plots, tables) were introduced previously (Figure 3.36) and are not further discussed at this point. Examples for the provided information and specific visual appearance will be discussed as part of the case study assessment in Chapter 5.

4.5 Conclusions

In this chapter, the software implementation of the previously proposed conceptual models has been described. The implementation is conducted in *MATLAB* and the applicable toolboxes, providing the most adequate software environment with respect to the defined requirements. A process model element library is built and enables a reproducible modelling to easily account for possible future adjustments. The derived simulation model fulfils all defined requirements, as confirmed by the conducted verification steps. Lastly, a GUI allows the user to control and assess the simulation routine with respect to usability and transparency.

5 Case study application of the evaluation method

In this chapter, the design (Sections 5.1-5.2) as well as the design and assessment of a case study (Section 5.3), including the model's validation are discussed. In Section 5.4, the conclusions are discussed.

5.1 Design of experiments

For the case study assessment, particular *experiments* are defined a priori. An experiment is the analysis of a modelled system if certain model parameters or aspects are varied in order to identify particular causes and effects. The following experiments (exp.), referring to the scenarios proposed in Section 3.6.2, are conducted:

1. exp.: Simulation model calibration and validation
2. exp.: Evaluation of today's maintenance
3. exp.: Evaluation of predictive maintenance based on defined model metrics

Table 5.1 provides an overview of the particular experiment characteristics:

Table 5.1.: Conducted experiments and their characteristics

Exp.	Varied input parameters	Analysed output parameters	Opt. criterion
1	$\Delta t_{L_l/A_l}$	K_{cal}, s_{cal}	$min(s_{cal})$
2	N_{MCS}	C_{LRU_i} and all subordinate costs	$s_{\text{ref}} \leq s_{\alpha=0.05}$
3	FNR, SFDR, Δt_{PF}, $C_{P_{LRU_i}}$	C_{LRU_i} and all subordinate costs	$min(C_{LRU_i})$

As can be derived from Table 5.1, the model calibration (exp. 1) is concerned with the adjustment of the input data process durations $\Delta t_{L_l/A_l}$, based on the minimisation of the calibration-based empirical standard deviation s_{cal} as the optimisation (opt.) criterion. Validation is conducted by applying the calibrated model parameters to separated validation data. For the current state maintenance representation (exp. 2), the variation of the simulation replications N_{MCS} is of importance in order to reach the desired results accuracy level $s_{\alpha=0.05}$ for a reference target value. For experiments 2 and 3, the total LRU-specific costs are the primary target value. In exp. 3, prediction-based simulation runs are conducted. Because for this work prediction model test results are unavailable, prediction metrics (FNR, SFDR, Δt_{PF}) are varied in order to virtually represent all possible model settings (see Section 3.5.5.2). Varying FNR and SFDR accounts for different FN- and FP-prediction errors, e.g. arising from variation of an algorithm's sensitivity (see Section 2.3.4). This way, differing ways of maintenance event initiation are represented. By varying the prognostic forecast, the time of event initiation is modified. The prediction-specific costs $C_{P_{LRU_i}}$ are adjusted in order to assess different cost-of-implementation scenarios. For exp. 3, the objective function is defined as minimising the component's total costs C_{LRU_i}, as also proposed in [War92].

By investigating the effects of prediction errors and investment costs on aircraft and maintenance operations, the overall cost-benefit is evaluated. In order to account for all possible outcomes, the variable input parameter's impact is analysed by means of a *sensitivity analysis*. This way, a well established technique in statistic planning of simulation experiments is applied [Ach10]. It identifies interdependencies between input parameters and the objective function (*input-output interactions*) by varying only single parameters (*decision variables*), while keeping all others constant. The third experiment's decision variables (var.) are summarised in Table 5.2:

Table 5.2.: Variation of exp. 3 decision variables

Decision var.	Unit	Variation range	Step size	Fixed values
FNR	[%]	[0; 100]	5	
SFDR	[%]	[0; 65]	5	
Δt_{PF}	[min]	[15; 3,000]		{15; 60; 300; 1,000; 3,000}
$C_{P_{LRU,i}}$	[€/a]	[0; 50,000]		{0; 17,500 ; 50,000}

The variation range defines the lower and upper boundary for the decision variable adjustments. Due to the SFDR's hyperbolic behaviour – e.g. an SFDR of 100% implies infinite FP cases – only values below 65% are analysed. Either a constant step size is applied (5% steps for FNR, SFDR) or pre-defined values are given, as for Δt_{PF} and $C_{P_{LRU,i}}$, derived from expert consultations. In general, the step size or the amount of fixed values results from the trade-off between desired output accuracy and acceptable simulation time. The non-equidistant prediction forecasts are chosen based on expert consultations in order to define realistic and useful examples.

5.2 Case study definition

This section introduces the case study characteristics. In particular, the applied input data is discussed in the following.

The real-world, operations-based input data is composed as introduced in Table 3.10 in Section 3.5.1. For confidential purposes, detailed aircraft operations and maintenance event data is withheld. Exemplary data for one maintenance event is provided in Tables D.1-D.6 in Appendix D.1. Table 5.3 gives an overview of general input data characteristics:

Table 5.3.: General input data characteristics

Input variable	Amount	Value/Name
LRUs	1	*LRU A*
Applicable PNs	3	*PN 1, PN 2, PN 3*
LRU-specific MEL RI	1	*A*
Recorded real-world LRU replacements	42	$Maint\_Event_1$ .. $Maint\_Event_{42}$
Events involving operational impact	38	$n_{Delay} + n_{Canc}$
Events classified as NFF	13	n_{NFF}
Time period with recorded data	4 years	*01/01/2011 - 31/12/2014*

In the case study, one representative network-carrier shorthaul aircraft component *LRU A* fulfilling the requirements in Section 3.2.1 is investigated. It comprises three different modification levels (*PN 1, 2, 3*). The LRU is dispatch-critical (MEL RI *A*), requiring immediate rectification in case of failure indication. Among the considered fleet, 42 maintenance events (only LRU replacements) were recorded in a time period of 4 years. 38 events involved operational irregularities, 13 were classified NFF.

In Table 5.4, the applied cost rates are summarised. All shown rates are LRU-independent. The yearly rates account for averaged annual real-world inflation rates given in [Eur15]. The labour rates are derived from expert consultations. It is distinguished between 3 different qualifications (qual.), enabling the representation of process-specific labour expenses. *Qual. 1* represents engineering-related

Table 5.4.: Applied labour, DCC and logistics cost rates

Cost rates			Year-specific cost rate values			
Description	**Variable**	**Unit**	**2011**	**2012**	**2013**	**2014**
Labour costs qual. 1	$c_{L,\text{ Q1}}$	[€/hr]	90.0	92.3	93.7	94.3
Labour costs qual. 2	$c_{L,\text{ Q2}}$	[€/hr]	50.0	51.3	52.1	52.4
Labour costs qual. 3	$c_{L,\text{ Q3}}$	[€/hr]	60.0	61.6	62.5	62.9
Delay cost rate	$c_{\text{Delay,avg}}$	[€/min]	86.6	88.9	90.2	90.8
Cancellation cost rate	$c_{\text{Canc,avg}}$	[€/ea]	16,790	17,226	17,485	17,600
Logistics transport inland	$c_{L,\text{ Log,inl}}$	[€/ea]	30.0	30.8	31.2	31.4
Logistics transport abroad	$c_{L,\text{ Log,abr}}$	[€/ea]	60.0	61.6	62.5	62.9

activities, e.g. troubleshooting tasks. *Qual. 2* refers to planning jobs, *qual. 3* is concerned with the actual maintenance tasks. The averaged DCC rates are derived from [Eur15] and account for varying real-world boundary conditions, e.g. passenger seats or flight distance. The delay cost rate is denoted per delay minute and refers to ground-based – including maintenance-induced – delays. The cancellation costs quantify the average costs of one cancellation event. The logistics costs are *activity quantity induced* costs. They are represented by global costs differentiating between inland and abroad transport processes.

In Table 5.5, proposed prediction costs are shown:

Table 5.5.: Applied prediction cost scenarios

Cost rates			Prediction cost scenarios		
Description	**Variable**	**Unit**	**Variant 1**	**Variant 2**	**Variant 3**
Prediction investment costs	$C_{P,\text{ Invest}}$	[€/a]	0	5,000	15,000
Prediction development costs	$C_{P,\text{ Develop}}$	[€/a]	0	5,000	15,000
Prediction software costs	$C_{P,\text{ S/W}}$	[€/a]	0	2,500	5,000
Prediction pers. training costs	$C_{P,\text{ Train}}$	[€/a]	0	5,000	15,000
Annual prediction costs	$C_{P_{LRU_i}}$	[€/a]	0	17,500	50,000

In Table 5.5, three cost scenarios represent *best-case* (variant 1), *realistic* (variant 2) and *pessimistic* (variant 3) estimates. Whereas variant 1 represents possible *economies of scale* effects, e.g. through the re-use of existing models, the pessimistic case considers disadvantageous effects through first-time implementation issues.

The prediction-based cost rates are rough estimates (for other rates, see e.g. [FSJ08]) and consider various aspects: the investment costs account for initial purchases of hardware and software in order to enable prediction-based analysis as part of the aircraft maintenance troubleshooting. The development costs represent investments for one-time as well as recurring prediction model enhancements. Because non-recurring costs are difficult to take into consideration with the ABC approach, they are estimated to average annual costs, equally representing initial costs as well as maintenance and modification expenses. Among the recurring costs, software (S/W) costs include annual licensing and service expenses. Personnel training costs are estimates for expenditures on personnel education concerning prediction-based analysis.

The shown prediction costs represent the initial rates in the year 2011. Increase in prices is accounted for by using the average annual inflation values given in [Eur15]. The complete data is provided in Tables D.7-D.8 in Appx. D.1. Among the prediction costs, only the development costs, including problem-specific algorithm design, development and testing, are considered to be LRU-dependent.

5.3 Case study results assessment

This section deals with the experiments' conduction. Section 5.3.1 provides the model calibration and validation results. Section 5.3.2 firstly addresses the determination of required simulation replications, and secondly presents and discusses results of the initial state maintenance's analysis. Section 5.3.3 provides simulation results with respect to prediction-based initiation, including their discussion.

The simulation is run on an *Intel* (R) *Core* (TM) *i5* 2.50 GHz system with 8 GB RAM. As an example, one MCS replication, comprised of the 42 real-world maintenance events, is conducted in approximately 474 seconds.

5.3.1 Exp. 1: Model calibration and validation

According to [OR10], validation is "the process of determining the degree to which a model is an accurate representation of the real world from the perspective of the intended use of the model" (also see Figure C.1 in Appendix C.2). The aim is to build credibility and confidence in the conducted simulations [Obe04]. In this context, the characterisation and minimisation of errors and uncertainties in the computational model is important. This step is also referred to as *model calibration* [Obe04]. According to [AIA98], calibration is "the process of adjusting numerical or physical modelling parameters in the computational model for the purpose of improving agreement with real-world data". [Buc06] distinguishes between two types of calibration procedures:

1. *Model structure validation* (Section 5.3.1.1)

2. *Parameter estimation* (or *parameter tuning*) (Section 5.3.1.2)

In the following sections, the two procedures are described and applied in detail.

5.3.1.1 Model structure validation

The model structure validation assesses and modifies any inaccurate model elements or states. As discussed in [Buc06], in order to conduct *event-based validation*, adequate real-world data is required. Besides the temporal data used for the process factor calibration, in this study, no further quantifying real-world information is available. A *theory-based validation* is not applicable either, due to the lack of comparable analytical models. In this case, [Buc06] proposes to apply *function-based validation* to assess a model's plausibility. For this purpose, the validation methods *trace analysis* and *face validity* are applied.

The *trace analysis* method was described previously in Section 4.3.2. According to [Buc06], it can be applied to verification as well as validation. For instance, concerning the simulation of maintenance processes, the model behaviour is checked for plausibility with respect to the process sequence, starting time as well as duration. *Gantt charts* (see example in Figure D.7) check the simulation for logical behaviour. For hierarchical models, [Law07] proposes to break down the complex model into subsystems and to conduct modular validation. Trace analysis can also be applied to the state variables, introduced in Section 3.3.1. Figure 5.1 illustrates one exemplary maintenance event's model states. The Tables D.1-D.6 in Appx. D.1 provide the corresponding data.

In Figure 5.1, the upper three variables $z_{\text{F. status}}$, $z_{\text{F. station}}$ and $z_{\text{Pl. maint}}$ indicate the aircraft's original flight plan characteristics, representing regular operation. If there is no faulty LRU state ($z_{LRU} = 1$), the aircraft operation state z_{AC} directly follows the three input flight plan variables. As soon as an LRU failure is indicated ($z_{LRU} < 1$) and the rectification process has started ($z_{LRU} = -1$), the aircraft state will switch from *on-ground* ($z_{AC} = -2$) to *unscheduled maintenance* ($z_{AC} = -4$).

Based on the defined state chart model (see Figure 4.2), the state variable allocation is checked for plausibility. In Figure 5.1, no contradictions can be found: the aircraft operation state z_{AC} and the LRU state variable z_{LRU} follow the input parameters as intended, correctly representing the aircraft and maintenance operations

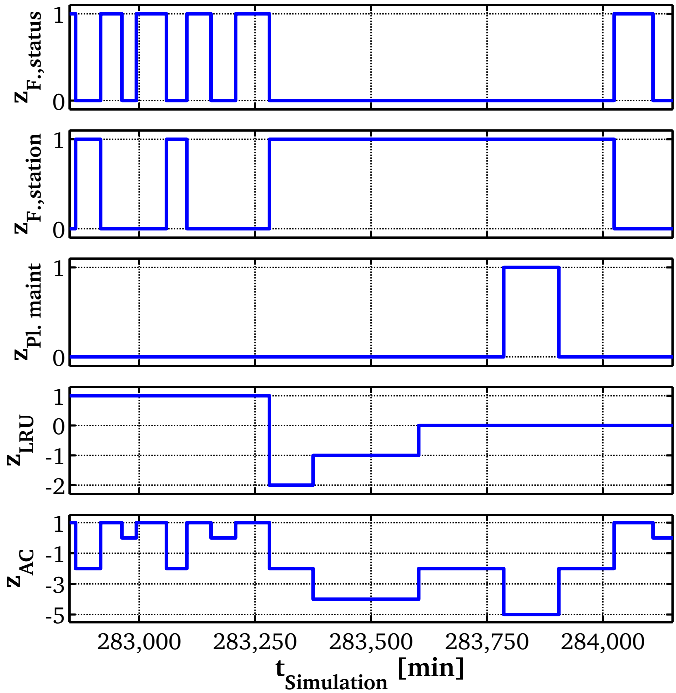


Figure 5.1.: Maintenance event representation by means of state variables

according to the available real-world information. The simulation time $t_{Simulation}$ refers to the reference time $t_{Start} = 0$ for the date 01/12/2010 00:00.

Face validity checks were conducted by presenting the model results to maintenance experts. This way, the simulation output is not compared to discrete real-world data, but instead assessed in a subjective manner. These checks e.g. include the assessment of simulated process sequences, the impact on flight operations through breakdowns as well as the range of target values concerning credibility.

Alternate validation methods, as e.g. *comparison to other models* or *historical data validation*, are not applicable due to lack of adequate validation models and validation data. Based on these insights, for the given purpose, the created model's structure is considered to be validated.

5.3.1.2 Model parameter estimation

In model calibration and validation, it is common to split available real-world information into *training data* and *validation data* [Buc06]. Training data is used for the calibration procedure itself, whereas the calibrated model is then applied to validation data in order to assess the performance on real-world information, independent of the training samples. For this study, among the available information on the 42 maintenance events, 30 are used for providing training data. The remaining 12 events provide validation data.

The calibration follows the procedure introduced in Section 3.6.2. The complete results are provided in Appendix B.4 and D.2 in the following order:

1. Initial process factor estimates (Tables B.4 and B.5)
2. Key activity durations and derived calibration factors (Tables D.9, D.10, D.11)
3. Modified process factors (Tables D.9 and D.10)
4. Application to validation data and standard deviations (Tables D.9 and D.10)

In Table 5.6, the modifications applied to three exemplary maintenance activities are presented and discussed thereafter:

Table 5.6.: Exemplary calibration results for three maintenance processes

Proc. ID	**Process time**			**EV**	**Cal. factor**	**Modified proc. time**			**Std. deviation**	
	t_{min} [min]	t_{mp} [min]	t_{max} [min]	μ [min]	K_{cal}	$t_{min,cal}$ [min]	$t_{mp,cal}$ [min]	$t_{max,cal}$ [min]	$s_{cal,\text{train}}$ [min]	$s_{cal,\text{val}}$ [min]
TS_5_7		1.00		1.00	1.26		1.26		0.28	0.21
I_1_1	1.00	15.00	40.00	18.67	0.76	0.76	11.40	30.40	3.70	6.78
I_1_11	3.00	7.50	15.00	8.50	1.00	3.00	7.50	15.00		

In Table 5.6, the exemplary processes *evaluate if immediate rectification reasonable* (*TS_5_7*), *collect and analyse documents* (*I_1_1*) and *deferred item documentation* (*I_1_11*) are shown. In the *process time* columns, the initial process duration estimates are given. To the right, the distribution's expectancy values (EV) are shown. The next column provides the derived calibration (cal.) factors. For *TS_5_7*, the original process duration estimates turned out too low, requiring an upscaling ($K_{cal} > 1$). For *I_1_1*, the calibration factor indicates that the simulation-based results lead to a decrease of the initial duration estimates ($K_{cal} < 1$). For *I_1_11*, no real-world information is available, leading to unchanged initial estimates. The applied calibration results are provided in the *modified process time* columns, derived from multiplication of the initial duration estimates and K_{cal}.

In the last two columns, empirical standard deviations as a measure for variation are given. The deviation with respect to the training data $s_{cal,\text{train}}$ becomes minimal around the modified distribution's EV. It is calculated by means of Eq. 3.22. Whereas the calibration factor increases the duration's accuracy, the variation is an indicator for a particular process duration's precision. The higher variation of process I_1_1 opposed to TS_5_7 shows that the I_1_1 training data duration is distributed wider. In order to account for the derived variation information, the distribution estimates t_{min} and t_{max} could be further adjusted. Because $s_{cal,\text{train}}$ is based on the assumption of a symmetric, normal distribution and parameter over-fitting shall be prevented, the distributions are not modified any further.

In the last column in Table 5.6, the variation concerning the validation data $s_{cal,\text{val}}$ is given, also based on Eq. 3.22. In this case, the calibrated data is compared to real-world maintenance information not accounted for within the calibration procedure. In order to consider the calibration results validated, adequate accuracy requirements have to be defined and met [OR10]. In Eq. 5.1, the validation metric is defined by means of an additional acceptable deviation of $\Delta t = 10\text{min}$, which is derived from accuracy requirements defined by involved experts:

$$s_{cal,\text{val}} \overset{!}{\leq} s_{cal,\text{train}} + 10\text{min} \tag{5.1}$$

If the process-specific deviation remains within this boundary, it is considered validated. For the examples in Table 5.6, it is concluded that for TS_5_7, the real-world data is approximated even better than the training data ($s_{cal,\text{val}} < s_{cal,\text{train}}$). On the other hand, applying the calibrated data of I_1_1 to the validation data shows an almost doubled deviation, still within the acceptable boundary. The procedure's accuracy could further be improved if the initial distributions were modified or methods as *cross validation* were conducted. It has to be considered that the empirical standard deviation's calculation is sensitive to the sample size n. Thus, for little validation data, the results are expected to be subject to high variation per se.

Table 5.7 gives insight into the derived calibration factors distinguishing between the particular maintenance process modules:

Table 5.7.: Derived calibration factors with respect to the main MRO departments

Derived calibration factors K_{cal} with respect to process modules and key activities

TS	**Planning**	**System maintenance**			**Logistics**	**Subsystem maint.**
Fault analysis	n.a.	Transit TS	Transit replacement	Hangar replacement	Service stat. transport	LRU tests and overhaul
1.26	(1.00)	0.81	0.76	0.95	1.85	0.71

Table 5.7 presents a summary of the detailed results provided in Tables D.9-D.11 in Appx. D.2. The calibrations factors $K_{cal} < 1$ indicate that especially the system and subsystem maintenance durations were overestimated initially. On the other hand, the troubleshooting and logistics efforts were underestimated ($K_{cal} > 1$). For the planning activities, no adequate information is available ($K_{cal} = 1$).

Briefly summarised, two factors influence the calibration procedure's correctness: firstly, the amount of conducted maintenance events (sample size) and secondly, an activity's degree of standardisation (variation tendency). As can be derived from Eq. 3.22 and the CLT in Section 3.7.4, for higher sample sizes n and similar key activity durations, the empirical standard deviation further decreases. A real-world procedure's complexity and the degree of process standardisation have a significant impact on the distribution's precision. In general, simple and repetitive activities are easier to be adequately represented in an abstract model.

The revealed initial process duration inaccuracies were expected. The calibration application enables to minimise accuracy- and partly precision-based errors. Thus, the process duration input parameters are considered validated, because the match to real-world data – as accurately as required – has been proven.

5.3.2 Exp. 2: Evaluation and discussion of today's maintenance

This experiment has two objectives, explained in the following:

- Determine adequate amount of simulation replications (Sec. 5.3.2.1)
- Analyse maintenance costs and characteristics in the initial state (Sec. 5.3.2.2)

5.3.2.1 Determine adequate amount of simulation runs

The adequate amount of simulation replications N_{MCS} is considered to be the optimum ratio of minimum computation time to maximum results exactness. The objective function J (see Eq. 5.2) aims to minimise a reference value's empirical standard deviation s_{ref} dependent on the total number of samples $n_{Samples}$. Concerning $n_{Samples}$, only the number of replications is variable, because the 42 maintenance events and the amount of processes are considered constant [LLGC12].

$$J = \min(s_{ref}) \quad \text{with} \quad s_{ref} = f(n_{Samples}), n_{Samples} = f(N_{MCS}) \tag{5.2}$$

$$J \overset{!}{\leq} s_{\alpha=0.05} \tag{5.3}$$

$$s \sim \frac{1}{\sqrt{N_{MCS}}} \tag{5.4}$$

Based on the objective function J, the *determination condition* of Eq. 5.3 defines that the number of simulation replications is increased as long as a pre-defined 95% confidence interval (CI) covering 95% of all calculated expectancy values is met. Alternately, a maximum number of replications could be defined, if computation time-based boundary conditions were considered. As shown in Eq. 5.4, the empirical standard deviation is inversely proportional to the replication number's square root [Pap11]. In other words: a deviation's bisection requires a quadrupled number of simulation runs.

According to [LLGC12], "convergence needs to be proven before making any decisions based on the results". As the results of a sensitivity analysis, the MCS convergence behaviour for the reference example of the overall maintenance event processing time in the initial state is presented in Figure 5.2:

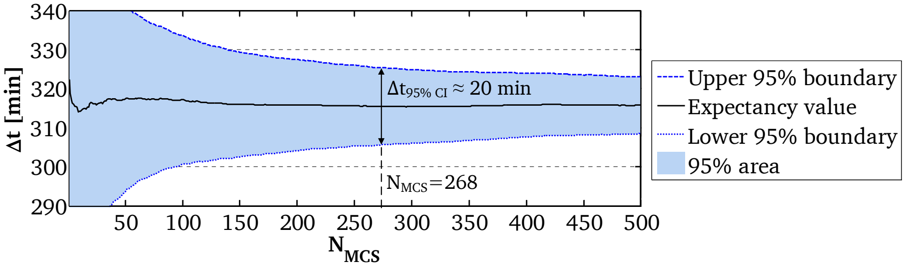
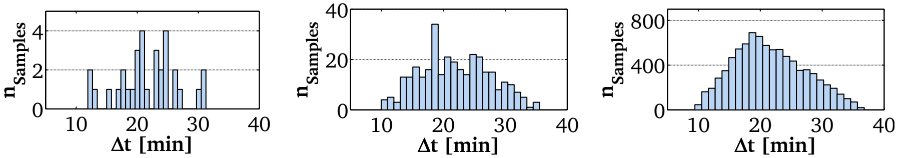


Figure 5.2.: Convergence of expectancy value and CI over number of replications

Figure 5.2 illustrates the cumulated results of various independent simulation replications. It shows varying arithmetic mean and CI values over increasing numbers of MCS runs. The calculated event processing time converges for large N_{MCS}. Additionally, the CI's decrease with increasing sample size is apparent. For a threshold of $s_{\alpha=0.05} \stackrel{!}{=} 10$min, meaning that the duration's expectancy value lies within the range of $\Delta\bar{t}_{\mu} \pm 10min$ with 95% probability, the required number of MCS replications is 268. The amount of 11,256 independent maintenance samples is considered in this case. Because the process duration distributions as well as the real-world key duration variations incorporate similar ranges of uncertainty, this degree of accuracy is considered to be sufficient for the further analyses.

