MSc. thesis

Airline maintenance rescheduling in a disruptive environment

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TU Delft

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by

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TU Delft

Preface

The past year I have had honor to work on my Master Thesis for TU Delft in collaboration with KLM Royal Dutch Airlines. The report that lies in front of you marks the end of my academic study at the TU Delft which has been a great adventure, both on personal and educational perspective.

I would especially like to thank my Thesis supervisor Dr. Bruno Santos for his guidance and support throughout the way. The discussions that we had gave me guidance but more importantly helped me change perspective of interpreting problems and come up with alternative solutions.

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Last but not least, I would like to thank my friends and family who have kept supporting me through ups and downs. Especially I would like to thank my parents for their emotional and financial support which enabled myself to develop as an individual but also as an intellectual.

I feel blessed for all the support that I have received throughout this five years that made my way through TU Delft enjoyable and rewarding, thank you all.

P. J. van Kessel
Delft, September 20, 2020

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Acronyms

4M's Manpower, Machinery, Method, Material. ii, 26–29, 31, 35, 50

AMCS Aircraft Maintenance Checks Scheduling. 62

AMSP Airline Maintenance Scheduling Program. 62

AOG Aircraft On Ground. 51, 58, 59, 61

ARP Aircraft Recovery Problem. 65–69

CPM Critical Path Method. 63, 76

CRP Crew Recovery Problem. 65, 66, 68

DMC Direct Maintenance Costs. 59

DSS Decision Support System. 62, 66, 75, 78

EASA European Union Aviation Safety Agency. 57

ETA Estimated Time of Arrival. 28

FAA Federal Aviation Administration. 57, 66

ILP Integer Linear Program. 60, 63, 66–68, 75

IMC Indirect Maintenance Costs. 59

JSP Job Shop Scheduling Problem. v, 59, 60, 70, 72–74

KLM KLM Royal Dutch Airlines. 62

LOF Line Of Flights. 60, 62

LP Linear Program. 28

MDP Markov Decision Process. 62, 75

MEL Minimum Equipment List. 57, 63, 64

MILP Mixed-Integer Linear Programming. 29, 63, 75

MIP Mixed Integer Program. 60, 66, 68

MMEL Master Minimum Equipment List. 57

MOP Multiple Objective Problem. 63

MPD Maintenance Planning Document. 57

MRO Maintenance, Repair and Overhaul. 57–59, 64

MRP Maintenance Recovery Problem. 70, 76–78

NSRE Non-Safety Related Equipment. 63

OCC Operations Control Center. v, 65

PRP Passenger Recovery Problem. 65–68

QCD Quality, Cost and Delivery. 59

RAP Resource Allocation Problem. 59

RCPSP Resource-Constrained Project Scheduling Problem. 60

ROADEF French Operational Research and Decision Support Society. iv, 66–69

TAT Turnaround Time. 31, 50, 51, 57

1 Introduction

Maintenance is an important factor of airline operations by taking up 11.8% of ground time[1]. As a result, several researches focused on optimization of maintenance schedules, with the aim of decreasing maintenance cost and increasing operational availability. However, despite having one efficient maintenance schedule, the reality within airlines is different due to disruptions taking place daily. These come in the form of unanticipated maintenance tasks, maintenance slot adjustments and resource availability alterations. As disruptions are inevitable, making one optimal long-term schedule is not feasible. Maintenance schedules are required to be adapted continuously while aiming to limit schedule changes and keeping the airline fleet in an airworthy state.

Within literature several approaches are already provided of disruption management for other airline departments such as network scheduling, passenger routing and crew pairing. However, for airline maintenance scheduling such an approach is not yet addressed. Up until now maintenance schedules are adjusted manually in case of disruptions.

This master thesis research focuses on scheduling and rescheduling of airline maintenance tasks in a disruptive airline environment. Once a disruption occurs the goal is not to create a new feasible maintenance schedule, as this would lead to a loss of taken preparations. Instead, maintenance rescheduling should take place, which results in a limited amount of changes while a close to optimal schedule is obtained. The goal of maintenance task rescheduling is therefore two folded:

- Creation of efficient maintenance schedules, such that operational availability of the aircraft is increased.
- Creation of stable schedules, such that future disruptions cause a limited number of schedule changes

This thesis research presents a decision support model for both of these scheduling objectives in the disruptive airline scheduling environment. The research question is therefore formulated as following:

To what extent can short- and long-term airline fleet availability be improved in a disruptive environment by means of a decision support tool for optimization of maintenance task rescheduling?

The remaining part of this thesis report outlines the development and performance analysis of the decision support model. Chapter 2 provides a scientific paper which outlines related literature, problem & model formulation, results and conclusions which can be drawn from this research. This

[1] Based on a long-term case study performed at a European airline

is followed by appendices which provide extra clarification regarding this research. Appendix A outlines extra information regarding the model formulation and implementation for the case study. Appendix B describes the verification procedure of the decision support tool. This is followed by Appendix C which elaborates further on the development of the 10-days model. The sensitivity analysis of the model is presented in Appendix D. At last, an analysis is performed on due tasks and slot flexibility in Appendix E and F, respectively. In Appendix G additional data tables are provided which have been used for the results provided in the scientific paper. In Appendix H and I a more extensive literature study and report regarding research methodologies is attached.

2
Scientific paper

Airline maintenance task rescheduling in a disruptive environment

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Abstract

Scheduling of airline maintenance tasks takes place in a disruptive environment. The stochastic arrival of non-routine maintenance tasks causes schedules to be adjusted continuously. Within this research a mixed integer linear programming model for airline maintenance task rescheduling in a disruptive environment is presented. Task scheduling is constrained by the availability of machinery, material, method and manpower (4M) requirements. Periodic workforce availability is included to satisfy task workforce requirements. The model is innovative as it is capable of both creating and adjusting maintenance schedules continuously in a disruptive environment. By means of the model a decrease in required ground time and schedule changes can be achieved while the task utilization rate stays similar to manually created airline schedules. Secondly, this model provides new opportunities to evaluate both the short- and long-term effects of disruptions as it is able to evaluate a 120-days scheduling horizon.

Keywords: Airline maintenance, Task rescheduling, Disruption management, Linear programming

1. Introduction

Maintenance is an important factor of airline operations by taking up 11.8% of ground time[1]. As a result, several researches focused on optimization of maintenance schedules, with the aim of decreasing maintenance cost and increasing operational availability [10]. However, despite having one efficient maintenance schedule, the reality within airlines is different due to disruptions taking place daily. These come in the form of unanticipated maintenance tasks, maintenance slot adjustments and resource availability alterations. As disruptions are inevitable, making one optimal long-term schedule is not feasible. Maintenance schedules are required to be adapted continuously while aiming to limit schedule changes and keeping the airline fleet in an airworthy state. Especially maintenance tasks which fall outside of letter checks and non-routine maintenance tasks require manual scheduling. The tasks which require execution in the hangar form the focus of this research. The case study of this research shows that these tasks have a significant impact on maintenance scheduling with non-routine tasks arriving every 4 hours on average and requiring more than 17 hours of daily ground time for a fleet of 60 aircraft.[2]

Because of the unexpected arrival of new maintenance tasks, the schedule needs to be adjusted continuously such that all tasks are scheduled ahead of their due date. This process currently takes place manually within commercial airlines, which can result in sub-optimal schedules and decision making during disruptions. In this paper the problem of scheduling and rescheduling of maintenance tasks is addressed, by means of an innovative decision support model. Implementation of the model in the airline decision making process contributes in an increase of both schedule efficiency (a reduction in ground time) and schedule stability (a limited number of schedule changes during disruptions). For an airline this results in an increase in potential revenue and a reduction of maintenance cost. At last, the model provides immediate insight in the long-term consequences of disruptions, by creating a new long-term schedule at every disruption.

[1] Based on a long-term case study performed at a European airline
[2] Based on data provided for this research

The remaining part of this paper is structured as follows: First a comprehensive literature review is provided, based on related work in section 2. Afterwards the problem formulation is specified in section 3. This is followed by the model formulation and model results in section 4 and section 5 respectively. The paper ends with conclusions and recommendations for future research in section 6.

2. Literature review

Maintenance scheduling in a disruptive environment combines two field of work, which already have been widely discussed in literature: maintenance task scheduling and disruptive scheduling. This research aims to combine both research fields to formulate a model, which should decrease the gap between scheduling theory and real practice.

Task scheduling

Airline maintenance task scheduling can have several objectives, which depend on airline or Maintenance, Repair and Overhaul (MRO) preferences. According to Knotts [10] the objective for airline maintenance task scheduling depends on both direct and indirect maintenance costs. There is a trade-off between providing fleet availability and scheduling tasks to prevent them from going due. Qin et al. [20] argues that an MRO business aims to minimize cost while maintaining their responsible fleet in maximum quality, best lead times and according to safety requirements. Maintenance scheduling is bounded to constraints due to resource availability. At last, Manalo and Manalo [16] aimed to create efficient maintenance task schedules such that fleet availability is maximized.

However, maintenance scheduling is not a standalone problem and is dependent on other factors. Maintenance schedules need to be made in collaboration with other airline departments such as flight scheduling, crew pairing and passenger scheduling. In 1996, Clarke et al. [3] provided an innovative approach for fleet scheduling in which additional constraints were added for maintenance scheduling and crew pairing. In 2003, Sriram and Haghani [25] elaborated more on maintenance scheduling, by evaluating maintenance opportunities for a 7-day interval whilst taking into account the flight schedule. This approach was limited to scheduling of letter checks. This research was followed by Jiang [9] which extended the scope of task scheduling by both considering letter checks on long-term and smaller checks on short-term. Research regarding scheduling of letter checks continued over time. In 2020, Deng et al. [5] created a long-term scheduling model for letter checks by means of dynamic programming. Aiming for interval optimization, a decrease in the number of required checks can be achieved.

Several other researches focussed on airline maintenance task scheduling instead of letter checks and independently of other airline departments. Marseguerra and Zio [17] went in detail regarding maintenance task scheduling independently of aircraft routing. Their approach aims to capture the stochastic element of maintenance scheduling at which maintenance tasks arrive irregularly. An optimal solution was defined as a combination of safety and economic factors. This research is followed up by Papakostas et al. [19] which takes the availability of resources into account during maintenance scheduling. The objective is to schedule tasks close to their due date with the aim of minimizing remaining useful life. An optimal schedule is defined by a combination of cost, operational risk, flight delay and remaining useful life. Yuan et al. [29] continued this area of research by studying the changing environments and circumstances during maintenance task scheduling in detail. The research aimed to find the optimum sequence of task execution, whilst considering the uncertain arrival of maintenance tasks. In 2019, Lagos et al. [12] created a maintenance task scheduling algorithm which should prevent tasks from going due. A distinction is made between critical tasks (resulting in an Aircraft On Ground) and non-critical tasks which obtain an extension. Scheduling is done by means of an Integer Programming (IP) model in combination with a Markov decision process. As scheduling is limited to a few days, an estimation of future costs is provided by means of rolling horizon and value function approximation. Result of this research are promising since this results in a robust schedule at which unknown future tasks can be scheduled ahead of their due date.

Also, researches focussed specifically on the availability of resources during maintenance task scheduling. In 2014, Schut [24] created a resource constrained scheduling model for maintenance task scheduling. Task scheduling is constrained by the availability of manpower, machinery, material and method (4M). In the past, several other researches performed detailed analysis on resource constraints for maintenance task scheduling. Yang et al. [27] and Quan et al. [21] took the supply of workforce into account for task scheduling at line maintenance. Samaranayake et al. [23] included a detailed availability of aircraft components and machinery in the model decision process. Qin et al. [20] optimized maintenance schedules with respect to the hangar and parking spot capacity.

Disruptive scheduling

Combining the literature mentioned above, plenty of aspects have been considered for airline maintenance scheduling in the past. However, many authors acknowledged that the majority of research has been focused on scheduling models, with little attention to schedule adjustments. [8, 18]. In 1981, Graves [8] was one the first researchers to acknowledge that there is a gap between production scheduling theory and practice. Clarke [4] confirmed this by concluding that airline scheduling has very little slack compared to what it used to be and therefore the consequences of disruptions are more severe. Several researches already included maintenance scheduling aspects within airline disruption management. Rosenberger et al. [22] included constraints for periodic maintenance requirements in an Aircraft Routing Problem (ARP). Abdelghany et al. [1] modelled an ARP at which scheduled maintenance was included in the airline schedule. Maintenance slots were not allowed to be adjusted in any form. Currently, one of the most in depth researches has been performed by Liang et al. [13], at which maintenance scheduling flexibility is included to a limited extend within the ARP. Maintenance slots can be swapped as long the maintenance task is executed ahead of the number allowed flight hours, cycles or calendar days.

The researches described above aim to optimize both the ARP and maintenance schedule at once during a disruption. A downside of the approaches is that maintenance scheduling relies on problem simplifying assumptions since otherwise, the model would become too complex and solution times would be insufficient. As a result, these models do not achieve the level of scheduling flexibility which is achieved by manual scheduling. However, in literature more general task rescheduling models, which are suitable for implementation of maintenance task scheduling, are already addressed. Nof and Hank Grant [18] investigated the schedule performance for a Job Shop Problem (JSP) in disruptive environments. Their approach focused on the creation of robust schedules, such that when disruptions take place, only minor changes are required due to the robustness. They conclude that rescheduling needs to take place often to remain adaptive to changing circumstances. Yuan et al. [28] created a rescheduling JSP at which disruptions are included in the form of unexpected arrival of new jobs. During a disruption, the sequence of tasks can be adjusted by making use of a genetic algorithm. Deviations from the original schedule are aimed to be prevented.

In other industries very similar research has been conducted compared to aircraft maintenance rescheduling. For the health care sector, Mahdi ValiSiar and Ramezanian [15] and Ballestín et al. [2] developed a rescheduling approach for the assignment of patients to operating rooms. The health care sector is naturally a disruptive environment with unexpected arrivals of patients and various levels of priorities. Mahdi ValiSiar and Ramezanian [15] used a Mixed Integer Linear Programming (MILP) approach, which aimed to reduce the waiting time of patients and minimize the number of tardy patients. Rescheduling was added in the form of a minimal distance function, to minimize deviations from the current schedule. Ballestín et al. [2], extended the MILP model and evaluated the results for different scheduling objectives. The scheduling objective was extended by not only to considering the current planning phase but also the effect of the current planning on the upcoming phases. Where the health care sector mostly has to cope with demand disruptions, the construction sector has to deal with resource availability disruptions, at which scheduled machinery or material arrives earlier/later than expected. Liu and Shih [14] provided a framework at which the goal is to make the least amount of changes to the schedule and the product cost is minimized.

Based on the research approaches provided in this literature review, it can be concluded that detailed implementation for airline maintenance task scheduling and rescheduling during disruptions, is currently not addressed in literature. Regarding airline maintenance scheduling research has merely gone into maintenance task scheduling together together with the corresponding requirements, such as 4M availability and prevention of tasks from going due. These approaches mainly regard disruptions as out of scope. For other airline departments, such as network operations, crew and passengers, extensive research has gone into recovery of operations during disruptions. Also other areas of research, such as the health care and the construction sector have similar methods already applied. This research therefore aims to connect both areas of research by aiming to develop a model for continuous maintenance task rescheduling. This combines the concept of task rescheduling and maintenance task scheduling in a commercial airline environment.

3. Problem formulation

Up until now task rescheduling takes place manually which can potentially introduce errors and inconsistent decision making. The implementation of a model for maintenance task scheduling can assist a maintenance scheduler in the decision-making process. Additional rescheduling options can be provided which difficult to be considered by means of manual scheduling. Where a manual approach is only able to create a schedule for the short-term, it is difficult to identify the underlying consequences for the long-term. According to both Dhanisetty et al. [6] and Koornneef et al. [11], short-term decisions can influence the scheduling performance on the long-term as well. The model considers both the short- and long-term, to prevent the postponement of problems to the long-term.

To increase the scheduling performance and assist the maintenance scheduler, the model presented in this paper aims for the following objectives:

1. Minimize maintenance ground time, to increase operational availability.
2. Limit number of rescheduling actions, to improve schedule stability.
3. Consider long-term consequences during scheduling.

3.1. Framework formulation

Based on the model objectives defined above, a framework is developed which captures the disruptive airline environment by means of simulation. The remaining part of this section will cover the formulation of the framework. To create a maintenance schedule and respond to disruptions, a maintenance scheduler makes use of three inputs: the maintenance slot schedule, task backlog and resource availability. These inputs are the same as for the framework provided in this paper and are defined in more detail as following:

1. Slot schedule: The maintenance slots schedule outlines ground time slots which are reserved to execute maintenance. Each maintenance slots has a start date, end date and a designated aircraft type. A maintenance slot needs to be allocated to an aircraft registration, To allocate tasks for execution. Maintenance slots can be further subdivided in two categories
   - Fixed slots: For fixed slots, the assigned aircraft is predefined and only additional maintenance tasks can be assigned to the maintenance slots. Fixed maintenance slots are far ahead in the future and are part of more extensive maintenance operations such as letter checks.
   - Flexible slots: For flexible maintenance slots the aircraft registration is variable and a maintenance scheduler is free to decide which aircraft to maintain.
2. Open tasks: This is the backlog of tasks which needs to be scheduled. Each task comes with its own unique set of requirements. It has a due date, required turnaround time (method), workforce (manpower) requirement and machinery & material requirements. To determine whether a task can be executed in a maintenance slot, all 4M requirements need to be satisfied. Maintenance tasks can be further subdivided in the following categories:

- Routine maintenance tasks: Routine maintenance tasks are prescribed by the aircraft manufacturer and conform regulations set by the European Union Aviation Safety Agency (EASA). These tasks are provided in the Maintenance Planning Document (MPD) together with their execution requirements. Airlines also have the opportunity to add additional tasks to the MDP. Once a task is executed the interval is reset [7].
- MEL tasks: For non-routine maintenance tasks, procedures for fault restoration are described in the Minimum Equipment List (MEL) [26]. The MEL states how many calendar days, cycles or flight hours the aircraft is allowed to be operated without resolving the fault. For both items stated in the MPD or in the MEL the aircraft will lose its airworthiness if the due date is exceeded.
- Adhoc tasks: These are non-recurring which only have to be executed once to make an alteration on an aircraft. An aircraft remains in most cases airworthy after missing the due date of an Adhoc task is exceeded.
- NSRE tasks: These tasks are referred to as Non Safety Related Equipment (NSRE). NSRE tasks have no impact on the operating safety of the aircraft. NSRE tasks are created by the airline itself. The airline describes for each NSRE tasks in how many days the fault should be resolved. However, since this concerns requirements set up by the airline itself, the aircraft remains airworthy after the due date has been exceeded. An example of an NSRE item can be a broken In-flight entertainment system. This causes passenger inconvenience, so therefore the goal should be to resolve the issue rather sooner than later. However, it is not a sufficient reason to cancel a flight once the due date is exceeded.

3. Resource availability: Execution of a maintenance task requires the availability of resources. In the form of maintenance slots, the resource requirement of ground time is provided. The remaining resources which are required for task execution are:
   - Material availability: If a task requires the availability of new material, this needs to be arranged ahead of task execution. For a task an expected date of material availability is provided.
   - Machinery availability: The execution of task can require special tools which need to be arranged in advance. Similar to material availability an expected date of availability is provided.
   - Workforce availability: The workforce availability is subdivided over multiple skills. While machinery, material and method are independent of other tasks scheduled in parallel, workforce needs to be assigned specifically to a maintenance slots. A maintenance task can only be scheduled if the corresponding manpower requirements are satisfied by means of assigned workforce to the corresponding maintenance slot. If maintenance slots are scheduled in parallel, workforce can be divided over the active maintenance slots. The workforce allocation differs slightly for fixed and flexible maintenance slots. Since fixed slots are part of a larger maintenance operation and are often executed by a different airline department, a fixed amount of workforce hours can be allocated to the slots, regardless of skill and workforce availability. For flexible slots, skilled workforce needs to be allocated to a maintenance slot depending on availability.

The three inputs provided above are indicated on the left of Figure 1 which illustrates the framework outline. Besides the three inputs, a disruption forms the trigger for maintenance task rescheduling. Once a disruption occurs, there is already an existing schedule in which tasks and manpower are allocated to slots. The addition of a disruption can potentially result in a schedule infeasability. If so, the schedule requires adjustments such that a feasible schedule is obtained again. The original maintenance schedule is the starting solution to recover from the disruption. From here the goal is to create an optimal schedule, but with a limited number of schedule changes. The formulation of the model for maintenance task rescheduling is provided in detail in the next chapter. Output of the rescheduling model is a revised schedule which forms the starting solution for the next disruption.

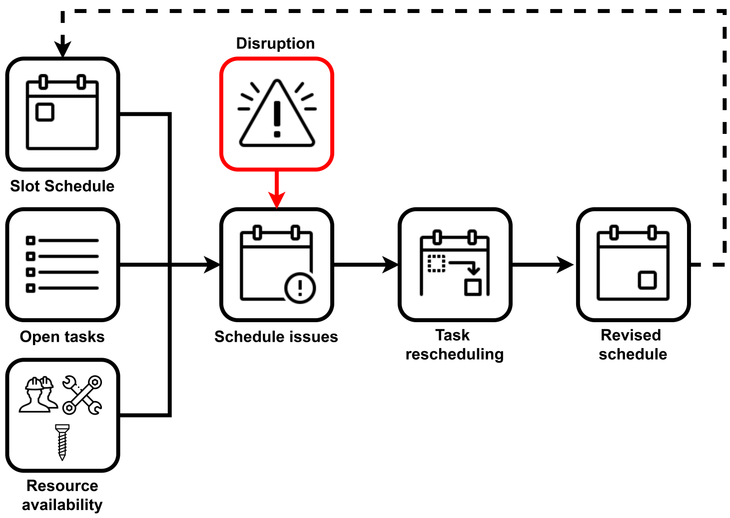

Figure 1: Outline of maintenance task rescheduling framework

The formulated framework is able to cope with all kinds of disruptions which can occur within commercial airlines, such as non-routine task arrival, network disruption and resource availability changes.

4. Model Formulation

Based on the framework outline provided in the previous section, in this section the model formulation will be discussed in a few steps. The model is formulated as a Mixed Integer Linear Program (MILP). To define the model formulation, this section is divided into five steps. Consecutively the model sets, parameters, decision variables, scheduling objectives and constraints are discussed.

4.1. Sets

The model consists out of six sets. The tasks which should be scheduled by the model are represented by the task group set, indicated by G. Tasks which should be executed simultaneously are grouped together and form one element within the task group set. If there is a stand-alone task this will form a group on itself. Out of task set G, a set of aircraft registrations with open maintenance tasks is obtained. This set is designated by R. Each registration belongs to an aircraft sub type group. Maintenance slots are provided within the model formulation by S.

For the current scheduling period, the time blocks in which workforce can be assigned to maintenance slots is provided in the time block set (T). Within the model formulation the scheduling horizon for workforce assignment is split up in blocks of 30 minutes. At last, there is a set of task skills (TS) and workforce skills (WS). Task skills define which skills are required to execute a task. Workforce skills depend on the certifications of the workforce. A task skill can potentially be performed by multiple workforce skills and a workforce skill can have the authorization to perform multiple task skills. The model sets and subsets are provided in Table 1.

Table 1: Defined sets for the rescheduling model

Sets	Explanation
$r \in R$	Set of aircraft registrations
$r \in R_s$	Set of aircraft registrations of the aircraft type of slot s
$g \in G$	Set of task groups
$g \in G_{\text{Due}}$	Subset of tasks which go due in the current scheduling interval ($G_{\text{Due}} \subset G$)
$g \in G_{\text{Defer}}$	Subset of tasks which do not go due in the current scheduling interval ($G_{\text{Defer}} \subset G$)
$g \in G_{\text{Routine}}$	Subset of routine tasks ($G_{\text{Routine}} \subset G$)
$g \in G_{\text{Non-routine}}$	Subset of non-routine tasks ($G_{\text{Non-routine}} \subset G$)
$g \in G_r$	Subset of tasks for aircraft registration r ($G_r \subset G$)
$g \in G_{r_s}$	Subset of tasks for aircraft registration r, which is attached to maintenance slot s ($G_{r_s} \subset G_r$)
$ts \in TS$	Set of task skills
$ws \in WS$	Set of workforce skills
$ws \in WS_{ts}$	Subset of workforce skills which can execute task skill ts ($WS_{ts} \subset WS$)
$t \in T$	Set of time blocks within the current schedule interval
$t \in T_s$	Subset of time intervals during execution of maintenance slot s ($T_s \subset T$)
$s \in S$	Set of maintenance slots within the current schedule interval
$s \in S_{Fixed}$	Subset of slots which the aircraft registration is fixed ($S_{Fixed} \subset S$)
$s \in S_{Flexible}$	Subset of slots which the aircraft registration is allowed to change ($S_{Flexible} \subset S$)
$s \in S_t$	Subset of maintenance slots active at time interval t ($S_t \subset S$)

4.2. Parameters

Based on the properties of the sets described above, the parameters provided in Table 3 serve as input for the model. Several parameters depend on the combination between a maintenance slots s and a task group g. For each of the variables an explanation is provided together with the corresponding unit.

One important parameter to elaborate on is the coefficient for task type ($C_{Type,g}$). This parameter denotes the criticality of task group g based on the task type. The values for $C_{Type,g}$ are determined based on the impact on the aircraft airworthiness of the task and are displayed in the following table:

Table 2: Weighting factor for task type

Task type	$C_{Type,g}$
Routine	4
MEL	4
Adhoc	2
NSRE	1

Table 3: Defined parameters for the rescheduling model

Parameters	Unit	Explanation
Current Date	Date	Current date of scheduling
$r_{s_{or}}$	[-]	Original aircraft registration r assigned to maintenance slot s
Start_s	Date	Start date of maintenance slots s
Arrival_g	Date	Arrival date of maintenance task group g
Due_g	Date	Due date of maintenance task group g
$Mav_{t,ws}$	Hours	Workforce available at time t of workforce skill ws
$\text{DD}_{g,s}$	[-]	1 if the start date of slot s is before the due date of task g, 0 otherwise
$\text{Workforce}_{g,ts}$	Hours	Workforce required for task group g of task skill ts
$\text{Material}_{g,s}$	[-]	1 if the material availability date for task group g is available before the start date of maintenance slot s, 0 otherwise.
$\text{Machinery}_{g,s}$	[-]	1 the machinery availability date for task group g is available before the start date of maintenance slot s, 0 otherwise.
$\text{TAT}_{g,s}$	[-]	1 if the turnaround time required to execute task group g is shorter than the duration of maintenance slots s, 0 otherwise.
$\text{AC-Type}_{r,s}$	[-]	1 if the aircraft type of slot s matches with aircraft registration r, 0 otherwise
Duration_s	Hours	Duration of maintenance slots s
Max-Tasks	[-]	Maximum number task groups in a maintenance slot
Max-Workforce_s	Hours	Maximum number of workforce hours that can be attached to maintenance slot s.
10 Days due_g	[-]	1 if task group g goes due in 10 days after the scheduling interval, 0 otherwise.
$C_{Type,g}$	[-]	Task type coefficient of task group g
W_{DUE}	[-]	Weighting factor of task going due
W_{GROUND}	[-]	Weighting factor of ground time
W_{RES}	[-]	Weighting factor for rescheduling assigned aircraft registration
W_{DEFER}	[-]	Weighting factor for task deferral
W_{INTERVAL}	[-]	Weighting factor for task interval utilization

4.3. Decision variables

The decision variables for the maintenance task rescheduling model are provided in Table 4.

Table 4: Defined decision variables for the rescheduling model

Decision variable	Explanation
$T_{g,s}$	1 if Task group g is assigned to slot s, 0 otherwise. If a task cannot be scheduled, this is registered as deferred ($s = \emptyset$).
$AC_{r,s}$	1 if aircraft r is assigned to slot s, 0 otherwise. If a slot is left empty, this is registered as dummy slot ($r = \emptyset$).
$\text{WA}_{s,t,ts,ws}$	Assigned workforce to maintenance slot s, at time t for task skill ts of workforce skill ws
$\text{AC}_{\text{clean},r}$	1 if aircraft r has no open tasks in the coming 10 days at the end of the interval, 0 otherwise

4.4. Objective function

In Figure 2 the hierarchy of scheduling objectives is visualized, which corresponds to the scheduling objectives which a maintenance scheduler keeps in mind. The main objective is to prevent tasks from going due. Secondly, in general the goal of an MRO is to provide fleet availability towards the airline. Since the goal is to create both efficient and stable maintenance schedules the third objective is set to the prevention of schedule changes. Next, the objective is to schedule aircraft clean for a fixed number of days. The last objective is to schedule maintenance tasks optimally with respect to their interval utilization. Besides task interval utilization there is also an option for task deferral if the task is not scheduled within the current scheduling interval. This is a function of task interval utilization or task execution based on how good of an option task deferral is.

