Integrating Maintenance Work Progress Monitoring into Aircraft Maintenance Planning Decision Support

Pieter Callewaert M.Sc.
Delft University of Technology
Kluyverweg 1, 2629 HS Delft, Netherlands

dr.ir. Wim J.C. Verhagen
Delft University of Technology
Assistant Professor
w.j.c.verhagen@tudelft.nl

prof. dr. Richard Curran
Delft University of Technology
Professor

ABSTRACT

A decision support framework is proposed, allowing for the integration of aircraft maintenance work progress monitoring into the aircraft maintenance planning decision support process. The framework is able to monitor the progression of planned maintenance by analysing real-time data on work progress. This can be used to explore optimal task planning in case of delays or maintenance being ahead of schedule. Using a combination of reliability analysis, cost analysis, decision alternative generation and ranking yields a decision support tool which is able to deal with the stochastic nature of maintenance task execution. Case study results indicate that the framework is able to generate decision alternatives with a lower total cost than the reference alternative, while at the same time optimising the maintenance planning, resulting in a possible reduction of the maintenance costs of 45 to 90% (depending on parameter settings).

KEYWORDS: *Maintenance planning, work progress monitoring, decision framework*

1 INTRODUCTION

Aircraft maintenance is a crucial part in the airline business: proper maintenance ensures fleet airworthiness and exerts a direct influence on the operating cost of an airline [1]. Maintenance planning is an essential element of maintenance management [2], aiming at ensuring system function and life, ensuring safety and human well-being. Aircraft maintenance management is the combination of all tasks/actions which retain an item or a system in, or restore it to, a normal state in which it can perform its required function Accurate, reliable and flexible planning may contribute directly to the efficiency of maintenance. Various approaches exists towards the optimisation of aircraft maintenance planning [1, 3-7]; general objectives are to minimise costs and delay, while at the same time maximising aircraft availability. Unfortunately, the majority of approaches in the state of the art fail to incorporate the stochastic nature of maintenance execution: deterministic assumptions are made to arrive at optimal planning of maintenance tasks. In reality, upon execution of planned tasks it is frequently found that tasks take more (or less) time than expected. Sometimes, tasks can lead to new, unscheduled maintenance tasks, each with their own demands in terms of task time and resources. With the advent of work progress monitoring systems (e.g., time registration and status updates using mobile tools [8], an opportunity is opening up to address this gap between research and practice.

Consequently, the goal of this research is to integrate aircraft maintenance work progress monitoring into the aircraft maintenance planning decision support process. In order to achieve this objective, a decision framework for maintenance planning is proposed. The framework is able to monitor the progression of planned maintenance by analysing real-time data on work progress. As such, the time

horizon considered spans an upcoming set of maintenance tasks (i.e., a short-term period covering 1 to 2 planned maintenance opportunities at maximum, which covers 24-48 hours), as opposed to problems which address longer-term time horizons (weeks, months or even years, including major letter checks). Though (maintenance) literature uses the terms planning and scheduling interchangeably, the short time horizon covered in this research effort will be referred to as planning. Having noted this, real-time work progress data can be used to explore optimal task planning in case of delays or maintenance being ahead of schedule. Using a combination of reliability analysis, cost analysis, decision alternative generation and ranking yields a decision support framework which is able to deal with the stochastic nature of maintenance task execution.
To validate these claims, the state of the art with respect to maintenance planning is briefly considered first (Section 2). This is followed by an introduction of the proposed approach in Section 3. Subsequently, the decision framework and its constituent models are applied to a case study incorporating data from a European maintenance, repair and overhaul (MRO) operator. Results show that the framework is able to address aircraft maintenance planning in an effective way, taking criticality and various cost factors into account. Framework validation and sensitivity analysis are performed, followed by conclusions and recommendations for future research.

2 THEORETICAL CONTEXT

Existing approaches to maintenance planning optimisation fall within the broader category of maintenance optimisation models. Typically, these models aim to find the optimum balance between the costs and benefits of maintenance, while taking relevant constraints into account (e.g., resource availability), and to find the most appropriate moment to execute maintenance [2, 9]. In general, maintenance optimisation models cover four aspects [2]:

- A description of a technical system, its function and its importance.
- A modelling of the deterioration of the system in time and possible consequences of the deterioration for the system.
- A description of the available information about the system and the actions open to management.
- An objective function and an optimisation technique which helps finding the best balance between the costs and the benefits of maintenance.