As another demonstrative example, Figure 5.3 illustrates the increasing accuracy over different N_{MCS} for the exemplary triangular distribution of process *L_3*. For one simulation run, see Figure 5.3 (a), the triangular distribution is not recognisable yet. For $N_{MCS} = 10$ (b), it becomes clearer and for $N_{MCS} = 268$ (c) the representation shows minor deviations only.

Figure 5.3 subfigures



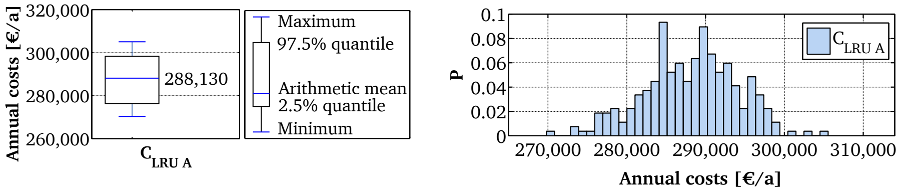
(a) $N_{MCS} = 1$ (b) $N_{MCS} = 10$ (c) $N_{MCS} = 268$

Figure 5.3.: Computed durations for process *Transport within service station* (*L_3*) with varying replications (count n_{amount} over process duration Δt)

5.3.2.2 Initial state maintenance analysis

This section's content refers to the evaluation tool's *specification* function, providing results based on the analysis of the initial state. The conducted simulation is based on the process factor calibration results and the determined number of replications. The results are presented in the order of the target value definitions in Sec. 3.2.2.

First of all, the reference LRU's initial state total costs are analysed in Figure 5.4:



(a) Total costs (box plot) (b) Total costs (PDF plot)

Figure 5.4.: Derived total costs of the initial state maintenance

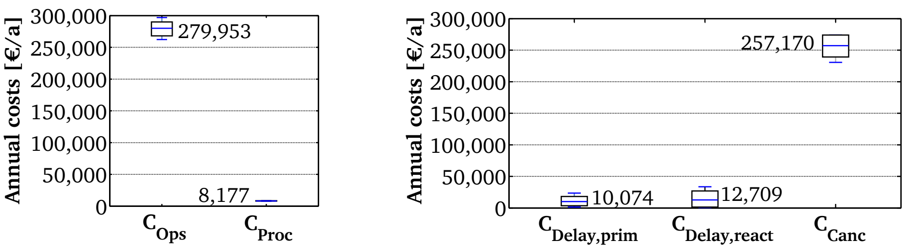
Figure 5.4 shows the cost distributions by means of a box plot (a) and a discrete PDF plot (b). The box plot provides detailed information on specific location parameters, such as $C_{LRU_A,\text{mean}} = 288{,}130$ €/a, indicated by the line in the box, quantiles referring to 95% of the results ($C_{LRU_A,2.5\%} = 276{,}254$ €/a, $C_{LRU_A,97.5\%} = 298{,}282$ €/a), illustrated by the box ends, as well as the absolute minimum and maximum values ($C_{LRU_A,min} = 270{,}320$ €/a, $C_{LRU_A,max} = 305{,}039$ €/a) at the so-called *whiskers*. Opposed to the common box plot definitions, alternate quantiles and the arithmetic mean are applied. Since the arithmetic mean considers outliers as opposed to the median, it is considered more adequate. The PDF plot (Figure 5.4 (b)) further visualises the distribution's shape. The apparent outliers probably result from (dis-)advantageous boundary conditions, representing especially rare outcomes.

As can be derived from Figure 5.4, the calculated costs are subject to broad variation (*range* $r = 34{,}719$ €/a). As an example, the cost difference between the quantile-based results ($\Delta C_{LRU_A,97.5\%\text{-}2.5\%} = 22{,}028$ €/a) can be verified through error propagation approximations. Eq. 5.5 provides an estimate for the expected cost difference based on the known input parameters:

$$\Delta C_{\text{expected}} = 2 \cdot s_{\alpha=0.05} \cdot (c_{\text{Delay,avg}} + c_{\text{L,avg}}) \cdot n_{\text{events,avg}} \quad [\text{€}/\text{a}] \tag{5.5}$$

Firstly, in Eq. 5.5, twice the previously discussed temporal threshold $s_{\alpha=0.05}$ is considered for the representation of the total time-based data variation. In order to account for extra costs, average time-based cost rates ($c_{\text{Delay,avg}}$, $c_{\text{L,avg}}$) are applied. For deriving the overall annual costs, the averaged amount of maintenance events per year ($n_{\text{events,avg}}$) has to be accounted for as well. Thus, for the values $s_{\alpha=0.05} = 10\text{min}$, $c_{\text{Delay,avg}} = 89.1$ €/min, $c_{\text{L,avg}} = 1.14$ €/min, $n_{\text{events,avg}} = 10.5$ 1/a, the expected cost difference is $\Delta C_{\text{expected}} = 18{,}951$ €/a. It is shown that the results derived from simulation almost equal the error propagation estimate. The remaining error is assumed to result from particular one-time-effects and yearly deviations not considered by an average-based approximation.

For more details on the initial state analysis, Figure 5.5 presents the total costs composition (a) as well as the DCC (b) with respect to Eq. 3.1 and 3.2:



(a) DCC and process costs (b) Delay (prim./react.) and cancellation costs

Figure 5.5.: Total costs composition

Figure 5.5 (a) shows that the DCC (C_{Ops}) account for the largest portion of the total costs (97.2% concerning the mean values). Additionally, the DCC's variation is larger, referring to the higher time-based impact shown in Eq. 5.5. This leads to the conclusion that the analysed LRU leads to more negative consequences on the airline operator's side than within the MRO company.

In order to further investigate the breakdown costs, Figure 5.5 (b) shows their detailed composition with respect to primary and reactionary delays as well as cancellations. Among the 42 analysed maintenance events, 6 involve delays and 32 cause cancellations. Figure 5.5 (b) highlights the significant impact of cancellation costs on the total DCC. To a large extent, this results from an LRU replacement's duration determining whether a delay or cancellation applies in case of ad-hoc maintenance. The implemented logic aims to minimise any negative economical impacts on the airline's side. For this reason, a decision-supporting break-even is calculated, according to Eq. 5.6:

$$\text{Decision} = \begin{cases} \text{Delay,} & \text{if } \Delta t_{\text{Maint}} < \Delta t_{\text{Threshold}} & \text{at service station} \\ \text{Delay,} & \text{if } \Delta t_{\text{Maint}} < \frac{1}{2}\Delta t_{\text{Threshold}} & \text{at non-service station} \\ \text{2x Canc,} & \text{if } \Delta t_{\text{Maint}} \geq \Delta t_{\text{Threshold}} & \text{at service station} \\ \text{1x Canc,} & \text{if } \Delta t_{\text{Maint}} \geq \frac{1}{2}\Delta t_{\text{Threshold}} & \text{at non-service station} \end{cases} \tag{5.6}$$

$$\text{with } \Delta t_{\text{Threshold}} = \frac{c_{\text{Canc,avg}}}{c_{\text{Delay,avg}}} \tag{5.7}$$

Eq. 5.6 distinguishes between service and non-service stations as well as the actual maintenance duration Δt_{Maint} as opposed to a threshold $\Delta t_{\text{Threshold}}$ (Eq. 5.7). At service stations, for long maintenance activities, two cancellation cost penalties are applied. This is justified through the fact that especially in shorthaul operations, *hub-and-spoke* (round-trips) routing strategies are applied and thus both flights affected. Unscheduled maintenance at non-service stations leads to cancellations earlier, due to the bisected threshold. Exemplary pre-analyses showed that for any long primary delay, approximately the same cumulated duration of reactionary delays has to be considered, because the initial delay can only be reduced incrementally over the next flights. For the case study, the threshold is defined as $\Delta t_{\text{Threshold}} = 193.88\text{min}$. This decision approach is the reason for the derived DCC variations: Whereas in some cases a maintenance event possibly leads to short delays, in other cases it will result in one or more flight cancellations. The implemented logic's results were validated according to the available flight schedule data, including information on real-world delays and cancellations.

For the detailed analysis of MRO efforts, the process costs composition with respect to the particular MRO departments (cost centres) is depicted in Figure 5.6. It can be derived that the (on-aircraft) system maintenance activities account for the most part of the MRO costs. They also incorporate the highest variation. The (off-aircraft) subsystem maintenance tasks and the transportation costs are significant as well. Whereas TS costs are comparatively low, the expenses arising at the planning department are insignificant. The derived results meet the expectations. Due to the corrective maintenance approach, almost no planning applies. Concerning the TS costs, not the absolute values are of importance, but the unscheduled

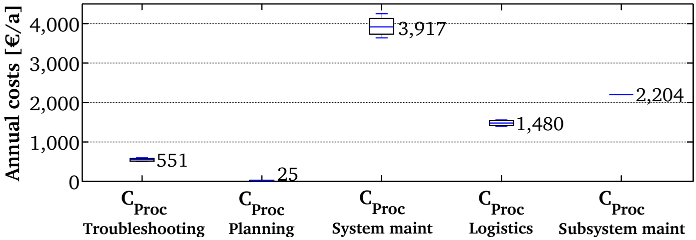


Figure 5.6.: Cost centre-specific maintenance process costs

occurrence during regular flight operations (see discussion w.r.t. Figure 2.6). The cost variations result from the input process duration distributions only.

In order to identify the particular impacts of diagnosis-related activities and NFF events, Figure 5.7 shows specific process costs, according to Eq. 3.10 and 3.11:

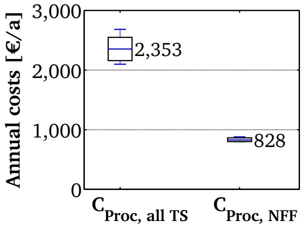


Figure 5.7.: Costs of all TS- and NFF-related activities

The TS process costs analysis (left box plot in Figure 5.7) reveals that fault isolation tasks account for approximately 28.8% of all process costs. Since fault isolation is conducted within the TS department as well as the system maintenance, its dimension has not become apparent in Figure 5.6 previously. The NFF-specific analysis (right box plot in Figure 5.7) shows that 10.1% of the MRO process costs are avoidable due to NFF declaration, because no added-value through any repair or overhaul is performed.

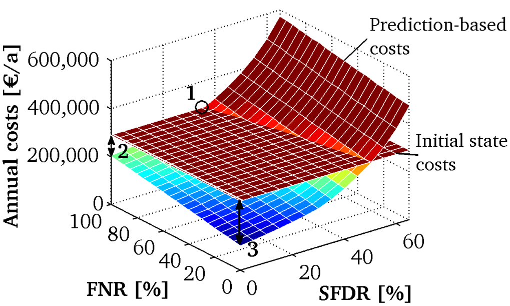
Based on the previously presented cost analyses, the total avoidable costs (Eq. 3.12) can be averaged to $C_{\text{avoidable,mean}} = 283{,}134$ €/a within the quantiles $C_{\text{avoid,2.5\%}} = 271{,}272$ €/a and $C_{\text{avoid.,97.5\%}} = 293{,}329$ €/a. The potentially avoidable costs account for estimated 98.27% of the total costs. Thus, the mean justified costs sum up to $C_{\text{justified,mean}} = 4{,}996$ €/a. If it is further distinguished between the airline and the MRO, 100% of the airline-specific costs resulting from unscheduled maintenance (DCC) are considered avoidable, whereas 38.9%

($C_{\text{avoid.,MRO,mean}} = 3{,}181$ €/a) of the MRO process costs are assumed to be avoidable. Firstly, the avoidable costs provide information on the LRU's savings potential. Secondly, they define the maximum allowable costs-of-implementation concerning a prediction model development. This will be discussed in the next section.

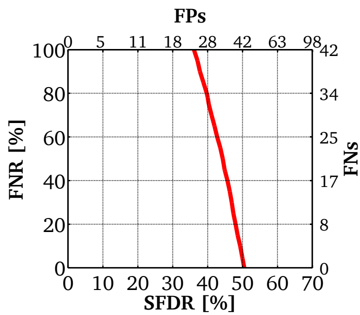
Additional analysis results, e.g. time-based and PN-specific target values, are provided in Appendix D.3 and not further discussed.

5.3.3 Exp. 3: Evaluation and discussion of prediction-based maintenance

The analysis of prediction-based simulation results is subject to the decision variables proposed in Section 5.1: FNR (rate of missed alarms), SFDR (rate of false alarms), Δt_{PF} (prediction forecast) and C_P (prediction costs). Based on the insights in Section 2.3.4, accuracy- and time-based prediction metrics are interdependent. Since univariate approaches as sensitivity analysis are not capable of accounting for input data relationships, *factorial experiments* consider simultaneous input data variations [Ach10]. The results are assessed by means of so-called *response surface graphs* (RSG) that visualise the impact of multivariate input data on the target values [MMAC09]. Due to the decision variables' discretisation (see Table 5.2), the response surface is locally approximated. In Figure 5.8 (a), for the exemplary prediction setting $\Delta t_{PF} = 300$min and $C_P = 17{,}500$ €/a, an RSG illustrates the total costs variation:



(a) Response surface graph



(b) Intersection curve

Figure 5.8.: Total costs example ($\Delta t_{PF} = 300$min, $C_P = 17{,}500$ €/a)

On the three axes in Figure 5.8 (a), the input values FNR and SFDR as well as costs as output are drawn. The FNR (Figure 5.8 (a) bottom left) and the SFDR (Figure 5.8 (a), bottom right) are varied according to Table 5.2. On the vertical axis in Figure 5.8 (a), the annual total costs are shown. For each prediction error setting, two calculated costs (prediction-based vs. initial state) are drawn and interpolated by spanning two planes. The planar plane represents the reference costs of the initial state (arithmetic mean of exp. 2 results). Since these costs are independent of the decision variables, they are constant. The prediction-based costs are variable and thus span a curved plane. If a particular error setting is beneficial, the calculated prediction costs plane will be below the initial state costs plane and vice versa.

In Figure 5.8 (b), the two plane's intersection curve is drawn. It can be interpreted as a break-even plot, indicating at which particular error settings the prediction costs are equal to the initial state costs. On the plot's bottom left, the varied error rates FNR and SFDR are drawn. On the plot's top right, the corresponding prediction error counts FP and FN are shown. For small error rate combinations (bottom left), prediction costs are lower than the initial costs. For high error rates (top right), prediction would lead to increased total costs. As can be derived from Figure 5.8 (b), the two error rates are interdependent: For instance, if the amount of false negatives is reduced (lower FNR), more false positives (higher SFDR) are allowable at the same total costs. With respect to the prediction cost plane, the parameter-specific gradients near the break-even curve show that the SFDR has the higher impact on total costs (higher SFDP-specific gradient than FNR). Thus, the break-even line's sensitivity towards SFDR variation is higher.

If one is interested in a particular prediction model's detailed benefits, additional information can be derived from the plot in Figure 5.8 (a): The *1*-marked intersection point between the cost curves indicates an error setting that almost represents the initial errors that apply in the real-world. At this point ($FNR = 100\%$, $SFDR \approx 36\%$), no TP predictions apply, thus all maintenance events are conducted correctively including all negative consequences. For the shown example, the SFDR of approx. 36% is slightly higher than the real-world value ($SFDR_{exp.2} = 31\%$). This arises from the advanced projectability that is also applied to FP predictions with a prediction forecast of $\Delta t_{PF} = 300\text{min}$. Thus, FP maintenance events are less costly than the real-world ones. In general, predictive maintenance concepts possibly lead to even more maintenance events within the same time period as opposed to today. Since they are scheduled in advanced, their overall costs can still be lower than in the initial state.

The *2*-marked difference ΔC_2 between the two cost planes in Figure 5.8 (a) approximates the savings potential through the reduction of FP prediction-related costs. This includes NFF costs as well as their consequences on flight operations.

The *3*-marked difference ΔC_3 between the two cost planes in Figure 5.8 (a) indicates the theoretical overall savings potential for the chosen prediction setting.

Although this ideal case implies that no prediction errors apply at all, for this prediction setting, the derived avoidable costs in exp. 2 ($C_{\text{avoidable}} = 283{,}134$ €/a) would be prevented only partially. This can be accounted to the prediction forecast $\Delta t_{PF} = 300\text{min}$ not being long enough in order to avoid all negative operational impacts.

Concerning the difference between the previously discussed two margins ($\Delta C_3 - \Delta C_2$), the impact of FN predictions on costs becomes obvious (independent of FP prediction errors). The cost difference represents the savings potential due to a correct prediction and its forecast only.

In the previous example, only the calculated cost distribution's mean values are considered. In the following, the assessment of numerous data distributions is discussed. Common statistic tests for the comparison of two distributions, such as the *t-test* or the *Mann-Whitney U test*, primarily evaluate the level of significance as a measure of the diversity between two distributions [RFHN06]. In this study, only absolute measures quantifying the difference between particularly representative values are required. Measures, such as e.g. *effect size*, only apply for the comparison of two distributions with identical variance. For this reason, concerning the exp. 3 simulation results specifiable as *non-central*, *variance-differing* distributions, the location parameters illustrated in Figure 5.9 are simply contrasted to the exp. 2 mean average results:

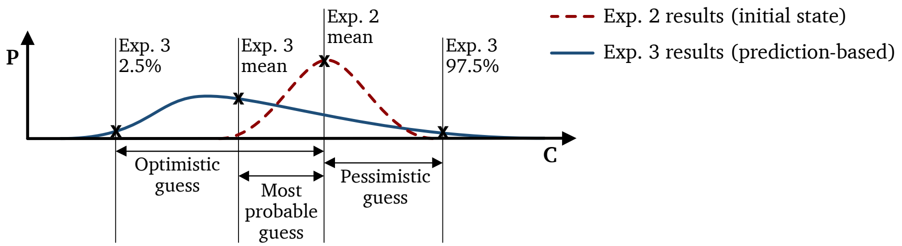


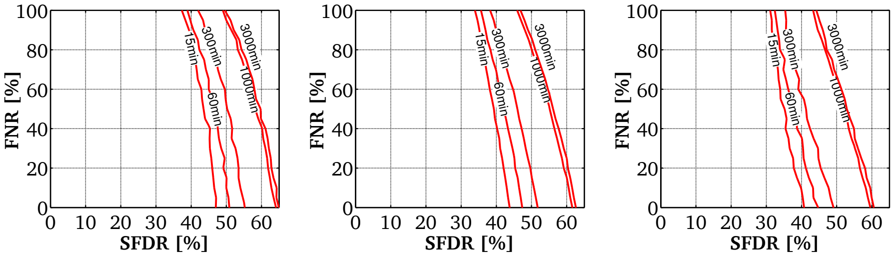
Figure 5.9.: Cost distributions, considered location parameters and their relations

Based on specific location parameters, in Figure 5.9, the considered cost differences with respect to the initial state's mean average costs are illustrated: An optimistic guess (exp. 3, 2.5% quantile) represents predicted costs that will not be underrun with 97.5% probability. Opposed to the median, the exp. 3 arithmetic mean accounts for outliers and enables the representation of the most probable difference. A pessimistic guess (exp. 3, 97.5% quantile) defines costs that will not be exceeded with 97.5% probability. In the following, the simulation results for exp. 3 with respect to the total costs are provided.

5.3.3.1 Exp. 3 total costs

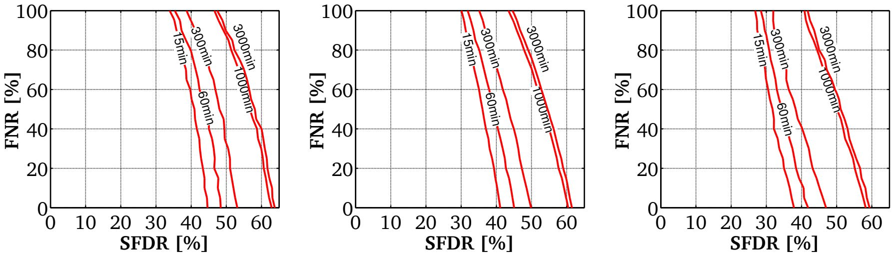
In Figure 5.10, the impact of prediction-based event initiation on total costs is analysed by means of break-even curves, further explained in the following:

Variant 1: Best-case prediction costs



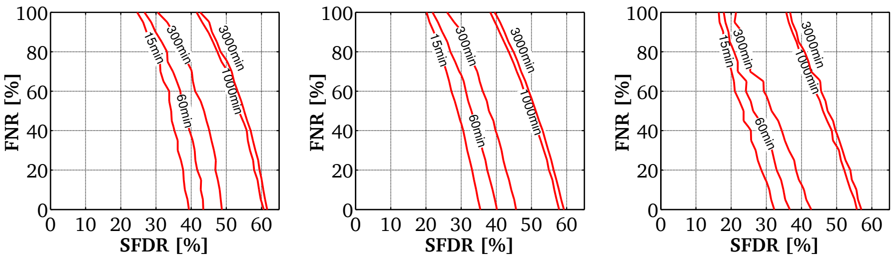
(a) 2.5% quantile (b) Mean average (c) 97.5% quantile

Variant 2: Realistic prediction costs



(d) 2.5% quantile (e) Mean average (f) 97.5% quantile

Variant 3: Pessimistic prediction costs



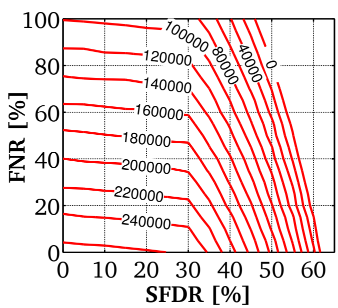
(g) 2.5% quantile (h) Mean average (i) 97.5% quantile

Figure 5.10.: Total costs break-even plots with respect to different prediction costs, location parameters and prediction forecasts

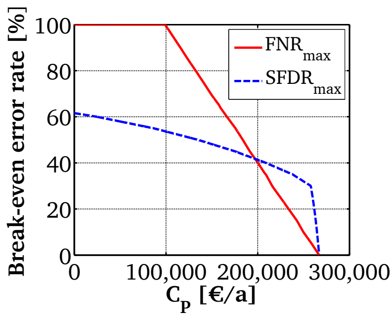
As discussed before, the simulation results are opposed to the initial state mean average costs. Furthermore, in Figure 5.10, various aspects are depicted: first of all, the rows refer to the different prediction costs scenarios. Row 1 shows the break-even plots if no prediction costs apply (variant 1). In the middle row, the results with respect to realistic prediction costs (variant 2) are shown and in the bottom row, the results for pessimistic prediction costs (variant 3). The three columns distinguish between the aforementioned location parameters: In the first column, the 2.5% quantiles of the prediction-based simulation results are considered. In the second column, the mean average values are applied. In the last column, the 97.5% quantiles are accounted for. Within each plot, the break-even curves for all computed prediction forecasts Δt_{PF} (indicated by the labels) are shown. Again, the curves are derived from the approximated intersection line between the previously discussed planes (see Figure 5.8 (a)). In the following, the results are discussed in detail with respect to these differentiating aspects.

Concerning the prediction cost scenarios (Figure 5.10, rows), their qualitative effects on the break-even curves become obvious. The higher the implementation costs, the less prediction errors are allowable if the break-even costs are considered as fixed boundary conditions. This equally applies for the different location parameters (columns) as well as prediction forecasts (set of curves in each plot). Prediction costs can be interpreted as an offset applied to the prediction-based costs towards higher cost levels. Thus, the particular break-even curve is further shifted to the plot's bottom left corner (less prediction errors allowed).