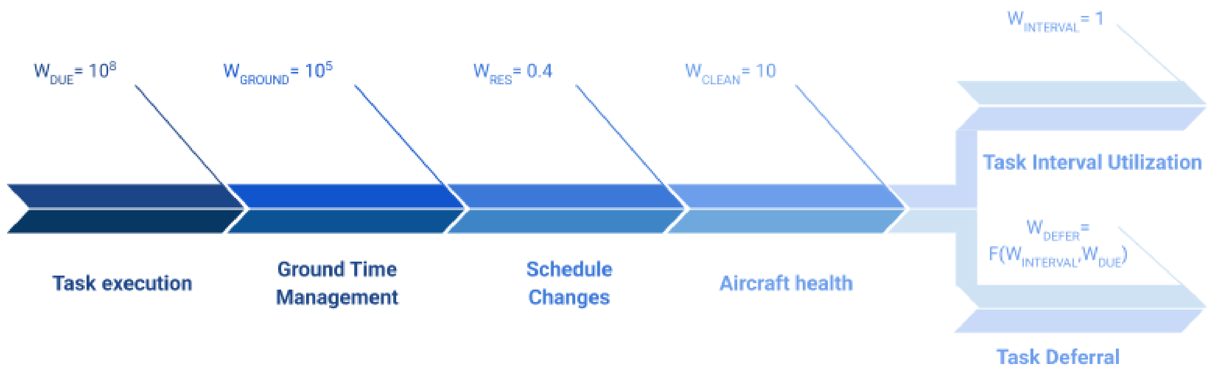

Figure 2: Hierarchy during task scheduling

The weighting factors displayed in Figure 2 are chosen based on the scheduling hierarchy such that they do not coincide with each other. Only for ground time management and schedule changes there is a conflict of interest. The value for W_{RES} is therefore elaborated upon in the results section. Taking these scheduling objectives together the goal is to minimize scheduling cost. The objective function can therefore be mathematically formulated as following:

$$
\begin{aligned}
\text{Min} \quad & \sum_{g \in G_{\text{Due}}} T_{g,\emptyset} \cdot W_{\text{DUE}} \cdot C_{\text{TYPE}} + \\
& \sum_{s \in S} \left(AC_{r_{s_{or}},s} + \sum_{r \in R_s} AC_{r,s} \cdot (1 + W_{\text{RES, s}}) \right) \cdot W_{\text{GROUND, s}} + \\
& \sum_{r \in R} (1 - \text{AC}_{\text{clean},r}) \cdot W_{\text{CLEAN}} + \\
& \sum_{s \in S} \left(\sum_{g \in G_{\text{Routine}}} T_{g,s} \cdot W_{\text{INTERVAL Routine, g,s}} + \sum_{g \in G_{\text{Non-routine}}} T_{g,s} \cdot W_{\text{INTERVAL Non-routine, g,s}} \right) \cdot C_{\text{TYPE}} + \\
& \sum_{g \in G_{\text{Defer}}} T_{g,\emptyset} \cdot W_{\text{DEFER, g}} \cdot C_{\text{TYPE}} \quad (1)
\end{aligned}
$$

In the upcoming subsections each scheduling objective and their weighting factor are discussed individually together with additional formulation of the weighting factor.

4.4.1. Task scheduling

Task scheduling consists of two parts, task execution and task interval usage. The primary goal of maintenance task scheduling is to schedule each task ahead of their due date. By exceeding the task due date, the aircraft will be stranded on the ground as it is no longer airworthy. Letting a task go due has the highest weighting in the model and is denoted by W_{DUE} and is the same for every task group g.

$$W_{DUE} = 10^8 \tag{2}$$

The second requirement, with lesser importance, is the moment in time at which the task is scheduled. For each task, an arrival date is known. Depending on the task characteristics it receives a due date. Maintenance tasks can be subdivided in two categories: routine and non-routine. For non-routine maintenance tasks it is preferable to schedule them as far ahead of their due date as possible. This aims to keep the aircraft in good shape, rather then waiting longer to resolve defects. Interval usage is taken into account in the objective function for a non-routine maintenance task group g and maintenance slots s as following ($W_{\text{INTERVAL}} = 1$):

$$W_{\text{INTERVAL Non-routine, g,s}} = \frac{\text{Start}_s - \text{Arrival}_g}{\text{Due}_g - \text{Arrival}_g} \cdot W_{\text{INTERVAL}} \tag{3}$$

This will result in an increasing scheduling cost if the task allocation moves closer to the due date. For routine maintenance, the goal is the other way around as it is preferable to schedule recurring tasks close to their due date. This prevents the loss of unused interval and having to execute routine maintenance more often. For routine maintenance task groups g and maintenance slot s the inverse relation can be used ($W_{\text{INTERVAL}} = 1$):

$$W_{\text{INTERVAL Routine, g,s}} = 1 - \frac{\text{Start}_s - \text{Arrival}_g}{\text{Due}_g - \text{Arrival}_g} \cdot W_{\text{INTERVAL}} \tag{4}$$

The model evaluates a maintenance schedule only for a fixed number of days within one horizon. For some tasks the due date can be beyond the maximum scheduling date. As a result, there are also feasible scheduling possibilities for a task outside of the current scheduling interval. If the task is not scheduled in the current interval and the due date lies outside of the interval, a task can be registered as deferred instead of due. The weighting of deferred tasks, W_{DEFER}, is based on the mean value of W_{UTIL} for the scheduling opportunities outside of the current interval. If there are no scheduling opportunities outside of the current scheduling interval W_{DEFER} equals W_{DUE}. W_{DEFER} for a maintenance task group g is therefore formulated as following:

$$W_{\text{DEFER, g}} = \begin{cases} \text{Mean}(W_{\text{INTERVAL, g,s}}), & \text{if Opportunities} \geq 1 \\ W_{\text{DUE}}, & \text{otherwise} \end{cases} \tag{5}$$

4.4.2. Ground time management

As long as all tasks are scheduled ahead of their due date, the aircraft will remain airworthy. In general, the goal of an airline is to use their aircraft optimally such that the number of flights can be maximized. Scheduling tasks ahead of their due date is an MRO objective. However, if the consequence of this is that aircraft need to spend lots of time within in the hangar, an airline can still not make use of their aircraft optimally. Besides maintenance task execution the goal is therefore to minimize the time an aircraft is scheduled for maintenance. As a result, the operational availability of an aircraft should increase. The goal of minimization of ground time is included in the objective function by minimizing the cumulative duration of maintenance slots which are being used. The duration is multiplied by the weighting factor for ground time $\left(W_{\text{GROUND}} = 10^5\right)$.

$$W_{\text{GROUND, s}} = \text{Duration}_s \cdot W_{\text{GROUND}} \tag{6}$$

4.4.3. Schedule changes

A schedule changes is defined as a change in assigned aircraft registration to a maintenance slot. The goal is to limit these changes made to the original schedule once is disruption occurs. Since they have a knock-on affect to other airline departments such as network scheduling. If there would be no restriction on the number of schedule changes, the schedule would be completely regenerated at the occurrence of a disruption. However, in case of disruptive scheduling, the goal is to minimize the difference between the original and rescheduled schedule. Reallocating tasks in between maintenance slots of the same aircraft registration is not considered as a schedule changes as this does not affect other airline departments and they are still executed according to airline regulations.

Once an aircraft registration has been assigned to a maintenance slot, it should preferably remain in that position. However, for a schedule change the number of days of notice is of high importance. An aircraft allocation change on the day of operation is more costly than an aircraft change a couple of days ahead.

The rescheduling cost as a function of the days of notice is illustrated in Figure 3. From T-10 days till T-3 days the rescheduling cost is set to 0, which means that there is no penalty involved in making a schedule change. Aircraft allocation to flights is usually planned two or three days ahead. Schedule changes which take place before an aircraft is assigned to flights should be non-restricted. By moving closer to the day of operation consequences of schedule changes become more severe and therefore the rescheduling cost also increases linearly from T-3 days to the day of operation.

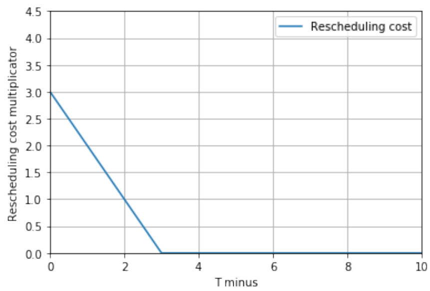

Figure 3: Maintenance slots rescheduling cost as a function of the days of notice

Within the objective function, W_{RES} for a maintenance slots s is defined as following ($W_{\text{RES}} = 0.4$):

$$W_{\text{RES, s}} = \max\left(3 - (\text{Start}_s - \text{Current Date}), 0\right) \cdot W_{\text{RES}} \tag{7}$$

$W_{\text{RES,s}}$ is multiplied by $W_{\text{GROUND,s}}$ for every aircraft registration other than the aircraft registration originally scheduled for maintenance slot s.

4.4.4. Aircraft cleanliness

An aircraft is considered clean if there are no open tasks for a fixed number of days. For this research the target number of clean days is set to a value of 10 days. This aims to minimize the required ground time outside of the current scheduling interval. A sensitivity analysis on the number of target clean days is provided in Appendix C.2. The objective of the model is to maximize the number of clean aircraft at the end of the current scheduling interval. As this model is a minimization problem the number of non-clean aircraft should be minimized. Therefore all dirty aircraft are multiplied with the aircraft cleanliness weighting factor W_{CLEAN}.

$$W_{CLEAN} = 10 \tag{8}$$

4.4.5. Constraints

At last, the constraints regarding the allocation of workforce and allocation of tasks to maintenance slots are defined as following:

$$\sum_{s \in S_t} \sum_{ts \in TS_{ws}} \mathrm{MA}_{s,t,ts,ws} \leq \mathrm{Mav}_{t,ws} \qquad \forall ws \in WS, t \in T \qquad (9)$$

$$\sum_{t \in T_b} \sum_{ws \in WS_{ts}} \mathrm{MA}_{s,ts,ws,t} \geq \sum_{g \in G} \mathrm{workforce}_{g,ts} \cdot T_{g,s} \qquad \forall s \in S_{\mathrm{Flexible}}, ts \in TS \qquad (10)$$

$$\sum_{r \in R_s} AC_{r,s} \leq 1 \qquad \forall s \in S \qquad (11)$$

$$\sum_{ts \in TS} \sum_{g \in G_{r_s}} \mathrm{Workforce}_{g,ts} \cdot T_{g,s} \leq \text{Max-Workforce}_s \qquad \forall s \in S_{\mathrm{Fixed}} \qquad (12)$$

$$AC_{r_{s_{or}}} = 1 \qquad \forall s \in S_{\mathrm{Fixed}} \qquad (13)$$

$$\sum_{s \in S} T_{g,s} = 1 \qquad \forall g \in G \qquad (14)$$

$$\sum_{g \in G_r} T_{g,s} \leq \text{Max-Tasks} \cdot AC_{r,s} \qquad \forall s \in S_{\mathrm{Flexible}}, r \in R_s \qquad (15)$$

$$\sum_{g \in G_r} T_{g,\mathrm{Defer}} * 10 \text{ Days due}_g \leq \text{Max-Tasks} \cdot (1 - \mathrm{AC}_{\mathrm{clean},r}) \qquad \forall r \in R \qquad (16)$$

$$\sum_{s \in S} (1 - \mathrm{DD}_{g,s}) \cdot T_{g,s} = 0 \qquad \forall g \in G \qquad (17)$$

$$\sum_{s \in S} (1 - \mathrm{TAT}_{g,s}) \cdot T_{g,s} = 0 \qquad \forall g \in G \qquad (18)$$

$$\sum_{s \in S} (1 - \mathrm{Material}_{g,s}) \cdot T_{g,s} = 0 \qquad \forall g \in G \qquad (19)$$

$$\sum_{s \in S} (1 - \mathrm{Method}_{g,s}) \cdot T_{g,s} = 0 \qquad \forall g \in G \qquad (20)$$

$$\sum_{s \in S} (1 - \text{Aircraft type}_{g,s}) \cdot T_{g,s} = 0 \qquad \forall g \in G \qquad (21)$$

$$\sum_{s \in S} (1 - \mathrm{Infeasible}_{g,s}) \cdot T_{g,s} = 0 \qquad \forall g \in G \qquad (22)$$

For flexible slots, constraints (9) restrict the model such that the total allocated workforce of skill ws during time block t cannot exceed the available workforce for that skill & time combination. Constraints (10) guarantee that the allocated workforce for maintenance slots s and task skill ts meet the workforce requirements of the allocated tasks. In constraints (11), at most one aircraft can be assigned to a maintenance slot. Otherwise it should be registered as a "Dummy" slot ($r = \emptyset$). For a dummy slot an artificial aircraft is assigned at which no tasks can be assigned.

For fixed slots, constraints (12) and (13) are implemented. The set of constraints limit the number of workforce hours which can be attached to a fixed maintenance slot. The second set of constraints fixes the maintenance slot to a scheduled aircraft registration, since there is no change in registration allowed for fixed slots.

For constraints (14), every task group should be scheduled by the rescheduling model. A task group (g) can be scheduled in any of the maintenance slots (s). If it is not possible to schedule the task group in any of the slots the task should be deferred or due ($s = \emptyset$). Constraints (15) ensure that only a maintenance task group g can be added to a maintenance slot s if the corresponding aircraft registration r is assigned to it. The constraints provided in (16) assure that an aircraft is registered as clean if there are no tasks going due in the coming 10 days after the scheduling interval.

The last set of constraints are of identical form and provide constraints for the feasibility of the task-slot combinations. Constraints (17) force that tasks must be scheduled ahead of its due date. Constraints (18), (19) and (20) provide the remaining 4M constraints besides manpower. At last, constraints (21) only allows tasks to be scheduled to slots with a matching aircraft type. Since the constraints from (17) till (21) are all the same format, the matrices are first element-wise multiplied by each other, and then added as one single constraint as can been seen at constraints (22). This reduces the number of constraints by a factor of five, for this set of constraints. Additional clarification regarding the model implementation is provided in Appendix A.

5. Results

The data for the results is provided by a European commercial airline. Over a period from 01-07-2019 till 01-12-2019 the final maintenance slot schedule, executed maintenance tasks and available workforce are provided. The results analysis is divided into four parts. First, the setup of the simulation procedure is discussed together with support of how this represents a disruptive airline environment. This is followed by the model performance trade-off analysis, at which the rescheduling cost is determined by means of a sensitivity analysis. Afterwards, a case study is performed to evaluate the performance of the model compared to executed maintenance schedule of the commercial airline. The results analysis is concluded by a stochastic disruption analysis to analyze the stability of the model. The model is verified based on slot disruption, new task arrival and 4M availability changes. The results of the verification are presented in Appendix B. The results analysis within this paper will focus solely on the stochastic arrival of new tasks as this is the most common disruption. A sensitivity analysis on the model is provided in Appendix D.

5.1. Simulation procedure

In reality, a schedule is not made for a fixed number of days and then executed as planned. As explained in section 1, maintenance schedules are continuously updated over time and are adapting to disruptions that take place. In an airline maintenance environment, tasks arrive continuously and slots change dynamically. For this analysis, a schedule is generated for a fixed number of days. Afterwards the scheduling horizon shifts one day ahead, at which new tasks arrive and a new day becomes available at the end of the day. Since the circumstances change daily, rescheduling actions will be required to keep the schedule in a feasible state. This process is visualized in Figure 4

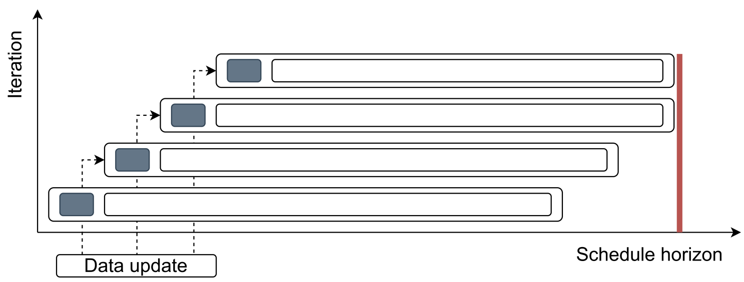

Figure 4: Simulation procedure for model

Within the airline of the case study, maintenance schedules are created manually till 10 days ahead. For the implementation within the current decision process, a 10-days model is created with a schedule horizon of 10 days and a clean target of 10 days. This corresponds to the approach used for manual scheduling. The formulation of the 10-days model is further discussed in Appendix C.

The model is able to schedule for a longer interval than the conventional 10 days. This opens the opportunity to evaluate the effect of scheduling on the long-term. A second model is therefore created in which the due dates of all tasks lies within the scheduling interval. At most, this is equal to 120 days as this is the maximum allowed interval for a non-routine maintenance task. Throughout the remaining part of this paper this is referred to the 120-days model. For both the 10-days and the 120-days model there are no scheduling opportunities beyond the scenario end date. This is indicated by the red line in Figure 4. The scheduling opportunities are therefore equal for both models. To benchmark the performance of both models, the results are compared to the final schedule produced by the airline. Since both the model and the airline schedule made use of the same input data, the results can be quantitatively compared with each other. For a lower bound reference a third model has been created with perfect information. Here all disruptions or known in advance and the schedule is created in one iteration.

5.2. Performance trade-off

As explained in Subsection 4.4 the maintenance rescheduling model has multiple scheduling objectives. There is a conflict of interest between aiming for minimum ground time and prevention of schedule changes. This section will therefore focus on the trade-off between ground time minimization and schedule changes. Based on the value of W_{RES} the relation between the two can be adjusted. A high value results in the preference of preventing schedule changes, a low value prefers ground time minimization.

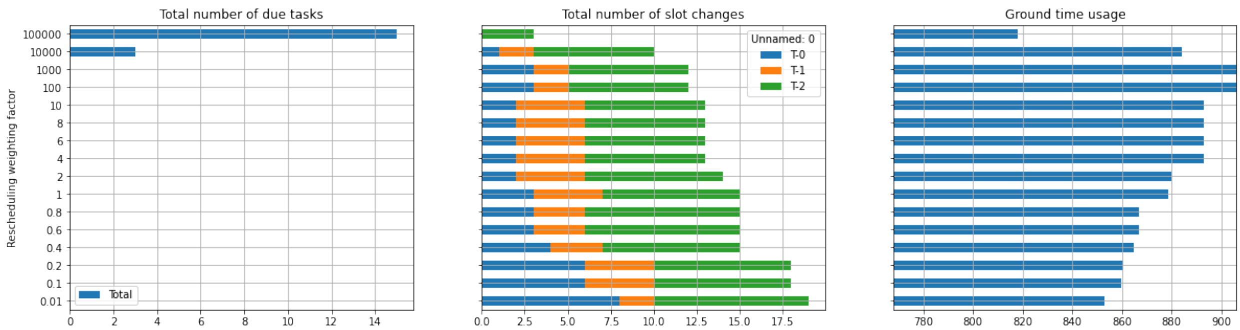

Figure 5: Number of due tasks, last-minute schedule changes and ground time for several values of W_{Res} with full interval analysis. T-0, T-1, T-2 refer to schedule changes made on the day of operation, the coming day and two days ahead respectively.

In Figure 5, the trade-off results are provided for the 120-days model. As expected, by increasing W_{Res}, the number of schedule changes decreases. However, by increasing from 1000 to 10000, a decrease in schedule changes goes at the cost of tasks going due. Since the prevention of due tasks has the highest priority these values are not feasible. Looking at the ground time required as a function of W_{RES} shows an initial increasing trend followed by a decreasing trend by increasing W_{Res} further. The initial increase in ground time is due to the preference for avoiding schedule changes. This results in more slots to be used and consequently more ground time is required. The decrease in ground time after passing $W_{\mathrm{RES}} = 1000$ is caused by the tasks going due. This causes less ground time to be required as tasks cannot be allocated to a maintenance slot.

Choosing a parameter from the figure above is subjective as this is dependent on airline preference. As mentioned in the introduction, there is a trade-off between fleet availability and schedule changes. Depending on the airlines preference a high or low value for W_{Res} can be chosen. For this paper, a value 0.4 is chosen for W_{Res}. This means that making an schedule adjustment on T-2, T-1, T-0, is 40%, 80% and 120% more expensive respectively, according to Figure 3. A value of W_{Res}=0.4, is preferred as this yields in a decrease in last minute schedule changes while the ground time does not yet increase steeply. The performance trade-off for the 10-days model is provided in Appendix C. The number of due tasks, schedule changes and ground time are displayed in Table 5 for the chosen value of W_{Res}.

Table 5: Number of due tasks, schedule changes and ground time of both models

	W_{Res}	Due tasks	Schedule changes	Ground time
120-days Model	0.4	0	15	865 Hours
10-days model	0.6	0	15	908 Hours

5.3. Case study

For the case study the performance of both models, the airline schedule and the model with perfect information can be quantitatively compared with each other. In Table 6 the hours of ground time used and the number of due tasks are given for each scheduling method. A significant decrease in required ground time can be seen for each of the three models compared to the airline schedule. Due to the increased scheduling horizon of the 120-days model, a decrease of 2.95% of ground time is achieved, compared to the 10-days model. Secondly, the 10-days model achieves a 17.2% decrease in ground time with respect to the actual schedule. Where the 10-days model uses maintenance slots of 4.62 hours on average, the airline schedule makes use of slots with an average duration of 5.57 hours. This gives an indication the model is able to schedule task more efficiently. However, the additional required ground time can also be partially caused by additional operational constraints which are not included within the scope of the model.

However, the added value of the 120-days model is underlined by the decrease in number of ground time slots while this was not a scheduling objective. This shows that the 120-days model is capable of merging maintenance slots together. The scheduling horizon of 120 days does not go at the cost of computational time. Where the 10-days model needs 6.9 seconds on average for scheduling, the 120-days model needs 48.1 seconds. This makes both models suitable for decision making during disruptions.

At last, the 120-days model can achieve scheduling results closer to the model with perfect information than the airline schedule in terms of ground time. Only 6.68% more ground time is required for the 120-days model compared to perfect information. This shows that the 120-days model is able to produce close to optimal schedules with uncertain information.

Table 6: Number of due tasks and ground time usage for analyzed scheduling methods

Schedule method	Due tasks	Scheduled tasks	Number of slots	Ground time
Airline schedule[3]	0	2549	475	2645.58 Hours
Perfect information	0	2549	451	1992.60 Hours
120-days model	5	2544	469	2125.75 Hours
10-days model	10	2539	474	2190.40 Hours

In exchange for a decrease in ground time, both models have tasks going due. This is caused by a lack of scheduling flexibility in the maintenance slot schedule. During validation of these results, the airline indicated that changes to the maintenance slot schedule are part of the solution space of the maintenance schedulers. A maintenance scheduler can extend or split-up an existing maintenance slot or create a new maintenance slot. As a result, new feasible scheduling opportunities for a task can be generated. This is confirmed by an analysis of the adjustments made to the slot schedule by the airline. This shows that 30,

[2]Results obtained after maintenance slots adjustments by maintenance scheduler

68 and 35 duration changes have been made in T-0, T-1 and T-2 respectively. Examples of maintenance slot flexibility are provided in Appendix F. For both models, this is not part of the solution space.However, the input for both models is a slot schedule which is fine-tuned according to the airline schedule. When the model takes a different decision path as the airline, there is no longer a fine-tuned maintenance schedule with the current task backlog. As a result, a task can be left without any feasible slots in which it can be scheduled. A more elaborate explanation together with an example is provided in Appendix E.

As explained in the beginning of this section, aiming for minimization of ground time should not go at the cost of an increase in last minute schedule changes. In Table 7 the number of schedule changes are provided. A comparison to the airline schedule shows that both models require significantly less last-minute schedule changes. The comparison gives an indication that the model produces more stable schedules. However, this needs to be verified by means of live testing. Since the case study in which the model is evaluated does not capture the full disruptive nature of an airline environment. Secondly, it can be concluded that the implementation of the 120-days model does not result in an increase of schedule changes compared to the 10-days model.

Table 7: Number of schedule changes close to the day of operation for analyzed scheduling methods

Schedule method	T-0	T-1	T-2
Airline schedule	24	25	22
120-days model	12	10	16
10-days model	13	8	18

At last, the utilization rates of both routine and non-routine tasks are evaluated for the scheduling methods in Table 8. It can be concluded that scheduling by making use of the model compared to the airline schedule results in slightly better interval utilization for both routine and non-routine maintenance tasks. A comparison between the 10-days model and the 120-days model shows that the additional decrease in both ground time and schedule changes does not go at the cost of interval utilization. The 120-days model is capable of achieving slightly better utilization numbers which are close to the numbers obtained for perfect information. As expected, for perfect information the best task utilization results are obtained. The non-routine task utilization goes from 56.1% to 53.4% by comparing the airline schedule with perfect information. Since disruptions are known in advance, maintenance slots can be reserved which results in a better non-routine task utilization.

Table 8: Task utilization for analyzed scheduling methods

Schedule method	Routine utilization	Non-routine utilization
Airline schedule	0.760	0.561
Perfect information	0.778	0.534
120-days model	0.773	0.546
10-days model	0.777	0.549

5.4. Stochastic disruption analysis

In the preceding section it is shown that the model can achieve a decrease in ground time. It also showed to added benefit of the 120-day interval with a further decrease in ground time and less due tasks with respect to the 10-days model. However, these conclusions are based on the evaluation of a single scenario. This section will provide an extended analysis of the model performance based on stochastic disruption analysis. Non-routine maintenance scheduling has a stochastic nature as the arrival of new tasks is unknown. Maintenance schedules should therefore have enough slack to cope with the irregular arrival of maintenance tasks. For the model, the goal is to create a close to optimal schedule with incomplete information. In this section, the unexpected arrival of tasks is simulated. To replicate a disruptive environment, a stochastic analysis is performed on the arrival of non-routine maintenance tasks based on the task data provided by the airline.

To find a suitable distribution for the arrival time in between non-routine maintenance tasks, the difference in arrival time for consecutive non-routine maintenance tasks is analyzed. An analysis on the non-routine task arrival revealed that the arrival of tasks are not independent of one another. A single failure can cause consequential failures. Therefore, multiple tasks arrive shortly after each other on one aircraft registration.

To account for this, the simulated arrival of tasks has been subdivided into two parts. First the stochastic arrival of tasks is determined by means of a distribution. Secondly, for each task arrival the number of tasks arriving at once is determined. In Figure 6, the distribution of arrival times is provided by the blue line for a historical set of non-routine tasks data. The historical distribution has been approximated by means of an exponential distribution indicated by the orange line. Fitting the distribution yields in an arrival frequency of $\lambda = 0.255[\frac{1}{\text{Hour}}]$. To demonstrate that the fitted exponential line is a suitable distribution, a generated set of arrival times is added in Figure 6 indicated by the green line. The generated set of data makes use of the same mean arrival time and has the same size as the historical data.

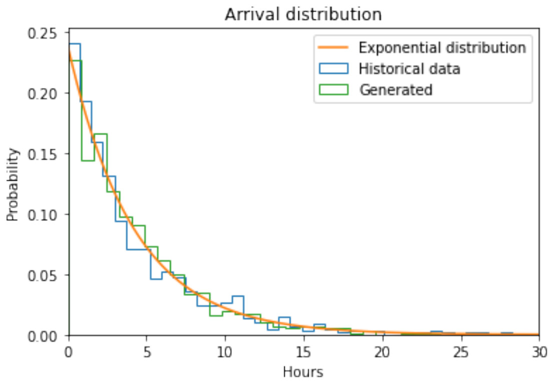

Figure 6: Probabilistic distribution of arrival of tasks together with sample of generated duration's

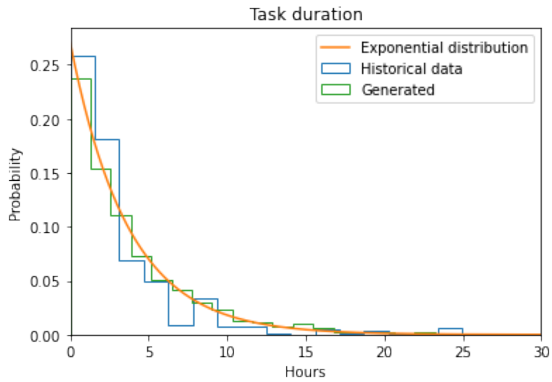

Figure 7: Probabilistic distribution of duration of tasks together with sample of generated duration's

The second step is the stochastic generation of the number of tasks arriving at once. Lagos et al. [12] approximated this by means of a Poisson distribution. However, since within the scope of this research only non-routine maintenance which is executed within the hangar is considered, no suitable distribution could be fitted on the historical data. Therefore, the number of tasks is determined by means of a weighted choice between 1, 2, 3 or 4 tasks arriving simultaneously. In similar manner, the tasks should be assigned to an aircraft registration. This is done by means of a weighted choice out of the available registrations. The weights are determined based on the historic probability of non-routine tasks of the corresponding aircraft registration. This is a valid assumption since there are specific aircraft registrations/types which require more non-routine maintenance than others.

The required duration for execution of a maintenance tasks within a slot shows a lot of variance. In Figure 7, the distribution of the maintenance task duration is plotted. To generate new task durations an exponential distribution has been fitted on the data, resulting in a duration frequency of $\lambda = 0.272[\frac{1}{\text{Hour}}]$. Again, a generated sample of durations is shown in Figure 7 to indicate that this is indeed a suitable distribution.

The type of tasks are determined by means of a weighted choice, this determines both the task criticality and available time interval. At last, the workforce requirements are taken as a sample from one of the historical tasks. The sequence of task generation is summarized in Algorithm 1. The weights for determination of number of tasks, task type and aircraft registration are provided in Appendix F.