Maintenance optimisation models can be classified into two main streams, namely qualitative and quantitative models. Qualitative models include maintenance approaches such as Reliability Centered Maintenance (RCM) [10] and Total Productive Maintenance (TPM) [11]. Quantitative models on the other hand include deterministic and stochastic models. A wide variety of models is available, including classical optimal replacement theory (including age-based, block-based and opportunity-based models [2, 9, 12-14], Bayesian models [15], heuristic approaches [7] and applications of various optimization techniques (such as (non-)linear programming [6, 16], dynamic programming [7], and evolutionary techniques such as genetic algorithms [17, 18]) to the maintenance domain.
A shared shortcoming of this range of models is a lack of generalizability, data availability and associated practical applications [2, 9]. Decision support systems (DSS) can help in bridging this gap. A decision support system is a system that is able to support the choice between alternatives. In other words, it is able to answer 'what-if' questions [9]. Furthermore, it can be helpful for the maintenance engineer in terms of time and effort that has to be put into the decision support process. The decision support system can help the user in the decision process by gathering and analysing data. Analysis typically consists of generating a number of alternatives and indicating which alternative is the best based on certain criteria or parameters.
There are two types of decision support systems, namely operational and strategic. Strategic DSS are generally more used for one-off problems at a higher level (systems or units). Since they are different each time, there is no need for complicated databases and extensive amounts of data. Operational DSS on the other hand are developed for repetitive problems, including planning and scheduling of maintenance [9]. Two prior research efforts are of particular interest.
The first contribution [14] describes an operational DSS named PROMPT. The objective of PROMPT is to give decision support for opportunity based preventive maintenance. According to Ab-Samat and Kamaruddin [19], opportunity maintenance is best described as the planning and scheduling of maintenance activities to repair a component, whilst at the same time opportunistically repair/replace

other components in the system, with the aim to avoid future failures and reduce the amount of machine downtime. The optimization problem faced by PROMPT is summarized by Dekker and van Rijn [14] as 'Plan and schedule a number of maintenance packages, each consisting of one or more activities, at randomly occurring opportunities of a restricted duration.' The authors [14] further state that the planning would include determining the long-term optimal policy, whereas the scheduling should indicate at a given opportunity which packages should be carried out at which priority, given the established long-term optimal policy. A drawback of PROMPT is the fact that it addresses opportunity maintenance only. Opportunity maintenance is forward-looking: it does not consider information gathered during actual execution of maintenance tasks.
The second relevant contribution discusses a maintenance decision support framework used for 1) addressing short-term operational maintenance decisions at line maintenance and for 2) deferring maintenance actions that affect the aircraft's dispatch [1]. The decision support framework has two main objectives, namely, having a high aircraft operability and low maintenance costs. The framework generates and ranks decision alternatives on the basis of multiple criteria, such as reliability, cost and resource availability. Drawbacks of the proposed support framework are its reliance on simplified forecasting assumptions regarding maintenance execution, in which maintenance execution time is modeled using normal distributions; actual execution time is not incorporated. Furthermore, the framework is tested using simulated data; validation using real-life maintenance data has not reported on in publicly available literature.

3 A DECISION SUPPORT FRAMEWORK FOR MAINTENANCE PLANNING

There is a need to address the mentioned shortcomings in the state of the art and to capitalize on increased capabilities to monitor actual maintenance task execution in real-time. Here, a decision support framework is proposed which is able to adjust and (re-)optimize maintenance planning on the basis of real-time work progress monitoring data, allowing the identification of multiple decision alternatives and suggesting an optimal outcome for various scenarios. The framework is given in Fig. 1.