In Figure 5.11, the insights concerning prediction costs are illustrated by means of an example for the mean average (2nd column in Figure 5.10) and $\Delta t_{PF} = 1{,}000\text{min}$:



(a) Impact of C_P on break-even curves



(b) Impact of C_P on break-even error rates

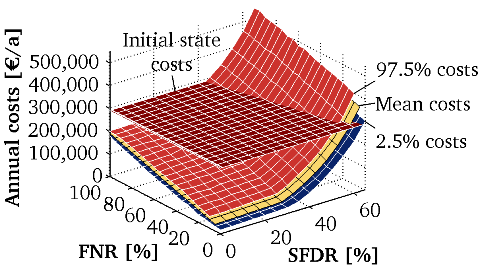
Figure 5.11.: Impact of fixed prediction costs on break-even curve and error rates (distribution's mean average, $\Delta t_{PF} = 1{,}000\text{min}$)

In Figure 5.11 (a), numerous break-even curves concerning alternating prediction costs C_P are plotted. As discussed before, higher prediction costs lead to less allowable error ratios. Concerning the curves' shapes, a second effect becomes apparent: whereas for low prediction costs, only the SFDR is limiting, for $C_P \gtrsim 100{,}000$ €/a the FNR becomes limiting as well. This particular value equals the cost difference *2* (ΔC_2) in Figure 5.8 (a) for this particular case.

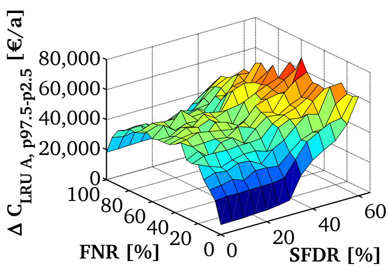
Due to the SFDR's hyperbolic behaviour, for small SFDR ratios, the FNR becomes more critical. Figure 5.11 (b) illustrates the break-even curves' intersection points with the error ratio axes. Here, the previously discussed characteristics become apparent as well. At $C_P \approx 200{,}000$ €/a, the FNR limit for break-even becomes more restricting than the SFDR limit.

Concerning the distribution's location parameter-specific analysis (Figure 5.10, columns), the results agree with the expectations. The simulated prediction cost distribution's 2.5% quantiles (Figure 5.10, left column) show particularly beneficial cases allowing to conduct more prediction errors at the break-even settings as opposed to the 97.5% quantile results (Figure 5.10, right column) representing especially expensive cases. These differences can also be interpreted as offsets at each calculated prediction cost value, although not being constant over different error rates as the offset arising from prediction implementation costs.

For every prediction error setting, a cost distribution is calculated providing the discussed location parameters. Figure 5.12 (a) illustrates the location parameter-specific cost planes for the exemplary setting $C_P = 0$ €/a and $\Delta t_{PF} = 1{,}000$min. Figure 5.12 (b) shows the error rate-specific cost differences between the best- (2.5%) and worst-case (97.5%):



(a) Total costs response surface graphs for the three location parameters



(b) Cost difference between the 97.5%- and 2.5%-quantile results

Figure 5.12.: Impact of location parameters on total costs (variant 1 ($C_P = 0$ €/a), $\Delta t_{PF} = 1{,}000$min)

In Figure 5.12 (a), the initial costs as well as three prediction-based cost planes referring to the three location parameters are drawn. The behaviour meets the expectations: the 2.5% results represent the lowest costs, the 97.5% plane the highest costs. Figure 5.12 (b) illustrates the cost differences per error setting between the 2.5% and 97.5% planes. Two characteristics are observed: firstly, for higher SFDR, the cost difference increases. This refers to wider variation of the underlying distributions, primarily arising from the SFDR's hyperbolic characteristic. Secondly, concerning the FNR, the cost differences, and thus uncertainty, become minimal at the extreme points, which represent either exceptional real-world event initiation ($FNR = 100\%$) or exceptional prediction-based event initiation ($FNR = 0\%$). Any setting in between refers to mixed event initiation types and thus an overlapping of the distributions at the extreme points. This results in a higher variation of the mixed cost distributions and thus increased ranges. This can also be explained by any step-wise effects concerning the prevention vs. generation of delays or cancellations, having a significant impact on costs. These characteristics also provide an explanation for the noisier data in the quantile plots in Figure 5.10.

The prediction forecast-specific analysis (see set of curves in each plot in Figure 5.10) also shows conformity with the expectations: the longer the PF, the more prediction errors apply at the break-even points, as indicated by the curve shift to the upper right. The economical benefit of longer forecasts refers to the advanced planning ability, further reducing consequential costs. In the following, the example of variant 1, mean prediction-based costs (Figure 5.10 (b)) compared with the results for $\Delta t_{PF} = 15$min and $\Delta t_{PF} = 1{,}000$min, is discussed in detail.

Concerning these particular break-even curves in Figure 5.10 (b), it can be derived that any point of the $\Delta t_{PF} = 15$min curve is left (lower SFDR) of the $\Delta t_{PF} = 1{,}000$min curve. Even if no FN predictions apply ($FNR = 0\%$), meaning all justified events are predicted in advance, the allowable ratio of FP predictions ($SFDR \approx 43\%$) is always lower than all break-even settings for $\Delta t_{PF} = 1{,}000$min. For the latter, even if all justified events were not predicted in advance ($TP = 0$, $FNR = 100\%$), the allowable FP ratio ($SFDR \approx 46\%$) is higher than the allowable maximum for $\Delta t_{PF} = 15$min. More generally, for one particular prediction error setting (FNR_i, $SFDR_i$), the prediction model with the higher prediction forecast reduces costs even further. The applicability of these results is limited, due to the trade-off discussed in Section 2.3.4 that a higher forecast horizon usually leads to increased prediction error ratios, which has not been accounted for so far. An exemplary relationship is proposed and discussed in Section 5.3.3.2.

In Figure 5.10, the significance of the non-equidistant PF value definition becomes apparent as well. The PF's impact on costs follows a regressive behaviour: for short PF intervals, e.g. see break-even curves for $\Delta t_{PF} = 15$min and $\Delta t_{PF} = 60$min, costs can be significantly reduced through interval quadruplication. The improvement for longer PFs, e.g. see plots for $\Delta t_{PF} = 1{,}000$min and $\Delta t_{PF} = 3{,}000$min, becomes incremental as indicated by the nearly superposed curves. This effect is accounted to the characteristics of available maintenance opportunities. For short PFs, any saved amount of time concerning on-ground maintenance preparations reduces any delay times and thus costs. For longer PFs, the improved planning effect on operations decreases.

In Figure 5.13, the allowable break-even error rates for pre-defined cost saving scenarios are depicted. Again, the example for variant 1 ($C_P = 0$ €/a) and the mean average values (Figure 5.10 (b)) is discussed:

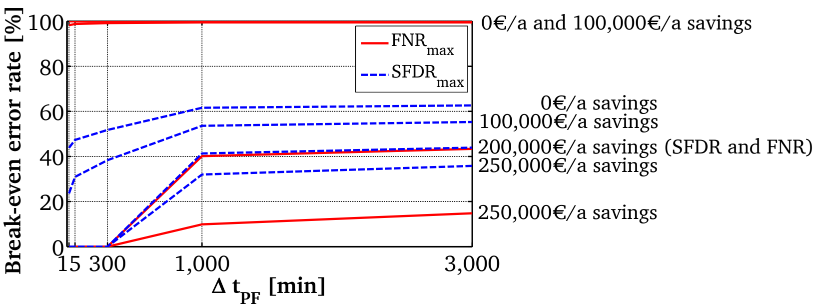


Figure 5.13.: Interdependency between prediction forecast and maximum allowable error rates for pre-defined saving scenarios ($C_P = 0$ €/a, mean)

Because only five prediction forecast settings are analysed, in Figure 5.13 the curves are drawn be means of linear interpolation. Again, it is distinguished between the FNR- and SFDR-break-even settings. The allowable rates for four different cost savings (0 €/a; 100,000 €/a; 200,000 €/a; 250,000 €/a) are shown. As discussed before, the curves' regressive behaviour becomes apparent. This plot provides valuable information to the prediction model developer: depending on which savings are aimed for – also keeping in mind the projected development costs – the interdependency between the prediction forecast and the allowable error rates is accounted for, providing rough specification parameters.

A parameter specifying a prediction model's optimum setting is the total savings potential ΔC_3. It applies if no prediction errors apply (ideal model: FNR=0%, SFDR=0%) and refers to the *3*-marked point in Figure 5.8 (a). In Figure 5.14, the savings potentials with respect to the different implementation cost settings as well as prediction forecasts are analysed:

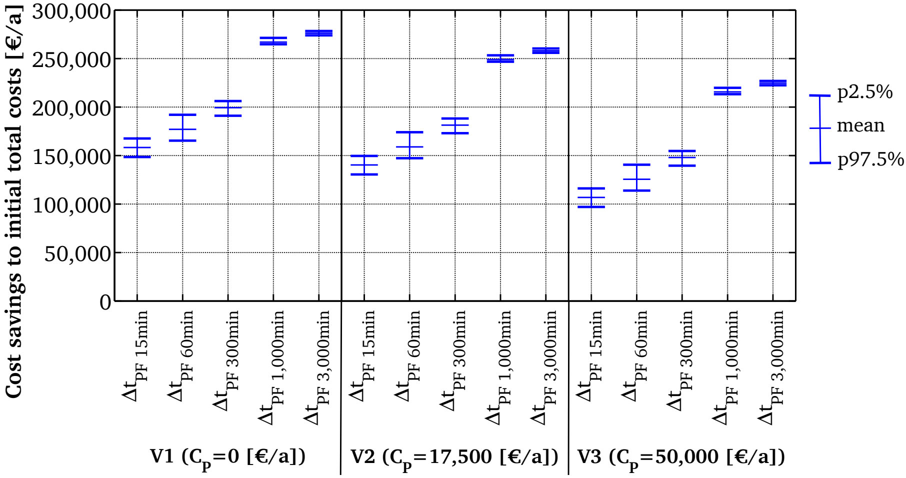


Figure 5.14.: Total savings potentials with respect to C_P and Δt_{PF}

The cost savings' decrease for higher prediction costs C_P arises from the incurring offset. Within one particular variant, the effect of the prediction forecast becomes apparent. Whereas $\Delta t_{PF,V1} = 15$min ideally can save 150,000-170,000 €/a, $\Delta t_{PF,V1} = 3{,}000$min possibly allows to save costs almost at the total avoidable costs level. Additionally, for longer PFs the distribution's variation decreases. This effect is expected to result from the ability to schedule predicted maintenance events in an optimal manner. For short PFs, the effects of varying maintenance event durations also have differing impacts on aircraft and maintenance operations.

Additional analysis results are provided in Appendix D.4 and not further addressed. In the next section, an optimisation procedure based on exemplary assumptions is discussed.

5.3.3.2 Optimisation example

The aforementioned analyses enable the specification of minimum requirements. As long as particular prediction model characteristics are not given, the interdependency between the error rates, the prediction forecast as well as the development and implementation expenses remains unknown. The prediction-based total costs' dependencies on the four decision variables can be expressed as shown in Eq. 5.8:

$$C_{LRU_i} = f(\mathrm{FNR}_i, \mathrm{SFDR}_i, \Delta t_{PF_i}, C_{P_i}) \tag{5.8}$$

In order to provide exemplary economical optimisation results determining the optimum prediction model setting, particular assumptions are met in the following (see Eq. 5.9-5.11). By formulating virtual parameter relations, their interdependencies are described. This way, the amount of unknown variables is reduced:

$$FNR \geq 5 \cdot \left(\frac{k_{PF}}{SFDR} - 1 \right) \tag{5.9}$$

$$C_P = (60 \cdot k_{PF} + 100) \cdot \left(e^{-4 \cdot FNR + 7} + e^{-11.4 \cdot SFDR + 7} \right) \; [€/a] \tag{5.10}$$

$$\text{with} \quad k_{PF} = \ln(\Delta t_{PF} + 1) \tag{5.11}$$

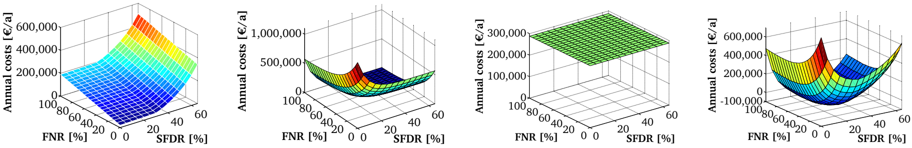
$$\text{for} \quad FNR \in [0;1], \, SFDR \in [0;0.65], \, \Delta t_{PF} \in [0;3{,}000]$$

Similar to the idea of ROC curves (e.g. see [Ekl13]), in Eq. 5.9, by reciprocally relating the FNR and SFDR, minimum prediction error settings are defined. A reduction of the SFDR is only possible if the FNR is increased and vice versa. By means of the inequality relation, especially low error rates – considered to be technically not feasible – are excluded. The correlation is also dependent on the prediction forecast, see k_{PF} (Eq. 5.11). Using the natural logarithm, the previously discussed regressive behaviour (see Figure 5.13) is approximated. A higher Δt_{PF} leads to a relationship characterised by increased prediction error ratios. The correlations of Eq. 5.9 and 5.11 are illustrated in Figure D.9 in Appendix D.4.

In Eq. 5.10, an exemplary formulation for prediction implementation costs is given. For the representation of progressively increasing development efforts in order to realise prediction errors tending to zero, the cost's dependency on FNR and SFDR is formulated by exponential functions. Again, with k_{PF}, a logarithmic dependency factor with respect to the prediction forecast is defined, further increasing costs for extended forecast windows. Figure D.10 in Appendix D.4 illustrates the behaviour defined by Eq. 5.10.

The relationship between the decision variables and the total costs is provided by means of the aforementioned simulation results. In order to obtain analytically solvable equations, the numerically approximated cost planes can be applied to curve fitting procedures. In Eq. D.1 in Appx. D.4, a 3rd degree polynomial approximation for the exemplary setting shown in Figure 5.10 (b) (variant 1, mean average, $\Delta t_{PF} = 1000$min) is given, not further addressed in the following. Subsequently, only mean average simulation results with respect to the five pre-defined prediction forecasts are considered.

The overall cost-benefit analysis covers the elements illustrated in Figure 5.15:



(a) $C_{Proc} + C_{Ops}$ (b) C_P (c) $C_{LRU\ A,\text{Exp.2}}$ (d) $\Delta C_{LRU\ A}$

Figure 5.15.: Optimisation example: Prediction-based total costs (a), approximated prediction costs (b), initial state total costs (c) and cost difference (d) for $\Delta t_{PF} = 1000\text{min}$

For the derivation of a prediction model's optimum setting, the cost data shown in Figures 5.15 (a)-(c) is required: The simulation results provide process costs and DCC (Figure 5.15 (a)) for a pre-set prediction forecast. In addition, prediction costs (Figure 5.15 (b)) are defined according to Eq. 5.10. If the exp. 2 results (initial state costs, Figure 5.15 (c)) are subtracted from the previous costs, the cost savings and additional costs $\Delta C_{LRU\ A}$ can be illustrated as shown in Figure 5.15 (d).

If the minimum prediction error setting restrictions (Eq. 5.9) are applied for each prediction forecast Δt_{PF}, the optimum cost-benefit prediction model setting $(FNR_{opt}, SFDR_{opt})$ can be determined, as summarised in Table 5.8:

Table 5.8.: Prediction forecast-specific optimum cost-benefit settings

Pred. forecast Δt_{PF} [min]	**Missed alarm rate** FNR_{opt} [%]	**False alarm rate** $SFDR_{opt}$ [%]	**Min. total costs** $C_{LRU_{opt}}$ [€/a]
15	75	20	265,655
60	85	25	267,463
300	90	30	264,880
1,000	95	35	232,688
3,000	95	40	250,539

In Table 5.8, the optimum setting for each considered prediction forecast is provided. As shown in columns 2 and 3, with increasing Δt_{PF} , the optimum points are shifted towards higher prediction error rates. It can be derived that for the given boundary conditions, the optimum cost-benefit case applies for the prediction forecast $\Delta t_{PF} = 1{,}000\text{min}$. At the optimum, the total costs $C_{LRU_{opt}} = 232{,}688$ €/a enable costs savings of $\Delta C_{LRU} = 55{,}442$ €/a as compared to the initial state. The derived optimum error rates ($FNR_{opt} = 95\%, SFDR_{opt} = 35\%$) are close to the initial state's characteristics: in this case, only 5% of the predictions were true (TP), whereas 95% failed to indicate a justified event in advance (FN). The SFDR is close the initial state's rate of FP predictions. So the prediction forecast primarily improves maintenance by optimising scheduling with relatively poor performance. The local maximum behaviour around $\Delta t_{PF} = 60\text{min}$ is accounted to approximation errors due to the step size of 5% with respect to FNR and SFDR variation.

For the minimum cost's derivation, the exclusion of inapplicable error ratios defined in Eq. 5.9 is applied. Figure 5.16 illustrates this restriction's application:

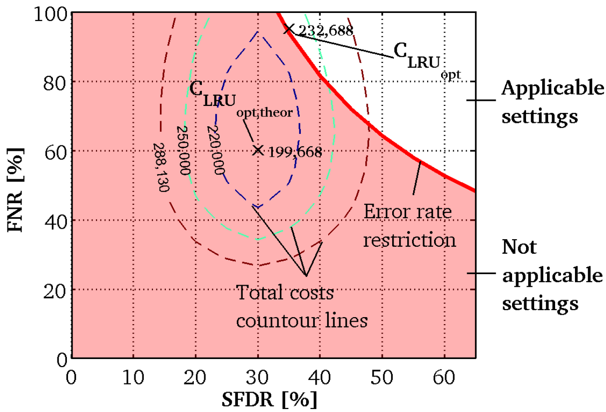


Figure 5.16.: Restrictions on applicable pred. model settings ($\Delta t_{PF} = 1{,}000\text{min}$)

By excluding the red shaded area under the error rate restriction curve in Figure 5.16, only cost values covering applicable prediction settings are accounted for (top right in Figure 5.16). Thus, the indicated theoretical cost savings optimum $C_{LRU_{opt,theor}} = 199{,}668€/a$ at $SFDR = 30\%$, $FNR = 60\%$ is not considered. Within the area of applicable prediction settings, the optimum applies at the prediction error combination with the lowest costs ($C_{LRU_{opt}}$). The optimum prediction settings analysis plots concerning the additional prediction forecasts are provided in Figure D.11 in Appx. D.4.

The next section summarises the gained insights based on the obtained results.

5.4 Conclusions

In this chapter, the evaluation method's application was described. A case study was designed covering an exemplary shorthaul aircraft component in the evaluation period of four years. The applied cost data is exemplary, based on published literature as well as expert consultations. The conducted model calibration and validation procedure (exp. 1) leads to the conclusion that the model's correctness strongly depends on the available data's quality and degree of standardisation. The less variation is incorporated in the real-world temporal data, the more precisely the underlying activities can be represented. The case study calibration and validation results show observable deviations that stay within pre-defined accuracy-boundaries, thus enabling model validation. The specific deviations show that actual on- or off-aircraft maintenance task durations were overestimated. In particular, transit replacements are accomplished faster, possibly due to stricter than expected priority requirements in the real-world.

In the initial state's cost analysis (exp. 2), today's savings potentials are analysed. First, the required amount of simulation replications is discussed. In the case study example, 11,256 samples were considered to be sufficient. Concerning the exemplary LRU, the cost-based analysis revealed that the majority of total costs is avoidable (98.27%). The DCC (C_{Ops}) account for the most part (97.2%), representing 100% avoidable costs applying for the airline only. Because the example component's replacement duration does not fit into regular flight schedule turnaround times, it leads to costly delays and cancellations. Among the MRO process costs (C_{Proc}), 38.9% are declared avoidable through troubleshooting and non-value added activities. Opposed to the delay and cancellation costs, the maintenance expenses do not imply significant potentials for cost reduction. Concerning the total costs ($C_{LRU_A,\text{mean}} = 288{,}130$ €/a), the 95% confidence interval spans a range of $\Delta C_{LRU_A,97.5\%-2.5\%} = 22{,}028$ €/a. The conducted error propagation example showed that this variation can be accounted to the defined accuracy requirements as well as the input data uncertainties.

By means of simulating prediction-based maintenance (exp. 3), the evaluation tool's specification function is applied. The RSG plots illustrate the sensitivity of costs to the missed alarm (FNR) and false alarm (SFDR) prediction error rates. The break-even plots specify minimum requirements to avoid more costly future concepts. With respect to the multivariate cost analyses in Figure 5.10, the impact of prediction costs, probabilistic characteristics as well as the prediction forecast (PF) was shown. The prediction costs are independent of the maintenance events conducted. They can be understood as a linear cost-based offset. The comparison of quantile-based values provides information on the best- and worst-case results. This way, the evaluation results address an analyst's preferences with respect to pessimistic or optimistic estimates. The influence of varying prediction forecasts is shown by a shift of the break-even curves. More prediction errors can be conducted if the forecast is extended at the same costs. This effect decreases for longer forecasts (see Figure 5.13).

In general, prediction models with higher PFs are not necessarily superior to models with shorter PFs, because the error ratio is expected to increase accordingly. For this reason, the optimisation example in Sec. 5.3.3.2 considers these aspects by means of exemplary mathematical formulations. The definition of minimum prediction error ratios restricts the solution space to applicable prediction settings only. A correlation parameter k_{PF} leads to increased error ratios for higher PFs. An additional relationship (Eq. 5.10) accounts for variant prediction costs and higher efforts for more sophisticated prediction models. This way, it is assumed that more sophisticated models are more expensive to build. The exemplary assessment shows that the overall cost optimum applies for a prediction model with long prognostic forecast and poor accuracy. Apparently, the improved projection ability seems to sufficiently compensate for any false predictions. For the prediction-based maintenance approach, more maintenance events are initiated as opposed to the initial state. Again, these results have to be considered as LRU-dependent.

As a summary, it can be concluded that a prediction model's cost effectiveness depends on its model performance (errors, forecast) as well as the related development and implementation costs. The introduced dimensionless error rates relate common prediction errors (FP, FN) to their cost-specific impacts on aircraft and maintenance operations. An FN prediction primarily affects flight operations, whereas an FP prediction leads to increased NFF efforts in maintenance. The PF is a measure for the model's projection ability and directly related to enabled (or allowed) error rates. A high PF improves the scheduling of maintenance events and reduces the negative impacts on the airline and MRO side. Concerning the analysis of a predictive future approach, one has to keep in mind that in the initial state maintenance, the same errors are made already: in corrective maintenance, all maintenance events are not predicted and prepared for in advance. Thus, all justified events can be classified as FN (no TP predictions). The maintenance events classified as NFF can be considered as false alarm (FP) cases.

6 Summary and conclusions

At the beginning of this thesis, today's perceptions concerning costs in aircraft maintenance in civil aviation were discussed. Opposed to the conventional maintenance concepts (corrective and preventive), the idea of prediction-based maintenance was introduced. Among its expected positive effects, e.g. increased aircraft availability and effectiveness of maintenance tasks, the additional risks concerning wrong decision making as well as cost-benefit issues were pointed out. As a result, two general goals were defined for this work: Firstly, from a component point of view, the cost savings potential of today's aircraft maintenance strategy should be identified. Secondly, the impacts of prediction-based maintenance approaches should be assessed in a detailed manner. For this purpose, a cost-benefit analysis was aimed to be conducted, taking equally into account aircraft and maintenance operations, as both are assumed to be affected. Because real-world operational data was available, a deterministic process-based simulation was chosen for the analysis.

In Chapter 2, the state of the art concerning aircraft maintenance, costs in civil aviation as well as fault prediction was explained. With respect to the characteristics of civil MRO operations, the general assignments and traditional concepts including the component-based view were discussed. Thereafter, the expected impacts of a prediction-based approach were introduced. Concerning costs in civil aviation, common cost classifications and exemplary cost distributions were presented. This included aircraft operations- as well as aircraft maintenance-based expenses. For the consideration of indirect costs, the *activity-based costing* (ABC) method was introduced. Lastly, general definitions and goals of fault prediction were discussed. By introducing common prediction metrics, adequate performance indicators were provided.

