# Optimisation of a component replacement policy at KLM E&M using Predictive Maintenance

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# MANAGEMENT SUMMARY

This research is an attempt to support KLM Engineering & Maintenance with the construction of a solid business case for a new data-driven maintenance application called 'Prognos'. Prognos is developed to improve Maintenance, Repair and Overhaul operations by forecasting component failures. Predictions about upcoming failures can be employed to implement a Predictive Maintenance (PdM) strategy, that aims to reduce cost in various aspects of the organisation.

This study investigates the impact of PdM on repair cost and spare part cost. It is the first time that a detailed analysis on these two cost factors combined is performed for components in a $k$-out-of-$N$ structure: not only for KLM E&M but also in literature. This addresses the following problem statement, that is of particular interest at KLM:

*'There is a lack of insight in how a predictive component replacement policy should be designed at KLM Engineering & Maintenance such that spare part and repair cost are minimised.'*

KLM's current situation is analysed and a literature study is performed in order to identify saving opportunities in repair and spare part cost. Three predictive component replacement policies are designed that are aimed at minimising these cost factors, and their performance is tested within a simulation model. The corresponding research question is formulated as:

*'How should a predictive component replacement policy be designed and implemented at KLM Engineering & Maintenance, in order to reduce repair and spare part cost?'*

It was found that the predictive policy that initiates replacement on an aircraft when at least 2-out-of-4 components are alerted and/or failed, is the most beneficial policy for a 3-out-of-4 system. When replacement is initiated, the aircraft with the highest number of alerted components should be prioritized in order to maximise repair cost savings.

When predictive policies also consider current on-hand stock levels in their replacement decision, the variability of components in repair can be reduced. The increased time frame realised by forecast information, enables to smoothen the inflow of repairs. This variability reduction has an effect on the minimum required stock level: it is shown in a case study that spare inventory for KLM's 787 fleet can be reduced with 20% for one particular system. The corresponding average total cost reduction is expected to be approximately 30%.

By using experimentation, the simulation study had the following findings:

- When fleet size is increased, the reduction of inventory levels is increased to 30%;
- Policy performance remains stable when the model is run with different failure distributions or added randomness in lead times;
- Changes in repair turnaround times and repair costs have the largest impact on spare levels and costs respectively;
- Low sensitivity rates and short prediction horizons also result in cost reductions.

This research provided promising results for the benefits related to the implementation of PdM at KLM E&M. However, it must be kept in mind that results could only be generated with the help of simplifying assumptions that include uncertainty.

We recommended KLM to implement predictive replacement policies for all components that have potential repair cost savings, provided that the ratio between the prediction horizon and the mean time to failure is small. In this way, repair cost can be saved while the decrease of the mean

time between removal, and therefore the increase in maintenance workload, is minor. It is also recommended to integrate current stock levels in replacement decisions, such that KLM is able to capitalize on benefits of spare part inventory reduction. This might lead to competitive advantage in the MRO market. Further research should be performed to investigate how decisions 'in the front' (i.e. the replacement decision) can be aligned with the situation 'in the back' (i.e. the current status of the supply chain), leading to optimised integral decision making.

# PREFACE

With this research I finish my master Industrial Engineering and Management and my time as a student. I have learned many things in the past few years about the field of research and myself, and had great pleasure while doing so at the University of Twente and the city of Enschede. It was a wonderful time with many new experiences and accomplishments.

This thesis is the final milestone, where I had the opportunity to learn about the dynamic world of aviation at one of Holland's greatest companies. I found the subject of the research very interesting and liked the associated complexity a lot. It was challenging to continuously make the right trade-off for the scope of the research, but I think this was done successfully and the final result provides valuable insights for KLM E&M.

All members of the graduation committee are accountable for this success, so thank you Sidney, Engin and Martijn for all your helpful feedback, insights, support and time. It improved the thesis a lot and made me learn many new things. I enjoyed working with you.

I would also like to thank all my family, friends, fellow students and colleagues that supported me during my studies. You have made my time as a student great and very special. I am proud of the result.

Irene van den Hof
02-05-2019

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# LIST OF ABBREVIATIONS

| ABBREVIATION | DEFINITION |
|---|---|
| **A/C** | Aircraft |
| **AFI** | Air France Industries |
| **AHM** | Aircraft Health Monitoring |
| **AOG** | Aircraft On Ground |
| **BAR** | Big Data, Analytics & Reliability |
| **CBM** | Condition-Based Maintenance |
| **CS** | Component Services |
| **CSF** | Critical Success Factor |
| **CSU** | Cooling System Unit |
| **DD** | Deferred Defect |
| **DIL** | Demand Initiation Level |
| **E&M** | Engineering & Maintenance |
| **EASA** | European Aviation Safety Association |
| **ERP** | Enterprise Resource Planning |
| **FDE** | Flight Deck Effect |
| **FIM** | Fault Isolation Manual |
| **GUI** | Graphical User Interface |
| **KLM** | Koninklijke Luchtvaart Maatschappij (Royal Dutch Airlines) |
| **KPI** | Key Performance Indicator |
| **LC** | Logistic Centre |
| **LRU** | Line Replaceable Unit |
| **MCC** | Maintenance Control Centre |
| **MEL** | Minimum Equipment List |
| **MRO** | Maintenance, Repair, Overhaul |
| **MSO** | Maintenance Support Order |
| **MTBR** | Mean Time Between Removal |
| **MTTF** | Mean Time To Failure |
| **NFF** | No Failure Found |
| **NRM** | Non Routine Maintenance |
| **OEM** | Original Equipment Manufacturer |
| **PdM** | Predictive Maintenance |
| **PH** | Prediction Horizon |
| **PHM** | Prognostics & Health Management |
| **RI** | Rectification Interval |
| **RM** | Routine Maintenance |
| **RUL** | Remaining Useful Life |
| **TAT** | Turn Around Time |
| **UGT** | Unplanned Ground Time |
| **WIP** | Work in Progress |

# 1 INTRODUCTION

Maintenance, Repair and Overhaul (MRO) activities are one of the major cost drivers in the competitive civil aviation market. The aim to be cost effective on these operations has drawn more and more attention over the past few years, due to technological developments, limited saving potential in other areas and the introduction of low-cost carriers (Doganis, 2010). A popular saying at the Royal Dutch Airlines (KLM) is that aircraft on ground only generate cost, and revenue while being in the air. Therefore, the organisation aims to minimise ground times and maximise aircraft availability. This results in tight schedules and high fleet utilisation rates compared to other airlines. This is realised due to an efficient organisation and close cooperation between the airline operator and MRO organisation.

To maintain high aircraft availability, the Big Data, Analytics & Reliability (BAR) team was recently established at KLM. The goal of the team is to improve MRO operations with data analytics support or by making them completely data-driven. This research is an attempt to help the BAR team with the quantification of the benefit of a new data-driven maintenance application called 'Prognos'.

This chapter is an introduction to the research, including context description (1.1), research motivation (1.2), research objective (1.3), scope and limitations (1.4), and finally the research questions and approach (1.5).

## 1.1 CONTEXT DESCRIPTION

To understand the context of our research, this section provides an introduction on KLM (1.1.1), (aircraft) maintenance (1.1.2 and 1.1.3) and Prognos (1.1.4). It provides insight in the industry, the capabilities of Prognos and some key concepts in maintenance, required to understand the problem of this research.

### 1.1.1 Company and fleet

The MRO organisation Air France Industries (AFI) KLM Engineering & Maintenance (E&M) is, in terms of revenue, the second largest MRO service provider in the world. It provides services to more than 200 airlines worldwide (Shay, 2017). With a workforce of 14,000 employees they offer technical support and services, including engineering, line maintenance, components, airframe and cabin modifications, engines, on wing services and technical training.

The 118-aircraft fleet of KLM is maintained by KLM E&M at their home base Schiphol-Oost. KLM E&M's organisation consists of six departments: Component Services, Engine Services, Logistics, Engineering, Aircraft Maintenance, and Staff (AIR FRANCE KLM GROUP, 2018). Table 1 shows an overview of KLM's fleet. The Boeing 787 aircraft ('Dreamliner'), from now on 787, was introduced at KLM in 2015 and is the youngest aircraft in KLM's fleet.

*Table 1: KLM fleet (Royal Dutch Airlines, 2017)*

| Aircraft | Multiplicity | Max. passengers | Range (km) | Short / long haul |
|---|---|---|---|---|
| **Airbus A330** | 13 | 268 - 292 | 8,200 – 8,800 | Long haul |
| **Boeing 747 (cargo)** | 13 (3) | 268 - 408 | 11,500 | Long haul |
| **Boeing 787** | 13 | 294 | 11,500 | Long haul |
| **Boeing 777** | 29 | 320 - 408 | 11,800 – 12,000 | Long haul |
| **Boeing 737** | 50 | 188 | 4,300 | Short haul |
| **Embraer 190** | 42 | 100 - 88 | 3,300 – 3,180 | Short haul |
| **Total** | **118** | - | - | - |

### 1.1.2 Maintenance in aviation

Safety requirements influence maintenance operations in aviation to a large extent. Regulations concerning airworthiness [1] requirements, approval of maintenance organisations, staff certification and training are supervised by the European Aviation Safety Agency (EASA) (European Union, 2003).

Maintenance actions to ensure airworthiness include required Routine Maintenance (RM) operations, which are executed during regular checks of the aircraft at predetermined time intervals, and Non Routine Maintenance (NRM). Repairs and other unplanned maintenance actions belong to NRM. The Mean Time Between (Unscheduled) Removal (MTB(U)R) is an indication of the duration of a component's 'time on wing' between replacements. It is a valuable measure that can be used to estimate resource demand for maintenance planning. The Mean Time To Failure is also used to estimate demand.

NRM is required when components fail before their next scheduled maintenance. From flight data that is logged by an aircraft, a Flight Deck Effect (FDE) can be generated. An FDE represents a fault that requires crew awareness or affects dispatchability (United States Patent No. 4943919, 1990). The required procedure that has to be performed based on an FDE, is specified in the Fault Isolation Manual (FIM)[2]. Sometimes FDEs can be solved with a system reset or a minor repair, but it can also lead to the replacement of a Line Replaceable Unit (LRU). This study only considers 'repair by replacement', which means that a failed system is always repaired by means of replacement. If an FDE requires an LRU replacement to be carried out, a technician can either replace directly, given a spare part is available, or defer the action. Common practice is that replacements are deferred, to keep local stock levels low. The Minimum Equipment List (MEL) specifies the Rectification Interval (RI), which is the time period in which the replacement has to be performed (no. of days within which the failure has to be solved), depending on the category.

*Table 2: MEL categories and corresponding deadlines*

| MEL Category | Rectification Interval (RI) |
|---|---|
| **A** | Part specific |
| **B** | 3 days |
| **C** | 10 days |
| **D** | 120 days |

The graph below shows the relation between the Time To Failure, Time Between Removal and Rectification Interval for a 3-out-of-4 system. A 3-out-of-4 system is a variant of a $k$-out-of-$N$ redundant system. Such systems have $N$ identical components and require $k$ of them to operate in order to have an operational system. In the 3-out-of-4 case, the system is down or/and MEL is violated if more than 1 component fails.

[1] Airworthiness represents the suitability of an aircraft for a safe flight.
[2] Fault isolation refers to the maintenance procedure of the isolation of faults as well as the determination of the significance of a fault for maintenance scheduling.

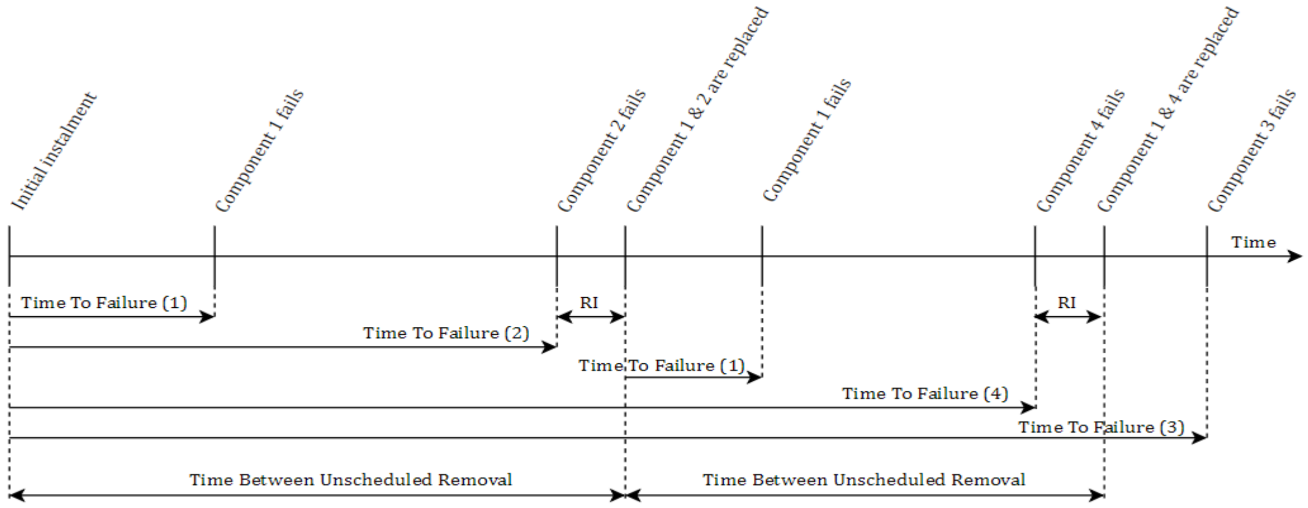



*Figure 1: Schematic timeline of a 3-out-of-4 aircraft system*

### 1.1.3 Maintenance policies

A lot of general maintenance policies exist in order to effectively maintain systems in terms of quality, costs and time. Policies are distinguished between three main categories: reactive (act after failure), proactive (act before failure), aggressive (minimise failure occurrence) (Tinga, 2013). Prognos is a PdM application, developed to predict future failure states of components. In aviation, component criticality is an important aspect for policy selection. Criticality of a component represents the impact of its functionality to the airworthiness of an aircraft. Critical components have short RI's or their failure leads to an Airplane On Ground (AOG; not airworthy) status right away. Usually a preventive policy is applied to these type of components. Non-critical components are mostly maintained according to a corrective policy. It is common practice to use redundancy for critical components in order to increase aircraft reliability[3]. In that case, a single component failure does not directly cause an AOG, provided that MEL requirements are still met. Redundancy increases complexity in maintenance and is an important aspect in this study.

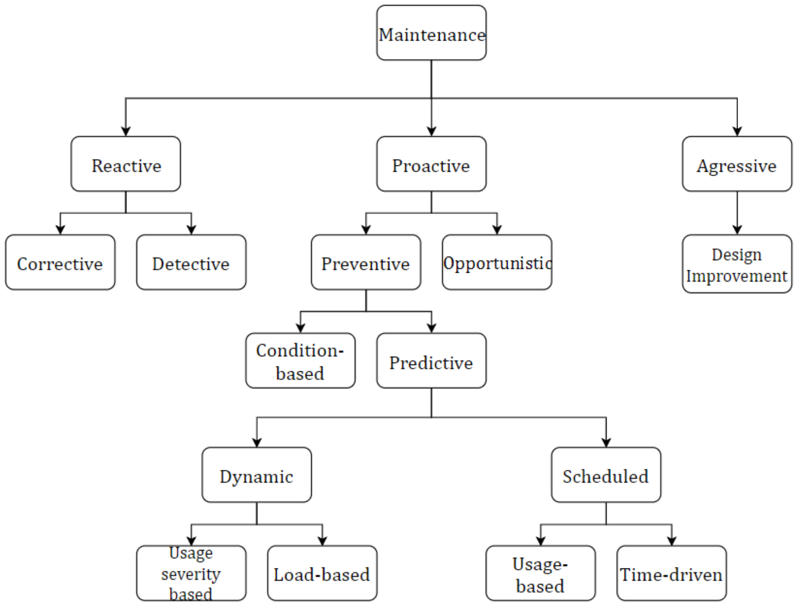



*Figure 2: Maintenance policies (Tinga, 2013)*

[3] Reliability = 1 – Probablity of failure, so high reliability means little failure occurrences.

### 1.1.4 Prognos

The Big Data, Analytics & Reliability (BAR) team is part of the Engineering division of KLM E&M. One of their major projects is the development of Prognos: a Predictive Maintenance (PdM) application designed to optimise MRO operations. The BAR team uses continuous data streams and in-depth system knowledge to develop algorithms that can predict upcoming failures, thereby potentially saving high maintenance costs and preventing technical delays. This differs from other health monitoring systems that use snapshot sensor data instead of continuous data, and only provide diagnostic information without predictions about future component failures. Prognos' models can be classified as 'Dynamic Predictive' in Figure 2.

Prognos started with the development of algorithms for a selection of LRUs of the Boeing 747 and, the majority, of the 787. LRUs were selected based on criteria such as data availability, repair costs and amount of operational disruptions due to failures. At the moment, algorithms for three selected LRUs are implemented in the Prognos software.

The software can create two types of signals: an alert (prognostic) or a failure indication (diagnostic). The failure indication, in combination with historical data about system behaviour, can provide troubleshooting support: It helps to 'do the right thing'. Predictive alerts provide additional support, namely also to perform maintenance 'at the right time'. Prognos creates a predictive alert based on sensor data collected during flights and predictive algorithms installed in the application. The alert represents an expected upcoming failure occurrence. The timing of an alert could be varied within a certain range. The maximum of this range varies per component and depends on a number of factors. The time between a predictive alert and a failure occurrence is referred to as the Prediction Horizon (PH). The accuracy[4] of alerts increases as the time to failure decreases: a predictive alert for a failure tomorrow might be 99,9% accurate whereas a prediction about a failure next month might be correct 50% of the time. Technicians are currently warned with a Prognos alert 10 days in advance of the expected component failure. This provides extra operational planning flexibility while not sacrificing too much Remaining Useful Life (RUL).

Prognos monitors several condition indicators, and using these parameters, it calculates an aggregate measure that indicates the health of a component. When this aggregate measure of a component exceeds a certain critical limit, it is expected to fail soon, or, it is considered as failure. The classification of failures and predictive alerts and the corresponding thresholds for the aggregate measures are continuously monitored and optimised by the BAR team. So far, the accuracy of the alerts and failure indications in Prognos has been very good, also with alerts that were generated 10 days in advance.

**Focus on 787 –** Prognos' focus is on the 787, the first "more electric aircraft" from Boeing. This aircraft has far more expensive components than the other aircraft. More electric aircraft are designed to push forward the concept of 'more electric', and, ultimately, 'all electric'. The aircraft contains a lot of new, innovative systems designed to reduce fuel consumption and environmental impact. The high costs related to maintenance of the 787 leads to the expectation of high saving potential with PdM. Since the 787 is an aircraft used for long haul flights with high passenger loads, the potential savings due to reduction of technical delays are also significant compared to short haul. Finally, the 787 enables the development of predictive analytics due to the huge amount of data that is collected during flights.

[4] The fraction of correct predictions (or alerts).

## 1.2 RESEARCH MOTIVATION

PdM can minimise total maintenance costs by optimising the timing of component replacements. This concept is embraced by the BAR team and is a motivation for this research, as it arises the question: How can KLM E&M minimise total maintenance cost with PdM? In the next subsection the concept of minimising maintenance cost by optimising the timing of replacements is discussed. Section 1.2.2 discusses a few recent issues at KLM E&M that are relevant for this study since Prognos might be able to contribute to solving these issues.

### 1.2.1 The concept of minimising cost with PdM

Detailed information about the occurrence of component failures enables to perform a more accurate trade-off between repair cost and prevention cost. Figure 3 shows the relation between repair, prevention and total costs in maintenance. As can be seen in the figure, prevention costs are high and repair costs are low with a preventive maintenance strategy (left section in the graph). This policy prevents failure occurrences due to timely replacements. This results in little failures and a high frequency of preventive replacements.

A reactive maintenance policy, which is shown on the right side in Figure 3, has a high number of failures, resulting in high repair costs. The number of preventive actions is low (or zero), resulting in low prevention costs. Predictive maintenance aims to set the maintenance policy such that total costs are minimised, by making the optimal trade-off between preventive – and corrective (repair) costs, by using predictive information, e.g. information about the health status of systems or components and predicted time of a future failure.

Currently, Prognos is only used for corrective maintenance. Yet, it is not used for proactive maintenance and does not consider the basic trade-offs explained in Figure 3. Current practice of the LRU's included in Prognos' scope can therefore be indicated with the red X in the figure. Most components fail before their estimated MTTF and are correctively removed before the expected MTBR, resulting in high total repair and replacement costs. The maximum saving potential of Prognos equals the decrease in total costs if the X shifts from its current position on the right to the green optimum point in the middle (the result of the decrease in repair cost and the increase in prevention cost, indicated with 1; (2) – (3) = (1)).

At this moment, the potential savings are calculated based on historical data about repair costs (indicated with 2) and technical delays, which presumably could have been prevented if Prognos' information was available at the time. This is an estimation based on a number of assumptions and excludes factors such as the increase in cost due to more frequent preventive actions. The expected size of this cost increase related to (3) is important to estimate for the purpose of employee awareness.

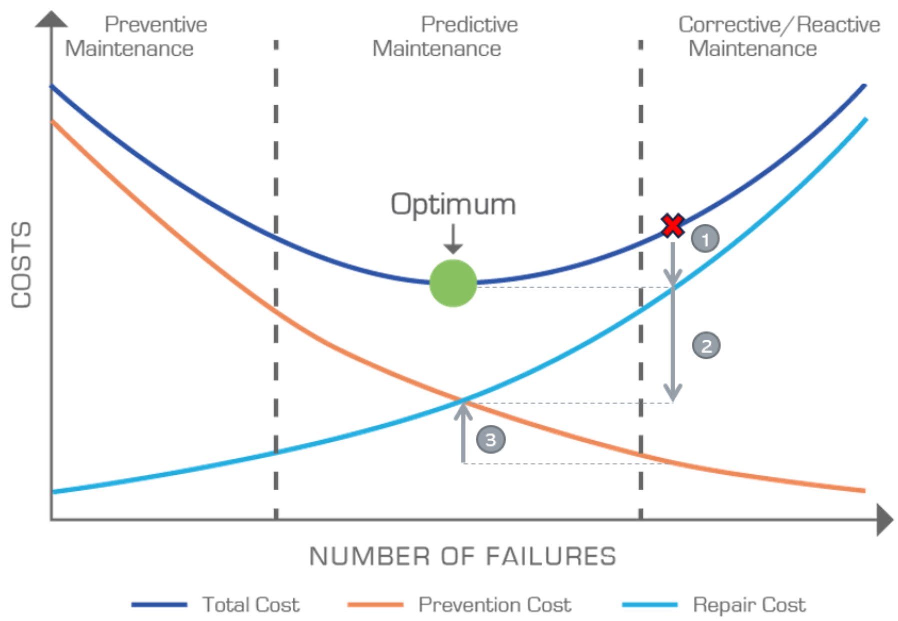


*Figure 3: Cost associated with traditional maintenance policies (Tchakoua, et al., 2014)*

The figure explains the trade-off between prevention cost and repair (or, corrective) cost in the traditional maintenance strategies. The study should focus on the cost related to repairing and replacing components on one hand, and on the other hand on the cost related to failure prevention. In the last category, spare part cost are identified as an important cost factor. Spare parts are expensive in aviation and an increased frequency of component replacements due to preventive actions, could result in high stock levels.

### 1.2.2 Research motivation for KLM E&M

At this moment, supply chain performance is poor for the supply of some components of the 787. One of the main reasons for the poor performance is the rather optimistic performance estimations that were made in advance of the 787 program kick-off, combined with the actual performance that turned out to be worse than the OEM MTTF/MTBR. This results in 787 component scarcity worldwide and capacity problems at KLM: delays in Turn Around Time (TAT)[5] for repairs, unavailability of components and high costs. Prognos can provide timely information about component failures, which can be used to improve the effectiveness of spare part decisions. It is unknown how and to which extent PdM can contribute to getting a grip on supply chain performance; this is a motivation for this study. In addition, timely information about component failure generates an opportunity for early component removal, resulting in minor repairs with low cost and short repair times instead of major repairs with high cost and long repair times. In order to show Prognos' full potential, maintenance operations have to be analysed in a more accurate and integral fashion. Potential benefits of a predictive replacement policy are, among others:

- Reduction of operational delays, by preventing technical delays due to improved scheduling;
- Repair cost savings, by using information about component condition to avoid major repairs;
- Repair time reduction, by reducing the work scope of repairs by avoiding major repairs;
- Reduction of inventory stock-out cost, due to alignment of demand for spares;

[5] The Turn Around Time is specified as the lead time in the repair shop.

- Reduction of inventory levels, as a result of improved planning and control enabled by PdM;
- Reducing the number of unjustified replacements, due to improved diagnostics.

It is unknown how KLM E&M can exploit these benefits with the current capabilities of Prognos and how a predictive replacement policy should be implemented for the components within Prognos' scope. Since the development of Prognos requires large investments, a detailed cost-benefit analysis is set as a high priority within the company. This cost-benefit analysis is also necessary for awareness creation and cooperation among KLM E&M employees, which is another motivation for this research. This is needed for successful implementation of PdM.

## 1.3 Research objective

Prior to setting the research objective, we need a more thorough understanding of the problem(s) we are trying to solve. Therefore, this section is divided in problem description (1.3.1), problem statement (1.3.2) and research objective (1.3.3).

### 1.3.1 Problem description

Figure 4 shows an overview of the problems related to unsuccessful PdM implementation at KLM. Prognos is already capable of indicating component failures, however this information is not used yet within the organisation to improve replacement decisions in an integral manner. At this point, Prognos predictive alerts are triggered 10 days before expected failure. However, 10 days is not the maximum PH with acceptable accuracy for some components and KLM should leverage the capabilities of Prognos to a larger extent to gain efficiency in planning and control, to match the 'right moment' of replacement. This 'right moment' should be set as a result of a trade-off between the cost related to preventive and corrective replacements. At this moment, a larger time frame can be used to plan a replacement, but only when a couple of constraints are met such as the presence of a maintenance message in one of the existing health monitoring system (due to warranty restrictions). It is unknown what the effect would be of potential other predictive replacement strategies, with larger or smaller prediction horizons and different replacement decisions taken based on the predictive alerts.

Some of the problems related to the lack of employment of predictive information are a motivation for this research, mentioned in the previous section. The problems are clustered in three categories: Maintenance & service planning aspects, Organisational aspects, and Data analysis and predictive modelling aspects.

**Problems related to Maintenance & Service planning –** It is complex to quantify the benefits of Prognos, since it involves a lot of uncertainty and different aspects within the organisation. Currently, Prognos' potential is not quantified to a full extent. This is due to the fact that it is unknown how PdM should be implemented to save cost in various areas of the organisation. Also, due to scarcity of spare parts, it is impossible to experiment with the implementation of PdM strategies. Implementation of PdM in the current organisation and process flows, will lead to a higher frequency of replacements due to early removals. This will (temporarily) increase work load in the supply chain, which is expected to result in a drop in service level. Therefore this (suboptimal) implementation is deferred until availability issues are solved. The lack of overview of all factors involved with predictive component replacement, also causes a lack of knowledge about the design and objectives of the future state. How can current practice be improved, with the help of Prognos' alerts? How should a predictive component replacement policy look like? When should Prognos trigger alerts? What are the consequences of using forecast information in various areas of the organisation? These questions remain unanswered in the current situation, which results in an unclear business objective. The answers to these questions are far from straightforward, due to the complexity involved with maintenance operations.

