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Airline maintenance task rescheduling in a disruptive environment

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ABSTRACT

Airline maintenance task scheduling takes place in a disruptive environment. The stochastic arrival of corrective maintenance tasks and changes in both fleet and resource availability require schedules to be continuously adjusted. An optimal schedule ensures that all tasks are executed before their due date in both an efficient (at minimum use of ground-time) and a stable (limited number of schedule changes) manner. This paper is the first study to address disruption management for the hangar maintenance task scheduling problem, proposing a practical and efficient modeling framework. The framework comprises a mixed integer linear programming model for airline maintenance task rescheduling in a disruptive environment, in which task scheduling is constrained by the availability of resources. The model's capabilities include creating and adjusting maintenance schedules continuously and dynamically reacting to new information when this becomes available. The modeling framework was tested in a case study provided by a large airline, and its performance was compared to the current practice of the airline. The results show that the proposed approach produces more efficient and stable results. A 3% ground time decrease was achieved, while the number of schedule changes in the last days before operations was decreased by more than half.

1. Introduction

Maintenance is an important factor of airline operations performance as it takes up around 10% of the total available time, and about 15% of total operational cost.[1] As the potential revenue for using a wide body aircraft for commercial operations equals around € 180.000,- per day (rough estimate), efficient maintenance scheduling is of key importance for the earning potential of a commercial airline. Past research has focussed on the optimization of maintenance schedules, with the aim of decreasing maintenance cost and increasing operational availability Knotts (2006). However, despite potentially having one efficient maintenance schedule prior to the start of operations, disruptions during operations are very common in reality. These disruptions, in the form of unanticipated maintenance tasks, maintenance slot adjustments, and resource availability alterations, compromise the efficiency and feasibility of the initial schedule. Creating new schedules each time a disruption emerges is not practical, as some degree of stability is needed for a feasible operational execution. In particular, the presence of maintenance tasks that fall outside of the preventive maintenance checks and the emergence of unexpected corrective maintenance tasks significantly impact the maintenance schedule. For instance, from the case study presented in the paper, it was observed that new corrective tasks arrive, on average, every 4 hours, and require more than 17 hours of daily ground time for a fleet of 60 aircraft (based on data provided for this research). For these reasons, maintenance schedules are required to be continuously adapted 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 decision-making during disruptions.

In this paper, an innovative continuous maintenance task rescheduling framework is presented to improve maintenance task scheduling in a disruptive environment. The core of the framework is an efficient mixed integer linear programming (MILP) optimization model that considers a hierarchy of rescheduling objectives and is constrained by the availability of material, machinery, method, and manpower (4M). The focus of this research is on tasks that require execution in the hangar. This is the first time that disruption management is considered for aircraft maintenance task scheduling. Up until now, research on airline maintenance scheduling did not include schedule flexibility and the occurrence of disruptions. Implementation of the framework in the airline decision-making process contributes to an increase in both sched-

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

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ule efficiency (a reduction in ground time) and schedule stability (a limited number of schedule changes during disruptions). For an airline, this results in a potential increase in the aircraft availability for operations and a reduction in maintenance costs.

The remaining part of this paper is structured as follows: first, a literature overview is provided in Section 2, describing work related to the topics of maintenance task scheduling and airline disruption management. Afterward, the problem is formulated in Section 3. This is followed by the modeling framework discussion in Section 4, including the optimization model formulation. The results obtained with the proposed framework in a real case study are presented and discussed in Section 5. The paper ends with conclusions and recommendations for future research in Section 6.

2. Literature overview

Scheduling of airline maintenance takes place in a dynamic environment that is constantly innovating to be both cost- and time-efficient. As described by Knotts (2006), the goal of the maintenance schedule is twofold; the first goal is to maximize the dispatch reliability such that flights are performed without technical delays, and the fleet availability is maximized. Secondly, the maintenance cost should be minimized. Historically, research in scheduling airline maintenance tasks has been focused on optimization of bundling maintenance and scheduling letter checks, see, for example, work by Sriram & Haghani (2003), Jiang (2012), Deng, Santos, & Curran (2020). With the current rise in prognostic health monitoring tools, as described by Dupuy, Wesely, & Jenkins (2011) and Alabdulkarim, Ball, & Tiwari (2014), the focus has shifted from interval-based maintenance towards predictive maintenance. Because of this, a change of maintenance scheduling strategy is required, at which maintenance scheduling has to be more dynamic to prevent disruptions.

Maintenance scheduling in a disruptive environment whilst taking resource availability into account combines multiple fields of research: task scheduling, resource allocation, and disruptive scheduling. Individually, they have been widely discussed in the literature. The remaining part of this section describes the current state of the art in these research areas and the opportunities that arise for further research.

2.1. Task scheduling

Scheduling of maintenance tasks and the allocation of maintenance slots (ground time) is widely discussed in the literature. In the past, researchers have focused on fleet assignment and routing problems to satisfy maintenance requirements, for example, in work by Feo & Bard (1989), Talluri (1998), Sriram & Haghani (2003). These approaches include maintenance on a strategic level, but the approach is too abstract to schedule maintenance tasks during the operational phase due to the extensive scope.

To achieve a higher level of detail regarding maintenance scheduling, other researchers shifted their attention to scheduling maintenance tasks as a stand-alone problem, leaving the airline network schedule out of scope. This is more applicable for this research as this gives the opportunity for a higher level of detail regarding maintenance scheduling. Marseguerra & Zio (2000) focussed on the scheduling implications of several replacement strategies. 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, Papachatzakis, Xanthakis, Mourtzis, & Chryssolouris (2010) which takes a combination of scheduling objectives into account during maintenance scheduling. An optimal schedule is defined by scheduling tasks close to their due date with the aim of minimizing remaining useful life, cost, and operational risk. Yuan, Han, Su, Liu, & Song (2018) 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.

The most recent and detailed work was presented in 2020 by Lagos, Delgado, & Klapp (2020) which created a maintenance task scheduling algorithm that 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 to design dynamic policies based on Approximate Dynamic Programming techniques. As the scheduling horizon is limited to a few days, an estimation of future costs is provided by means of rolling horizon and value function approximation. The results of this research are promising. However, it lacks the implementation of a few key aspects such as the availability of resources (e.g., machinery, material) as well as the possibility to revise a schedule in case of disruptions.

2.2. Resource allocation

The research described above focuses on the execution of tasks mostly related to the availability of the aircraft. However, as a requirement for task execution, the availability of resources has to be taken into account. Several researchers performed analyses on resource constraints for maintenance task scheduling. In 1991, Dijkstra, Kroon, van Nunen, & Salomon (1991) created a manpower scheduling tool used for line maintenance at KLM. It was used to allocate qualified engineers to execute tasks to match the projected workload with the required capacity. However, the scope was limited to long-term workload prediction as day-to-day simulation was out of scope. Yang, Yan, & Chen (2003) went into more detail regarding the supply of manpower for line maintenance task scheduling. By taking both skills and shifts the research aims for a decrease in the required workforce. More recently, Witteman, Deng, & Santos (2021) modeled the workforce availability and requirement per task at the skill level when considering the problem of scheduling preventive tasks according to a multi-year letter check maintenance schedule, as produced by Deng et al. (2020). The authors considered eight different skill types in their case study. The works described above show that extensive research has gone into the allocation of resources for scheduling airline maintenance tasks, however, a method at which task scheduling and rescheduling are dependent on the change in availability of resources is still missing.

Besides the workforce, other types of resources have been taken into account in research into airline maintenance scheduling. Samaranayake, Lewis, Woxvold, & Toncich (2002) included the availability of aircraft components and machinery in the scheduling decision process, while Qin, Chan, Chung, & Qu (2017) optimized maintenance schedules whilst taking into account hangar and parking spot capacity. This research was followed up by the same authors, at which a rolling horizon technique was applied to cover large-scale problems. Qin, Wang, Chan, Chung, & Qu (2019)

Disruptive scheduling

Many authors acknowledged that the majority of research has been focused on scheduling models, with little attention to schedule adjustments (e.g., Nof & Hank Grant, 1991). In 1981, Graves (1981) was one of the first researchers to acknowledge that there is a gap between production scheduling theory and practice. Clarke (1998) 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. Previous research already included maintenance scheduling aspects within airline disruption management. Rosenberger, Johnson, & Nemhauser (2003) included constraints to satisfy periodic maintenance requirements in an Aircraft Routing Problem (ARP), while Abdelghany, Abdelghany, & Ekollu (2008) modeled an ARP in which scheduled maintenance was included in the airline schedule. While flights were allowed to be rescheduled, maintenance slots were considered fixed and modeled as a constraint. Currently, one of the most in-depth researches has been performed by Liang et al. (2018), in which maintenance scheduling flexibility is included to some extent within the ARP. Maintenance slots can be swapped as long the maintenance task is executed ahead of the number of allowed flight hours, cycles, or calendar days. The reader is referred to the recent paper from Hassan, Santos, & Vink (2021) which reviews the airline disruption management literature and analyses the inclusion of maintenance requirements when solving the ARP.

The research described above aims to optimize the ARP whilst taking maintenance scheduling into account (mostly in the form of constraints). A downside of combining the ARP with maintenance scheduling is that it 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 that is achieved by manual scheduling.

Looking at other fields of work there are other frameworks that are suitable for airline maintenance scheduling. For the health care sector, Vali-Siar, Gholami, & Ramezanian (2017) and Ballestín, Pérez, & Quintanilla (2019) 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. Vali-Siar et al. (2017) 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. (2019), extended the MILP model and evaluated the results for different scheduling objectives. The scheduling objective was extended by not only 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 & Shih (2009) provided a framework in which the goal is to make the least amount of changes to the schedule and the product cost is minimized. Both the healthcare and the construction industry show similarities to airline operations when it comes to managing disruptions. However, fixed departure times as in airline schedules, together with disruptions in both task-demand and resource availability, make airline task rescheduling in a disruptive environment a unique problem.

Based on this literature review, it can be concluded that the airline maintenance task scheduling and rescheduling problem during disruptions is currently not addressed in the literature. Regarding airline maintenance scheduling research, the focus has been on maintenance task scheduling together with the corresponding resource availability and prevention of tasks from going due. Disruptions management solutions have been proposed in the literature for airline schedule problems, but most studies do not consider aircraft maintenance or, if they are considered, maintenance rescheduling is often very limited. This research, therefore, aims to connect both areas of research by aiming to develop a framework for continuous maintenance task rescheduling whilst takings resource availability into account. This research combines the fields of the research described above, to decrease the gap between scheduling theory and practical implementation.