Algorithm 1 Stochastic creation of non-routine maintenance tasks

Generate arrival times based on exponential distribution of Figure 6
for each arrival time **do**:
    Generate aircraft registration r based on weighted choice
    Generate number of tasks based on weighted choice
    for each task **do**:
        Generate duration based on exponential distribution Figure 7
        Generate workforce requirements based on historic sampling
        Generate task type based on weighted choice
    end for
end for

For stochastic disruption analysis, a scenario is created which runs from 01-07-2019 till 01-09-2019 and makes use the maintenance slot schedule obtained from the case study. In total 20 scenarios are evaluated with different sets of stochastic tasks. For each scenario only the non-routine tasks are replaced by stochastically created tasks, while the routine tasks are identical for each scenario. Depending on airline fleet size and fleet age the task arrival distribution can shift. Therefore, several disruption loads are evaluated for the arrival time in between tasks. Starting from a disruption percentage of 50%, the time frequency of the arrival of tasks is increased with steps of 25% till a frequency of 150%. The performance of both the 10-days and 120-days model is compared to the model with perfect information. The 10-days model is included within the analysis as this replicates the current manual decision making within an airline, with a scheduling horizon of 10 days.

Within Figure 8, the number of due tasks are displayed for an increasing disruption rate. In case of perfect information, tasks go due because of a lack of scheduling opportunities. For tasks with a short interval there is sometimes no suitable maintenance slot available, which causes tasks to go due even with perfect information. This phenomenon is not observed for the case study provided in Subsection 5.3 as this maintenance slots schedule was fine-tuned to the task backlog. Within the case study each task had at least one scheduling opportunity while for this analysis this is not necessarily the case. If there would be no feasible scheduling opportunity for a task, a maintenance scheduler would manually create one. Furthermore, the analysis shows that the 120-days model is able to prevent more tasks from going due compared to the 10-days model. Even though the confidence intervals between the 120-days model and 10-days model coincide with each other, an element-wise comparison for each scenario shows that the 120-days model has less or equal due tasks in 97.5% of the scenarios.

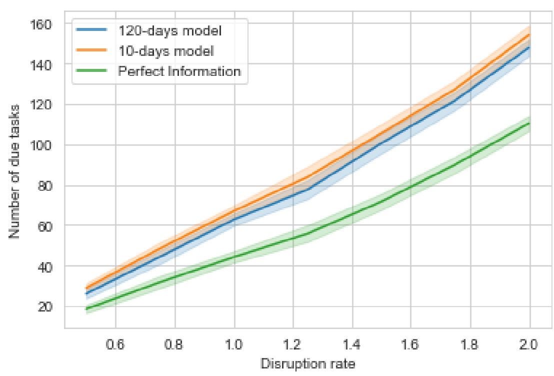

Figure 8: Number of tasks going due as function of disruption rate

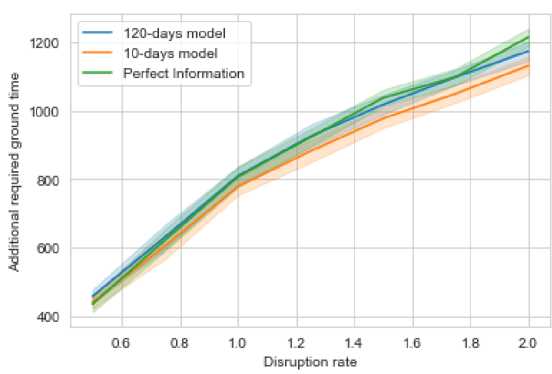

Figure 9: Additional ground time required as function of disruption rate

The decrease in number of due tasks goes at the cost of an increase in required ground time, as shown in Figure 9. The 10-days model requires less ground time than the 120-days model. This can be explained since more tasks are going due in the 10-days model and consequently this results in less tasks which are scheduled. Thereby, less ground time is required. This explanation is also confirmed by the fact that the 10-days model requires less ground time than the perfect information model. Secondly, the decrease in ground time can also be explained by the fact that an increase in disruption rate causes a more congested schedule. Consequently, the benefit of scheduling in the long-term disappears as most maintenance slots in the short-term need to be used anyway. Long-term scheduling, with the current scheduling hierarchy, can even be worse than short-term scheduling. If schedule availability in the long-term is assumed while this eventually result in a congested schedule as time progresses. However, this only becomes an issue by increasing the disruption rate beyond values evaluated for this study.

Table 9: Average scheduling results for a disruption rate of 1

Schedule method	Due tasks	Scheduled tasks	Ground time usage	Number of slots
10-days model	66.91 (17.3%)	320.87	778.29 Hours	84.96
120-days model	62.70 (16.2%)	325.09	809.57 Hours	89.00
Perfect Information	44.17 (11.4%)	343.61	806.19 Hours	87.17

For a disruption rate value of one, the average results are summarized in Table 9. By making use of the 120-days model a decrease of 1.1% in due tasks can be achieved. A larger scheduling interval provides more insight into future scheduling opportunities and therefore results in less tasks going due. However, the gap to perfect information remains 4.8%. Because of the lack of scheduling opportunities for some tasks, the model with perfect information is able to use the available maintenance slots more efficiently and achieve a reduction in due tasks. A comparison between the average ground time per executed task shows that the 120-days model requires 2.6% more than the 10-days model. It is likely that the 10-days model would require more ground time if there would be scheduling opportunities for the due tasks. This is because that the 10-days model requires less ground time than a scenario with perfect information. Whether the 10-days model would require more or less ground time compared to the 120-days model is a question which cannot be answered.

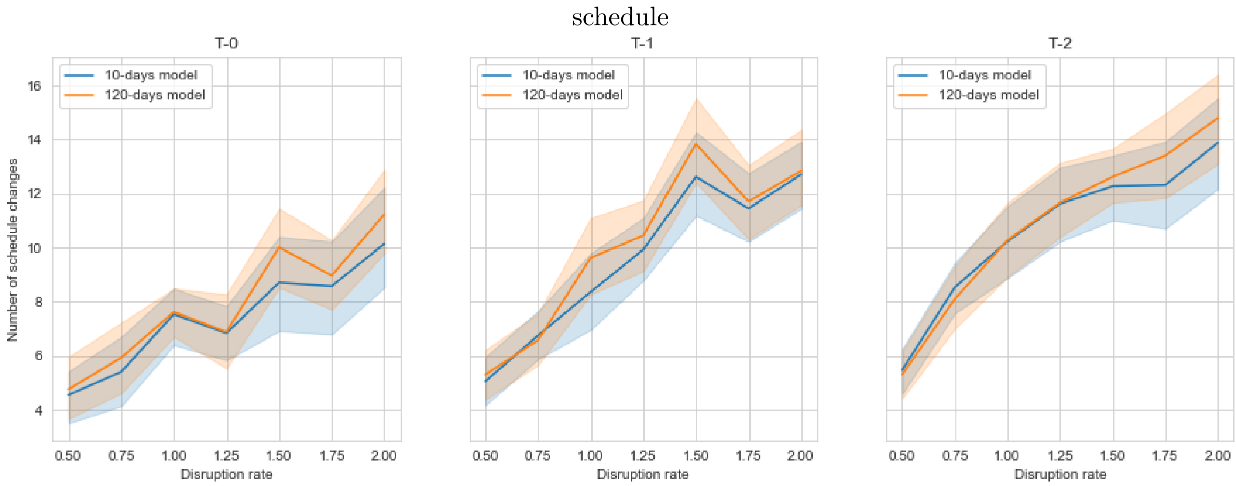

Figure 10: Number of schedule changes for 120-days model and 10-days model for T-0, T-1 and T-2

The difference in terms of schedule changes is provided in Figure 10. As expected, an increase in disruption rate also increases the number of schedule changes. Both the 120-days model and 10-days model show similar trends for all intervals. For T-0 and T-1 the disruption rate is slightly higher for the 120-days model. Since the 120-days model prevents more tasks from going due tasks, this can cause an increase of last-minute schedule changes. Also, for both models the absolute number of schedule changes is very small compared to the length of the scheduling interval (2 months).

The results from this section show that the 120-days model is more stable than the 10-days model as less tasks are going due with similar schedule changes. However, the 120-days model is not able to achieve a decrease in ground time similar to the airline case study. Secondly, the performance of the model with perfect information shows the need for a fine-tuned maintenance schedule. While for the airline case study no tasks were going due, for the stochastic disruption analysis the 120-days model has to let 11.4% of the tasks go due.

6. Conclusions and recommendations

The case study performed on the airline scenario showed that implementation of a model can aid to schedule stability, as both models had less schedule changes compared to the airline case study. Secondly, the case study demonstrated that a slight improvement can be realized in terms of both routine and non-routine task utilization by means of the models. At last, it showed the value of scheduling with a larger horizon, since this results in less due tasks, less ground time, decrease in number of slots and better task utilization.

The value of a 120 day scheduling horizon is further confirmed by the stochastic disruption analysis. With stochastically generated tasks the 120-days model was able to prevent more due tasks compared to the 10-days model. Compared to perfect information, the model was capable of scheduling around 94.6% of the tasks. Based on the model with perfect information it can be concluded from the stochastic disruption analysis that maintenance slots flexibility is required to achieve a decrease in ground time and prevention of due tasks. The stochastic disruption analysis also showed that schedule stability was preserved, by means of limited schedule changes for a range of disruption rates.

Based on the case study, it can be concluded that by means of the 120-days model a 2.95% decrease of ground time can be achieved. For an commercial airline a wide-body aircraft has a potential revenue of €200,000,- per day. The achieved decrease in ground time would result in a yearly €1.29 million of additional potential revenue for the airline case study. With the scope & assumptions of this research, a comparison between the airline schedule and 10-days model shows that there is potential for a further decrease of 17.2% ground time. This equates to an additional €9.10 million revenue. Further research needs to be done to confirm the added benefit by means of live testing.

To conclude, the implementation of a model of task rescheduling with a 120 day scheduling interval can result in a decrease of required ground time and thereby an increase in schedule efficiency. Based on the number of last-minute schedule changes it can be concluded that both models provide more schedule stability. Furthermore, the 120-days model gets rid of uncertainty of task deferral and provides insight in the schedule for both the short- and long-term. At last, it should be noted that both models had a limited number of tasks going due. Therefore, at the current stage of development it is not able to replace manual scheduling.

The results of this research open up possibilities for further research. The stochastic disruption analysis showed that adding slot flexibility is required to prevent to occurrence of due tasks. Expanding the model formulation such that alterations can be made to the slot schedule can prevent the occurrence of unscheduled tasks. The addition of slot flexibility will be a challenge without sacrificing on computational time.

Secondly, the data quality is currently insufficient to fully rely on a model for task scheduling in an airline environment. It is an illusion that data quality will ever reach a level at which task scheduling can take place autonomously. Expertise knowledge is required for task scheduling and therefore user input is one of the key requirements for further model development. User input can also be used to address to problem of slot flexibility in which the user interactively adjusts the maintenance schedule and the model schedules tasks. This should prevent the model from letting tasks go due and the model would add in the decision process by achieving a decrease in required ground time. A cooperation between the model and maintenance scheduler would therefore result in more efficient and stable schedules.

At last, an increase of scope can be addressed in further research. For this research, only non-routine and out of phase routine maintenance which is executed within the hangar is considered. In real practise, line maintenance play are significant role as well as maintenance tasks can be interchanged in between the two. Including line maintenance increases the model flexibility and opens up the opportunity for further operational savings.

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A

Extended methodology

Within this chapter the methodology will be discussed in extended format. First the scope and assumptions will be elaborated. This is followed by an extended explanation regarding the 4M's scheduling requirements and an overview of how scheduling regeneration is achieved. At last two practical model implementations are discussed, with decreasing the model size and reservations for workforce by progressing through time.

A.1. Scope & Assumptions

The scope of this research focuses on non-routine maintenance and out of phase tasks which can't be executed on line maintenance. These tasks arrive irregularly and need to be executed ahead of their due date. Regarding aircraft types the scope is limited to wide body aircraft. A wide body aircraft has at most one ground time interval at the home base per day, where a narrow-body aircraft can have three or more opportunities. Disruptions therefore have a bigger impact on the wide body fleet since these typically have a high utilization and less ground time at the airlines hub.

A.1.1. Maintenance slots

Regarding the allocation of aircraft registrations to maintenance slots, the assumption has been made that there is freedom in the assignment of aircraft registrations to maintenance slots. Therefore, network restrictions are considered out of scope. In reality, some schedule changes might be restricted because of network limitations. Furthermore, maintenance slots can be scheduled in parallel, however the workforce availability is then shared between the parallel maintenance slots.

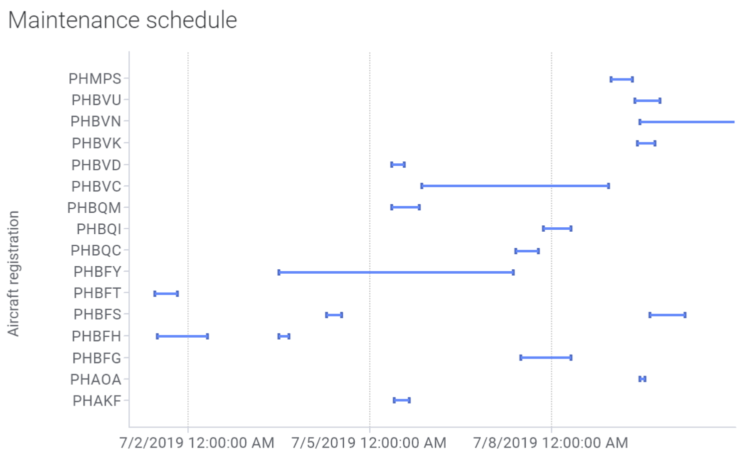


Figure A.1: Example of maintenance slot schedule

As explained in the introduction, airline maintenance scheduling takes place in a dynamic environment. Therefore, maintenance slots also change in duration, both before and after the start of the slot. For this approach, maintenance slots are considered fixed over time. An example of a maintenance slot schedule at which the slots are already allocated to maintenance slots is provided in Figure A.1. For the slot schedule used for the airline case study, the start and end dates are the same as during the start of the slot in reality. Two types of maintenance slots are included within the scope of this research:

- Fixed maintenance slots: These slots consist out of letter checks at which larger maintenance is scheduled. As a result, the aircraft registration is predefined and cannot be changed. Depending on the size of the letter check a fixed number workforce hours can be assigned. The required turn-around time of a task is always assumed to be feasible.
- Flexible maintenance slots: These are slots which are created specifically for non-routine and out-of-phase maintenance tasks. The slots require hangar availability and change dynamically over time. Therefore aircraft registrations can be freely assigned to slots as long as the aircraft type of the maintenance slot matches.

A.1.2. Maintenance tasks

Non-routine maintenance can be subdivided into two sub-categories. There are deferred maintenance tasks which have been found but not solved right away. Secondly, there are non-routine maintenance which are executed right away. These tasks can be reported by the flight crew or they can be found during execution of a maintenance task. For this analysis, only deferred maintenance tasks are considered as these need to be scheduled in a maintenance slot. Faults which are found during the execution of other maintenance tasks are considered out of scope and therefore also don't require any resources in this analysis. At last the arrival of tasks is rounded up to days, since the model is only ran once per day.

A.2. 4M's scheduling requirement

As described by Schut [8], the feasibility of the schedule can be checked by considering, the 4M's requirements for each scheduled maintenance task. The 4M requirement consists of the availability of Material, Machinery, Method and Manpower. In case of airline maintenance, there is also a subdivision of workforce for each required skill level. If all 4M's are available, maintenance can be performed during the scheduled time interval. If not, there is a schedule infeasability and the maintenance task should be rescheduled. Because of a disruption, the 4M availability can change and cause infeasibilities to the maintenance schedule.

The availability of machinery, material and method can directly be obtained from the data. However, there is uncertainty in the arrival date of material and machinery. Within the data it can only been seen if it is currently available or not. However if it is currently not available, there is no indication of future availability. To account for this, the following two assumptions are applied:

- If material is indicated not to be present, the assumption is made that it will be present on the day of actual task execution. Otherwise, the material is assumed to be present starting from the arrival date.
- If machinery is indicated not to be present, the assumption is made that it will be present on the day of actual task execution. Otherwise, the machinery is assumed to be present starting from the arrival date.

To satisfy the manpower requirement is more complicated as there is a discrepancy between the skills of the available workforce skills and the skills required to perform maintenance tasks. In order to check for workforce availability a similar approach as Yang et al. [9] is used. A Linear Program (LP) model assigns workforce to maintenance tasks which aims to meet all maintenance requirements. Each task requires one or more task skills. A mechanic should have the authorization for this task skill to execute the task. However, a mechanic can have the authorization to perform multiple task skills.

Workforce is available 24/7 throughout the weeks. However, the availability of workforce differs per day and shift. Within Figure A.2 the availability of workforce subdivided per task skill level is displayed.

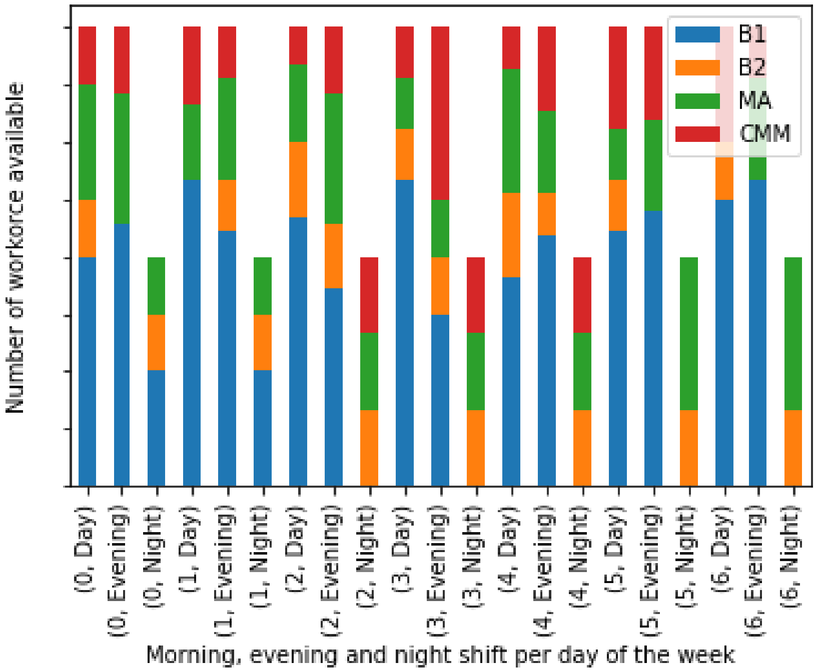


Figure A.2: Number of available workforces subdivided on workforce skill level for shifts throughout the week

To summarize the 4M's requirements are formulated as indicated in Table A.1.

Table A.1: Formulation of **4M** requirements within the analysis

4M's	Explanation
Method	Estimated duration should be smaller than duration of maintenance slot
Machinery	Available for a slot which start after ETA of all required machinery
Material	Available for a slot which start after ETA of all required material
workforce	Workforce of required task skill should be allocated to maintenance slot to satisfy workforce skill requirements.

A.3. Schedule regeneration

In order to be able to come up with a good rescheduling solution, the model needs to be capable of regenerating the original schedule and consider it to be feasible.

In theory, the original schedule should be adhering to the same constraints as the rescheduling model. However, in reality constraints are accidentally violated. This can happen for multiple reasons such as insufficient data quality or one-time exceptions which are allowed by the maintenance facility. For example, in some occasions tasks which require 8 hours of execution were placed in a slot of 6 hours. This can for example be done when the workforce is already familiar with executing this maintenance task. In order to determine exceptions which are granted, constraint violations of the original schedule should be determined. The schedule infeasibilities from the regular schedule are provided to the rescheduling models as allowed constraint violations. The verification process is visualized in Figure A.3. The regular maintenance schedule check is running separately from the rescheduling model. The output of the schedule check is provided as input for the rescheduling model.

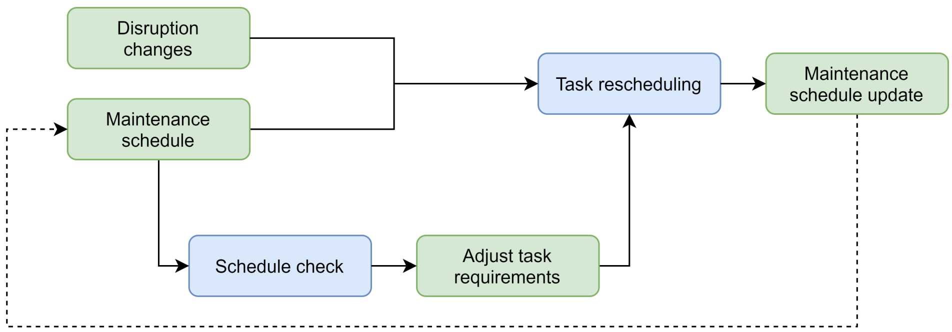


Figure A.3: Flow of maintenance task rescheduling

Schedule infeasibilities can come in the form of 4M's or due date violation. The due date, machinery, method and material constraints can be evaluated independently from each other. For manpower this is not an option as maintenance slots can run in parallel. The available workforce can therefore be allocated to one of the two slots. To check for workforce availability a MILP is created which is explained more elaborately in the following subsection.

A.3.1. Workforce shortage model

The workforce model is a stripped-down version of the rescheduling which aims to minimize the shortage of workforce in the current schedule. The task allocation to maintenance slots is fixed and is equal to the original schedule. Within the model, workforce can be assigned to maintenance slots per time block of 30 minutes. If there are multiple maintenance slots scheduled in parallel, a subdivision of allocated workforce can be made. Workforce can only be allocated to a maintenance slot and skill up until the required amount of workforce for that slot.

Sets

There are four sets of variables of the workforce model. The first set consist of the maintenance slots in which tasks are scheduled. Currently the duration of a single time block is set to 30 minutes. A slot is set to be active during a time block if the start time of the time block is between the start time and end time of the maintenance slot.

For required skills there are two different kinds of sets. The first set consists of all task skill variables. Within this set all skills are included which can be required to execute a maintenance task. The other set consists of the workforce skills. Each workforce skill level is allowed to execute several task skills. Some task skills can only be executed by external workforce. Since the availability of external workforce is not known, this can't be solved during the workforce check. Therefore, the allocated workforce for a task skill which can only be executed by external workforce is set to 0 and will therefore form a shortage.

Table A.2: Sets for workforce shortage model

Sets	Explanation
$ts \in TS$	Set of skills required for tasks
$ws \in WS$	Set of workforce skills
$t \in T$	Set of time blocks within the current schedule interval
$t \in T_s$	Subset of time blocks which during maintenance slot s ($T_b \subset T$)
$s \in S$	Set of maintenance slots within the current schedule interval
$s \in S_t$	Subset of maintenance slots active at time interval t ($S_t \subset S$)

Parameters

Within the workforce model there are two parameters. One is the availability of workforce for each combination between time block t and each workforce skill ws. Secondly, there is the required workforce for all combinations between maintenance slots s and task skills ts. These values are determined based on a summary made of the tasks scheduled within a maintenance slot.

Table A.3: Parameters for workforce shortage model

Parameters	Unit	Explanation
$Wav_{t,ws}$	Hours	Workforce available from at time t of workforce skill ws
$Wreq_{b,ts}$	Hours	Workforce required for slot s of task skill ts

Decision variables

The rescheduling model is stripped down such that there are only two remaining decision variables in the model formulation. They are provided in Table A.4. First decision variable is the assignment of available skilled workforce to task skill requirements of a maintenance slot. Second decision variable is the shortage of task skills for each maintenance slot. Both variables are modelled as positive continuous variables.

Table A.4: Decision variables of rescheduling model

Decision variable	
$\text{WA}_{b,t,ts,ws}$	Assigned workforce to maintenance slot s, at time t for task skill ts of workforce skill ws
$\text{WS}_{b,ts}$	Shortage of workforce for slots s of task skill ts

Objective function

The objective is to minimize the shortage of hours of task skills ts for each maintenance slots s. If there are no schedule infeasibilities, then the objective function is equal to 0. Within the model all maintenance shortages are weighted equally. It could be the case that some task skill or slot has a higher priority. This can easily be added to the model formulation but is currently left out of scope. The objective function is therefore formulated as following:

$$\min \sum_{b\in B} \sum_{ts\in TS} WS_{b,ts} \tag{A.1}$$

Subject to

$$\sum_{s\in S_t} \sum_{ts\in TS_{ws}} \text{WA}_{b,t,ts,ws} \leq \text{Wav}_{t,ws} \qquad \forall ws \in WS, t \in T \tag{A.2}$$

$$\text{WS}_{s,ts} + \sum_{t\in T_b} \sum_{ws\in WS_{ts}} \text{WA}_{s,ts,ws,t} = \text{Wreq}_{s,ts} \qquad \forall s \in S_{Flexible}, ts \in TS_s \tag{A.3}$$

$$\text{WA}_{s,t,ts,ws} \in \{0, \mathbb{R}+\} \qquad \forall s \in S, \forall t \in T, \forall ts \in TS, \forall ws \in WS \tag{A.4}$$

$$\text{WS}_{s,ts} \in \{0, \mathbb{R}+\} \qquad \forall s \in S \forall ts \in TS \tag{A.5}$$

The constraint provided in Equation A.2, guarantees that the allocated workforce of workforce skill ws during time block t cannot exceed the available workforce for that skill & time combination. Secondly, the constraint given in Equation A.3 forces that the allocated workforce for maintenance slot and task skill meets the required number of workforce hours. If not, this will be registered as workforce shortage. Based on the workforce shortage in the regular schedule, the task workforce requirements are adjusted as described in the following subsection.

A.3.2. Task alteration

Based on the schedule infeasibilities which occur in the actual schedule, the properties of tasks need to be altered. The output provided by the model described in subsection A.3.1 indicates a shortage of workforce per maintenance slots s and task skill ts. In case of a shortage, all tasks g scheduled within maintenance slot s and requiring ts are updated as following:

$$\text{Workforce}_{g,ts\,\text{new}} = \text{Workforce}_{g,ts\,\text{or}} \cdot \frac{\text{WS}_{s,ts}}{\text{Wreq}_{s,ts}} \tag{A.6}$$

Where $\text{WS}_{s,ts}$ is the workforce shortage and $\text{Wreq}_{s,ts}$ is the required workforce for maintenance slots s and task skill ts. Besides a shortage in workforce there can also be a constraint violation in any of the other 4M's requirements or due date restrictions. If a task violates the constraint regarding due date, machinery availability or material availability this is considered as an infeasability. The task slot combination of the original schedule is considered to be feasible scheduling option as an exception.

If the method constraint is violated for a task, this means that the prescribed TAT to execute the task is larger than the duration of the maintenance slot. In this case the required TAT is adjusted to the duration of the maintenance slot, such that the task can also be placed in another maintenance slot of equal or longer duration. The required TAT of a task is adjusted during the schedule check by taking the minimum value out of the scheduled duration and the slot duration:

$$\text{TAT}_{\text{new}} = \min(\text{TAT}_{or}, \text{Duration}_s) \tag{A.7}$$

A.4. Decrease model size

In order to decrease the problem size, and model creation time, only decision variables are created if they are feasible. Especially the assigned workforce variables can really become extensive in the number of variables, since it is including every combination between four sets. To decrease the number of variables Algorithm 1 can be used at which only workforce assignment variables are created which are feasible. This means that a decision variable will only be created if a maintenance slot s is active at time block t and that workforce skill ws is allowed to perform task skill ts. There is a slight difference in the algorithm between the schedule check model and the rescheduling model. For the schedule check there is an additional requirement in which task skill ts should be required by at least one task scheduled within maintenance slot s. For the rescheduling model the variable is created for every task skill ts, since it is unknown which tasks will be scheduled in a maintenance slot. For the rescheduling model the logic is provided in Algorithm 2.

For the rescheduling model the problem size can be decreased further by adding only feasible rescheduling possibilities. Constraints (22) in the Thesis paper forces that all infeasible decision variables

Algorithm 1 Creation of workforce assignment variables - [Schedule check]

```
for each maintenance slot s do:
    for each time block t of which the start time is between the start and end time of block s do
        for each maintenance task skill ts required for tasks within slot s do:
            for each workforce skill which can perform ws do:
                Add variable MA_{b,t,ts,ws} to model
```

Algorithm 2 Creation of workforce assignment variables - [Rescheduling model]

```
for each maintenance slot s do:
    for each time block t of which the start time is between the start and end time of slot s do:
        for each maintenance task skill ts do:
            for each workforce skill which can perform ws do:
                Add variable MA_{b,t,ts,ws} to model
```

should be equal to zero. However, since it is already known upfront whether a decision variable is feasible or not, they can already be omitted during the model creation. Constraints (22) of the model formulation in the paper no longer has to be added to the model. For the model this yields in a significant reduction of the model creation and solving time. Regarding task allocation to maintenance slot there are only combinations provided which are feasible according to the due date, arrival date, machinery, method, material and aircraft type constraints.

A.5. Workforce reservations

Maintenance slots can have durations of multiple days, depending on the required turnaround time of the scheduled tasks. During maintenance scheduling, not only tasks scheduled in the future should be considered. Task scheduled in the past can also have their influence on the current day of operation. The execution of tasks requires the allocation of workforce. In case of maintenance slots with multiple days of duration, task scheduled in the past can require part of the available workforce capacity of the current day of operations. Once a maintenance slot is started the allocation of workforce and task to slots is considered final. If a slot requires workforce in the second day of the slot, a reservation is placed in the workforce availability for the days to come. This prevents the model from using the same workforce multiple times.