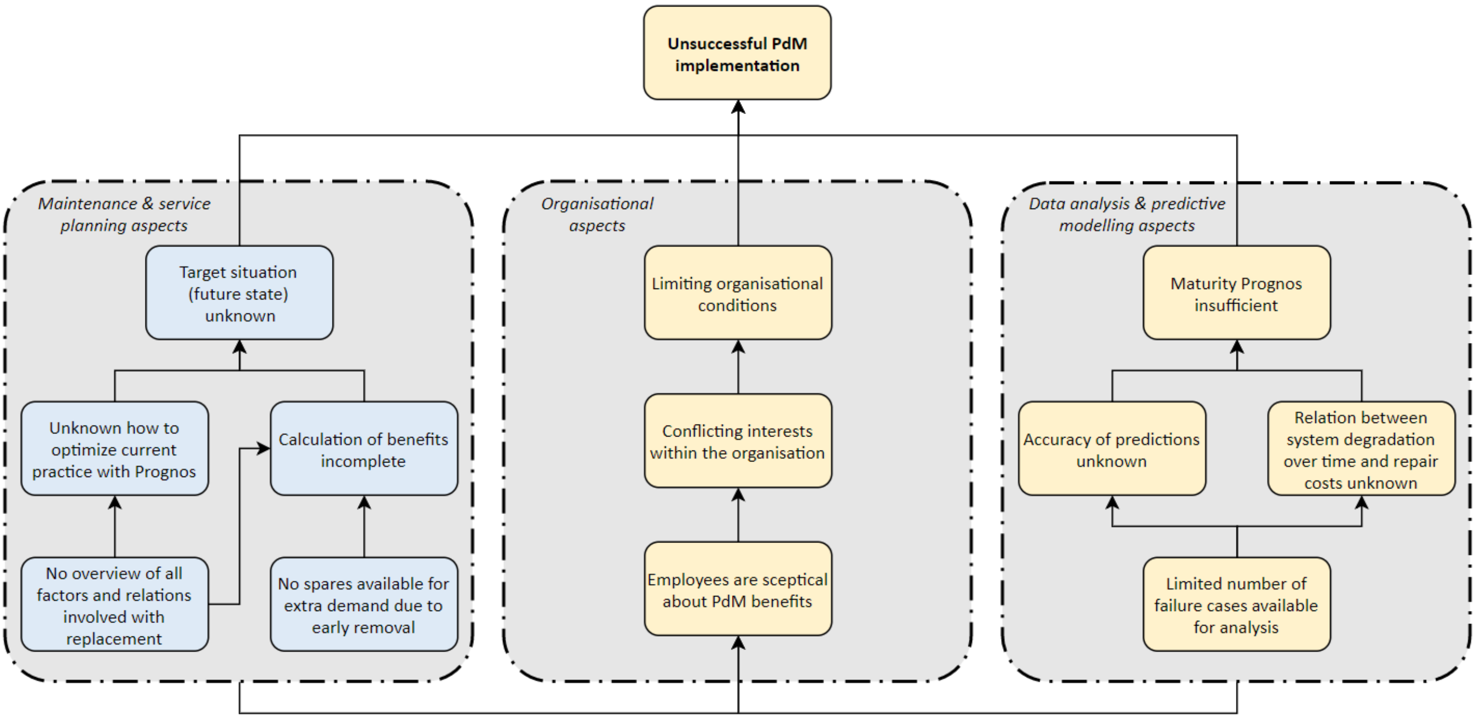



*Figure 4: Problem cluster*

**Problems related to Organizational aspects –** Ambiguity and uncertainty about the benefits (and drawbacks) of the implementation of PdM, and the risks related to it, contribute to the scepticism among various stakeholders at KLM E&M. Divisions have conflicting interests, as they all pursue their own objectives. Since the mutual business objective and the target situation is not defined in detail yet, benefits are not fully recognized and some stakeholders remain critical about PdM implementation and Prognos' capabilities. One of the main counterarguments is that predictive replacements result in more frequent replacements, due to a decrease in the time between removals (a shorter time on wing).

**Problems related to Data Analysis & Predictive Modelling –** Prognos is in its development stage. Although some components are successfully implemented in the application, some models are still being optimised and new models are developed. Due to the limited amount of failure cases available, it is hard to measure performance of predictions or to define the relation between system degradation over time and the effect on repair workload (time and cost). One could argue that the maturity of the application in its current state is insufficient for successful implementation of a PdM strategy. However, it is expected that performance develops rapidly due to high investments, team expansion and increased data availability enabled by partnerships. Therefore, a study on implementation is very relevant at this point.

### 1.3.2 Problem statement

This research focuses on the problems related to maintenance and service planning (indicated with blue in the left square of Figure 4). Within the target situation that KLM should aim for, benefits of predictive maintenance are exploited. That is, ideally, all aspects have been aligned and the situation of the green dot in Figure 3 is reached. This 'target situation' is unknown due to the lack of insight in how all aspects influence the position of 'the green dot' (Figure 3) and depends on Prognos' capabilities. This research will focus on the impact of a predictive component replacement policy on spare part and repair cost. We aim to find out how this policy should be designed in order to reduce cost and create some understanding on how the benefits of PdM depend on Prognos' prediction performance. The related problem can be best described according to the following statement:

***'There is a lack of insight in how a predictive component replacement policy should be designed at KLM Engineering & Maintenance such that spare part and repair cost are minimised.'***

The concept of spare part and repair cost savings was briefly mentioned in the list with potential benefits in the Research motivation section on page 12. In the remainder of this research the impact of these aspects shall be investigated in more detail. The problem owners of the problem mentioned above are the manager of the BAR team and the product owner of Prognos.

### 1.3.3 Objective

The aim of the research is to evaluate the potential impact of PdM at KLM E&M and how to maximise the benefits by designing a predictive component replacement policy. A cost trade-off must be made, including repair – and spare part costs, and the policies should satisfy operational constraints. The research aims to provide insight in the factors that are affected by PdM, including their mutual relations. This insight helps to set the right priorities, for future development of Prognos and for the implementation of the application. This will contribute to the overall success of PdM at KLM E&M. The research should provide:

- An estimation of the impact of a predictive replacement policy on current operations;
- Insight in cost fluctuations in the maintenance supply chain, under various scenarios;
- Prognos' requirements in order to capitalize on benefits.

## 1.4 Scope and limitations

This study will focus on the 787 aircraft only, because most of the components within the scope of Prognos are 787 components.

We focus on the problems that are indicated with a blue colour in the problem bundle of Figure 4. RM activities will be out of scope; we will focus only on corrective maintenance activities that are indicated by the degradation of components and which have the potential of using predictive maintenance. Decisions regarding the implementation of PdM include spare part investments and the replacement policy. Decisions regarding repair shop capacity allocation and repair priority rules are out of scope. The benefits related to improved planning of airline operations, are also out of scope. That is, the savings realised due to the prevention of technical delays.

## 1.5 Research questions & approach

This research will be conducted by consecutively answering a number of sub research questions, resulting in a final conclusion to the main research question. This addresses the problem statement formulated in Section 1.3. The main research question of this study is:

***'How should a predictive component replacement policy be designed and implemented at KLM Engineering & Maintenance, in order to reduce repair and spare part cost?'***

The research investigates how KLM can shift from corrective to predictive maintenance. This final section presents the research approach, which is based on the conceptual modelling framework of Robinson (2011), which will be described in more detail in later sections. In this chapter, the problem KLM E&M currently faces is introduced. To improve component replacements, we should analyse current processes and aspects related to this problem. Benefits increase when the performance of predictions is optimised. Therefore, we need to know the maturity of Prognos, providing us information about the capabilities of the application. This will be addressed in the second Chapter 'System description' with the following research questions:

1. *What is the current component replacement policy?*
    a. *Which stakeholders are involved with non-routine component replacements and what are their interests?*
    b. *Which process steps are involved with component replacement?*
    c. *What is the performance of the current component replacement policy?*
2. *What is Prognos and what are the capabilities of the application?*
    a. *Which components are included in the application?*
    b. *What does the application look like?*
    c. *What cost reduction is expected?*

After we have described all relevant aspects of the system, we perform a literature study to search for studies related to PdM (implementation). Based on knowledge from literature, a solution can be designed for our research problem. Chapter 3 is a literature review and answers the third question:

3. *What can we learn from related studies, when we want to improve the component replacement policy with predictive maintenance?*
    a. *What are the risks and opportunities related to predictive maintenance?*
    b. *Which aspects should we focus on when designing a predictive replacement policy?*
    c. *Which method is suitable to compare policies in our research?*

In Chapter 4 predictive component replacement policies are designed that use Prognos information in order to reduce repair and spare part cost. The chapter proposes potential solutions and the fourth research question is addressed:

4. *How should predictive component replacement policies be designed for k-out-of-N systems, that capitalize on repair and spare part benefits?*

In Chapter 5, a model is constructed for a case study of one of the components within Prognos' scope. The model should represent the system described in Chapter 2 and be able to analyse the performance of the designed policies from Chapter 4. For this purpose, all input factors have to be determined as well as the scope and level of detail of the model. The corresponding research questions is:

5. *How should we construct a model that is able to test the impact of predictive component replacement policies for k-out-of-N systems?*
    a. *How can we abstract a conceptual model from the system description?*
    b. *What does the model design look like?*
    c. *How can we use the model to find the best solution?*

The next step is to implement the model in software and analyse the results. Model validation is included in this chapter and various experiments are executed in order to evaluate the impact of certain factors on cost. This experimental study and its numerical results will be discussed in this Chapter 'Results' and has the corresponding research questions:

6. *What is the expected performance of the predictive replacement policies, when they are applied to a 787 component at KLM E&M?*
    a. *Which policy has the best performance?*

*b. What is the required performance of Prognos' prediction models?*

*7. What are the benefits and drawbacks of using a predictive replacement policy at KLM?*

Chapter 7 'Implementation' is the last chapter that answers research questions, namely:

*8. How should KLM E&M implement predictive maintenance?*

Chapter 8 includes a discussion about the results and Chapter 9 answers the main research question, including final conclusions and recommendations. Figure 5 is a representation of the research approach in chapters 2-7 (blue blocks) and the corresponding research questions (yellow blocks).

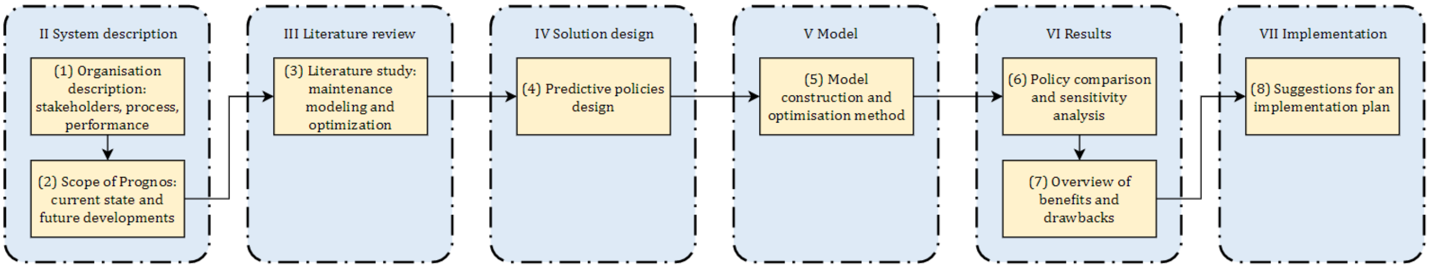



*Figure 5: Research approach*

# 2 SYSTEM DESCRIPTION

The first two research questions will be addressed in this chapter:

1. *What is the current component replacement policy?*
    a. *Which stakeholders are involved with non-routine component replacements and what are their interests?*
    b. *Which process steps are involved with component replacement?*
    c. *What is the performance of the current component replacement policy?*
2. *What is Prognos and what are the capabilities of the application?*
    a. *Which components are included in the application?*
    b. *What does the application look like?*
    c. *What cost reduction is expected?*

The aim of this chapter to analyse the context at KLM E&M and to identify all relevant aspects involved with corrective component replacement. The first section describes the current situation, including an introduction of the stakeholders, a description of the process flow and a description of Prognos.

The second section describes current performance of the component replacement process and Prognos related performance measures. Section 2.3 is a conclusion of this chapter.

## 2.1 CURRENT SITUATION

This section describes the process for corrective component replacement. Therefore, this excludes all planned maintenance activities, resulting from preventive maintenance. These planned maintenance activities are performed during letter checks [6] at the base, at a predetermined time. This mid-term and long-term planning of maintenance within letter checks is not within the scope of this research.

### 2.1.1 Direct stakeholders

There are multiple stakeholders involved with corrective component replacement process. The most important ones are introduced.

**Line maintenance** – At Schiphol and many other airports around the globe, AFI KLM E&M provides line maintenance services. Maintenance staff perform inspections, replacements, refuelling and troubleshooting between flights. A ground mechanic is responsible for executing all required actions to ensure safety. If a complaint is deferred, the Maintenance Control Centre (MCC) plans the activity.

**Maintenance Control Centre (MCC)** – The MCC is, together with line maintenance, responsible for planning and preparing corrective maintenance activities. Corrective maintenance can be planned within the available time window according to MEL. In addition, the MCC provides technical advice to line maintenance and pilots. Technical specialists from the MCC monitor aircraft's technical status via health monitoring systems, such as Aircraft Health Monitoring (AHM). Their goal is to minimise technical delays during flight operations and optimise reliability. Thus, line maintenance primarily executes corrective maintenance while the MCC plans the activities and provides technical support.

**Repair shop** – KLM E&M has two repair shop divisions with numerous repair shops, both part of Component Services (CS). The Plant Shop MRO repairs hydraulics, low/high frequency

[6] Letter checks are periodic inspections that are performed at the base of the MRO organisation. Light, more frequent checks are indicated with A and B, while C and D are considered to contain more heavier maintenance.

components, computers, indicators, air data systems and galleys. The Plant Shop Hub handles mechanical systems, such as panels, toilets, aircraft kitchens, flight controls, doors, plastic/carbon fibre parts, wheels, brakes, chairs and emergency equipment. If KLM does not have the capability to repair a certain part, the repair activity is outsourced to a vendor.

### 2.1.2 Indirect stakeholders

**Big Data, Analytics & Reliability (BAR) team** – Three engineers of the BAR team are working on the development of Prognos for 787 components. The product owner of Prognos is responsible for the development and performance of the application. The manager of the BAR team is responsible for defining the strategic purpose related to PdM (mission, vision and objectives related to becoming a data-driven organisation) and the coordination of the implementation of Prognos.

**Component Availability** – Each type of aircraft has its own 'availability team', responsible for spare part availability and consisting of an operations team and a support team. The operations team is responsible for operational control, making sure repair TATs are met. This means they are responsible for contact with the airlines and the suppliers and solve operational disruptions. TAT's are contracted in service contracts with customers and vendors. For most components, the TAT corresponds with 14 calendar days and it varies per supplier and component whether these agreements are met.

Supply chain specialists from the support team are responsible for long-term decisions, such as determining spare part levels and new sales cases. Together, the component availability team is responsible for the coordination of component flows and their timely availability. This is for all airlines included in the pool (so not only the KLM fleet). Currently this consists of approximately 160 aircraft (787) from 19 airlines around the globe. This number is growing rapidly.

### 2.1.3 Stakeholder's interests

Stakeholders within the organisation can have conflicting interests regarding component replacement. These differences are easy to explain but difficult to manage. To create a better understanding of the various objectives, Table 3 provides an overview of stakeholder's interests.

*Table 3: (conflicting) interests among stakeholders*

| Stakeholder | Objective (regarding component replacement) |
|---|---|
| **Line maintenance** | Minimise technical delays while minimizing line maintenance effort |
| **MCC** | Maximise aircraft availability and reliability, by responding effectively on health monitoring information and minimizing operational disruptions |
| **Repair shop** | Maximise reliability (by performing good quality repairs), deliver on time |
| **BAR team** | Minimise overall cost by providing support with data-driven optimisation tools |
| **Component Availability** | Minimise spare part cost and maximise service level |

All these aspects have to be taken into account when one wants to improve the replacement policy.

### 2.1.4 Corrective maintenance process flow at KLM

This section describes the current process involved with corrective component replacement at KLM as shown in Figure 6 (without PdM).

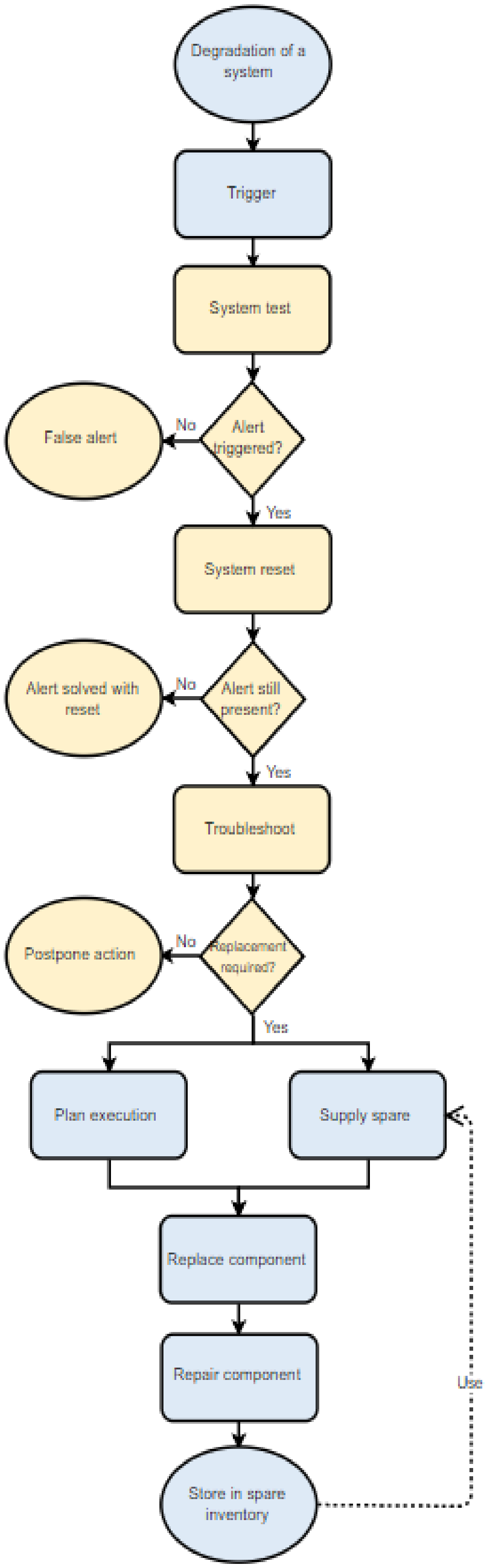



*Figure 6: Process for component replacement (without prognostics)*

**Process flow exclusively for KLM corrective replacements (non-routine)** – The process starts with a trigger from one of the aircraft health monitoring systems (such as AHM) or a technical complaint from the pilot. The MCC or ground technician receives and evaluates the trigger by consulting all information systems. In between flights, a technician tests the system. If the fault message does not appear again, the process ends and the alert is labelled as a false alarm.

If the alert is still present after testing, the technician performs a system reset. If this doesn't solve the problem, troubleshooting has to be performed to find the cause of the error. If replacement is not required right away, the action is usually postponed and placed on the 'Deferred Defect' (DD) list. The MCC creates maintenance orders for the parts on this list and plans the activities at a later time. If the replacement cannot be deferred, it can lead to an AOG. The MCC aims to solve MEL items as soon as possible, however, due to scarcity of some 787 components, current practice for these parts is that replacements are postponed to a moment close to the due date.

In order to perform component replacement, the execution needs to be planned and a spare needs to be supplied. It depends on the component and the required equipment whether it is possible to remove a component at the line. Some components can only be removed at the base. CS is responsible for on time spare delivery. After replacing the component with a spare, the defective component will be sent to the repair shop and put back into the serviceable inventory once it is repaired.

**Impact of PdM on process** – The system test, reset and troubleshooting (yellow boxes) will not be part of the process flow with (solely) Prognos alerts, since the test limits are not adjusted to Prognos sensitivity. That means, a component that was replaced based on a Prognos alert will pass a system test (in principle), since it is still within the bounds of the quality limits.

**Spare supply and repair procedure** – The standard logistic process of component replacement is best described according to Figure 7. This process is the same for all (pool) customers of KLM E&M. The process starts with a customer order. If a spare is available at the Logistic Centre (LC) it is picked and shipped. If there is no spare available, KLM can decide to lease or exchange a part. KLM has multiple partners worldwide that could deliver a lease spare, however these components are costly and not always available. If a part is leased, common practice is to exchange the part with another service part once there is one available. So, a random other spare can be returned for the outstanding lease part: it does not have to be the same component. The price of exchanging a component is 10% of the component price on average. Leasing of components is an exception rather than regularity.

After shipping, the serviceable unit is installed into the aircraft. The unserviceable unit is shipped to the LC. A repair order is created and the part is sent to an internal or external repair shop. After repair the part is received in serviceable condition at the LC. New spares are ordered by supply chain specialists, based on expected demand and expected component performance.

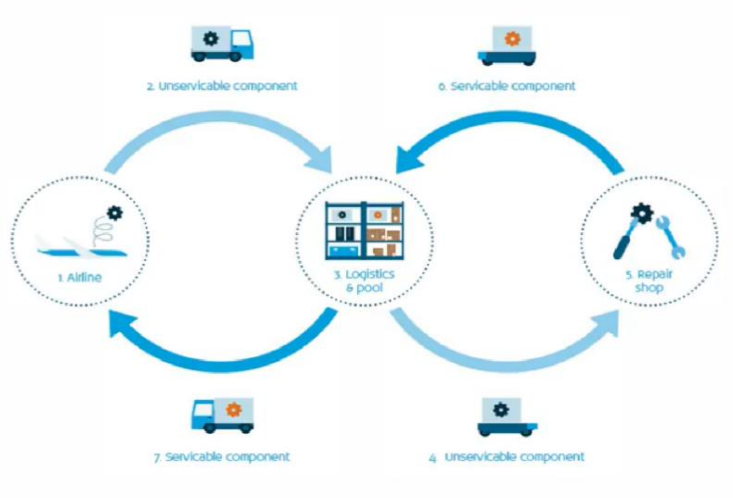



*Figure 7: Logistic process related to component replacement*

### 2.1.5 Prognos

Together with data engineers and data scientist, the BAR team develops algorithms to indicate component failures. It depends per component which parameters indicate failure modes. An example is the increase of temperature in a component used for cooling, or high power usage due to degradation in the filter. Another example is an anomaly in the oscillation pattern of a motor controller, indicating a certain failure mode. Most failure modes can be detected with Prognos.


*Figure 8: Process of prediction model construction*

Table 4 shows the LRUs that are implemented in Prognos' Graphical User Interface (GUI) in 2018. Users of the GUI navigate between all the tails (aircraft) of the fleet and per tail an overview is presented of current and historic performance of the LRU's on that tail.

*Table 4: Systems implemented in Prognos in Q3 and Q4 2018*

| Component (Q3) | Repaired by | QPA[7] | Criticality (MEL restrictions) |
|---|---|---|---|
| 747 Electrical Generator (EG) | KLM E&M | 4 | Solve within 3 days if 1-out-of-4 are failed |
| 787 Cooling System Unit (CSU) | OEM | 4 | Solve within 10 days if 2-out-of-4 are failed |
| 787 CSU Motor Controller (CSU MC) | AFI/OEM | 4 | Solve within 10 days if 2-out-of-4 are failed |
| 787 Air Compressor | Epcor[8] | 4 | Solve within 10 days if 1-out-of-4 are failed |

[7] Quantity per aircraft
[8] Epcor is a component overhaul and repair company, part of the KLM Group.

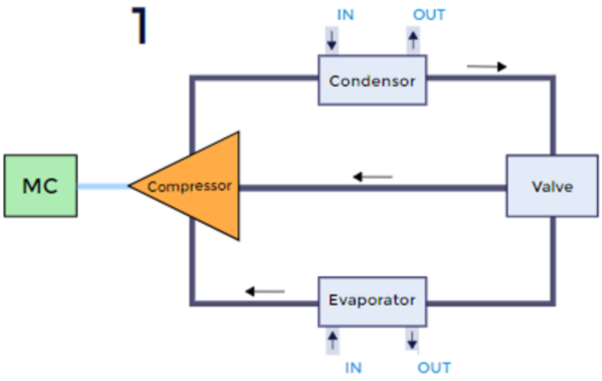



*Figure 9: Configuration diagram with a predictive*

In a system's configuration diagram in the GUI, failed components are indicated with a red colour and predictive alerts are indicated with orange. Figure 9 shows a screenshot from the GUI of Prognos with a configuration diagram of a component with a predictive alert on the compressor. The time window for predictive alerts is aligned with the planning window for scheduling replacements: 10 days in advance of an expected failure an alert is triggered. This increases the planning flexibility of the MCC and thereby helps to reduce Unplanned Ground Time (UGT) and AOGs. Ten days after an alert the component will fail and move to the red zone.

As an example, Figure 10 provides a (fictional) relation between the accuracy of the predictions and the prediction horizon. The maximum PH in the figure is 50 days. Currently, Prognos' algorithms are set such that a predictive alert is triggered (at least) 10 days before expected failure, indicated with the yellow X on the right. So, at that point the icon in the GUI corresponding to the observed component turns orange, as Figure 9 illustrated as example. This 10-day interval was chosen by the MCC, as it would give them more planning flexibility. A larger interval would be ineffective for them since their planning horizon for corrective replacements only considers short term. In that case, a larger PH will only have the negative effect of RUL reduction (if potential repair savings are not considered). If the graph in the figure were true, it would also be possible to trigger alerts sooner: for instance 30 days in advance with >85% accuracy. Prognos' developers are not yet able to provide a curve such as Figure 10, however they can provide an estimation of the accuracy of their predictions at various time intervals. This estimation provided by the BAR team, based on extensive research, is assumed to be correct.

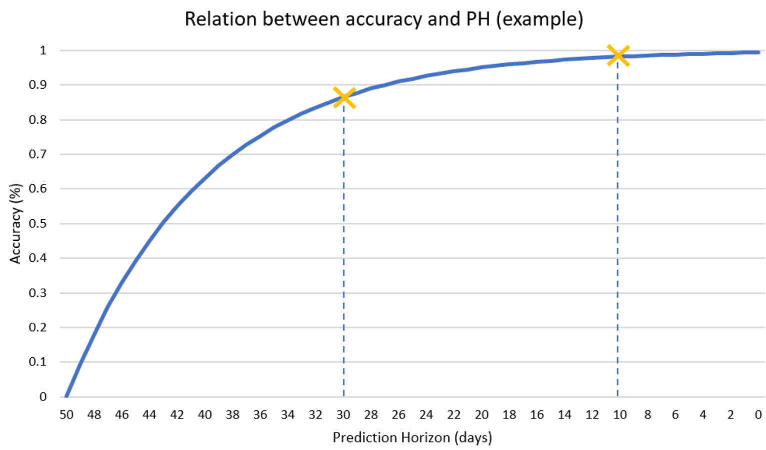



*Figure 10: Example of the relation between accuracy and PH (fictional)*

Larger prediction horizons might provide additional benefits for KLM E&M that are not utilised at this moment. If one also considers repair savings and spare part decisions, this threshold might be more efficient when it is set at another level. This could enable the avoidance of expensive repairs and the extra flexibility in spare part planning could be used to gain efficiency and reduce inventory. This study aims to provide a recommendation about the timing of alerts, while considering these repair and spare savings, such that threshold values in Prognos can be adjusted to the right requirements.

Besides a fleet overview and configuration diagrams, Prognos provides historical performance data per tail. The algorithms 'behind' the GUI generate graphs. Based on these graphs, an algorithm can generate an alert, as shown in Figure 9. Thresholds can be varied according to the preferred PH. The definitions of the thresholds vary per component and are defined by the BAR team and other stakeholders, such that an alert is triggered at the right time and with acceptable accuracy. Anomalies in the performance graphs (clearly detectable on the components with the red lines on the PH-BHC[9] in Figure 11) can exceed threshold values which results in alerts or failure indications in the configuration diagrams and fleet overview.

*Figure 11: Component behaviour graphs per tail*

In these graphs, data of a system with four components is plotted over time: each component represents a colour. Each dot in the graph represents a summary of a flight and the value on the y-axis represents the fraction of time within which the component had a temperature above a certain threshold. So if a red dot is plotted on [2018-07, 0.6], it means that component number 1 had a temperature above the threshold value for 60% during a flight in July 2018. The data models account for all kinds of noise and interaction effects. These algorithms have proven to be very effective: so far there have been no false alerts[10] at all.

## 2.2 PERFORMANCE MEASUREMENT

To create more insight in our system and its characteristics, we elaborate on the performance related to component replacements and Prognos. From Section 2.1.3 we know that there are multiple objectives related to component replacements, such as the minimization of maintenance effort, maximization of aircraft availability, maximise reliability, maximise service levels and minimise cost. Performance can be measured in terms of Key Performance Indicators (KPI's). The

[9] These five letter codes are aircraft registrations. PH represents the Dutch registration prefix. The B is for Boeing and the H indicates that the aircraft is a 787 model.
[10] A false alert or false alarm is a wrong prediction: the prediction value is 'failure', but the actual value is 'no failure'.

most important KPI's related to this study are costs and service level. Repair- and spare cost cover the largest fraction of total maintenance cost and the service level KPI is expressed as the fraction of on time deliveries. High service levels are required to ensure high fleet availability.

In Figure 6 a flowchart of component replacements was presented. The performance and cost related to this process depends on a number of factors. In this section the most relevant are highlighted. The steps indicated with yellow in the figure are out of scope, as these are considered irrelevant to PdM implementation at this moment.