3. Problem definition

Within commercial airlines, disruption maintenance management and, in particular, the process of constantly rescheduling maintenance tasks takes place manually. As this is a both complex and time-demanding task, doing this manually can lead to inconsistent and inefficient decision-making when the problem becomes too large. The implementation of a framework for maintenance task rescheduling can assist a maintenance scheduler in the decision-making process. As 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, as acknowledged by both Dhanisetty, Verhagen, & Curran (2018) and Koornneef, Verhagen, & Curran (2019). Not taking long-term consequences into account during scheduling can be problematic, as postponed tasks can pile up and cause operational disruptions. By means of decision support, it is possible to identify problematic tasks upfront. A well-designed framework thereby identifies problems at an earlier stage compared to manual scheduling where it is difficult to foresee long-term problems.

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

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

By means of the scheduling objectives defined above, the framework contributes to an improvement in maintenance scheduling in multiple ways. Increasing schedule efficiency consequently leads to an increase in operational availability and thereby an increase in potential revenue for an airline. In terms of schedule stability, a decrease in last-minute schedule changes contributes to maintaining the reliability of operations. In case of a disruption, changes to the maintenance slot schedule can be made, but it is undesirable as this consequently also leads to airline network changes. At last, taking long-term consequences into account increases schedule robustness as problems potential scheduling problems are identified upfront.

A general overview of the maintenance task rescheduling framework is provided in Fig. 1. On the left side, the four inputs of the framework are outlined. Ground time is allocated in the form of maintenance slots to reserve time for maintenance. These slots can be assigned to aircraft to schedule maintenance tasks for that aircraft. Before a disruption occurs there is an existing schedule in which aircraft, tasks, and resources are allocated to maintenance slots. In reality, a schedule is not made for a fixed number of days and is 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. The type of disruption that is included within the scope of this framework relates to the inputs defined in Fig. 1 and comes in the following forms:

- Irregular arrival of new tasks.
    - *Example*: An occurrence of a fault during flight.

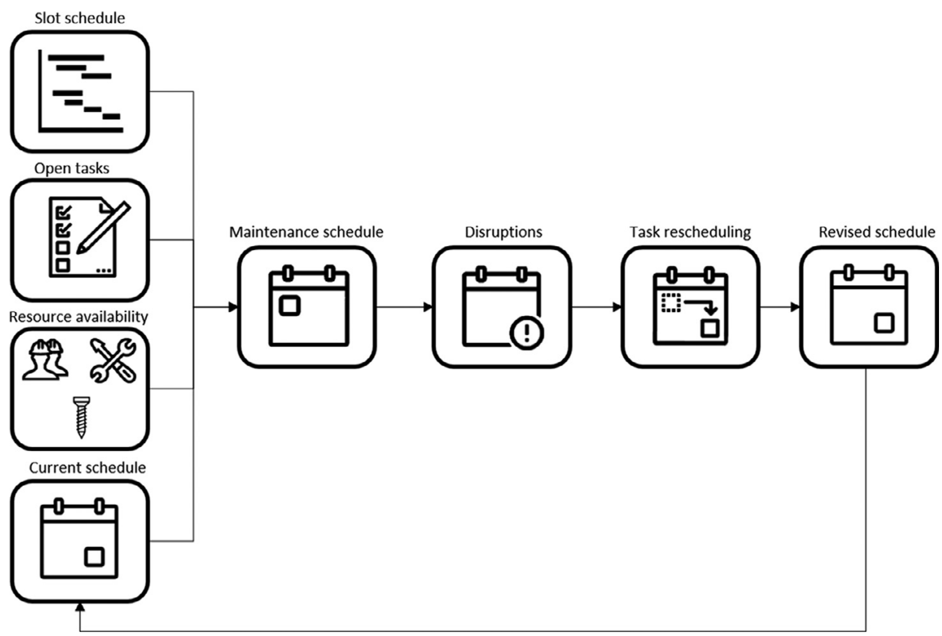


Fig. 1. Outline of maintenance task rescheduling framework (Icons from: Flaticon.com).

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

4M's	Explanation
Method	The estimated execution duration of a task needs to fit within the scheduled duration of a maintenance slot
Machinery	The scheduled execution date needs to be after the Estimated Time of Arrival (ETA) of the required machinery.
Material	The scheduled execution date needs to be after the ETA of the required material.
Manpower	Workforce which satisfy the skill requirements of the task, need to be scheduled to the corresponding maintenance slot for the required amount of workforce hours.

- Adjustments to the slot schedule.
  - *Example*: Late arrival of an aircraft shortens the duration of a maintenance slot.
- Adjustments in the availability of resources.
  - *Example*: Decrease in workforce availability due to unforeseen absence.

When a disruption takes place as defined above, the framework is executed to evaluate if there are any infeasibilities in the schedule and if task rescheduling is required. If necessary, rescheduling takes place according to the scheduling objectives defined above. Within a large commercial airline, disruptive tasks arrive on average once every 4 hours (for a fleet of 60 aircraft). The framework continuously keeps track of the schedule and keeps it in a feasible state. This state is then considered as the updated maintenance schedule and the starting solution for the next disruption.

The process of scheduling and rescheduling tasks is constrained by the availability of resources, in the form of 4M requirements. An explanation of each of those requirements is provided in Table 1. Each of the 4M requirements needs to be satisfied in order for a task to be able to be scheduled.

Besides the scheduling constraints regarding tasks, there are also limitations in terms of the allocation of aircraft to maintenance ground slots. Maintenance ground slots are reservations in time in which the aircraft is not required for operations. The reservations in time are done on aircraft type level (i.e. Boeing 737–800) because aircraft of the same type are interchangeable with each other. Aircraft (i.e. PH-BXA) can therefore only be assigned to maintenance slots of the corresponding aircraft type.

4. Modelling framework

Based on the framework defined above, an optimization model is developed which captures the disruptive environment of a commercial airline by means of simulation. The remaining part of this section will cover the formulation of the framework.

4.1. Input

To create a maintenance schedule and respond to disruptions, a maintenance scheduler generally makes use of four inputs: the existing maintenance schedule, 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 follows:

1. Current maintenance schedule: A feasible schedule before a disruption takes place. In a feasible schedule, maintenance tasks are assigned to maintenance slots such that they are scheduled for execution before their due date using resources that are available at the time of execution.
2. Slot schedule: The maintenance slots schedule outlines ground time reserved at the hangar to execute maintenance. Each slot is assumed to have a start date, an end date, and a designated aircraft type. We considered two types of maintenance slots:
   - Fixed slots: For fixed slots, an assigned aircraft is predefined and only additional maintenance tasks from that aircraft can be assigned to the maintenance slots. Fixed maintenance slots are usually scheduled several weeks in advance and consist of more extensive maintenance operations such as letter checks.
   - Flexible slots: For flexible maintenance slots the aircraft is variable and a maintenance scheduler is free to decide which aircraft to allocate to the slot, provided that the aircraft type matches the slot type. These slots are generally used for last-minute maintenance operations to execute corrective maintenance tasks.

3. Open tasks: This is the backlog of tasks that are required to be scheduled. Each task comes with scheduling requirements, including the due date, required execution time (method), workforce (manpower) requirement and machinery, and material requirements. These last four requirements are typically referred to as the 4M requirements. For airline maintenance, tasks can generally be subdivided into two categories:
   - Preventive maintenance tasks: Preventive maintenance tasks are prescribed by the aircraft manufacturer and conform to regulations set by the regulatory agencies, like the European Aviation Safety Agency (EASA) and the American Federal Aviation Authority (FAA). These tasks are provided in the Maintenance Planning Document (MPD) together with their execution requirements. Eriksson & Steenhuis (2015) Airlines also have the opportunity to add additional tasks to the MDP. Once a task is executed the interval is reset.
     - *Example:* The visual inspection of aircraft brakes wear, taking place every fixed number of landings.
4. Corrective maintenance: Scheduling of corrective maintenance tasks can be split up into three categories, which come with their own scheduling requirements and priorities. They are explained in more detail below:
   - MEL tasks: In the case of a corrective maintenance task, in some cases, an aircraft is allowed to continue operations despite the open corrective task. The Minimum Equipment List (MEL) provides the minimum configuration at which an airline is allowed to operate. Talluri (1996) If the MEL specifically allows an aircraft to be operated with the corrective task unresolved, this is referred to as MEL tasks. Otherwise, the aircraft has lost its airworthiness instantly. 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.
     - *Example:* The replacement of brakes in case the preventive maintenance action concluded that the condition of the brakes was outside of the operating limits. This leads to the creation of a MEL task
   - NSRE tasks: These tasks, referred to as Non Safety Related Equipment (NSRE), have no impact on the operating safety of the aircraft. NSRE tasks are created by the airline itself. Depending on the specific fault, the airline defines the NSRE task required and the due date associated. However, the aircraft remains airworthy after the due date has been exceeded.
     - *Example:* A broken in-flight entertainment system is an example of an NSRE. This causes passenger inconvenience but does not compromise the aircraft's airworthiness.
   - Ad-hoc tasks: These are non-recurring tasks that only have to be executed once to make an alteration on an aircraft.
     - *Example:* The replacement of a malfunctioning system following the recommendation from the OEM, according to an Airworthiness Directive (AD). These tasks are usually one-time executed tasks.
5. Resource availability: As mentioned above, the execution of a maintenance task requires the availability of all 4M requirements. These can be satisfied by means of resources. Besides providing ground time, the 4M requirements can be satisfied by the following resources:
   - Material availability: If a task requires the availability of new material, this needs to be arranged ahead of task execution. For each task, the expected date of material availability is provided.
   - Machinery availability: The execution of a 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 into multiple skills. While machinery, material, and method are independent of other tasks scheduled in parallel, the workforce needs to be assigned specifically to maintenance slots. A maintenance task can only be scheduled if the corresponding manpower requirements, per skill type, are satisfied by means of the assigned workforce to the corresponding maintenance slot. If maintenance slots are scheduled in parallel, the workforce can be divided over the active maintenance slots. The workforce allocation differs for fixed and flexible maintenance slots:
     - *Fixed slots:* They 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.
     - *Flexible slots:* Skilled workforce needs to be allocated to be divided between parallel maintenance slots and cannot exceed availability

4.2. Tasks rescheduling model

A key part of the framework is the rescheduling model that adjusts the maintenance schedule based on disruptions. In this section the model -formulated as a Mixed Integer Linear Program (MILP)- will be discussed. The model sets parameters, decision variables, scheduling objectives and constraints are discussed below.