The proposed evaluation concept was introduced in Chapter 3. Based on further narrowing the focus of the study, correctively maintained components (LRUs) having negative impact on flight and maintenance operations were defined as the targeted level of detail. Subsequently, adequate cost- and time-based target values were established. Besides deriving target values on a top-level, as e.g. total costs, the generation of more specific measures was aimed for as well. This includes airline-specific delay and cancellation costs, MRO-specific department expenses or component modification-specific costs. The assessment was defined to be based on a maintenance modelling approach. Resulting from the literature review, a mostly deterministic approach on a microscopic assessment level was selected. The proposed evaluation method comprises three types of model building procedures: An aircraft operation model, a business process model (BPM) as well as a maintenance event initiation model. The aircraft operation model defines the system's boundary as well as the model's main elements. Specific state indicators were introduced to represent flight operations and maintenance as well as their interdependencies. Proposed modifications to the real-world flight schedule data enabled a more realistic representation with respect to the evaluation goals. The BPM was supposed to cover all relevant activities within an exemplary MRO company. By mapping the identified processes and defining descriptive as well as quantifying process factors, a generic framework for an activity-based assessment of maintenance costs was provided. The effects of prediction-based concepts were accounted for by particular model modifications. The event initiation model opposes real-world and virtual prediction-based triggering of maintenance events. For this purpose, different cases such as TP-, TN-, FP-, and FN-prediction were defined. A proposed relational data model provided the basis for the data-based analyses. A discrete event simulation (DES) is supposed to conduct retrospective Monte-Carlo simulation (MCS) replications by varying probabilistically defined input parameters, such as process durations. The introduced post-processing procedure enabled a results assessment on various levels of detail. The calculated target values should be statistically processed and presented to the user by means of a graphical user interface (GUI).

In Chapter 4, the concept's software implementation including its verification was described. *MATLAB* as the global software environment provides an adequate framework for the model implementations. As examples, the built state chart model as well as the BPM element library were discussed. Eventually, the conducted verification steps and the created GUI were described.

An exemplary case study was conducted in Chapter 5. The available input data refers to one shorthaul dispatch-critical aircraft component involving 42 maintenance events in the investigation period of 4 years. Concerning economical input parameters, labour rates and consequential costs of operational impacts were collected from literature. An assessment using historical costs covers inflation rate effects. Based on real-world data, the estimated process durations were calibrated first. An application to independent test data enabled the model's validation. A posteriori, the analysis of the maintenance's initial state was conducted. After the MCS convergence was proven, the cost-based target values of the initial state maintenance were statistically analysed. The airline-based breakdown costs are the most significant expenses (279,953 €/a, 97.2% of total costs) opposed to maintenance-related efforts (8,177 €/a, 2.8% of total costs). A more detailed view on maintenance process costs revealed that on- and off-aircraft tasks account for the most part. Avoidable troubleshooting-based expenses sum up to 2,353 €/a and NFF costs to 828 €/a. Thus, the overall avoidable costs reach 283,134 €/a.

The conduction of prediction-based simulation experiments enabled to oppose the initial state costs to virtual future state's results. In order to account for different prediction models, pre-defined metrics representing prediction errors (false negative rate *FNR*, specific false discovery rate *SFDR*) as well as prediction forecasts (Δt_{PF}) and costs-of-implementation (C_P) were varied within reasonable ranges. This way, unknown dependencies and possibilities were accounted for by creating a global solution space. By visualising the cost's sensitivity to the decision variables, the user is provided an intuitive results assessment. If specific parameters are fixed, the corresponding maximum allowable prediction model design parameters can be determined. The definition of break-even settings (prediction-based costs equal to initial state costs) enabled to derive minimum requirements.

The results concerning a predictive maintenance approach showed that the combination of the prediction model immanent, interdependent characteristics (FNR, SFDR, Δt_{PF}) is a key factor in a model's cost-benefit. Increased prediction forecasts further improve the scheduling of maintenance, in particular leading to less negative impact on flight operations. Opposed to that, higher forecasts also lead to increased prediction errors. It was shown that the specified minimum requirements concerning error rates and forecasts also depend on the development and implementation costs of a predictive concept. An exemplary optimisation routine showed the interdependency of the aforementioned factors. For the given constraints, a prediction forecast Δt_{PF} of 1,000min provided the cost optimum enabling savings of 55,442 €/a in the mean average. For this particular setting, more maintenance events are conducted than in the initial state. Because the scheduling is improved, prediction still leads to a more economic business case.

The main perceptions derived from this study are summarised as follows: A cost-benefit analysis of the initial state is considered a meaningful step in order to assess a particular component's cost savings potential. By this assessment, instantaneous decision-support is provided by either justifying further analyses and prediction model development efforts or possibly preventing any additional expenditures. Concerning the results' validity, the analysis of aircraft components being subject to highly standardised maintenance procedures should be aimed for in order to minimise the output values' variation. The costs expected to be avoidable arise from negative impacts on flight operations, ad-hoc MRO troubleshooting activities as well as NFF-declared events. The component-specific MRO cost distribution largely depends on LRU-specific requirements and maintenance characteristics.

Concerning the analysis of various prediction model settings, the effects on costs met the expectations to a large extent: generally, higher prediction forecasts allow more prediction errors. Because these metrics' interdependency also follows this pattern–when looking further into the future, the uncertainty is increased–the exact outcome can only be assessed by providing distinct prediction model information quantifying the parameter correlations. It was shown that even short prediction forecasts enable significant cost savings if the error rates are similar to the initial state's ratios. On the other hand, prediction forecasts Δt_{PF} greater than 1,000min do not seem to provide any additional benefits. This is expected to result from aircraft operations-specific boundary conditions, e.g. daily planned maintenance ground times. The statistical assessment shows that the cost difference between worst-case and best-base conditions can be significant. Thus, detailed information on the potentials and risks of particular prediction settings is provided.

It has to be considered that the discussed results represent one exemplary case. From the observed cost-benefit analysis characteristics, it is concluded that the economical benefit strongly depends on the particular component's savings potential as well as the feasible prediction model performance. For especially safety-relevant components, a preventive strategy will still be the first choice. On the other hand, for wear-out components not requiring scheduling in advance, e.g. because the rectification can be deferred or the rectification does not affect flight operations, corrective maintenance still is expected to be the adequate approach.

The novelty of this dissertation comprises to deterministically represent aircraft maintenance operations based on real-world operations data. By conducting detailed analyses, particular event-specific causes and effects between different MRO departments as well as aircraft operations are exactly accounted for. For instance, any step-wise effects of extended prediction forecasts can be considered by applying the real-world flight schedule information *to-the-minute*. By relating dimensionless prediction metrics to costs, a general assessment method has been developed. It intuitively illustrates the break-even cost requirements and allows a comparison of prediction results for different components. This way, particular potentials and risks are visualised. Eventually, the basis for decision making concerned with a shift to a new maintenance strategy is provided.

A weakness of the method comprises the dependency on available real-world information. It only allows to evaluate a prediction strategy's effectiveness by opposing it to the initial state. The more accurate and detailed the available data is, the more meaningful the results are expected to be.

6.1 Recommendations

The derived recommendations are addressed to the corresponding stakeholders identified to be involved in the method's field of application. Figure 6.1 illustrates the way the developed evaluation tool is embedded into the existing environment:

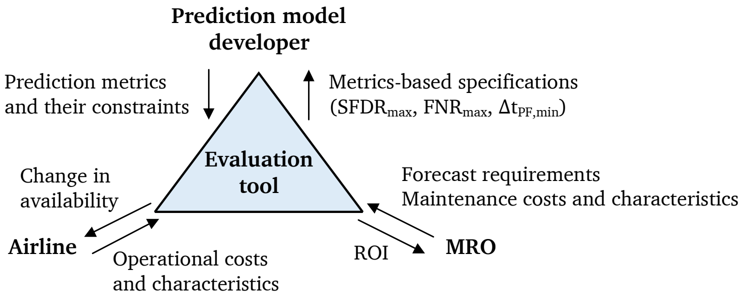


Figure 6.1.: Evaluation tool at the interface between developer, airline and MRO

The tool provides interfaces to the airline, the maintenance company (MRO) as well as the prediction model developer. Whereas the airline has to contribute operational characteristics and costs, it receives information on how the aircraft availability is expected to be affected by a prediction-based maintenance strategy. The MRO company needs to provide detailed operational information in order to describe the initial state as well as the forecast requirements. In turn, detailed *return-on-investment* (ROI) information accounting for avoided costs opposed to investment costs is given. Concerning the developer, the tool either provides minimum/maximum specifications based on analysis results or accounts for available model metrics including their constraints.

Based on these insights and grouped according to the addressed stakeholders, the derived recommendations are presented below:

Airline

- Because the airline needs to provide information on cost saving potentials concerning maintenance-induced operational impacts, it is advised to provide valid cost data as detailed as possible. For instance, because available spare aircraft can possibly compensate for any other aircraft's ad-hoc flight cancellations, these effects should be accounted for in the economical considerations. Any relevant time- (e.g. delay durations) and cost-based (e.g. costs of spare aircraft) characteristic further improves the analyses' credibility.

- For privacy protection reasons, many airlines in civil aviation still forbid extensive usage of aircraft in-flight data. If the overall benefit of predictive maintenance for flight operations becomes clearer, their doubts can possibly be eliminated in the future, enabling even more detailed component information.

MRO company

- In order to maximise the evaluation's benefit, the MRO company should select adequate components. This includes LRUs either causing operational irregularities (airline side), intensive troubleshooting, ad-hoc efforts or NFF expenses (all MRO side). The aforementioned impacts can further be related to the discussed prediction metrics:
  - Airline side: In order to reduce the impact on flight operations, the prediction metrics improving the ability to correctly predict in advance should be optimised (low FNR, high Δt_{PF})
  - MRO side, ad-hoc efforts: For reducing the negative consequences of unscheduled ad-hoc maintenance events, the prediction forecast should be maximised (high Δt_{PF})
  - MRO side, NFF costs: To reduce the negative impact on non-value added maintenance costs (e.g. NFF), the metric preventing false alarms should be optimised (low SFDR)
  - MRO side, TS efforts: Troubleshooting efforts can be prevented by the implementation of diagnosis or prognosis systems per se
- In order to minimise the economical risks for the implementations of prediction, also because the investment costs are unknown in the first place, in the beginning the most promising components should be selected. Further implementation cases are then expected to benefit from economies of scales effects. Because a lot of considered expenses are fixed *step costs*, only the application of prediction to numerous components is expected to actually reduce costs, e.g. through an optimised allocation of resources (*production levelling*).
- The analysis of aircraft components being subject to highly standardised maintenance procedures should be aimed for. This way, the simulation output data's variation is minimised and more valid results are derived.
- If prevailing certification burdens concerning a shift from safety-relevant, preventively maintained items to predictive maintenance have been overcome, preventively maintained LRUs should be considered for the analyses as well.

- As discussed by [GV15], the actual decision making based on prediction-derived information has to be enforced in maintenance operations. Otherwise the expected benefits will not be achieved. For instance, the analyst can be confronted with contradicting information concerning his personal experience and a prediction model's algorithm-based decision. So the question is, how should the information be processed and illustrated in order to be trustworthy and useful (e.g. *yes/no* vs. $P_{yes} = 79\%$)? In the end, the human being has to decide. Human errors are proven to have significant impacts on maintenance effectiveness, as extensively discussed in [Ach10].

- The MRO company is enabled to gain additional insights into weak spots in the existing maintenance procedures. So particular time-based analyses allow to investigate cycle- or wait-time-related issues (*critical path*). Today's misinterpretations, e.g. causing NFF maintenance events, can be further investigated concerning causes and effects.

- The simulation results concerning a PN-specific analysis were not discussed in detail (see Appendix D.3 and D.4). The result's variation for particular component modifications suggests to account for any unique characteristics while developing and tuning prediction algorithms. Possibly, different features and prediction error thresholds should be applied.

Prediction model developer

- In order to facilitate the development of prediction algorithms that are tuned by means of time-consuming training procedures, the pre-specification of metrics as detailed as possible is useful. With the evaluation tool, the developer can assess, whether the built models' metrics satisfy the break-even boundary conditions. If tuning procedures lead to incremental improvements only, an estimation of increased development costs possibly helps to identify abort criteria at an early stage. Thus, the prediction model's degree of sophistication can be adjusted to the approved development and implementation expenses.

- In case the developer encounters that a prediction model is not capable of operating within the given break-even error rate boundaries, it should be identified if this is caused by model-immanent deficiencies or by poor training data quality. For the latter, the data provider (e.g. MRO company) should then be given as detailed information on data quality or sampling rate requirements as possible.

In the next section, recommendations with respect to future scientific work are given.

6.2 Future scientific work

The potentials concerning future scientific work mainly arise from this work's assumptions and simplifications as well as their resulting limitations.

In this study, false predictions are represented in a very abstracted manner. If a prediction is conducted, maintenance will be performed accordingly. Any human experience-related or other contradicting effects are not considered, possibly ignoring or partially accounting for prediction outcomes. Furthermore, any more profound impacts of false positive predictions, as expected lifetime extension through the installation of a new component, are not considered. If the general assessment is not based on deterministic information, but probabilistically defined component failures, this effect can be accounted for more appropriately.

As discussed before, the analysis of preventively maintained components is advised to be conducted as well. Thus, a further description of routine maintenance tasks and extensions of the corresponding process model would be required. Because fault-specific deterministic empirical data will not be available in many cases, a shift to more probabilistic methods is expected to be inevitable.

In order to minimise the model's complexity, in this study, the interdependencies between different aircraft components and systems are not represented. If the proposed LRU-specific state indicators were extended by additional super- respectively sub-indicators, including mathematical definitions of their correlations, this aspect could be covered as well.

Opposed to the consumption of resources, their availability is not represented in the model. Especially, if simultaneous activities are simulated, this aspect becomes more important due to limited capacities in real-world (e.g. personnel or hangars). Thus, the implementation of capacity provision model extensions would further enhance the evaluation tool's value.

Spare parts inventory aspects have not been covered. In this field, a lot of research has been conducted already. Thus, a simulation module covering spare part logics and boundary conditions (e.g. minimum service level) would increase the tool's significance.

The Monte-Carlo simulation method comprises drawbacks related to computation time and thus long analysis response times. Primarily, the method was chosen due to the probabilistically defined process durations. If more exact empirical information were available, the simulation duration could be considerably shortened.

The analyses' value can further be increased by providing information on more maintenance events per component (higher sample size). This way, the results' variation is reduced and the credibility of the derived conclusions increased.

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A State of the art supplementaries

A.1 Maintenance, repair and overhaul in civil aviation

Table A.1.: Classification of exemplary maintenance events. Based on [Lin05]

Object	Routine Maintenance	Non-Routine Maintenance
Aircraft	Preflight checks, daily/weekly checks, A-check, C-check, D-check	Troubleshooting, airworthiness directives, modifications
Engine	Oil checks, trend monitoring, overhaul	
Component	Checks, overhaul	

B Concept supplementaries

B.1 Financial target values

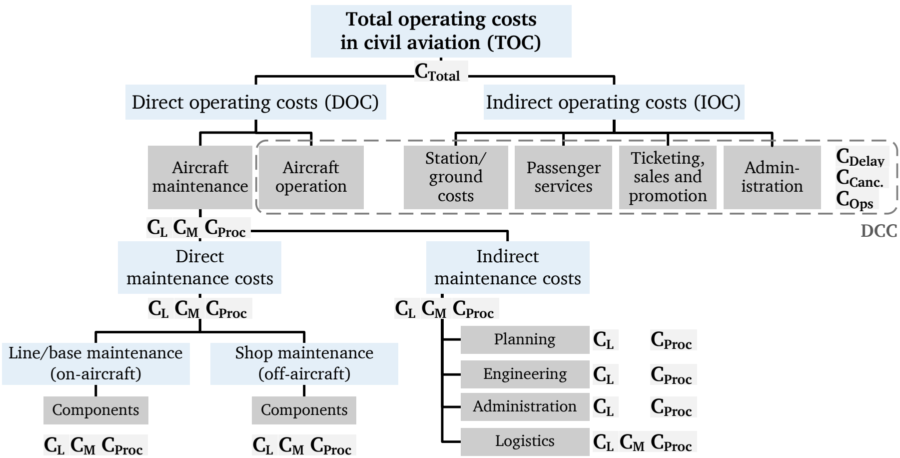


Figure B.1.: Applied cost structure

B.2 Literature review

Table B.1.: Literature review of maintenance modelling approaches

Literature	Title	Method keywords
[Ach10]	Modelling, simulation and optimization of maintenance strategies under consideration of logistic processes	Probabilistic, process model
[El 06]	Optimizing life-cycle maintenance cost of complex machinery using advanced statistical techniques and simulation	Probabilistic
[FJS09]	A methodology for determining the return on investment associated with prognostics and health management	Probabilistic, cost-benefit analysis
[Fro09]	Assessment of innovative maintenance scenarios in early stages of the innovation process in aviation	Probabilistic, process model, life cycle analysis
[HSNG12]	System analysis of prognostics and health management systems for future transport aircraft	Probabilistic, life cycle analysis
[Lin05]	Performance measurement in civil aircraft maintenance	Deterministic
[Van15]	Integrated systems health management as an enabler for condition based maintenance and autonomic logistics	Probabilistic
[Wun02]	Cost simulation – simulation-based cost-benefit-control of complex production systems	Deterministic, cost-benefit analysis

B.3 Model building

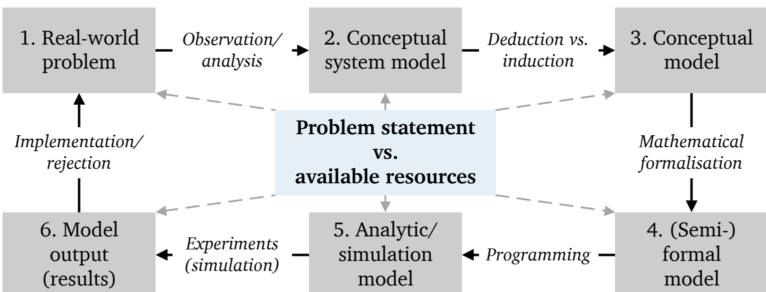


Figure B.2.: General model building procedure [Buc06]

Table B.2.: Overview of modelling principles. Based on [BPV12]

Principle	**Description**
Validity	Validity can be split into syntactic and semantic validity. A modelling language is defined by its syntax that defines the unique grammar, in case of a textual language, or the visual appearance for a graphical modelling language. If the syntax is followed exactly during the building process, the model is syntactically valid. Examples are the correct use of information objects or notation symbols. A more detailed description and examples can be found in [BPV12]. A model is semantically valid, if the transfer of a conceptual system model to a formal model is correct, meaning without any logical discrepancy. Semi-formal models are created, if semi-formal model languages are used, e.g. the event-driven process chain (EPC) method. These can be characterised by the lack of some unique syntax definitions, as described in [Sta06].
Relevance	The principle of relevance implies to only model what is needed to sufficiently represent the real-world problem. It also comprises to limit or extend an existing modelling languages, if this increases the relevance of the resulting model [BPV12, Buc06].
Efficiency	The standard of efficiency results from the aforementioned conflicting goals of problem statement description and resource availability. Using existing reference models and modelling tools are examples for efficiency increasing methods [BPV12, Buc06].
Clarity	Clarity implies comprehensibility, readability and clearness of a model. A model can provide increased relevance by the extension of an existing modelling language, while reducing clarity at the same time. On the other hand naming conventions allow to improve both criteria. An advantage of graphical modelling languages is that they are even clear to persons not familiar with the syntax and are therefore widely spread in the industry for communication purposes [BPV12].
Comparability	A model's comparability can be split into two parts. Syntactic comparability assumes that using different modelling languages syntactically correct for the same problem eventually enables to compare and transfer different models. The semantic comparability implies that similar real-world problems should also appear similar in the derived models [BPV12].
Systematic composition	System composition demands to correctly transfer different organisational, functional, data- or process-related levels from reality to a model [BPV12].

B.4 Business process modelling

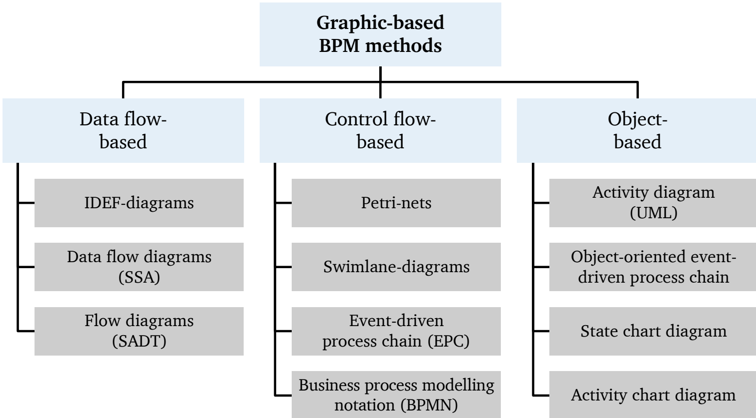


Figure B.3.: Classification of graphic-based BPM methods. Based on [Gad08]

Triangular distribution:

$$P(t) = \begin{cases} 0, & t \leq t_{min} \\ \frac{2(t-t_{min})}{(t_{max}-t_{min})(t_{mp}-t_{min})}, & t_{min} < t \leq t_{mp} \\ \frac{2(t_{max}-x)}{(t_{max}-t_{min})(t_{max}-t_{mp})}, & t_{mp} < t < t_{max} \\ 0, & t_{max} \leq t \end{cases} \tag{B.1}$$

Table B.3.: Characteristics of the most significant BPM methods. Based on [AR12, AS04, Koc11, SHG, Sta06]

Method	Description	Advantages
EPC/eEPC	• Visualisation of process analysis • Based on flow diagram • Element of ARIS concept • Org. levels connected to functions	• Established, highly standardised • Allows fast, economical modelling • Small, transparent element library • Interface to common SAP system
BPMN	• For analysts, modellers, implementers • Based on flow diagram • Variety of individual elements • Org. levels represented by swimlanes • Enhancement of existing methods	• Customisable • Enables very detailed modelling • Supports collaborative processes
UML diagrams	• Object-oriented modelling • 3 concepts: Objects, classes, messages • Origin in software development	• Established, highly standardised • Adequate for complex systems