Regarding the KPI's, the 'time on wing', 'time off wing' and service level mainly determine the costs related to spare parts. These costs, together with repair costs, are considered to have the most impact on total cost. In the next subsections this is explained in further detail.

### 2.2.1 Time on wing

A component on wing degrades while being operational and fails eventually. A number of factors determine when this will happen, for instance its operating environment, component quality and number of flight cycles. The most important performance measure at KLM regarding this process is the Mean Time Between Removal, which basically measures the average operational life cycle of a component (see also Figure 1). This measure determines the expected number of replacements on the fleet to a large extent. The formula used at KLM to estimate the total number of replacements on a fleet, is given as follows:

$$no. of\ replacements = \frac{fleet\ size * QPA * average\ flight\ hours\ per\ year}{MTBR}$$

For non-redundant systems with short rectification intervals, the MTBR ≈ MTTF. In that case a failure will result in replacement almost right away. For $k$-out-of-$N$ systems, the MTTF and MTBR can vary: the MTTF is a characteristic of a component and the MTBR is the result of a policy. For instance, in a 2-out-of-4 system one is obliged to replace components with less than 2 operational components (so at least 3 failures). However, one could also decide to preventively replace components when the system has 1 or 2 defective components. Here, preventively refers to 'before MEL violation'. In the latter case, the MTBR will be shorter as when replacements are postponed until there are at least 3 failures (MEL violation)[11]. The MTTF is unchanged.

One of the main counter arguments for the implementation of PdM is that it will reduce the MTBR, which results in a larger number of replacements. This is expected to result in higher spare levels, according to the defenders of this argument.

The given example illustrates the impact of replacement policies on the MTBR. From the formula it can be concluded that the MTBR is the most determining factor in the number of replacements, as the fleet size, quantity per aircraft and average flight hours per year are given. The number of replacements impacts the demand for spare parts. So, the replacement policy influences the demand for spares through the MTBR in $k$-out-of-$N$ systems.

### 2.2.2 Time off wing

Once component replacement is required, the component needs to be taken off the aircraft and sent to repair. This requires maintenance time, shipping time and repair time. In this research only repair time is considered. Replacement actions take up to half a day, which is negligible. Shipping times from and to customers can take up to weeks (when waiting times are included), however, for KLM's fleet shipping is always performed within a day. Therefore, in this research the time off wing is set as the repair TAT. For repair shops, this TAT is contracted and set to 14

[11] In Figure 16 (Chapter 4) this is the case for policy 2.

days in most of the cases. This contracted time is not always met and can include high variability and uncertainty.

The TAT is the most important measure in determining the 'average number in repair', or Work In Progess (WIP). This WIP determines, together with the number of replacements, the demand for spare parts since spares are required to fulfil demand during repair lead time. This relation is shown in the formula below, also known as Little's Law. The formula is later used to estimate spare demand, which is explained further in the next subsection.

$$average\ in\ repair = number\ of\ replacements * \frac{Repair\ TAT\ (+shipping\ times)}{365\ days}$$

### 2.2.3 Service level

To maintain high fleet availability, the service level of spare part delivery has to be high. At KLM, the target service level is set at 95% for most the components with MEL category C. This means that 95% of the components have to be delivered on time. There is no KPI related to the lead time. To estimate spare levels, the formula below is used:

$$number\ of\ spares\ needed = F^{-1}_{Normal(\mu,\sigma^2)}(service\ level)$$

Where $\mu$ represents the average number of spares in repair and $\sigma^2$ is the variance of the number of spares in repair. It is assumed that this number can be approximated with a Normal distribution. Therefore, the inverse Normal distribution at the service level will provide an estimation of the required spares. At KLM, the formula for variance is given as:

$$\sigma^2 = \sqrt{\mu}$$

This formula is used based on historic research at KLM. It is unknown whether this Normal approximation and approximation for the variance provide reasonable estimates.

New spares should be delivered within 7 days, however due to scarcity issues with 787 components, lead times can run up to months. If on-hand inventory cannot meet spare demand, KLM has the option to lease components. A lease component costs 10% of the purchasing price on average, and can be exchanged with a random other spare part when one becomes available.

Lease units can be sourced from all over the world; from other airlines but also at MRO competitors. The lead time of lease parts depend on the urgency of the shipment (1 – 10 days).

### 2.2.4 Repair cost

Repair cost can vary greatly. Many repairs have no cost as they are performed within the warranty period. When a component enters the repair shop, a test can result in No Failure Found, a minor repair or an overhaul (major repair). Cost of repairs are mainly determined by the cost of labour and piece parts. This research considers fixed cost related to minor and major repairs. Warranty periods are not taken into account.

Current estimations of Prognos' benefits greatly depend on repair savings. Total expected savings on KLM 787 fleet in 2019-2020 due to Prognos are estimated to be more than $x$ million dollar[12]. This is based on the top 10 systems that are included in the (future) scope of Prognos. It is estimated that 1/3 of the delay costs (out of scope in this research) can be saved and that the repair costs are reduced with 1/6. It is unknown how accurate these estimations are. Historical data from 2016-2018 was used as input for the calculation. Although the benefit calculation provides a first estimate for potential savings, it is a rough estimate. Figure 12 illustrates the ratio

[12] This was calculated medio November 2018 by the product owner of Prognos for the value case of 2018-2020.

of potential savings between the two categories, when delay and repair cost are reduced with 0.333% and 0.167% respectively. The figure emphasizes the impact of repair savings with PdM.

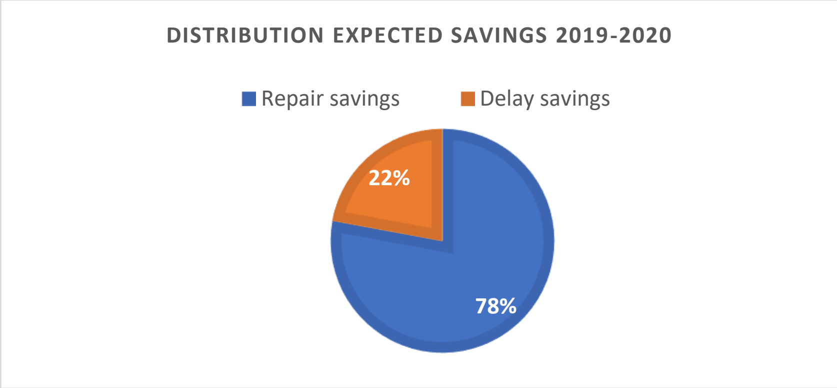



Figure 12: Distribution expected savings Prognos 2019-2020 (for the 787)

## 2.3 Conclusion

This chapter provided a system description: it discussed the process related to corrective component replacements and reviewed the factors that have great impact on cost and service level. From Section 2.2 we can conclude that the formulas used to estimate spare and repair cost, are simplified. To estimate the impact of PdM on spare demand, a more detailed analysis of the effects might be required. From this section we have learned that the impact of a policy on the MTBR plays an important role in spare part management. A reduced MTBR will result in more frequent replacements and increase inventory, however, PdM might also be able to reduce the variance of the average number of components in repair by improved planning. The latter will have a positive impact on inventory by reducing spare levels.

In this chapter we also created more insight in the capabilities of Prognos. The performance can be evaluated in terms of the accuracy of predictions and the prediction horizon. Currently, KLM has chosen to trigger alerts 10 days before expected failure. However, for some components, this does not correspond with the maximum PH. In Appendix A, a table is given with all values for the KPI's related to component replacement of the CSU, one of the components in Prognos' scope. In this example the maximum PH is three times larger than the current PH of 10 days.

At this point we have acquired, partially by assumption, all information about the system related to our problem introduced in Chapter 1. The remaining tasks are to design a predictive replacement policy that reduces spare part and repair cost, while satisfying constraints regarding service level and aircraft availability, and to find a method to test the impact of this predictive policy on various organisational aspects. In the next chapter a literature review is performed to search for studies that helps us with the design of this policy and method.

# 3 LITERATURE REVIEW

In order to analyse, model and optimise maintenance processes related to PdM, we search for related studies in literature. This will address the third research question:

3. *What can we learn from related studies, when we want to improve the component replacement policy with predictive maintenance?*
    a. *What are the risks and opportunities related to predictive maintenance?*
    b. *Which aspects should we focus on when designing a predictive replacement policy?*
    c. *Which method is suitable to compare policies in our research?*

Section 3.1 discusses the risks and benefits related to the use of prognostics in maintenance. In Section 3.2 relevant factors are identified that determine the potential benefit of PdM. In section 3.3 a model is selected for our research and 3.4 is a conclusion of the chapter.

## 3.1 PROGNOSTICS IN MAINTENANCE: POTENTIAL RISKS AND BENEFITS

Application of PdM or Prognostic Health Management (PHM) can either (significantly) reduce operational costs, or result in a less economic situation when the investment costs of the PHM technology are considered. In literature both situations are present (Wu, Jia, Lei, & Wang, 2013).

Although there is an excessive amount of literature about health monitoring systems, prognostics, PdM, and combined optimisation of maintenance, repair <u>or</u> spares, relatively little has been published on the interaction between (predictive) maintenance, spares <u>and</u> repairs (de Smidt-Destombes, van der Heijden, & van Harten, 2009). Most PdM applications in literature are based on over-idealistic experimental data that fails to represent real-world challenges (Vinck, 2018). Therefore, PdM is not very well understood in practice. This section discusses the risks and opportunities related to the use of prognostics in maintenance. We aim to identify important factors related to the design of a predictive replacement policy, so that we select the right variables and parameters to include in our analysis.

### 3.1.1 Risks

**Complexity** – The lack of suitable reference cases in this early stage of the PdM life cycle, makes it hard for companies to construct solid business cases (Price Waterhouse Coopers and Mainnovation, 2017). The integral optimisation of maintenance, spares and repairs is not straightforward, especially when the civil aviation market is concerned and one also has to deal with the interaction with flight scheduling and other complexity issues such as component redundancy ($k$-out-of-$N$ systems), legal matters, high variabilities and complex failure modes. Too many simplifying assumptions to deal with complexity can cause difficulties in the derivation of valuable conclusions or create misleading results.

**Uncertainty** – An essential part for the use of a maintenance optimisation model, is the true representation of relevant deterioration and failure mechanisms. Effective and efficient maintenance actions can only be taken if this holds (Verma, Srividya, & Gaonkar, 2007). A critical element of any prognostic system is the assessment of the prediction uncertainties, which is required to allow the conversion of remaining life estimates into actionable decisions. Accuracy, the degree of closeness of a predictive estimate to its actual value, represents one of the most important factors in determining the usefulness of prediction (Roemer, Byington, Kacprzynski, Vachtsevanos, & Goebel, 2011). A study from Hölzel et al., found that many factors, such as operational constraints, current maintenance concepts and the influence of a part on safety and reliability of the aircraft (criticality), influence whether the implementation of PHM for a specific system may be beneficial in the end (Hölzel N. , Gollnick, Schilling, & Neuheuser, 2012).

### 3.1.2 Opportunities

PHM and PdM have become more and more appealing in aviation business. Logistic optimisation, asset availability maximization and reduction of maintenance costs are among the benefits (Nicchiotti & Rüegg, 2018). A drawback of all proactive strategies is the waste of RUL due to early removal. With PdM, this waste can be minimised due to sophisticated information about the RUL. Prognostic information enables predictive logistics, which can improve the planning, scheduling, and control of activities in the supply chain (Kim, An, & Choi, 2016).

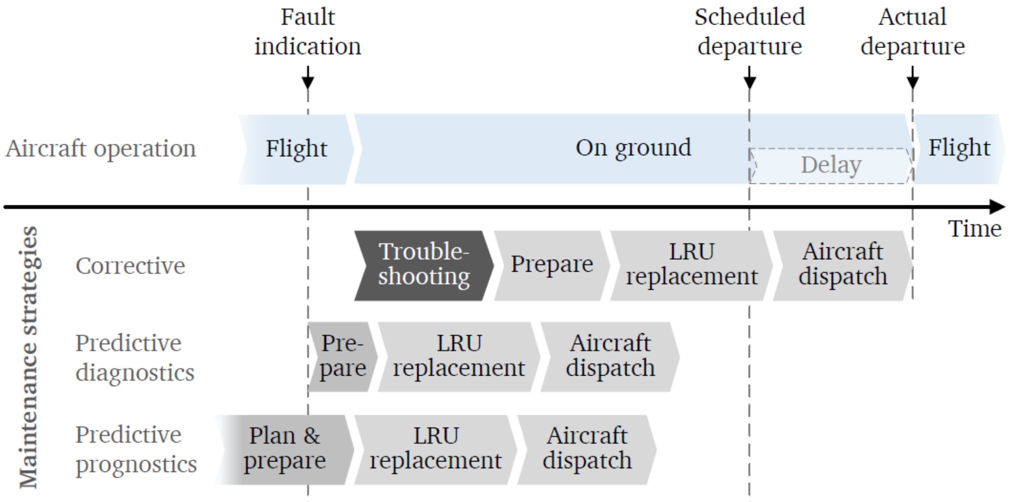



*Figure 13: Visualisation of impact of predictive maintenance in aircraft operations (Kahlert, 2017)*

The optimisation opportunities related to the aircraft operation are visualized in Figure 13. The benefit from a prognostic fault indication on flight operations can be derived from the figure. Regarding maintenance operations, resource planning and preparing activities can also be performed in advance.

In literature all kinds of optimisation techniques are designed based on Advance Demand Information (ADI), such as revenue management (pricing, reservation policies) and capacity control (inventory management). Predictive signals about component failures can be considered as a demand signal (or ADI) for spare parts, as failures generate demand for spares. This can be used to optimise spare parts supply decisions (Topan, Tan, & van Houtum, 2018). Hariharan and Zipkin (1995) also employ early warnings for demand, to improve performance of basic inventory models. Demand lead times (time between a customer order and an order due date) are, in a precise sense, the opposite of supply lead times. That is, the effect of a demand lead time on overall system performance is precisely the same as corresponding reduction in the supply lead time (Hariharan & Zipkin, 1995). A predictive alert can be interpreted as an early warning for demand, where the prediction horizon corresponds with the demand lead time. Although the inventory policy at KLM E&M does not correspond with one of the basic inventory models mentioned in Hariharan & Zipkin's paper, it motivates to explore the benefits of demand lead times in inventory management at KLM.

## 3.2 IMPACT OF PREDICTIVE MAINTENANCE

From the previous section we can identify relevant factors that determine the potential benefit of PdM. Regarding the risk of *complexity* related to maintenance operations, one should aim to make the right trade-off between complexity and variability. Variability can be reduced by **planning**, which itself introduces complexity.

Related to *uncertainty*, the **prediction performance** determines whether maintenance decisions are effective: false predictions lead to wrong decisions. The **operational context** in which PdM is applied, including constraints and current maintenance concepts, is also an important factor. The extent to which a component influences this operational environment (its impact on reliability) is expressed as component **criticality** (which is regularly reduced in aviation with redundant $k$-out-of-$N$ systems). Failure prevention of critical components yield higher benefits then non-critical components, which makes it an essential factor to consider when optimising policies. These four factors marked with bold are considered to determine the impact of a predictive maintenance policy to a large extent and are discussed in more detail in the next sections.

### 3.2.1 Planning

Planning is to create and cleverly use flexibility to deal with variability in demand and supply (Schutten & Hans, 2017). The maintenance supply chain is a complex system involving uncertainty and variability. Mathematically speaking, this corresponds to a complex stochastic system so that a common deterministic approach for planning and managing the system can be expected to be inadequate (Shahani, 1981).

**Inventory management context** – From Chapter 2 we know that KLM uses a rather basic approach with average lead times and average long-term demand to indicate spare levels. Stock levels are based on the average WIP level and a safety stock to account for variation. This long-term approach might not account for short term (demand) variability. The uncertainty and variability of the timing and content of both the information flow and the component flow imply uncertain planning and, possibly, increased costs, stockouts and delays (Gudum, 2002). More general, it may hamper performance output of the supply chain (Patil, Shrotri, & Dandekar, 2012). Therefore, PdM can realise supply chain benefits by reducing uncertainty and variability. The additional information realised by PdM regarding upcoming demand (ADI), can support this reduction of uncertainty and variability.

In addition to the reduction of variability and uncertainty, the repair TAT of component could also be reduced with PdM when major repairs are avoided. According to Little's law (WIP = throughput * flow time), a reduction of the repair TAT (flow time) would reduce the repair inventory and therefore the (safety) stocks for spares (Little & Graves, 2008). This can be identified as a major benefit. The downside of early removal to avoid major repairs is an increase in throughput due to a decrease in operational time on the aircraft.

### 3.2.2 Prediction performance

The most common way to express prediction uncertainties is a confusion matrix. A confusion matrix may be defined as a table of conditional probabilities, showing the proportion of instances in which the prediction indicated $x_p$ while the actual value was $X_a$ ($x_p, X_a$ = positive, negative) (Clarke, 1957).

*Table 5: Confusion matrix*

| | | Predicted Class | | |
|---|---|---|---|---|
| **Actual Class** | | Positive | Negative | Total |
| | Positive | TP | FN | P |
| | Negative | FP | TN | N |
| | Total | P' | N' | P+N |

Based on the confusion matrix various performance indicators can be derived. In a spare part inventory context, Topan et al. identify precision and sensitivity as the most important measures together with the time interval between the prediction signal and the component failure, which corresponds with the RUL estimation. Precision is expressed as the proportion of True Positive (TP) to sum of TP and False Positive (FP) and sensitivity is expressed as the proportion of TP to sum of TP and False Negative (FN) (Topan, Tan, & van Houtum, 2018):

$$Precision = \frac{TP}{TP + FP} \qquad Sensitivity = \frac{TP}{TP + FN}$$

### 3.2.3 Operational context

If PHM is applied to systems with a preventive maintenance strategy, it will lead to a reduction of waste of RUL and overall maintenance efforts (Hölzel N. , Gollnick, Schilling, & Neuheuser, 2012). This can also affect spare part pooling. Within a corrective maintenance strategy, PdM can reduce the number delays and repair cost, provided that an organisation is able to respond on predictive alerts (orders) on time. The speed of the operation of transferring information is vital in order for PdM to be as effective as possible as any delay in this operation will lead to the failure developing further (Carmen Carnero, 2006). Other more general aspects of the operational context, such as all kinds of cost factors, can determine the impact of a predictive policy to a large extent.

### 3.2.4 Criticality

A component's criticality (impact on reliability) determines the impact on operational benefits to a large extent, since downtime is one of the most important cost factors. Critical components are often redundant, such that a single component failure does not result in down time. In that case, the system is operational if $k$-out-of-$N$ components are operational. In literature we find some models that optimise maintenance on $k$-out-of-$N$ systems (de Smidt-Destombes, van der Heijden, & van Harten, 2006) (de Smidt-Destombes, van der Heijden, & van Harten, 2009). In fact, the model objective from paper of de Smidt-Destombes et al. from 2006 has quite a few similarities with our problem. They consider a model for the trade-off between spare part inventory, repair capacity and maintenance policy for a $k$-out-of-$N$ system under a condition based maintenance (CBM) policy with detectable wear-out. However, they consider a single system (our study involves multiple aircraft), variable repair capacity (ours variable repair cost) and optimise availability (instead of cost minimization).

The MEL category is related to the criticality of a component and is an important aspect in this research. Critical components have small MEL RI's; less critical components have large RI's. Small intervals result in little planning flexibility and therefore little opportunity to deal with variability.

## 3.3 SYSTEM MODELLING

We aim to create a model to (i) create more insight in system dynamics, and (ii) test possible replacement strategies. The model should be able to consider all four aspects mentioned in the previous section (planning, prediction performance, operational context and criticality) while evaluating the various policies.

### 3.3.1 Model selection

Based on system complexity and the amount of time available in the research, a suitable model can be selected for our study. Figure 14 categorizes methods to evaluate a system. In our case, a physical model is not applicable due to time constraints, costs, regulations and safety issues. Therefore, we search for a mathematical solution.

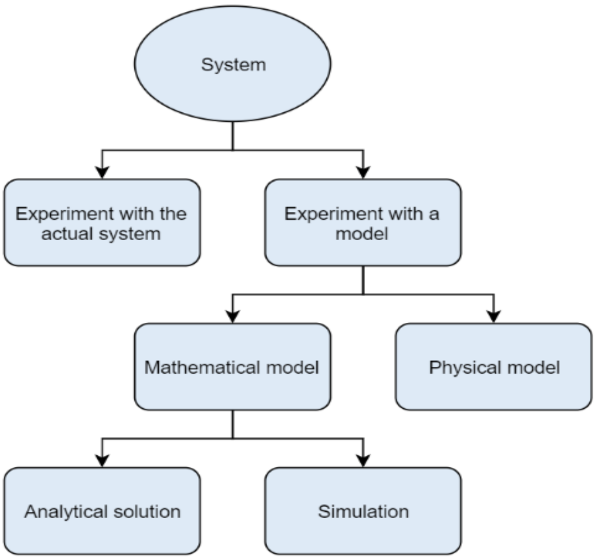



*Figure 14: Methods to analyse a system (Law & Kelton, Simulation Modelling and Analysis, 1991)*

Maintenance systems are often evaluated with the help of simulation. Duffuaa et al. mention numerous studies that apply simulation in a maintenance environment and provide a generic conceptual simulation model for maintenance systems (Duffuaa, Ben-Daya, Al-Sultan, & Andijani, 2001). In more recent studies, related to (the cost-benefit analysis of) PHM on aircraft, we find discrete-event simulation as a frequently used method to model maintenance activities (Feldman, Jazouli, & Sandborn, 2009) (Iyer, Goebel, & Bonissone, 2006) (Hölzel N. , Gollnick, Schilling, & Neuheuser, 2012) (Hölzel, Schilling, & Gollnick, 2014) (Hölzel & Gollnick, 2015).

We find analytical models based on Markov chains that relate to the scheduling of maintenance intervals (Baars, 2018) (Crespo Márquez, 2009), but do not include spare part and repair planning improvement. There are spare part inventory models based on Markov chains that are somewhat relevant to this study, such as the multi-item, single site optimisation model with lost sales. This last model aims to minimise expected relevant cost per year, while attaining a certain target waiting time service level (van der Heijden, 2017). However, it does not incorporate early demand signals, $k$-out-of-$N$ systems or exchange lease parts, which are all relevant aspects in this research.

Regarding the optimisation of spare parts in a system with (uncertain) ADI, Topan et al. use a dynamic programming recursion in order to find optimal order- and return levels for a single-item, single-location, period-review inventory system. De Smidt-Destombes et al. use both an analytical solution and a discrete-event simulation to find model solutions (de Smidt-Destombes, van der Heijden, & van Harten, 2006).

Simulation can be used in order to understand system behaviour or to evaluate various strategies for the operation of the system (Shannon, 1975). In this study we aim to understand system behaviour and we want to test optimisation policies based on PdM information. We find simulation as the most appropriate method to apply in this research.

### 3.3.2 Simulation model design

There are multiple types of simulation, such as discrete-event simulation (DES) and continuous simulation. A. M. Law is an expert in simulation modelling, who distinguishes simulation models based on three criteria (Law, 2014):

- Static versus dynamic. This refers to the time dimension. Static models represent a fixed point in time whereas dynamic models show system behaviour over a time horizon;

- Deterministic versus stochastic. Deterministic models do not include any randomness, stochastic models do;
- Discrete versus continuous. In discrete models, the system state changes in discrete points in time and in continuous models this happens continuously.

For the purpose of this research we select dynamic stochastic DES as the most appropriate method to evaluate the system. DES refers to a modelling technique where only changes in system states are represented. Essentially, it creates a queue of events that affect the system state and arranges them based on their timings (Alrabghi & Tiwari, 2016).

A dynamic model is more suitable than a static model since we want to evaluate the impact of PdM over time. Failure occurrence, failure triggers and processing times have a stochastic nature, which makes a stochastic model the right choice. Finally, we select a discrete model over a continuous model, because our system's state changes at a particular point in time and then remains in that state, until a new event occurs (e.g. a repair is completed or an alert is triggered).

## 3.4 CONCLUSION

In this chapter we searched for relevant studies regarding the improvement of component replacements with PdM, when considering repair and spare part cost as the most important cost saving factors. From Chapter 2 (Section 2.2.4) we learned that early removal can result in a significant reduction of repair cost. In literature we identify variability and uncertainty reduction, for instance by using ADI in spare part management, as another interesting potential benefit of PdM. To summarize, Figure 15 was constructed as a conceptual framework for this study, related to predictive component replacements compared to corrective component replacements. The predictive component replacement policies that will be designed in the next chapter should leverage on the characteristics explained in the figure, namely:

- Use the bigger time frame to plan replacements (prediction horizon or demand lead time), to reduce variability in repair inflow. Thereby, spare part levels could reduce;
- Avoid major repairs with long repair lead times and high cost;
- Trade-off the benefits of early removal with more frequent repairs (lower MTBR);

Benefits and risks related to PdM are also mentioned in the figure.

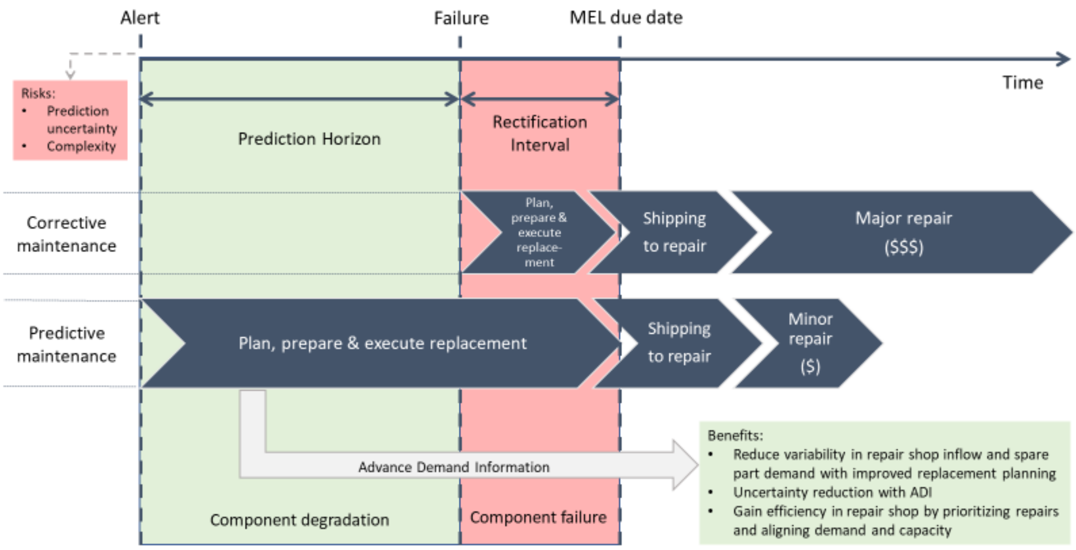



*Figure 15: Conceptual framework*

We could not find a study in literature that addresses the optimisation of repair- and spare part cost of a multi-item $k$-out-of-$N$ system with wear-out which also includes the evaluation of prediction uncertainties on performance. The optimisation problem at hand requires the development of a (dynamic) model that is able to deal with a large number of real-world constraints. The application task is extremely complex and requires quite some research effort (Bäck & Manegold, 2016) – which does not match with the scope of this thesis. However, this research can provide an exploratory study about replacement policy optimisation with PdM at KLM. Based on the conceptual framework presented in Figure 15 we can design policies that capitalize on the identified benefits.

With some model simplifications and the use of simulation, one can gain valuable knowledge about system dynamics and the impact of different policies on this system behaviour. In this section, planning, prediction performance, operational context and component criticality were identified as important aspects to consider while evaluating policies.

Dynamic stochastic discrete event simulation was identified as the most appropriate method to create insight in the dynamics of system behaviour. The simulation should experiment with multiple factors, such as prediction model performance and the replacement policy. Experimenting with the model should help us find the best policy for KLM E&M.

In Chapter 4 the predictive component replacement policies will be designed and in Chapter 5 a model will be constructed to analyse the performance of these policies.

# 4 SOLUTION DESIGN

In this chapter we design predictive component replacement policies, that are aimed are minimizing repair and spare part cost. The corresponding research question is:

4. *How should predictive component replacement policies be designed for k-out-of-N systems, that capitalize on repair and spare part benefits?*

The first section describes a general notation. After that, three policies are designed in Section 4.2. Section 4.3 is a conclusion of the chapter.

## 4.1 NOTATION

Prior to the design of the policies, this section introduces a general notation in Table 6 that helps us to report the policies. All values in the table are integers. If a constraint applies to a variable, it is also given in the table. The notation is used throughout the remainder of the report.