4.2.1. Notations

The model consists of six indices and six sets. The tasks which should be scheduled by the model are indexed per task group by g, and are bundled into set G. Tasks that 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 in itself. Out of task set G, a set of aircraft with open maintenance tasks is obtained. Each aircraft is indexed by a and are bundled by set A. Each aircraft belongs to an aircraft sub-type group. Maintenance slots are provided within the model formulation by index s and set S.

For the current scheduling window, the time blocks in which workforce can be assigned to maintenance slots are provided by index t and bundled in the time block set (T). For this research, the interval of a time block is set to 30 min. At last, each workforce skill is indexed by ws and combined in set WS. Workforce skills depend on the certifications of the workforce. Task skills are indexed by ts and grouped by set TS. Task skills define which skills are required to execute a task. 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 2.

Next to the sets provided in the table above there are parameters required which can be fixed values or relate back to properties of either one of the sets provided above. The parameters required from the framework are provided in Table 3. The explanation of each parameter is provided in the second column of the tables. Each of the parameters will be used in either the objective function or in one or more of the constraints. The values of some parameters are fixed and depend on the properties of one of the sets and indices. The remaining weights and parameters which are

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

Table 2
Defined sets for the rescheduling model.

Indices	Definition
g	Group of tasks which require combined execution
a	Indicator of unique aircraft
t	Time block in which workforce can be assigned
s	Indicator of unique maintenance slot
ts	Indicator of skill required for task execution
ws	Indicator of skill of workforce
Sets	**Definition**
$g \in G$	Set of task groups ($G = G_{\text{Due}} \cup G_{\text{Defer}}$ and $G = G_{\text{Preventive}} \cup G_{\text{Corrective}}$)
$g \in G_{\text{Due}}$	Subset of tasks which go due in the current scheduling window ($G_{\text{Due}} \subset G$)
$g \in G_{\text{Defer}}$	Subset of tasks which do not go due in the current scheduling window ($G_{\text{Defer}} \subset G$)
$g \in G_{\text{Preventive}}$	Subset of preventive tasks ($G_{\text{Preventive}} \subset G$)
$g \in G_{\text{Corrective}}$	Subset of corrective tasks ($G_{\text{Corrective}} \subset G$)
$g \in G_a$	Subset of tasks for aircraft aircraft a ($G_a \subset G$)
$g \in G_{a_{Fix}}$	Subset of tasks for aircraft a, which is attached to a fixed maintenance slot s ($G_{a_s} \subset G_a$)
$a \in A$	Set of aircraft
$a \in A_s$	Set of aircraft of the aircraft type of slot s
$s \in S$	Set of maintenance slots within the current schedule window
$s \in S_0$	Set of maintenance slots within the current schedule window plus a fictitious slot accommodating tasks deferred to after the schedule window
$s \in S_{Fixed}$	Subset of slots which the aircraft is fixed ($S_{Fixed} \subset S$)
$s \in S_{Flexible}$	Subset of slots which the aircraft is allowed to change ($S_{Flexible} \subset S$)
$s \in S_t$	Subset of maintenance slots active at time block t ($S_t \subset S$)
$t \in T$	Set of time blocks within the current schedule window in which workforce can be assigned
$t \in T_s$	Subset of time blocks during execution of maintenance slot s ($T_s \subset T$)
$ws \in WS$	Set of workforce skills
$ws \in WS_{ts}$	Subset of workforce skills which can execute task skill ts ($WS_{ts} \subset WS$)
$ts \in TS$	Set of task skills

Table 3
Defined parameters for the rescheduling model.

Parameters	Unit	Definition
Current Date	Date	Current date of scheduling
$a_{s_{or}}$	[-]	Original aircraft registration a 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
$Wav_{t,ws}$	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
$\text{Wreq}_{g,ts}$	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.
$\text{AC-Type}_{a,s}$	[-]	1 if the aircraft type of slot s matches with aircraft a, 0 otherwise
Duration_s	Hours	Duration of maintenance slots s
Max-Tasks	[-]	Maximum number of task groups possible in a maintenance slot
Max-Workforce_s	Hours	Available number of workforce hours that can be assigned to fixed maintenance slot s.
n	Days	Number of days after the schedule window in which no tasks should go due.
ndd_g	[-]	1 if task group g goes due in n days after the scheduling window, 0 otherwise.
$C_{Type,g}$	[-]	Task criticality coefficient of task group g
W_{DUE}	[-]	Objective function weighting factor of task going due
W_{GROUND}	[-]	Objective function weighting factor of ground time
$W_{\text{RES,s}}$	[-]	Objective function weighting factor for rescheduling assigned aircraft for maintenance slot s
$W_{\text{DEFER,s}}$	[-]	Objective function weighting factor for task deferral for maintenance slot s
W_{CLEAN}	[-]	Objective function weighting factor for aircraft health
$W_{\text{INTERVAL Preventive, g,s}}$	[-]	Objective function weighting factor for task interval utilization of task group g and for maintenance slot s
$W_{\text{INTERVAL Corrective, g,s}}$	[-]	Objective function weighting factor for task interval utilization of task group g and for maintenance slot s

Table 4
Defined decision variables for the rescheduling model.

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

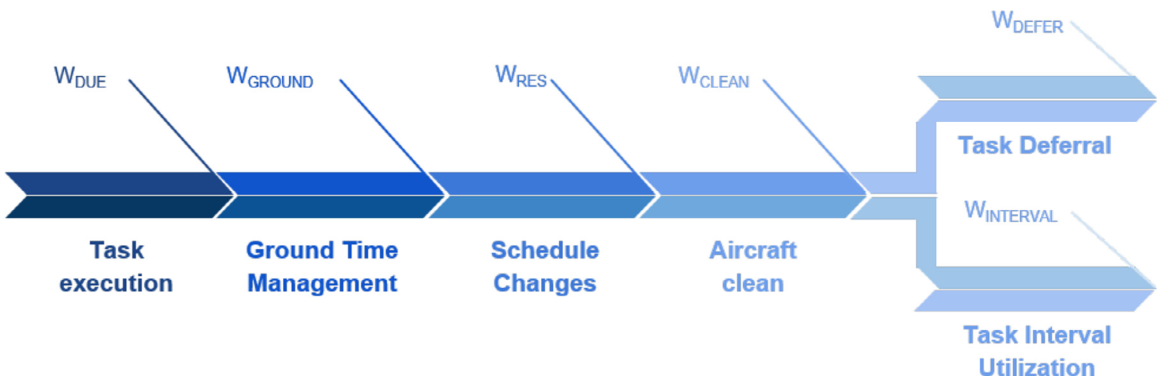


Fig. 2. Hierarchy during task scheduling.

the capabilities of the framework. The framework is able to schedule and reschedule both maintenance tasks as well as aircraft. In order for a maintenance task to be allocated to a slot, the corresponding aircraft registration should be assigned to the same slot as well. Once an aircraft registration is assigned to a slot multiple tasks can be assigned. For task and aircraft assignment there are two decision variables, $T_{g,s}$ and $AC_{a,s}$.

For the workforce requirements of tasks, the available workforce during a time slot has to be allocated to the corresponding maintenance slot. Since there is a difference between task skills and workforce skills, each feasible combination has to be included. As a result, the workforce assignment variable is dependent on four sets, and is formulated as follows: $\mathrm{WA}_{s,t,ts,ws}$.

At last, as will be discussed within the objective function formulation, the goal is to schedule free from any open tasks for a certain horizon. As a result, a fourth set of decision variables is added, for keeping track of the objective. A detailed description of the formulation of each decision variable is provided in Table 4.

4.2.2. Objective function

Based on the multiple scheduling objectives provided in Section 3, we opted to formulate the objective function as a weighted sum of objectives. We followed a hierarchical structure to formulate and prioritize the objectives, corresponding to the priorities typically considered by the maintenance schedulers (Fig. 2). The distribution of weights depends on airline preferences. The process of determining these weights will be elaborated upon in the case study, provided in Section 5. Mathematically the objective function can be formulated according to Eq. (1).

$$
\begin{aligned}
\mathrm{Min} \; & \sum_{g\in G_{\mathrm{Due}}} T_{g,s=0}\cdot W_{\mathrm{DUE}}\cdot C_{\mathrm{TYPE,g}} \\
& + \sum_{s\in S}\left(AC_{a_{s_{or}},s} + \sum_{a\in A_{s}\setminus a=a_{s_{or}}} AC_{a,s}\cdot(1+W_{\mathrm{RES},\,s})\right)\cdot \mathit{Duration}s_s\cdot W_{\mathrm{GROUND}} \\
& + \sum_{a\in A}(1-\mathrm{AC}_{\mathrm{clean},a})\cdot W_{\mathrm{CLEAN}} \\
& + \sum_{s\in S}\left(\sum_{g\in G_{\mathrm{Preventive}}} T_{g,s}\cdot W_{\mathrm{INTERVAL\ Preventive,\ g,s}}\right. \\
& \left. + \sum_{g\in G_{\mathrm{Corrective}}} T_{g,s}\cdot W_{\mathrm{INTERVAL\ Corrective,\ g,s}}\right)\cdot C_{\mathrm{TYPE,g}} \\
& + \sum_{g\in G_{\mathrm{Defer}}} T_{g,s=0}\cdot W_{\mathrm{DEFER,\ g}}\cdot C_{\mathrm{TYPE,g}}
\end{aligned}
\tag{1}
$$

In more detail the scheduling objectives are as follows:

- The first objective is to *execute tasks* ahead of their due date. When exceeding the task due date, the aircraft is no longer airworthy and would have to be kept on the ground until the task is performed, inducing major costs to the airline. Therefore, this goal was considered as a soft constraint and a very large weight (W_{DUE}) is given to the case a task goes due. In between tasks there is possibility for a hierarchy of importance by multiplying with $C_{\mathrm{Type,g}}$.
- Secondly, after guaranteeing the execution of tasks in time, the goal of an MRO should be to provide fleet availability towards the airline. This was considered by penalizing the *ground time* associated with the slots used to perform maintenance. By means of this objective, if a maintenance slot s is not used, the weight W_{GROUND} will not be activated as it provides the airline more fleet availability.
- The third objective is to guarantee the stability of the schedule by preventing *schedule changes*. A schedule change was defined to be a change in the aircraft assigned to a flexible maintenance slot when compared with the original schedule. Reallocation of tasks between maintenance slots of the same aircraft was not considered a schedule change since it does not affect the availability of the aircraft for operations. The weight for rescheduling maintenance slots s depends on airline preferences. An example of a cost function for $W_{RES,s}$ is provided in the case study in Section 5.2.
- The next objective is to avoid leaving maintenance tasks open with a due date in the days after the schedule window. This can lead to the indefinite postponement of scheduling maintenance tasks outside of the scheduling window. For this, we introduced the concept of *'aircraft clean'*, meaning that the aircraft does not have open tasks with a due date in the n days after the schedule window. The goal is to minimize the number of non-clean aircraft at the end of the schedule window. A constant cost coefficient per non-clean aircraft was assumed, W_{Clean}. This objective is only applicable for a limited scheduling window, which will be elaborated upon in Section 5.2.3.
- The last objective is to plan individual tasks at the optimal moment in time. For a maintenance scheduler, there is a degree of freedom in terms of the moment in time a task is scheduled. To allow for a hierarchy in between tasks the weights are multiplied with $C_{\mathrm{Type,g}}$. Within this framework, a distinction is made between interval utilization and task deferral as displayed in Fig. 2.
  - The moment in time a task is executed relative to the length of the interval of the task refers to *task interval utilization*. For preventive tasks, the goal is to schedule close to their due date, to minimize interval waste. For corrective tasks, it's preferable to execute them as soon as possible for quality reasons.
  - In case the task due date exceeds the scheduling window there is an option to schedule the task within the schedule window or defer the task. In the case of *task*

deferral the decision is made to postpone the task execution to a later moment within the schedule horizon. W_{DEFER} is defined as the mean of the interval utilization for the scheduling opportunities behind the scheduling window or equal to W_{DUE} if there are no scheduling opportunities remaining. Similar to the aircraft clean objective, this objective is only applicable for a limited scheduling window.

4.2.3. Model constraints

Taking the constraints into account regarding the allocation of tasks to maintenance slots, the constraints of the mixed integer linear programming model can be formulated as follows:

Constraints:

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

$$\sum_{t \in T_b} \sum_{ws \in WS_{ts}} \text{WA}_{s,ts,ws,t} \geq \sum_{g \in G} \text{Wreq}_{g,ts} \cdot T_{g,s} \qquad \forall s \in S_{\text{Flexible}}, ts \in TS \tag{3}$$

$$\sum_{a \in A_s} AC_{a,s} \leq 1 \qquad \forall s \in S \tag{4}$$

$$\sum_{ts \in TS} \sum_{g \in G_{a_{Fix}}} \text{Workforce}_{g,ts} \cdot T_{g,s} \leq \text{Max-Workforce}_s \qquad \forall s \in S_{\text{Fixed}} \tag{5}$$

$$\sum_{s \in S^0} T_{g,s} = 1 \qquad \forall g \in G \tag{6}$$

$$\sum_{g \in G_a} T_{g,s} \leq \text{Max-Tasks} \cdot AC_{a,s} \qquad \forall s \in S_{\text{Flexible}}, a \in A_s \tag{7}$$

$$\sum_{g \in G_a} T_{g,\text{Defer}} \cdot \text{ndd}_g \leq \text{Max-Tasks} \cdot (1 - \text{AC}_{\text{clean},a}) \qquad \forall a \in A \tag{8}$$

$$\sum_{s \in S} (1 - \text{DD}_{g,s}) \cdot T_{g,s} = 0 \qquad \forall g \in G \tag{9}$$

$$\sum_{s \in S} (1 - \text{TAT}_{g,s}) \cdot T_{g,s} = 0 \qquad \forall g \in G \tag{10}$$

$$\sum_{s \in S} (1 - \text{Material}_{g,s}) \cdot T_{g,s} = 0 \qquad \forall g \in G \tag{11}$$

$$\sum_{s \in S} (1 - \text{Machinery}_{g,s}) \cdot T_{g,s} = 0 \qquad \forall g \in G \tag{12}$$

$$\sum_{s \in S} (1 - \text{Aircraft type}_{g,s}) \cdot T_{g,s} = 0 \qquad \forall g \in G \tag{13}$$

$$\sum_{s \in S} (1 - \text{Infeasible}_{g,s}) \cdot T_{g,s} = 0 \qquad \forall g \in G \tag{14}$$

$$T_{g,s} \in 0, 1 \qquad \forall g \in G, s \in S \tag{15}$$

$$AC_{a,s} \in 0, 1 \qquad \forall a \in A, s \in S \tag{16}$$

$$\text{WA}_{s,t,ts,ws} \in 0, C+ \qquad \forall s \in S, t \in T, ts \in TS, ws \in WS \tag{17}$$

$$\text{AC}_{\text{clean},a} \in 0, 1 \qquad \forall a \in A \tag{18}$$

For flexible slots, constraints (2) restrict the model such that the total allocated workforce of skill *ws* during time block *t* cannot exceed the available workforce for that skill and time combination. Constraints (3) guarantee that the allocated workforce for maintenance slots *s* and task skill *ts* meet the workforce requirements of the allocated tasks. In constraints (4), at most one aircraft can be assigned to a maintenance slot. Otherwise, it should be assigned to a fictitious aircraft ($a = 0$). In this case, the slot remains unused and no tasks can be assigned. For fixed slots, constraints (5) are implemented. The set of constraints limits the number of workforce hours that can be attached to a fixed maintenance slot.

Constraints (6) guarantee that every task group should be scheduled by the rescheduling model, either to a slot within the schedule window or, if not possible, deferred to after the window (i.e., to $s = 0$). Constraints (7) ensure that only a maintenance task group *g* can be added to a maintenance slot *s* if the corresponding aircraft *a* is assigned to it. The constraints provided in (8) assure that an aircraft is registered as clean if there are no tasks going due in the coming *n* 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 (9) force that tasks must be scheduled ahead of their due date. Constraints (10), (11) and (12) provide the remaining 4M constraints besides workforce. At last, constraints (13) only allow tasks to be scheduled to slots with a matching aircraft type. Since the constraints from (9) till (13) are all the same format, the matrices are first element-wise multiplied by each other, and then added as one single constraint as can be seen at constraints (14). This reduces the number of constraints by a factor of five, this set of constraints.

5. Case study

A case study is performed to analyze the performance of the framework in comparison to the manually obtained airline schedule. Within commercial airlines, the continuous process of maintenance task scheduling currently takes place manually. This is not necessarily the best benchmark to assess the optimality of the solution obtained with the framework. However, since the framework models the same method currently adopted in practice, it can be a solid benchmark for estimating potential impact and viability. As we are modeling within a new innovative area of research, no comparison methodology is available in the literature.

The analysis of the case study is divided into four parts. Firstly, the simulation setup and procedure are discussed. This is followed up by the parameter determination and trade-off. Afterwards, the results of the airline case study are presented to evaluate the performance of the model compared to the executed maintenance schedule of the commercial airline. This is followed by a stochastic disruption analysis to analyze the stability of the model. The analysis of results within this paper will focus solely on the stochastic arrival of new tasks as this is the most common form of disruption. Even though the case study only considers disruptions related to the arrival of new tasks, other disruptions, like variations

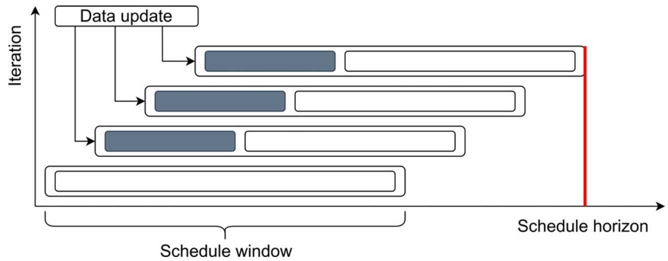


Fig. 3. Outline of the simulation procedure for the framework.

in the 4M resources availability and slot disruptions can also easily be considered.

5.1. Simulation set-up and procedure

To simulate the dynamic process of continuously updating the maintenance schedule (adapting to disruptions), a rolling horizon simulation is proposed in Fig. 3. The schedule is generated for a fixed number of days (schedule window). Afterward, the scheduling horizon shifts one day ahead, during which new tasks may arrive, slot allocations may be adjusted, and the availability of one of the 4M resources may change. Since these disruptions may compromise the feasibility of the schedule, rescheduling actions will be required to keep the schedule in a feasible state. This way, a new optimal schedule is produced by considering the current schedule (computed in a previous iteration) and the disruption information. While proposing a new optimal schedule, one of the objectives is to prevent too many schedule changes during the next 3 (δ) days (the highlighted section of the scheduling window in Fig. 3). The schedule is re-computed for the considered schedule window till the end of the scheduling horizon has been reached. No scheduling opportunities were considered beyond the schedule horizon.

The manual process currently makes use of a tight scheduling window of at most 10 days. For larger windows, potential maintenance scenario's become too large to practically evaluate by human planners. Hence to compare the performance of the framework to the airline decision-making, a similar scheduling window of 10 days for the model is chosen for a fair comparison. However, this framework works to its fullest potential when the model makes use of a large scheduling window of (for example) 120-days. As such, the case study also evaluates the performance of the framework when using longer scheduling horizons.

To benchmark the performance of the proposed models (with 10 and 120 days respectively), the results were compared to two references: i) the schedule produced by the airline itself during the considered period and ii) the schedule produced by our MILP model when considering perfect information. This later benchmark schedule was used as a best-case scenario, and it was computed assuming that all disruptions are known in advance and that the schedule is created with one single iteration. The two proposed models can be directly compared to the benchmark results since the same input data was used by both the optimization model and the airline when producing the schedules.

The proposed modeling approach was applied to a European commercial airline case study for a fleet of 67 wide-body aircraft. Maintenance tasks that were part of the case study all required execution in the hangar and were not part of a letter check. However, letter checks are included as scheduling opportunities in the case they have the capacity to execute additional tasks, according to the model definition provided above (constraints (5)). The tasks included both preventive and corrective maintenance tasks. This scope has been chosen as the corrective maintenance tasks have a disruptive impact on maintenance schedules. The tasks can be executed in dedicated hangar maintenance slots for which the availability changes over time. Workforce capacity is available according to a weekly schedule with three shifts a day and dedicated availability for each workforce skill. The evaluated time frame of the case study runs from 01-07-2019 till 01-12-2019. Data was provided by the airline containing the final maintenance slot schedule, the arrival of maintenance tasks, and the available workforce.