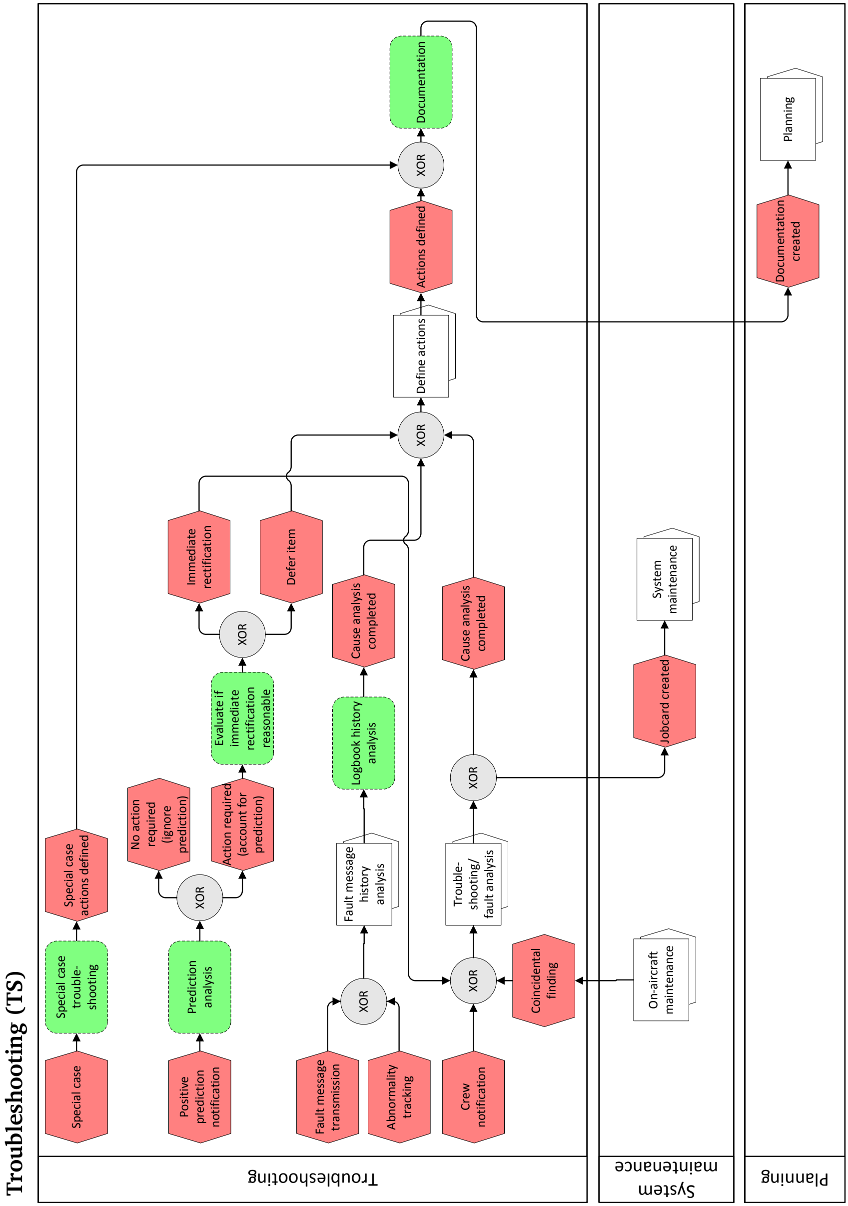
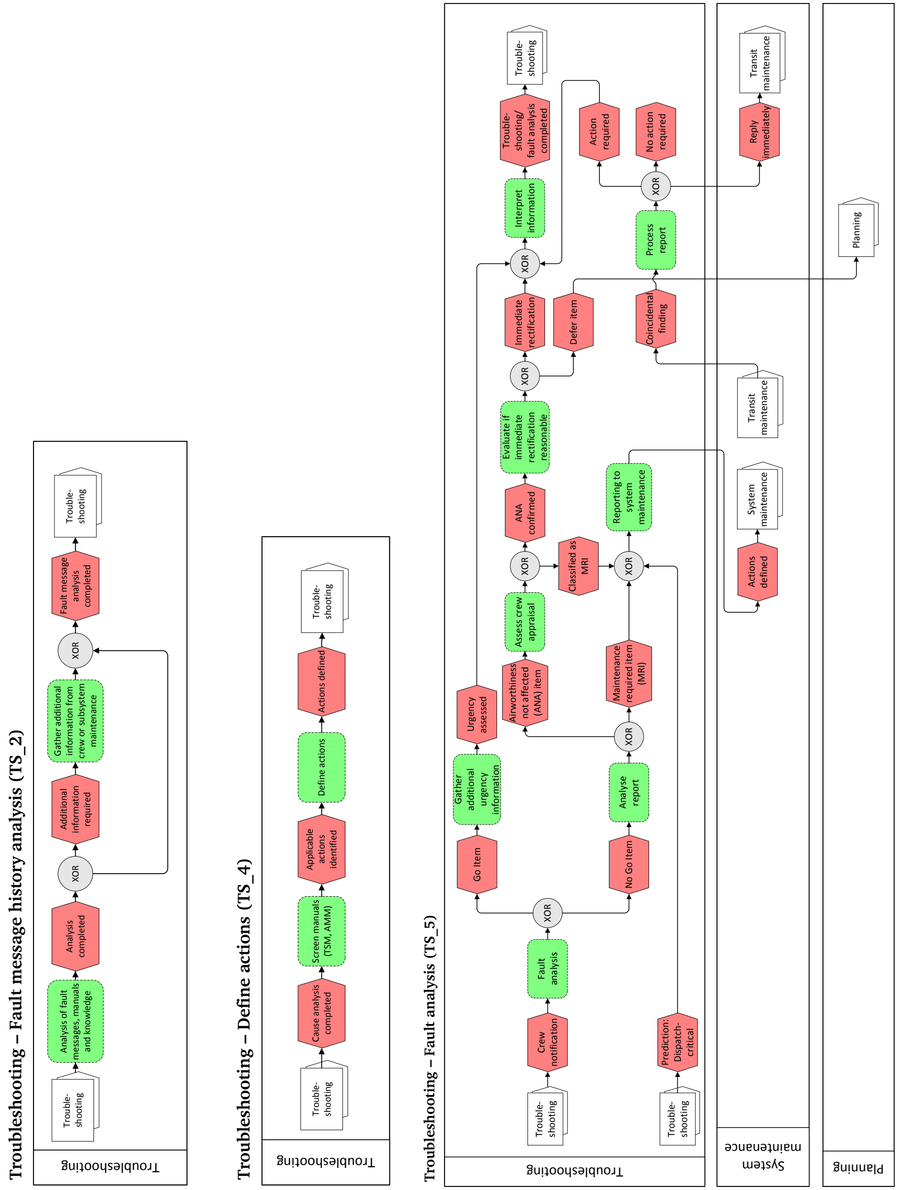
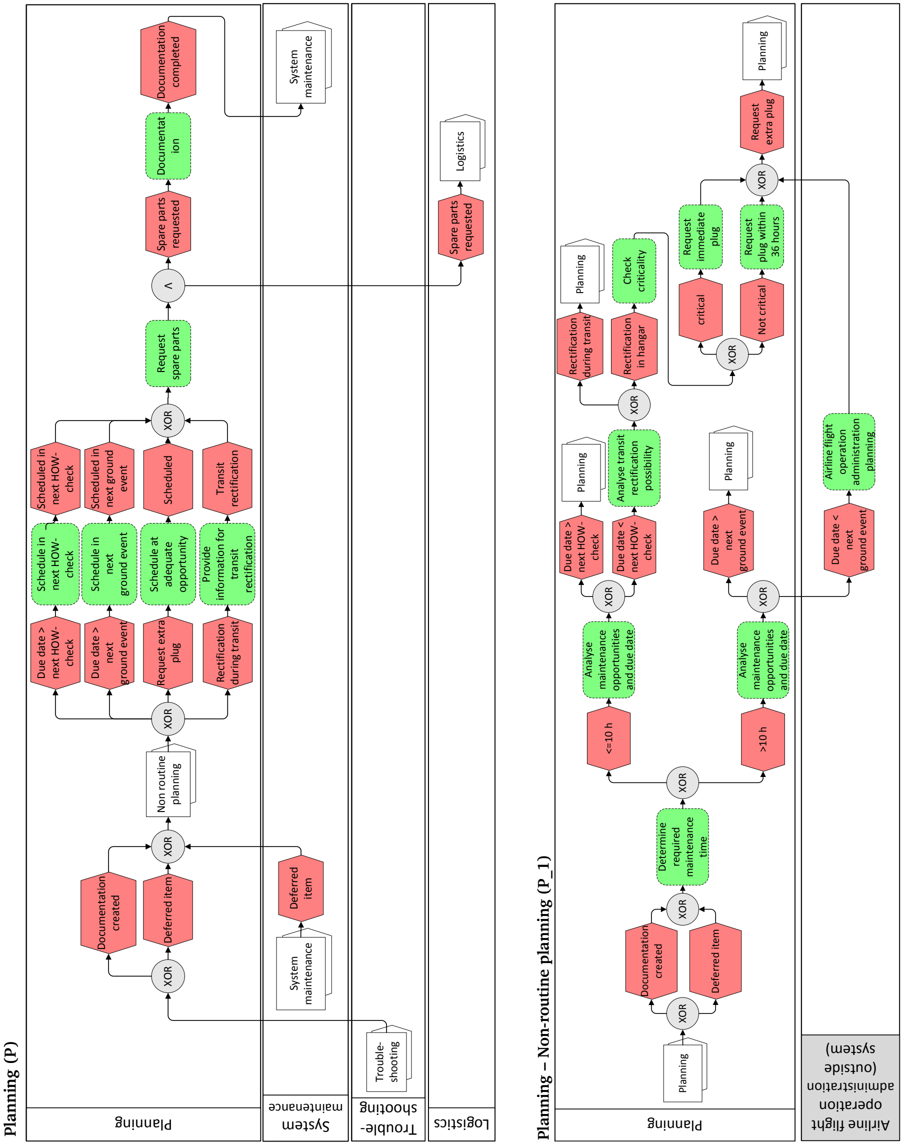


Figure B.4.: Troubleshooting global process map



(a) FM history analysis (b) Define actions (c) Fault analysis

Figure B.5.: Troubleshooting process maps



(a) Planning process map

(b) Non-routine planning process map

Figure B.6.: Planning department

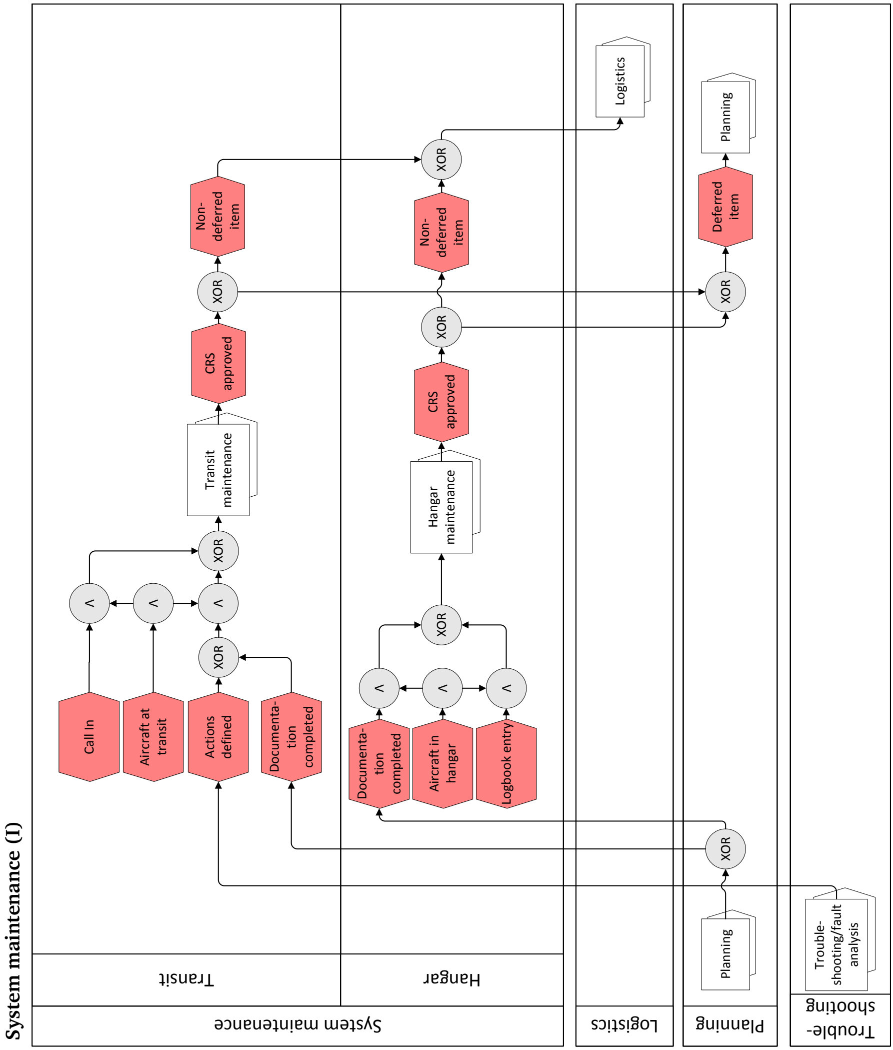
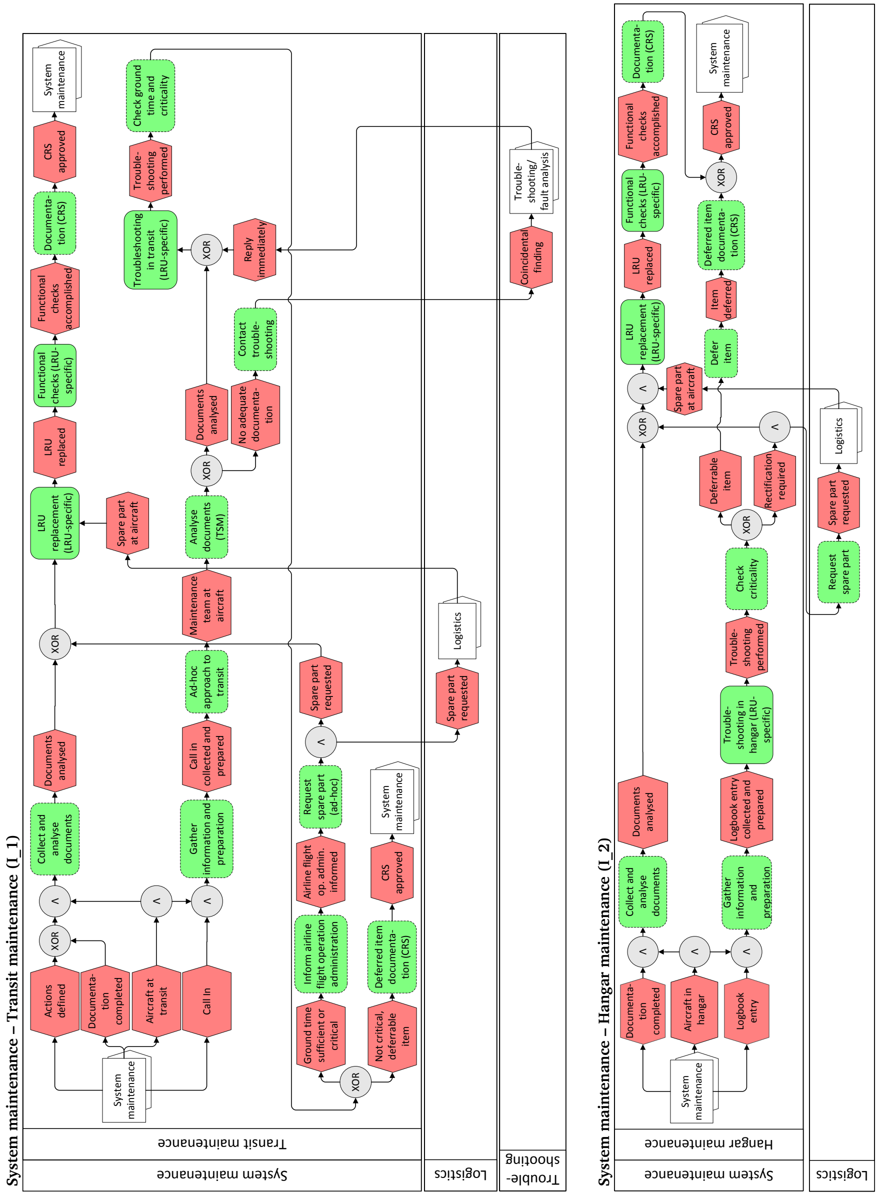
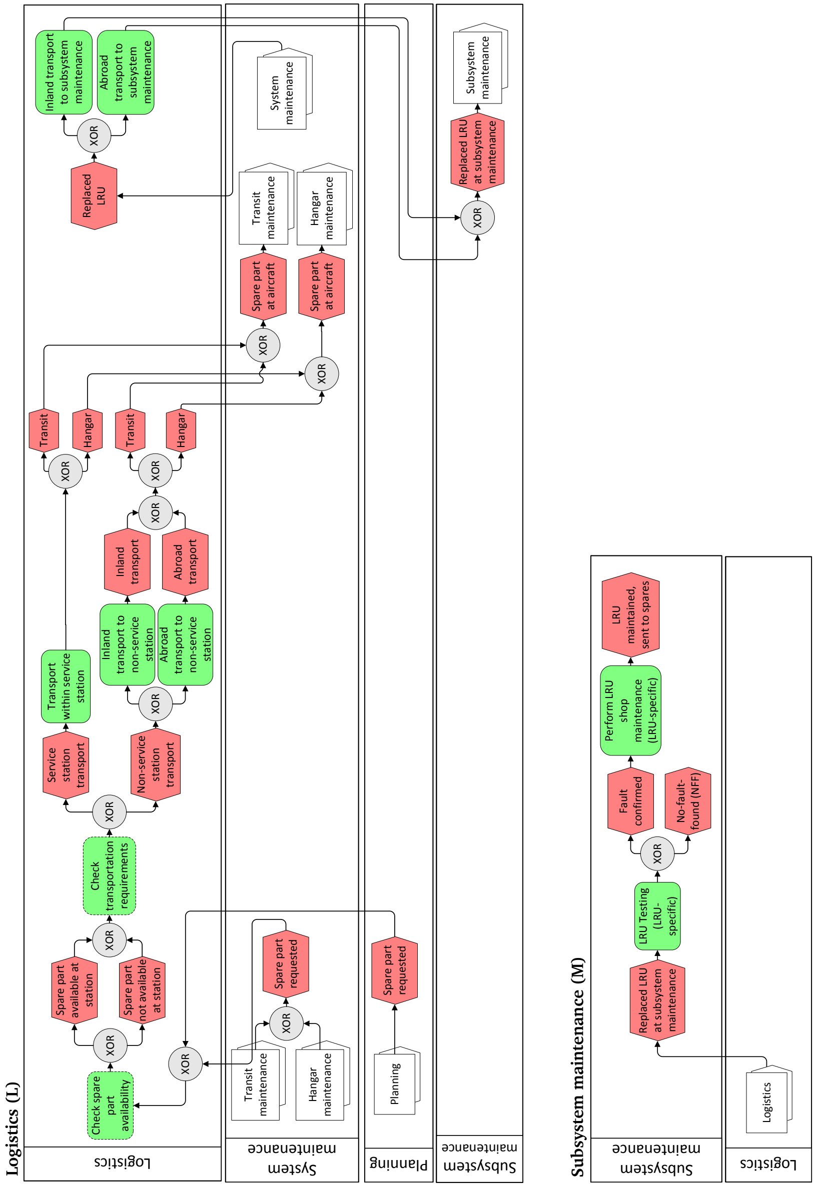


Figure B.7.: System maintenance global process map



(a) Transit (b) Hangar

Figure B.8.: System maintenance process maps



(a) Logistics (b) Subsystem maintenance

Figure B.9.: Logistics/subsystem maintenance process maps

Table B.4.: Defined process factors (part 1)

Process name	Process ID	Process time [min]			WT	Q1	Q2	Q3
		t_{min}	t_{mp}	t_{max}				
Collect and analyse documents	I_1_1	1	15	40	L			1
LRU Replacement_Removal	I_1_2_LRU_Rem	40	45	60	L			1
LRU Replacement_Installation	I_1_2_LRU_Inst	30	40	55	L			1
Functional checks	I_1_2_FC	20	25	60	L			2
Documentation (CRS)	I_1_3	3	4	15	L			1
Gather information and preparation	I_1_4	4	7	20	L			1
Ad-hoc approach to transit	I_1_5	2	10	25	L			1
Analyse documents (TSM)	I_1_6	5	10	30	L			1
Contact troubleshooting	I_1_6_1	1		4	L			1
Functional Check	I_1_7_TS	5	100	300	L			2
Check ground time and criticality	I_1_8	1	5	15	L			1
Inform airline fl. op. administration	I_1_9	2	5	10	L			1
Request spare part (ad-hoc)	I_1_10	2	5	7	L			1
Deferred item documentation (CRS)	I_1_11	3	7.5	15	L			1
Collect and analyse documents	I_2_1	1		30	L			1
Documentation (CRS)	I_2_2	15	30	50	L			1
LRU Replacement_Removal	I_2_3_LRU_Rem	50		65	L			1
LRU Replacement_Installation	I_2_3_LRU_Inst	45		60	L			1
Functional checks	I_2_3_FC	30		50	L			2
Gather information and preparation	I_2_4		5		L			1
Check criticality	I_2_5	1	5	10	L			1
Troubleshooting in hangar (LRU-specific)	I_2_6_TS	90	120	240	L			2
Request spare part	I_2_7	2	3.5	5	L			1
Defer item	I_2_8	5		10	L			1
Deferred item documentation (CRS)	I_2_9		10		L			1
Check spare part availability	L_1		1		A			
Check transportation requirements	L_2		1		A			
Transport within service station	L_3	5	10	20	A			
Inland transport to non-service station	L_4	10	60	120	A			
Abroad transport to non-service station	L_5	60	90	120	A			
Inland transport to subsystem maint.	L_6	120		600	A			
Abroad transport to subsystem maint.	L_7	300		900	A			
LRU Testing (LRU-specific)	M_1	85	110	140	L			1
Perform LRU shop maint. (LRU-specific)	M_2	200	300	350	L			1

Table B.5.: Defined process factors (part 2)

Process name	Process ID	Process time [min]			WT	Q1	Q2	Q3
		t_{min}	t_{mp}	t_{max}				
Determine required maintenance time	P_1_1	2		5	L		1	
Analyse maint. opportunities and due date	P_1_2	2	5	10	L		1	
Analyse maint. opportunities and due date	P_1_3	2	5	10	L		1	
Analyse transit rectification possibility	P_1_4	2		5	L		1	
Check criticality	P_1_5	2		5	L		1	
Request immediate plug	P_1_6	5		10	L		1	
Request plug within 36 hours	P_1_7	5		10	L		1	
Airline flight op. administration planning	P_1_8	5		10	L		1	
Schedule in next HOW-check	P_2	5		10	L		1	
Schedule in next ground event	P_3	5		10	L		1	
Schedule at adequate opportunity	P_4	5		10	L		1	
Provide information for transit rectification	P_5	5		10	L		1	
Request spare parts	P_6	2		5	L		1	
Documentation	P_7	2		5	L		1	
Special case troubleshooting	TS_1	1		30	L	1		
Analysis of recorded fault messages	TS_2_1	5	15	20	L	1		
Gather add. inform. from crew/subsyst. maint.	TS_2_2	3	5	10	L	1		
Logbook history analysis	TS_3	30		60	L	1		
Screen manuals (TSM, AMM)	TS_4_1	10		25	L	1		
Define actions	TS_4_2	5		10	L	1		
Fault analysis	TS_5_1	5	7.5	10	L	1		
Gather additional crew information	TS_5_2	5		15	L	1		
Assess crew appraisal	TS_5_3	2		15	L	1		
Analyse report	TS_5_5	10		20	L	1		
Reporting to system maintenance	TS_5_6	5	10	15	L	1		
Evaluate if immediate rectification reasonable	TS_5_7		1		L	1		
Process report	TS_5_8	3	8	10	L	1		
Interpret information	TS_5_9	1		5	L	1		
Request spare parts	TS_5_10	2		5	L	1		
Documentation	TS_6	10	15	20	L	1		
Prediction analysis	TS_7	3	5	15	L	1		
Evaluate if immediate rectification reasonable	TS_8		1		L	1		

B.5 Data models

A data model is based on simple tables that are related to each other by keys, or linking *fields*, particular attributes that are unique to an entity (marked with # in the column header in Table B.6):

Table B.6.: Relational data model: Class representation as a table. Based on [Sta05]

	#Attribute_Name_1	**Attribute_Name_2**
Entity_1	00001	Attribute_Value_1
Entity_2	00002	Attribute_Value_2

While the table can be referred to as the class, each row represents an entity with its attribute values in separate columns. Each column header is the corresponding attribute name [Sta05].

The relationship between two classes is defined by the so-called *cardinality*. It describes, for how many entities of a class on either side a relationship applies. Examples for possible relations are summarised in Table B.7 [Sta05]:

Table B.7.: Cardinalities of a relational data model. Based on [Sta05]

Cardinality	**Description of relation**	**Example**
$1 : 1$	one-to-one	One aircraft has one Auxiliary Power Unit (APU)
$1 : 1..n$	one-to-many	One aircraft component fits into one or n aircraft
$1..m : 1..n$	many-to-many	One or m aircraft can serve one or n destinations
$1 : 0..n$	one-to-many (optional)	One aircraft can carry zero to n passengers

The simplest relation is *one-to-one*, meaning that for every entity of one class there is exactly one related entity in the corresponding relational class. If in one class there are more than one corresponding entities, the *one-to-many* cardinality applies. Furthermore, in case there are multiple objects on both sides, the relationship is called *many-to-many*. If not corresponding entity is available, the *optional* relation, represented by a zero, is possible as well [Sta05].

UML is the common modelling language for a relational data model. Based on the software development background, it allows to visualise, organise and prepare the existing data for the database building. For static data modelling UML class diagrams are applied (see example in Figure B.10):

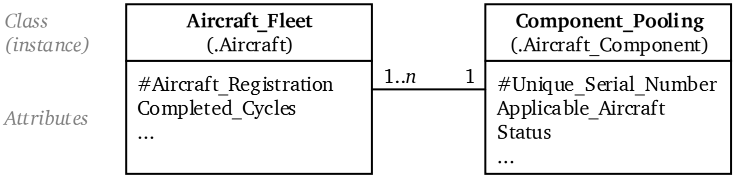


Figure B.10.: Example of a class relation in a UML class diagram

A UML class diagram typically consists of different sections. The name compartment provides information about the class and possibly its object (*instance*). The attribute compartment shows all applicable attributes. In case the model-based view is extended by physical data parameters, one can also include the data types, e.g. string, integer, double or boolean. Functions can be defined in an optional operation compartment. The example in Figure B.10 also shows the graphical representation of the relation between a component and an aircraft. The appropriate many-to-one cardinality is specified as well. In this case it shows that one component can be utilised in one or more aircraft. On purpose the relationship is unidirectional.