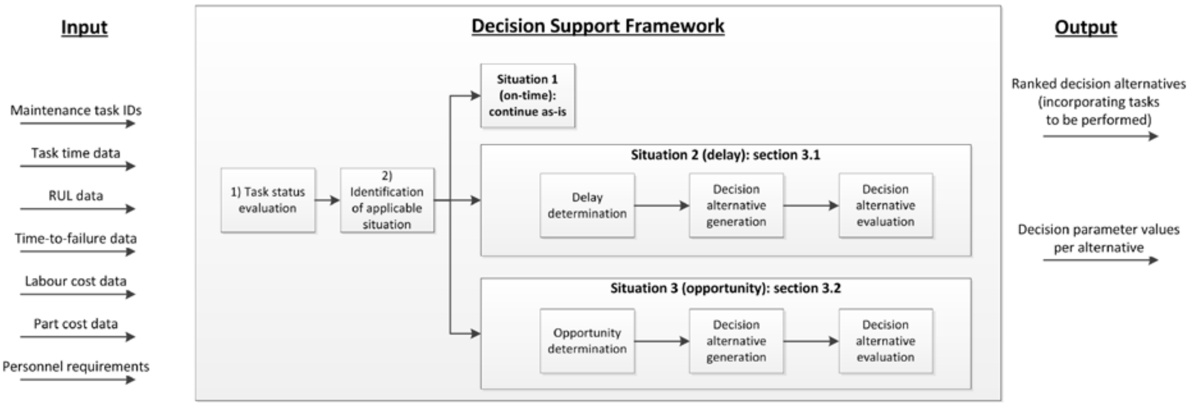

Figure 1: Decision support framework for maintenance planning

Assuming availability of the input data mentioned in Fig. 1, the *decision point* must first be determined. Since the monitoring of work progress is a real-time process, the decision point is set to be the time during the planned maintenance at which the aircraft maintenance planner/dispatcher invokes the framework to analyse the current situation and associated decision alternatives. The decision point strongly influences the latitude for alternative generation and associated maintenance planning. If a decision point is chosen early during the execution of maintenance, few tasks will have been executed. This leaves less opportunity for delays or being ahead of time, whereas the number of decision alternatives will be larger (given the higher amount of tasks that still need to be executed). In contrast, a late decision point leads to more accurate assessment of delays or time wins, but leaves less space for decision alternatives.

Given a choice for the decision point, the framework will start the analysis of work progress by determining for each task in the planning what its current state is. There are three states in which a task can be:

- **Completed:** This is the case when a task is started and finished before the decision point.
- **In progress:** This is the case when the execution of a task has already started, but is not finished before the decision point.
- **To be done:** This means that a task is not yet started and therefore still needs to be performed.

When all the tasks are evaluated, a status list of the planned tasks is generated, indicating the current situation. There are three possible situations that can occur when monitoring and analysing work progress of previously planned maintenance tasks. The first of these is the default situation, when execution of planned maintenance tasks is going as planned and no actions are required. The other two situations are covered in Sections 3.1 and 3.2, which expand on the framework components and functionality.

3.1 Situation 2 – Delay

The second situation is one where one or more maintenance tasks are not performed on time and therefore a delay has occurred. A decision framework is proposed which incorporates a number of steps (with attendant models) to move from delay determination to a ranked list of decision alternatives. The associated flowchart is given in Fig. 1.

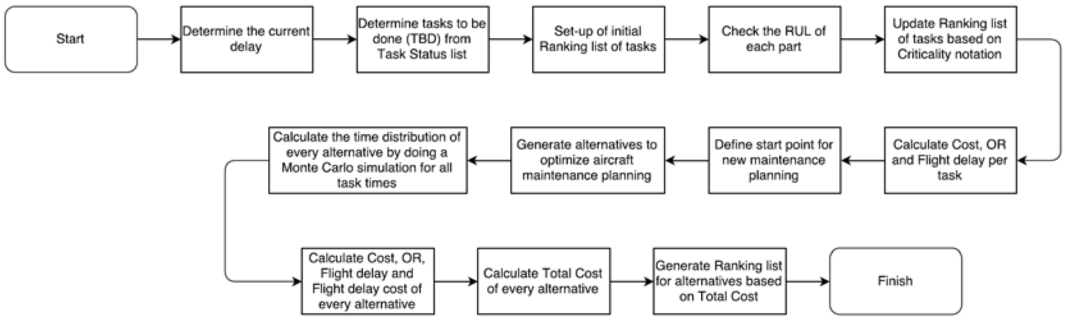

Figure 2: Decision framework flowchart for situation 2 (delay)

For situations with delay in process execution, the following steps are incorporated into the decision support framework:

1) **Delay determination:** The first step in the analysis is to determine the current delay of the planned maintenance. The current delay is calculated by subtracting the planned start time from the actual start time of the current task, using the relation $t_{delay\_current} = t_{start\_currenttask} - t_{planned\_currenttask}$. If delay occurs, a choice may have to be made with respect to which tasks are prioritized for execution: it is very feasible that not all tasks can be executed anymore, given the incurred delay.
2) **Task determination & initial ranking:** tasks that still need to be done are derived from the generated task status list (see introduction of Section 3), after which an initial ranking is generated to determine which tasks take precedence in execution. For the initial ranking, the remaining maintenance tasks are just ordered in the sequence they were originally planned.
3) **Ranking parameter evaluation:** to determine which task(s) are most suitable for execution in the limited time left due to the incurred delay, various ranking parameters are adopted and evaluated. In this research, the following parameters are included:
   a. **Criticality & Remaining Useful Life:** remaining useful life (RUL) of components related to specific maintenance tasks is adopted from available prognostic models, or classical reliability model output. If the RUL of a component is sufficient to make it to a next planned maintenance opportunity, it is seen as non-critical. If the RUL is not sufficiently large to make it to the next opportunity, the component is assumed to fail between the current and next maintenance opportunity, with attendant disadvantages. Therefore, the component is labelled 'critical' when this condition

applies. Critical components are prioritized, i.e., ranked highest in the tasks to be performed in the remaining maintenance time. Subsequently, the remaining non-critical components are ranked in order of RUL magnitude (the lower the RUL, the higher its ranking).