5.2. Framework parameter determination

As discussed in Section 4.2.2 the weights and parameters of the objective function depend on airline preferences. As for the case study, the results from the framework are compared with the airline schedule, the parameters need to be defined according to the airline's preferences. The following section outlines the parameters definition and fine-tuning process required to implement the framework into a commercial airline. In this subsection, first, the hierarchical order of objectives will be determined. This will be followed by the fine-tuning process of the rescheduling factor η and the objective for the number of clean days n, respectively. At last, an overview of the framework parameters for the case study is provided.

5.2.1. Objective function hierarchy

All objectives were formulated as costs and the goal was to minimize the total scheduling costs. To reflect the priorities, higher priority objectives were associated with higher weights (i.e., cost coefficients) For the case study the airline opted to choose a scheduling hierarchy identical to the order displayed in Fig. 2. Task execution is the most critical objective in order to remain airworthy for each aircraft. Therefore W_{DUE} receives the highest weight. Secondly, ground time management and schedule changes were considered as both critical behind task execution. Within the objective function this should be formulated as: $W_{\mathrm{DUE}} >> (W_{\mathrm{GROUND}}, W_{\mathrm{RES},s})$. Third in hierarchy comes aircraft cleanliness as it should not compromise ground time or schedule changes more important than interval utilization. The last remaining weights should therefore be formulated as following: $(W_{\mathrm{GROUND}}, W_{\mathrm{RES},s}) >> W_{\mathrm{CLEAN}} >> W_{\mathrm{INTERVAL}}$. W_{INTERVAL} is defined as a linear increasing or decreasing function, for corrective and preventive tasks respectively. The weights range linearly between 0 and 1 as a function of the interval utilization. As defined in Section 4.2.2, the weight of W_{DEFER} depends on the availability of scheduling opportunities outside of the scheduling window and is defined as: $W_{\mathrm{DEFER}} = f(W_{\mathrm{INTERVAL}}, W_{\mathrm{DUE}})$.

As mentioned above, there is a trade-off between schedule changes and ground time. First of all, not all schedule changes should receive the same weight. An aircraft allocation change on the day of operations is more costly than an aircraft change one week ahead. Therefore the weight associated with this objective ($W_{RES,s}$) was expressed according to a function of the number of days of notice, as presented in Fig. 4 and reflected in Eq. (19).

$$W_{\mathrm{RES},\,s} = \max\left(\eta \cdot \delta - \frac{\eta}{\delta} \times (\mathrm{Start}_s - \mathrm{Current\ Date}), 0\right) \tag{19}$$

By replacing $W_{\mathrm{RES},\,s}$ by Eq. (19) there is still a trade-off between minimizing ground time and minimizing schedule changes. The balance between these two can be adjusted by fine-tuning η. In the coming section, an analysis of η is provided.

5.2.2. Rescheduling costs

As explained above, the maintenance rescheduling model has multiple scheduling objectives. There is a conflict of interest between aiming for minimum ground time and the prevention of schedule changes. This section will therefore focus on the trade-off between ground time minimization and schedule changes. Based

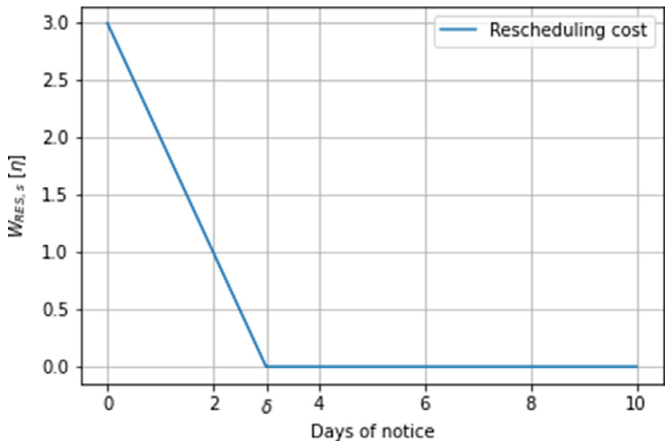


Fig. 4. Maintenance slots rescheduling cost as a function of the days of notice.

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

	η	Due tasks	Schedule changes	Ground time
120-days model	0.4	0	15	865 Hours
10-days model	0.6	0	15	908 Hours

on the value of η, described above, the relation between the two can be adjusted. A high value results in the preference for preventing schedule changes, a low value prefers ground time minimization.

In Fig. 5, the trade-off results are provided for the 120-days model. As expected, by increasing η, 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. Looking at the ground time required as a function of η, we observe a general increasing trend followed by a decreasing trend for cases where the model cannot avoid tasks from going due and thus requiring less ground time. The general 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 results represent a trade-off analysis considering a 3-month data set. Therefore the number of slot changes is not monotonically decreasing as there is a limited data scope and variations in the optimal solutions between parameters. A larger data set would assist in the trade-off analysis for future improvement.

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 to be made between fleet availability and schedule changes. For the rest of this paper, a value 0.4 is chosen for η, since it yields in a decrease in last-minute schedule changes while the ground time does not yet increase steeply.

This means that making a schedule adjustment on T-2, T-1, T-0, is 40%, 80% and 120% more expensive respectively, according to Fig. 4 and Eq. (19). A similar trade-off is performed for the 10-days model, provided in Appendix A. From this, a value of 0.6 is chosen for η. The number of due tasks, schedule changes, and ground time are displayed in Table 5 for the chosen η value.

5.2.3. Number of clean days

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. The clean days constraint is not applicable to the 120-day model, since the extended scheduling window, includes the full interval of all open tasks in scope.

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 the required ground time after the current scheduling period. Since the consumption of ground time is the most expensive part of maintenance releasing an aircraft “clean” is important. An aircraft is considered “clean” if there are no deferred tasks within the clean days target interval. This is also visualized in Fig. 6. If a task is deferred within the clean days target interval, the aircraft clean penalty is activated for that aircraft registration. Based on the requirements given above, the aircraft clean constraint is formulated as follows:

$$\sum_{g\in G_r} T_{g,\text{Defer}} * \text{Within clean days due}_g$$
$$<= \text{Max-Tasks} \cdot (1 - \text{AC}_{\text{clean},a}) \quad \forall a \in A \tag{20}$$

In Fig. 7 the number of due tasks, last-minute slot changes, and ground time used are illustrated for a range of clean day targets. It can be seen that increasing the clean days target causes a decrease in both the number of due tasks and the 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. The decrease in due tasks and ground time goes at the cost of deterioration of preventive task utilization. This is visualized in Fig. 8b. Since task deferral becomes more restricted, preventive tasks are scheduled earlier which results in lower utilization rates. Secondly, it also results in a slight increase in corrective task utilization, as shown in Fig. 8a. As less ground time is used and thereby also fewer maintenance slots, the schedules become more compact which causes a slight deterioration of preventive task interval.

With an increasing number of target clean days, it is expected that the number of deferrals would decrease. This is due to a penalty for deferral of tasks that go due within the clean days limit. This phenomenon is confirmed by Fig. 9 which shows a decreasing trend of task deferral when increasing the clean day target. At last, Fig. 10 shows the total number of schedule changes as a function of the target clean days. Where in Fig. 7, 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. Based on the expert knowledge of maintenance schedulers within the commercial airline, the target for the number of clean days is set to 10. This is despite the results in Fig. 7 which might give the impression that a higher value is better because of a decrease in due tasks and a decrease in required ground time. However, 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 preventive task utilization. This means that preventive tasks will have to be executed more often throughout the year and consequently also requires more ground time. Since the repetitive occurrence of preventive tasks is considered out of scope for this research, this effect is not visible in the figures above.
2. As can be seen in Fig. 10, 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.

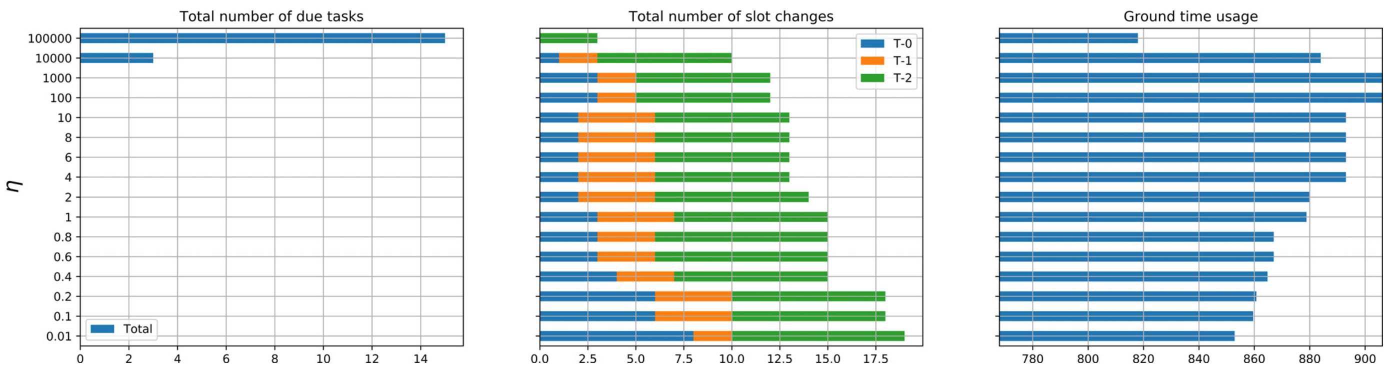


Fig. 5. Number of due tasks, last-minute schedule changes and ground time for several values of η (y-axis) for the 120-day model. T-0, T-1, T-2 refer to schedule changes made on the day of operation, the day before, and two days ahead, respectively.

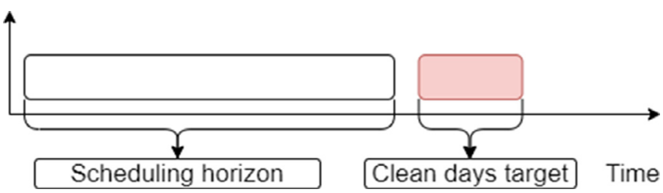


Fig. 6. Illustration of clean days objective.

Table 6
Set values for parameters of rescheduling framework.