B
Model verification

The verification performed in this chapter, serves as a way to verify whether the model is implemented correctly and behaves as expected. The verification is split up in two parts. First the model is verified whether it is capable of regenerating the original schedule. Secondly, the model is verified by means of disruption scenarios. In collaboration with a European airline, a set of disruption scenarios is provided to see if the model makes the correct schedule adjustments.

B.1. Schedule verification

For this research data are provided by a commercial airline and thereby the original schedule executed during 2019 can be obtained. As explained in section A.3, the original schedule should be considered as being feasible. The first step in the verification procedure is therefore to verify whether the rescheduling model is capable of regenerating the original schedule without any constraint violations.

Within this section a comparison will be made between the airline schedule and a model with perfect information. As both schedules receive identical inputs the rescheduling model with perfect information should produce identical or better results compared to the airline schedule. The verification of results is performed on the airline schedule which runs from 01-07-2019 till 01-09-2019. Inputs for the model are the tasks executed within the time interval, the used maintenance slots and the workforce availability per shift subdivided on skill level.

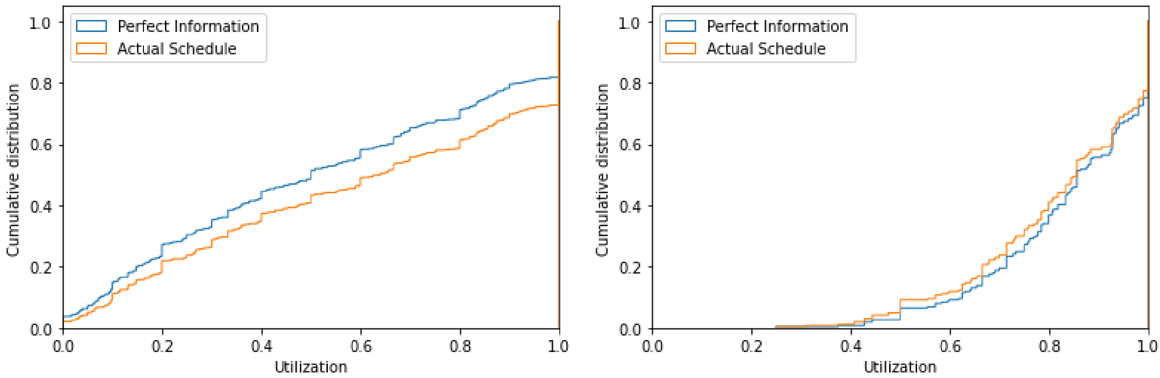
Table B.1: Rescheduling model verification with comparison between regular schedule and model output

Scenario	Number of tasks	Number of slots	Ground time
Airline schedule	1682	202	1904.3 Hours
Perfect information	1682	197	1797.55 Hours

The scheduling results for the airline schedule and the perfect information model are provided in Table B.1. It can be concluded that the model is indeed able to schedule all tasks without any constraint violations. Secondly, the model is also able to achieve a slight decrease in required ground time and number of maintenance slots. The improvement in performance is also confirmed by an improvement in task utilization for the model compared to the airline schedule. The results for this are shown in both Figure B.1 and Table B.2. The model is capable of scheduling non-routine tasks earlier in their interval, while for routine maintenance tasks it is able to schedule them slightly closer to the due date. This results in an increase of interval utilization for routine maintenance tasks and results in the long-run in less maintenance interventions.

Scenario	Non-routine utilization	Routine utilization
Airline schedule	0.596388	0.820214
Perfect information	0.522424	0.838194

Table B.2: Rescheduling model verification with comparison between regular schedule and model output



(a) Non-routine maintenance tasks

(b) Routine maintenance tasks

Figure B.1: Cumulative distribution plot interval utilization

At last, the utilization of each task type is provided in Table B.3. It can be seen that the utilization numbers of task types with a high value for $W_{Type,g}$ result in slightly higher utilization numbers. This can be concluded by comparing MEL C tasks with NSRE 10 and MEL D with NSRE 120. Both tasks have an identical interval but differ in criticality. Tasks with a higher criticality are scheduled first. This is as expected since the model gives priority to scheduling tasks with a higher priority. It can also be seen that tasks with a larger schedule interval achieve the best utilization numbers. As there are more scheduling opportunities for tasks with a larger interval it is also as expected that they can be scheduled more optimally with respect to their interval.

Table B.3: Task utilization subdivided on task type

Task type	Utilization	$W_{Type,g}$	Interval (days)
Routine	0.84	4	-
MEL A	0.69	4	1
MEL B	0.74	4	3
MEL C	0.52	4	10
MEL D	0.24	4	120
Adhoc	0.53	2	-
NSRE 5	0.68	1	5
NSRE 10	0.68	1	10
NSRE 20	0.51	1	20
NSRE 120	0.35	1	120
NSRE Man	0.37	1	-

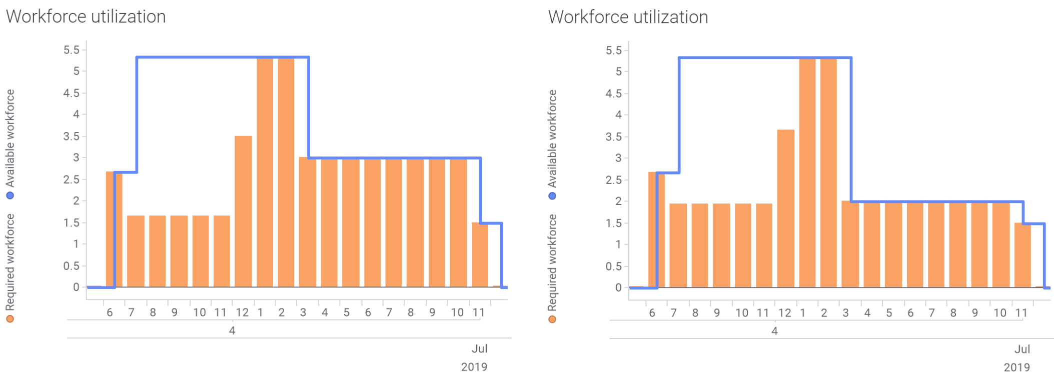
B.2. Disruption analysis

Airlines operate in a disruptive environment. Because of disruptions maintenance slots schedules need to be adjusted continuously and new tasks arrive irregularly. In order to implement the model for maintenance task scheduling, it needs to be verified whether it takes the correct decisions at the occurrence of disruptions. A set of disruption scenarios has been set up which occur during commercial airline operations. The disruption scenarios can be divided in three categories: slot changes, task changes and 4M's availability changes. For each of those categories one or more specific disruption scenarios is provided:

1. Slot changes
   - 1.1. Cancellation of maintenance slot
   - 1.2. Decreasing duration of maintenance slot
   - 1.3. Merge two maintenance slots together as one
   - 1.4. Rescheduling maintenance slot from day to night
2. 4M's availability changes
   - 2.1. A decrease in B1 workforce availability
3. Task changes
   - 3.1. Addition of task on aircraft registration with scheduled maintenance slot
   - 3.2. Addition of task on aircraft registration without scheduled maintenance slot
   - 3.3. Addition of task on aircraft registration in between two scheduled maintenance slots

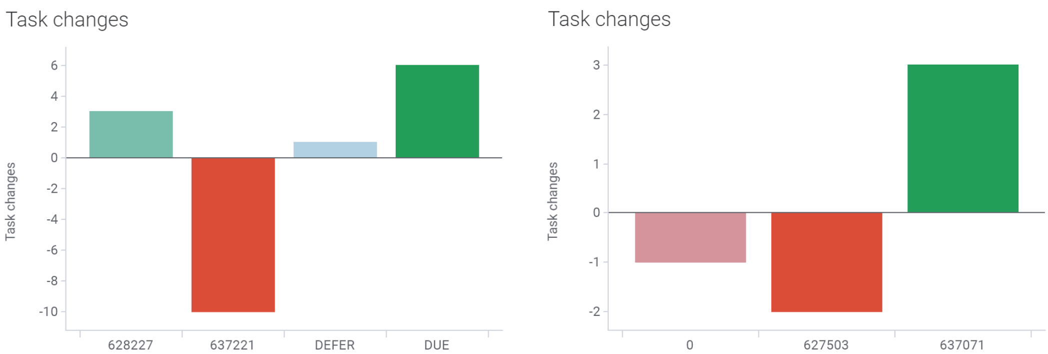
Within the disruption verification scenarios there is little scheduling flexibility as the scheduling horizon only runs over a period of one week. Therefore, there are only between 2 and 5 maintenance opportunities for each aircraft type. A single disruption is therefore likely to cause a task going due or deferral. The scenarios provided in this chapter therefore only serve as a way to verify whether the decision making is as expected. The results of the disruption scenarios are presented in Table B.4. Within the disruption scenarios only a change in workforce availability is considered out of the 4M's requirements. However the other requirements have still been verified by means of unit test which are not provided in this report. Secondly, the influence of the machinery and materials constraints is further verified in section D.2 by means of constraint relaxation.

Within Table B.4 the model solution is provided for disruption scenarios as defined in the enumeration above. Each of the scenarios runs from 01-07-2020 till 10-07-2020. In the experiments column a short description is provided of the disruption which is provided to the model. For each disruption the number of task changes, block changes, task deferral and due tasks is provided together with a short-written explanation of this disruption. In Figure B.2 the allocated workforce with respect to the available workforce is displayed, for experiment 2.1. In Figure B.3 task rescheduling is displayed for two disruption scenarios. A green bar (positive) denotes an increase in the number of tasks allocated to maintenance slots or number of due or deferred tasks. A red bar (negative) denotes a decrease in total number in one of those categories. For each scenario, the total numbers indicated by the red and green bars should equal each other.



(a) Before disruption (b) After disruption

Figure B.2: Effect on workforce scheduling after capacity decrease



(a) Slot cancellation (b) Task rescheduling because of task arrival

Figure B.3: Visualization of task rescheduling because of disruptions

The outcome of the disruption scenarios has been verified with maintenance schedulers from a commercial airline. Hereby it is acknowledged that the rescheduling solutions provided by the model are both logical and feasible.

Table B.4: Verification of individual disruption scenarios

Experiments	**Task changes**	**Block changes**	**Deferred tasks**	**Due tasks**	**Model solution**
1.1: Maintenance slot cancellation on 07-07-2019	12	0	1	6	5 tasks can be placed in a fixed maintenance slot on 02-07-2020. To make space for these tasks one NSRE task is deferred from this maintenance slot. Furthermore, 6 tasks go due as no suitable replacement slot is available The results of task rescheduling are displayed in Figure B.3a
1.2: Shortening of maintenance slot duration from 8 to 6 hours	1	0	1	0	Within this maintenance slot a task was scheduled with a required TAT of 7 hours. Since the execution of this task is no longer feasible this task is deferred.
1.3: Merger of two maintenance slots on 07-07-2019	22	2	4	7	One of the aircraft remains attached to the slot, while for the other aircraft registration some tasks can be placed in in a maintenance slot of 02-07-2019. However, this slot does not meet the scheduling requirement for all tasks and therefore 7 tasks go due.
1.4: Change of start and end date of maintenance slot from 09:00 till 14:00 to 00:00 till 05:00	1	0	0	1	During the night there is no workforce availability for workforce skill B1. Since the execution of task requires the B1 workforce skill, this task can no longer be scheduled in this maintenance slot and is registered as due.
2.1: B1 workforce availability for the evening shift on 04-07-2020 is change from 3 till 2	0	0	0	0	As can be seen in Figure B.2a all available B1 workforce of the afternoon shift was originally allocated. The decrease in availability causes the allocated workforce to shift to the morning shift as can be seen in Figure B.2b. Therefore, no task rescheduling is required.
3.1: Task arrival on 01-07-2019	1	0	0	0	For the same aircraft registration there was already a scheduled slot for 05-07-2020, the task is added to this slot.
3.2: Task arrival on 05-07-2019	0	0	1	0	There are no scheduling possibilities for this task. Because of the remaining interval outside of the scheduling horizon the task is registered as deferred.
3.3: Task arrival on 03-07-2019	4	0	0	0	The task is placed in a fixed maintenance slot on 08-07-2019. As a result, the workforce requirements maintenance slot now exceeds the available capacity. This causes three routine maintenance tasks to be brought forward to a maintenance slot on 01-07-2019. The task changes are also visualized in Figure B.3b

C
10-days model development

The 10-days model has been included in the results analysis of the paper to indicate the difference between long-term and short-term scheduling. Extensive effort has been put in the development of the 10-days model as the goal is to achieve an increase in schedule efficiency and robustness. For the 10-days model there are two main differences with respect to the 120-days model. One is the option to defer tasks instead of scheduling. The addition of the deferral action is explained in section C.1. Secondly, the aircraft cleanliness constraint is added to the model formulation. The influence of this constraint is elaborated upon in section C.2.

C.1. Defer cost estimation

For the 10-days model the interval of maintenance task scheduling is set to 10 days. This is similar to the horizon currently used for manual scheduling within airlines. For short term maintenance tasks such as Cat B faults this is not a problem since the tasks due date lies within the current scheduling interval. However, for less critical tasks, such as Cat D faults (120 days), there is also an option to perform maintenance outside of the current scheduling interval. In this case, the model has to choose between scheduling now or deferring an item to execute it at a later stage. Deferring an item adds uncertainty to the scheduling process as it is not guaranteed that a task can be executed. To make matters more complex, for recurring maintenance tasks it can actually be favorable to defer a task by aiming to increase the task interval utilization. Deferring maintenance also brings in an extra risk. If in the upcoming days, there will be no opportunity to schedule the task it will eventually go due.

In the remaining part of this section several defer cost estimation methods will be discussed. This is concluded by a quantitative comparison between the estimation methods, provided in subsection C.1.4

C.1.1. Average upcoming task scheduling objective

Even though the 10-days model only schedules for a period of 10 days, it is able to evaluate the maintenance slots schedule for an interval of 120 days. Based on the task characteristics, feasible future slots are determined. If a slot is feasible then the scheduling objective in terms of utilization for this slot can be calculated by Equation C.1 and Equation C.2 for non-routine and routine maintenance tasks respectively.

$$W_{\mathrm{UTIL}} = \frac{\mathrm{Start}_s - \mathrm{Arrival}_g}{\mathrm{Due}_g - \mathrm{Arrival}_g} \tag{C.1}$$

$$W_{\mathrm{UTIL}} = 1 - \frac{\mathrm{Start}_s - \mathrm{Arrival}_g}{\mathrm{Due}_g - \mathrm{Arrival}_g} \tag{C.2}$$

Based on the feasible maintenance slots outside of the current scheduling interval, the average scheduling objective is taken as deferral cost. Since the expectation is that the maintenance task will be scheduled, the expected scheduling cost should equal the average scheduling objective. If there are no feasible scheduling opportunities in case of deferral, the defer cost should equal the cost of letting a task go due.

$$W_{\text{DEFER}} = \begin{cases} \text{Mean}(W_{\text{UTIL}}), & \text{if Opportunities} \geq 1 \\ W_{\text{DUE}}, & \text{otherwise} \end{cases} \tag{C.3}$$

C.1.2. 90% interval upcoming task scheduling objective

This defer cost estimation method is a variant of the defer method provided in the preceding subsection. For the method described in the previous section only the average objective function value was included. However, once a task comes closer to its due date, the risk increases that a task eventually goes due. Within this approach, once a task exceeds a utilization of 90%, a defer penalty is activated. This penalty is half of the due penalty (10^8) and therefore discourages to exceed the task utilization above 90%. W_{DEFER} is therefore defined as following.

$$W_{\text{DEFER}} = \begin{cases} \text{Mean}(W_{\text{UTIL}}), & \text{if Utilization} < 0.90 \text{ and Opportunities} \geq 1 \\ W_{\text{DUE}}, & \text{Utilization} \geq 1 \\ \frac{1}{2} W_{\text{DUE}}, & \text{otherwise} \end{cases} \tag{C.4}$$

C.1.3. Myopic policy

With the myopic policy all tasks are aimed to be scheduled as quick as possible. Therefore, a high scheduling penalty is set on deferring a task. If the model is able to schedule the task within the current interval it will do so. If not, there is only a distinction between a task going due after deferring or not. For the myopic policy the deferral cost is therefore formulated as following:

$$W_{\text{DEFER}} = \begin{cases} W_{\text{DUE}}, & \text{Utilization} \geq 1 \\ \frac{1}{2} W_{\text{DUE}}, & \text{otherwise} \end{cases} \tag{C.5}$$

C.1.4. Results

In Figure C.1 the results are provided for the deferral methods described above. As expected, the myopic policy results in the lowest number of due tasks. Since all tasks are encouraged to be scheduled as soon as possible this leads to less tasks going due. The consequences of this policy are also clearly visible in terms of the number of ground time and task utilization, provided in Figure C.2. The required ground time is significantly higher and the utilization decreases for both types of tasks. For non-routine this is beneficial however for routine maintenance a utilization of 65% requires routine tasks to be executed more often and consequently also requires more ground time.

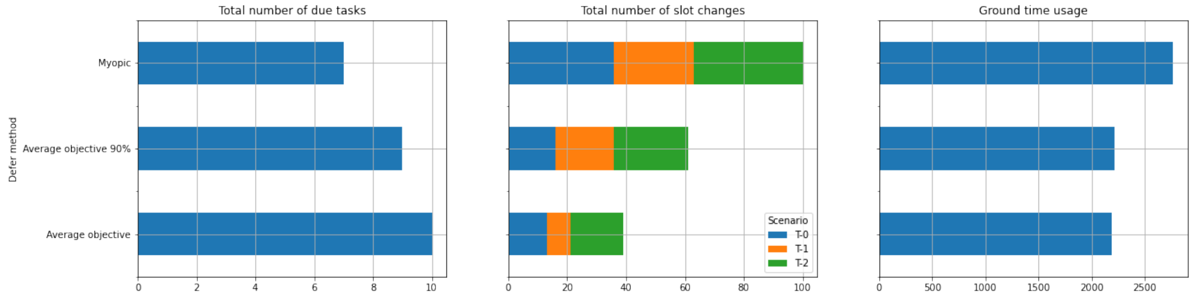


Figure C.1: Number of due tasks, schedule changes and ground time usage for different deferral methods

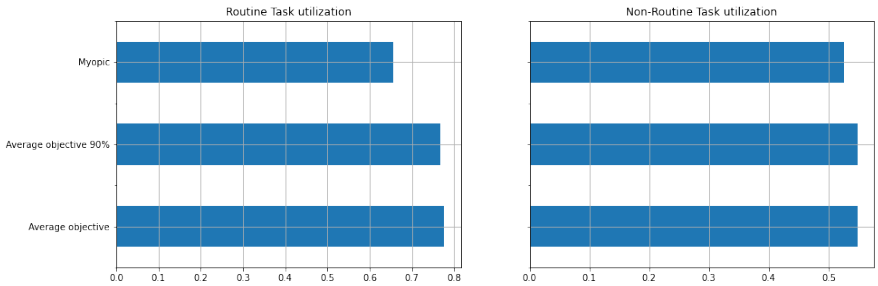


Figure C.2: Task utilization of routine and non-routine maintenance tasks for different deferral methods

A comparison between the average scheduling objective defer strategy and the strategy with the additional penalty for utilization above 90% shows some interesting differences. The addition of the penalty for exceeding 90% of task utilization causes one task less to go due. Besides this, it was also expected that this policy would greatly impact the task utilization numbers. However as shown in Figure C.2, the utilization for both routine and non-routine tasks decrease by only less than 1%. The addition of the 90% penalty does increase the number of schedule changes over 50% from 39 to 61. At last, also the required ground time increases by a slight amount. Preventing one task from going due does not weigh up to these consequences. As a result, the regular average task scheduling objective is chosen as defer cost estimation method.

C.2. Aircraft clean constraint

The aircraft clean constraint has been added to the 10-days model to prevent the postponement of tasks at the cost of better utilization rates. In some cases, it is better to sacrifice task utilization by bundling maintenance tasks together into one maintenance slot. If those tasks are not bundled together, they need to be executed in separate maintenance slots which likely results in more ground time. For the 10-days model the aircraft cleanliness constraint is therefore added. This constraint aims to prevent deferring tasks from going due, within the predefined number of clean days after the current model interval end date. Secondly, it also aims to limit required ground time after the current scheduling period. An aircraft registration is considered “clean” if there are no deferred tasks within the clean days target interval. This is also visualized in Figure C.3. If a task is deferred within the clean days target interval, the aircraft clean penalty is activated for that aircraft registration. Within section 4.4 of the paper a target for the number of clean days was set to 10. Within this section several clean day targets are evaluated, and support is provided for a target of 10 days. Based on the requirements given above, the aircraft clean constraint is formulated as following:

$$\sum_{g \in G_r} T_{g,\text{Defer}} * \text{Within clean days due}_g <= \text{Max-Tasks} \cdot (1 - \text{AC}_{\text{clean},r}) \qquad \forall r \in R \qquad \text{(C.6)}$$

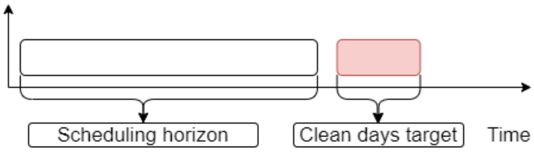


Figure C.3: Illustration of clean days objective

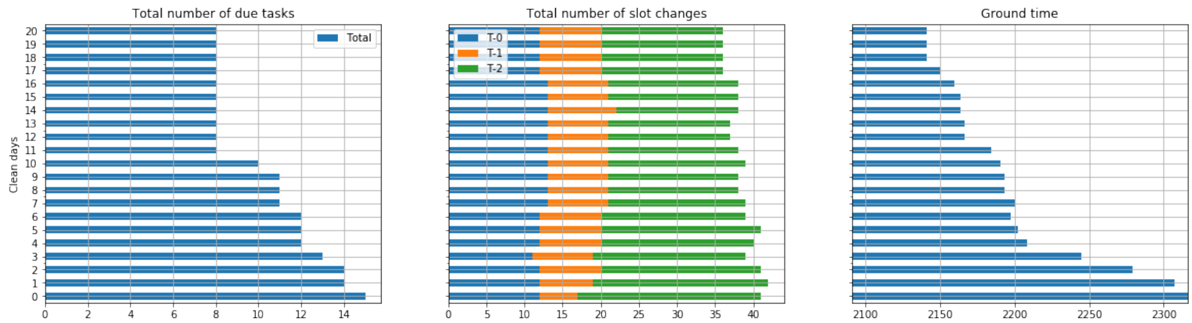
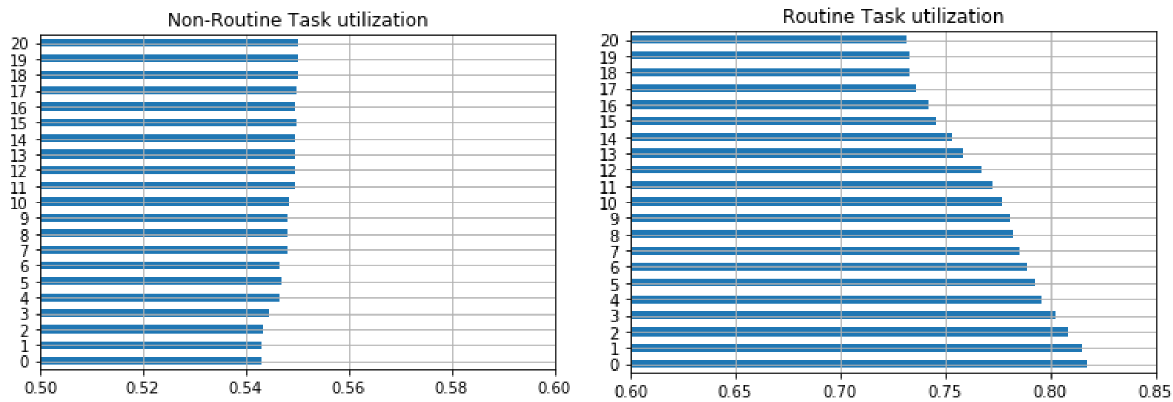


Figure C.4: Effect of aircraft clean constraint on number of due tasks, schedule changes and ground time.

In Figure C.4 the number of due tasks, last-minute slot changes and ground time used is illustrated for a range of clean day targets. It can be seen that by increasing the clean days target, this causes a decrease in both number of due tasks and ground time used. Both of these decreases are as expected since it becomes less attractive to defer tasks with the aim of improving interval utilization. As expected, the decrease in due tasks and ground time goes at the cost of a deterioration of routine task utilization. This is visualized in Figure C.5b. Since task deferral becomes more restricted routine tasks are scheduled earlier which results in lower utilization rates. Secondly, it also results in a slight increase of non-routine task utilization, as shown in Figure C.5a. As less ground time is used and thereby also less maintenance slots the schedules become more compact which causes a slight deterioration of routine task interval.



(a) Non-routine task utilization

(b) Routine task utilization

Figure C.5: Effect of aircraft clean constraint on task utilization

With an increasing number of target clean days, it is expected that this would cause a decrease in the number of deferrals. Since there is a penalty for deferral of tasks which go due within the clean day limit. This phenomenon is confirmed by Figure C.6 which shows a decreasing trend of task deferral by increasing the clean day target. At last, Figure C.7 shows the total number of schedule changes as a function of the target clean days. Where in Figure C.4, the last-minute schedule changes showed to be mostly constant, there is an increasing number of schedule changes between T-3 and T-10. As the number of task deferrals decreases, the slot schedule becomes more congested. This is due to the fact that tasks are more often scheduled right away. A congested schedule is more likely to result in more schedule changes to satisfy each of the task requirements.

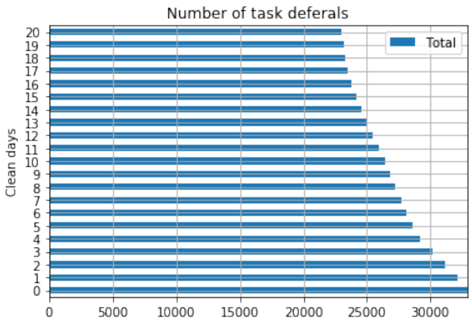


Figure C.6: Effect of aircraft clean constraint on number of task deferrals.

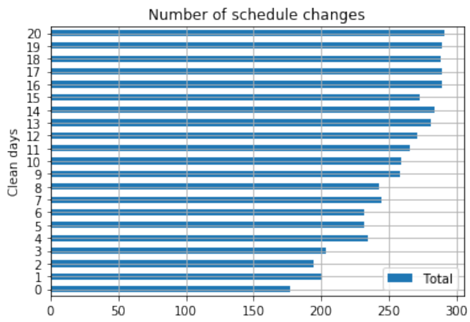


Figure C.7: Effect of aircraft clean constraint on number of schedule changes

Based on the expertise knowledge of maintenance schedulers within the commercial airline, the target for number of clean days is set to 10. Even though the results in Figure C.4 might give the impression that a higher value is better because of a decrease in due tasks and a decrease in required ground time. There are two downsides of increasing the target of number of clean days further:

1. An increase in the number of target clean days results in a lower routine task utilization. This means that routine tasks will have to be executed more often throughout the year and consequently also requires more ground time. Since the repetitive occurrence of routine tasks is considered out of scope for this research, this effect is not visible in the figures above.

2. As can be seen in Figure C.7, increasing the target due date results in more overall schedule changes. This causes a decrease in the schedule robustness and also causes more uncertainty for the schedule in the coming days.

C.3. Performance trade-off

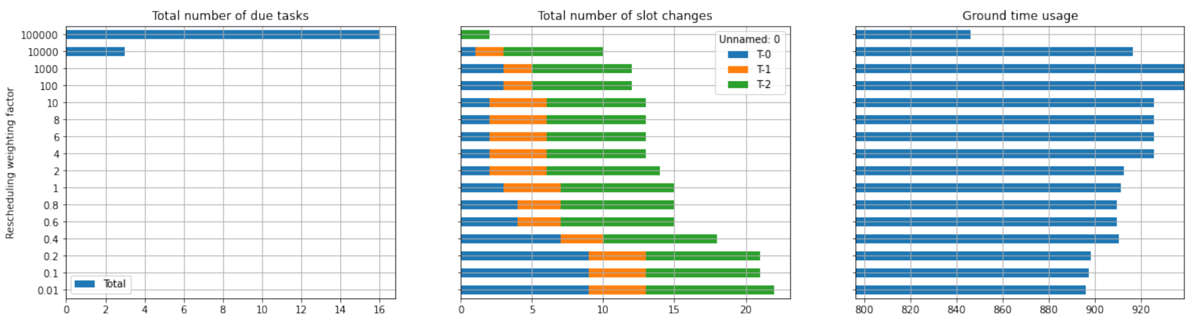


Figure C.8: Number of due tasks, schedule changes and ground time for several values of W_{Res} with limited interval analysis

Similar to the analysis provided in section 5.2 of the paper, an analysis is performed on the relation between minimization of ground time and prevention of schedule changes for the 10-days model. The relation between the two scheduling objectives can be fine-tuned by varying the value of W_{RES}.

The results of this analysis are shown in Figure C.8. Overall, the results between the 120-days model and 10-days model are very similar. By increasing W_{RES} beyond values of 10000, the prevention of due tasks is sacrificed by the prevention of schedule changes. In consult with the commercial airline, a value of 0.6 is chosen for W_{RES} since this yields in a decrease of last-minute schedule changes with a limited increase of required ground time.