B.6 Simulation

Table B.8.: Differences between scenario (sc.) 2 and 3

Affected model	Discrepancy	Symbol	Description
Event initiation model	Point in time of event initiation	t_E	For sc. 2 real-world ($t_{E,RW}$) data is used, for sc. 3 prediction-based ($t_{E,P}$) data
	Number of events	$n_{Removal}$	In sc. 3 FP predictions generate new events, TN predictions possibly prevent RW NFF events
	Initiation type	n.a.	For sc. 2 only correctively initiated ad-hoc events apply, for sc. 3 prediction-based planned events (TP) as well as ad-hoc events (FN) apply
Maintenance process model	Processing logic	n.a.	For sc. 3, a modified processing of prediction-based indications applies (according to Fig. 3.15)
Aircraft operations model	Effects on flight operations	n.a.	Through the advanced knowledge due to prediction, in sc. 3 flight operations are expected to be less affected by unscheduled maintenance

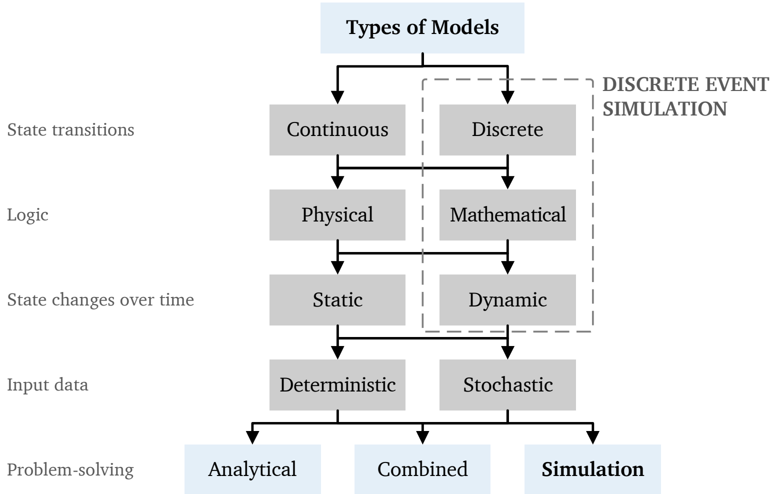


Figure B.11.: Classification of Models. Based on [STK+05]

Table B.9.: Characteristics of simulation. Based on [Ban10]

Advantages	**Disadvantages**
• Analysis of systems that cannot be observed or do not exist (yet)	• High costs and expenditure of time for model building process
• Experiments on the real system are not possible, too costly or destructive	• Probability assessment: Requires input data to be representative for stochastic analysis
• Any input value changes do not affect the real-world problem	• Expert knowledge for result interpretation
• Time compression: Long term time periods can be simulated in shorter time (and the other way around)	• Strict requirements concerning V&V
• Sensitivity analysis through input data variation	
• Visualisation/animation with high usability	
• Applicable, where analytical methods are not	

B.7 Discrete event simulation

Table B.10.: Elements of discrete event simulation. Based on [Ban10, San15c]

Element	Description
System state	A collection of variables that contain all the information necessary to describe the system at any time. All system states are steady between two events.
Entity	Any object or component in the system that requires explicit representation in the model (e.g. an aircraft or an aircraft component)
Attributes	The properties of a given entity (e.g. the aircraft registration or the ATA chapter of an aircraft component)
List	A collection of (permanently or temporarily) associated entities, ordered in some logical fashion (e.g. all aicraft on ground currently)
Event	An instantaneous occurrence that changes the state of a system or the attribute of an entity (such as begin of aircraft maintenance or failure of an aircraft component). An event itself does not consume simulation time, but may be the start of a time-consuming process
Event notice	A record of an event to occur at the current or some future time, along with any associated data necessary to execute the event; at a minimum, the record includes the event type and the event time
Event list	A list of event notices for future events, ordered by time of occurrence (*sequentialisation*)
Activity/ server	A duration of time of specified length (e.g. a service or transmission time), which is known when it begins (it may also be defined in terms of a statistical distribution)
Clock	A variable representing simulation time

Table B.11.: Determination of z_{LRU} based on the component's MEL RI referring to fault indication at t_0

MEL RI	$t_0 \leq t \leq t_0 + 3d$	$t_0 + 3d < t \leq t_0 + 10d$	$t_0 + 10d < t \leq t_0 + 120d$	$t_0 + 120d < t$
A	$z_{LRU} = -2$	$z_{LRU} = -2$	$z_{LRU} = -2$	$z_{LRU} = -2$
B	$z_{LRU} = -4$	$z_{LRU} = -2$	$z_{LRU} = -2$	$z_{LRU} = -2$
C	$z_{LRU} = -4$	$z_{LRU} = -4$	$z_{LRU} = -2$	$z_{LRU} = -2$
D	$z_{LRU} = -4$	$z_{LRU} = -4$	$z_{LRU} = -4$	$z_{LRU} = -2$
none	$z_{LRU} = -4$	$z_{LRU} = -4$	$z_{LRU} = -4$	$z_{LRU} = -4$

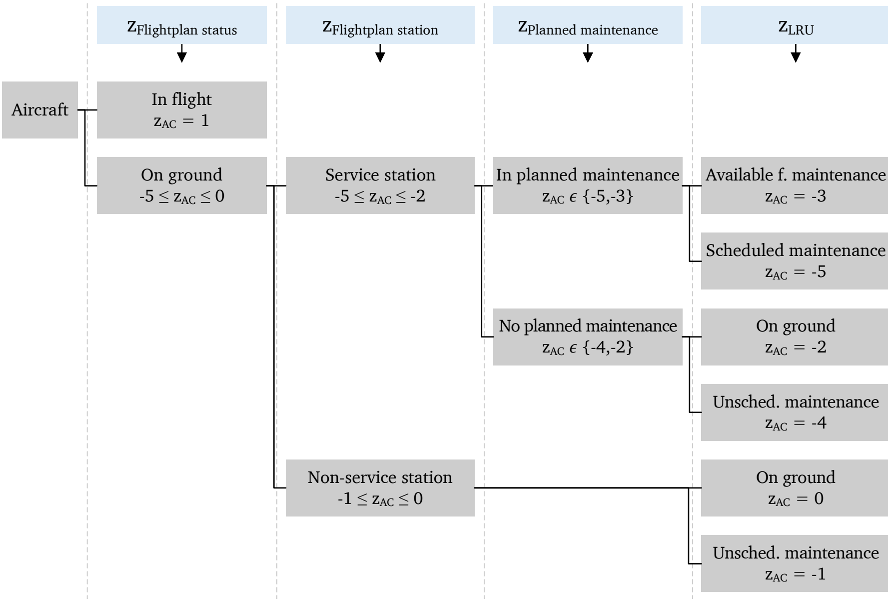


Figure B.12.: Logic of interdependent state variables

B.8 Cost rates

Table B.12.: Advantages/disadvantages of different cost rate types. Based on [Pos15]

Cost rate type	Advantages	Disadvantages
Historical costs	Enables the representation of real, historical costs.	Cost rates incorporate fluctuation possibly superposing the analysed maintenance effects. Future effects cannot be covered.
Normal costs	No fluctuation in cost rates. Low efforts in data acquisition.	No one-to-one real-world association concerning historical events. Future effects cannot be covered.
Planned costs	Consideration of future effects enabled	No one-to-one real-world association concerning historical events

B.9 Cost calculation procedure

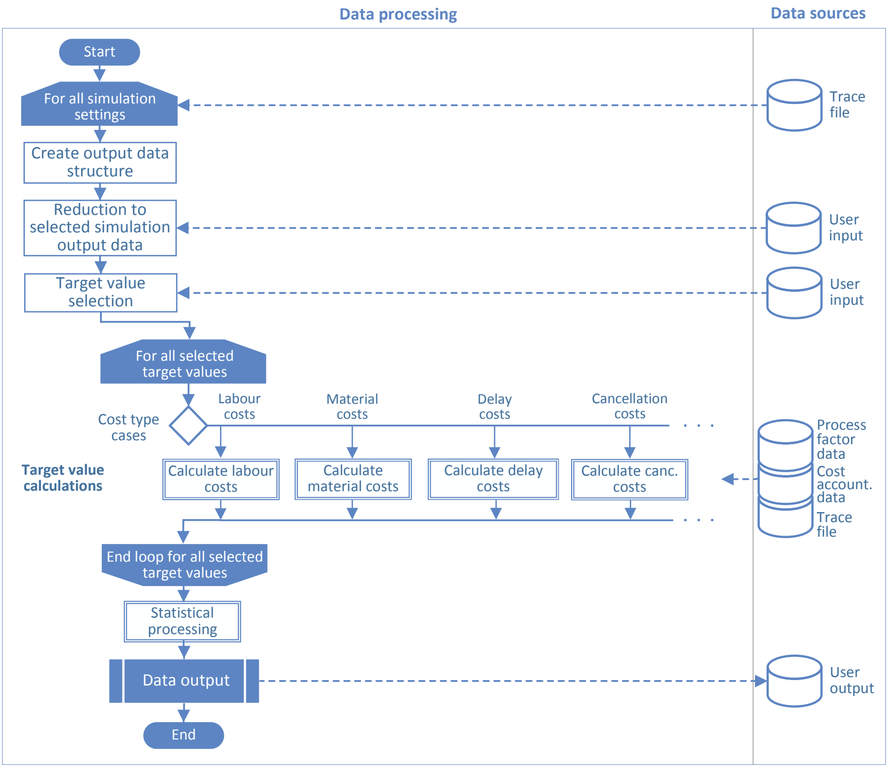


Figure B.13.: Overview cost calculation procedure. Based on [Pos15]

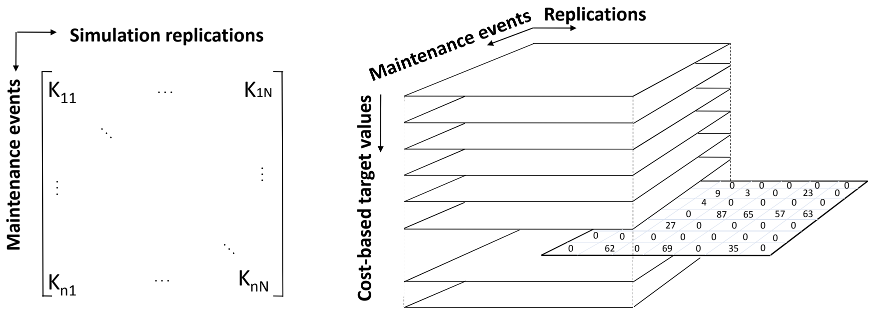


Figure B.14.: Cost matrix structure. Based on [Pos15]

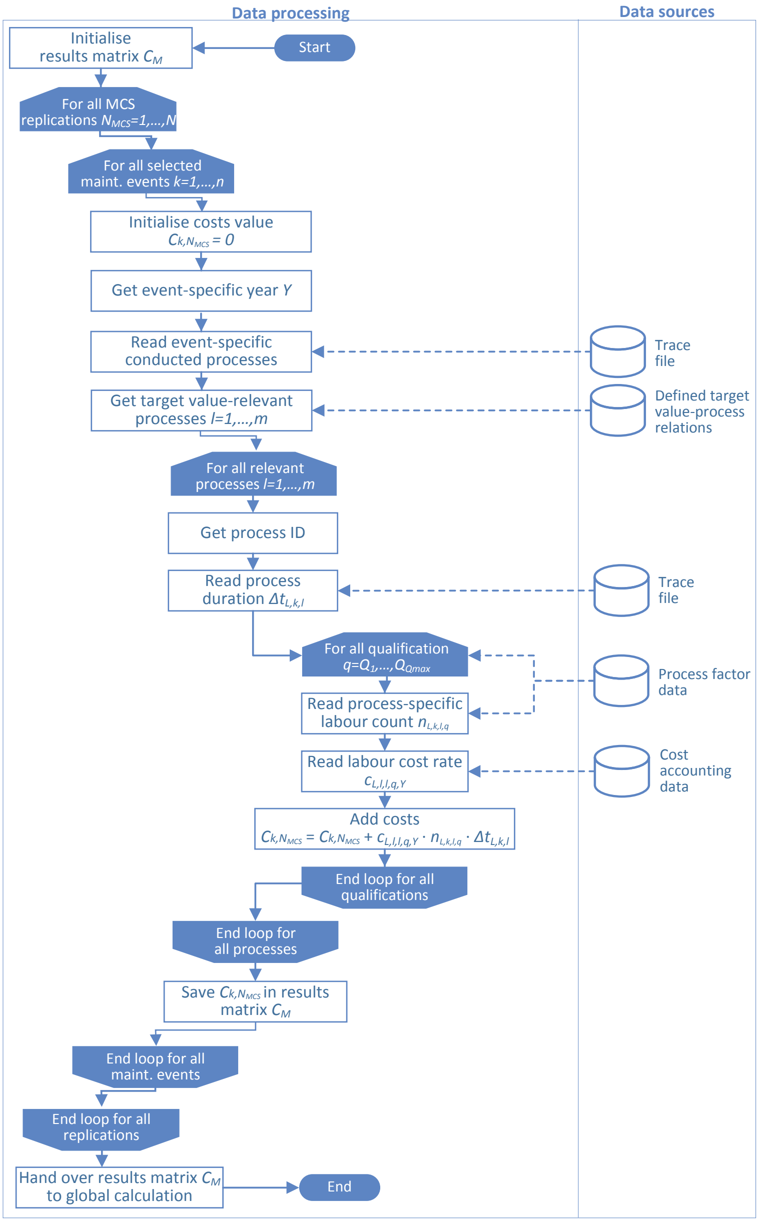


Figure B.15.: Overview labour cost calculation. Based on [Pos15]

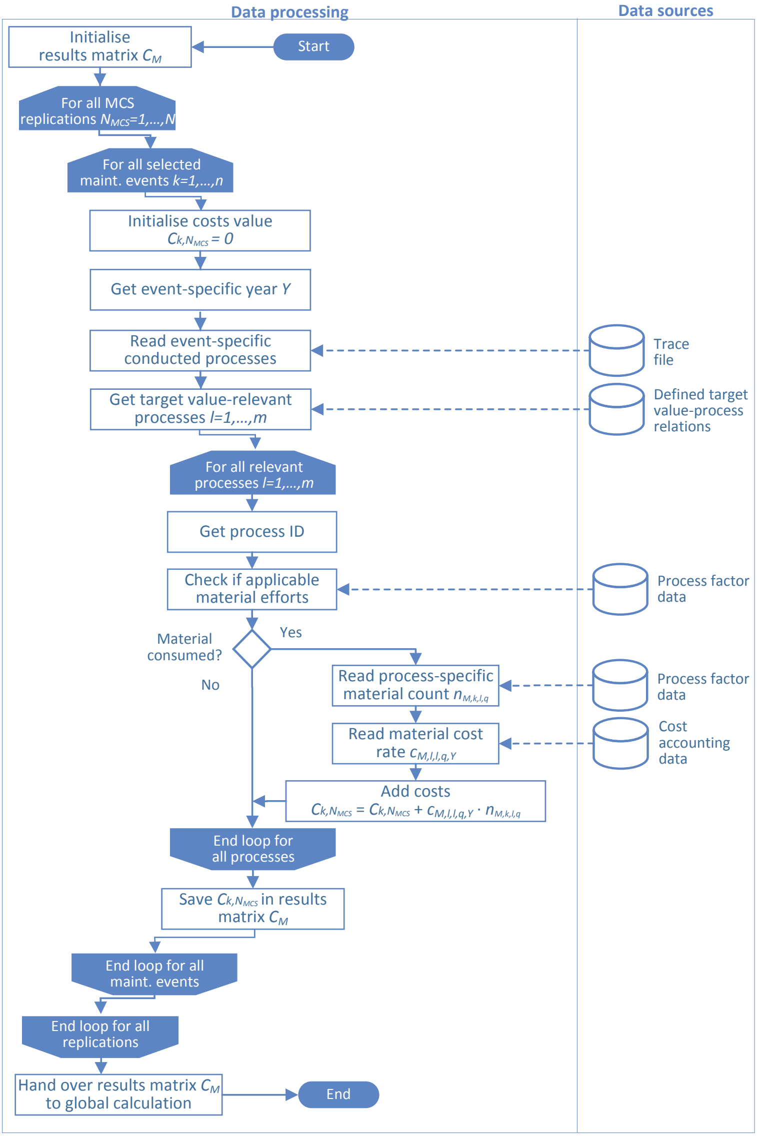


Figure B.16.: Overview material cost calculation. Based on [Pos15]

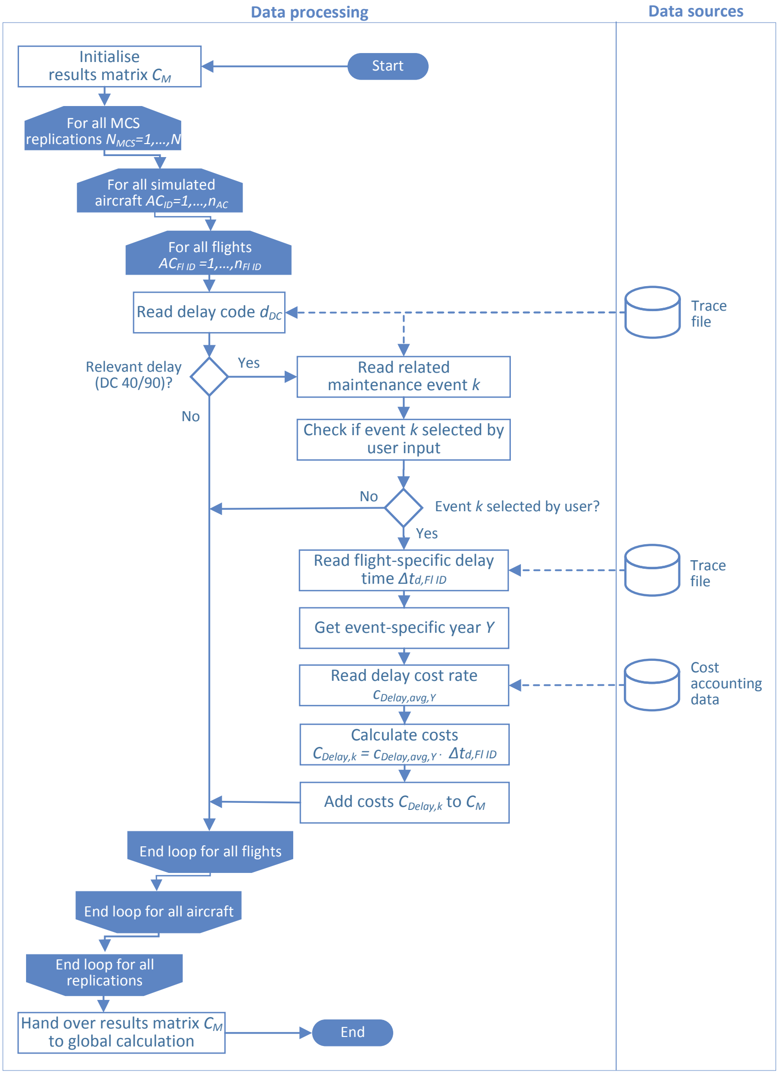


Figure B.17.: Overview delay cost calculation. Based on [Pos15]

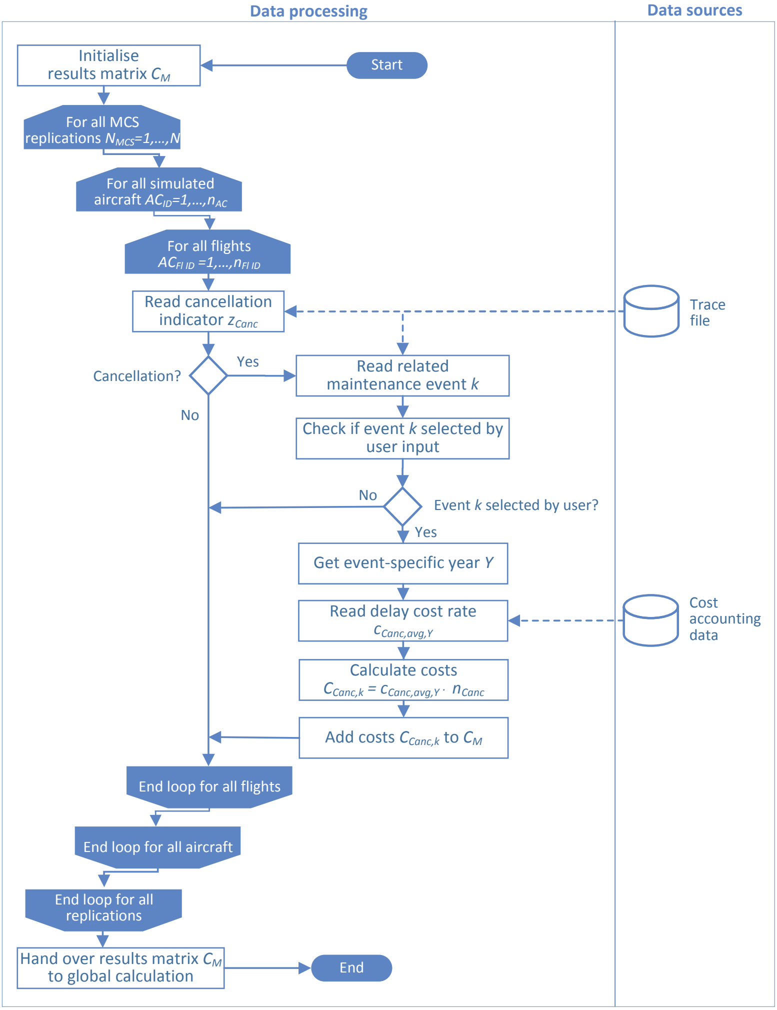


Figure B.18.: Overview cancellation cost calculation. Based on [Pos15]

C Software impl. supplementaries

C.1 Software selection

Table C.1.: Assessment of applicable software environments (+ = 1, o = 0, – = -1). Weight factors from paired comparison assessment. Based on [Bad13]

ID	Weight	Requirement	SimEvents	ARENA	Plant Sim.
1.1	0.02	Hierarchical structuring	+	+	+
1.2	0.02	Modelling enabled with standard elements	–	o	o
1.3	0.02	Powerful programming language available	+	+	+
1.4	0.02	Entity definition without restrictions	o	+	o
1.5	0.02	Attributes definable, adjustable, readable	o	+	+
1.6	0.02	Mathematical/boolean operators available	+	+	+
1.7	0.02	Debugging functions available	+	+	+
1.8	0.02	Run-time version available	+	+	+
1.9	0.02	User-specific KPI analysis	o	o	o
1.10	0.02	Representation of information flow	+	o	o
1.11	0.02	Acquisition costs	o	–	o
1.12	0.02	Data import/export of common formats	+	+	+
1.13	0.02	Data types enable user-specific structuring	+	o	+
1.14	0.02	Process model import from *MS Visio*	–	+	–
1.15	0.02	Cost calculation module included	–	+	+
2.1	0.05	Entity animation	–	+	+
3.1	0.05	Random-based number generation included	+	+	+
3.2	0.05	Variety of probability functions included	+	+	o
3.3	0.05	Discrete distributions supported	+	+	o
3.4	0.05	Monte-Carlo simulation possible	o	+	o
3.5	0.05	Statistical post-processing tools	o	+	–
3.6	0.05	Optimisation routine	+	+	o
4.1	0.025	Technical support	+	o	o
4.2	0.025	Extensive, comprehensive documentation	+	+	+
5.1	0.3	Flexible report/visualisation management	+	o	o
	$\sum = 1$		**0.60**	**0.56**	**0.24**

C.2 Verification and validation

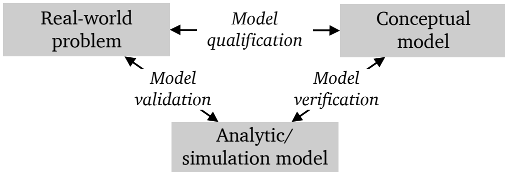


Figure C.1.: Verification and validation in modelling building. Based on [OR10]

Table C.2.: Aircraft operation model verification criteria

Verification criterion	Verified?
Adjusted point in time not before scheduled /after actual flight plan	✓
Only LRU-related delays are accounted for and modified	✓
Reactionary delays are only modified to the extend of the previous delay adjustment	✓
The arrival time adjustment is smaller than or equal to the next departure adjustment	✓
After a night stop no further adjustments apply	(✓)