Parameter	Value
W_{DUE}	10^8
W_{GROUND}	10^5
η 120-days model	0.4
η 10-days model	0.6
W_{CLEAN}	10
W_{INTERVAL}	[0–1]
Aircraft cleanliness value n	10 Days
Schedule change prevention δ	3 Days

5.2.4. Parameter overview

Based on the determination of the scheduling objective hierarchy and the model fine-tuning for η and n a quantitative overview of the model parameters can be obtained. The overview of parameters is provided in Table 6.

At last, there are the parameters $C_{Type,g}$, creating the hierarchy between tasks groups. The values for $C_{Type,g}$ are determined based on the impact on the aircraft airworthiness of the task and are displayed in Table 7.

Table 7
Weighting factor for task type.

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

Table 8
Number of due tasks and ground time usage for analyzed scheduling methods.

Schedule method	Due tasks	Scheduled tasks	Total ground time
Airline schedule[a]	0	2549	2645.58 Hours
Perfect information	0	2549	1992.60 Hours
120-days model	5	2544	2125.75 Hours
10-days model	10	2539	2190.40 Hours

[a] Results obtained after maintenance slots adjustments by maintenance scheduler, in order to schedule all tasks before their due date.

The determination of the values above is based on airline preferences and the expertise of maintenance schedulers within the airline.

5.3. Results analysis

In this subsection, the performance of both models -the airline schedule and the model with perfect information- can be quantitatively compared to each other for a 6-month period. Table 8 summarizes the hours of ground time used and the number of due tasks resulting from the schedules obtained from each scheduling method. The most significant benefit accomplished by the

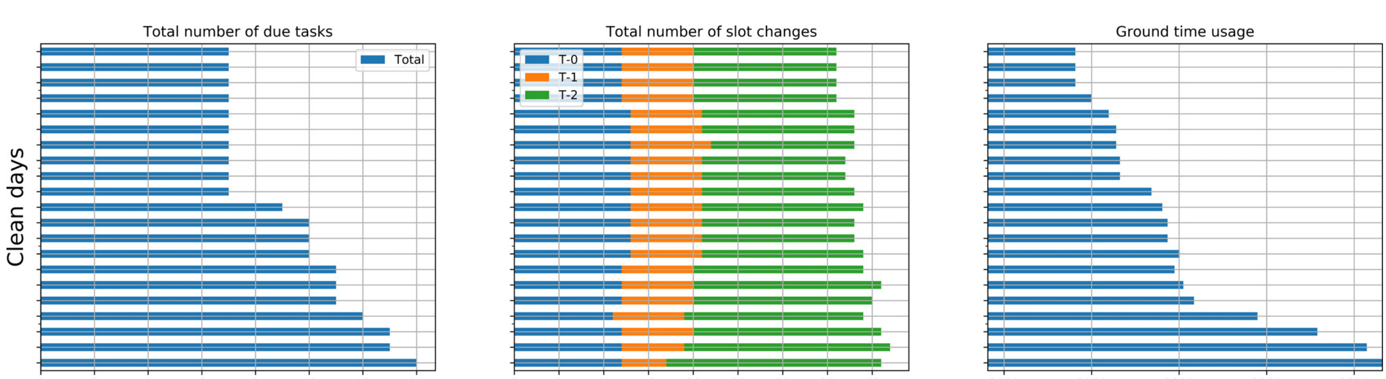
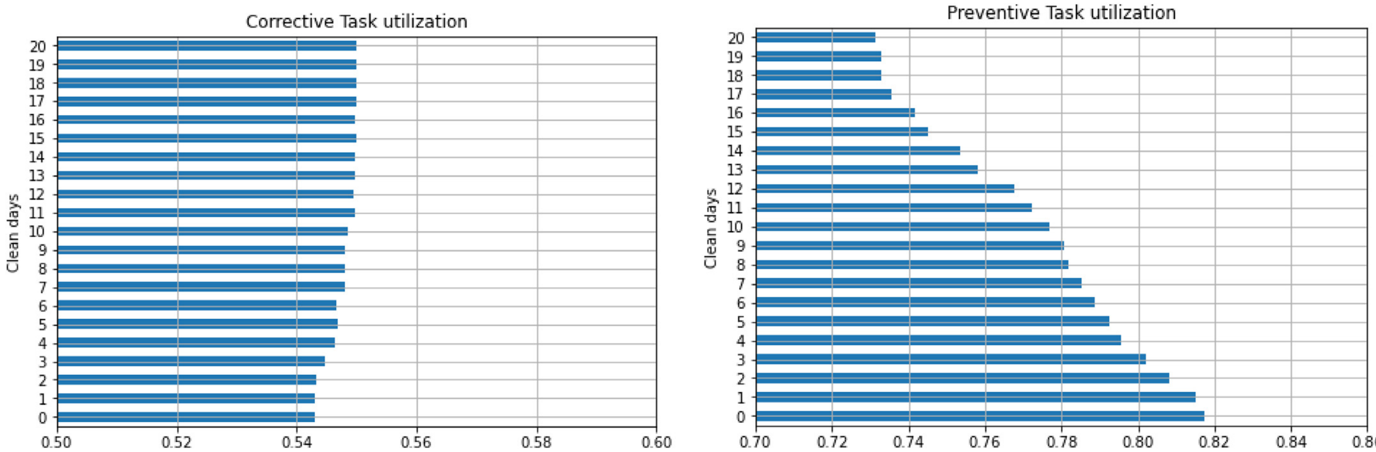


Fig. 7. Effect of aircraft clean constraint on the number of due tasks, schedule changes (T-0, T-1, T-2), and ground time.



(a) Corrective task utilization (b) Preventive task utilization

Fig. 8. Effect of aircraft clean constraint on task utilization.

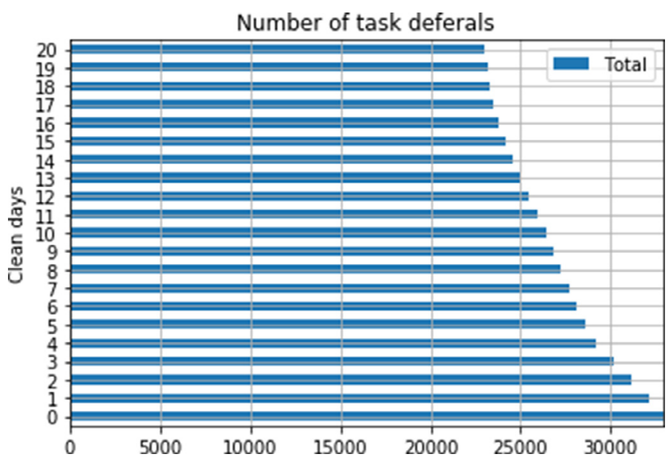


Fig. 9. Effect of aircraft clean constraint on the number of task deferrals.

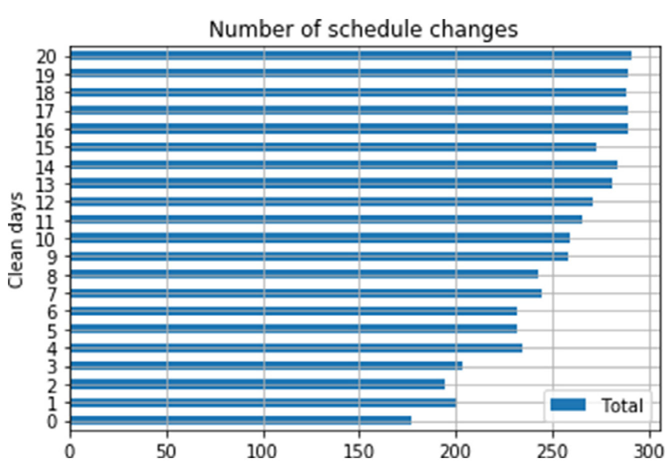


Fig. 10. Effect of aircraft clean constraint on the number of schedule changes (T-0 till T-10.

framework is the reduction in ground time. Due to the increased scheduling horizon of the 120-days model, a decrease of 2.7 days of ground time can be achieved, compared to the 10-days model. Secondly, the 10-days model saves a further 18.9 days 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 that the model is able to schedule tasks 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.

In terms of total ground time, both the 10-days and 120-days models can achieve scheduling results closer to the model with perfect information than the airline schedule. Only 6.68% more ground time is required for the 120-days model compared to the model with perfect information while operating in a disruptive - instead of static environment. This shows that the 120-days model is able to produce close to optimal schedules even when disruptive tasks arrive during operations.

In exchange for a decrease in ground time, both models could not avoid tasks from going due. This is caused by a lack of scheduling flexibility in the maintenance slot that was available to the proposed models. 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 in case the existing slots cannot resolve the disruption. As a result, new feasible scheduling opportunities for a task can be generated, sometimes even on same the day of the slot. This option was not part of the solution space for the MILP model. When, at any point of the simulation procedure, the model takes a different decision path than the airline had taken, the real aircraft allocation and set of slots used as inputs are are no longer tailored to the tasks task backlog in the proposed model's scenario. As a result, a task can be left without any feasible slots in which it can be scheduled.

Still, in a qualitative assessment of the results produced, the airline maintenance schedulers were pleased with the limited number of tasks going due in the schedules produced by the MILP models. According to them, these due tasks could have been easily solved manually. The additional required ground time for these remaining tasks would still result in an overall reduction compared to the airline schedule.

As explained at the beginning of this section, aiming for minimization of total ground time should not go at the cost of an increase in short-notice schedule changes. In Table 9, the number of schedule changes at short notice is provided. A comparison to the airline schedule shows that both models require significantly fewer last-minute schedule changes. The comparison gives an indication that the model produces more stable schedules. Secondly, it can

Table 9
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

Table 10
Average task utilization for analyzed scheduling methods.

Schedule method	Preventive utilization	Corrective 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

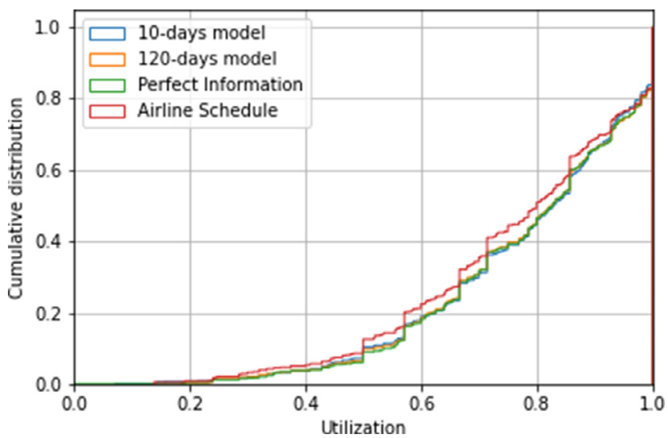


Fig. 11. Interval utilization distribution of preventive maintenance tasks. For preventive maintenance tasks the objective is to achieve a high interval utilization.