b. **Maintenance cost:** cost is calculated for execution of a task at the current (planned) time, at the next maintenance opportunity (e.g. the next planned A-check), or at an unplanned instance (when a component breaks down unexpectedly in between maintenance opportunities). Contributing cost elements include labour, overhead and component costs.

c. **Operational risk:** if a maintenance task is postponed to a next opportunity, a certain risk is incurred that the related component will not survive until that time. As such, operational risk is calculated by taking the probabilities of planned and unplanned maintenance and multiplying these with their respective costs. This approach is akin to that of Papakostas et al. [1]. These probabilities are assessed by evaluating component time-to-failure data using lifetime distributions (e.g. Weibull and normal distributions) and assessing goodness-of-fit characteristics. Next, the cumulative distribution function of a chosen distribution can be set to a certain value a, representing an assumed value of lifetime at which a component failure occurs. This value is set at a baseline value of 75% for this study; sensitivity analysis is performed in the results section to investigate the effect of this assumption.

4) **Decision alternative generation:** the next step is to define the remaining time to plan tasks in, which can be estimated by calculating the time between the start point and the end of planned maintenance. The start point, in turn, is defined as the time at which the task that is in progress at the time of the decision point is finished. This is in fact unknown, as task completion is stochastic. Here, an assumption is made that the mean time denoted for the task at hand (available from historic data) can be added to its starting time.
With the remaining time for planning known, alternatives can be generated. This is a two-step procedure: first, the tasks denoted as critical are pushed to the top of the list and will definitely be executed during the current planned maintenance. Second, every combination of k tasks from the set of n non-critical tasks is explored, using the binomial coefficient $\binom{n}{k}$. In other words, every combination of k tasks of the set of n non-critical tasks will be added together with the critical tasks to the new maintenance planning, creating a different alternative every time. This is done for every possible value of k. The tasks that are not included in an alternative will be deferred to the next maintenance opportunity. An example is given in Fig. 3.

Critical tasks:	6, 10		Non Critical tasks:	8, 9, 7

Binomial Coefficients or Combinations	k=1	k=2	k=3
	8	8, 9	8, 9, 7
	9	8, 7	
	7	9, 7	

Alternatives	Tasks in alternative
Alternative 1	6, 10
Alternative 2	6, 10, 8
Alternative 3	6, 10, 9
Alternative 4	6, 10, 7
Alternative 5	6, 10, 8, 9
Alternative 6	6, 10, 8, 7
Alternative 7	6, 10, 9, 7
Alternative 8	6, 10, 8, 9, 7

Figure 3: Generation of decision alternatives

5) **Decision alternative evaluation and final ranking:** Now that all the alternatives are generated, the time necessary for every alternative is calculated. This is done by using a Monte-Carlo simulation. For all the tasks of an alternative, a completion time is simulated 10000 times. The MC simulation is based on an underlying distribution composed by the maintenance operation task time distribution of the considered tasks, which are estimated using historical data. Every alternative exist out of a combination of the remaining tasks. The

time necessary to complete an alternative is equal to the sum of the generated expected values for all the tasks within the alternative. An example is given in Section 4.

With the time necessary for every alternative being established, the final step is to evaluate and rank the decision alternatives. Evaluation comprises calculation of the total costs of every alternative, which is a sum of the maintenance costs, operational risk and flight delay costs. Flight delay costs are based on the characteristics of a decision alternative, where a flight delay may be incurred if a set of tasks takes more time than originally planned for a maintenance check. The costs of this (potential) delay are evaluated by applying the following equation

$$Cost_{delay}(Alt) = Cost_{delay_{pp}}(Alt) \cdot Pax \cdot LF$$

Where $Cost_{delay_{pp}}(Alt)$ is the delay cost per passenger associated with a decision alternative, Pax represents the maximum number of passengers and LF represents the load factor. Delay costs per passenger are calculated on the basis of the piece-wise linear function presented by Cook [20], which incorporates soft and hard delay costs.

A ranked list of alternatives is composed based on the total costs, with the alternative with the lowest costs being ranked highest. This list is finalised by a reference alternative, which reflects a decision to carry on with the original maintenance planning.