*Table 6: General notation*

| | |
|---|---|
| $\boldsymbol{a_{it}}$ | Number of predictive alerts on aircraft $\boldsymbol{i}$ at time $\boldsymbol{t}$, $\boldsymbol{i \in 1, \dots, M, t \geq 0}$ |
| $\boldsymbol{f_{it}}$ | Number of failures on aircraft $i$ at time $t$, $i \in 1, \dots, M$, $t \geq 0$ |
| $\boldsymbol{M}$ | Fleet size |
| $\boldsymbol{N}$ | No. of identical components in an aircraft |
| $\boldsymbol{k}$ | No. of operational components required for an operational system |
| $\boldsymbol{f_{MEL}}$ | Threshold expressed in no. of failures that violate MEL restrictions, $f_{MEL} = N - k + 1$ |
| $\boldsymbol{s_t}$ | No. of spares in inventory at time $t$, $s_t \in 1, \dots, S_j$, $t \geq 0$, $j \in 1,2,3,4$ |
| $\boldsymbol{S_j}$ | Total spares in the system (maximum inventory level) with policy $j$, $j \in 1,2,3,4$ |
| $\boldsymbol{l_t}$ | Number of outstanding lease components at time $t$. |
| $\boldsymbol{X_{ijt}(a_{it}, f_{it}, s_t)}$ | No. of components replaced on tail $i$ at time $t$ with policy $j$ in system state $(a_{it}, f_{it}, s_t)$. $j \in 1,2,3$, $t \geq 0$ |
| $\boldsymbol{X_{i4t}(A_t, F_t, s_t)}$ | No. of components replaced on tail $i$ at time $t$ with policy 4 in system state $(A_t, F_t, s_t)$ where $A_t = \sum_{i=1}^{M} a_{it}$ and $F_t = \sum_{i=1}^{M} f_{it}$ and $t \geq 0$ |
| | $X_{ijt} \leq a_i + f_i, \forall j\ \forall t$ (do not replace parts that are not alerted or failed)<br>$s_t = s_{t-1} - X_{ijt}$ (the inventory level is reduced with the number of replaced parts)<br>$l_t = l_{t-1} + 1$ for $X_{ijt} = 1$ *and* $s_t = 0$ (lease a part if replacement is needed, but there is no stock)<br>$l_t = l_{t-1} - 1$ for $l_{t-1} \geq 1$ *and* $s_t \geq 0$ (send a spare back to emergency supplier for exchange) |
| $\boldsymbol{DIL_j}$ | The Demand Initiation Level of predictive policy $j$ ($j = 2,3,4$) |
| $\boldsymbol{q}$ | Variable for $DIL_4$. $2 \leq q \leq f_{MEL} * M$ |
| $\boldsymbol{Z_{jt}}$ | The system state space. $j \in 1,2,3,4$ and $t \geq 0$ |
| $\boldsymbol{c}$ | The number of components replaced[13]. $X_{ijt}\left(a_{it}, f_{it}, s\right) = c, 0 \leq c \leq N$ |
| $\boldsymbol{r_t}$ | The number of components in repair at time $t$. $r_t = S - s_t$ and $t \geq 0$ |
| $\boldsymbol{x_{jt}}$ | Total no. of replacement actions with policy $j$ at time $t$. $x_{jt} = \begin{cases} x_{j,t-1} + 1, & X_{ijt}(a_{it}, f_{it}, s_t) \geq 1 \\ x_{j,t-1}, & otherwise \end{cases}$ |

[13] The constraint is also valid for policy 4: $X_{i4t}\left(A_t, F_t, s_t\right) = $ c. This also applies to the constraints of $x_{jt}$ and $s_t$.

As can be seen in the table, the number of replaced components depend on the state of the system. Policies $j = 1,2,3$ consider alerts and failures on tail level (single aircraft); meaning that a decision is made individually for each aircraft $i$. Policy 4 considers demand on fleet level; meaning that a decision is made based on the total number of alerts and failures in the entire fleet (multiple aircraft). The state space for $j = 1,2,3$ at time $t$ is given as:

$$Z_{jt} = \begin{bmatrix} a_{1t}, & f_{1t}, & \\ a_{2t}, & f_{2t}, & \\ \vdots & , \vdots & , s_t \\ a_{Mt}, & f_{Mt}, & \end{bmatrix}$$

And as $Z_{jt} = (A_t, F_t, s_t)$ for $j = 4$. Every time the state space changes, a decision is made: Replace $c$ components ($0 \leq c \leq N$). The state space changes after a replacement, or when a new alert is triggered, a failure occurs or when a spare is put in inventory (from repair). The number of components in repair are not included in the state space. This is not used as input for replacement decisions, and, in the current setup, the number is directly dependent of $s$ and $S$.

Recall that not all failures are predicted in advance, as a result of a fraction of 'missed failures', or, False Negatives (see Table 5: Confusion matrix). Prognos' sensitivity[14] ratio determines the size of the fraction of missed failures. Therefore, predictive policies should consider failures as well as alerts as input for their decision.

Regardless of any policy, exchanging lease components will receive highest priority at all times. When a spare part is put in stock from repair and there is an outstanding lease component, this spare part is sent back to the emergency supplier as an exchange component.

## 4.2 POLICY DESIGN

The replacement strategies aim to minimise repair and spare part cost. Just as in the paper of de Smidt et al., we may use a maintenance policy based on the number of failed and degraded (predicted) components. For example, if the number of failed components is low but many components are alerted, it may be wise to initiate maintenance to avoid system failure during the lead-time (de Smidt-Destombes, van der Heijden, & van Harten, 2006).

From the literature review, we have concluded that policies should benefit from the following aspects:

- Use the bigger time frame to plan replacements (prediction horizon or demand lead time), to reduce variability in repair inflow. Thereby, spare part levels could reduce;
- Avoid major repairs with long repair lead times and high cost;
- Trade-off the benefits of early removal with more frequent repairs (lower MTBR).

When a predictive policy includes predictive alerts as input, the bigger time frame is automatically utilised, as the timing of an alert is always before the timing of a failure notification. When a predictive policy replaces component with an alerted status, a major repair is potentially prevented. Whether a policy results in an unacceptable decrease in MTBR, will be evaluated with the model designed in Chapter 5. All policies are based on a 3-out-of-4 system, as this is a common structure in aircraft systems. In the following subsections the policies are described.

[14] $Sensitivity = \frac{TP}{TP+FN}$, see Section 3.2.2.

### 4.2.1 Policy 1

Policy 1 represents the benchmark policy of the current situation. Although the MCC is experimenting with acting on alerts, this research considers the old situation where alerts are not considered in the replacement decision. The benchmark policy is given below (for all $i, t$ and $a_i$):

$$X_{i1t}(a_{it}, f_{it}, s_t) = \begin{cases} 0, & f_{it} < f_{MEL}, \forall s \\ 1, & f_{it} = f_{MEL} \text{ and } s_t \in \{0,1\} \\ 2, & f_{it} = f_{MEL} \text{ and } s_t \geq 2 \end{cases}$$

When $f_{it} = f_{MEL}$ and $s_t = 0$, a spare part must be leased to perform replacement and solve the MEL violation. So, in that case the decision is to replace 1 component despite of the lack of on-hand stock.

The policy does not take the Rectification Interval into account. A MEL violation has to be solved at $t$. However, the technical model designed in Chapter 5 does account for the RI to some extent[15]. Due to this assumption, it is not possible to have more than 2 failures on the same tail at the same time. In theory this could occur when a third component fails during the RI. It is considered very unlikely and therefore the impact of this assumption is believed to be negligible.

The other 3 policies are designed predictive policies that also consider alerts in their decision. The decisions presented above are mandatory due to MEL, so all policies will also include these decisions.

### 4.2.2 Policy 2

Policy 2 initiates replacement as soon as there is 1 alert or failure. In other words, the Demand Initiation Level of policy 2 equals 1, or: $DIL_2 = 1$. This will maximise the repair cost savings, but might result in a large decrease in MTBR, which is expected to have an effect on inventory levels. The model designed in Chapter 5 should test whether this reduction in repair cost compensates for the consequences of the MTBR decrease. The policy is given below (for all $i$ and $t$). Figure 16 is a representation of policies 1, 2 and 3, which help to understand the concept of policies.

$$X_{i2t}(a_{it}, f_{it}, s_t) = \begin{cases} 0, & a_{it} + f_{it} \leq DIL_2 - 1, \forall s_t \\ 1, & \begin{cases} a_{it} + f_{it} \geq DIL_2 \text{ and } s_t = 1, or \\ f_{it} = f_{MEL} \text{ and } s_t \in \{0,1\} \end{cases} \\ 2, & \begin{cases} a_{it} + f_{it} \geq 2 \text{ and } s_t \geq 2, or \\ f_{it} = f_{MEL} \text{ and } s_t \geq 2 \end{cases} \end{cases}$$

For notational simplicity, the decisions related to MEL (independent of the policy) are left out:

$$X_{i2t}(a_{it}, f_{it}, s_t) = \begin{cases} 0, & a_{it} + f_{it} \leq DIL_2 - 1, \forall s_t \\ 1, & a_{it} + f_{it} \geq DIL_2 \text{ and } s_t = 1 \\ 2, & a_{it} + f_{it} \geq 2 \text{ and } s_t \geq 2 \end{cases}$$

In practice, $a_{it} + f_{it} \geq 2$ should almost never occur, but an exception is that an aircraft has 3 alerts or 2 alerts and 1 failure. Therefore, the symbol $\geq$ is used in notation. In that case, all 3

[15] This is discussed in the technical model description in the Appendix, in the description of the method 'GetRepairSpare' (see section 'II Shiphol Frame', component inflow).

alerted/failed components will be replaced if on-hand stock is sufficient. As this is an exception, the decision to replace 3 (or even 4) components is left out of all policy notations.

### 4.2.3 Policy 3

Policy 3 is designed to reduce repair cost while keeping the MTBR reduction to a minimum. Therefore, it only replaces components when at least 2 component out of 4 are alerted or failed[16]. This means that $DIL_3 = 2$. If we compare policy 3 to policy 2 in Figure 16, it can be concluded that this increase in $DIL$ has significant impact on the MTBR.

The component that triggered the first alert, probably failed during the time that the policy was 'waiting' on the second alert or failure, such that $DIL_3$ is exceeded. This is the case in Figure 16: policy 3 does not act on the first alert in a timely manner, and therefore this alert has resulted in a failure. Thereby, this policy does not capitalize on the potential repair savings of the component corresponding with that first alert. In this case, only the second alert is utilised. This is a trade-off and the results will be evaluated in Chapter 6.

In policy 3, the only difference compared to the benchmark policy is that it also considers alerts as demand. Its notation is given below. Again, the decisions related to MEL violations are excluded from notation.

$$X_{i3t}(a_{it}, f_{it}, s_t) = \begin{cases} 0, & a_{it} + f_{it} \leq DIL_3 - 1, \forall s_t \\ 2, & a_{it} + f_{it} \geq DIL_3 \ and \ s_t \geq 2 \end{cases}$$

### 4.2.4 Visualisation of policies 1, 2 and 3

Figure 16 below is an example of the functioning of the policies. The top lane represents a timeline, where all 4 components in the aircraft fail one after another. Prognos was able to predict the first 3 failures, but the last component failed with the absence of a predictive alert. Thus, the observed sensitivity rate in this particular example is 75%. The lanes below the timeline represent the policies, where the dashed vertical lines represent a replacement action. The arrows corresponding with $TBR_j(x)$ represent the Time Between Replacements $x_{jt}$ with policy $j$. Within replacement $x_{jt}$, $c$ components are replaced. From the figure it can be concluded that policy 1 results in the longest MTBR. Policy 2 has a higher frequency of replacements (a shorter MTBR) and replaces all alerted components before failure. Policy 3 has the same number of replacements in this example and a slight decrease in MTBR, because $TBR_3(1) < TBR_1(1)$. The difference between $TBR_3(1)$ and $TBR_1(1)$ is the prediction horizon.

[16] This number, 2, results from: $N - k + 1$, which is 2 for a 3-out-of-4 system ($4 - 3 + 1 = 2$).

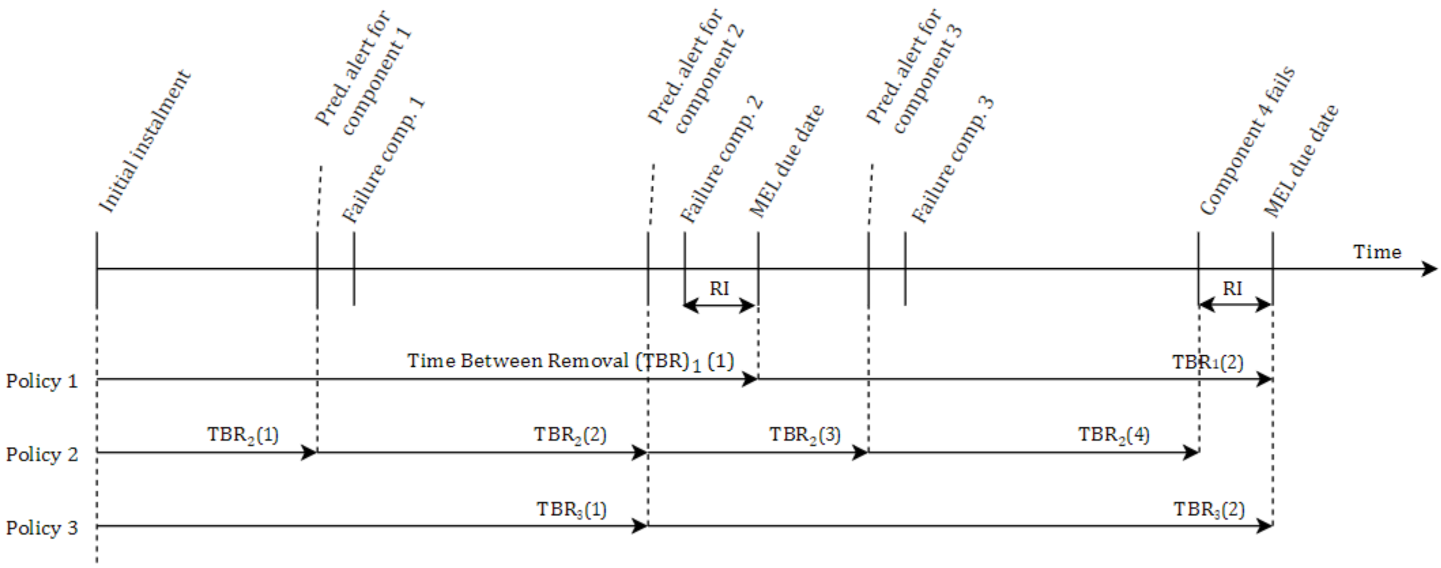



*Figure 16: Example of a timeline with component replacement per policy*

Recall that spare levels are not considered in this example. Therefore, exceedance of the $DIL$ will always result in replacement. If spare levels were included, a decision could be to Do Nothing ($X_{ijt} = 0$) while $DIL$ is exceeded (namely when $s_t < DIL$). When a spare becomes available from repair, the state space $Z_{jt}$ changes and the decision $X_{ijt}$ is reconsidered.

If the total number of spares in the system ($S$) is 0, policies 2 and 3 will function the same as policy 1. In that case, the value for on-hand stock, $s_t$, is always 0. Then, $X_{ijt} = 1$ only for $Z_{jt} = (a_{it}, f_{MEL}, 0)$ (for all values of $a_{it}$) and $X_{ijt} = 0$ otherwise (when $f_{it} < f_{MEL}$). In words: due to the lack of inventory, replacements will never be performed, unless there is a MEL violation. In case of MEL violation, replacement will always be performed with a lease component and the number of lease parts will move to infinity for $t \to \infty$. In Chapter 5 a model will be constructed that includes constraints regarding the total number of lease parts. This must remain within a certain bound that is acceptable for KLM E&M.

### 4.2.5 Policy 4

The fourth and final policy differs from the first 3 policies as it considers the state space as $Z_{4t} = (A_t, F_t, s_t)$. All alerts (A) and failures (F) on the fleet are used as input. The DIL is a variable ($q$) that should be set such that cost are minimised. The model designed in Chapter 5 should be able to vary this variable in order to find the value that results in lowest total cost. The policy notation is given below.

$$X_{i4t}(A_t, F_t, s_t) = \begin{cases} 0, & A_t + F_t \le q - 1, \forall s_t \\ 1, & A_t + F_t \ge q \text{ and } s_t = 1 \\ 2, & A_t + F_t \ge q \text{ and } s_t \ge 2 \text{ and } q \ge 2 \end{cases}$$

The idea of this policy is to minimise variability in spare part demand (and therefore minimise inventory) by considering all fleet demand in the replacement decision. In the next section it is discussed how to determine aircraft $i$ that needs replacement.

### 4.2.6 Selecting aircraft $i$ for replacement

In addition to determining the value for $c$, we also need to determine the value for $i$. This is straightforward when there is only one aircraft $i$ that satisfies the constraint $a_{it} + f_{it} \ge DIL_j$ (for

$j = 2,3$). However, it could be the case that multiple aircraft satisfy this constraint and, with policy 4, this constraint is not aircraft-specific. Therefore we need to add an extra step to determine the final value for $X_{ijt}$.

This section discusses the priority rules for selecting aircraft $i$ for replacement with policy 4 and for policies 2 and 3 when multiple $i$'s satisfy the constraint. Obviously, an aircraft with a MEL violation receives highest priority with any policy. For all other possible situations, Table 7 provides an overview of the priority rules. The logic behind these rules is:

- The aircraft with the most alerted and failed components has the highest priority;
- When $a_{it} + f_{it} = 2$ for multiple $i$, priority is given to the aircraft with 2 alerts (if there are any). The same holds for $a_{it} + f_{it} = 1$;
- The time passed since the alert notification in Prognos is not considered in prioritizing. Therefore, if multiple $i$ have the same priority, the value for $i$ is randomly determined.

The priority rules emphasize alerts because these components have repair cost saving potential (minor repair cost). Failed components have high probability on major repair cost. Therefore, these rules are expected to have greater benefit than priority rules that emphasize failures. The time passed since the alert notification is not included in prioritizing as this is considered too detailed and not feasible at this point for the MCC to take into account when scheduling replacements.

Recall that the value for $c$ has already been determined, also based on the value of $s$ (if $a_{it} + f_{it} \geq 3$ for any $i$, $c$ can be 0, 1, 2 or 3 for $s \leq 3$). So, these rules are not used to determine $c$, but to determine $i$. The table presents the priorities of the policies per column. It can be seen that policy 1 has no varying priorities and policy 3 only prioritizes aircraft with $a_{it} + f_{it} \geq 2$.

*Table 7: Priority rules for selecting aircraft i (when c > 0)*

| **Priority of aircraft $i$** | **Policy 1** | **Policies 2, 4** | **Policy 3** |
|---|---|---|---|
| **1** | MEL | MEL | MEL |
| **2** | N/A | $a_{it} + f_{it} \geq 3$ | $a_{it} + f_{it} \geq 3$ |
| **3** | N/A | $a_{it} = 2$ | $a_{it} = 2$ |
| **4** | N/A | $a_{it} + f_{it} = 2$ | $a_{it} + f_{it} = 2$ |
| **5** | N/A | $a_{it} = 1$ | N/A |
| **6** | N/A | $f_{it} = 1$ | N/A |

### 4.2.7 Clustering replacements

All policies as designed in previous subsections cluster their replacements. When $s_t \geq 2$ and $a_{it} + f_{it} \geq 2$, $X_{ijt} = 2$ for $j = 2,3,4$ and for policy 1, $X_{ijt} = 2$ when $s_t \geq 2$ and $f_{it} = 2$. In words: when the number of components with an alerted or failed status on aircraft $i$ is 2 or larger at time $t$ and the on-hand inventory is also 2 or larger, both alerted/failed components are replaced at the same time. The component replacements are clustered.

As an experiment, the predictive policies are adjusted such that replacements are only clustered when there are multiple alerts on a tail. In this experiment, failed components are only replaced when MEL is violated. One might state that non-MEL replacements of failed components is serving no practical purpose (based on the same logic as in 4.2.6: failed components have no repair saving potential). The adjustment in notation is presented for policy 3:

$$X_{i3t}(a_{it}, f_{it}, s_t) = \begin{cases} 0, & a_{it} + f_{it} \leq DIL_3 - 1, \forall s_t \\ a_{it}, & a_{it} + f_{it} \geq DIL_3 \text{ } and \text{ } s_t \geq a_{it} \end{cases}$$

Policy-independent MEL replacements change to:

$$X_{ijt}(a_{it}, f_{it}, s_t) = \begin{cases} 0, & f_{it} < f_{MEL}, \forall s_t \\ 1, & f_{it} = f_{MEL}, \forall s_t \end{cases}$$

The adjustment works similarly for the other policies and the same priority rules are applied for selecting $i$. The aim of these adjusted policies is to find out what the effect would be on repair cost and MTBR. In Chapter 6, the effect of these adjusted policies is discussed. In the remainder of this report, these adjusted policies are referred to as ‘extended policies’. A regular reference to policy $j$ indicates the clustered policy, as described in Sections 4.2.1 to 4.2.5.

## 4.3 CONCLUSION

In this section, 3 predictive component replacement policies were designed for a 3-out-of-4 system, that aim to reduce spare part and repair cost. All policies use predictive alerts from the application ‘Prognos’ as input for decisions. The decision to replace $c$ components depends on the state space. The state space is expressed in the number of alerts, failures and on-hand stock. The aircraft $i$ that will be selected for replacing $c$ components, is selected based on priority rules that aim to maximise repair savings.

Predictive policies use a larger time frame for their decisions by acting on alerts instead of failures. Hereby, the inventory level could potentially reduce. Also, components with an alerted status might result in lower repair cost, but a trade-off with a decrease in MTBR has to be made. The policies were designed such that a balanced trade-off can be made. In the next chapter, a model is constructed that is able to evaluate the performance of the policies.

# 5 Model

In this chapter we design a model that allows to evaluate the performance of the policies designed in Chapter 4 under various scenarios. The corresponding research questions is:

5. *How should we construct a model that is able to test the impact of predictive component replacement policies for k-out-of-N systems?*
   a. *How can we abstract a conceptual model from the system description?*
   b. *What does the model design look like?*
   c. *How can we use the model to find the best solution?*

In Chapter 3 we have identified discrete-event simulation as the most appropriate method for our research. In this section, this simulation model is abstracted from the real world problem. This process is known as conceptual modelling and will be performed based on the paper of Robinson (2011). Figure 17 presents the steps related to a simulation study. At this point, the problem domain, consisting of the Real world problem (Ch.1) and the System description (Ch.2), has been described.

In Section 5.1 the conceptual model will be abstracted. Section 5.2 discusses the model design and experimental design, and Section 5.3 the computer model. Section 5.4 is a conclusion of the chapter.

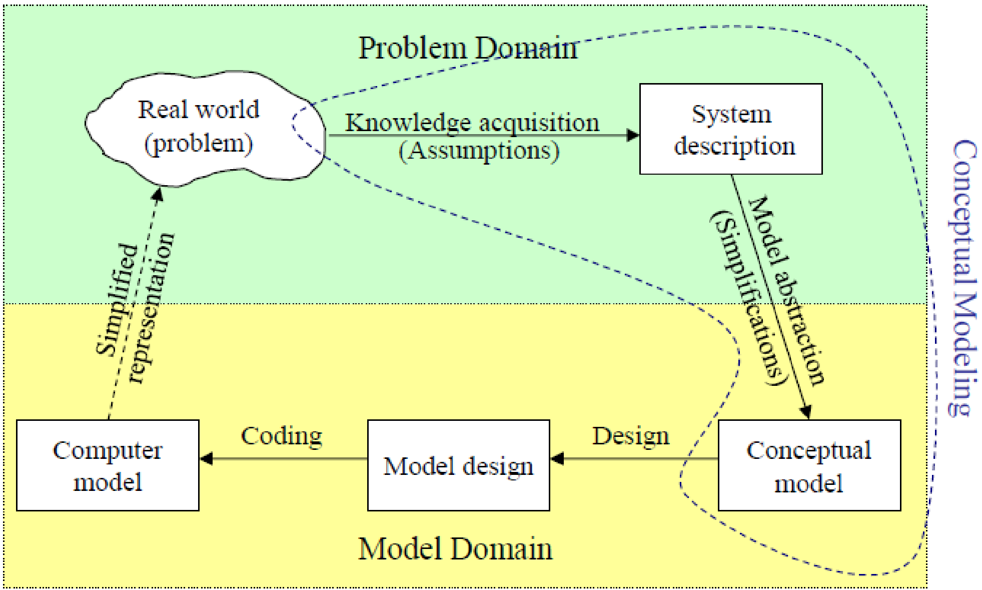



*Figure 17: Conceptual modelling (Robinson, Conceptual Modeling for Simulation., 2011)*

## 5.1 Conceptual model

A conceptual model is defined as 'a non-software specific description of the computer simulation model (that will be, is or has been developed), describing the objectives, inputs, outputs, content, assumptions and simplifications of the model' (Robinson, 2008a). Each subsection of this section discusses one of the elements of the conceptual model.

The policy design from Chapter 4 is, in fact, also part of the model domain (Figure 17). As the solution design is a great part of this study, it was discussed separately. It is the backbone of the model and we will refer continuously to these policies in the remainder of the modelling procedure.

### 5.1.1 Model objective

The objective of the model is to assess the performance of predictive component replacement policies for a 3-out-of-4 system in terms of cost and to compare this with the current corrective replacement policy at KLM E&M, while also reflecting on the effect on maintenance capacity and service level.

Solutions should satisfy a lease constraint regarding the average total number of leases, based on a fleet of 13 aircraft (= fleet size of KLM 787 aircraft). This average number may not increase 1 lease per year. If larger fleet sizes are considered, this number is adjusted proportionally. Leasing components is seen an exception at KLM E&M; therefore this threshold is set very low.

### 5.1.2 Inputs

Inputs are experimental factors that are varied within a certain range in order to find the settings corresponding with the best solution of the model. Experimental factors are distinguished in decision variables, variable parameters and fixed parameters.

The decision variables are the replacement policy $j$, the total number of spares $S$ and $q$, the Demand Initiation Level of policy 4. The model should find the values for $j$, $S$ and $q$ that minimise cost, while the lease constraint is satisfied. Therefore, values for $j$ are varied from 1 to 4 and $S$ is increased with 1 after each model run until the constraint is met, for $j \in 1,2,3$. If $j = 4$, $q$ is varied within its range of $2 \leq q \leq f_{MEL} * M$.

The model should enable analysis of policy performance under various circumstances. Therefore, other experimental factors that are expected to have significant impact on the result are also varied. These factors, such as the Prediction Horizon, are called variable parameters and are derived from the conceptual framework (Figure 15) and the system description (Chapter 2). A composition of parameter values is called a scenario. Table 8 lists the parameters of the model. In Appendix A, the values of the parameters in the benchmark scenario (default scenario) are given and the failure distribution is derived from available replacement data at KLM E&M. The table in the appendix also includes values for 'fixed parameters': parameters that are not varied within this study, such as labour cost, fixed replacement cost and the price of a spare. The benchmark scenario aims to represent the case of the CSU component at KLM E&M. The model design addresses how experimental factors are varied to analyse policy performance under various circumstances, and is presented in Section 5.2.2.

*Table 8: Variable model parameters*

| Parameter | Parameter |
|---|---|
| Prediction Horizon | Lease restriction |
| Sensitivity rate of predictive alerts | Failure distribution |
| Minor repair cost | Extended policies |
| Major repair cost | Stochastic PH, TAT |
| TAT | Fleet size |
| TAT of a minor repair | |

### 5.1.3 Outputs

The output of the model (reports) are the number of replacements; expressed as the number of repaired spares and the number of replacement actions (maintenance intervals), and total cost; consisting of repair cost, replacement cost, lease cost and spare part investment cost. If a replacement action clusters replacements, then $c = 2$ (number of replaced components, or repaired spares) and $x_{jt} = 1$ (number of replacement actions, or maintenance intervals): so 2 components are replaced at the same time. In the remainder of the report this will be referred to as: number of repaired spares (total $c$) and number of maintenance intervals (total $x_{jt}$ over all $t$).

### 5.1.4 Content

**Scope –** The objective is to perform a comparison between predictive component replacement policies on a high-level, therefore, the level of detail in the model is low. This results in simplifications and the exclusion of some aspects.