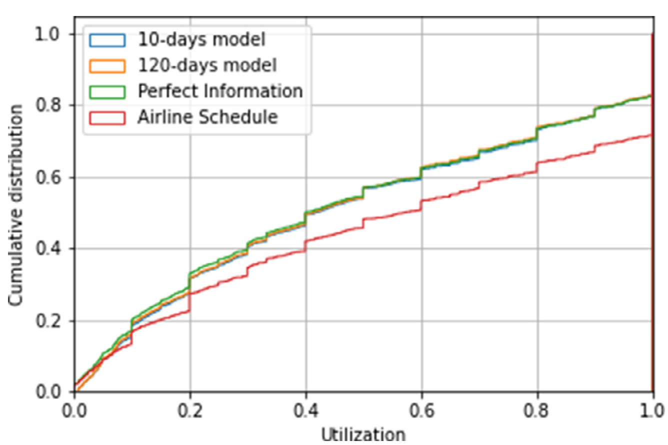


Fig. 12. Interval utilization distribution of corrective maintenance tasks. For corrective maintenance tasks the objective is to achieve a low interval utilization.

be concluded that the implementation of the 120-days model does not result in an increase in schedule changes compared to the 10-days model.

The utilization rates of both preventive and corrective tasks are evaluated for the scheduling methods in Table 10, Figs. 11 and 12. It can be concluded that scheduling by making use of the model compared to the airline schedule results in better interval utilization for both preventive and corrective maintenance tasks. For both versions of the model, it is able to schedule corrective tasks further away from the due date while for preventive tasks the model schedules closer to the due date. This shows that for both the 10-day and 120-day models not only the schedule stability and efficiency objective taken into account but also improvements in terms of interval utilization can be achieved and thereby scheduling spillage can be decreased. As expected, for perfect information the best task utilizations are obtained. Since disruptions are known in advance, maintenance slots can be reserved which results in better corrective task utilization. The framework provides a bigger improvement for corrective tasks rather than preventive tasks because they are more of a disruptive nature. Preventive tasks are known upfront and can be scheduled close to optimal by a scheduler. Corrective tasks often demand adjustments from the scheduler, in which the framework is able to assist.

At last, the case study shows that the framework is suitable to be used in a disruptive environment with respect to solution times. As the 120 days framework and the 10-days framework have a solution time of 48.1 and 6.9 seconds per day respectively, this makes them suitable for ad-hoc decision making. Even though the saving in terms of schedule changes may seem modest, it provides the airline with a significant decrease in ground time and a decrease in workload for planners.

5.4. Stochastic disruption analysis

In the preceding section, it is shown that the proposed framework can achieve a decrease in ground time when compared with the airline schedule. It also showed the added benefit of the 120-day window with a further decrease in ground time and fewer tasks going due with respect to the 10-days framework. However, these conclusions are based on the evaluation of a single scenario. Therefore, in this section, we conduct an analysis of a scenario in which the unexpected arrival of tasks is simulated as a stochastic process defined according to the task data provided by the airline.

5.4.1. Scenario generation

To find a suitable distribution for the arrival time in between corrective maintenance tasks, the difference in arrival time for consecutive corrective maintenance tasks was analyzed. An analysis on the corrective task arrival revealed that the arrival of tasks are not independent of one another. A single failure detected can cause the identification of consequential failures or it may require the execution of several tasks to solve this failure. 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 distribution. Secondly, for each task arrival, the number of tasks arriving at once is determined. In Fig. 13, the distribution of arrival times is provided by the blue line for a historical set of corrective 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 Fig. 13 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.

The second step is the stochastic generation of the number of tasks arriving at once. Lagos et al. (2020) approximated this by means of a Poisson distribution. However, since the scope of this research is smaller, no suitable distribution could be fitted to 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, based on a historical analysis of the number of tasks arriving at once. In a similar manner, the tasks should be assigned to a specific aircraft. This is done by means of a weighted choice out of the available registrations. The weights are determined based on the historic probability of corrective tasks of the

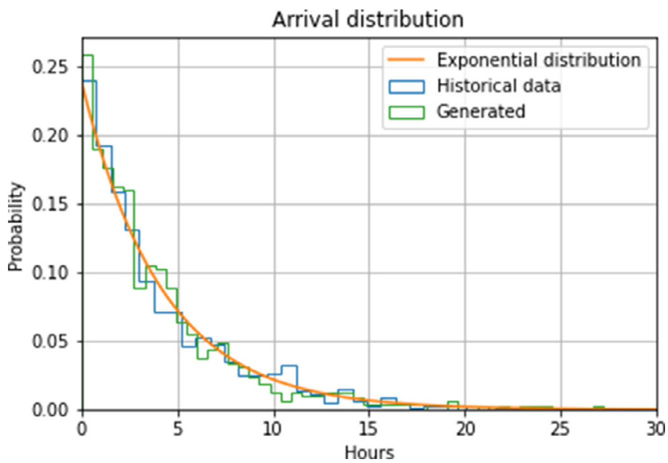


Fig. 13. Probabilistic distribution of arrival of tasks together with a sample of generated duration's.

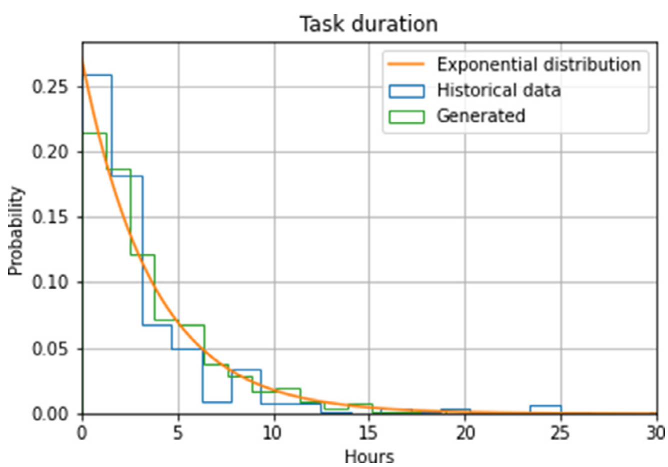


Fig. 14. Probabilistic distribution of duration of tasks together with a sample of generated duration.

corresponding aircraft registration. This is a valid assumption since there are specific aircraft registrations/types which require more corrective maintenance than others.

The required duration for the execution of maintenance tasks within a slot shows a large variance. In Fig. 14, the distribution of the maintenance task duration is plotted. To generate new task durations an exponential distribution has been fitted to the data, resulting in a duration frequency of $\lambda = 0.272[\frac{1}{\text{Hour}}]$. Again, a generated sample of durations is shown in Fig. 14 to indicate that this is indeed a suitable distribution.

The type of tasks is determined by means of a weighted choice, this determines both the task criticality and the task due date. 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.

For the stochastic disruption analysis, a scenario is created which runs for a 2-month period and makes use of 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 corrective tasks are replaced by stochastically created tasks, while the preventive tasks are identical for each scenario and to the airline case study.

5.4.2. Results analysis

Figure 15 relates the number of due tasks as a function of the disruption rate (i.e., the time-frequency of the arrival of tasks). To assess the impact of having different airline fleet sizes and ages, we considered that the disruption rate could vary between 50% and 150% of the value of the disruption rate computed with the historical data.

In the 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. Furthermore, the analysis shows that the 120-days framework is able to prevent more tasks from going due compared to the 10-days framework.

The decrease in a number of due tasks go at the cost of an increase in required ground time, as shown in Fig. 16. The 10-days framework requires less ground time than the 120-days frame-

Algorithm 1 Stochastic creation of corrective maintenance tasks.

Generate arrival times based on exponential distribution ofFigure~ 13
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~ 14
    Generate workforce requirements based on historic sampling
    Generate task type based on weighted choice
  end for
end for

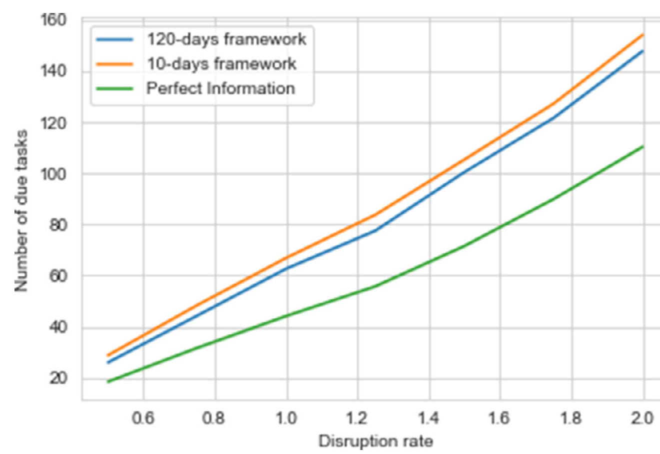


Fig. 15. Number of tasks going due as function of disruption rate.

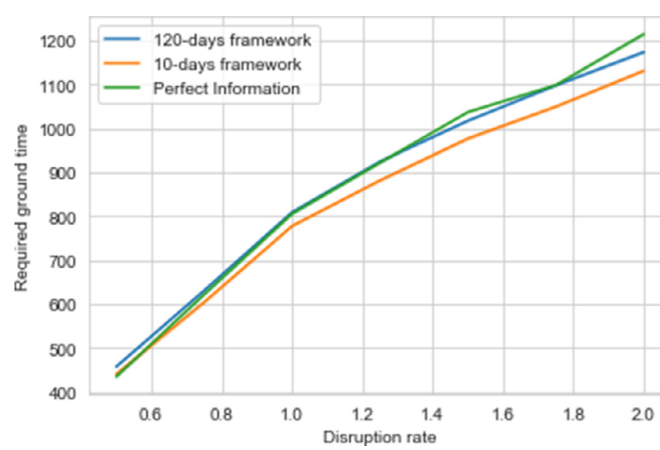


Fig. 16. Ground time required as a function of disruption rate.

Table 11
Average scheduling results for a disruption rate of 1.