Table C.1: Number of due tasks, schedule changes and ground time for the 120-days model and 10-days model for chosen parameter of W_{RES}

Scheduling method	W_{Res}	**Due tasks**	**Schedule changes**	**Ground time**
120-days model	0.4	0	15	865 Hours
10-days model	0.6	0	15	908 Hours

In Table C.1 the schedule results are provided for the chosen value of W_{RES} of both the 120-days model and 10-days model. The rescheduling weighting factor for the 10-days model is 0.2 higher which means that making schedule changes in the 10-days model is more expensive than for the 120-days model. As a result, both the 120-days model and 10-days model require 15 schedule changes. However, the 120-days model is able to achieve this with less ground time.

D
Sensitivity analysis

Within this section the model sensitivity is evaluated based on variations of model objectives, constraints and assumptions. Within section 5.2 of the paper the sensitivity of the model on a variation of rescheduling cost has been already evaluated. Furthermore section 5.4 of the paper showed the model sensitivity based on a variation of disruption loads. In this chapter several other sensitivity analyses will be performed. First the influence on the assumption task arrival will be provided in section D.1. This is followed by a sensitivity analysis on a couple of model constraints. The model referred to in this chapter is the 120-days model. The 10-days model will show similar results and IS therefore not presented.

D.1. Task arrival sensitivity

A limitation to the results analysis provided in the paper is that the model performance is only evaluated by scheduling once a day for a scenario. This deviates from the airline scheduling method in which rescheduling takes place continuously throughout the day (disruptive scheduling). Every time a disruption occurs the schedule is adjusted to gain back schedule feasibility. For the results presented in the paper, increasing the schedule flexibility beyond once a day would result in computational times which were not feasible for the scope of this research.

Mostly, there will not be a performance impact between daily scheduling and disruptive scheduling. However, one of the downsides of daily scheduling is that part of the solution space is removed for the allocation of tasks to slots. If a task arrives at 03:00 in the morning there could be a scheduling opportunity at 15:00 in the afternoon for disruptive scheduling. For the model, the task will be added to the backlog on the next day. This means that the scheduling opportunity on the day of task arrival isn't available anymore.

To evaluate the performance influence of this model limitation, a variation to the model has been made. The model is adjusted such that there is perfect information for the day to come. In the example given above the model thereby is able to make use of the first scheduling opportunity. The model performance in case of disruptive scheduling will be in between the result of the model and the model with a daily perfect information.

D.1.1. Case study

The results for the daily perfect information model and the model are provided in Table D.1, D.2 and D.3. As can be seen in Table D.1, the daily perfect information model achieves a decrease in the number of due tasks with respect to the model. Also, in terms of ground time the results improve by making use of daily perfect information. In terms of ground time the daily perfect information model requires only 2.93% more ground time than perfect information as opposed to 6.68% for the model. A closer look at the taskS which go due reveals that one of the due tasks arrives 2 days before the end of the analysis interval, while it has only one scheduling opportunity. In reality this task would have 18 days of interval left at which it is very likely that there would be a suitable scheduling opportunity.

Table D.1: Number of due tasks and ground time usage for model and daily perfect information model

Schedule method	Due tasks	Scheduled tasks	Number of slots	Ground time
Airline schedule	0	2549	475	2645.58 Hours
Perfect information	0	2549	451	1992.60 Hours
Daily perfect information model	2	2547	462	2051.08 Hours
Model	5	2544	469	2125.75 Hours

Table D.2: Number of schedule changes close to the day of operation for model and daily perfect information model

Schedule method	T-0	T-1	T-2
Airline schedule	24	25	22
Daily perfect information model	6	8	9
Model	12	10	16

Regarding schedule changes counter intuitive results are obtained. Since the daily perfect information model provides only extra scheduling opportunities for the day of operation, the expectation was that this would result in an increase of last-minute schedule changes. However, as can be seen in Table D.2 the schedule actually becomes more robust with less schedule changes in any of the intervals. A potential explanation for this is that the model with daily perfect information has a slightly larger interval to schedule tasks and is thereby more robust to task disruptions.

Table D.3: Task utilization for model and daily perfect information model

Schedule method	Routine utilization	Non-routine utilization
Airline schedule	0.760	0.561
Perfect information	0.778	0.534
Daily perfect information model	0.769	0.535
Model	0.773	0.546

Regarding the task interval utilization the results are very close to each other. Interestingly, the utilization results of the daily perfect information model improves of non-routine maintenance tasks and deviates only 0.001 from perfect information. For routine tasks, the utilization rate becomes slightly worse with respect to both perfect information and the model. These changes in utilization are due to the fact that with daily perfect information only scheduling opportunities are added with very low utilization numbers. As a consequence, the utilization decreases for both task types.

D.1.2. Stochastic disruption analysis

With daily perfect information the performance on the stochastic disruption analysis also improves. Figure D.1 shows that a decrease in number of due tasks can be achieved with respect to the regular model performance. The performance is similar to the daily perfect information as the number of due tasks is closer to the performance with overall perfect information. In terms a ground time each of the three models show very similar trends and the in term of ground time there is a minimal difference.

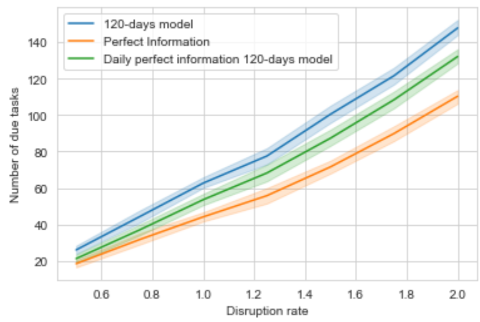


Figure D.1: Number of tasks going due as function of disruption rate

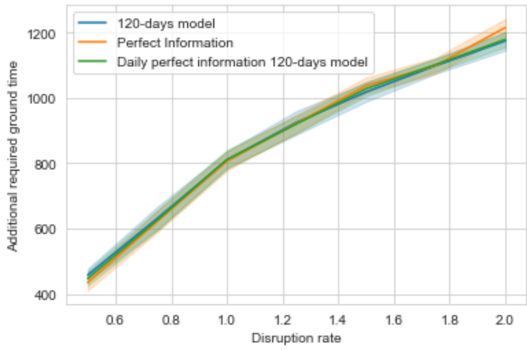


Figure D.2: Additional ground time required as function of disruption rate

This is confirmed by the average results for a disruption rate of 1, provided in Table D.4. With an average of 13.8% due tasks, the daily perfect information model lies exactly in between the model and the model for complete perfect information. Interestingly, the decrease in number of due tasks does not go at the cost of an increase in required ground time. This suggests that by increasing the frequency of scheduling, the model performance improves in term of due tasks, without sacrificing ground time. Also, in terms of schedule changes, favorable results are obtained which can be seen in Figure D.3. Similar to the results from the case study, daily perfect information results in less schedule changes.

Table D.4: Average scheduling results for a disruption rate of 1

Schedule method	Due tasks	Scheduled tasks	Ground time	Number of slots
Daily perfect information model	53.61 (13.8%)	334.17	810.91 Hours	88.09
Model	62.70 (16.2%)	325.09	809.57 Hours	89.00
Perfect Information	44.17 (11.4%)	343.61	806.19 Hours	87.17

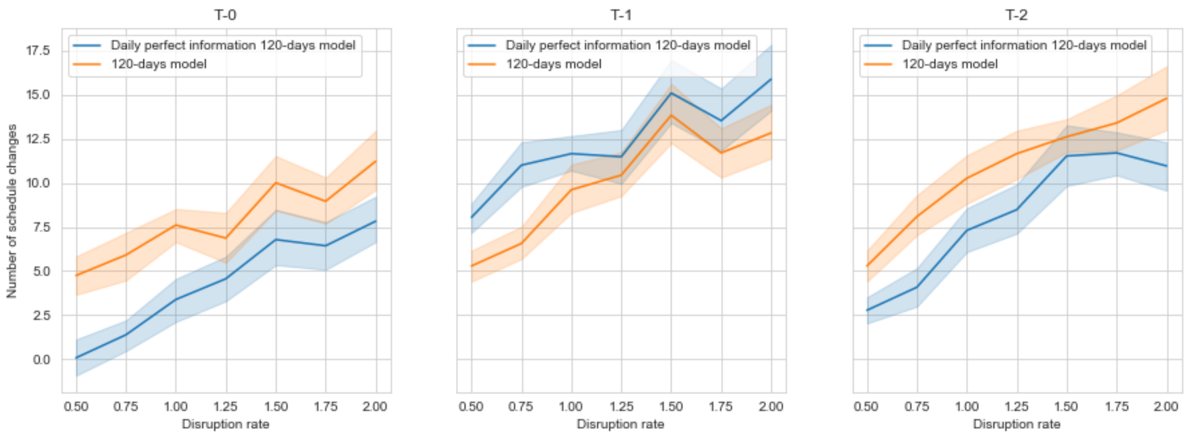


Figure D.3: Number of schedule changes for model and daily perfect information model for T-0, T-1 and T-2

The daily perfect information analysis shows that the model is able to get closer to the solution for perfect information. In real practice, the model would be able to achieve similar results by rescheduling at the occurrence of disruptions (referred to as disruptive scheduling) rather than rescheduling at a daily basis. With disruptive scheduling no scheduling opportunities are lost and similar results can be obtained as for daily perfect information.

D.2. Constraint sensitivity

Within the model several constraints are added which limit the allocation of tasks to maintenance slots. Within this section the influence of constraints on the model performance is evaluated by means of constraint relaxation. The constraints that are relaxed in this section are:

1. Aircraft type relaxation: Within the model aircraft can only be assigned to a maintenance slot if the designated aircraft sub-type of the maintenance slot matches with sub-type of the aircraft registration. This limits the solution space of the model significantly since all tasks can only be assigned to a subset of the maintenance slots. Relaxation of this constraint increases the solution space of the model since aircraft registration can make use of all the available maintenance slots. In reality, the slot flexibility lies in between the model assumption and the corresponding relaxation. Slots can be interchanged between aircraft types. However, this is very much dependent on the operation characteristics of the two types. If a maintenance slot is occupied by a different aircraft type this means that the fleet availability of the airline network will be different. For example, a Boeing 787-9 can be interchanged with a A330-300 without many complications since they have similar range and passenger capacity. However, the interchange of a Boeing 787-9 with a Boeing 777-300ER can cause operational complications.

2. Material & Machinery availability: This constraint heavily relies on assumptions as the data quality regarding the availability is poor. Material and machinery are considered to be ready from the arrival of the maintenance task if their indicator is set to true. If not, material and machinery is assumed to be available from the start date of the allocated maintenance slot in the airline schedule. This assumption is very conservative as it is likely that material and machinery are already available at an earlier stage. Relaxation of this constraint means that all tasks can be allocated to maintenance slots starting from the arrival date.

The analysis for constraint relaxation is performed on the same data set used for the case study, provided in the paper. In Table D.5, Table D.6 and Table D.7 the results are provided for the relaxation scenarios. In the following subsections the result of each of the constraint relaxations is evaluated.

Table D.5: Number of due tasks and ground time usage for analyzed scheduling methods

Schedule method	Due tasks	Scheduled tasks	Number of slots	Ground time
Model	5	2544	469	2125.75 Hours
Aircraft type relaxation	2	2547	487	1806.75 Hours
Material & Machinery relaxation	5	2544	463	1734 Hours

Table D.6: Number of schedule changes close to the day of operation for analyzed scheduling methods

Schedule method	T-0	T-1	T-2
Model	12	10	16
Aircraft type relaxation	12	12	22
Material & Machinery relaxation	17	12	25

Table D.7: Task utilization for analyzed scheduling methods

Schedule method	Routine utilization	Non-routine utilization
Model	0.773	0.546
Aircraft type relaxation model	0.783	0.556
Material & Machinery relaxation	0.765	0.476

D.2.1. Aircraft type relaxation

The relaxation of the aircraft type constraint provides more scheduling flexibility to the model. For the same time span the model now has a wider range of options to schedule maintenance tasks to a slot. This can also be seen by the decrease in number of due tasks which is achieved by relaxing the aircraft type constraint. Interestingly in terms of ground time usage, the ground time duration decreases significantly while the number of slots increases. This means that the model is making use of more and shorter maintenance slots. This is as expected as the model has the option to choose more “finetuned” slots for a set tasks, due to the increase of the number of available slots. More short maintenance slots are used and thereby achieving a decrease in ground time is achieved. This does go at the cost of a slight decrease of performance in terms of non-routine interval utilization while for routine maintenance a slight improvement of utilization numbers is visible.

D.2.2. Material & Machinery relaxation

The implementation of material & machinery relaxation provides more scheduling opportunities for a maintenance task in the earlier stage of a task interval. As expected, a decrease in the interval usage is obtained for both routine and non-routine maintenance tasks. Secondly, since tasks have more scheduling opportunities, tasks for the same aircraft registration can be more bundled together. This is visible in Table D.5 which shows a decrease in the required number of maintenance slots. The increase in scheduling opportunities also opens up the opportunity to find more fine-tuned maintenance slots. This results in a significant decrease of ground time. The downside of the constraint relaxation can be seen in the number of schedule changes, which is significantly higher compared to the model. Since maintenance tasks are scheduled earlier in the interval, this creates a more congested schedule. Because of the disruptive arrival of new tasks, more schedule changes are required.

E

Due tasks analysis

In the case study provided in Section 5.2 of the paper, the model had 5 tasks going due while the model with perfect information was able to prevent any task from going due. First an illustrative example will be provided to explain how the model ends up with due tasks while in the airline schedule this does not happen. Secondly, within this chapter an analysis will be performed on the tasks which went due in the airline case study.

E.1. Example of due task

Within the model two types of tasks are included:

- Deferred non-routine tasks: These tasks are immediately resolved once they are found. The tasks are required to be executed within the hangar and therefore need to be allocated to a maintenance slot.
- Out-of-phase tasks: These are routine maintenance tasks which are not executed as part of a larger maintenance block. They therefore need to be executed separately, and depending on the task characteristics, they can be executed in the hangar or on line maintenance

For the airline case some out-of-phase tasks were scheduled for hangar maintenance because they required hangar facilities. However, in other cases out-of-phase tasks are added to hangar maintenance even though they could be executed at line maintenance. The reason behind this is, that according to maintenance schedulers, it is better to execute it simultaneously with already scheduled hangar maintenance. Otherwise two maintenance slots would have to be created, one for line maintenance and one for hangar maintenance. Within the data it is unfortunately not distinguishable which tasks can also be executed at line maintenance.

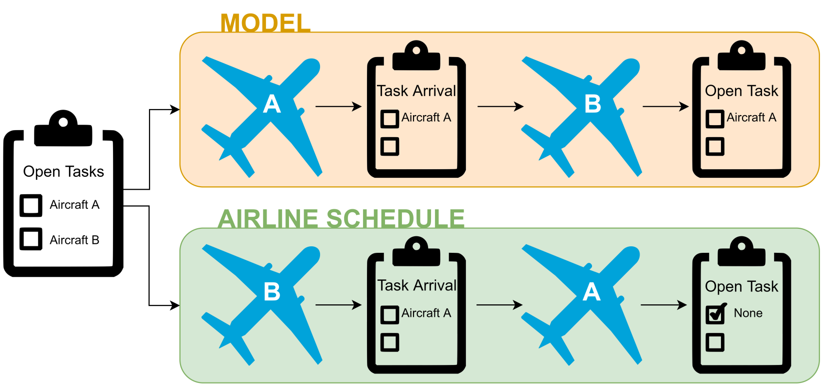


Figure E.1: Due task scenario for model compared to airline schedule

Figure E.1 illustrates an example in which the model ends up with due tasks where the airline schedule does not. There are two open tasks in which the model decides to execute the other maintenance task compared to the airline schedule. After execution, a new maintenance task arrives for aircraft A. For the airline schedule this is not an issue since aircraft A is already scheduled for maintenance. However, for the model there is no slot available for aircraft A and therefore this task has to go due. In reality the behavior of the model could be corrected in two ways.

1. The maintenance scheduler adjusts the slot schedule, which creates an extra scheduling opportunity for aircraft A.
2. The second maintenance task for aircraft A can potentially be executed on line maintenance. If in reality, aircraft A was not scheduled for maintenance, the added would also task not be added to the task backlog since it would be executed on line maintenance.

By expanding the scope of this research with line maintenance and implementing slots flexibility these two issues can be resolved.

E.2. Due tasks from case study

Within the airline case study, a total of 5 tasks went due. Their task characteristics are provided in Table E.1. For two of the tasks the model has a very limited interval at its disposal for scheduling the tasks. The task on aircraft registration AC 1 arrives throughout the first day of the interval. The task therefore needs to be scheduled in one day. However, the most suitable maintenance slot was in the evening of 07/01/2019 which is no longer possible. This problem can be resolved by disruptive scheduling as explained in section D.1. Secondly for the task on the AC 4 the model also has only one day to schedule the tasks, at which apparently no suitable slot is available. Since this is a NSRE 20 task, there are still 18 days remaining following the end of the simulation interval.

Table E.1: Due tasks of model for airline case study

Aircraft	Manpower	Method	Task type	Arrival	Due	Opportunities
1	2.32 Hours	2	MEL A	7/01/2019 12:00	7/02/2019 23:59	1
2	1.35 Hours	3	NSRE 5	8/25/2019 20:02	9/29/2019 23:59	3
3	1 Hours	1	MEL B	7/9/2019 01:03	7/12/2019 23:59	2
4	2 Hours	0	NSRE 20	11/29/2019 21:29	11/30/2019 23:59	1
5	20 Hours	8	ADHOC	10/19/2019 23:59	10/24/2019 23:59	1

The task for AC 2 went due even though it had three scheduling opportunities. A detailed analysis showed that the task was initially scheduled for a maintenance slot. At T-1 this task was removed from the maintenance slot due to the arrival of both a routine and a non-routine maintenance task. The model prefers to one NSRE task go due compared compared to one routine and one non-routine task.

For the remaining tasks provided in Table E.1 (AC 3 & AC 4) it can be seen that both tasks have limited scheduling opportunities according to the 4M's requirements besides manpower. Especially considering that the average number of scheduling opportunities is 23.56. If the few suitable maintenance slots are already occupied by another aircraft, the model does not have another option apart from letting the task go due. A low number of scheduling opportunities is caused by either material & machinery availability which lies close to the task due date or can be caused by a high required TAT (method) as it is the case for the task on the AC 4. Besides the number of scheduling opportunities also the manpower requirements can constrain the allocation of tasks to slots.

F
Slot flexibility

As discussed in the airline case study and the paper's conclusion, one the biggest model limitations is the lack of slot flexibility. In this chapter the concept of slot flexibility is elaborated together with examples how within a commercial airline schedule adaptations could take place.

In general there are a couple of adjustments which can be made to maintenance slots in a way that they become a feasible alternative for maintenance task scheduling. The examples are provided in the list below and visualized in Figure F.1.

1. Maintenance slot duration extension: A maintenance slot can be increased in duration such that a task with a required TAT can fit in the adjusted maintenance slot.

2. Maintenance slot split-up: In case there are several tasks for different aircraft registrations, a maintenance slot can be split up. As a result, maintenance tasks can be executed on two different aircraft registrations. However the duration of the maintenance slot will also be split-up. This makes it more difficult to schedule tasks with respect to their required TAT.

3. Maintenance slot creation: If there are no feasible maintenance slots to schedule a task, a new maintenance slot can be created. This is the least favourable option as this requires network adjustments. However if a task goes due otherwise this would result in an Aircraft On Ground (AOG).

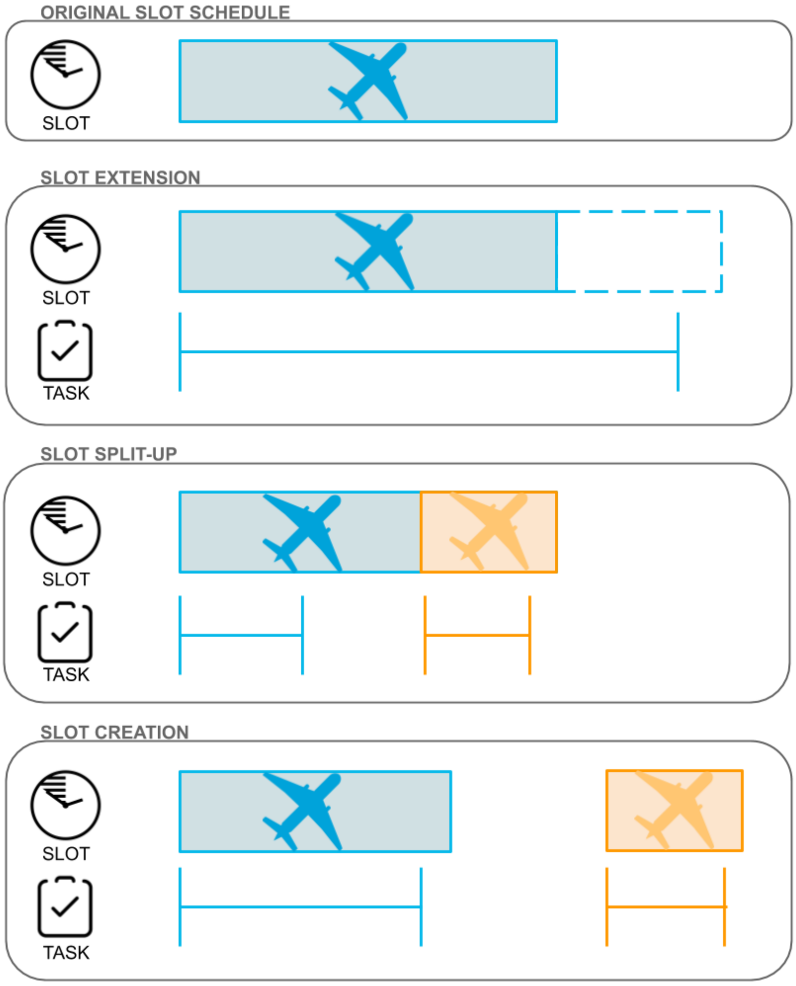


Figure F.1: Examples of slot flexibility

G
Task distributions

G.1. Probability of number of tasks

Table G.1: Probability of number of tasks

Number of tasks	Probability
1	0.829885
2	0.128736
4	0.006897
3	0.033333
5	0.001149

G.2. Probability of task type

Table G.2: Probability of task type

Task type	Probability
MEL A	0.032015
MEL B	0.016949
MEL C	0.338041
MEL D	0.141243
NSRE 5	0.032015
NSRE 10	0.022599
NSRE 20	0.099812
NSRE 120	0.256121
NSRE Man	0.061205

G.3. Aircraft registration task probability

Table G.3: Aircraft registration task probability

Aircraft registration	Aircraft sub type	Probability	Aircraft registration	Aircraft sub type	Probability
1	1	0.001091	35	2	0.013086
2	1	0.002181	36	3	0.013086
3	1	0.002181	37	2	0.014177
4	1	0.002181	38	3	0.014177
5	1	0.003272	39	3	0.014177
6	1	0.003272	40	2	0.015267
7	1	0.003272	41	3	0.016358
8	2	0.004362	42	7	0.016358
9	1	0.004362	43	3	0.016358
10	1	0.004362	44	4	0.016358
11	3	0.005453	45	3	0.017448
12	3	0.007634	46	5	0.017448
13	1	0.007634	47	5	0.019629
14	4	0.007634	48	5	0.019629
15	3	0.008724	49	2	0.02072
16	2	0.008724	50	4	0.02072
17	5	0.008724	51	5	0.02072
18	6	0.009815	52	3	0.02181
19	4	0.009815	53	7	0.022901
20	3	0.009815	54	2	0.022901
21	5	0.009815	55	2	0.022901
22	3	0.009815	56	7	0.023991
23	3	0.009815	57	3	0.025082
24	1	0.009815	58	8	0.027263
25	2	0.010905	59	7	0.027263
26	2	0.010905	60	6	0.027263
27	4	0.010905	61	5	0.028353
28	2	0.010905	62	8	0.029444
29	2	0.010905	63	8	0.029444
30	5	0.011996	64	3	0.029444
31	6	0.011996	65	7	0.031625
32	2	0.011996	66	8	0.035987
33	2	0.011996	67	8	0.040349
34	6	0.011996			

H

Literature study

Already graded under AE4020

H.1. Introduction

Maintenance is an important factor of airline operations, by taking up 11% of the operational cost.[10] By performing maintenance, the aircraft remains in an airworthy state and is available to airline operations. Since maintenance is such an important cost factor, the goal is often to schedule maintenance as efficiently as possible. This causes a decrease in maintenance cost and an increase in operational availability. By making well thought decisions both money and time can be saved.

Despite efficient maintenance schedules, within a commercial airline disruptions take place daily. As a result, airline schedules are rarely executed as planned. An investigation of the factors causing airline delays shows that maintenance is by far the biggest contributor. Airline maintenance represents 22.3 % of the number of delays and in terms of minutes, this is close to 40%. [11]. First of all, these disruptions can be caused by unexpected failure of aircraft components. Secondly, scheduled maintenance tasks can take up more time than anticipated if non-routine maintenance is found during execution. Last of all, maintenance can also be disrupted by other airline departments, which causes a knock-on effect on maintenance operations.

As a result of disruptions, maintenance schedules need to be adjusted to regain a feasible schedule. This can be achieved by postponing and reallocating scheduled maintenance tasks. This is often seen as an operational burden. However, implementing a flexible maintenance strategy can mitigate the risks and enhance the overall airline performance.

Rescheduling of maintenance, in case of disruptions, is required to keep the fleet in an airworthy state. Decisions on the day of operation can affect the days to come as well. Currently, maintenance rescheduling mostly relies on expertise knowledge. [4] Consequently, often shortsighted decisions are taken at which the coming days of operation are saved. However, the consequences of a change in the long run should be considered as well. In the future disruptions are guaranteed to take place. If a schedule is already heavily constrained this is likely going to result in a decrease of fleet availability and thereby an increase in delays. Therefore, during a disruption also the consequences for the long term should be taken into account.

Since the effectiveness of a maintenance schedule can only be truly known in retrospective, maintenance scheduling takes place in a complex environment. [12] Disruption management for maintenance scheduling is therefore crucial to remain in control of the dynamic environment. In order to solve maintenance disruptions there is a conflict of interest. On one hand the maintenance department would like to minimize cost by optimizing their own operations. On the other hand, the airline aims to optimize the overall operations. However, this comes with an increase in maintenance cost as more flexibility is required. Both interests should be taken into account during the handling of maintenance disruptions.

This literature study will therefore focus on potential methods to reschedule maintenance in a complex environment in case of disruptions. In Appendix H.2 the requirements for maintenance scheduling will be outlined, as maintenance task rescheduling is dependent on the same requirements. In Appendix H.3, literature related to airline disruption management will be discussed to analyze how other airline departments handle disruptions and which methods have been used. Finally, in Appendix H.4 literature from general task rescheduling models will be discussed together with literature from other fields of work which covers similar problems. In Appendix H.5, a conclusion will be drawn from the analyzed literature.

H.2. Airline Maintenance scheduling

Airlines must meet Federal Aviation Administration (FAA) or European Union Aviation Safety Agency (EASA) standards for maintenance of their fleet [13]. These standards are given within the Master Minimum Equipment List (MMEL). However, since airlines impose stricter restrictions upon themselves, the MMEL is modified by the airline with additional constraints. This document is referred to as Minimum Equipment List (MEL). [14] Maintenance can either be done by an internal Maintenance, Repair and Overhaul (MRO) service agency or outsourced to external MRO's. [11, 15–17] This third party has to guarantee fleet availability through a service level agreement. [18]. As discussed in the introduction maintenance scheduling has a significant impact of the airlines operating cost. Improving maintenance scheduling, can therefore improve operational effectivity.

The remainder of this chapter outlines the research that has been performed in airline maintenance scheduling. subsection H.2.1 elaborates on the requirements of airline maintenance. General models for task scheduling are defined in subsection H.2.2. At last application of task scheduling models for airline maintenance operations are discussed in subsection H.2.3.

H.2.1. Maintenance requirements

The goal of a MRO is to minimize cost while maintaining their responsible fleet in maximum quality, best lead times and according to safety requirements, as explained by Qin et al. [16]. Since these objectives are conflicting with each other, determining the optimal strategy is a challenge

As defined in the Maintenance Planning Document (MPD), airline maintenance is subjected to numerous requirements. Within the MPD the requirements for repetitive maintenance tasks which need to be executed. There are multiple kinds of maintenance which need to executed: [11]

- Base maintenance & modifications
- Engine maintenance
- Line maintenance

Base maintenance can be subdivided in multiple sub categories. Aircraft need to undergo periodic maintenance in the form of A-, B-, C- and D-checks.[19] Each of these checks have recurring intervals based on flight cycles, hours or calendar days. An A-check is the most frequent check with a Turnaround Time (TAT) and the D-check is the most demanding maintenance check wit a TAT of several weeks. Optionally, airlines can also choose to perform A-checks by line maintenance instead of base maintenance. [20] Next to the recurring letter checks, base maintenance also includes non-routine maintenance due to unforeseen defect on an aircraft.

Each scheduled block for maintenance consists of a set of tasks which need to be executed. To execute a task material, method, machinery and manpower should be arranged. These are known as the . [8] Even though several tasks have fixed routine interval according to the MPD, the MRO has some degree of freedom in terms of their maintenance strategy. Knotts [3] divided maintenance strategies in three sub categories, as can been seen in Figure H.1.