First of all, the flight operation is not included in our model. This aspect determines when a replacement (or other non-routine maintenance action) can be fit into the operational schedule. It is assumed that all replacement actions are executed at the same time as the replacement decision is taken. There will be no cost involved with an alternative maintenance plan. The total number of replacements will be counted, in order to compare results regarding this matter.

Details about the repair process are excluded from the model. Sufficient repair capacity and/or reliable vendors are assumed. The repair TATs are fixed within contracts, which makes this a reasonable assumption for our model.

At KLM E&M, Component Services delivers spare parts to various customer airlines around the globe. Customer requests for spare parts are delivered from the spare parts pool. In the model, the entire fleet belongs to one customer only (KLM). Therefore, shipping times are neglected and there are no varying priority rules concerned with customer requests. Table 9 is an overview of the scope.

*Table 9: Scope overview*

| In scope | Out of scope |
|---|---|
| Analysis of repair savings | Component pool concept |
| Spare part management | Flight operation |
| Replacement policy evaluation | Repair process |
| | Scheduling of replacements |

**Model content and level of detail –** The list below provides an overview of the model content and its level of detail. It is derived from the system description in Chapter 2.

1. The model consists of a fleet of $M$ ($1 \leq M \leq 13$) aircraft (tails), the logistic centre (LC) where spare inventory $s$ is kept and a repair shop with infinite capacity.
2. All aircraft have $N$ components installed that fail according to a failure distribution $F(t)$. A fraction of all component failures, corresponding with the sensitivity rate, are predicted by Prognos. The number of days between the predictive alert signal and the actual failure is specified by the prediction horizon. Consequently, the Time To Alert (TTA) equals the Time To Failure (TTF) minus the Prediction Horizon (PH). See Table 10.

*Table 10: Relation between MTBF, MTBA, PH and Sensitivity*

$MTTF - PH = MTTA$, or
$t_{failure} = t_{alert} + t_{PH}$

| Sensitivity% with alert | (1-sensitivity)% without alert |
|---|---|
| $\boldsymbol{E[F(t)] = MTTF - PH}$ | $E[F(t)] = MTTF$ |

By default the PH is a deterministic value, however in an analysis this could be changed to a random variable. The time to alert and/or the time to failure for a component is derived from the failure distribution.

3. The time to schedule a replacement is assumed to be 0, so when $X_{ijt} \geq 1$, replacement is performed at the same $t$.
4. When MEL is violated and there is no spare available to perform replacement, a spare is leased. Lease cost are 10% of the component procurement price per lease. When a

serviceable spare becomes available from repair, it is exchanged for the outstanding lease component to the emergency supplier. Component lease for non-MEL replacements is not allowed. Lease components have no supply lead time.

5. A replacement decision is taken when the system state changes: when a new alert is generated, when a new failure occurs, or when a new spare becomes available from repair. According to the current policy a decision is made ($X_{ijt}$): Replace 1 or more component(s) with spares from stock or a lease component, or, Do Nothing.
6. Replacements are assumed to have fixed setup cost and variable labour cost. Combined replacements on an aircraft are economically more attractive, as the fixed cost are charged once. Fixed cost for corrective replacements (replacements that are performed in a MEL rectification interval) are higher compared to fixed cost for predictive replacements, since the latter have more planning flexibility. Short term capacity at line or base maintenance is unrestricted, which means that all replacements can be executed at the desired time.
7. After removal from the aircraft, a component is repaired in the shop. The TAT specifies the number of days a component is in repair. When a component is replaced just after an alert was created, it results in a minor repair with low cost and, optionally, a shorter TAT. The longer replacement is deferred after an alert, the higher the risk of a major repair with high cost and regular TAT. Failed components always result in major repairs. TAT's are predetermined and deterministic by default. After repair, a spare is put back in stock. Repairs are as good as new, however, after two consecutive minor repairs the next shop visit always results in a major repair (the component is overhauled). Inventory holding cost are neglected. Figure 18 represents the relation between the time since alert and repair cost.

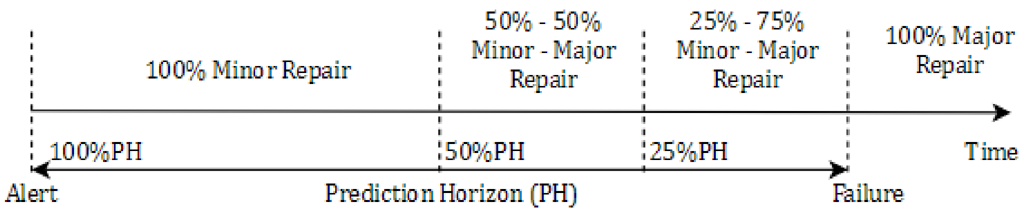



*Figure 18: Relation between time and repair cost*

8. After a simulation run, the reports are derived. A solution is valid when it satisfies the constrain related to the number of lease components. The target values for this constraint can be varied. When a solution does not meet the constraint, the experimental factors are adjusted and the model is run again. This is explained in more detail in 5.2.1.

**Flowchart –** Figure 19 represents a model flowchart. The green circles represent a change in system state and the numbers between brackets refer to the corresponding model content listed above. After a change in the system state, $X_{ijt}$ should be determined according to the formulas given in Chapter 4. The output of this step is either to Do Nothing ($c = 0$, stop) or to supply a spare from stock or lease a spare (corresponding with point 4 in the list above). The replacement action has two outputs: the alerted/failed component is removed and sent to repair (corresponding with point 7) and the supplied spare has to be installed on aircraft $i$. Prior to instalment, $t_{alert}$ or $t_{failure}$ must be set, according to point (2). In between the steps of the flowchart, cost and the number of leases have to be tracked.

After $t_{TAT}$, $t_{alert}$ or $t_{failure}$ the dashed lines will trigger a new change in system state and the flowchart is executed again.

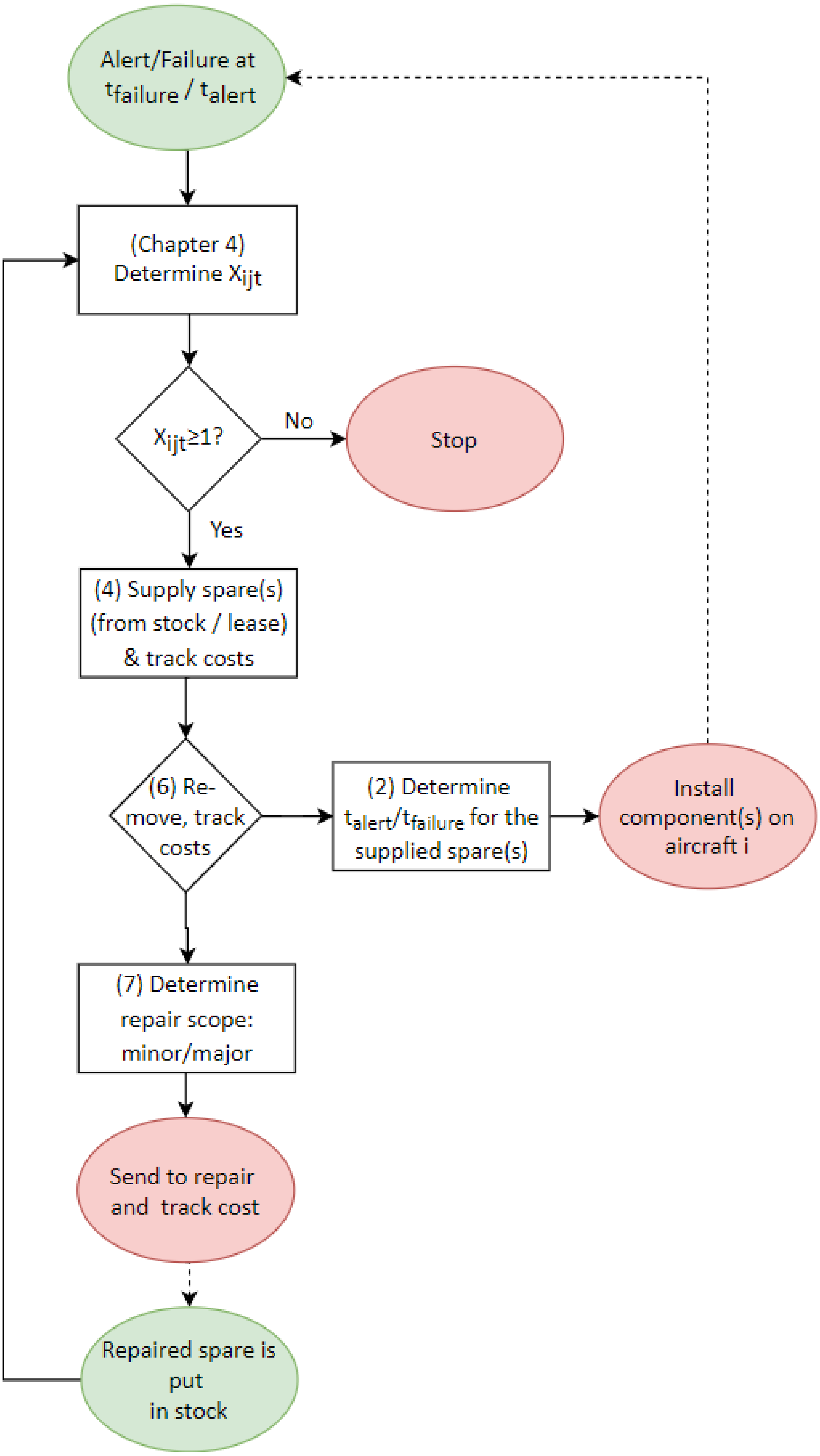



*Figure 19: Model flowchart*

### 5.1.5 Assumptions and simplifications

Most assumptions and simplifications have been mentioned in previous sections. Below, an overview of all assumptions is given.

- Components in the $k$-out-of-$N$ are identical and independent: an anomaly in the behaviour of one component does not affect the performance of the other components.
- Components fail according to the same failure distribution;
- All repairs are as good as new, but after two consecutive minor repairs the next repair on that component will always be major;
- Repair and replacement capacity is unlimited;
- Minor repairs have minor repair cost, major repairs have major repair cost;
- The probability on a minor repair for an alerted component decreases over time, according to Figure 18;
- Line/base maintenance capacity is unrestricted, replacements can always be performed.

## 5.2 MODEL DESIGN

In this section we elaborate on how the conceptual model from Section 5.1 should be designed such that when it is implemented in a computer model, it generates meaningful results. Recall that the objective is to find the best settings for the decision variables, so, the model must be able to minimise cost while attaining the lease constraint. For every experiment, the output of the model is represented by the values of the decision variables and the corresponding reports (see Section 5.1.3). The values of the decision variables are found with an iterative procedure, which is discussed in Section 5.2.1. The spare level corresponding with the best solution is indicated with $S_j$*. Policy performance should be analysed under varying circumstances. This is addressed in Section 5.2.2: the experimental design.

### 5.2.1 Model execution

The model is run according to the following order, for policies 1,2 3:

0. Initialize. Set $j$ and $S_j = 0$
1. Update $S_j = S_j + 1$
2. Run the model and determine average values for all reports, including the average number of lease components.
3. Stop if the constraint is met (then, $S_j = S_j$*), else go back to 1.

And for policy 4:

0. Initialize. Set $j = 4$ and $S_4 = 0$
1. Update $S_4 = S_4 + 1$, $q = 1$
2. Update $q = q + 1$
3. Run the model and determine average values for all reports, including the average number of lease components.
4. If the constraint is met, store current spare level as $S_{constraint}$ and set $S_{stop}$ to $S_{stop} = S_{constraint} + 1$. Stop when $S_4 = S_{stop}$, else:
   a. Go back to 1 if $q = f_{MEL} * M$.
   b. Go back to 2 if $q < f_{MEL} * M$.

For $j = 1,2,3$ it was found that $S_j$* $= S_j$ for the first value of $S_j$ that satisfies the lease constraint ($= S_{constraint}$). For policy 4 it was found that better solutions can be found when $S_4$ is increased one more time after the lease constraint was satisfied for the first time. Extra iterations with $S_4 > S_{constraint} + 1$ always result in worse solutions and are therefore not considered.

### 5.2.2 Experimental design

Within an experiment, the model finds the values for the decision variables that results in lowest cost according to the model execution procedure explained in the previous section. This section presents the experiments that are executed in order to understand policy behaviour to a greater extent and the impact of parameters values. In Table 8 all input parameters were specified that can be varied within experiments.

The benchmark scenario refers to a case study of the CSU component. The component has clearly detectable wear-out behaviour far in advance to failure, which results in stable performance of Prognos algorithms. The improvement of supply chain performance for the CSU is relevant, as it is in the top 3 of the 'disruptors'[17]. Currently, the CSUs are being repaired at an external vendor, but KLM E&M is developing capabilities to repair this component at Schiphol. Therefore, it is interesting to explore the impact of repair TAT fluctuations in experiments, as KLM E&M might have more possibilities in the future to influence this TAT.

A factorial design (Law, 2014) is used to create scenarios by varying parameters. A 2k-factorial design and the one-factor-at-the-time approach are selected as the most appropriate methods in this research. Both methods keep the number of experiments manageable and a 2k-factorial design also studies interaction effects. For the 6 parameters in the left column of Table 8 a 2k-factorial design is used. In a 2k-factorial design the values of the experimental factors are varied between two levels: a low value and a high value, indicated with '–' and '+'. Table 28 in the appendix shows the input values for the 2k-factorial design corresponding with a '–' or '+'. A low value can be interpreted as: A value that is disadvantageous for the final result. For instance for minor repair cost, the '–' value corresponds with the high cost value, as high cost are unfavourable. The input values corresponding with each '-' and '+' are derived from the system description.

Table 11 shows the layout of the 2k-factorial design. The responses (expressed in total cost) are evaluated per policy, as parameters might influence the individual policies in a different manner. Parameter 3 'TAT reduction' is an experimental factor that represents the hypothesis of KLM E&M that minor repairs could result in shorter repair times. This factor is a boolean with a TRUE or FALSE value. If the boolean is TRUE ('+'), the repair TAT is halved for minor repairs. The 2k-factorial design for the 6 parameters result in $2^6 = 64$ scenarios.

*Table 11: 2k-factorial design for 6 parameters*

| | **Parameters** | | | | | | **Scenario responses** | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | PH | TAT | TAT reduction | Sensitivity | Minor cost | Major cost | In total cost, per policy | | | |
| **Scenario** | 1 | 2 | 3 | 4 | 5 | 6 | $j = 1$ | $j = 2$ | $j = 3$ | $j = 4$ |
| 1 | - | - | - | - | - | - | $R_{1,1}$ | $R_{1,2}$ | $R_{1,3}$ | $R_{1,4}$ |
| 2 | + | - | - | - | - | - | $R_{2,1}$ | $R_{2,2}$ | $R_{2,3}$ | $R_{2,4}$ |
| 3 | - | + | - | - | - | - | $R_{3,1}$ | $R_{3,2}$ | $R_{3,3}$ | $R_{3,4}$ |
| 4 | - | - | + | - | - | - | $R_{4,1}$ | $R_{4,2}$ | $R_{4,3}$ | $R_{4,4}$ |
| … | … | … | … | … | … | … | … | … | … | … |
| 64 | + | + | + | + | + | + | $R_{64,1}$ | $R_{64,2}$ | $R_{64,3}$ | $R_{64,4}$ |

[17] A list of components with bad supply chain performance. Based on performance data of October 2018.

The parameters in the right column of Table 8 are varied one at the time. In these experiments, all other parameters values remain at their benchmark value (see Appendix A, II). Together, this results in a total of seven experiments, as shown in Table 12.

*Table 12: Design of experiments*

| Experiment | Scenario | Analysis |
|---|---|---|
| **1** | Benchmark | Model validation and analysis of performance of all policies, in a case study for the CSU component. |
| **2** | 64 scenarios from the 2k-factorial design | Main effects and interaction effects of 6 selected variable parameters. |
| **3** | Benchmark* | Effect of a less tight lease constraint. |
| **4** | Benchmark* | Impact of a varying failure distribution. |
| **5** | Benchmark* | Performance of the extended policies (explained in section 4.2.7) in the benchmark scenario |
| **6** | Benchmark* | The effect of stochasticity in PH and TAT, compared to deterministic values for these parameters. |
| **7** | Benchmark* | Effect of an increased fleet size. |

*All values for the parameters correspond with their benchmark values except for the one that is analysed in that specific experiment.

With the execution of these experiments, we aim to provide insights for KLM. For each experiment, there is an underlying thought or hypothesis that we aim to address. The corresponding question(s) or tested hypotheses are listed below.

1. Which policy results in the lowest cost and what is the impact on maintenance capacity?
2. Which parameters have the largest impact on performance, and should therefore be focused on in the future when implementing Prognos?
3. Currently, leasing components is seen as an exception because cost are high. Does the model confirm this finding?
4. If we use a different failure distribution as input for our model, do we find similar policy performance as in experiment 1? If that is the case, the best policy might also be beneficial for other 3-out-of-4 components.
5. What is the 'price' in terms of increase in maintenance capacity, if the extended policies are applied? Do these extended policies result in lower repair cost?
6. What is the impact of the assumption that PH and repair TAT are deterministic?
7. If Prognos adopts customers of KLM E&M in their application, the fleet size included in Prognos increases. What is the effect on policy performance?

## 5.3 Computer model

Guided by the design of the policies and the (conceptual) model, the model is implemented in computer software. For this purpose, Siemens Tecnomatix Plant Simulation 13 software is used. A technical description of the computer model is added in Appendix B.

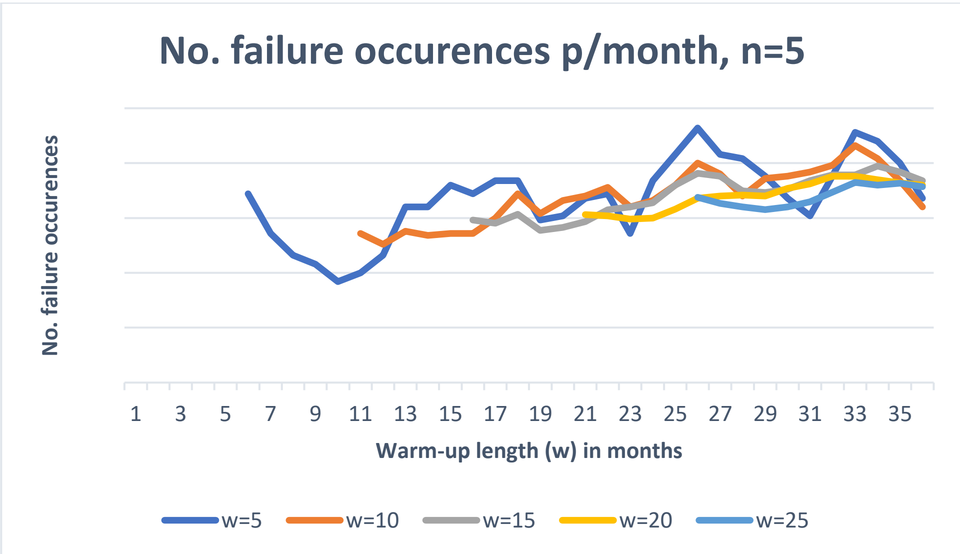
The results of the model have to be statistically significant in order to derive conclusions. To achieve this, we derive values for the warm-up length, number of replications and run length with the computer model in the next sections. Verification is also part of this section and the construction of confidence intervals is discussed.

### 5.3.1 Verification

With the construction of the model, various simplifying assumptions were made in order to keep complexity to a manageable level. Verification implies that the computer model should correspond with the paper model. The paper model of this study is explained in Chapter 4 and Sections 5.1 and 5.2. The computer model was tested and debugged repeatedly to check correctness. Step-by-step model debugging was applied extensively and intermediate results were checked for reasonableness in multiple scenarios. In addition, model coding was checked with multiple stakeholders, including a simulation model expert.

### 5.3.2 Warm-up length, run length and number of replications

The system that is being evaluated is a non-terminating system, which means there is no natural event that specifies the end of a simulation run (such as a factory shutdown or the end of a flight). Therefore, system behaviour should be evaluated only when observations no longer depend on initial conditions and a steady-state is reached. A warm-up period should be set in which observations are deleted. Welch's graphical method is used to determine the warm-up length and the number of replications of a simulation (Welch, 1983). In our case, the initial number of alerts and failures have the most impact on performance, as they determine the majority of the state space. Their initial value is zero, which results in no cost, as there are no replacements required in the state space $Z_{jt}(0,0,s_t)$ for all $j$. The number of alerts and failures will be used to determine when a steady state is reached. When Welch's graphical method creates a smooth plot, the warm-up length and the number of replications is set at an appropriate value. Figure 20 presents the plots for the number of failures, with various values for the warm-up length $w$ (days). Graphs for the number of alerts have similar results. A 'reasonably smooth' graph means that the warm-up length and number of replications (n) are set correctly. The graphs below show the results for the number of failures with n=5, 10 and 15. The warm-up length is given in months. The graph at the bottom zooms in at the lines for w=25 with n=10 and n=20. It shows that the variation in the number of failure occurrences remains within the bounds of 1.5 and 175. The model will run experiments with n=20, except for experiment 2 (with 64 scenarios) in order to keep run time manageable.



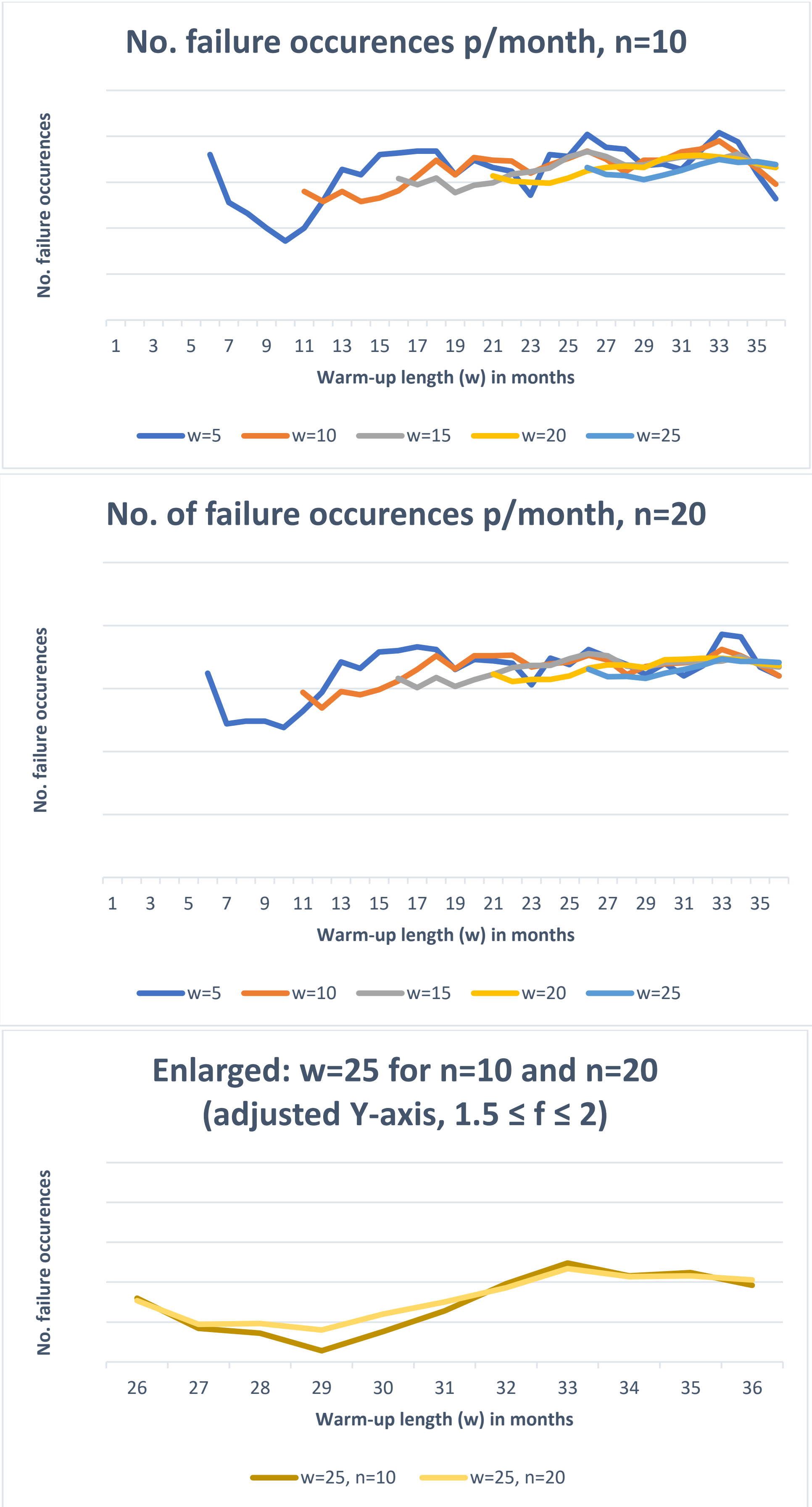



*Figure 20: Welch's graphical method for n=5, 10 and 20*

In two consecutive years, the number of failure occurrences can vary quite a bit. Therefore, the simulation run length is set to 3 years, such that variability between experiments is reduced. The warm-up length is set to the same value. From Figure 20 we can expect that this should be sufficient and an analysis on relative error found that the relative error with $n = 20$ is within acceptable bounds with $\alpha = 0.10$.

### 5.3.3 Comparing results

Policy performance can be compared with a paired-t approach. This is the most suitable method in our case as Plant Simulation allows to use common random numbers and to control the number of observations. In the model, random numbers are used for:

- Generation of time to failure and time to alert
- Determining the length of the time interval the MCC needs to schedule a replacement in the rectification interval when there is a stockout. If there is a repair finished within that interval, leasing a new component can be avoided (see footnote 15)
- Determining the repair cost
- Determining the TAT and PH in the experiment with stochastic TAT and PH.

Each experiment consists of a number of runs (replications). Each replication has its own common random number stream. So, the first run of the first experiment uses the same random numbers as input as the first run of the second experiment, the first run of the third experiment, and so on. Therefore, differences in total cost are caused by the difference in policy performance and not the difference in random number generation.

Average values for KPI's can be calculated per experiment based on the computer model output. Each experiment will be replicated 20 times, so $n = 20$. The experiment that will be compared to the first experiment, is also run 20 times; $m = 20$. Now a confidence interval can be constructed for the difference between the average total cost per experiment (per policy).

$$X_i = total\ cost\ of\ experiment\ 1\ in\ replication\ i, i = 1, \dots, n$$
$$Y_i = total\ cost\ of\ experiment\ 2\ in\ replication\ i, i = 1, \dots, m\ (m = n)$$
$$W_i = X_i - Y_i, the\ difference\ in\ total\ cost\ of\ the\ two\ experiments$$

Then, the confidence interval is given by (Law, 2014):

$$\bar{W} \pm t_{n-1,1-\alpha/2}\sqrt{Var[\bar{W}]}$$

Where

$$\bar{W} = \frac{1}{n}\sum_{i=1}^{n} W_i$$

And

$$Var[\bar{W}] = \frac{1}{n}Var[W] = \frac{1}{n(n-1)}\sum_{i=1}^{n}[W_j - \bar{W}]^2$$

A confidence interval of 95% for W represents that in 95% of the cases the difference between total cost of experiment X and Y will lie between the bounds of the interval. If 0 is not part of the interval, the two experiments are significantly different.

Confidence intervals (CI) can also be constructed for the output of a single experiment, instead of a comparison between two experiments. A 95%-CI with lower bound LB and upper bound UB represents that it can be stated that in 95% of the cases the output of the experiment will be within the bounds of [LB, UB].

## 5.4 CONCLUSION

In this chapter the model was presented that allows to test various predictive replacement policies. Factors that are expected to have significant impact on performance were distinguished and used to setup an experimental design. This experimental design allows to analyse policy performance under various circumstances, and to estimate the impact of the individual experimental factors on performance. Performance is measured based on total cost and the number of replacements.

To make sure results are statistically significant, a warm-up length, the number of replications and the run length were derived in Section 5.3. It also discussed the paired-t approach and the use of confidence intervals to analyse results. In Chapter 6 the results of the experimental design are presented.

# 6 RESULTS

In this chapter, research questions 6 and 7 are addressed:

6. *What is the expected performance of the predictive replacement policies, when they are applied to a 787 component at KLM E&M?*
    a. *Which policy has the best performance?*
    b. *What is the required performance of Prognos' prediction models?*
7. *What are the benefits and drawbacks of using a predictive replacement policy at KLM?*

The first section of this chapter discusses the performance of the policies in the benchmark scenario. Policies are compared based on average total cost and replacements. The consecutive sections discuss the experiments of the experimental design as introduced in Section 5.2.2. The design is displayed once more in Table 13 with the corresponding section allocation.