3.2 Situation 3 - Ahead of schedule (opportunity maintenance)

The final possible outcome to be evaluated is one where work is ahead of schedule. This creates a possibility to perform some maintenance tasks that were not originally planned, otherwise known as opportunity maintenance. One has to decide what maintenance tasks to perform during the opportunity, taking the restricted duration and time of the opportunity into consideration.

The decision framework proposed in Section 3.1 is adapted to incorporate a number of steps which deal with opportunity maintenance. The output is similar: a ranked list of decision alternatives. The associated flowchart is given in Fig. 4.

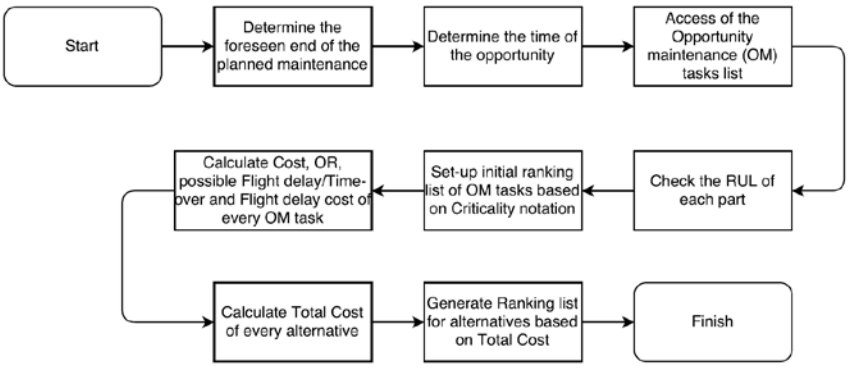

Figure 4: Decision framework flowchart for situation 3 (opportunity maintenance)

The constituent models, inputs and analysis of situation 3 are closely related to the approach highlighted in Section 3.1. The focus is however on the determination of how much time is available to perform additional tasks, which can occur in two forms: either maintenance is ahead of schedule at the decision point, or planned maintenance is completed before the planned end time. In both cases, the flowchart as given above applies. Two major differences with respect to the approach highlighted in Section 3.1 are discussed:

1) **Opportunity maintenance tasks:** These tasks can be drop-out tasks from previous planned base maintenance or tasks that could not be executed at line maintenance. The list of opportunity maintenance (OM) tasks is a combination of these tasks.

2) **Total cost evaluation:** delay cost is incorporated into the total cost evaluation. This bears some explanation: why consider delay cost when you have time left? The reason is straightforward: when opportunity tasks are selected, these fill up the remaining time and are

stochastic in nature themselves. As such, adoption of opportunity tasks can lead to unanticipated delays.

The remainder of the decision framework is the same as described for situation 2.

4 RESULTS

Implementation of the decision framework has been performed in Matlab, in a single integrated format for situations 1, 2 and 3. This is possible because of the high degree of overlap in steps employed to generate, analyze and rank alternatives. In this Section, a case study application is discussed. The input data used for this case are described first, followed by case study results. The Section is wrapped with validation.

4.1 Input data

The case study application incorporates data from an European MRO provider. The data consists of maintenance package data (including package number, task IDs, aircraft registration numbers, and Maintenance Planning Document (MPD) codes), data on interval limits and task execution (including historical data on man-hours spent on maintenance tasks), reliability data (including 'raw' time-to-failure data for selected components), and cost data. The data spans 47 tasks related to the A2.26 maintenance package from the Airbus A320 MPD. This set is split up into two subsets: 1) 25 tasks representing a de-phased A-check, constituting the planned task list; 2) 22 tasks that can be considered for opportunity maintenance (under situation 3 of the framework).
On the basis of the available data, the following variables are estimated or calculated:

- **Maintenance task time distributions:** the available data on man-hours spent per maintenance task is used to fit probability distributions and estimate the associated parameters. Maximum Likelihood Estimation (MLE) is used for parameter estimation. Goodness-of-fit is assessed using a χ^2 test statistic.
- **Component RUL:** in this case study, the RUL is simply assumed to be the difference between the component interval limit as described in the MPD (given in flight hours, cycles or calendar time) and its current accrued use (similarly in flight hours, cycles or calendar time). No use is made of RUL estimation using prognostic approaches; ergo, the selected RUL is purely derived from the preventive maintenance limits imposed by the maintenance program. This is, in effect, a conservative approach.
- **Reliability estimates:** the reliability data is used to establish failure and survival distributions for the component population under consideration. This informs the calculation of operational risk during evaluation of decision alternatives.