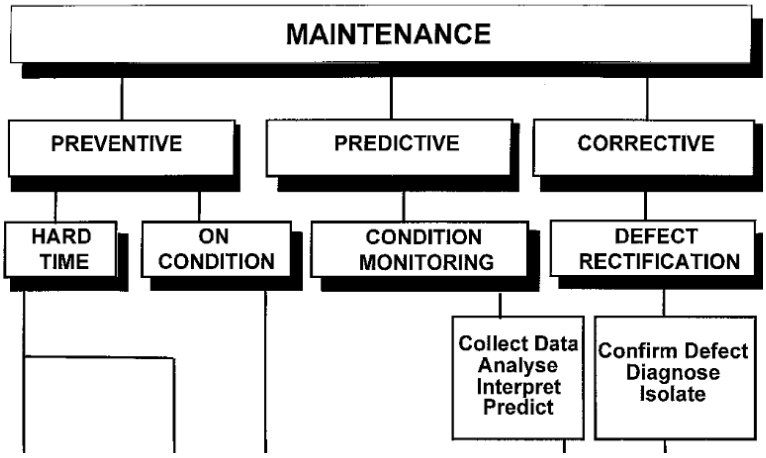


Figure H.1: Breakdown of different kind of maintenance processes [3]

Preventive maintenance includes periodically maintaining aircraft components. In case of corrective maintenance, the component is maintained after failure. At last, predictive maintenance actively monitors the component and should raise an alert when the component is likely to fail within a certain time frame. [3] Eriksson and Steenhuis [11] and Alabdulkarim et al. [21] added a proactive maintenance strategy besides those given Figure H.1. This is a combination of preventive and predictive maintenance, in which you both monitor the system and replace it at given intervals.

Lately, a lot of effort has been put in developing and improving predictive maintenance models. Predictive maintenance aims to combine the benefits of both preventive and corrective maintenance. Preventive maintenance has a downside that components are being maintained while they are in sufficient condition. On the positive side, the chance of unexpected failures is lower, since it is maintained more often. In case of corrective maintenance the lifespan of components are used maximally, but the failures occur irregularly. Predictive maintenance aims at less maintenance interventions but also with a minimum number of unexpected failures. Even though the implementation of predictive maintenance seems beneficial, it requires flexibility from the MRO. Since components fails irregularly maintenance also need to be performed irregularly and potentially in short notice. [22]

For components which needs to preventive maintenance and defects on aircraft, the required maintenance receives a due date. This is the deadline at which the maintenance needs to be performed the latest, to prevent Aircraft On Ground (AOG). [23]

Besides due dates, maintenance is subjected to several other requirements. In order to perform maintenance the aircraft needs to be available from operations as described by Liang et al. [5] and Rhodes-Leader et al. [24]. Manpower should be assigned which have the required authorisations [9]. The required materials and methods should be ready before start of planned maintenance [9, 16, 17]. At last the aircraft needs to be assigned a hangar and platform parking bay [16, 17].

Besides providing fleet availability to the airline, the MRO should aim to minimize cost with maintenance scheduling. Since the goal of the MRO is to maximize profit. Scheduling maintenance tasks is directly related to cost and this should therefore always be taken into account, as described by Manalo and Manalo [18]. Furthermore, Dupuy et al. [22] explains that allocated time for maintenance should be used as effectively as possible. Unnecessary replacements should be prevented, and high priority replacement should receive a high alternative cost. Knotts [3] provided as framework for this in which the cost of maintenance is divided up in two sub-categories:

1. Direct Maintenance Costs (DMC): The labour and material costs of performing maintenance.
2. Indirect Maintenance Costs (IMC): The number of flight which were delayed due to maintenance activities and flights which were affected by maintenance shortcomings. As well as penalties if the MRO targets are not met.

In order to minimize cost prioritization of maintenance tasks is crucial, such that performance targets are met. Jiang [23] describes that maintenance scheduling is divided into long term and short term scheduling. Maintenance needs to be planned optimally to prevent Aircraft On Ground (AOG). A task priority is therefore required which is dependant on the severity of the task and the due date. Exceeding a due date results in an AOG. Based on priority and due dates an order of tasks can be generated, as described by Samaranayake et al. [25].

At last, Manalo and Manalo [18] describes that the priority of tasks should be based on three factors: Quality, Cost and Delivery (QCD). Quality is dependant on the satisfaction delivered to the customer. Cost can directly be deduced from the costs of performed activities. At last, delivery is dependant on the deliveries made to customers. By using this approach the priority determination links directly back to the cost aspect.

H.2.2. Task scheduling

Within literature multiple approaches have been researched to solve task scheduling problems. In this subsection some of these methods are highlighted and explained how they differ from each other. Applications of these approaches for airline maintenance are explained in detail in subsection H.2.3.

The most general kind of problem is a Job Shop Scheduling Problem (JSP). In a JSP a set of jobs needs to be scheduled onto a set of machines. Each job has its own fixed order of operations to which it needs to go through, together with a specified duration. The objective of a JSP is to minimize the makespan. **[26]** As explained by Lenstra and Rinnooy Kan [27], Job shop scheduling problems fall under the NP-Complete category. Which is an indication of the computational complexity. Lenstra and Rinnooy Kan [27] therefore describe that in case of a NP-Complete problem a heuristic approach such as branch-and-bound or approximation algorithms might be a better solution.

Adams et al. [28] was one of the first researchers which implemented a heuristic approach for a JSP. His approach was the shifting bottleneck procedure in which the JSP is solved separately for each machine. Afterwards, the individual machine are re-optimized iteratively. With this he claimed to have one of the first heuristic approaches with near optimal solutions. Years later, Binato et al. [26] applied a greedy randomized adaptive search procedure as a heuristic method to solve JSP's

A variant based on the JSP is the Resource Allocation Problem (RAP). This kind of problem focuses on the allocation of resources to tasks, rather than task scheduling. The goal is to find an optimum allocation of resources to tasks such that the allocation cost is minimized. **[29]** Chryssolouris et al. [30] implemented a RAP into the concept of manufacturing decision making. The resource distribution is performed in two steps. First, the resources are distributed into work centers. Secondly, for each work centre the resource are distributed for tasks. The model makes use of a randomized search procedure and is able to take multiple performance measure into account which made it stand out. A follow up research has been performed in which the effect of decision horizon, maximum number of alternatives and sampling rate is discussed. With this a trade-off can be made between quality of the outcome and computational time can be made. [31]

At last, another variant of the JSP is the Resource-Constrained Project Scheduling Problem (RCPSP). The goal of RCPSP is to satisfy precedence and resource constraints while the project duration should be minimized. There are precedence constraints which impose that a task can only task after another task has been completed. Resources are demanded by the activity for a constant rate. The resources are also available in a constant amount. A heuristic approach proposed by Demeulemeester and Herroelen [32] in the form of partial scheduling by making the branch and bound method. At each node, a subset of activities is added to the problem to keep the size acceptable. A follow up paper of Demeulenmeester and Herroelen [33] discussed minor changes together with hardware improvements which offered the possibility to solve more complex problems. Furthermore, Kolisch [34] extended the model of Demeulemeester and Herroelen [32] with the addition of task priority rules which improved the quality of the scheduling results.

H.2.3. Maintenance scheduling

As described in subsection H.2.2 there are several kinds of different approaches to solve task scheduling problems. Within this subsection these approaches are discussed in detail for research that has specifically addressed scheduling of airline maintenance. However, since maintenance covers several aspect there is also a variation in the kind of maintenance problems that can be solved. This section is divided in multiple subsections to discuss the following fields of work:

1. Fleet assignment problem and aircraft routing
2. Task planning
3. Resource allocation
4. Aircraft dispatch

Fleet assignment problem and aircraft routing

During fleet assignment a type of aircraft is assigned to a flight leg. Clarke et al. [13] describes the fleet scheduling problem in which he incorporated additional constraints for crew paring and maintenance scheduling. Maintenance was taking into account by the model, by creating maintenance opportunities in the flight schedule of different duration. The applied method was an Integer Linear Program (ILP) in combination with a branch and bound approach to solve the Mixed Integer Program (MIP).

After fleet assignment has been performed the second step is usually aircraft routing. Gopalan and Talluri [35] discussed that fleet assignment should be done independently of maintenance scheduling, since the model can become computationally too expensive or lack required details. Feo and Bard [36] were one of the pioneers to include maintenance requirements within the aircraft routing problem. The four day interval for A-checks should be met and capacity constraints were neglected. Since the problem is NP-complete a probability set covering approach was used. Gopalan and Talluri [35] approached the problem by using the concept of Line Of Flights (LOF) in every tail number should spend a night at a maintenance station at recurring intervals to perform A-checks. This model was later extended by Talluri [14] at which it was proven that the problem is NP-complete but can be solved in polynomial time by using heuristics. However, the model is only able to include A-checks because otherwise it would become too complex. According to Barnhart et al. [37], solving the aircraft routing problem independently of the fleet assignment problem can lead to maintenance constraints violation. By combining aircraft routing with the fleet scheduling problem better solutions can be generated from a maintenance perspective. However, as a consequence the crew scheduling problem becomes more challenging to solve.

Years later, Sriram and Haghani [38] used a 7 day planning horizon to schedule aircraft at their required maintenance opportunity. However within the model still only A-checks were considered. The heuristic approach is modelled as a combination of depth first search and random search. The heuristic solution comes up to 95% of the exact solution generated by CPLEX. In 2012, Jiang [23] was one of the first to take multiple aspects of maintenance into account. The maintenance planning was subdivided up in two parts, short term and long term. Maintenance task should be planned optimally to prevent AOG. The user could define in which time interval the maintenance tasks should be executed. The method used to model the aircraft routing problem was an Artificial Bee Colony. The author claims that this has a faster convergence rate than conventional artificial intelligence algorithms such and ant colony optimization and genetic algorithms.

Maintenance task planning

Maintenance task planning is an aspect that has not received much attention in literature yet. However lately the attention is shifting from aircraft routing problems to maintenance task scheduling, due to task fragmentation. **[20]** Since the concept maintenance disruption management is very much related to maintenance task planning, the performed literature is discussed in detail.

Marseguerra and Zio [39] published one of the first researches which went in detail about maintenance task scheduling. Within the paper multiple maintenance and repair policies are described in which both safety and economical factors are taken into account. The cost of assigning maintenance personnel is included as well the cost of scheduling the maintenance task itself. As an approach to solve the problem, Marseguerra and Zio [39] use a combination of monte carlo simulations and a genetic algorithm. The monte carlo simulation models the stochastic nature of the occurrence of defects on aircraft, while the genetic algorithm improves the computational time.

Later, Papakostas et al. [40] focussed on the short-term aspect of maintenance scheduling, by taking resource constraints into account. The approach provides an outline for scheduling line maintenance tasks before its due dates. As a result, a schedule is created of line maintenance tasks during ground time of an aircraft at their home base. The best schedule is determined based on cost, operational risk, flight delay (due to exceeding maintenance time) and remaining useful life. The approach focussed on an economic analysis for the optimum planning of scheduling maintenance tasks. The following costs were taken into account:

1. Equipment and facility costs
2. Supplies and logistics costs
3. Personnel costs
4. Overhead costs (scheduling costs etc.)

Yuan et al. [41] describes support operations that are required for an aircraft carrier. The problem is defined as a multi-resource constrained multi-project scheduling problem within an uncertain environment. The method used to solve the problem is a dual population genetic algorithm in combination with a rolling horizon approach to solve large scale problems. Also, stochastic elements have been added since the arrival if new tasks is uncertain. Furthermore, an additional feature is added to the analysis in which disruptions can be handled as well. In case of a disruption the objective gets an additional part added which takes the difference in start time into account with respect to the original schedule. The objective in this case is minimise to sum of the earliness and tardiness of tasks.

At last, Lagos et al. [42] describe the set up of an Airline Maintenance Scheduling Program (AMSP) at which the maintenance tasks should be scheduled before their due date. The model decides which aircraft to maintain and which tasks need to be executed. The goal is to minimize cost and future tasks outside of the planning horizon. AMSP is unique from other scheduling programs since it contains stochastic information. Also, the usage of resources is included in the approach in the form of different skill levels of maintenance personnel.

The model includes a distinction between critical and non critical tasks. The cost of solution is calculated by taking the number of cancellations because of exceeding required tasks and expiration of non-critical tasks. The model uses a Markov Decision Process (MDP). In such a process there individual state which are formed because of the actions taken in the previous state. The cost is a combination of the state and the chosen action. Three different methods were evaluated for the expected cost of future states:

1. Myopic policy: Taking the best option for each individual time interval without taking the future time intervals into account.
2. Rolling horizon: The last few elements for the previous time interval is also taken into included for the following time interval. The approach is myopic to potential future actions which fall outside of the current time interval.
3. Value Function Approximation: Based on the current state, the future value is estimated for states coming up. The values are approximated by approximate value iteration and linear regression techniques. This is mainly dependant on the number of tasks that is still left for the next period to determine a score.

Furthermore, Lagos et al. [42] implemented additional flexibility by allowing to change Line Of Flights (LOF) between aircraft of the same type The possibility of switching LOF in between aircraft registration causes a decrease of 13% in the number of expired tasks. A limitation of the model was that smaller maintenance has not been included since only A- and B-checks were considered.

A variation of maintenance task scheduling is described by Deng et al. [19] with an approach for Aircraft Maintenance Checks Scheduling (AMCS). This study specifically focussed on the A- and C-checks schedules on the long term. The difference between an AMCS and an AMSP is that an A- or C-check already consist of a predefined set of tasks. The goal of a AMCS is to maximize utilization of the airline fleet. In the long run this results in less scheduled checks which is cost beneficial. The utilization is based on the number of flight hours, flight cycles or calendar day, whichever comes first. Also, the capacity of at the maintenance facility is considered and maintenance scheduling restriction due to aircraft routing are neglected. A 4-year schedule can be obtained in a matter of minutes by making use of a dynamic programming approach.

Resource allocation

The resource allocation problems described in this chapter focus on the assignment of one or more specific resources. The main difference between the researches described in this subsection compared to item H.2.3 is that the focus is aimed on the assignment of resources and not necessarily on the assignment of tasks.

A research performed by Dijkstra et al. [43] describes the development of a manpower scheduling tool used for line maintenance at KLM. An engineer with appropriate qualifications is required to perform dedicated tasks. The Decision Support System (DSS) described within this research makes a match between the projected workload and determined capacity. As a result, the DSS can be used to determine the required number of personnel. This has been achieved by making use of Lagrangian Relaxation. The model could only be used for semi-long term workload predictions. Day to day simulation was by then out of scope.

Ten years later, Yang et al. [9] created a maintenance manpower planning model which focuses on the short term aspects of manpower planning at line maintenance. The goal of this approach was to create a schedule which minimizes manpower supply and increases the punctuality of the airline while meeting all safety standards. The proposed model is in the form of an ILP, which also included some degree of flexibility. The start and end times of shifts, number of member in a squad and number of work hours for personnel can be changed in combination with a penalty. The downside of using the ILP approach is that the model becomes too complex if multiple aircraft types are combined or if multiple kind of maintenance are included.

Afterwards, Quan et al. [44] describes the trade-off between the number of maintenance personnel and the completion of tasks in time. Focusing on one of those two is not sufficient, therefore a Multiple Objective Problem (MOP) is created. A novel aspect of their approach was that the preferences of the manager are taken into account. In order to solve the MOP in acceptable time an evolutionary algorithm was developed which aimed to create the most cost effective schedule, while taking preferences into account. Required improvements for their approach are that the task duration is currently not dependant on the number of personnel assigned to the tasks and that task priority can change trough out the time.

According to Samaranayake et al. [25] maintenance schedule can be divided in two parts: overall maintenance scheduling (hangar etc.) and detailed scheduling of components. Samaranayake et al. [25] focussed on the second aspect and especially on the effect of material supply of performing maintenance at Qantas. Resources and material should be in the facility in time such that scheduled maintenance is not disrupted. The approach implemented both a CPM and material requirements planning. The CPM approach provides an indication of which activities are critical to be completed in a timely manner.

Qin et al. [16] researched aircraft hangar scheduling together with parking stand planning problem. This kind of problem take the physical arrangement of aircraft inside a hangar into account. While rolling the aircraft in and out of the hangar it should not be obstructed by other aircraft. This has to be taken be into account while scheduling maintenance block times for aircraft. The problem was defined as a Mixed-Integer Linear Programming (MILP). In a follow up research by Qin et al. [17], the model was extended with a rolling horizon technique. This was required since the original model was not able to cover large scale problems. Their approach only lacked the possibility to add additional maintenance constraints and incorporate stochastic modelling because of unscheduled maintenance.

Aircraft dispatch

Aircraft dispatch includes the short term decision making during an aircraft turnaround. An assessment needs to be made whether an aircraft can safely perform the next scheduled flight. If a defect is found by an engineer during a turnaround, quickly a decision should be made whether this defect is deferred or is repaired right away. Koornneef et al. [45] describes the alternative maintenance approaches in case a defect is found. If an item is stated in the MEL or is registered as Non-Safety Related Equipment (NSRE), there is an option to defer the item. Otherwise, the defect always needs to be resolved first.

Dhanisetty et al. [46] describes a multi-criteria decision making approach for aircraft dispatch problems. This problem is two folded. First, alternatives of maintenance approaches should be identified. Alternative approaches can for example be a temporary repair first followed by a full repair afterwards or performing a full repair right away. Secondly, the alternatives should be evaluated and a decision should be made. The authors, propose a Boolean decision tree in which a trade off is made between survivability, cost and downtime. These three factors are combined by using a weighted sum method. Afterwards, the alternatives can be quantitatively compared with each other. Koornneef et al. [45] applied a similar approach and presented the model in the form of a mobile tool including interface.

H.2.4. Conclusion

Aircraft maintenance scheduling develops over time from a high-over planning towards a detailed assignment of tasks and resources. The initial step is the Aircraft routing problem in which time is allocated for maintenance. **[14, 35, 36]**. Afterwards, maintenance tasks should be assigned to an aircraft registration, which is also referred to as task scheduling. **[19, 20, 39–42]** After maintenance has been scheduled, resources should be assigned to tasks. **[16, 17, 25, 43, 44]**

On the day of operation, aircraft dispatch becomes of importance. This concept is also related to airline disruption management. Both Dhanisetty et al. [46] and Koornneef et al. [45] acknowledge that decisions made on the short term can have influence on scheduled maintenance in the long term. By deferring defects, the day of operation can be saved but can also cause an overload of work for the days to come.

Based on the various areas of research described above some general requirements for maintenance scheduling can be deduced:

- Task ordering & prioritization: Maintenance tasks should be ordererd correctly such that urgent tasks are executed before non-ciritical task. Tasks can receive a higher priority depending on their MEL category and proximity to due date.
- Resources: If maintenance tasks are scheduled, the required resources should be available and assigned as well
- Cost: Scheduling of maintenance should be cost-driven to optimize the performance of both the MRO and airline operations.

The approaches described in this chapter have an excellent performance in a perfect un-disrupted environment. However, in reality schedules are rarely executed as originally planned. **[6, 47]** As described in the introduction, airline maintenance is a complex environment. Making a "optimal" schedule upfront will likely not result in the optimal outcome. A disrupted schedule can no longer be executed as planned. There is therefore a need of methods that minimizes the effects of disruptions and outputs a new schedule that is again close to optimal. This will be discussed in the upcoming chapters.

The maintenance scheduling aspects discussed in this chapter are of importance in the context of rescheduling airline maintenance as well. These factors are of influence in creating the feasible maintenance schedule. Therefore, they should also be considered in case of rescheduling to prevent violation of constraints.

H.3. Airline Disruption Management

The schedules of airlines created nowadays have very little slack compared to what it used to be. As a result, the effect of disruptions is more severe. Throughout the day an airline is often faced with irregularities within the schedule. Therefore, real time decisions should be made. Decisions that are made now can have significant impact future activities which are not considered by the controller. As a result, in literature there is an increasing amount of effort put into disruptions management approaches to minimize the effect of disruptions on airline operations. [4]

Within this chapter, research related to airline disruption management is discussed. First the different kind problems of airline disruption management are explained in Appendix H.3.1. Afterwards, Aircraft Recovery Problem (ARP) problems are addressed specifically in Appendix H.3.2. In this section, special attention is given to literature which implemented airline maintenance in their problem formulation.

H.3.1. Variations in disruption management

Airline disruptions need to be solved by the airline Operations Control Center (OCC). In Figure H.2 a general outline is given of an OCC. In case of a disruption, airline coordinators have to find a solution that minimizes airlines operational cost but also minimizes operational difficulties.

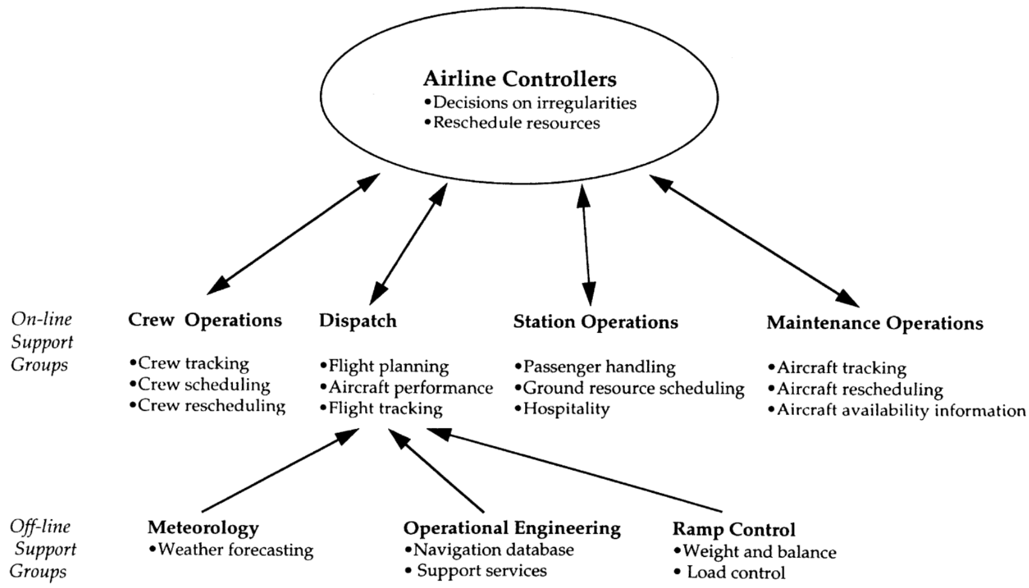


Figure H.2: Diagram of typical Operations Control Center (OCC) for a commercial airline [4]

In 2011, Le et al. [48] described the state of art in airlines disruption management. The paper was divided up in three parts:

1. Aircraft Recovery Problem (ARP): In case of a disruption, the ARP determines the new routing of each aircraft registration and if necessary, delays or cancels flights.
2. Crew Recovery Problem (CRP): The CRP reassigns a set of crews to a set of flights. This problem is heavily constrained by regulations set by the FAA and policies of the airline itself. [49]
3. Passenger Recovery Problem (PRP): The PRP, reassigns passenger to flights. The goal in this case is often to minimize cost and reputation damage. It is therefore preferable that passenger keep their original itinerary. Alternatives are creating a new itinerary for passengers or cancel itineraries of passengers.

By comparing the list given above together with Figure H.2 one can see that three of the four support groups have been discussed in literature. However, this does not mean that maintenance is neglected in literature. In multiple ARP formulations maintenance is included in the form of a constraint, which will be discussed in the upcoming section.

H.3.2. Aircraft Routing Problem

Within this chapter the research that has been performed to Aircraft Recovery Problem (ARP) is discussed in detail. The ARP receives special attention in the literature study since maintenance is often included as a requirement. This section will therefore mostly focus in literature which implemented maintenance constraints. In some cases, the ARP is also combined with CRP and/or PRP. The literature which is discussed in the remainder of this chapter is mostly ordered in chronological to illustrate the development over time.

In 1996, Talluri [50] solved the ARP by applying aircraft swap operations. By making use of a shortest path algorithm, a feasible solution could be found in a matter of seconds instead of a couple of hours which were required for finding the exact solution. However, since their approach only considered a small subset of flights for swapping, the solution is not necessarily optimal. Also, there was no possibility in delaying or cancelling flights. A heavily disrupted airline network would therefore result in an unfeasible solution.

Thengvall et al. [49] included to options of delaying or canceling flights. The authors recognized that the implementation of Decision Support System (DSS) can yield into substantially different solutions. In order to solve the ARP a multi objective function is implemented which minimizes delays and cancellations but also minimizes the deviation from the original schedule. The aspect of this research that stood out from the others was that the users of the DSS could give their preference for delaying flights, cancelling flights or keep a sequence a flights performed by the same aircraft. The problem was modelled as an ILP. However, to decrease the computational time LP relaxation was used together with an integer rounding heuristic to get a near optimal solution.

Afterwards, Rosenberger et al. [51] implemented maintenance constraints in the ARP. According to rules of the FAA each aircraft needs to undergo periodic maintenance service. An aircraft routing schedule can therefore only be feasible if those requirements are met. Within the model formulation, a route is said to maintenance feasible if it visits an airport where maintenance can be performed within the required time interval. The method makes use of a set-packing heuristic at which only selects a subset of aircraft is considered for recovery. This should result in near optimal solutions. A downside of this approach is that only flights of one aircraft type can be reassigned. A change in equipment type is therefore not an option. Also, an alternative objective function is added which aims to maintain crew and passenger connections.

Abdelghany et al. [52] also implemented maintenance constraints into an ARP in combination with a CRP. Scheduled maintenance activities should not be violated; therefore the aircraft needs to be at at a given location and a given point in time. The problem was modelled as a MIP with prepossessing to decrease the problem size. Also, the time range was divided in multiple parts by using a rolling horizon technique to speed up the decision time.

In 2009 the French Operational Research and Decision Support Society (ROADEF) started an open challenge at which research develop a DSS for commercial aviation disruption management. The data and constraints were provided by the organization, but the researchers were free to choose their approach. The main goal is to minimize costs. In the problem formulation, passengers can be reaccommodated to a new itinerary or their itinerary can be cancelled. Also maintenance constraints are given to which the solution should meet. An aircraft can fly a given number of flight hours between two consecutive maintenance checks. In order to perform maintenance, the aircraft needs to be located at a given airport be available for a given amount of time. Afterwards, the remaining flight hours is reset to the default value. Within the ARP formulation, it is possible to reschedule maintenance for an aircraft as long as the next scheduled maintenance activity lies within the allowed range of flight hours. The objective function for the problem is to minimize the costs of the disruption. This is based on the operational costs due to making adjustments in the aircraft routing schedule. As well as the associated costs of rescheduling or cancelling passengers itineraries. At last, penalty costs are implemented if the schedule does not return to normal operations after the given interval. **[53]** Multiple researchers participated in the ROADEF competition, and the most interesting results are given below.

Eggenberg et al. [47] modelled the problem as an ILP together with column generation to speed up computation time. This approach reached near optimum solutions compared to the complete ILP formulation. Also, the effect of maintenance planning was studied in detail. By neglecting maintenance flexibility in disruption management the number of delayed flights turned out to be a factor ten higher as well as twice as much cancellations. Eggenberg et al. also implemented additional flexibility in maintenance scheduling. He compared different maintenance scheduling strategies with each other based in the utilization of the maintenance interval. It turned out that from a cost perspective it was better to allow an aircraft to undergo maintenance at a low utilization rate. Greedy maintenance scheduling at 90% of maintenance interval consumption performed worse than maintenance scheduling at which lower utilization's are allowed as well.

The winner of the ROADEF challenge was the model presented by Bisaillon et al. [54]. This made use of a large neighborhood search heuristic for ARP. Within this process there are three main phases: construction, repair and improvement. With this approach the ARP and PRP are solved in an iterative manner. This method is able to find an optimal solution since it it makes use of very simple calculations rapidly after each other.

A couple of years later other authors performed a follow up research on the ROADEF challenge. These researches still used the same data set and assumptions and can therefore be quantitatively compared with each other. In 2015, Zhang et al. [1] split the problem up in three separate parts: Aircraft schedule recovery, flight re-scheduling and passenger re-accommodation. The last two steps is an iterative process. All the individual steps were modelled as an ILP. The results show that the overall performance is better than the model given by Bisaillon et al. [54].

Sinclair et al. [55] also performed research with the same data set put applied a column generation approach instead. The basic model is a MIP together with an improvement of the repair, construction, and improvement procedure of Bisaillon et al. [54]. As a result, the computational time decreases significantly. The results obtained by this approach are very similar to the ones obtained by Zhang et al. [1]. Depending on the kind of disruption the model of Sinclair et al. [55] or Zhang et al. [1] performs better.

Table H.1: Score as percentage of the optimal solution based on the ROADEF challenge [1]

Team	**Data set 1**	**Data set 2**
Zhang et al. [1]	100 %	98.16 %
Bisaillon et al. [54]	96.46 %	74.66%
Eggenberg et al. [47]	2.92 %	16.64 %

In Table H.1 a quantitative comparison is given of the results obtained by the authors described above based on the data of the ROADEF challenge[1]. There is a distinction between two data sets since the second one contains more complicated problems. As can be seen from the table above the approach by Zhang et al. [1] yields the best results. Please note that factors such as computational time are not considered in this case.

Hu et al. [56] solved the ARP and PRP simultaneously by making use of an ILP approach. In order to find solutions within reasonable time, a time-band network approach was used. With this approach the time gets divided into intervals of equal length. A shorter time interval yields in a better solution but requires more computational time. As a recommendation for future development of the model, the goal is to implement constraints together with the addition of the CRP.