*Table 13: Design of experiments*

| Exp. No. | Scenario | Analysis | Section |
|---|---|---|---|
| **1** | Benchmark | Model validation and analysis of performance of all policies, in a case study for the CSU component. | 6.1 |
| **2** | 64 scenarios from the 2k-factorial design | Main effects and interaction effects of 6 selected variable parameters. | 6.2 |
| **3** | Benchmark* | Effect of a less tight lease constraint. | 6.3 |
| **4** | Benchmark* | Impact of a varying failure distribution. | |
| **5** | Benchmark* | Performance of the extended policies (explained in section 4.2.7) in the benchmark scenario | |
| **6** | Benchmark* | The effect of stochasticity in PH and TAT, compared to deterministic values for these parameters. | |
| **7** | Benchmark* | Effect of an increased fleet size. | |

*All values for the parameters correspond with their benchmark values except for the one that is analysed in that specific experiment.

## 6.1 BENCHMARK SCENARIO

The first subsection discusses to what extent the model represents current practice at KLM E&M, by analysing the performance of policy 1 in the benchmark scenario (model validation). The second sub section discusses the performance of the predictive policies and compares them with the current corrective policy.

### 6.1.1 Validation

To validate our model, the model is run with an empirical failure distribution based on MTBR data of the CSU component. The derivation of this distribution is discussed in Appendix A III.

In this case, MTBR data is used to derive a failure distribution. In Figure 1 we have seen that the MTBR can differ significantly from the MTTF, as it is the result of a replacement policy. However, it is the only data available regarding component failures/replacements. The model is tested with the assumption that $MTBR \approx MTTF$. If the result approaches the actual historical values regarding replacements, we can use this distribution from now on to compare policies. In Chapter 7 we discuss the impact of this assumption and in Section 6.3 we run the model with standard failure distributions and reflect on the impact of this change.

Various probability distributions were plotted to the replacement data, to check whether a standard distribution could be used to generate failures. No standard distribution was found to fit, although the Weibull distribution was a quite good approximation. Weibull, Poisson and Gamma were tried. An empirical distribution was implemented in the software, based on the histogram of Figure 28 (constructed in Excel). The histogram bins are copied to a table which is used as input for the derivation of the time to failure.

For validation, the model is run with replacement policy 1 as active policy, as this policy aims to represent the current corrective policy. The KPI 'number of replacements' is used to validate the model, in combination with the number of spares and average number of leases. These numbers can be derived from KLM data of 2018. The spare level at KLM needs to fulfil demand for all pool customers, corresponding with 160 aircraft (787 type). To derive $S_{benchmark}$ for the model validation, the following formula is used, where $M_{pool} = 160$ and $M_{KLM} = 13$ (fleet size):

$$S_{benchmark} = \frac{S_{pool}}{M_{pool}} * M_{KLM}$$

The value for $S_{pool}$ and absolute results from the validation run can be found in Appendix A, Section V. The model is run with the rounded values for $S_{benchmark}$: $\lceil S_{benchmark} \rceil$ (rounded up) and $\lfloor S_{benchmark} \rfloor$ (rounded down) as $S$ needs to be an integer in the model. If the computer model is run for a year with $\lceil S_{benchmark} \rceil$ and $\lfloor S_{benchmark} \rfloor$, it results in the numbers given in Table 14. The results are close to the actual values for the number of replacements in 2018 (max percental change 3.5%) and the number of leases (max deviation: 3.2 leases).

*Table 14: Output validation runs*

| | | **No. Replacements** | **No. Leases** |
|---|---|---|---|
| *Values 2018* | | | **0** |
| *Model results* | $\lceil S_{benchmark} \rceil$ (up) | -3.4% | 0.3 |
| | $\lfloor S_{benchmark} \rfloor$ (down) | +1.2% | 3.2 |

In addition to this validation analysis, the replacement data of individual runs was analysed to check whether this could be a representation of actual replacement data. No counter arguments could be found based on this analysis.

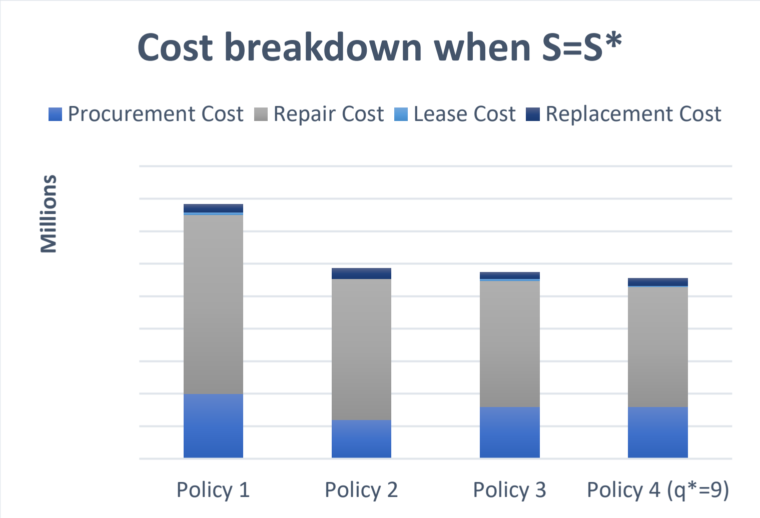
As the model results approximate actual values for the selected KPI's, the empirical distribution from Appendix A is used in the benchmark as failure distribution.

### 6.1.2 Policy comparison

This section presents the results of all policies in the benchmark scenario (Table 27). The run length is 3 years.

Recall that the model includes a service constraint regarding the number of leases, but not regarding maintenance capacity. A (very) high number of maintenance intervals results in high work load for line/base maintenance, and might be considered as unfeasible in the current organisation with tight flight schedules to sustain. However, this constraint is excluded in the model as policies approach the same general behaviour with strict constraint settings regarding the number of replacements (no clear distinction in $X_{ijt}$ for various values of $j$). We have illustrated this concept in Section 4.2.4 (below Figure 16) by means of an example with unlimited spare parts.

Therefore, a comparison should always include the number of maintenance intervals as well as total cost. A policy with low average total cost but a very high number of maintenance intervals is not a good solution. The average total cost and number of maintenance intervals for all policies are presented in the left and right graph of Figure 21 respectively. The relative error of the total cost is at most 3,2% (for all policies), with a probability of 90% ($1 - \alpha$). In other words, if we construct 100 independent 90%-CI, we would expect that the total cost has a relative error of at most 3,2% in about 90 percent of the 100 cases, and in the other 10 cases the relative error would be greater than 3,2% (Law, 2014).



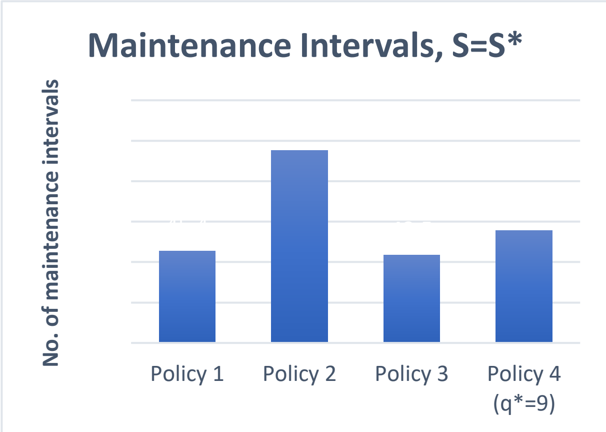




*Figure 21: Results benchmark scenario*

From the results it can be concluded that all predictive policies result in lower total cost. Repair cost are the largest fraction of the average total cost. When maintenance intervals are also considered, policy 3 or 4 has the best performance. The next graphs provide more detailed insight in policy performance, when spare levels are varied. The lines represent policies $j$ and in between the brackets in the legend the values for $S_j{}^*$ are given. For these values the lease constraint is met and the best solution is found (in terms of cost and replacement intervals).

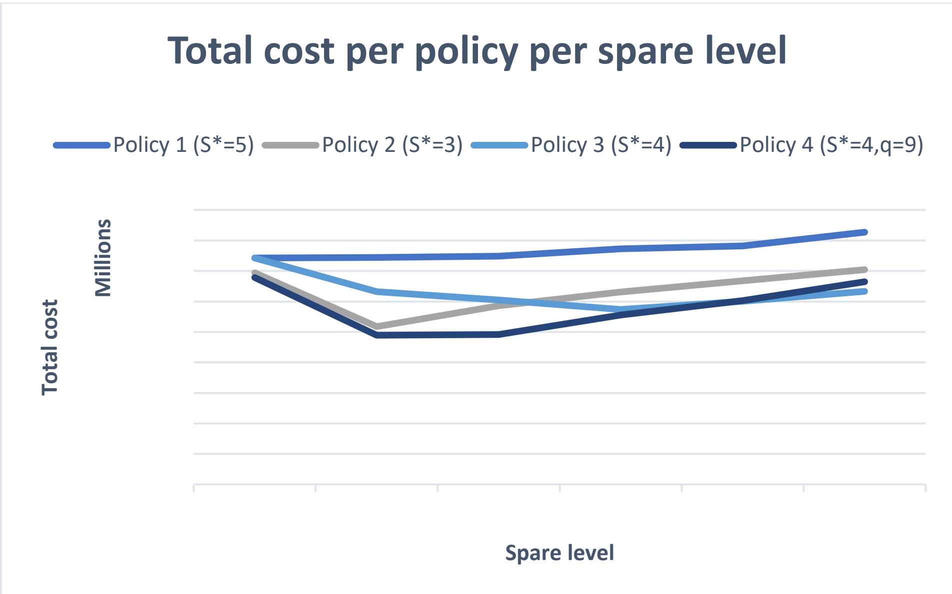



*Figure 22: Total cost for varying spare levels*

From Figure 21 it can be seen that repair cost are the greatest cost factor. The pattern of the repair cost stabilizes when $S$ increases. This can be explained with the fact that the timing of replacements stabilize, as $X_{ijt}$ becomes independent of $s_t$ (always sufficient spares to perform replacement). Then, $X_{ijt}$ only depends on the number of (alerts and) failures, which are generated from the same constant failure distribution. The difference in total cost between $S = 5$ and $S = 6$ is close to the price of a spare. This pattern is repeated for larger values of $S$.

Regarding the number of maintenance intervals and the average value for $c$ (number of components replaced within the same interval) we find that policy 2 always performs single replacements and the other policies show increasing values for $c$ as $S$ increases.

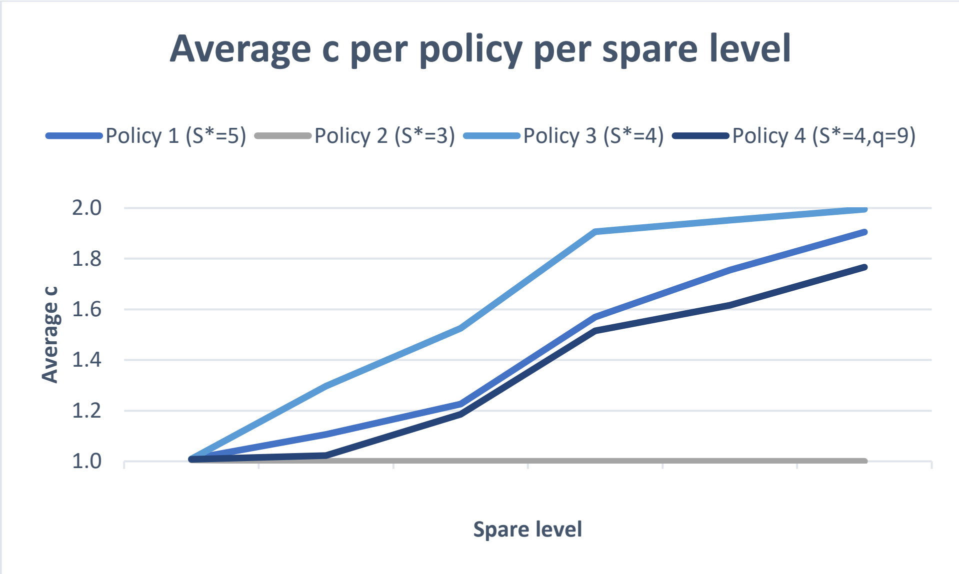



*Figure 23: Value of c for varying spare levels*

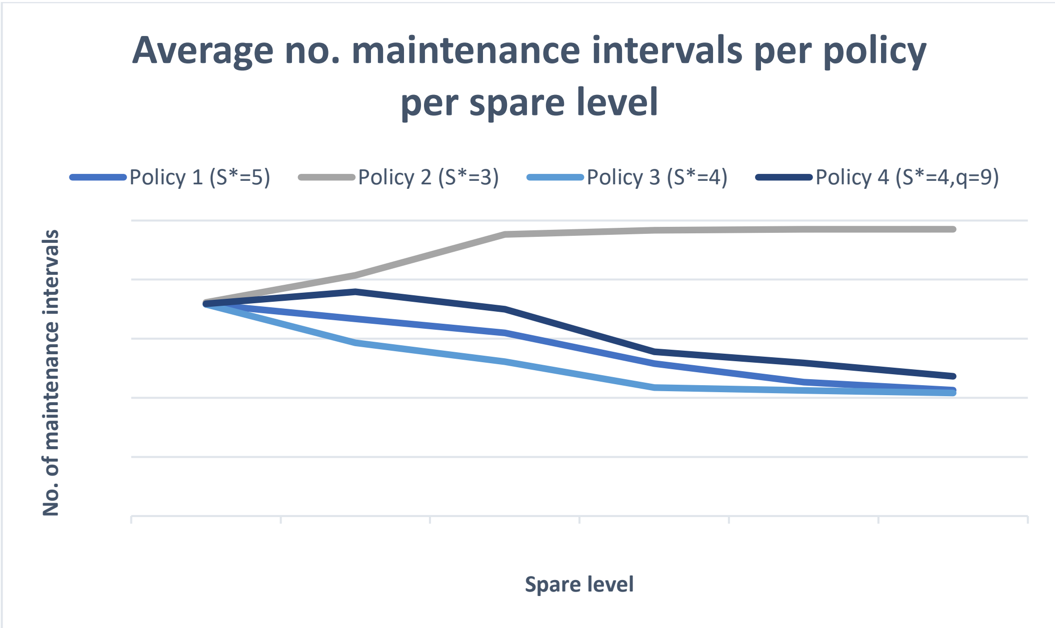



*Figure 24: Average number of maintenance intervals for varying spare levels*

In the overview of Table 15 the four policies are compared based on cost and maintenance intervals. In addition, the variation in $S$ is included. The effect on spare levels is of special interest at KLM and in this study, due to the hypothesis that PdM results in higher spare levels (due to a decrease in MTBR). In Chapter 2 we explained this is one of the main counter arguments at KLM for the implementation of PdM, and we also mentioned a hypothesis that PdM could reduce $S$.

Below we find the results of the predictive policies (compared to policy 1, the current corrective policy).

In the last column, the average percental change for the three mentioned KPI's was given. Based on this evaluation with average %change, policy 3 is the best policy.

*Table 15: Policy comparison overview (run length = 3 years)*

| Policy | %change | %change | %change | Average %change |
|---|---|---|---|---|
| **1** | N/A | N/A | N/A | N/A |
| **2** | -25% | -40% | +110% | +15% |
| **3** | -27% | -20% | -4% | -17% |
| **4 (q=9)** | -29% | -20% | +23% | -9% |

The total cost of the predictive policies differ little from each other. However, spare levels and maintenance intervals have high variations. All policies replace approximately the same amount of components (total $c$), however, policy 2 always performs single replacements. This is identified as the cause for the lower spare level with policy 2. Combined replacements result in higher peaks in demand, and therefore stockouts and lease components. So, to satisfy the lease constraint, policies that combine replacements require higher spare levels. The main drawback of policy 2 is the major increase in number of maintenance intervals: +110%. This would have a major effect on maintenance capacity at KLM.

Policies 3 and 4 result in lower total cost, due to reduction of repair and spare cost. The number of maintenance intervals also has a significant increase with policy 4 (> 20%).

In Section 5.3.3 the formulas for confidence intervals were given. First, the 95%-CI of total cost was derived for all policies, given in Table 16. It can be concluded that average total cost are not significantly different for the predictive policies because the intervals overlap. The 95%-CI are narrow as the width is at most $x$% of the observed mean.

*Table 16: 95%-Confidence Intervals for average total cost*

| Policy | Lower Bound (LB) | Upper Bound (UB) | UB – LB (width) |
|---|---|---|---|
| **1** | | | |
| **2** | | | |
| **3** | | | |
| **4 (q=9)** | | | |

When a paired-t approach is applied for the number of maintenance intervals, it can be clearly identified that the policies have different behaviour. $W$ is defined as the difference in number of maintenance intervals of policies $j$. A 95%-CI for $W$ is constructed for $j = 2,3,4$. Table 17 shows that there are no intervals that contain the value 0, so therefore the policies are significantly different in this KPI.

*Table 17: 95%-Confidence Intervals for number of maintenance intervals*

| $W$ | LB | UB |
|---|---|---|
| $\boldsymbol{W = 2 - 3}$ | 50 | 54 |
| $\boldsymbol{W = 3 - 4}$ | -15 | -10 |
| $\boldsymbol{W = 2 - 4}$ | 37 | 42 |

## 6.2 2K-FACTORIAL DESIGN

In Table 11 the layout of the 2k-factorial design was presented. The responses of all the scenarios are expressed in total cost. Here we define $\mu_j$ as the average total cost of policy $j$ in the benchmark scenario, see also column 2 of Table 15. The effects of the parameters are given as a fraction of $\mu_j$.

Table 18 shows the main effects of the parameters included in the 2k-factorial design. Recall that this can be interpreted as: 'the average change in total cost when the parameter value shifts from '$-$' to '+''. The parameter values corresponding with '$-$' and '+' can be found in Table 28 in the Appendix. From the results in Table 18 we can conclude a few things:

- A change in major repair cost has the largest effect on total cost for all policies;
- A shift from the '– value' to the '+ value' in Prognos' sensitivity ratio has more impact on cost than a similar shift in the prediction horizon;
- A reduction in repair TAT always saves cost, for all policies.

When these numbers are interpreted, the reader should be aware that these results are generated with 10 replications instead of 20. Randomness can have a larger impact in these results. Therefore, only general conclusion are derived to identify focus points for improvement.

*Table 18: Main effects of the 2k-factorial design parameters, expressed as the relative impact on total cost*

| Policy | PH | TAT | TATreduction. | Sensitivity | MinorRC | MajorRC |
|---|---|---|---|---|---|---|
| **1** | N/A | -4% | N/A | N/A | N/A | -21% |
| **2** | -1% | -8% | -4% | -5% | -12% | -20% |
| **3** | -3% | -12% | -2% | -10% | -9% | -20% |
| **4** | -4% | -9% | -3% | -12% | -13% | -18% |

Regarding interaction effects, we are cautious in deriving conclusions, because of the potential large variability. When the interaction effects are expressed as a fraction of total cost, effects remain between the bounds of $-3\%$ and $+3\%$. Knowing that the influence of randomness might be large in this analysis, the differences are considered insignificant and we do not derive conclusions regarding this aspect. Further research should be performed to estimate the impact of potential interaction effects. Thereby it may be mentioned that results so far of the analysis on interaction effects did not show any unexpected results. Also, results seemed to indicate that:

- An increase (form – to +) in PH has more effect when the repair TAT has its '+' value. Because then:
  - In the '–' PH case: $PH < TAT$
  - In the '+' PH case: $PH > TAT$

This seems to indicate that this ratio is important for benefits, which corresponds with the theory of demand lead time mentioned in Section 3.1.2.

From Table 16 and Table 17 in the previous section we know that a single analysis based on total cost can be misleading: Table 16 shows that the average total cost of the predictive policies are not significantly different (because the confidence intervals overlap), however, Table 17 shows that the behaviour of the policies is definitely different because the replacement pattern varies a lot per policy. The cost structure of the model leads to the same total cost, but the performance on terms of impact on maintenance capacity should not be neglected.

To create more insight in effect of parameter shifts, the main effect on spare levels is also given in the table below. Here, the spare level corresponds with the minimum number of spares required to satisfy the lease constraint (also for policy 4).

*Table 19: Main effects of the 2k-factorial design parameters, expressed as the relative impact on minimum S ($S_{constraint}$)*

| Policy | PH | TAT | TATreduction. | Sensitivity | MinorRC | MajorRC |
|---|---|---|---|---|---|---|
| **1** | N/A | -20% | N/A | N/A | N/A | N/A |
| **2** | -4% | -38% | -13% | -13% | N/A | N/A |
| **3** | -3% | -47% | -9% | -16% | N/A | N/A |
| **4** | -6% | -26% | -7% | -7% | N/A | N/A |

From Table 19 we can conclude that the repair TAT has a major impact on spare levels, which corresponds with all knowledge from literature and also with the formulas used at KLM to estimate spare levels. In addition, these results also imply that a change in sensitivity ratio has more effect on total cost than a change in prediction horizon. This result can be explained with the fraction of repair cost in total cost, which is very large (see Figure 21). A decrease in sensitivity will directly result in more major repairs with high cost, while a decrease in PH will also result in higher cost but this depends on more factors and has a more complex relation. This makes it more difficult to quantify the benefits of a larger PH.

## 6.3 OTHER EXPERIMENTS

In Table 8 all variable parameters that are input for the experimental design were introduced. The previous section discussed the impact of the parameters included in the 2k-factorial design. This section provides an analysis for the other factors (given in the right column of Table 8): the threshold for the lease constraint, the failure distribution, extended policy performance, the impact of stochastic PH and TAT and policy performance in a large fleet. These experiments are run with 20 replications.

### 6.3.1 Lease constraint analysis

To analyse the impact of a varying threshold of the lease constraint, Figure 25 shows the average number of leases per year for different spare levels. For this purpose, the average number of leases from the model output with a run length of 3 years was divided by 3. It can be shown that policies 2 and 4 satisfy the lease constraint at $S = 3$ when the lease constraint is set to 1 per year on average. The other policies require higher spare levels. This is explained with the fact that policies 2 and 4 act very early on demand, and therefore MEL situations are mostly avoided.

From this figure it can easily be derived what the 'price' is for a different lease constraint threshold in terms of spare levels. For instance, if one would like to reduce spare levels in policy 1, it will approximately result in an increase of 3 to 4 lease components on average per year. When the price of a lease part is considered, it might be more cost efficient (in terms of spare part cost) to increase the inventory level. This corresponds with current practice at KLM E&M: leasing parts is an exception.

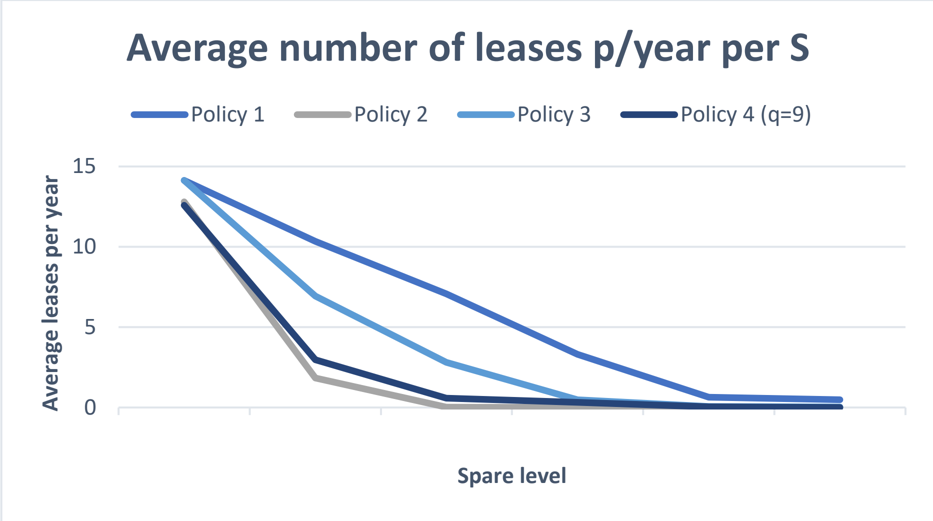



*Figure 25: Average number of leases per policy for varying spare levels*

### 6.3.2 Failure distribution

To analyse the impact of a different failure distribution, a Weibull distribution was used as input. This distribution was the best fit for the empirical distribution derived in Appendix A. In addition, the Weibull distribution is one of the most widely used distributions in reliability and survival analysis (Asgharzadeh, Valiollahi, & Kundu, 2015). All other settings of the benchmark scenario are kept the same. The Weibull distribution is given as (Papoulis & Unnikrishna Pillai, 2002):

$$f(x;\lambda,k) = \begin{cases} \frac{k}{\lambda}\left(\frac{x}{\lambda}\right)^{k-1} e^{-\left(\frac{x}{\lambda}\right)^{k}} & x \geq 0, \\ 0 & x < 0 \end{cases}$$

Where $k$ is the shape parameter and $\lambda$ the scale parameter. When the Weibull distribution was plotted to the replacement data from KLM, the values $k = 1.575$ and $\lambda = \cdots$ (days) approximated the histogram best. When the model is run with Weibull distribution f(x; $\lambda$, 1.575) and the values for the decision variables found in Section 6.1 (benchmark scenario), we find that the model results deviate little from the benchmark result. The percental difference is given in Table 20. It can be seen that the Weibull distribution results in slightly less frequent failures, as all policies replace 8%-10% less components during a model run (total $c$).

*Table 20: Percental differences between empirical F(t) and Weibull F(t) per policy per KPI*

| **Policy** | **1 (S=5)** | **2 (S=3)** | **3 (S=4)** | **4 (S=4, q=9)** |
|---|---|---|---|---|
| **Total cost** | -6% | -8% | -8% | -2% |
| **Maintenance intervals** | -9% | -8% | -11% | -14% |
| **Total *c*** | -8% | -8% | -10% | -9% |
| **Average *c* per interval** | 1% | 0% | 1% | 5% |

From this comparison we conclude that the effect of using a Weibull distribution is rather small, as all differences are smaller than 14%. Since the Weibull distribution seems a good approximation, the model is also run with $k = 1.575$ and $\lambda = 0.5\lambda$ to evaluate the effect of more frequent failure occurrences on policy performance. The results are given in the same layout as used in Table 15.

*Table 21: Policy comparison in the scenario with a Weibull failure distribution with high frequency of failure occurrences*

| Policy | %change | %change | %change | Average %change |
|---|---|---|---|---|
| **1** | N/A | N/A | N/A | |
| **2** | +8% | -25% | +133% | +39% |
| **3** | -16% | -25% | 5% | -12% |
| **4 (q=12)** | -20% | -25% | 20% | -8% |

From these results it can be concluded that the predictive policies perform less good compared to the current corrective policy, when a Weibull distribution is run with more frequent failure occurrences. Policy 3 still has the best performance but policy 2 is far worse and even results in higher total cost due to the major increase in number of repairs and the associated cost. When the same experiment is performed with $k = 1.575$ and $\lambda = 2\lambda$, we find opposite results: compared with policy 1, policies 2-4 perform better in this scenario. Policy 3 still has the best results overall.

### 6.3.3 Extended policies performance

In this experiment the extended policies (explained in Section 4.2.7) are tested. The extended predictive policies only replace alerted components, which results in an increase in maintenance intervals. When a failed component is left on wing, the next DIL exceedance will occur within a shorter time. Model output shows that it does not have an effect on spare levels. The effect on total cost and maintenance intervals is shown in Table 22. It is shown that the extended policies save total cost (by saving repair cost, up to 20%), but the effect on maintenance intervals is significant. Policy 2 has the same results (there is no difference between the extended version and default version of this policy) and is therefore left out of the results in Table 22.