4.2 Case study results

To generate aggregated results and verify the functionality of the framework, the input data has been used to simulate execution of the planned set of tasks for 1000 iterations. Given the stochastic nature of many of the inputs, both the delay and opportunity maintenance situations are encountered. For all 1000 simulated cases, several assumptions have been taken: personnel required for a task was set at 1, cost rates were assumed to be equal at different maintenance locations, and part costs were not incorporated into total cost calculations due to a paucity of data.
As a first step, Table 1 presents an overview of the task status list, with associated planned and actual start times for 3 out of the 1000 simulated cases. Each of these 3 cases represents a particular situation: on-time (situation 1), delay (situation 2), and opportunity (situation 3). From this point on, results are presented for the delay case, i.e., 1 of the 1000 simulated cases. This is representative for presenting the framework functionality and output. In section 4.3, some generalized conclusions (covering the full set of 1000 simulated cases) are presented.

Table 1: Task status list (including planned and actual start times) for 3 cases

Task status list			Planned start time	Actual start time		
Job Order/Task ID		Status		Situation 1	Situation 2	Situation 3
2421 00000002438 A	⊳	Completed	0,00	0,00	0	0
2421 00000002438 B	⊳	Completed	0,18	0,18	0,08	0,49
2421 00000002448 A	⊳	Completed	0,36	0,36	0,32	0,63
2421 00000002448 B	⊳	Completed	0,51	0,51	0,61	0,7
2530 00000004200 A	⊳	Completed	0,66	0,66	0,9	0,82
2530 00000004200 B	⊳	Completed	0,76	0,76	0,98	1,04
2744 51000003310	⊳	Completed	0,86	0,86	1,16	1,2
2760 00000001600	⊳	Completed	1,46	1,46	1,97	1,79
2900 00000001100	⊳	Completed	1,74	1,74	2,28	1,83
2911 43000001435	⊳	Completed	2,65	2,65	3,66	1,98
2911 43000001445	⊳	Completed	2,77	2,77	3,87	2,09
3210 00000001741	⊳	In progress	2,91	2,91	3,93	2,17
3220 00000003710	⊳	To be done	5,71	Not started	Not started	Not started
3413 00000010120	⊳	To be done	8,14	Not started	Not started	Not started
7110 00000001440	⊳	To be done	8,63	Not started	Not started	Not started
7113 00000003430	⊳	To be done	8,78	Not started	Not started	Not started
7113 00000003440	⊳	To be done	8,91	Not started	Not started	Not started
7113 00000010430	⊳	To be done	9,05	Not started	Not started	Not started
7113 00000010440	⊳	To be done	9,17	Not started	Not started	Not started
7910 00000005450	⊳	To be done	9,31	Not started	Not started	Not started
7920 00000001435	⊳	To be done	9,51	Not started	Not started	Not started
8011 10000003436 A	⊳	To be done	9,65	Not started	Not started	Not started
8011 10000003436 B	⊳	To be done	9,86	Not started	Not started	Not started
8011 10000003446 A	⊳	To be done	10,04	Not started	Not started	Not started
8011 10000003446 B	⊳	To be done	10,24	Not started	Not started	Not started

Table 2 presents the initial ranked list of the remaining tasks associated with the selected delay case. Note that there are 4 critical tasks and 9 non-critical tasks. The generation of decision alternatives will consequently lead to 512 alternatives, as $\binom{9}{0} + \binom{9}{1} + \ldots + \binom{9}{9} = 512$.

Table 2: Initial ranking list of remaining tasks

Ranking	Job Order/Task ID	RUL (FH)	Criticality	t_{mean_task} (hours)
1	7110 00000001440	36	Critical	0,16
2	7113 00000010430	36	Critical	0,12
3	7113 00000010440	36	Critical	0,14
4	7910 00000005450	36	Critical	0,21
5	7113 00000003430	65	Non Critical	0,12
6	7113 00000003440	65	Non Critical	0,14
7	7920 00000001435	65	Non Critical	0,14
8	3413 00000010120	139	Non Critical	0,49
9	8011 10000003436 A	515	Non Critical	0,20
10	8011 10000003436 B	515	Non Critical	0,19
11	8011 10000003446 A	515	Non Critical	0,20
12	8011 10000003446 B	515	Non Critical	0,19
13	3220 00000003710	2928	Non Critical	2,43

After generation of decision alternatives, the associated maintenance costs, operational risk, anticipated delay (on the basis of MC simulation of the remaining task times), delay costs and total costs are evaluated. Delay costs have been calculated on the basis of an A320 two-class configuration (having a maximum of 168 passengers) and a load factor of 80%. The resulting final ranked list of decision alternatives is (partially) shown in Table 3, giving the best and worst five outcomes. Alternative number 512 is the worst outcome in this particular delay case, and corresponds to the reference case, where it is assumed that the original planning is executed. A clear difference of approximately 2230 euro can be discerned between the total cost of the best and worst alternative.