Schedule method	Due tasks	Scheduled tasks	Ground time usage
10-days framework	66.92	82.7%	778 Hours
120-days framework	62.70	83.8%	810 Hours
Perfect Information	44.17	88.6%	806 Hours

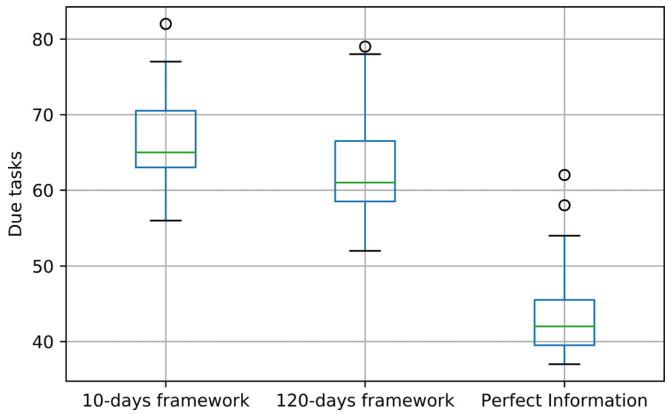


Fig. 17. Distribution of the number of due tasks for a disruption rate of 1.

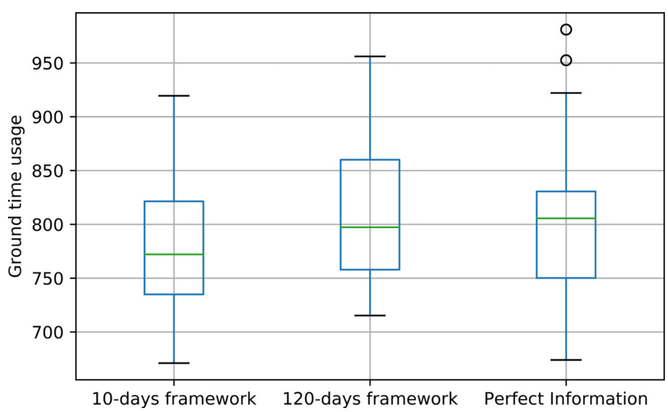


Fig. 18. Distribution of ground time for a disruption rate of 1.

work. This can be explained since more tasks are going due in the 10-days framework and consequently this results in fewer tasks which are scheduled. Thereby, less ground time is required. This explanation is also confirmed by the fact that the 10-days framework requires less ground time than the perfect information framework.

For a disruption rate value of 100%, the average results are summarized in Table 11 and the distribution is visualized in Figs. 18 and 17. In the results, the performance of both the 10-days and 120-days framework is compared to the framework with perfect information. The 10-days framework is included within the analysis as this replicates the current manual decision-making within an airline, with a scheduling horizon of 10 days. The framework with perfect information shows that unlike in the case study, a high percentage of tasks are going due. This can be explained by the fact that for each scenario in this analysis, a new set of tasks is used together with the slot schedule from the case study. In the case study, the slot schedule is supervised by the maintenance scheduler to guarantee scheduling opportunities, but for the stochastic analysis, this is not the case. The method assuming perfect information, therefore, shows that without a fine-tuned maintenance schedule, not all tasks can be scheduled before going due.

A comparison between the 10-days and 120-days framework shows that a larger scheduling window provides more insight into future scheduling opportunities and therefore results in fewer tasks going due. However, there is a gap of 4.8% with respect to perfect information. The model with perfect information is able to use the available scheduling opportunities more efficiently and achieve a reduction in the number of tasks going due. With an extended scheduling window of 120-days, the framework is also able to make use of more scheduling opportunities (and thereby prevent more tasks from going due) compared to the 10-days framework. Looking at the distribution provided in Fig. 17 the range of number of tasks going due is also lower for the 120-days framework. An element-wise comparison of each scenario shows that the 120-days framework has less or equal due tasks in 97.5% of the scenarios. This goes at the cost of a 2.6% rise of average ground time per executed task. From the scenario with perfect information, it can be concluded that more ground time would be required for any framework if none of the tasks would go due. It is expected that the 120 days framework would require less ground time than the 10 days framework. However, this cannot be concluded from these results, because both models have a different number of tasks going due.

While for the airline case study no tasks were going due, the 120-days framework could only schedule 83.8% of the tasks and thereby let 16.2% go due in the stochastic disruption scenario. A maintenance scheduler has the ability to create new maintenance scheduling opportunities and thereby prevent tasks from going due. Hence the results from this section show that the extended scheduling window of 120-days aids in the prevention of tasks going due. It also shows the need for a fine-tuned maintenance slots schedule based on the backlog of tasks. This can be provided by means of a maintenance scheduler supervising the framework.

6. Conclusions and recommendations

This paper presented a task rescheduling framework that can be readily applied in a disruptive airline maintenance scheduling environment. The framework has proven to be capable of being applied in an operational airline environment in which it has to cope with disruptions as well as rescheduling of maintenance tasks. An evaluation of the framework within an airline case study shows that the framework can aid to improve schedule stability and efficiency, as respectively fewer schedule changes and ground time were observed compared to the rescheduling process followed by the airline. Secondly, it showed the value of scheduling with a larger window as this resulted in fewer schedule changes, less ground time, and better task utilization, all within fast computational times that are not feasible for humans.

Results from the case study allow the quantification of both the increase in schedule efficiency and stability. In terms of schedule efficiency, using a larger scheduling window reduced the required ground time by 3%. This results in an increase in fleet availability for the airlines' operational department. The benefit of fleet availability can be addressed in the form of potential revenue. For a commercial airline, a wide-body aircraft has a potential revenue of € 18.000,- per day (rough estimate), hence the proposed framework could result in a yearly € 17.000,- additional potential revenue per commercial aircraft. With the scope and assumptions of this research, a comparison between the airline schedule and the 10-days framework shows that there is potential for a further decrease of 17.2% in ground time. This could potentially result in an additional yearly € 120.000,- revenue per commercial aircraft. The saving reported above are in the form of fleet availability. More importantly, in terms of schedule stability, the number of last-minute schedule changes decreased by almost 50%. This reduces both the risk of operational delays and cancellations, which yield significant cost reductions for an airline.

The stochastic disruption analysis further confirms the value of a 120-day scheduling window. With stochastically generated tasks, the 120-days model prevented more due tasks than the 10-days model. Compared to the model assuming perfect information, the model was capable of scheduling around 94.6% of the tasks. Both the case study and the stochastic disruption analysis show the need for fine-tuned scheduling opportunities based on the backlog of tasks. This can be provided by a maintenance scheduler supervising the framework. Where the modeling framework can improve scheduling efficiency and stability, a maintenance scheduler can provide additional scheduling opportunities if required. A maintenance scheduler can also supervise the outcome to ensure scheduling opportunities are available for each task. The framework will assist in an increase in schedule stability, efficiency, and interval utilization while the maintenance scheduler ensures task execution before the due date at all times.

Even though the results of the framework show promising results, there are some limitations that can be addressed in future research. For this research solely maintenance which required execution in the hangar was included. Within commercial airlines, many maintenance disruptions are resolved in line maintenance. Expanding the framework with line maintenance can increase schedule efficiency. Secondly, the stochastic disruption analysis showed that adding slot flexibility is required to prevent to the occurrence of tasks going due. This issue can be addressed by including the maintenance scheduler in the framework or extending the model formulation. However, the addition of slot flexibility in the model formulation will be a challenge without sacrificing computational time. At last, with the current development of Prognostic Health Monitoring (PHM) tools for airline maintenance, an increase in scope can be considered which focuses on the prediction of future disruptions. By receiving feedback from PHM systems, the quality of a disruption mitigation approach from the framework can be improved.

Airline maintenance task scheduling is currently a manual process throughout the aviation industry. This research demonstrates that decision support can aid in an improvement of schedule stability and potential revenue. Airline maintenance task scheduling is a complex environment that we have tried to simulate to the best of our knowledge. The benefits of the model presented in this paper will likely result in a better performance than reported, as the result analysis is based on conservative assumptions:

- Tasks are not able to be scheduled on the day on which it arrives but only the day after.
- Constraint violations are not allowed which a supervising planner could allow for.
- Network flexibility is not taken into account

By implementing this framework into the decision-making of a commercial airline, the limitations can be resolved. The model computational power combined with the scheduler expertise enables an increase in quality and efficiency of maintenance task rescheduling in a disruptive environment.

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Appendix A. Rescheduling cost trade-off 10-days model

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 η. The results of this analysis are shown in Fig. A.1. Overall, the results from the 120-days model and 10-days model are very similar. By increasing η 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 η since this yields in a decrease of last-minute schedule changes with a limited increase of required ground time.

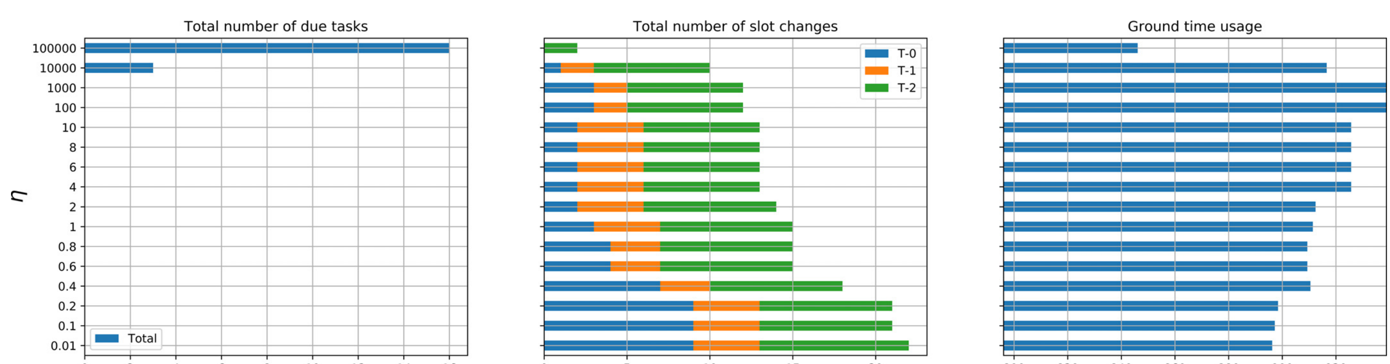

Fig. A.1. Number of due tasks, last-minute schedule changes and ground time for several values of η for 10-days model. T-0, T-1, T-2 refer to schedule changes made on the day of operation, the day before, and two days ahead, respectively.

Supplementary material

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.ejor.2022.11.017.

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