*Table 22: Results extended policies*

| Policy | Total cost | Maintenance intervals | Average |
|---|---|---|---|
| **1** | -5% | +58% | +26% |
| **3** | -18% | +69% | +25% |
| **4** | -20% | +32% | +6% |

### 6.3.4 Stochasticity for PH and TAT

So far, the model assumed that the PH and TAT has deterministic values. To evaluate the impact of this assumption to some extent, the model is run with randomly generated values for the prediction horizon and repair TAT. For this purpose, the PH and TAT are modelled with the help of a normal distribution:

$$PH \sim Normal(PH_{deterministic}, x^2)$$
$$TAT \sim Normal(TAT_{deterministic}, y^2)$$

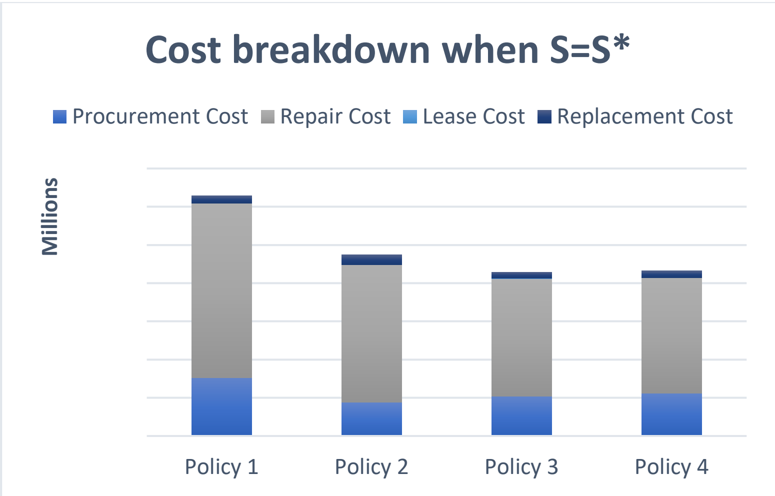
Where the values $x$ and $y$ represent half the difference between the '+' and '−' value from the factorial design. In Table 23 it can be seen that stochasticity increases cost and maintenance intervals, but the effect is small.

*Table 23: Comparison deterministic and stochastic scenario*

| Policy | %change Total cost | %change Maintenance intervals |
|---|---|---|
| **1** | +1.1% | +3% |
| **2** | +1.7% | +1% |
| **3** | +2.0% | +4% |
| **4** | +0.2% | +4% |

### 6.3.5 Large fleet size

The final experiment evaluates the impact of an increased fleet size. In this experiment, the fleet size is increased to four time the size of the original fleet of KLM: from 13 aircraft to 52 aircraft. The results are reported the same way as in Section 6.1.



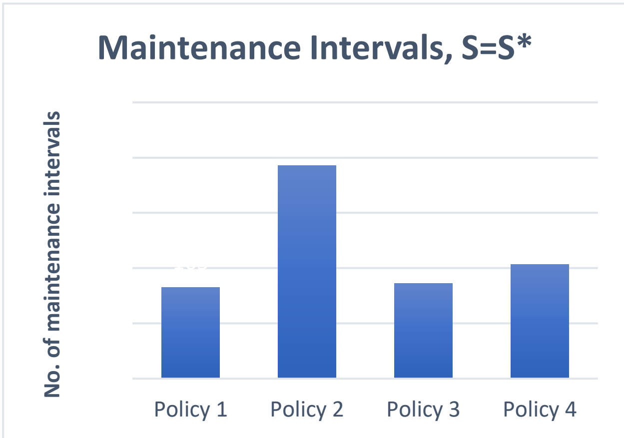
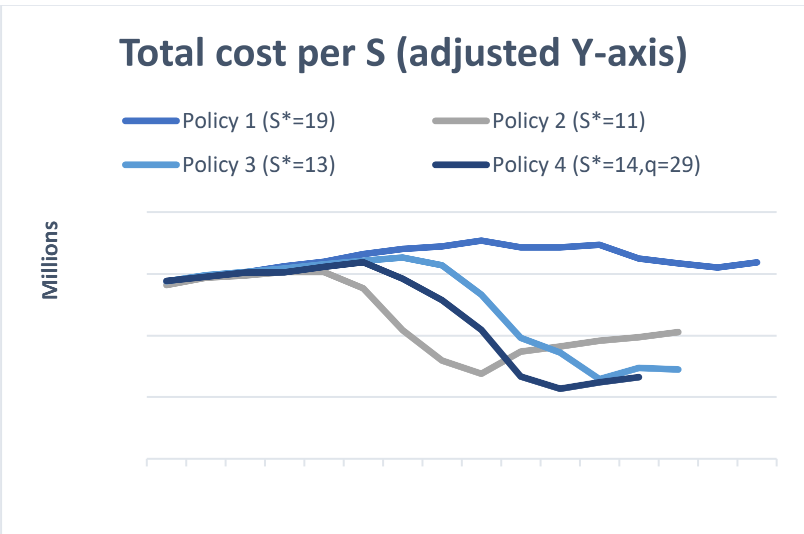




*Figure 26: Results experiment with large fleet*



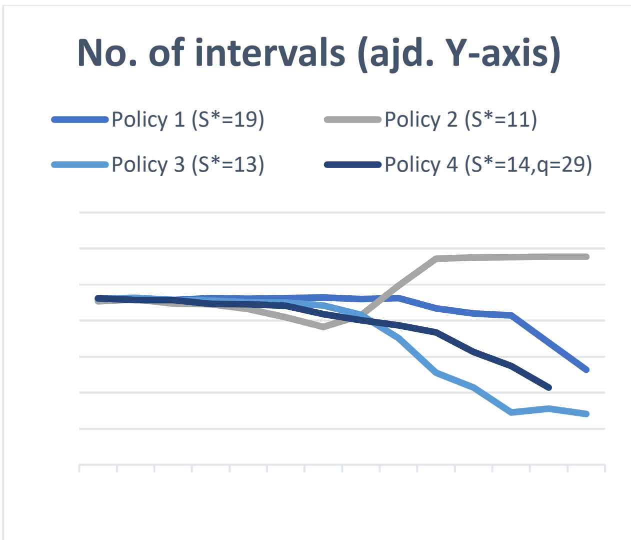




*Figure 27: KPI values per policy per spare level*

*Table 24: Policy comparison overview (large fleet)*

| Policy | %change | %change | %change | Average %change |
|---|---|---|---|---|
| 1 | N/A | N/A | N/A | N/A |
| 2 | -25% | -42% | +134% | +22% |
| 3 | -32% | -32% | +4% | -20% |
| 4 (q=29) | -31% | -26% | +25% | -11% |

All predictive policies perform better (when compared with policy 1) when a large fleet is considered. On average, policy 3 shows the best results with an average total cost reduction of 32% and a reduced spare level from 19 to 13.

## 6.4 CONCLUSION

The case study performed in this chapter shows promising results for predictive maintenance on the CSU component at KLM E&M and for PdM in general. In the benchmark scenario, which aims to represent to current situation of the CSU as accurate as possible, average total cost are decreased with 25% to 29% with predictive policies. When the impact on maintenance capacity is also considered, policy 3 has the overall best performance in the benchmark scenario. This policy realises a total cost reduction of 27% while not increasing the impact on maintenance capacity. The cost reduction is realised due to a reduction in repair cost as well as a reduction in spare part cost. All predictive policies result in lower required inventory levels. The latter is accomplished with variability reduction of the average number of components in repair. The bigger time frame realised by alert notifications increases flexibility in the planning of replacements. This enables to avoid high peaks in spare part demand and therefore the lease constraint can be satisfied with smaller inventories. With this result, the main counter argument for PdM implementation (that it would increase spare levels) is rejected within this study.

The average total cost are close with all predictive policies, and the confidence intervals have shown that these values are not significantly different. However, the individual cost factors, such as repair cost and replacement cost, are significantly different. Also the number of maintenance intervals are significantly different with all predictive policies. Therefore it can be concluded that although the policies have similar output for average total cost, their behaviour is clearly different.

A major drawback of predictive policies that are aimed at minimizing repair cost, is the major increase in number of maintenance intervals. Although the number of repaired spares remains within certain bounds (total $c$), the frequency of single replacement actions can become very high. This will result in an increase in workload for line (or base) maintenance and could create scheduling issues.

To benefit from inventory reductions, this study showed that Prognos' sensitivity is the most important performance measure of predictions. An increase in sensitivity has a larger effect on spare levels than the Prediction Horizon when the 2k-factorial design of Table 28 is considered.

# 7 IMPLEMENTATION

With the results from the case study and the knowledge gained from literature, this chapter provides suggestions for the implementation of Predictive Maintenance at KLM E&M, and thereby answers research question 8. It proposes a few guidelines on how KLM should benefit from new available information about component health.

8. *How should KLM E&M implement predictive maintenance?*

In the first section, the implementation of PdM for the CSU component from the case study is discussed. Section 7.2 provides suggestions for the other components in Prognos' current and future scope, and section 7.3 provides recommendations for PdM at KLM E&M in general. Finally, Section 7.4 is a conclusion of the chapter.

## 7.1 IMPLEMENTATION OF A PREDICTIVE POLICY FOR THE CSU COMPONENT

In our case study we found that policy 3 was the most suitable policy in terms of number of maintenance intervals, average total cost and spare part inventory. This policy replaces components on a tail when at least 2-out-of-4 components have an alerted or failed status. It is recommended to adopt this policy for the CSU component. This policy is similar to the current corrective policy, however there are two important differences:

1. The policy acts on predictive alerts;
2. The policy uses current spare levels as input for a replacement decision to reduce variability in spare part demand.

With (1), repair savings are realised and with (2) spare part levels can be reduced. To benefit from repair savings, the MCC has to schedule replacements on aircraft as soon as there 2 alerted components on a tail or a combination of 1 predictive alert and 1 failure. When KLM E&M also proactively wants to benefit from spare part optimisation, the decision in the MCC has to be coupled with current inventory levels. This requires additional implementation effort, however a rather simple solution might already suffice. For instance, Prognos could include inventory levels in the application and together with Component Services, a recommendation regarding predictive replacement can be provided to the MCC. When the inventory level exceeds a certain threshold (safety stock limit), predictive replacements can always be performed. When stocks drop below the threshold, inventory is dedicated to MEL replacements only. That way, repair savings can be realised while the risk on a stockout is kept low. Further research should determine how this threshold for safety stocks should be set, when demand for all other pool clients is also considered.

The speed of the operation of transferring information is vital in order for PdM to be as effective as possible as any delay in this operation will lead to the failure developing further (Carmen Carnero, 2006). In the current organisation of KLM E&M it is not directly clear who would be responsible for coordinating replacement decisions that are coupled with supply chain capacity. This study included spare levels in replacement decisions, but the state space is obviously not limited to inventory levels as an indication of the maintenance supply chain status. Especially when repairs of the CSU component are performed in-house in the future, it might also be preferable to consider repair shop workload in replacement decisions. Experiments have shown that repair TAT has a large impact on cost and spare levels, so if an increased repair workload results in longer TATs, cost reductions might be small or even worse; it results in a cost increase. To facilitate the coordination of supply chain and replacement decisions, a 'control tower' might be a solution for non-routine replacements. Future research should address how to design this coordination process and studies like the paper of de Smidt-Destombes et al. (2006) can be used as guidance for integrating replacement decisions with repair capacity.

## 7.2 Other components in Prognos' (future) scope

The implementation suggestions mentioned in the previous section are applicable to the CSU component, however, some aspects also concern other components from Prognos' current and future scope. In the experiments from Table 12 a few scenarios were tested, to analyse the impact of factors such as repair cost and failure distribution. In the next sub sections, we discuss the findings that are relevant for implementing PdM with other components as the CSU.

### 7.2.1 Absence of variation in minor and major repair cost

Figure 21 has shown that the major cost factor in the average total cost in our study is repair costs. The 2k-factorial design also showed that repair costs have the largest main effect on total cost. Therefore, it can be concluded that the impact of repair savings is significant in the expected benefits with PdM. Components with expected repair cost reduction are therefore preferred to include in Prognos scope.

When the effect of minor and major repairs is absent, spare part cost can be reduced. Our study has shown that inventory levels can be reduced with at least 20% for components in 3-out-of-4 systems. This percentage increases as failure occurrences or fleet size increases. So, if the effect of minor and major repairs is absent it is advised to prioritize components with high spare part cost.

### 7.2.2 Worse prediction model performance

The performance of Prognos prediction models on the CSU component is very high. Not a single false alert has been signalled and all failures could have been predicted far in advance. However, not all components have characteristics that allow Prognos to generate such stable alerts. For instance, failure behaviour of electrical components often has a much more random nature. The experiment with the 2k-factorial design varied the values of the parameters Sensitivity and Prediction Horizon to estimate the impact of poor prediction performance on cost. Table 18 and Table 19 shows the result of this experiment and it can be concluded that the cost reductions do not decrease proportionally with the decrease in performance (in the CSU case). Thus, relatively poor prediction performance on Sensitivity and PH can already lead to significant cost reductions and should therefore not be a reason to refrain from implementing PdM on a system. High false alarm rates however might lead to an increase in cost and should therefore also be considered when implementing PdM (Hölzel N. , Gollnick, Schilling, & Neuheuser, 2012). False alarms were not considered in this study.

### 7.2.3 Components in a 3-out-of-4 structure with a Weibull failure distribution

In the default scenario where the case study of the CSU component was tested, an empirical distribution was used to simulate component failures. Other components can be simulated according to the same method, however, when a component's failure distribution approximates a Weibull distribution, the results from Experiment 4 (Section 6.3.2) can be used to estimate policy behaviour for that component (provided that the component has a 3-out-of-4 structure). When a component has more or less frequent failure occurrences (with a Weibull distribution), policy 3 is always advised.

### 7.2.4 Components in other $k$-out-of-$N$ structures

Component redundancy is very common in aircraft systems. MEL restrictions are violated when 1 or 2 components (out of $N$) are failed. These restrictions need to be solved within a certain Rectification Interval. In this section we provide recommendations for the other components in Prognos' scope based on their system structure and RI. The components are listed again below.

*Table 25: Sytems implemented in Prognos in Q3 and Q4 2018*

| Component (Q3) | Repaired by | QPA | Criticality (MEL restrictions) |
|---|---|---|---|
| 747 Electrical Generator (EG) | KLM E&M | 4 | Solve within 3 days if 1-out-of-4 are failed |
| 787 Cooling System Unit (CSU) | OEM | 4 | Solve within 10 days if 2-out-of-4 are failed |
| 787 CSU Motor Controller (CSU MC) | AFI/OEM | 4 | Solve within 10 days if 2-out-of-4 are failed |
| 787 Air Compressor | Epcor | 4 | Solve within 10 days if 1-out-of-4 are failed |

As the CSU Motor Controller has the same characteristics as the CSU component, policy 3 is also recommended. The 747 Electrical Generator is more critical to airworthiness as the CSU (MC) component and has no 'slack' component: 1 failure results in MEL violation right away. Therefore, the designed policies from this study are not suitable. However, based on the insights from the conceptual framework in Figure 15, it is advised to replace all degraded items preventively, if a spare is available. That way, repair cost might be saved and there will be no (significant) effect on spare levels. The same advice holds for the Air Compressor as long as the model performs well.

## 7.3 Development of Predictive maintenance at KLM E&M

Chapter 1 presented a problem cluster with an overview of the problems related to unsuccessful implementation of PdM at KLM E&M. This study designed and tested various predictive replacement strategies in order to provide insight in how the 'future state' with PdM should be designed. It is recommended to adopt predictive replacement policies that replace components according to their current corrective 'Demand Initiation Level' but to also consider alerts as demand. Thus, instead of initiating replacement when 2-out-of-4 are failed, the MCC should now initiate replacement when 2-out-of-4 are alerted and/or failed. This strategy can be applied for other components with a 3-out-of-4 structure, provided that repair savings are expected. To benefit from inventory reductions, replacement decisions have to be integrated with current stock levels. It is recommended to also include repair workload in replacement decisions and maintenance planning. The latter was not included in this research.

Regarding the organisational aspects in the problem cluster of Figure 4, this study provided some insight as well. The main counter argument for the implementation of PdM was a decrease in MTBR, with all its consequences, such as an increase in resource demand and operational disruptions. These consequences conflict with various stakeholders interest and objectives, as mentioned in Table 3. However, in this study it was shown that a predictive policy, that benefits from increased flexibility by reducing repair cost and spare part cost, can be implemented with a negligible decrease in MTBR. This can be used in communication about PdM implementation throughout the organisation.

Finally, to succeed in implementing PdM, the process related to component replacements requires adjustments. For instance, warranty restrictions of components need to be considered and test limits of equipment used in troubleshooting need to be adjusted to predictive removals.

## 7.4 Conclusion

To capitalize on potential benefits related to PdM, it needs to be implemented correctly. In this chapter a few suggestions were provided for this implementation:

- Apply policy 3 for the CSU component;
- Integrate replacement decisions with the current status of supply chain KPI's, such as spare levels and repair workload;
- Communicate the findings of the case study throughout the organisation. Include that the decrease in MTBR is negligible when policy 3 is applied and that spare part inventory can be reduced;
- Look for similarities with this research in other case studies. This might enable to derive similar conclusions for these components, and increase potential benefits;
- Use repair cost savings and high spare part procurement prices as criteria for adopting new components in Prognos' scope;
- Implement predictive policies for the other components within Prognos' scope as discussed in 7.2.4.

# 8 DISCUSSION

This Chapter provides a discussion on the chosen method, policy and model desgin, the results and the implementation of Predictive Maintenance at KLM E&M.

## 8.1 METHOD

This research aimed to estimate the potential benefits of implementing PdM at KLM E&M, by designing predictive component replacement policies that use Prognos information as input, and are aimed at minimising repair and spare part cost. Policies were designed with the purpose of:

- Minimising repair cost (policy 2)
- Minimising spare part levels (policy 4)
- Reducing repair cost and spare levels while minimising the impact on MTBR (policy 3).

When the policies were tested it turned out that repair cost as well as spare part levels can be minimised with policy 2, but this policy drastically increases the number of replacements. Policy 4 did not distinguish itself based on the criteria.

With the chosen approach, policies do not lead to optimality: it remains uncertain whether the policy with the best performance, policy 3, is an optimal policy. An estimation of benefits was set as the highest priority in this research such that this research helps to construct a solid business case for Prognos. Due to a gap in literature, policies were designed from scratch. If the objective of this research was to find an optimal policy, the scope of the research had to be narrowed down. Proving optimality is complex and time consuming, and would therefore have an effect on scope.

## 8.2 POLICY AND MODEL DESIGN

The simulation model also has limitations, due to simplifying assumptions. First of all, it neglects the operational flight schedule and shipping time. Once a replacement is required according to the active policy, it replaces the components immediately given that the required spares are available. In reality, the MCC needs to assign a time slot in the maintenance schedule and allocate all resources required for replacement. This can take multiple days in which the aircraft is operational and components degrade further, which results in higher repair cost. This will not have an impact on the preferred policy, but can reduce cost savings. On the other hand, there are also potential cost reductions when the flight schedule is considered, such as the reduction of AOG or UGT occurrences due to increased planning flexibility.

The model assumes perfect demand information for all alerts. All alerts result in failures within exactly the Prediction Horizon. It would be a valuable addition to include uncertainty to this timing aspect as well and also include the effect of false alarms. False alarms can increase cost and when failures occur earlier than expected, this reduces expected benefits. On the contrary, when failures occur later than predicted it could increase repair savings. If predictions are structurally too early, the effect of a decrease in MTBR is expected to be minor, provided that the ratio of PH:MTTF is small (which is the case for the CSU) and there is a 3-out-of-4 structure.

Another simplifying assumption that was made in the policy design and the simulation model, is the classification of alerts and failures. Although Prognos makes this classification based on its implemented algorithms, thresholds and inputs from sensor data, there might be more information to take into account. This study assumed that a failure or alert is True of False (as given in the GUI of Prognos), all failures result in major repair cost and alerts always result in failure after the PH. There might be more information in the sensor data to take into account that make these assumptions unnecessary, about various failure modes, expected prediction horizon, associated repair TAT and cost. When more information becomes available (with acceptable accuracy), policies can be formulated more specific. In this exploratory study and with the current maturity of Prognos, the inclusion of these aspects was considered too detailed and too uncertain. However, the potential benefit of this extra information should not be underestimated.

Finally, the usability of the computer simulation model is low as it is very specific and constructed in software that is not available at KLM E&M. However, the conceptual model and the policy design can be used in future research at KLM E&M.

## 8.3 Results

Results are a consequence of the input factors and the model. Comments on the simulation model are discussed in the previous section. Regarding the input factors, cost factors are hard to estimate. Therefore, the policies were evaluated based on relative differences. Although this helps to compensate for the effect of input factors, it does not account for the fact that cost factors are not always deterministic. For instance, the cost incurred with replacement include variable labour cost and fixed setup cost. However, when a replacement requires 2 flights to be adjusted (for instance, an aircraft scheduled for a certain flight needs to be swapped with another aircraft), it requires more effort (and also cost) to schedule this replacement than when a replacement can be performed during base maintenance or during line maintenance in between flights.

To simulate failure occurrences, the model uses a failure distribution to determine the timing of failures. However, the replacement data used to construct a histogram that serves as empirical failure distribution represents the time between removals (see also Figure 1). The time to removal is a consequence of a certain replacement policy and therefore the histogram does not provide an accurate representation of the failure behaviour of the CSU component. Validation of the model with the empirical distribution resulted in a good approximation of the historical values of 2018 for the number of replacements and leases; however these historical values are also just 1 observation. Fortunately, model results were similar when a standard Weibull distribution was used to generate failure occurrences. In the future, the BAR team could address this issue by using data from Prognos to construct actual failure distributions. That way, the MTTF can be used for future studies instead of the MTBR.

## 8.4 Conclusion

In this chapter the limitations of the research were discussed. Most limitations were caused by incomplete data and due to simplifying assumptions that had to be made to reduce complexity. The simplifications can both have negative and positive effects on the estimated benefits.

The study provided insight in the size of supply chain benefits and the impact of predictive policies on system dynamics. The objective of the research was to perform an exploratory study on potential repair savings and spare part inventory reductions of predictive component replacement policies; the results should be interpreted with that objective in mind. Future research should tell whether a better policy can be designed, but this study has already shown that PdM can realise significant cost savings in repair and spare part cost.

Although this research has contributed to a solution of the problems in the problem cluster (Figure 4), it did not solve them. The unknown 'target situation' is still not clear after this thesis. However, the study has shown that repair cost and spare part cost are reduced in the target situation with PdM. It provides motivation to further explore supply chain optimisations with PdM.

# 9 CONCLUSION AND RECOMMENDATIONS

This research performed an exploratory study on the effect of predictive maintenance on repair and spare part cost. It aimed to provide insight in how a predictive component replacement policy should be designed such that spare part and repair cost are minimised, and how this could be implemented for components within KLM E&M's Prognos' scope.

It can be concluded from literature that supply chain benefits are promising. In Chapter 4, predictive component replacement policies that capitalize on these benefits were designed for a 3-out-of-4 system. The design of these policies and the insight in their performance is a contribution to literature, as it provides a case study that evaluates predictive replacement policies that are aimed to reduce spare part investment and repair cost for aircraft components in a $k$-out-of-$N$ structure. This joint improvement in a predictive maintenance context was not found in literature.

The case study results confirm what was found in literature: prognostic failure information can result in reduced spare part inventory. The most beneficial policy that was found in our study was a policy that initiates replacement on an aircraft when at least 2 out of 4 components are alerted and/or failed. This policy is expected to result in a cost reduction of approximately 27% compared to the current policy for the CSU component on KLM's 787 fleet, while the number of replacements remain the same. When a large fleet of 52 aircraft is considered, this policy reduces the CSU spare part inventory levels with 32%. Cost reductions are realised by repair cost reduction and lower required spare levels. The predictive policies enable to lower stock levels by reducing the variability of components in repair. This variability is reduced as a result of the inclusion on-hand stock levels in replacement decisions.

'A structural redesign of the spare parts planning at the operational level is possible after the company extends their predictions to more parts. Therefore, developing this redesign of the spare parts planning is another step that needs to be taken and would require additional research by the company' (Topan, Tan, & van Houtum, 2018). In the context of this research we can derive a similar conclusion as Topan et al. At KLM E&M spare part inventories could be reduced with the implementation of PdM, however it would require that replacement decisions have to be integrated with information about current on-hand stock levels (and, potentially, also repair capacity). In addition, KLM E&M has to change from traditional corrective decision making to proactively acting on prognostic information. These two aspects require an organisational redesign of spare parts planning and replacement decision making.

This research has shown that without this redesign, predictive component replacement policies will already save cost with the reduction of repair cost. Therefore it is recommended to adopt predictive replacement policies for all components that have potential repair cost savings, provided that the ratio PH:MTTF is small. When KLM E&M is able to capitalize on spare part benefits as well, it might lead to a competitive advantage in the MRO market.

The quantitative results of the study presented in Chapter 6, showed that a focus on repair cost reduction and repair TAT has the largest effect on average total cost and spare levels respectively. Therefore it is recommended to focus on the improvement of these factors in the future in combination with PdM.

Components that have short repair TAT's and/or long expected prediction horizons are expected to benefit most from spare part benefits. These two criteria, preferably combined, will result in high planning flexibility. This can be considered as a major benefit, especially for components that are scarce or difficult to obtain.

## 9.1 SUGGESTIONS FOR FURTHER RESEARCH

A future step in implementing PdM at KLM E&M is the redesign of spare parts planning and replacement decision making. It is challenging to drive change in a rather fragmented maintenance organisation, therefore this process requires a clear definition of all the phases involved with this change. It should be investigated how decisions 'in the front' (i.e. the replacement decision) can be aligned with the situation 'in the back' (i.e. the current status of the supply chain), leading to optimised integral decision making. The introduction of a 'control tower' was mentioned as a potential solution for the coordination of these aspects. This coordination should include decisions regarding prioritising replacements and deliveries, grouping replacements and allocating resources. Further research should address how this coordination could be implemented and how KLM E&M can ensure that all data that is used for these decisions is accurate.

This study focused on repair cost and spare part cost, however there are more cost factors to consider when a business case is constructed for Prognos. Prognos can reduce the number of 'no failure found' occurrences in the repair shop with improved diagnostics and optimise scheduling of replacements when a bigger time frame can be used. New studies should investigate how the latter can be exploited.

This study can be improved with the development of an optimal policy or (and) with expansion of inputs used for decision making. For the latter, it is recommended to explore more factors, such as the impact of including current levels of repair capacity, lease components and the time passed since an alert notification, but also to improve the input variables that were used in the policies of this study. For instance, instead of defining a failure as a binary variable, different failure modes could be specified and their associated expected repair work scope. In addition, KLM E&M should explore how to include multiple inventory locations and shipping components to airlines worldwide in a spare part management model and how to manage the associated complexity.

All these recommendations for further research are aimed at achieving a future target situation for aircraft maintenance. Up to this point, traditional preventive and corrective aircraft maintenance strategies have been widely applied in MRO organisations. The 'new era' of data-driven decision making, driven by advanced sensor technologies and data science, is expected to have a major impact on future aircraft maintenance. Traditional maintenance concepts need to make place for condition-based maintenance enabled by real-time monitoring of continuous data streams without sacrificing safety constraints. These new concepts should enable to optimise maintenance activities by performing maintenance at the right time and at the lowest cost. A shift must be made, 'from reactive monitoring to proactive monitoring', which will bring challenges on all organisational aspects. KLM E&M should push forward to this shift by continuously improving monitoring, developing smart maintenance policies, investing in an agile organisation and discussions with OEMs on how to improve the monitoring of their aircraft systems for a data-driven maintenance perspective. In this way, KLM E&M can enable development of a future proof maintenance organisation and keep its competitive advantage in the MRO market.

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## APPENDIX A: NUMBERS AND FIGURES

### I. KPI's for CSU component

*Table 26: Performance indicators for the CSU component*

| Performance Indicator | Value |
|---|---|

### II. Benchmark scenario parameters

*Table 27: Default values of fixed and variable parameter in benchmark scenario*

| Parameter | Value | Parameter | Value |
|---|---|---|---|

### III. 2k-factorial design input factors

*Table 28: 2k-factorial design*

| Experimental factor | − value | + value |
|---|---|---|

### IV. Derivation of the empirical failure distribution

$$No.\,of\ operational\ days = \frac{FH}{average\ FH\ per\ day}$$

To derive a failure distribution, replacement data was exported from the information management systems at KLM. This data includes all replacement data of all pool customers and presents the number of flight hours between instalment and removal. After cleaning the data, a histogram was plotted as shown in Figure 28. The X-axis shows intervals representing the number of days a CSU component was operational on an aircraft. On the Y-axis the number of replacements within that interval are given (or, frequency). The number of operational days was derived by dividing the flight hours with the average flight hours (FH) of pool customers and the average FH of KLM.