Sousa et al. [57] combined the ARP together with the fleet assignment problem. This gives more flexibility to the solution since flights can be operated by an aircraft with more capacity to accommodate disrupted passengers. In order to find a feasible and close to optimal solution ant colony optimization was used. A downside of this approach is that deviations with respect to the original schedule are not taken into account, and maintenance and crew constraints are not considered.

Rhodes-Leader et al. [24] created a two-step optimization model for the ARP. First, a low fidelity integer program searches for feasible solutions, which increases the problem size significantly. Secondly, a high fidelity model considers stochastic elements and aims to find the optimal robust schedule. In the high fidelity model maintenance is also taken into account, in the form of planned and unplanned maintenance. There is increase in chance of unplanned maintenance if the interval between two maintenance checks increases.

At last, Liang et al. [5] take more maintenance flexibility into account for the ARP approach. According to the authors swapping planned maintenance can save up to 20% to 60% of airlines disruption cost. Maintenance is seen as a flexible factor which can easily be changed in time. There are no costs associated to swapping scheduled maintenance. A maintenance task can go due on flight hours, cycles or calendar days, whichever comes first. It is possible to swap maintenance tasks as long as it takes place before its due date. Therefore, the following recovery actions are considered: Flight delays, flights swaps, flight cancellation and maintenance swaps. With their problem approach, maintenance can be performed at multiple airports. As can be seen in Figure H.3, maintenance is originally scheduled at Airport A. However, the green aircraft can also perform an additional blue

[1]The results of Sinclair et al. [55] could not be compared, since numerical results were missing

dotted flight and undergo maintenance at airport B instead of A.

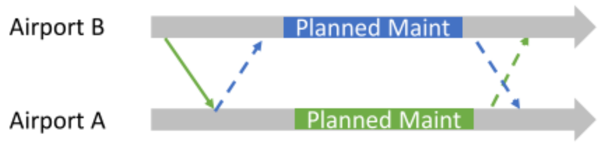


Figure H.3: Changing start and end times in case of disruption. [5]

A column generation is applied to save computational time. This research is revolutionary in the way maintenance is included within the ARP. However, there is still room for improvement. There is currently only one kind of maintenance included and the availability of resources to perform maintenance is not taken into account.

H.3.3. Conclusion

This chapter mostly focused on literature that considered maintenance in an airline disruption management context. In Table H.2 a summary table is provided which outlines the kind of problems that are considered by the authors discussed in Appendix H.3.2. Throughout the year more research has been performed which combines two or more of these aspects. There is an increasing interest in these approaches since all aspects are considered in one problem which should result in a global optimum. If aircraft, passenger and crew recovery are solved separately this will result in sub optimal solutions.

Table H.2: Kind of problems covered by authors for airline disruption management

Author	**Aircraft recovery**	**Passenger recovery**	**Crew recovery**	**Maintenance**
1996: Talluri [50]	✓	✗	✗	✗
2000: Thengvall et al. [49]	✓	✗	✗	✗
2003: Rosenberger et al. [51]	✓	✗	✗	✓
2008: Abdelghany et al. [52]	✓	✗	✓	✓
2010: Eggenberg et al. [47]	✓	✓	✗	✓
2011: Bisaillon et al. [54]	✓	✓	✗	✓
2015: Sousa et al. [57]	✓	✗	✗	✗
2016: Zhang et al. [1]	✓	✓	✗	✓
2016: Sinclair et al. [55]	✓	✓	✗	✓
2018: Liang et al. [5]	✓	✗	✗	✓
2019: Rhodes-Leader et al. [24]	✓	✗	✗	✓

A downside of combining multiple recovery problems into one is that it becomes computationally more difficult to find an optimal/good solution. Therefore, the majority of the authors in Table H.2 applied a heuristic approach to speed up the computation time.

Most of the authors from Table H.2, see maintenance often seen as a requirement rather than a variable within the concept of disruption management. In case of scheduled maintenance, an aircraft needs to be at a given airport at a given point in time. Only Liang et al. [5] and participants of the ROADEF challenge [53] implemented methods at which maintenance was able to shift in time. However, these researches still included many simplifications in their approach for maintenance scheduling. As already stated in Appendix H.3.1 there is still no research performed in the so called

Maintenance Recovery Problem (MRP). This should solely focus on scheduled maintenance operations and recover the schedule in case of disruptions.

H.4. Task Rescheduling

In case an airline disruption occurs, the original schedule cannot be operated as anticipated. [48] This effects not only the flight schedule of an airline, but also effects scheduled maintenance. In order to recreate a feasible maintenance schedule within revised circumstances, rescheduling has to take place. As explained in Appendix H.2.1, a maintenance work package consists of multiple tasks. In case of a disruption, the maintenance schedule needs to be adjusted such that all constraints are still satisfied again. As concluded in Appendix H.3, no research has yet been performed in a Maintenance Recovery Problem (MRP).

Therefore, this chapter will give insight in general task rescheduling models and other applications where task rescheduling is already widely applied. First, the different kind of rescheduling models will be discussed in Appendix H.4.1. Afterwards different fields of work where rescheduling is already widely applied are discussed. First, Rescheduling of a general Job Shop Scheduling Problem (JSP) is discussed in Appendix H.4.2. Afterwards rescheduling applications in the health care sector and construction sector are discussed in Appendix H.4.3 and Appendix H.4.4 respectively. For each of the different applications the literature is mostly covered in chronological order to illustrate the development over time.

H.4.1. Rescheduling classification

Many authors acknowledged that the majority of research has been focused on scheduling models, with little attention to rescheduling models. [2, 7, 58–60]. In 1981 Graves [58] was one the first researchers to acknowledge that there is gap between production scheduling theory and practice. In order to reduce the differences, he emphasized on two improvements regarding rescheduling. First, schedule interaction should be improved in which the schedule becomes part of the operating system and is easily accessible. Secondly, more focus should be given to schedule flexibility in which rescheduling can be performed in case of disruptions and addition of new tasks to the schedule.

A literature study performed Vieira et al. [2] describes a framework of rescheduling techniques, classifications of the strategies, policies and methods. In general there are three areas of research regarding rescheduling:

1. Repairing a disrupted schedule
2. Creating schedules that are robust for disruptions
3. Analyzing effect of policies to the performance of the system

The use case of rescheduling problems varies widely. As a consequence, the requirement for rescheduling vary accordingly. In order to identify the differences between reschedule strategies, Vieira et al. [2] proposed a reschedule classification scheme with three parameters: kind of environment, kind of rescheduling strategies and kind of environments.

The first parameter is the kind of environment in which rescheduling should take place. This indicates what the requirements are of the jobs which are being processed and in whether their arrival is variable. In Table H.3, the subdivision is given for different kinds of environments. In case of airline maintenance, process flow variability fits the environment best. There is an infinite dynamic flow of new tasks which also vary in processing requirements.

Rescheduling environments				
Static		Dynamic		
Deterministic	Stochastic	No arrival variability	Arrival variability	Process flow variability

Table H.3: Different kind of rescheduling environments [2]

Secondly, the kind of rescheduling strategy determines when an existing schedule should be altered. In Table H.4 the subdivision of strategies is given. In case of hybrid scheduling, the schedule can be rescheduled in case of events but it will be rescheduled by default periodic.[61] For maintenance disruption management the main interest would go out to the event-driven approach which adapts the schedule in case of disruptions.

Rescheduling strategies				
Dynamic		Predictive-reactive		
Dispatching rules	Control-theoretic	Rescheduling policies		
		Periodic	Event-driven	Hybrid

Table H.4: Different kind of rescheduling strategies [2]

At last, the different methods which can applied for rescheduling are given in Table H.5. Many authors emphasize on the importance of robust schedules, since this both enhances and prevents the use of rescheduling. [59, 62–64] In case of schedule repair there are multiple approaches which are described in more detail in the following sections. For airline maintenance scheduling the most promising method is partial rescheduling. In order to perform airline maintenance the 4M's are required. [8] A minimal deviation from the original schedule is therefore preferred such that a loss of preparation effort is prevented.

Rescheduling methods				
Schedule generation		Schedule repair		
Nominal schedules	Robust schedules	Right-Shift rescheduling	Partial rescheduling	Complete regeneration

Table H.5: Different kind of rescheduling methods [2]

Herrmann [61] created a follow up literature study regarding rescheduling strategies, policies and methods. This is partly a summary of the research by Vieira et al. [2] and provided additional detail of rescheduling strategies. In this research he made the division between rescheduling strategies for dynamic scheduling and predictive-reactive scheduling.

H.4.2. Job Shop Problems

As described in Appendix H.4.1, rescheduling is dependent on the environment for which the model is intended. This literature study is mainly focused on rescheduling models which operate in a dynamic process flow variability environment, in which partial rescheduling is applied. To the best knowledge of the author, there has currently no research been performed to rescheduling models for airline maintenance tasks. However, in other fields of work, the usage of rescheduling models is already widely applied. The following sections will focus on rescheduling application in other fields of work.

The literature discussed in this chapter covers general applications. Airline maintenance scheduling matches best with a Job Shop Scheduling Problem (JSP). The concept of this kind of problem has been explained elaborately in Appendix H.2.2. Disruptions in job shop problems are often modelled as machine being unavailable for a given amount of time. This has a knock-on effect in two ways, as can be seen in Figure H.4 The jobs which are scheduled on this machine afterwards are delayed. The job which was occupying the machine at the point of the disruption will be delayed for further steps. [6]

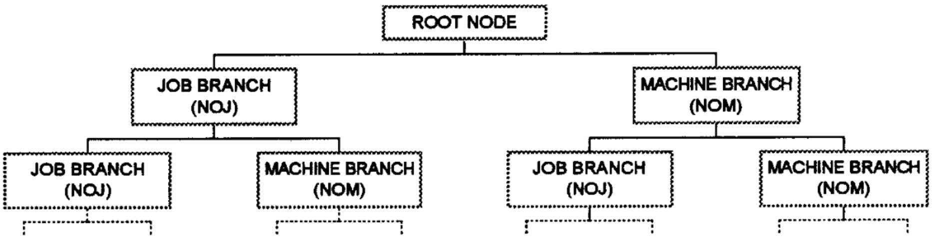


Figure H.4: Knock-on effect of machine disruption in JSP. [6]

Wu and Li [63] addressed that schedules in a JSP are subject to inevitable changes. This can be due to disruptions but also due to additional operational constraints shortly after creating the schedule. In order to recover a feasible schedule, a reschedule strategy was proposed which consists of three steps:

1. Evaluation step: The effect of factors which cause deviations from the original schedule.
2. Solution step: Rescheduling solutions than can enhance the performance of the existing schedule.
3. Revision step: Same as the evolution step but with the updated schedule. If the result is not satisfactory, step 2 and 3 should be iterated.

The rescheduling problem was solved by making use of a Gantt chart. This represents the interrelationship between scheduled jobs and machines.

The approach of Wu and Li is an extension of the model described by Li et al. [65], which uses a binary scheduling tree. Their model is beneficial in the sense that not all of the operations need to be reevaluated with respect to the previous schedule. However, their solution lacked the opportunity to alter the sequence of scheduled jobs.

Wu and Li [63] provided users the opportunity to specify which tasks should be added/rescheduled. However, the model does still not make adjustments in the sequence by itself if this would be beneficial. After giving input, the new start and end time of the operations are recalculated. The described model is therefore only able to implement start and end time adjustments and does not find the optimal solution in terms of sequence of jobs.

In 1997, Abumaizar and Svestka [6] performed a quantitative research for several rescheduling methods in case of disruptions within a JSP. His research compared the performance of three different rescheduling techniques:

1. Right shift scheduling: If a disruption occurs; all current and remaining jobs are paused until the disruption has been resolved. This means that a disruption of one task will delay all other tasks.

2. Affected operations rescheduling: Only the jobs which are scheduled for the disrupted machines and the jobs that are disrupted by themselves are rescheduled.
3. Total rescheduling with no regards to previous schedule: Regardless of the severity of the disruption, the schedule is rescheduled entirely.

The first method will create a new schedule in which all jobs will get a delay which is equal to the duration of the disruption. Only the start and end time in the original schedule is updated. The second method works well in case there is slack time in between the jobs for the machines. The disruption will then have limited effect on any successive jobs. A downside of affected operations rescheduling is that the order of jobs cannot be changed. At last, total rescheduling gives the most optimal result in terms of make span. However, a limitation of the model is there is no constraint on the amount of changes that is allowed with respect to the original schedule. As a result, the schedule can be completely rearranged. Also, the model is limited to disruptions which results in idle time of a machine.

In 1991, Nof and Hank Grant [59] focused on the creation of robust schedules. As a result, the consequences of disruptions on the schedule is reduced. In case of disruptions complete scheduling should be applied. However, due to the robustness this often still leads to the original schedule with a few minor changes. This research was followed up by Shafaei and Brunn [64] who researched the effect of robustness on schedules. In their approach schedules were made short up front by making use of a rolling horizon approach, while taking into account the task criticality, processing time and due date. Since constantly new information is provided to the model, frequent rescheduling is applied. This is seen as way to minimize the impact during disruptions. According to the authors rescheduling should therefore take place regularly and not necessarily only in case of disruptions.

Afterwards Akturk and Gorgulu [66] described a reactive hierarchical scheduling approach which makes use of match-up scheduling. The approach to the problem is heuristic due to the computational complexity. The application of the model is a modified version of Job Shop Scheduling Problem (JSP) at which jobs can only go through a predefined set of paths of machines. A match up point needs to be found where the state of the new schedule is identical to the original schedule. Between the machine breakdown and the match up point, the schedule completely rescheduled. However, the objective was to create a new schedule that is consistent with other production planning decisions such as material flow and tooling. The model is unable to implement changes further ahead in the future than the match-up point. In order to make this approach work well, a robust schedule is required to be able to apply match-up scheduling. If case of a non-robust schedule the match up point will be too far ahead and as a result require too much computational time

In 2007, Yuan et al. [67] studied rescheduling a JSP under disruptions to minimize the makespan. During rescheduling the change in sequence should be prevented and jobs should be completed before their release date. Disruptions are modelled in the form of unexpected arrival of new jobs. In order to define the environment, the author uses the $\alpha|\beta|\gamma$ classification scheme defined by Graham et al. [68]. α defines the scheduling environment, β defines the job characteristics such as constraints and γ defines the optimality criteria. An approximation algorithm in the form a greedy max approach was developed. By default jobs the original schedule remains unchanged. New jobs can be inserted in non-decreasing order of release date if the schedule allows.

Tantardini et al. [69] researched the impact of rescheduling planned maintenance activities on a maintenance service contract in different kind of environments. A case study was first performed to investigate which cost factors are of importance in case of disruptions. The following performance parameters were found to be of importance in case of rescheduling:

1. Period to which a task is rescheduled; weekend, or committed to other maintenance etc.
2. Type of maintenance that needs to be rescheduled
3. Number of interventions required in the remaining schedule
4. Anticipation of the rescheduling notice
5. Number of shifting periods for workforce and spare parts availability

Based on these performance parameters Tantardini et al. created a model which quantifies the costs for rescheduling maintenance interventions. The cost is calculated by a set of linear equations in which the consequences of rescheduling a task is determined by coefficients based on the performance parameters given above. However, the model itself does not make changes to the schedule itself. The user needs provide a set of changes to the original schedule. The method serves as a way to determine the cost and consequences of a new schedule compared to the original.

Liu and Ro [62] studied the effect of rescheduling production schedules in case of machine disruptions for a JSP. The environment is very similar to the one described by Yuan et al. [67]. The goal is to prevent deviations from the original schedule. The time shift for each job is therefore modelled both as a constraint and a objective. The research compares the performance of three different models: pseudo polynomial, constant factor approximation and fully polynomial. The research mainly focused on the implementation and comparison of those three methods. Therefore, several extensions are possible such as the implementation of multiple machines and addition of resource constraints.

In 2018 Luo et al. [70] created a rescheduling model which minimizes the alteration to the original schedule compared to the original schedule. This is measured as the absolute deviation between the two schedules. The maximum time deviation is both modelled as objective function and constraint. The research is therefore related to Liu and Ro [62]. However, Luo et al. [70] added the possibility to assign different levels of priority tasks. Consequently, the make span of the schedule is not necessarily the shortest possible. The model makes use of a fully polynomial time approximation scheme and dynamic programming which is able to find the exact solution in the presented cases.

Research on the effect of machine scheduling under disruptions was done by Liu and Zhou [60]. Since schedules do not operate as planned, they need to be updated frequently. During rescheduling there should be a stability between the deviation between the original and new schedule. In order to solve the problem in polynomial time the author makes use of an evolutionary algorithm. The limitation of this model is that it only applies for a single machine. Also the type of disruptions that were studied was limited to unexpected arrival of jobs. According to the authors, future research should be done concerning cancellations, change in due dates or job reworks.

Wang et al. [71] added the effect of preventive maintenance actions and arrival of new jobs on production schedules. The research is closely related to the work performed by Liu and Zhou [60]. The schedule performance was assessed based on the number of deviations from the current schedule and the total operational cost to achieve the new schedule. After maintenance has been performed, the effectivity of the machine increases. The model that has been used for rescheduling was a multi objective evolutionary algorithm. In order to increase the performance of the model a better prediction method can be used of which jobs need to be rescheduled.

H.4.3. Health Care

The health care sector is a very dynamic environment, where rescheduling models are applied. The arrival of emergency patients or the unavailability of doctors can require adaptation to the operation schedule. This problem is in many aspects similar to the maintenance scheduling problem to which this literature study is aimed. Both patients and maintenance tasks have levels of priority, due dates and resource requirements.

In 2012, Hulshof et al. [72] performed a literature study on methods to create a resource capacity planning within the health care sector. This study especially focused on the several departments present within hospitals. Hulshof et al. concluded that several reschedule models were already developed, however each of them specifically focused on either patient rescheduling or staff rescheduling. In the same year van Essen et al. [73] created a decision support tool for operating room scheduling models. This aimed to create a new scheduled which both satisfies the schedule of the manager and the preferences of the patients. To achieve this, two decision rules were implemented for rescheduling. Surgeries could be shifted in time or breaks could be scheduled in between surgeries. The order of surgeries should remain the same.

In 2017, Mahdi ValiSiar and Ramezanian [74] developed a scheduling-rescheduling approach patients in operating rooms. This problem was modelled as a MILP together with with a rolling horizon technique. Multiple levels of priority were considered in combination with due dates and surgeries of different duration. The objective was to minimize tardiness of patients and prevent idle and overtimes of operating rooms.

Ballestín et al. [75] preformed a follow-up research which aims both to minimize the percentage of tardy passengers (scheduled after due date) and maximize the utilization rate of the operating rooms. The different policies are evaluated by creating multiple scenarios with different objective functions. The goal of rescheduling is not only to consider the current planning phase but also the effect of the current planning on the upcoming phases. This is taken into in the objective function. By solving the ILP model both the future consequences of current decisions are taken into account as well as the number of changes between the new and original schedule. This model can be further improved by including resource constraints, such as manpower availability.

Thompson et al. [76] focused on the assignment and re-assignment of passengers to hospital floors. Especially during demand surges, hospital floors need to be scheduled effectively in order to prevent waiting time for patients. By implementing a DSS, passenger capacity can be increased which results in an increase of both revenue and passenger satisfaction. Instead of using a Decision Support System (DSS) many hospitals use a myopic policy for scheduling patients, which leads to suboptimal solutions. An approximation algorithm was developed for the problem by creating a MDP with a finite rolling horizon. Each interval is optimized with respect to the cost in the current period and an expected future cost. The approach is therefore very similar to the Lagos et al. [42], which combined a rolling horizon strategy with value function approximation.

H.4.4. Construction

Projects within the construction industry are dependant on a lot of factors such as the environment and deliveries of third parties. Rescheduling is therefore an extremely important aspects since projects rarely go according to their original schedule. Liu and Shih [7] describe a framework where construction rescheduling can be applied based on a manufacturing rescheduling framework. The framework takes several kind of construction tasks into account and has implemented constraints to stick to the previous schedule as much as possible. As objective function, there are three variations. The goal can be set to minimize the total project cost, duration or a combination of both.

The research took the productivity aspects into account for the rescheduling decision making process in the construction sector. The rescheduling mechanism should therefore cater the management needs. The authors prefer to use partial rescheduling if the impacts can be overseen. Otherwise complete rescheduling should be considered.

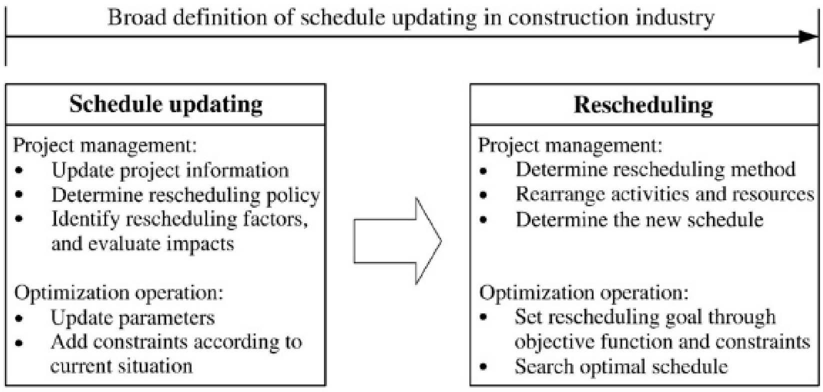


Figure H.5: Differences and relations between schedule updating and rescheduling. [7]

The model uses constraint programming which is a form of artificial intelligence in which feasible solutions are found out of a large set of candidates.[77] The method makes use of branches where forward and backward calculations are performed by using the Critical Path Method (CPM). However, there is no guarantee that the found solution is optimal. The generation of a new schedule is a trade-off between cost, time and influence of delaying activities.

H.4.5. Conclusion

As discussed in Appendix H.4.1, a Maintenance Recovery Problem (MRP) should be based on a dynamic environment with variability in the arrival order of task. Literature discussed in this chapter is mainly subdivided in two categories: complete rescheduling and partial rescheduling. Partial rescheduling is only alters the affected elements of the schedule due to the disruption. For airline maintenance rescheduling it is preferable to partially reschedule, such that the schedule mainly remains the same.

Partial rescheduling is dependant on the requirements of the original schedule. As stated in the conclusion of Appendix H.2, there are three requirements which are of importance for scheduling of maintenance: task prioritization, resources availability and cost. Task prioritization and resources should be taken into account within the model to prevent violation of constraints. Cost should be considered in the form of the number of changes made to the schedule and the quality of the new schedule, based on task ordering and resource utilization. In Table H.6, the research covered in this chapter is evaluated with respect to those three requirements. If an aspect of rescheduling is discussed by one of the authors this is indicated by a check mark (✓).

Table H.6: Table with overview of aspects taken into account for rescheduling

Author	Task ordering & prioritization	Resources	Cost
1993: Li et al. [65]	✗	✗	✗
1995: Wu and Li [63]	✓	✗	✗
1997: Abumaizar and Svestka [6]	✗	✗	✗
1997: Akturk and Gorgulu [66]	✓	✓	✗
2009: Liu and Shih [7]	✗	✓	✓
2012: van Essen et al. [73]	✗	✓	✗
2014: Tantardini et al. [69]	✓	✗	✓
2014: Liu and Ro [62]	✓	✗	✗
2015: Liu and Zhou [60]	✓	✗	✗
2015: Wang et al. [71]	✓	✗	✓
2017: Mahdi ValiSiar et al. **[74]**	✓	✓	✗
2017: Ballestín et al. [75]	✓	✓	✗
2018: Luo et al. [70]	✓	✗	✗

It can be concluded, that each of the subjects is at least discussed by two separate authors. However, there is no research that combined all of the aspects into one approach. The researches performed by Mahdi ValiSiar and Ramezanian [74] and **[75]** takes most of those aspects into account but applied their model to reschedule operating rooms. However, their models shows many similarities with airline maintenance.

In the context of maintenance disruption management, disruptions can happen in multiple forms. Additional tasks can be added, tasks can take longer than expected or the availability of resources can change. A limitation of most research discussed in this chapter, is that only one specific kind of disruption is considered in their approach. Liu and Shih [7] stands out from other researches, by making use of a two-step optimization process. In the first step, the schedule is updated in which all kind of disruptions can be included. This also outlines the shortcomings of the current schedule.

At last, the research performed by Thengvall et al. [49] created an interactive model at which the users could give input and preferences before rescheduling. This approach is promising, since the expertise of the user is combined with the computational power of the model.

H.5. Conclusion

This literature study outlined research that relates to maintenance rescheduling in case of disruptions. It has been divided into three parts: maintenance requirements, airline disruption management and task rescheduling. Appendix H.2 showed that maintenance scheduling develops from a high-over planning towards a detailed assignment of tasks. Three main requirements were deduced for maintenance scheduling: Task ordering & prioritization, Resources and Cost. Maintenance is often mentioned as a point of improvement for further research to achieve more flexibility and cost savings. **[4]**

In the context of airline disruption management, Appendix H.3 showed that the Maintenance Recovery Problem (MRP) as displayed is the only aspect which has not been discussed individually in literature. It can be concluded that nowadays there is an interest increase in solving multiple aspects of disruption management simultaneously. In some of these approaches maintenance is included, however from a maintenance standpoint these models lack the required detail. Maintenance is often seen as a fixed requirement rather than a variable.

Because the MRP has not been discussed individually in literature, Appendix H.4 provided applications at which task rescheduling is applied. From other fields of work, methods have been applied which show many similarities for rescheduling of maintenance. For example scheduling patients for surgery.[54, 74] Liu and Shih [7] showed how multiple kinds of disruptions can be modelled to create an adaptive decision support tool.

As explained in the introduction of this report, the airline maintenance department is a complex environment. It is therefore an illusion that having a well-planned schedule up front will also result in optimal operations. The adaptiveness of the scheduling process is just as important as the schedule itself. A Decision Support System (DSS) cannot take over the tasks of humans in a complex environment, since humans are not limited to a predefined set of rules.[12] A DSS should therefore assist the users in the decision making. The research of Thengvall et al. [49] is thus especially interesting since human interaction is taken into account. The conflict of interest during maintenance disruptions, as explained in the introduction, is confirmed by multiple researches. [18, 22] During maintenance rescheduling both standpoints should be taken into account in a cost-benefit analysis.

From this literature overview a clear gap in research can be obtained. Maintenance task rescheduling in case of airline disruptions is not covered in literature. The remainder of this research will focus on this subject, in the form of a Maintenance Recovery Problem (MRP). This combines the practical concept of airline disruption management together with the theoretical concept of task rescheduling with the requirements of maintenance scheduling. The research question will therefore be as following:

To what extent can short- and long-term airline fleet availability be improved in a disruptive environment by means of a decision support tool for optimization of maintenance task rescheduling?

The decision support tool should address the Maintenance Recovery Problem (MRP). In order to create a decision support tool, more information should be gathered about the decision making behind maintenance scheduling as well as potential approaches which can be applied to maintenance task rescheduling. Therefore, the following sub-questions have been defined which should aim to answer the research question:

1. How are maintenance tasks currently scheduled?
    - 1.1. Which factors influence task prioritization?
    - 1.2. Which decision rules are currently used for task scheduling?
    - 1.3. Which types of maintenance are currently scheduled?
    - 1.4. How are due dates of tasks currently taken into account?
    - 1.5. How are () currently taken into account for maintenance task scheduling?
    - 1.6. How does the technical knowledge of a maintenance scheduler influence the schedule?
2. How are disruptions currently handled within the maintenance department?
    - 2.1. What kind of disruptions take place?
    - 2.2. Which factors are currently taken into account during handling of disruptions?
    - 2.3. What are the recovery options for handling disruptions?
    - 2.4. How is a trade-off performed between multiple recovery options?
3. What methodology can be applied to maintenance task rescheduling?

3.1. Which of the known models meet the requirements for maintenance rescheduling?
3.2. How can user preference be implemented in a decision support tool?
3.3. Which constraints should be implemented in the model for maintenance task rescheduling?

4. What are the main objectives for the cost-benefit analysis of maintenance task rescheduling?

   4.1. How is the fleet availability in the long term taken into account during task rescheduling?
   4.2. What are the costs of reassigning maintenance?
   4.3. What are the costs of violating resource constraints (in order to improve outcomes)?
   4.4. What is the benefit of an increase in fleet availability?

5. To what extent is an exact model for maintenance task rescheduling able to find feasible recovery options during disruptions?

   5.1. Is the model able to find similar solution to those manually found by using expertise knowledge?
   5.2. Is the model able to achieve a higher fleet availability in the long term compared to manually found solutions?

[resume]What is the performance of a heuristic approach with respect to an exact model for maintenance task rescheduling?

1. 1.1. Which heuristic approaches are suitable for maintenance task rescheduling?
   1.2. Is the heuristic approach able to find a close to optimal solution?
   1.3. Is the heuristic approach able to find a solution within 5 minutes?

I
Research methodologies

Already graded under AE4010

Executive Summary

Within commercial airlines disruption take place daily. As a result, adjustments need to be made to return to a feasible schedule. Extensive research has been performed in recovery models for aircraft, crew and passengers. For maintenance, a strategy during disruptions is not yet covered in literature and will therefore be the focus of this project. The project will use data provided by KLM Royal Dutch Airlines to simulate disruptions and compare the outcome of this project to the decision making in reality. The goal of this project is to achieve an increase in fleet availability by means of a decision support tool for maintenance task rescheduling during disruptions. Currently decisions during maintenance disruptions are shortsighted, at which the focus is on the coming days of operation. The decision support tool should consider the entire scheduling interval of 14 days.