Table 3: Decision framework output for selected delay case - five best and worst decision alternatives

Rank	Alternative number	Cost (€)	OR (€)	Delay (hours)	Time left (hours)	Delay cost (€)	Total cost (€)
1	85	236,22	59,70	0	0,02	0	295,92
2	100	236,22	60,00	0	0,03	0	296,22
3	265	236,22	60,38	0	0,05	0	296,60
4	270	236,22	60,70	0	0,05	0	296,92
5	271	236,22	60,94	0	0,06	0	297,16
⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
508	506	236,22	9,37	0,83	0	1453,23	1698,81
509	510	236,22	11,24	0,88	0	1648,40	1895,87
510	509	236,22	10,94	0,88	0	1666,08	1913,24
511	511	236,22	9,81	0,89	0	1727,30	1973,33
512	512	236,22	0,00	1,02	0	2289,32	2525,54

4.3 Validation

A systematic validation process has been carried out, in which the impact of different settings for the decision point and labor costs are explored in tandem with the aggregated simulation results. This lends more insight into framework performance and output, going beyond the (restrictive) results of a single delay case as discussed in the previous section.
Six cases are explored: three cases assume that cost of labor is equal at the current and next maintenance location, with case 1 having a decision point at 25% of the planned maintenance time (PMT), case 2 a decision point at 50% PMT, and case 3 a decision point at 75% PMT. Cases 4 to 6 cover the same decision point settings, but cost of labor is assumed to change from current to next location, with a factor of two being applied. For each case, 1000 iterations are simulated, leading to aggregate output per case. Each case takes 1 to 2 minutes to compute.

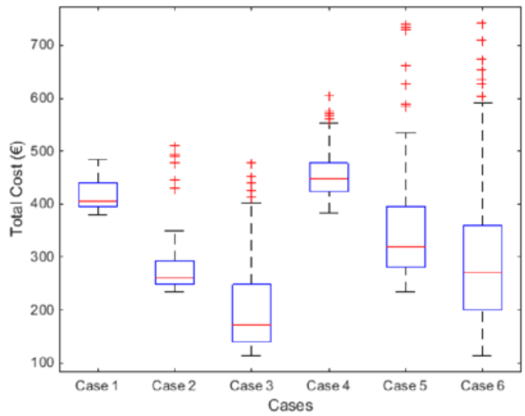

Figure 5: Total cost of best alternative

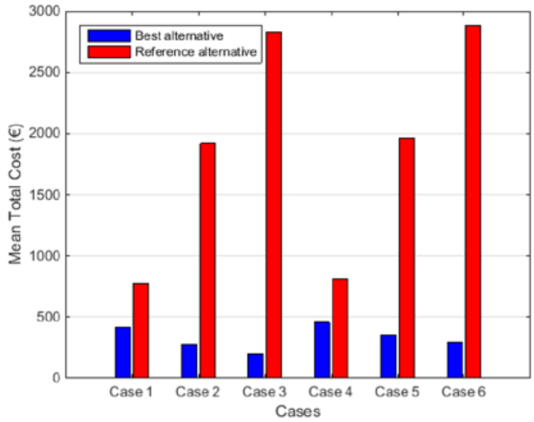

Figure 6: Comparison of mean total cost

Fig. 5 shows the total cost of the best alternative (aggregated for 1000 iterations) for cases 1 up to 6. Three main observations can be made: first, the mean cost decreases when the decision point occurs later in the PMT. This can be explained by the fact that maintenance cost is smaller at a later stage in the PMT, as there are simply less maintenance tasks remaining to be executed. Secondly, the variation is higher at later stages in the PMT. This is motivated by the fact that there is less 'buffer' to absorb the variance in the remaining set of maintenance tasks. Finally, the total cost of the best alternative is higher for the second group of cases (i.e., cases 4-6). This relates to the influence of the assumption regarding maintenance costs at different locations.
Several additional parameters have been subjected to sensitivity study. While detailed results are not represented here, this analysis shows that the impact of the probability of failure and the cost of unplanned maintenance has a very small impact on the output of the decision framework.
Fig. 6 gives a comparison of mean total cost for the best alternative with respect to the reference alternative. The difference in the mean total cost ranges from approximately 500 to 2500 euro, resulting in potential maintenance cost reductions of 45% to 90%. The reason why the mean total cost of the reference alternative is generally much higher than the mean total cost of best alternative is due to the fact that delay cost (biggest part of cost of reference alternative) is often much higher than the operational risk cost (biggest part of the best alternative)."