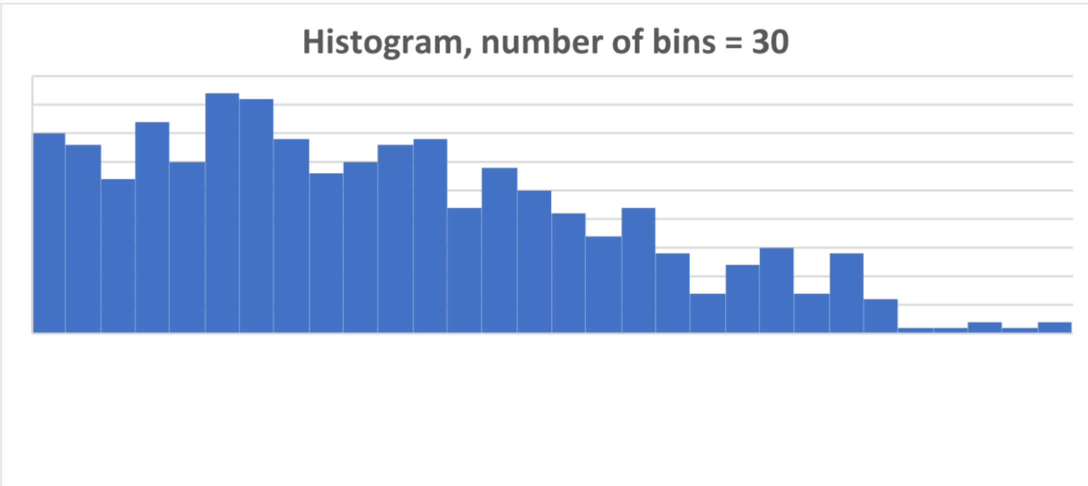



*Figure 28: Histogram of replacement data*

## V. Model validation results

From KLM data it is known that there were x CSU replacements on KLM fleet, x spare components in total and there were no leases. These x spare parts needed to fulfil demand for all pool customers, corresponding with 160 aircraft (787 type). This corresponds with x spares for the 13 aircraft of KLM (see formula below). If we run the computer model for a year with x and x spares, it results in the numbers given in Table 29. The results are close to the actual values for the number of replacements and the number of leases.

$$S_{benchmark} = \frac{S_{pool}}{M_{pool}} * M_{KLM} = \frac{x}{160} * 13$$

*Table 29: Output validation runs*

| | **No. Spares** | **No. Replacements** | **No. Leases** |
|---|---|---|---|
| *Values 2018* | | | |
| *Model results* | | | |
| | | | |

# APPENDIX B: TECHNICAL DESCRIPTION OF THE SIMULATION MODEL

## I. Control Panel frame

*Figure 29: Control panel frame*

The control panel is the main frame of the model from which the system is managed. In the upper left corner we find links to the other frames of the model: Schiphol, the Logistic Centre and the Repair shop. These are described later in the other sections.

The blue headers indicate modules: Experimental Factors, Model Output, Event Control, Experimentation, Performance Measurement and Fixed Input Parameters. The content of these modules will be explained in the next subsections.

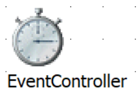
The icons with a blue M are methods and include logic programming in order to customize the simulation behaviour.

**Experimental Factors, Fixed Input Parameters and Model Output**

These three modules contain all variables that determine input and output. Input is categorized in experimental factors and fixed input parameters. The fixed input parameters remain unchanged during model runs. The experimental factors are categorized in decision variables and parameters. Given a scenario, which is expressed in parameters, the model finds the values for the decision variables that result in the best solution.

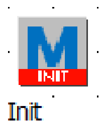
**Event control**

This section is responsible for starting and stopping simulation runs. Every time a new run starts, this section ensures that all settings are put back to default. Also, it controls the execution of methods that need to be triggered on a given date.




The EventController starts, pauses and ends the simulation clock. It also lists all the discrete events in the event list.

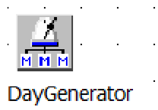

Method that is called before a new simulation run starts. It resets all variables, counters and table files. Also, it removes the components from the previous run from the system.




Method is executed right after the start of a new run. It initializes all parameters, variables and (experiment) settings:

- It calls the method 'SetSchipholSettings' to install the right settings in that frame.
- It initializes the table FleetStatus, which contains an overview of the fleet and the number of alerts and failures on each tail
- It checks whether the selected input settings are valid, otherwise an error message is created


This method is called only once, at the beginning of all simulation runs and experiments. It sets all variables related to experimentation to zero. It calls the method SetExpSettings, to set all the variables related to experimentation and the method UpdateScenario to set all parameter values.




This generator makes sure the method 'SetDay' is called every day.


This method:

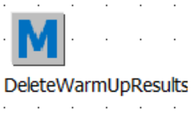
- Sets the counter t_current every day
- Measures the inventory level at the beginning of the day and stores the information in the table ‘Inventory’
- Calls the method ‘DeleteWarmUpResults’ on the day corresponding with the warm-up length
- After the run length is over, it calls the method ‘CalculateRunResults’ to produce the results of that run and store it in the table ‘RunResults’
- If the total number of runs of an experiment is executed, it calls the methods ‘CalculateExpResults’ and ‘SetExpSettings’. If the total number of runs is not reached yet, it resets and starts the simulation
- If the total number of experiments is reached, it stops the simulation

**Experimentation**

This section is responsible to manage the model execution. It sets all parameters corresponding to the scenarios and updates the decision variables until the best solution is found. When a solution is found the next scenario is run. Scenarios should be entered by the model user before the run is started.

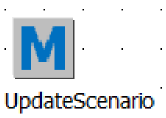

Method responsible for the calculation of relevant run results and storing them in the table ‘RunResults’. At the end of an experiment, the table has results for the TotalRuns number of runs.


Method responsible for the calculation of experiment results and storing them in the table ‘ExpResults’. The method also evaluates whether an experiment satisfies service constraints. The result of an experiment is the average value of all runs (replications). So the total cost of an experiment is the average total cost of all runs.

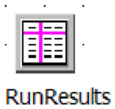



In the ControlPanel the user can specify the length (in days) of the warm-up period. This method is called at the end of this period and deletes all intermediate results.

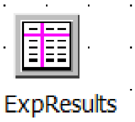

The code in this method sets the decision variables to new values. Depending on the results of previous experiments, it increases or resets the number of spares or/and DIL.




Once the best values for the decision variables are found, the simulation stops experimenting in that scenario. The method UpdateScenario is called to move on to the next scenario (next row in the table ‘Scenarios’) and update all the corresponding experimental parameters.




Stores the results of each run. Values are used to determine average values for KPI’s of experiments.




Stores the results of experiments in each scenario. Deleted in between scenario’s to keep programming structured.


The user has to copy the scenarios (s)he wants to evaluate in this table.
Large factorial designs can be generated easily in programs such as Minitab.


Table with total results of all experiments and scenarios for policy *j*. After running the model, this output can be exported to Excel for analysis.

**Performance measurement**

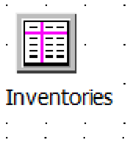
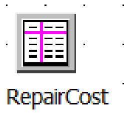



Table used to determine the inventory level at the beginning of each day. It is useful for the determination of average inventory levels and, if the model is run with a high number of spares, it can create insight in demand patterns if the levels are plotted in a graph.




Tracks the repair cost of all repairs.

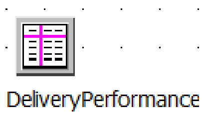
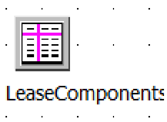



Table used to track the delivery performance. It logs the date when demand arises on a component and logs the replacement date. The time in between is the lead time. It creates insight for analysis and validation. For the derivation of service constraints, a more general method is applied (which is not component specific).




This table is a log of all lease components. It is used to count the total number of leases and the associated cost. It also tracks the time between the supply of a lease component and the exchange of another serviceable spare.

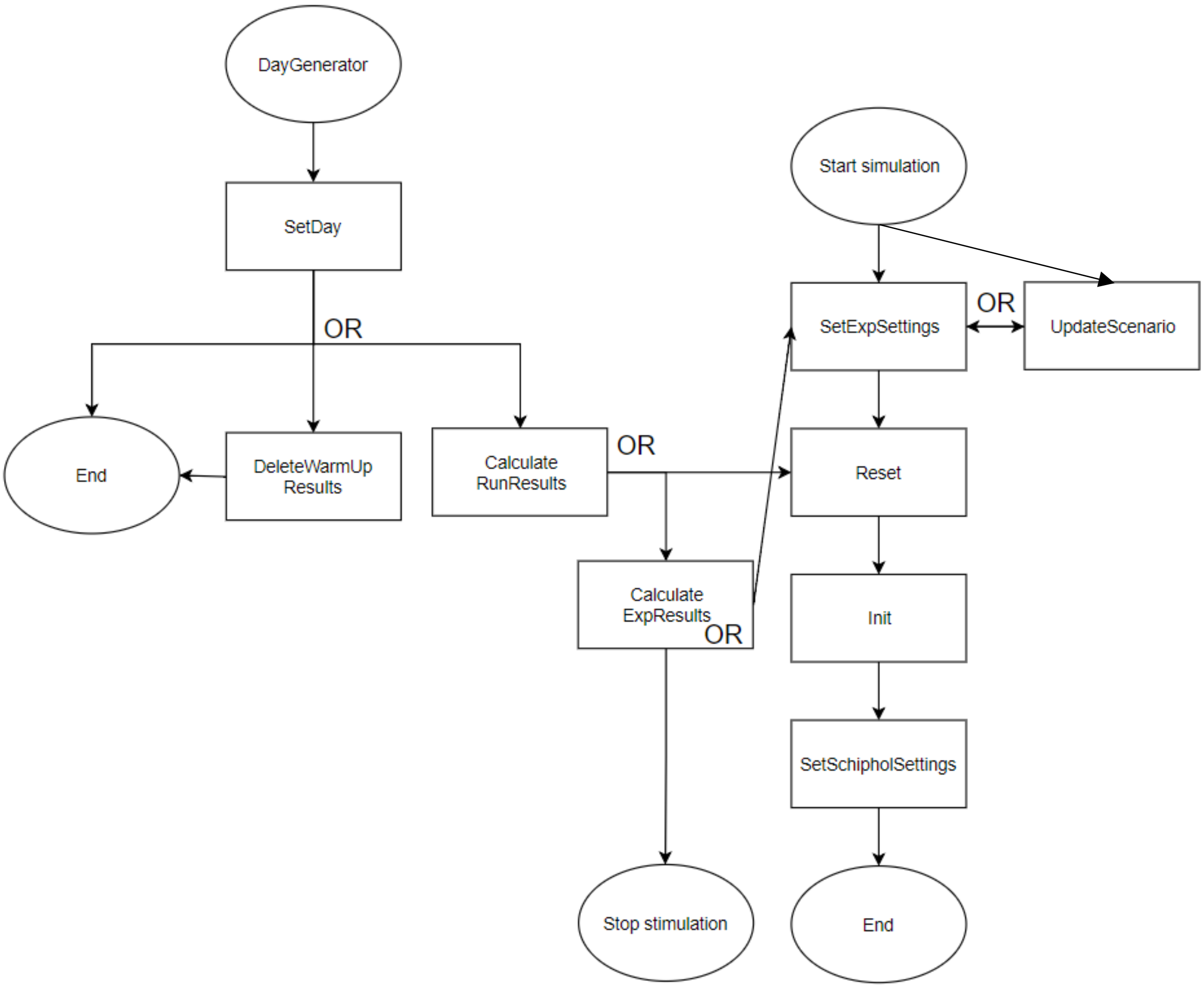



*Figure 30: Structure of methods in the Control Panel frame*

## II. Schiphol frame

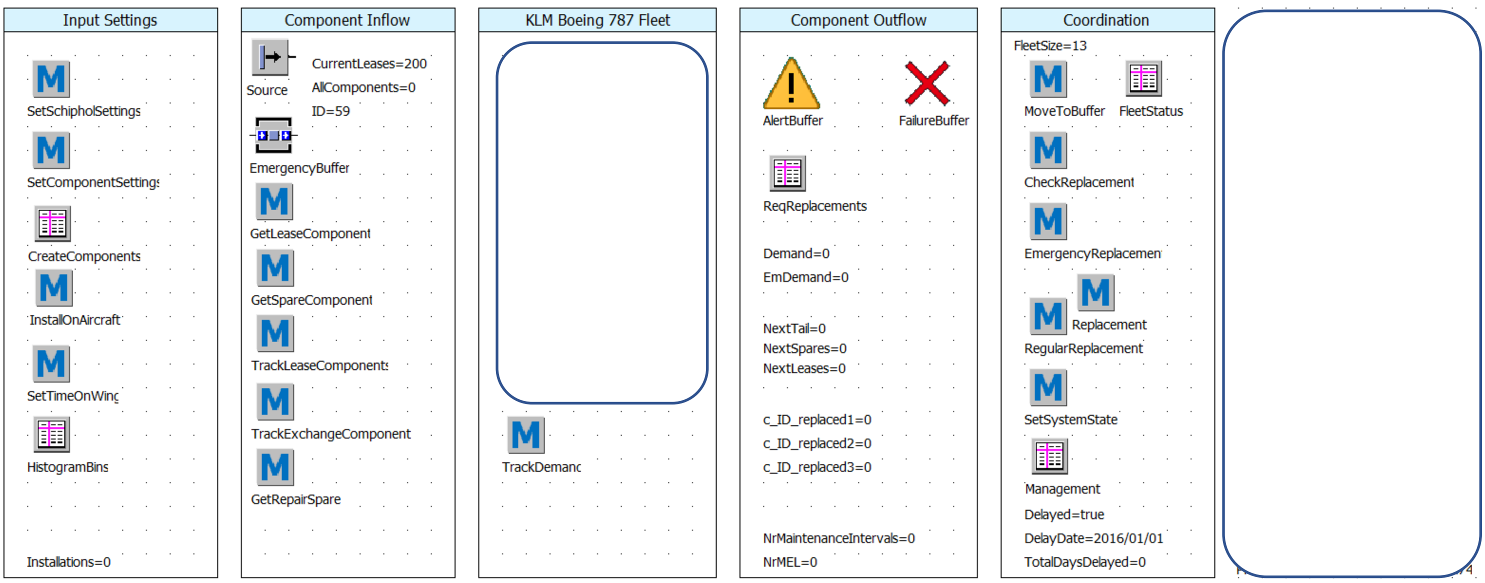
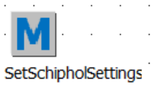



*Figure 31: Schiphol frame*

## Input Settings




Method responsible for setting the initial settings in the Schiphol frame, such as the prediction horizon (time components spend in the 'AlertBuffer' before proceeding to the 'FailureBuffer') and it writes the right values in the 'CreateComponents' table, which is used by the source to create components.


When components are created in the source, this method is called. It assigns all the component specific values to MU's (moving units), such as the aircraft registration and the component ID. When an user-defined attribute (uda) is unknown yet, it set to a default value.

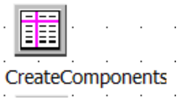
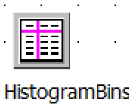



Table used by the source to find how many components it should generate.


This method installs components to the right aircraft. It can be called in the beginning of the simulation, to facilitate initial instalment. It is also called later in the simulation when a component is replaced and a tail needs a new part to be installed. This method can also be seen as 'the gate' before instalment on an aircraft. Therefore, this method also tracks performance data, such as delivery performance. Prior to installation on the aircraft, this method calls 'SetTimeOnWIng' to determine the Predicition Horizon, Time To Alert, or Time To Failure on a specific tail.

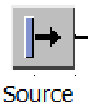

Assigns the user defined attribute 'Time To Alert / Failure', in the program named as .MTBR. This time is set as the 'processing time' (operational time) on an aircraft. The code is programmed such that it derives this operational time from a failure distribution (experimental factor). The prediction horizon can be deterministic or stochastic (also an experimental factor). The prediction horizon is the time a component stays in the AlertBuffer.

If the failure distribution is empirical, a random number is generated by the software which determines from which histogram bin the operational time is derived. Another random number determines, together with the value for Prognos' sensitivity, whether the failure will be detected by Prognos (resulting in a time to alert instead of a time to failure).

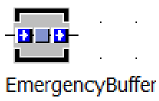



This table represents the empirical distribution and should be determined prior to running the simulation.

## Component Inflow




Responsible for creating components.




This represents an 'infinite' supply of lease components. In the beginning of the simulation, a large number of lease components is created and stored in this EmergencyBuffer. If a stockout occurs, and replacement is required according to MEL restrictions, this buffer supplies extra components. When a spare part becomes available from repair, it is sent back to the EmergencyBuffer.


Basic method that returns a lease component to the method that called this method.

GetSpareComponent

Same as GetLeaseComponent, now for a spare from inventory.

GetRepairSpare

The model includes some extra coding to make the computer model more representative for current operations at KLM. When there is a stock out and MEL violation (model requires lease), it checks whether a repair is expected to be finished within the planning interval of the MCC. MCC normally needs 5 to 10 days to plan a corrective replacement. In the method 'EmergencyReplacement' a random number is generated between 5 and 10. This corresponds with the time the MCC needs to plan replacement. When a repair is expected to be finished within that interval, the model 'pulls' a repair from the repair shop instead of leasing a component. This specific method is responsible for returning a spare from repair and called by the method 'EmergencyReplacement'.

TrackLeaseComponents

When a component leaves the EmergencyBuffer, it tracks performance data regarding lease components and stores it in the table 'LeaseComponents'

TrackExchangeComponent

Same, but for returning exchange components.

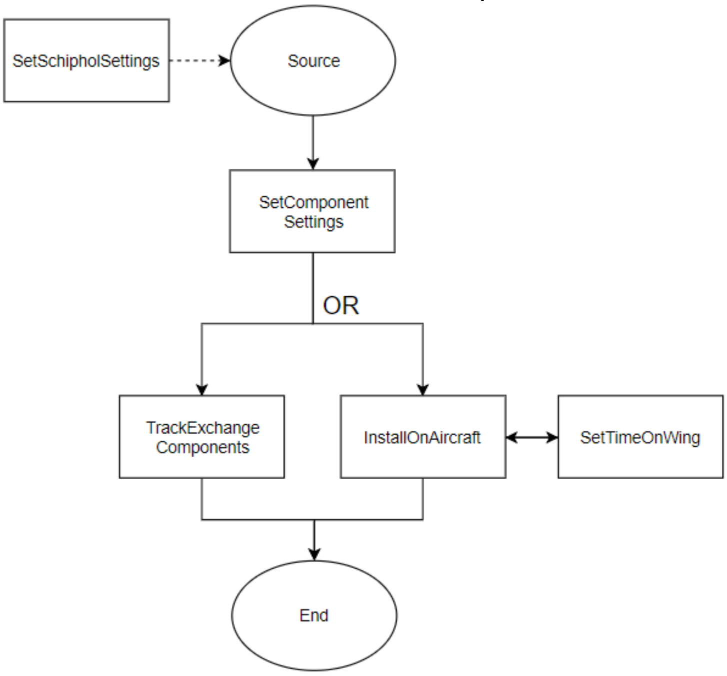



*Figure 32: Method structure for initial component instalment*

### KLM Boeing 787 Fleet

PHBHA

Represents a 787 aircraft. N components can be installed on the aircraft. The processing time on an aircraft is an uda: @.MTBR. After the processing time, the component is sent to the AlertBuffer or FailureBuffer.

FleetStatus

Table filled with the active status of the Fleet. It includes all tail registrations, the number of alerts, failures and the total of these two per aircraft.

### Component Outflow

AlertBuffer

A buffer where components stay for -PredictionHorizon- days. After the prediction horizon, components are sent to the FailureBuffer with the method MoveToBuffer.

FailureBuffer

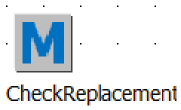
The place for failed components that are still installed on an aircraft.

ReqReplacements

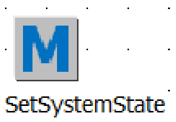
This table is used as input to determine whether replacement is required on the fleet. It provides all alerted and failed components that are still installed on aircraft.

## Coordination


When a component 'leaves' an aircraft after its time to failure or time to alert, it is sent to the AlertBuffer or FailureBuffer; this method is responsible for managing that process.




This methods determines the value for $X_{ijt}$. The method evaluates the decision every time the system state changes. When replacement is required (demand arises), it calls the method regular replacement or emergency replacement. it logs the demand date in the table DeliveryPerformance. The method is also responsible for sending spares back to the emergency buffer for exchange (when there are outstanding lease components).




Method responsible for updating the current system state.

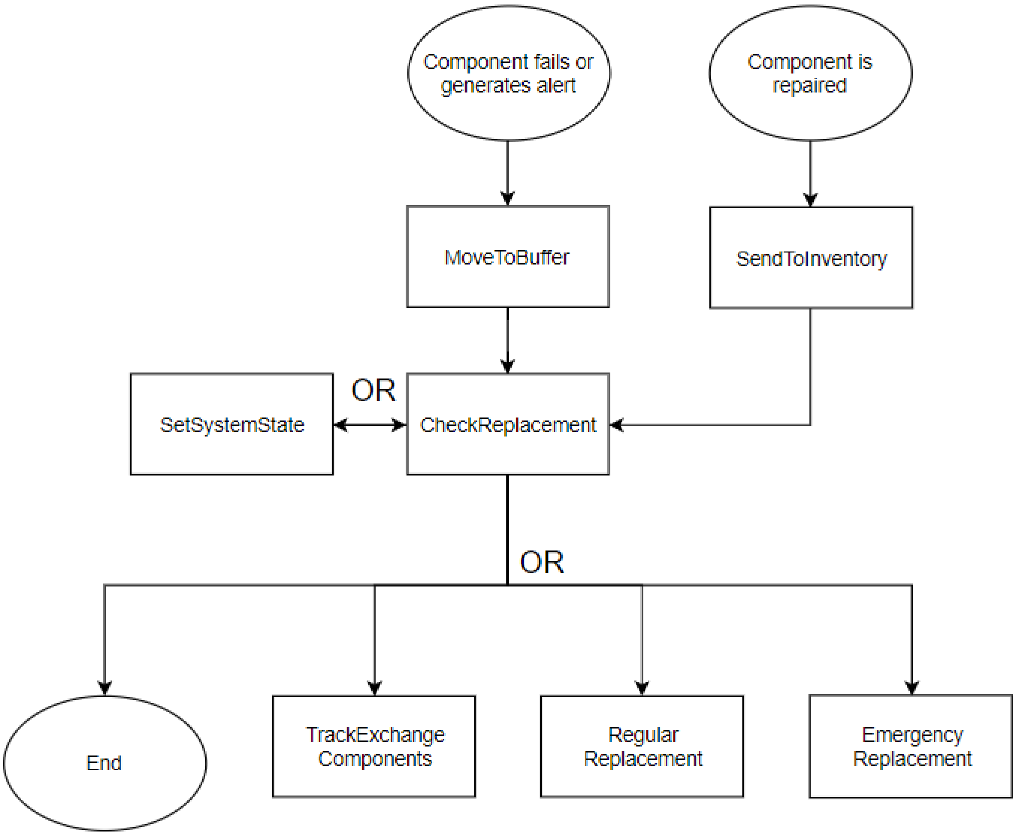
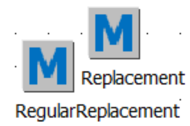



*Figure 33: Method structure for replacement (1/2)*


Performs a replacement for a component that was on an aircraft with 2 failures (aircraft are airworthy when 3-out-of-4 components are operational) and replaces it with a lease or with a component that is expected on a short notice from repair (see also the explanation of the 'GetRepairSpare' method in the subsection 'Component Inflow')




Responsible for performing replacements with spares from on-hand stock.


Method that writes values to the table ‘FleetStatus’. This table is used to sort removals.

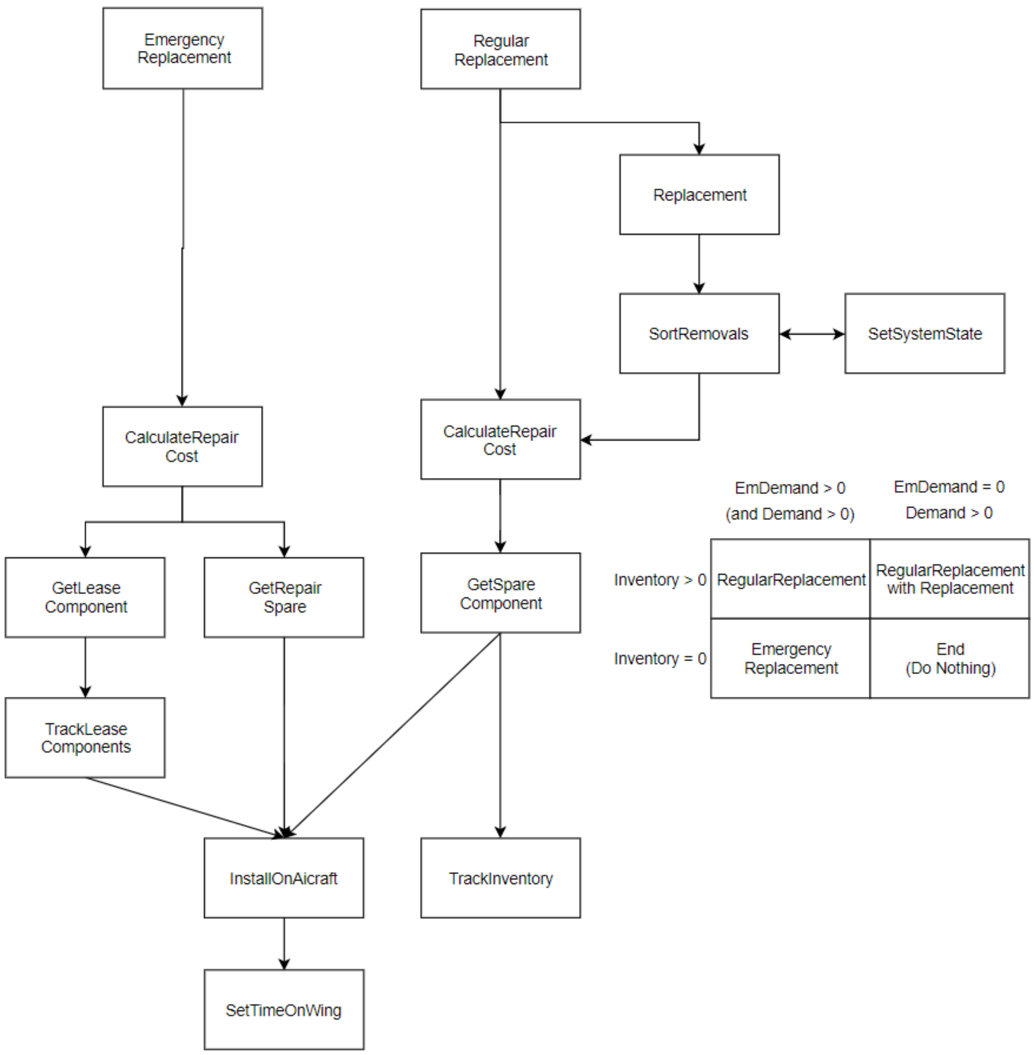
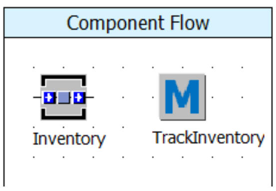


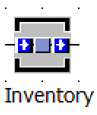

*Figure 34: Method structure for replacement (2/2)*

On the right side in Figure 34 a table overview shows which method is called in case of demand.

## III. Logistic Centre

### Component Flow

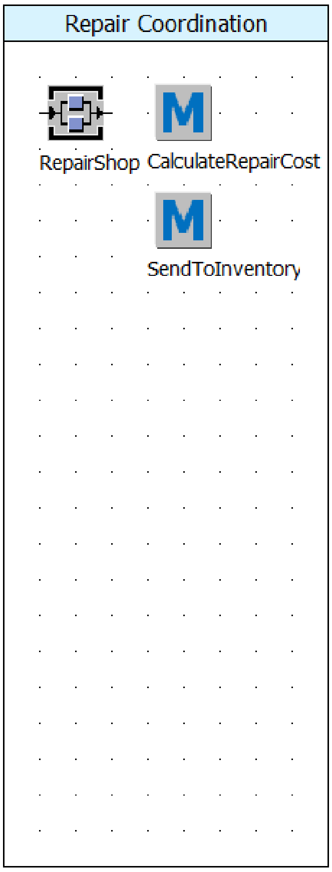



A buffer where spares are kept.

## IV. Repair Shop

### Repair Coordination





Processing station for repairs, with unlimited capacity. When components enter and leave repair, it calls methods to manage the process.


Method which determine the repair time and cost of a component. Components that are replaced preventively, can result in minor repairs, with associated probabilities:

1 if replaced within '50% of PH'-days

0.5 if replaced within '75% of PH'-days

0.25 if replaced after '75% of PH'-days.

After the PH a part is failed, which is always a major repair.

Minor repairs have minor repair cost and, if TATreduction is activated, minor TAT.


Moves components to inventory when repair is finished.