To achieve this, a mixed integer linear programming (MILP) approach will be implemented which reschedules maintenance tasks. The 4M requirements; machinery, method, manpower and material, form the constraints which need to be satisfied in order to schedule maintenance. Secondly, the maintenance due date is the ultimate date at which a certain maintenance tasks needs be scheduled. Ideally, maintenance tasks are executed as early as possible and this will therefore be the objective of task rescheduling. Since (re)scheduling problems are NP-complete, a rolling horizon applied to the MILP together with value function approximation.

By implementing a decision support tool, which takes both the long- and short-term aspect into account, the airline the goal is to achieve a higher fleet availability. This would result in significant operational benefits for both the MRO and the airline overall performance.

I.1. Introduction

Maintenance is an important cost factor of airline operations, by taking up 11% of the operational cost, according to the [10]. By performing maintenance, the aircraft remains in an airworthy state and is available to airline operations. Since maintenance is such an important cost factor, the goal of a Maintenance, Repair, Overhaul (MRO) to schedule maintenance as efficiently as possible. This causes a decrease in maintenance cost and an increase in operational availability. By making well thought decisions, both money and time can be saved.

Despite efficient maintenance schedules, within a commercial airline disruptions take place daily. As a result, airline schedules are rarely executed as planned. An investigation of the factors causing airline delays shows that maintenance is by far the biggest contributor. [11] showed that airline maintenance represents 22.3% of the number of delays and in terms of minutes, this is close to 40%. First of all, these maintenance disruptions can be caused by unexpected failure of aircraft components. Secondly, scheduled maintenance tasks can take up more time than anticipated if non-routine maintenance is found during execution. Last of all, maintenance can also be disrupted by other airline departments, which causes a knock-on effect on maintenance operations.

As a result of disruptions, maintenance schedules need to be adjusted to regain a feasible schedule. This can be achieved by postponing and reallocating scheduled maintenance tasks. Often this is seen as an operational burden. However, implementing a flexible maintenance strategy can mitigate the risks and enhance the overall airline performance as already proven by **[5]**.

Rescheduling of maintenance, in case of disruptions, is required to keep the fleet in an airworthy state. There is a conflict of interest between providing fleet availability and the cost of performing maintenance according to **[22]**. Clarke [4] indicated that maintenance rescheduling currently mostly relies on expertise knowledge. Decisions on the day of operation can affect the days to come as well. Since humans are only able to take a limited number of factors simultaneously into account, the future consequences of decisions are currently not taken into account. This research will therefore focus on the decision making during maintenance disruptions and transform the decision making from relying on expertise knowledge to data-driven decisions. Such that both short- and long-term consequences are considered simultaneously.

The remaining part of this report gives a more detailed of airline maintenance disruption management. First a theoretical overview will be provided followed by the research questions and goals of this project. Based on this, the theoretical background will be provided together with the experimental set-up. Afterwards the presentation of results will be discussed combined with the conclusions which should be able to be drawn from the project. At the end of this report the planning of this project is provided.

I.2. State-of-the-art/Literature Review

The literature review section is divided into three parts. First, literature which discusses airline maintenance will be discussed, followed by research covering disruption management strategies for airlines. At last, literature covering rescheduling problems in other fields of work are discussed. In case of airline maintenance disruptions, rescheduling needs to be performed. Aircraft maintenance needs to be performed according to strict regulations set by the EASA (in Europe). Scheduling of airline maintenance, whilst taking regulations into account, is already widely applied in literature. Maintenance scheduling develops over time from a high-over planning towards a detailed assignment of tasks and resources. Jiang [23] was one of the first to take multiple aspects of maintenance into account during the aircraft routing allocation. Maintenance planning was subdivided up in two parts, short term and long term. In the long term, time should be allocated for aircraft maintenance. In the short term, maintenance tasks should be planned optimally to prevent a stranded aircraft. The user could define in which time interval the maintenance tasks should be executed.

Marseguerra and Zio [39] focused on maintenance task scheduling alone without taking aircraft routing into account. Multiple maintenance and repair policies are given which are compared to each other based on safety and economic factors. The cost of assigning maintenance personnel is included as well the cost of scheduling the maintenance task itself. Later, Papakostas et al. [40] provided an outline for scheduling line maintenance tasks before its due dates. During the ground time of the aircraft at the airlines home base, line maintenance tasks could be scheduled. The best schedule is determined based on cost, operational risk, flight delay and remaining useful life. The approach focussed on an economic analysis for the optimum planning of scheduling maintenance tasks in which costs of the facility, supplies and personnel were taken into account.

Quan et al. [44] went into more detail about resource allocation for airline maintenance. The research makes a trade-off between the number of maintenance personnel and the completion of tasks in time. Focusing on one of those two is not sufficient, therefore a multi objective problem is created. A novel aspect of their approach was that the preferences of the manager are taken into account. Samaranayake et al. [25] focused on a different aspect of resource allocation, with scheduling of component replacements. This research outlined the effect of material supply of performing maintenance at Qantas. Resources and material should be in the facility in time such that scheduled maintenance is not disrupted.

At last, Lagos et al. [42] described the set-up of an airline maintenance scheduling program at which the maintenance tasks should be scheduled before their due date. The model decides which aircraft to maintain and which tasks need to be executed. The goal is to minimize cost and future tasks outside of the planning horizon. The order of task scheduling is based on criticality. Resource usage is included within the approach in the form of different skill levels of maintenance personnel.

Based on the various areas of research described above some general requirements for maintenance scheduling can be deduced which also should be taken into account during maintenance rescheduling:

- Task ordering & prioritization: Maintenance tasks should be ordered correctly such that urgent tasks are executed before non-critical task. Tasks can receive a higher priority depending on their criticality category and proximity to due date.
- Resources: If maintenance tasks are scheduled, the 4M requirements; machinery, manpower, method and material, need to be available to execute maintenance as described by **[8]**.
- Cost: Scheduling of maintenance should be cost-driven to optimize the performance of both the MRO and airline operations.

The researches described above include all the aspects which be taken into account for maintenance scheduling. None of these researches takes the effect of disruptions on the maintenance schedule into account. However, research has been performed in disruption management that focused on other airline departments. In some cases, airline disruption management research included maintenance aspects, but it has never been the focus. **[51]** included maintenance constraints in an aircraft recovery problem. Within the model formulation, a route is said to maintenance feasible if it visits an airport where maintenance can be performed within the required time interval. Abdelghany et al. [52] included maintenance constraints within the aircraft recovery and crew recovery problem formulation. Scheduled maintenance activities should not be violated, therefore the aircraft needs to be at a given location and a given point in time. Both **[51]** and **[52]** see maintenance as a requirement and not as a variable.

Eggenberg et al. [47] implemented maintenance flexibility into the aircraft recovery problem. Rescheduling maintenance activities is allowed as long as the next scheduled maintenance activity lies within the allowed range of flight hours. Only A-checks are considered in his problem formulation and resource constraints are not included in the model. Rhodes-Leader et al. [24] divided the aircraft recovery problem up in two parts. In the first stage, maintenance is neglected at which the aim is to create a robust schedule. In the second step, maintenance scheduling is included in the problem formulation to fine-tune the schedule.

At last, Liang et al. [5] takes more maintenance flexibility into account within the aircraft recovery problem. A maintenance task can go due on flight hours, cycles or calendar days, whichever comes first. It is possible to swap maintenance tasks as long as it takes place before its due date. Therefore, the following recovery actions are considered: Flight delays, flights swaps, flight cancellation and maintenance swaps. According to the authors swapping planned maintenance can save between 20% to 60% of airlines disruption cost.

As can be concluded from the researches given above, maintenance rescheduling in case of disruptions has not been covered in literature yet. For airline disruption management, some researches included maintenance in their problem formulation in the form a constraint. Lately maintenance flexibility is also considered to some degree. However, these researches still included many simplifications in their approach for maintenance rescheduling.

However, in other fields of work, research has been performed which shows many similarities with maintenance rescheduling. For example in the medical sector, rescheduling is already widely applied in the form of schedule changes in the assignment of patients for operating rooms. **[74]** implemented a model where multiple levels of priority are considered in combination with the due date and duration of surgery. The objective was to minimize tardiness of patients and prevent idle and overtimes of operating rooms.

Ballestín et al. [75] preformed a follow-up research on **[74]**, which aims to minimize both the percentage of tardy passengers (scheduled after due date) and maximize the utilization rate of the operating rooms. The different policies are evaluated by creating multiple scenarios with different objective functions. The goal of rescheduling is not only to consider the current planning phase but also the effect of the current planning on the upcoming phases. For rescheduling both the future consequences of current decisions are taken into account as well as the number of changes between the new and original schedule.

Liu and Shih [7] describes a rescheduling model that can be applied in the construction sector. Projects within the construction industry are dependent on many external factors such as the weather and deliveries of third parties. Rescheduling is an important aspect since projects rarely go according to their original schedule. Liu and Shih [7] describe a framework where construction rescheduling can be applied based on a manufacturing rescheduling framework. The framework takes several kind of construction tasks into account. During rescheduling to aim is to make the least amount of changes as required. The rescheduling process is split up in two parts. First, schedule updating aims to get an overview of the actual processes, together environmental changes and present conflicts. This gives an overview of the shortcomings in the current schedule. In the second phase, activities are rescheduled such that constraints are satisfied again. The researches described above are very similar in terms of requirements compared to airline maintenance and their approach can therefore be applied to maintenance rescheduling.

I.3. Research Question, Aim/Objectives and Sub-goals

As can be concluded from the previous section, there is gap in literature in the adaptiveness of maintenance scheduling, in the form of disruption management for airline maintenance. This combines the practical concept of airline disruption management together with the theoretical concept of task rescheduling with the requirements of maintenance scheduling.

Currently maintenance rescheduling in case of disruption relies on expertise knowledge. As a result, solution are often optimal in the short-term. However, in the long term this can have adverse effect if maintenance has been postponed. The project will therefore focus on a transition from manual decision making during maintenance disruptions to a state of data-driven decisions. The development of a decision support tool should assist maintenance schedulers in the decision-making. Both the short and long term aspects should be included within the model and the consequences of the disruptions should be given quantitatively. The focus will be on a decision support tool instead of decision tool as expertise knowledge can never be fully integrated into one model for a complex environment such as maintenance scheduling. There should therefore be room for user input and adaptiveness to the model such that disruptions can be solved in the complex environment.

I.3.1. Research Question(s)

The benefit of implementing a decision support tool for maintenance task rescheduling is that this should result in better decision making and as a result an increase in operational performance. However, in operational performance there is a conflict of interest. On one hand, the MRO aims to achieve maximum fleet availability for the airline. On the other hand, it aims to minimize maintenance cost. Aiming to optimize one of those two does not necessarily satisfy the other. The decision support tool should aim to achieve an increase in airline fleet availability as long as this weighs up to a potential increase in maintenance cost. A cost-benefit analysis should be performed between fleet availability and maintenance cost. The main research questions is therefore a following:

To what extent can short- and long-term airline fleet availability be improved in a disruptive environment by means of a decision support tool for optimization of maintenance task rescheduling?

In order to create a decision support tool, more information should be gathered about the decision-making behind maintenance scheduling as well as potential approaches that can be applied to maintenance task rescheduling. Therefore, the following sub-questions have been defined which should aim to answer the research question:

1. How are maintenance tasks currently scheduled?
2. How are disruptions currently handled within an airline maintenance department?
3. What methodology can be applied to maintenance task rescheduling?
4. What are the main objectives for the cost-benefit analysis of maintenance task rescheduling?
5. To what extent is an exact model for maintenance task rescheduling able to find feasible recovery options during disruptions?
6. What is the performance of a heuristic approach with respect to an exact model for maintenance task rescheduling?

I.3.2. Research Objective

The corresponding research goal is defined as following:

Achieve an increase in fleet availability in the short- and long-term by means of a decision support tool for maintenance task rescheduling during disruptions.

In Figure I.1 the research goal is outlined in the form of a project model flow. For maintenance disruption management there are two required inputs: the current maintenance schedule and a set of required changes due to a disruption. By taking these inputs together, a schedule check should be performed which checks if there are any infeasibilities in the schedule due to the disruption. For

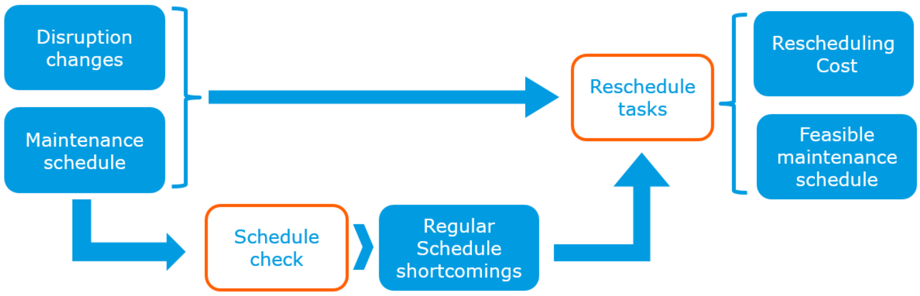


Figure I.1: Proposed model flow for disruption management research

scheduled maintenance tasks the 4M's should be available. Secondly, regulations may not be violated due to the disruption changes.

Next to schedule shortcomings, user input is added by a dotted line. A user needs to be able to add or remove shortcomings if this required because of operational reasons. However, by default no user input should be required. Based on the schedule shortcomings, task rescheduling should take place, which takes the schedule back to a feasible state. During rescheduling, both the 4M availability and maintenance regulations should be satisfied. A cost-benefit analysis should be performed between fleet availability and maintenance cost. There should be two model outputs: the rescheduling cost (in the form of a KPI) due to the disruption and the adjusted maintenance schedule.

I.4. Theoretical Content/Methodology

Within KLM, there is the expectation that maintenance disruption management is currently driven on shortsighted decisions. Maintenance tasks are often postponed if regulations allow this. By doing so, the coming days of operation are saved but this can cause additional problems for the days to come. The objective for maintenance task rescheduling will therefore be to schedule maintenance tasks as quick as possible rather than postponing maintenance tasks. Ultimately, a task always needs to be scheduled before the due date. Secondly, the model horizon should not look only at the coming days but at the full 14 days scheduling horizon that is currently used within KLM. This should prevent providing solutions on the short term but creating problems on the long term.

Referring back to Figure I.1, there are two models which need to be created for this project. First, the schedule check needs to be performed, to evaluate the current status of the schedule. As described by Schut [8], the feasibility of the schedule can be checked by considering, the 4M requirements for each scheduled maintenance task. The 4M requirement consists of the availability of Material, Machinery, Method and Manpower. In case of airline maintenance, there is also a subdivision of manpower for each required skill level. If all 4M's are available, maintenance can be performed during the scheduled time interval. If not, there is a schedule infeasibility and the maintenance task should be rescheduled. Because of a disruption, the 4M availability can change and cause infeasibilities to the maintenance schedule.

The availability of machinery, material and method can directly be obtained from the data. The estimated time of arrival or the availability is indicated. For manpower this is more complicated since the assignment of manpower is dependent both on the required skills for tasks as well as the available skilled manpower. In order to check for manpower availability a similar approach as Yang et al. [9] will be used. A linear programming (LP) model assigns manpower to maintenance tasks which aims to meet all maintenance requirements. Each maintenance task is also subdivided per required type of skill.

The second model will focus on rescheduling of maintenance. In this case the availability of 4M's needs to be satisfied again for all maintenance tasks. This can be achieved by rescheduling maintenance to other points in time where the 4M's are available. Lagos et al. [42] researched the development of a maintenance scheduling model in the form of a mixed integer linear program (MILP). Instead of 4M availability, Lagos et al. focused on task criticality, hangar availability and due dates of maintenance. The due date is the deadline before maintenance needs to be performed. By combining the models of Yang et al. [9], Lagos et al. [42] and **[8]** both the 4M requirements and airline maintenance scheduling constraints can be implemented.

The model will be optimized with respect to a Key Performance Indicator (KPI). The approach for the KPI will be similar to Ballestín et al. [75], at which the goal is to schedule tasks as early as possible based on the due date. This holds for deferred defects and other faults. For recurring maintenance the goal is almost identical however, maintenance should be scheduled at least after 90% of the maintenance interval. Otherwise that kind of maintenance would need to be executed too often. The closer a maintenance task is scheduled to its due date, the higher the priority and thereby the cost of scheduling will be. By doing so, it is encouraged to schedule maintenance further away of its due date.

As explained in section I.2, currently no method has been developed for airline maintenance rescheduling. In order to add rescheduling to a LP model, approaches from research in the health care sector are used. Mahdi ValiSiar and Ramezanian [74] developed a patient rescheduling MILP model, at which the goal was set to make the least amount of changes to the original schedule. The goal holds for both rescheduling of patients and rescheduling of airline maintenance tasks. Rescheduling causes a loss of already taken preparations. Mahdi ValiSiar and Ramezanian [74] takes this into account be setting penalty values on making changes to the original schedule.

One of the requirements for decision support tools in a disruptive environment, is a rapid decision time. The computational time can be at most a matter of minutes. Scheduling problems are NP-complete as proven by Talluri [14]. As a result, the computational time increases non-linearly by increasing the problem size. MILP's therefore often can take up a very long time to compute the outcome. To compensate for this a hybrid approach can be implemented which combines the MILP with a heuristic to decrease computational time without sacrificing the solution quality.

The goal for this project is to apply two heuristic approaches; a rolling horizon strategy in combination with value function approximation. Abdelghany et al. [52] applied a rolling horizon strategy into an airline disruption management problem that focused on the allocation of aircraft to flights. By a rolling horizon approach, the time horizon is split up in parts. This results in a decrease of computational time since the relation between scope and time is non-polynomial. After the first horizon has been solved, the model moves on to the next horizon that overlaps partially with the previous horizon. This process is repeated until the complete horizon has been covered.

A downside of the rolling horizon approach is that the model does not take into account what is coming in the next horizons. In the context of a task rescheduling algorithm this can result in tasks being indefinitely postponed outside of the scheduling horizon since there are still more horizons to come. To overcome this side effect, value function approximation can be applied, as described by Lagos et al. [42]. This is a form of reinforcement learning at which unscheduled tasks receive an approximated value if it is postponed to be scheduled in the next horizon. The value function approximation method serves as a way to give an estimation of the cost of scheduling the task in the next interval. This method aims to prevent indefinitely postponement of tasks.

I.5. Experimental Set-up

The development of the model for this project can be performed by using dummy maintenance data. However, in order to be able to evaluate the performance of the model with respect to the reality, data for this project will be provided by KLM Royal Dutch Airlines. Since real airline data will be use for this project, the results of the research will form an accurate representation of reality.

The first stage of the project will be used to define the scope and sample size. The initial sample size for the project will be the wide-body technical defects team of KLM. This team focuses on executing deferred defects. If parts of an aircraft unexpectedly break this usually needs to be repaired right away in order to remain airworthy. In some cases, the fault can be registered as deferred defect at which the aircraft is allowed to continue operations for a given amount of days before it needs to be repaired or replaced. Since these aircraft parts break down unexpectedly disruptions happen regularly. Rescheduling needs to be applied to bring the schedule back to a feasible state. If the project scope allows, the goal is to increase the problem size to other teams of the wide-body fleet. The sampling error can decrease by this since there will be more rescheduling flexibility. The quality of the provided data also needs to be evaluated to verify that there are no inconsistencies. More in-depth research is required regarding the scope and sample size. This research should also lead to the answers of research sub-questions 1 till 4.

On the technical side, the model will be implemented in Python 3.7.1. As described in section I.4 the problem will be formulated as a mixed integer linear programming (MILP) model. The MILP will be optimized by making use of Gurobi 9.0.0 since both these software packages are used throughout the master curriculum and internally at KLM. Schedule infeasibilities and the result of tasks rescheduling will be displayed in TIBCO Spotfire 10. This software can be used to display data in an interactive manner. The model will be run on a local workstation with 16GB of RAM and an Intel Core i7-8650 clocked at 1.90 GHz. This is a standard machine set-up such that the model can easily be run by potential end-users. Documentation of the model will also be created, such that others can reproduce the results.

I.6. Results, Outcome and Relevance

In order to reschedule maintenance in case of airline disruptions the following three data sources are required:

- Maintenance task data: This data includes all maintenance tasks that need to be executed for each aircraft registration. The data includes a task description, critically of the task as well as the 4M requirements. For method, machinery and material it is also indicated whether this is already available.
- Maintenance schedule: The maintenance schedule outlines at which times there is a reserved slot for maintenance operations. Initially a slot is assigned to an aircraft sub-type. Close to the day of operations, a specific aircraft registration is assigned.
- Work package data: If an aircraft is assigned to a maintenance slot, a work package is created. This outlines which maintenance tasks are scheduled to be executed during the maintenance slot.
- Manpower availability: This data outlines the number of personnel that is available throughout for each kind of skill. In order to execute a maintenance task, personnel of with the re-

quired skill needs to be assigned to it. If there is no personnel available, the manpower requirement out of the 4M's cannot be satisfied.

Based on these input data sources together with a disruption input, maintenance task rescheduling can be performed. The output of the model should both be the new schedule as well as the corresponding rescheduling cost. Verification of the model will be performed by means of dummy cases. The model can be evaluated whether it makes the right decisions by means of these simple scenarios. For the dummy cases, the output of the model should be equal to the already known solution. The model is therefore verified whether it behaves as expected and if maintenance constraints are implemented correctly.

Secondly, the model needs to be validated whether it is capable of finding solution in case of real disruption scenarios. This is also required to answer research sub-question number 5 given in section I.3. The given solution by the model needs to be both feasible and at least equivalent to the decision made by the maintenance scheduler. The validation will be done based on real disruptions scenarios provided by KLM where the manual decision making can be compared the model output. The performance of the heuristic approach will be evaluated based on a comparison between computational time combination with the differences in solution quality. With this analysis research sub-question number 6 can be answered.

As described in section I.3 the main goal achieve an increase in fleet availability by means of a decision support tool, compared to the decisions that are currently performed manually. The fleet availability is calculated by means of the KPI described in section I.4. To evaluate if by means of the model a higher fleet availability can be achieved, a set of scenarios will be generated based on past disruptions. The actions that were taken during these disruptions are known as well. For each scenario, the difference in fleet availability will be compared between the manual solution and the model solution. By evaluating all scenarios, a conclusion can be drawn whether the model can achieve a higher fleet availability for KLM.

I.7. Project Planning and Gantt Chart

The project has been divided into four main parts: literature study, initial phase final phase and finishing phase as can be seen in Figure I.2. Between the initial phase and final phase, there is a period of 5 months where the research is on-hold. During this period, additional theoretical experience will be gained which can be implemented during the final phase. The literature study has already been performed which is summarized in section I.2.

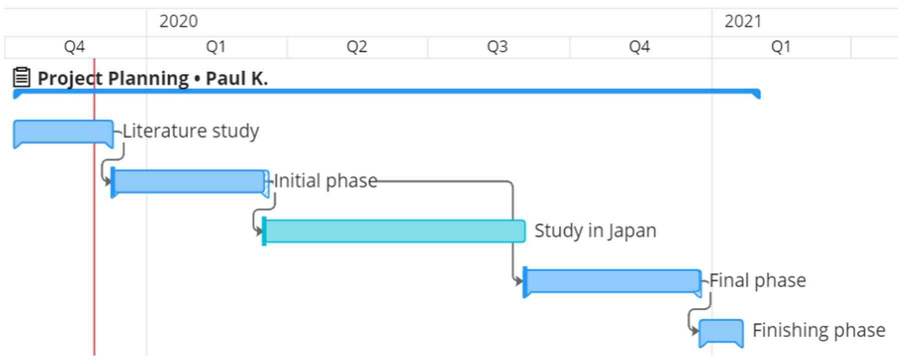


Figure I.2: Gantt chart of general project planning

Figure I.3, included in section I.9, provides a more detailed outline of the project planning. To start with the project, there are three steps that need to be executed: scope determination, KPI formulation and data analysis. These steps are required to verify if the research question given in section I.3 can be answered.

The initial phase will also be used to fine-tune the research question if this proves necessary based on one of those tasks described in the Gantt chart. During the initial phase a start will also be made on the development of the MILP's for the maintenance check and maintenance rescheduling. During the final phase the MILP's will be fine-tuned based on feedback from users together with implementation of heuristic approaches. During this phase verification and validation is performed as well. In the finishing phase, the final results will be obtained together with presentation of results in a report.

I.8. Conclusions

Commercial airlines are faced daily with disruptions that require changes to the original schedule. Several airline departments are affected by this, such as operations, passengers, crew and maintenance. Disruption management strategies for the first three departments have already elaborately been discussed in literature. However for airline maintenance, disruption management has not yet been the focus of research. Maintenance schedulers currently remove schedule infeasibilities manually during a disruption. Often, this results in a solution that is good in the short term but bothersome in the long term. To transform the decision making from relying on expertise knowledge to data-driven decision making the following research question has been defined:

To what extent can short- and long-term airline fleet availability be improved in a disruptive environment by means of a decision support tool for optimization of maintenance task rescheduling?

By making use of a decision support tool maintenance schedulers are assisted in their decision making during disruptions. The decision support tool will consist of a MILP that reschedule maintenance tasks. During rescheduling, the availability of the 4M's is considered in combination with maintenance regulations. To increase the time performance of the decision support tool, a rolling horizon approach together with value function approximation will be applied as heuristic approaches. By implementing a decision support tool, the goal is to increase the fleet availability by focusing both on the short- and long-term. This should benefit both the overall airline organization as well as the MRO since maintenance is rescheduled more effectively.

I.9. Gantt Chart

See next page

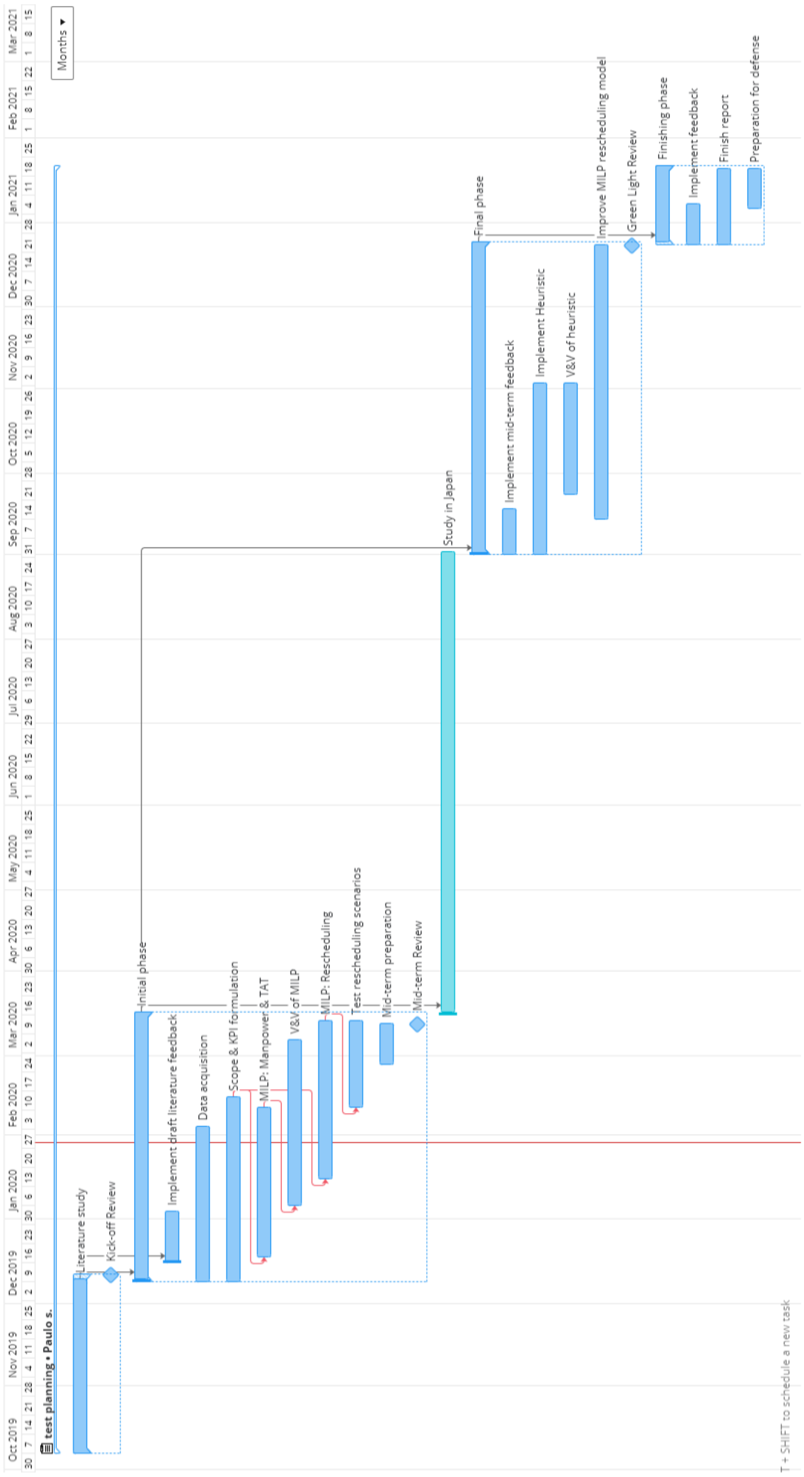


Figure I.3: Detailed Gantt chart of project planning

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