Table C.3.: Data model verification criteria

Verification criterion	Verified?
No empty data or data conflicts within related data samples	✓
Only data within ± 2 weeks in related data samples	✓
Defined data structure is accounted for	✓

Table C.4.: Event initiation verification criteria

Verification criterion	Verified?
The sum of TP and FN predictions equals the amount of RW (non-NFF) events	✓
Prediction-based event initiation only applies before RW initiation/after prediction	✓
Higher priority of RW ad-hoc event initiation opposed to pred.-based is accounted for	✓
For both input types: The prediction metrics ratio and the PF is correctly simulated	✓

D Case study application supplementaries

D.1 Case study input data

Table D.1.: Exemplary flight schedule information (part 1)

Aircraft reg.	STA	ATA	STD	ATD	DC	DT	Canc	Location
Reg_003	02.06.2011 20:35	02.06.2011 20:22	03.06.2011 04:55	03.06.2011 04:59	85	4		Service station
Reg_003	03.06.2011 06:35	03.06.2011 06:34	03.06.2011 07:25	03.06.2011 07:37	82	12		Service station
Reg_003	03.06.2011 09:55	03.06.2011 09:54	03.06.2011 10:45	03.06.2011 11:00	89	15		Non-service stat.
Reg_003	03.06.2011 13:20	03.06.2011 13:33	03.06.2011 14:15	03.06.2011 15:30	41	75		Service station
Reg_003	03.06.2011 16:15	03.06.2011 17:28	03.06.2011 17:05	03.06.2011 18:16	93	71		Non-service stat.
Reg_003	03.06.2011 19:05	03.06.2011 20:06	04.06.2011 05:25	04.06.2011 05:48	81	23		Service station
Reg_003	04.06.2011 06:35	04.06.2011 07:05	04.06.2011 07:25	04.06.2011 07:42	93	17		Non-service stat.
Reg_003	04.06.2011 08:40	04.06.2011 08:39	04.06.2011 09:30	04.06.2011 09:35	87	5		Service station
Reg_003	04.06.2011 10:30	04.06.2011 10:30	04.06.2011 11:15	04.06.2011 11:14				Service station
Reg_003	04.06.2011 12:25	04.06.2011 12:18	04.06.2011 13:15	04.06.2011 13:17	3	2		Service station
Reg_003	04.06.2011 14:50	04.06.2011 14:40	04.06.2011 16:10	04.06.2011 16:27	89	17		Non-service stat.
Reg_003	04.06.2011 17:40	04.06.2011 17:52	04.06.2011 19:35	04.06.2011 19:50	49	15		Service station
Reg_003	04.06.2011 22:15	04.06.2011 22:19	05.06.2011 05:45	05.06.2011 05:45				Non-service stat.
Reg_003	05.06.2011 08:20	05.06.2011 08:15	05.06.2011 09:10	05.06.2011 09:12	3	2		Service station
Reg_003	05.06.2011 11:00	05.06.2011 10:58	05.06.2011 11:45	05.06.2011 11:45				Non-service stat.
Reg_003	05.06.2011 13:45	05.06.2011 13:36	05.06.2011 15:10	05.06.2011 15:12	3	2		Service station
Reg_003	05.06.2011 16:20	05.06.2011 16:21	05.06.2011 17:05	05.06.2011 17:13	93	8		Non-service stat.
Reg_003	05.06.2011 18:20	05.06.2011 18:14	05.06.2011 19:05	05.06.2011 19:17	85	12		Service station
Reg_003	05.06.2011 20:10	05.06.2011 20:13	06.06.2011 05:15	06.06.2011 05:15				Non-service stat.
Reg_003	06.06.2011 06:25	06.06.2011 06:22	06.06.2011 08:20	06.06.2011 08:24	49	4		Service station
Reg_003	06.06.2011 09:15	06.06.2011 09:18	06.06.2011 10:00	06.06.2011 09:56				Service station
Reg_003	06.06.2011 11:05	06.06.2011 10:57	06.06.2011 12:15	06.06.2011 12:18	3	3		Service station
Reg_003	06.06.2011 13:15	06.06.2011 13:20	06.06.2011 14:05	06.06.2011 14:04				Service station
Reg_003	06.06.2011 15:15	06.06.2011 15:03	06.06.2011 17:10	06.06.2011 17:12	3	2		Service station
Reg_003	06.06.2011 19:30	06.06.2011 19:35	07.06.2011 06:15	07.06.2011 06:15				Service station
Reg_003	07.06.2011 08:45	07.06.2011 08:40	07.06.2011 10:10	07.06.2011 10:18	87	8		Service station
Reg_003	07.06.2011 11:45	07.06.2011 11:55	07.06.2011 12:30	07.06.2011 12:37	93	7		Non-service stat.
Reg_003	07.06.2011 14:10	07.06.2011 14:09	07.06.2011 15:20	07.06.2011 15:20				Service station
Reg_003	07.06.2011 16:10	07.06.2011 16:11	07.06.2011 16:45	07.06.2011 16:50	9	5		Non-service stat.
Reg_003	07.06.2011 17:40	07.06.2011 17:53	08.06.2011 05:30	08.06.2011 05:46	83	16		Service station
Reg_003	08.06.2011 07:05	08.06.2011 07:32	08.06.2011 08:05	08.06.2011 08:23	93	18		Non-service stat.
Reg_003	08.06.2011 09:35	08.06.2011 09:53	08.06.2011 11:00	08.06.2011 11:33	71	33		Service station
Reg_003	08.06.2011 12:30	08.06.2011 12:58	08.06.2011 13:10	08.06.2011 13:48	93	38		Service station
Reg_003	08.06.2011 14:50	08.06.2011 15:27	08.06.2011 15:50	08.06.2011 16:03	93	13		Service station
Reg_003	08.06.2011 16:35	08.06.2011 16:50	08.06.2011 17:10	08.06.2011 17:21	93	11		Non-service stat.
Reg_003	08.06.2011 18:05	08.06.2011 17:58	08.06.2011 19:05	08.06.2011 19:06	3	1		Service station
Reg_003	08.06.2011 20:10	08.06.2011 20:05	09.06.2011 05:15	09.06.2011 05:23	49	8		Service station
Reg_003	09.06.2011 06:25	09.06.2011 06:34	09.06.2011 07:25	09.06.2011 07:31	49	6		Service station
Reg_003	09.06.2011 09:45	09.06.2011 09:45	09.06.2011 10:30	09.06.2011 10:44	34	14		Non-service stat.
Reg_003	09.06.2011 13:00	09.06.2011 12:58	09.06.2011 13:50	09.06.2011 13:52	3	2		Service station
Reg_003	09.06.2011 15:00	09.06.2011 15:05	09.06.2011 15:40	09.06.2011 15:59	93	19		Non-service stat.
Reg_003	09.06.2011 16:55	09.06.2011 16:59	10.06.2011 05:35	10.06.2011 05:41	85	6		Service station
Reg_003	10.06.2011 06:35	10.06.2011 06:41	10.06.2011 07:20	10.06.2011 07:23	3	3		Service station
Reg_003	10.06.2011 08:30	10.06.2011 08:25	10.06.2011 09:25	10.06.2011 09:28	3	3		Service station
Reg_003	10.06.2011 10:25	10.06.2011 10:25	10.06.2011 11:15	10.06.2011 11:09				Service station
Reg_003	10.06.2011 12:25	10.06.2011 12:06	10.06.2011 14:40	10.06.2011 14:36				Service station
Reg_003	10.06.2011 16:00	10.06.2011 15:56	10.06.2011 17:25	10.06.2011 17:25				Non-service stat.
Reg_003	10.06.2011 18:55	10.06.2011 18:52	10.06.2011 19:55	10.06.2011 19:53				Service station
Reg_003	10.06.2011 21:55	10.06.2011 21:54	11.06.2011 05:40	11.06.2011 06:00	63	20		Non-service stat.

Table D.2.: Exemplary flight schedule information (part 2)

Aircraft reg.	STA	ATA	STD	ATD	DC	DT	Canc	Location
Reg_003	11.06.2011 07:40	11.06.2011 08:18	11.06.2011 08:25	11.06.2011 09:01	93	36		Service station
Reg_003	11.06.2011 10:25	11.06.2011 11:08	11.06.2011 11:10	11.06.2011 12:00	93	50		Non-service stat.
Reg_003	11.06.2011 13:10	11.06.2011 13:57	11.06.2011 14:35	11.06.2011 14:51	41	16		Service station
Reg_003	11.06.2011 15:45	11.06.2011 16:11	11.06.2011 16:30	11.06.2011 17:23	93	53		Service station
Reg_003	11.06.2011 17:50	11.06.2011 18:30	11.06.2011 19:35	11.06.2011 19:48	49	13		Service station
Reg_003	11.06.2011 20:20	11.06.2011 20:21	12.06.2011 04:40	12.06.2011 04:50	85	10		Service station
Reg_003	12.06.2011 05:35	12.06.2011 05:43	12.06.2011 06:35	12.06.2011 06:45	85	10		Service station
Reg_003	12.06.2011 07:55	12.06.2011 07:54	12.06.2011 08:40	12.06.2011 08:40				Non-service stat.
Reg_003	12.06.2011 10:10	12.06.2011 10:11	12.06.2011 11:00	12.06.2011 11:06	87	6		Service station
Reg_003	12.06.2011 12:30	12.06.2011 12:37	12.06.2011 13:10	12.06.2011 13:30	84	20		Service station
Reg_003	12.06.2011 14:50	12.06.2011 15:12	12.06.2011 15:55	12.06.2011 16:02	87	7		Service station
Reg_003	12.06.2011 16:55	12.06.2011 16:54	12.06.2011 17:45	12.06.2011 17:45				Service station
Reg_003	12.06.2011 18:55	12.06.2011 18:48	13.06.2011 05:00	13.06.2011 05:13	6	13		Service station
Reg_003	13.06.2011 05:55	13.06.2011 06:03	13.06.2011 06:30	13.06.2011 06:41	93	11		Service station
Reg_003	13.06.2011 07:30	13.06.2011 07:35	13.06.2011 08:15	13.06.2011 08:23	93	8		Service station
Reg_003	13.06.2011 10:15	13.06.2011 10:30	13.06.2011 11:00	13.06.2011 11:15	93	15		Non-service stat.
Reg_003	13.06.2011 13:00	13.06.2011 13:11	13.06.2011 14:20	13.06.2011 14:24	89	4		Service station
Reg_003	13.06.2011 15:55	13.06.2011 15:50	13.06.2011 17:05	13.06.2011 17:04				Non-service stat.
Reg_003	13.06.2011 18:35	13.06.2011 18:41	13.06.2011 19:45	13.06.2011 19:46	3	1		Service station
Reg_003	13.06.2011 21:45	13.06.2011 21:39	14.06.2011 04:40	14.06.2011 04:40				Service station
Reg_003	14.06.2011 06:45	14.06.2011 07:05	14.06.2011 07:35	14.06.2011 07:48	93	13		Service station
Reg_003	14.06.2011 08:30	14.06.2011 08:37	14.06.2011 09:10	14.06.2011 09:19	93	9		Non-service stat.
Reg_003	14.06.2011 10:10	14.06.2011 10:23	14.06.2011 11:05	14.06.2011 11:17	93	12		Service station
Reg_003	14.06.2011 11:50	14.06.2011 12:03	14.06.2011 12:25	14.06.2011 12:34	93	9		Non-service stat.
Reg_003	14.06.2011 13:20	14.06.2011 13:39	14.06.2011 14:20	14.06.2011 14:23	3	3		Service station
Reg_003	14.06.2011 15:20	14.06.2011 15:15	14.06.2011 16:00	14.06.2011 16:08	84	8		Non-service stat.
Reg_003	14.06.2011 17:10	14.06.2011 17:21	15.06.2011 05:30	15.06.2011 05:44	83	14	Y (2)	Service station
Reg_003	15.06.2011 07:05	15.06.2011 07:08	15.06.2011 08:05	15.06.2011 08:00				Non-service stat.

Table D.3.: Exemplary LRU-related planned maintenance information

Location	Aircraft reg.	Begin planned maint.	End planned maint.
Service station	Reg_003	06.06.2011 22:30	07.06.2011 01:00
Service station	Reg_003	08.06.2011 00:35	08.06.2011 03:05
Service station	Reg_003	08.06.2011 22:00	09.06.2011 00:30
Service station	Reg_003	10.06.2011 00:30	10.06.2011 03:00
Service station	Reg_003	12.06.2011 01:04	12.06.2011 03:00
Service station	Reg_003	12.06.2011 22:00	13.06.2011 02:00
Service station	Reg_003	13.06.2011 00:20	13.06.2011 02:20
Service station	Reg_003	13.06.2011 21:39	13.06.2011 22:30
Service station	Reg_003	15.06.2011 01:46	15.06.2011 03:45

Table D.4.: Exemplary LRU-related maintenance information (event *1* in Table D.11)

Time stamp description	Time stamp
First related report	14.06.2011 17:21
Request spare part	14.06.2011 18:55
Spare part delivered	14.06.2011 19:20
LRU replaced	14.06.2011 23:08

Table D.5.: Exemplary LRU event information

Information	Value
Component name	LRU A
Component modification	PN 1
NFF	N

Table D.6.: Exp. 3 prediction time instances (preponing based on flight hours only)

Prognostic forecast Δt_{PF} [min]	Prediction time stamp t_P
15	14.06.2011 17:06
60	14.06.2011 16:21
300	14.06.2011 08:37
1,000	13.06.2011 08:56
3,000	09.06.2011 10:55

Table D.7.: Prediction costs variant 2: Impact of inflation rate

Year	2011	2012	2013	2014
Average inflation value [%]		2.60	1.50	0.66
$C_{P,\text{ Invest}}$ [€/a]	5,000	5,130	5,207	5,241
$C_{P,\text{ Develop}}$ [€/a]	5,000	5,130	5,207	5,241
$C_{P,\text{ S/W}}$ [€/a]	2,500	2,565	2,603	2,621
$C_{P,\text{ Train}}$ [€/a]	5,000	5,130	5,207	5,241
$C_{P_{LRU_i}}$ [€/a]	17,500	17,955	18,224	18,345

Table D.8.: Prediction costs variant 3: Impact of inflation rate

Year	2011	2012	2013	2014
Average inflation value [%]		2.60	1.50	0.66
$C_{P,\text{ Invest}}$ [€/a]	15,000	15,390	15,621	15,724
$C_{P,\text{ Develop}}$ [€/a]	15,000	15,390	15,621	15,724
$C_{P,\text{ S/W}}$ [€/a]	5,000	5,130	5,207	5,241
$C_{P,\text{ Train}}$ [€/a]	15,000	15,390	15,621	15,724
$C_{P_{LRU_i}}$ [€/a]	50,000	51,300	52,070	52,413

D.2 Model calibration results

Table D.9.: Model calibration results (part 1)

Process ID	EV [min]		Modified process time [min]			Std. deviation [min]	
	μ	K_{cal}	$t_{min,cal}$	$t_{mp,cal}$	$t_{max,cal}$	$s_{cal,\text{train}}$	$s_{cal,\text{val}}$
I_1_1	18.67	0.76	0.76	11.4	30.40	3.70	6.78
I_1_2_LRU_Rem	48.33	0.76	30.40	34.20	45.60	9.58	17.55
I_1_2_LRU_Inst	41.67	0.76	22.80	30.40	41.80	8.26	15.13
I_1_2_FC	35.00	0.76	15.20	19.00	45.60	6.94	12.71
I_1_3	7.33	0.76	2.28	3.04	11.40	1.45	2.66
I_1_4	10.33	0.81	3.24	5.67	16.20	2.89	2.64
I_1_5	12.33	0.81	1.62	8.10	20.25	3.45	3.16
I_1_6	15.00	0.81	4.05	8.10	24.30	4.20	3.84
I_1_6_1	2.50	0.81	0.81		3.24	0.70	0.64
I_1_7_TS	135.00	0.81	4.05	81.00	243.00	37.78	34.55
I_1_8	7.00	0.81	0.81	4.05	12.15	1.96	1.79
I_1_9	5.67	0.81	1.62	4.05	8.10	1.59	1.45
I_1_10	4.67	0.81	1.62	4.05	5.67	1.31	1.19
I_1_11	8.50	(1.0)	3.00	7.50	15.00	n.a.	n.a.
I_2_1	15.50	0.95	0.95		28.50	3.88	3.43
I_2_2	31.67	0.95	14.25	28.50	47.50	7.93	7.00
I_2_3_LRU_Rem	57.50	0.95	47.50		61.75	14.40	12.72
I_2_3_LRU_Inst	52.50	0.95	42.75		57.00	13.15	11.61
I_2_3_FC	40.00	0.95	28.50		47.50	10.02	8.85
I_2_4	5.00	(1.0)		5.00		n.a.	n.a.
I_2_5	5.33	(1.0)	1.00	5.00	10.00	n.a.	n.a.
I_2_6_TS	150.00	(1.0)	90.00	120.00	240.00	n.a.	n.a.
I_2_7	3.50	(1.0)	2.00	3.50	5.00	n.a.	n.a.
I_2_8	7.50	(1.0)	5.00		10.00	n.a.	n.a.
I_2_9	10.00	(1.0)		10.00		n.a.	n.a.
L_1	1.00	(1.0)		1.00		n.a.	n.a.
L_2	1.00	(1.0)		1.00		n.a.	n.a.
L_3	11.67	1.85	9.25	18.50	37.00	2.53	3.00
L_4	63.33	(1.0)	10.00	60.00	120.00	n.a.	n.a.
L_5	90.00	(1.0)	60.00	90.00	120.00	n.a.	n.a.
L_6	360.00	(1.0)	120.00		600.00	n.a.	n.a.
L_7	600.00	(1.0)	300.00		900.00	n.a.	n.a.

Table D.10.: Model calibration results (part 2)

Process ID	EV [min]		Modified process time [min]			Std. deviation [min]	
	μ	K_{cal}	$t_{min,cal}$	$t_{mp,cal}$	$t_{max,cal}$	$s_{cal,\text{train}}$	$s_{cal,\text{val}}$
M_1	111.67	0.71	60.35	78.10	99.40	28.14	29.66
M_2	283.33	0.71	142.00	213.00	248.50	71.41	75.25
P_1_1	3.50	(1.0)	2.00		5.00	n.a.	n.a.
P_1_2	5.67	(1.0)	2.00	5.00	10.00	n.a.	n.a.
P_1_3	5.67	(1.0)	2.00	5.00	10.00	n.a.	n.a.
P_1_4	3.50	(1.0)	2.00		5.00	n.a.	n.a.
P_1_5	3.50	(1.0)	2.00		5.00	n.a.	n.a.
P_1_6	7.50	(1.0)	5.00		10.00	n.a.	n.a.
P_1_7	7.50	(1.0)	5.00		10.00	n.a.	n.a.
P_1_8	7.50	(1.0)	5.00		10.00	n.a.	n.a.
P_2	7.50	(1.0)	5.00		10.00	n.a.	n.a.
P_3	7.50	(1.0)	5.00		10.00	n.a.	n.a.
P_4	7.50	(1.0)	5.00		10.00	n.a.	n.a.
P_5	7.50	(1.0)	5.00		10.00	n.a.	n.a.
P_6	3.50	(1.0)	2.00		5.00	n.a.	n.a.
P_7	3.50	(1.0)	2.00		5.00	n.a.	n.a.
TS_1	15.50	(1.0)	1.00		30.00	n.a.	n.a.
TS_2_1	13.33	(1.0)	5.00	15.00	20.00	n.a.	n.a.
TS_2_2	6.00	(1.0)	3.00	5.00	10.00	n.a.	n.a.
TS_3	45.00	(1.0)	30.00		60.00	n.a.	n.a.
TS_4_1	17.50	1.26	12.60		31.50	4.86	3.71
TS_4_2	7.50	1.26	6.30		12.60	2.08	1.59
TS_5_1	7.50	1.26	6.30	9.45	12.60	2.08	1.59
TS_5_2	10.00	(1.0)	5.00		15.00	n.a.	n.a.
TS_5_3	8.50	1.26	2.52		18.90	2.36	1.80
TS_5_5	15.00	1.26	12.60		25.20	4.17	3.18
TS_5_6	10.00	(1.0)	5.00	10.00	15.00	n.a.	n.a.
TS_5_7	1.00	1.26		1.26		0.28	0.21
TS_5_8	7.00	(1.0)	3.00	8.00	10.00	n.a.	n.a.
TS_5_9	3.00	1.26	1.26		6.30	0.83	0.64
TS_5_10	3.50	(1.0)	2.00		5.00	n.a.	n.a.
TS_6	15.00	1.26	12.60	18.90	25.20	4.17	3.18
TS_7	7.67	(1.0)	3.00	5.00	15.00	n.a.	n.a.
TS_8	1.00	(1.0)		1.00		n.a.	n.a.

Table D.11.: Real-world key activity durations

Event k	Key activity durations [min] Transit replacement	Transit TS	Hangar replacement	Transport service station	Subsystem maintenance	Trouble-shooting	Valid-ation data
1			228	25	137	94	
2	131	65		16	343	92	
3	85	126		20	300	108	
4			144	20	301	99	
5	90	188		24	463	124	
6	95	207		28	221	86	
7	119	234		20	248	133	
8			168	22	304	79	
9			179	20	169	134	
10	149	117		21	368	103	
11	149	129		22	265	89	
12			160	21	275	139	
13			237	22	205	99	
14	93	71		26	360	61	
15	155	137		22	179	96	
16			234	22	205	74	
17			199	22	241	95	
18			267	19	325	95	
19	88	171		22	284	75	
20	119	142		22	355	98	
21			255	25	12	59	
22	59	184		19	322	89	
23	134	163		22	337	74	
24	142	244		21	345	103	
25	96	131		19	118	96	✓
26	115	188		20	116	111	✓
27			151	21	294	92	
28	44	68		22	277	75	✓
29			179	23	312	97	
30			131	22	193	74	
31			158	28	176	117	
32			188	23	480	71	
33			84	20	314	90	
34	59	142		19	251	64	✓
35			176	18	363	79	✓
36			162	21	230	113	✓
37			145	21	425	109	✓
38			227	17	271	100	✓
39	34	197		22	328	95	✓
40	108	186		21	443	87	✓
41			204	23	367	76	✓
42			117	16	270	97	✓

D.3 Exp. 2 simulation results

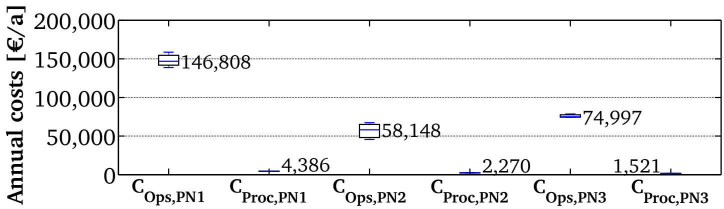


Figure D.1.: Initial state analysis: DCC and process costs w.r.t. different PNs

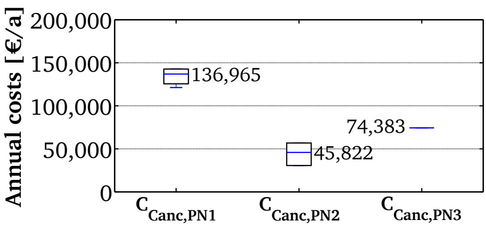


Figure D.2.: Initial state analysis: Cancellation costs w.r.t. different PNs

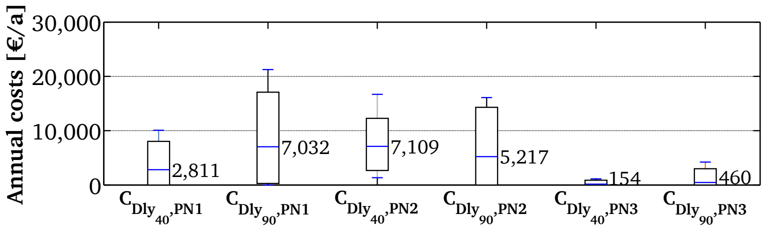


Figure D.3.: Initial state analysis: Delay (prim. and react.) costs w.r.t. different PNs

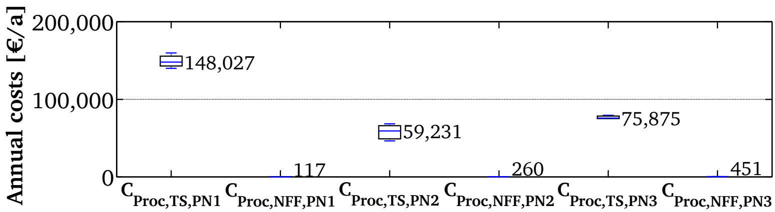


Figure D.4.: Initial state analysis: TS- and NFF-process costs w.r.t. different PNs