5 CONCLUSIONS

A decision support framework has been proposed to assist in operational maintenance planning, allowing the use of work progress data to adjust and re-optimise planning. The stochastic nature of maintenance task execution can be incorporated by using the proposed framework. Case study results indicate that the framework is able to generate decision alternatives with a lower total cost than the reference alternative, while at the same time optimising the maintenance planning, resulting in a possible reduction of the maintenance costs of 45 to 90% (depending on parameter settings).
Future research will investigate the impact of the probability of failure and the value of cost of unplanned maintenance, as well as introducing more realistic assumptions with respect to manpower

availability and allocation. Furthermore, task deferral including extension of the planning horizon beyond the next maintenance check is subject to study. As a final element, heuristics are considered to mitigate the effect of combinatorial explosion when considering larger sets of tasks.

REFERENCES

1. Papakostas, N., et al., *An approach to operational aircraft maintenance planning.* Decision Support Systems, 2010. **48**(4): p. 604-612.
2. Dekker, R., *Applications of maintenance optimization models: a review and analysis.* Reliability Engineering & System Safety, 1996. **51**(3): p. 229-240.
3. Gavranis, A. and G. Kozanidis, *An exact solution algorithm for maximizing the fleet availability of a unit of aircraft subject to flight and maintenance requirements.* European Journal of Operational Research, 2015. **242**(2): p. 631-643.
4. Sarac, A., R. Batta, and C.M. Rump, *A branch-and-price approach for operational aircraft maintenance routing.* European Journal of Operational Research, 2006. **175**(3): p. 1850-1869.
5. Sgaslik, A., *Planning German Army Helicopter Maintenance and Mission Assignment*. 1994, Naval Postgraduate School: Monterey, CA, USA.
6. Verhoeff, M., W.J.C. Verhagen, and R. Curran, *Maximizing Operational Readiness in Military Aviation by Optimizing Flight and Maintenance Planning.* Transportation Research Procedia, 2015. **10**: p. 941-950.
7. Moudani, W.E. and F. Mora-Camino, *A dynamic approach for aircraft assignment and maintenance scheduling by airlines.* Journal of Air Transport Management, 2000. **6**(4): p. 233-237.
8. AIRMES. *AIRMES Project*. 2017 26-07-2017]; Available from: http://www.airmes-project.eu/.
9. Dekker, R. and P.A. Scarf, *On the impact of optimisation models in maintenance decision making: the state of the art.* Reliability Engineering & System Safety, 1998. **60**(2): p. 111-119.
10. Rausand, M., *Reliability centered maintenance.* Reliability Engineering & System Safety, 1998. **60**(2): p. 121-132.
11. Ahuja, I.P.S. and J.S. Khamba, *Total productive maintenance: literature review and directions.* International Journal of Quality & Reliability Management, 2008. **25**(7): p. 709-756.
12. Dekker, R. and I.F.K. Roelvink, *Marginal cost criteria for preventive replacement of a group of components.* European Journal of Operational Research, 1995. **84**(2): p. 467-480.
13. Dekker, R. and E. Smeitink, *Preventive maintenance at opportunities of restricted duration.* Naval Research Logistics: an international journal, 1994: p. 335-353.
14. Dekker, R. and C. van Rijn, *PROMPT, A Decision Support System for Opportunity-Based Preventive Maintenance*, in *Reliability and Maintenance of Complex Systems*, S. Özekici, Editor. 1996, Springer Berlin Heidelberg: Berlin, Heidelberg. p. 530-549.
15. David, F.P. and A.H.K. Khairy, *Preventive maintenance modelling: A Bayesian perspective.* Journal of Quality in Maintenance Engineering, 1996. **2**(1): p. 15-24.
16. Sriram, C. and A. Haghani, *An optimization model for aircraft maintenance scheduling and re-assignment.* Transportation Research Part A: Policy and Practice, 2003. **37**(1): p. 29-48.
17. Lapa, C.M.F., C.M.N.A. Pereira, and M.P. de Barros, *A model for preventive maintenance planning by genetic algorithms based in cost and reliability.* Reliability Engineering & System Safety, 2006. **91**(2): p. 233-240.
18. Saranga, H., *Relevant condition-parameter strategy for an effective condition-based maintenance.* Journal of Quality in Maintenance Engineering, 2002. **8**(1): p. 92-105.
19. Hasnida, A.-S. and K. Shahrul, *Opportunistic maintenance (OM) as a new advancement in maintenance approaches: A review.* Journal of Quality in Maintenance Engineering, 2014. **20**(2): p. 98-121.
20. Cook, A., G. Tanner, and A. Lawes, *The Hidden Cost of Airline Unpunctuality.* Journal of Transport Economics and Policy (JTEP), 2012. **46**(2): p. 157-173.