Time-based target values

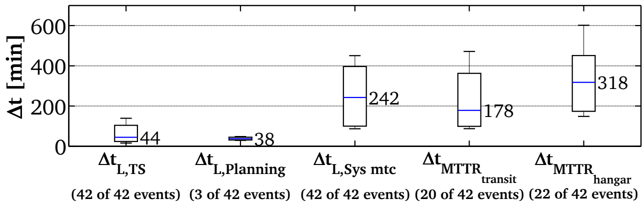


Figure D.5.: Initial state analysis: Time-based target values

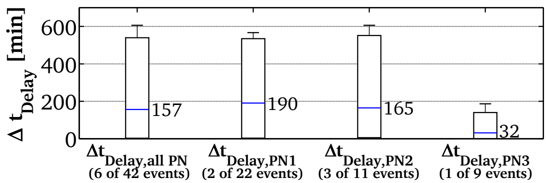


Figure D.6.: Initial state analysis: Time-based annual delays w.r.t. PNs

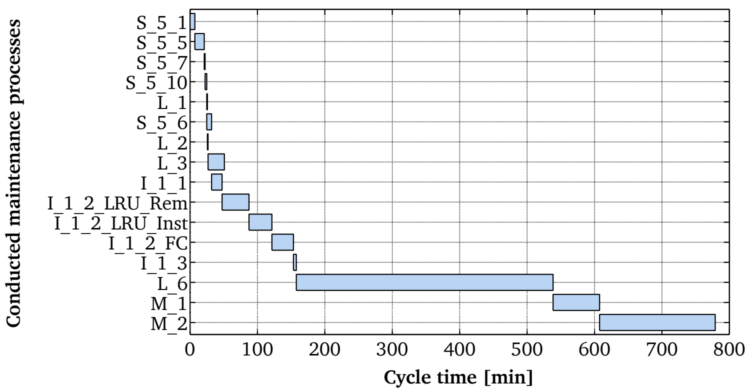


Figure D.7.: Exemplary Gantt chart

D.4 Exp. 3 simulation results

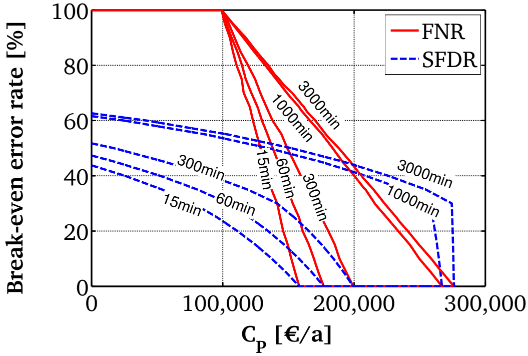
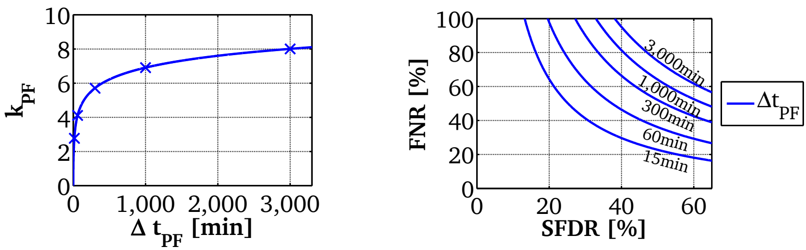


Figure D.8.: Impact of C_P and Δt_{PF} on break-even error rates



(a) Exemplary prediction forecast impact: $k_{PF} = f(\Delta t_{PF})$ (Eq. 5.11)

(b) Exemplary minimum prediction error rates for varying Δt_{PF} (Eq. 5.9)

Figure D.9.: Exemplary formulations of prediction model immanent characteristics

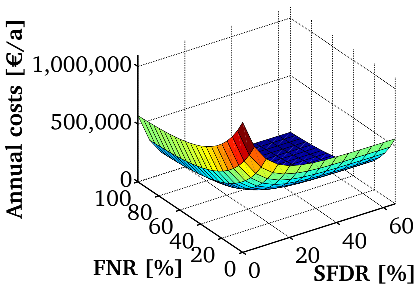


Figure D.10.: Prediction costs C_P approximation (Eq. 5.10) for $\Delta t_{PF} = 1{,}000$min

C_P approximation according to Eq. 5.10 for $\Delta t_{PF} = 1{,}000\text{min}$:

$$C_{\text{LRU}} = a_1 + a_2 \cdot \text{SFDR} + a_3 \cdot \text{FNR} + a_4 \cdot \text{SFDR}^2 + a_5 \cdot \text{SFDR} \cdot \text{FNR} + a_6 \cdot \text{SFDR}^3 + a_7 \cdot \text{SFDR}^2 \cdot \text{FNR} \quad (D.1)$$

with

$$a_1 \approx 22{,}967.68 \quad (D.2)$$
$$a_2 \approx 18.2232 \quad (D.3)$$
$$a_3 \approx 1{,}681.58 \quad (D.4)$$
$$a_4 \approx -33.49 \quad (D.5)$$
$$a_5 \approx -0.15 \quad (D.6)$$
$$a_6 \approx 1.67 \quad (D.7)$$
$$a_7 \approx 0.0024 \quad (D.8)$$

$$SSE = 3{,}257{,}901{,}136 \quad (D.9)$$
$$R\text{-}square = 0.999123 \quad (D.10)$$
$$RMSE = 3{,}369.2094 \quad (D.11)$$

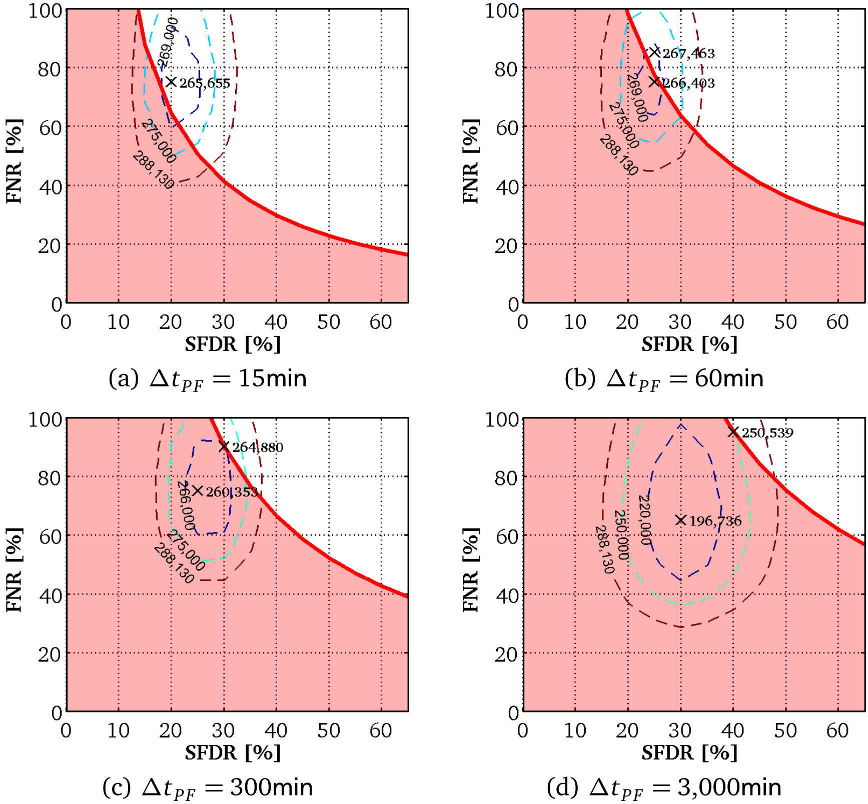
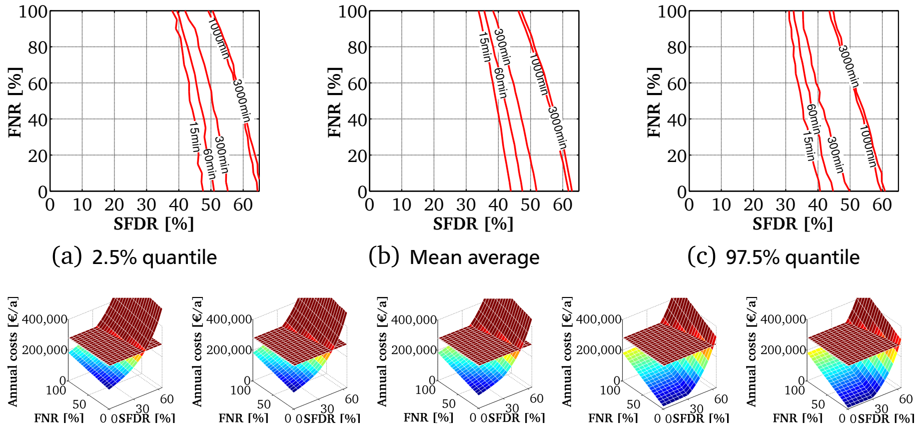


Figure D.11.: Restrictions on applicable prediction model settings

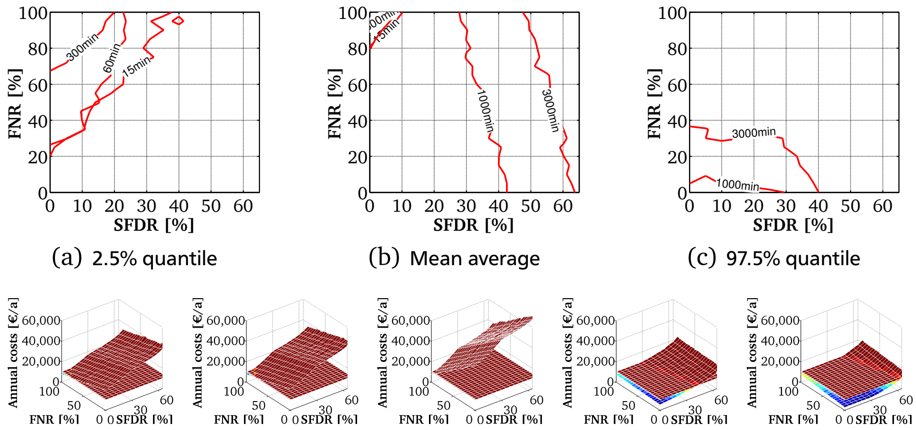
Results of specific costs



(a) 2.5% quantile (b) Mean average (c) 97.5% quantile

(d) 15min (e) 60min (f) 300min (g) 1,000min (h) 3,000min

Figure D.12.: DCC: Break-even plots and cost curves w.r.t. location parameters and PFs (no prediction costs)



(a) 2.5% quantile (b) Mean average (c) 97.5% quantile

(d) 15min (e) 60min (f) 300min (g) 1,000min (h) 3,000min

Figure D.13.: Primary delay costs: Break-even plots and cost curves w.r.t. location parameters and PFs (no prediction costs)

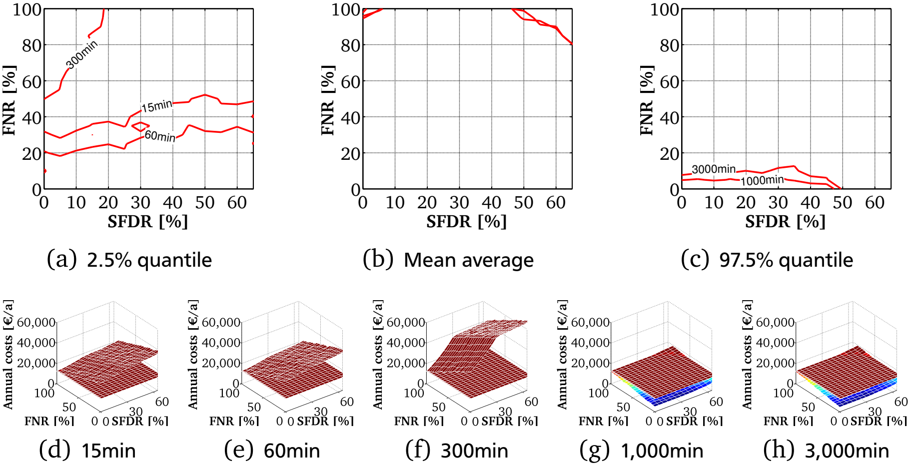


Figure D.14.: Reactionary delay costs: Break-even plots and cost curves w.r.t. location parameters and PFs (no prediction costs)

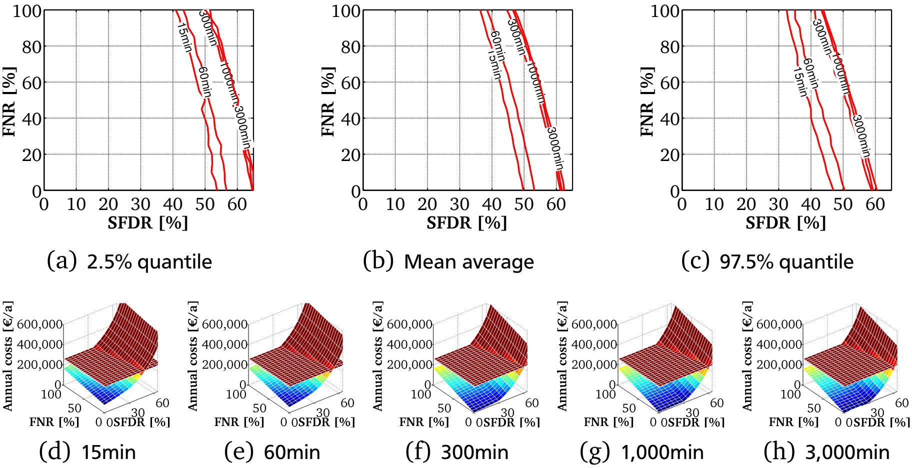


Figure D.15.: Cancellation costs: Break-even plots and cost curves prediction-based vs. today w.r.t. PFs (no prediction costs)

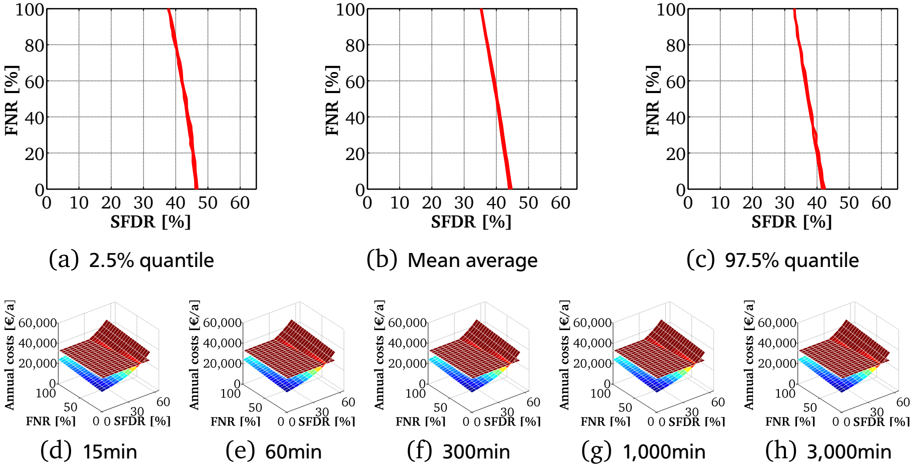


Figure D.16.: Maintenance costs: Break-even plots and cost curves prediction-based vs. today w.r.t. PFs (no prediction costs)

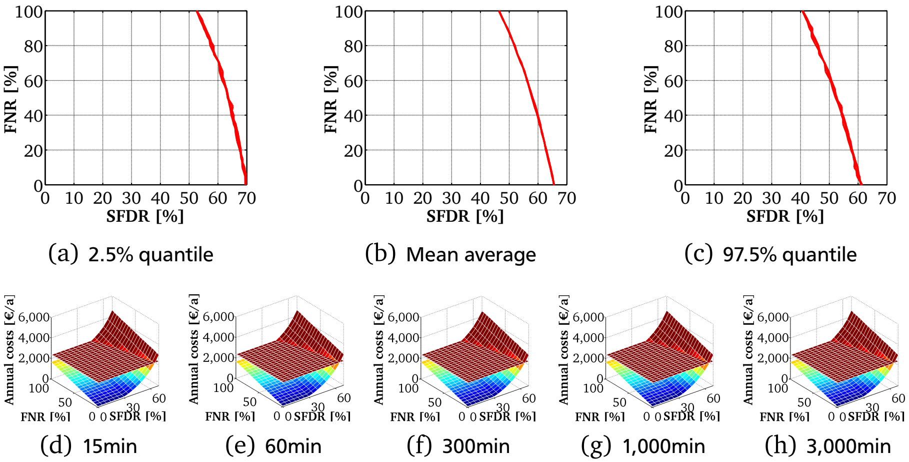
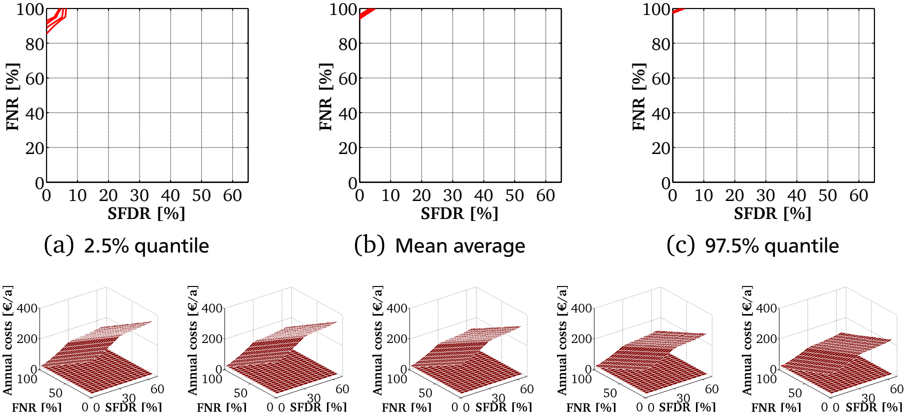


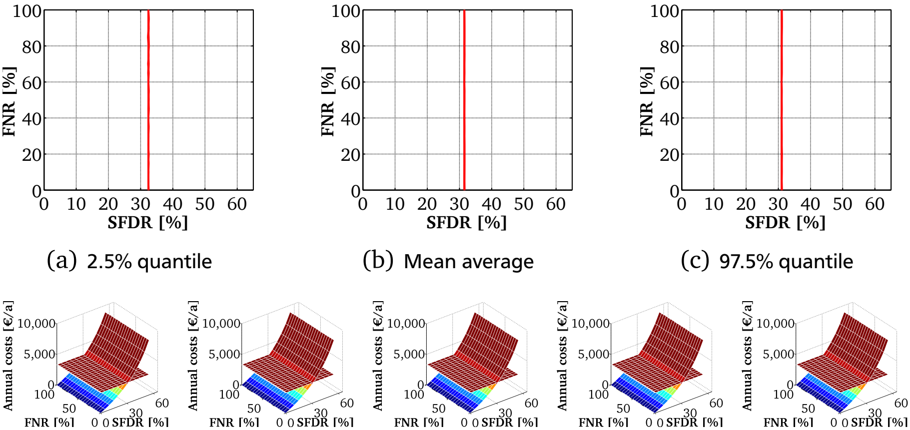
Figure D.17.: TS costs: Break-even plots and cost curves w.r.t. location parameters and PFs (no prediction costs)



(a) 2.5% quantile (b) Mean average (c) 97.5% quantile

(d) 15min (e) 60min (f) 300min (g) 1,000min (h) 3,000min

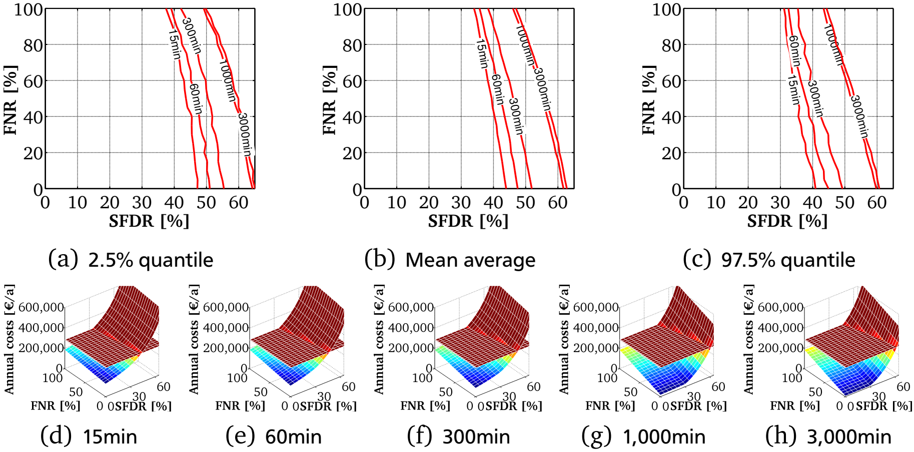
Figure D.18.: Planning department costs: Break-even plots and cost curves w.r.t. location parameters and PFs (no prediction costs)



(a) 2.5% quantile (b) Mean average (c) 97.5% quantile

(d) 15min (e) 60min (f) 300min (g) 1,000min (h) 3,000min

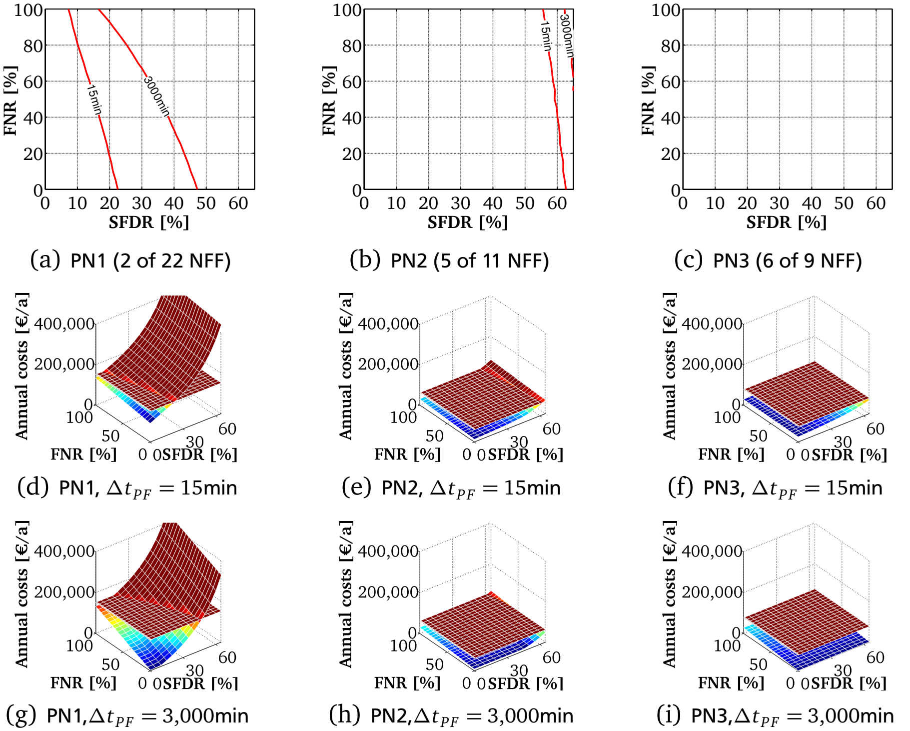
Figure D.19.: NFF costs: Break-even plots and cost curves w.r.t. location parameters and PFs (no prediction costs)



(a) 2.5% quantile (b) Mean average (c) 97.5% quantile

(d) 15min (e) 60min (f) 300min (g) 1,000min (h) 3,000min

Figure D.20.: Avoid. costs: Break-even/cost curves exp. 3 vs. 2 w.r.t. loc. param. and PFs (no C_P)



(a) PN1 (2 of 22 NFF) (b) PN2 (5 of 11 NFF) (c) PN3 (6 of 9 NFF)

(d) PN1, $\Delta t_{PF} = 15$min (e) PN2, $\Delta t_{PF} = 15$min (f) PN3, $\Delta t_{PF} = 15$min

(g) PN1,$\Delta t_{PF} = 3{,}000$min (h) PN2,$\Delta t_{PF} = 3{,}000$min (i) PN3,$\Delta t_{PF} = 3{,}000$min

Figure D.21.: PN total costs: Break-even and cost curves pred.-based vs. today w.r.t. PNs (no C_P)