FACULTY OF ECONOMICS AND
BUSINESS ADMINISTRATION

The impact of failure predictive information in maintenance planning in the aviation industry

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Summary

Over the years, the aviation industry has been characterized by dramatic growth and increasing competitiveness. Recently, the environmental impact of the industry has been subject to great controversy. Although this master's dissertation does not aim to contribute directly to resolving this major issue, increasing operational efficiency provides the opportunity for aviation companies to address these concerns. Data transmission technology enables aircraft manufacturers to equip their aircrafts with systems that provide realtime information on the status of the aircraft components. This information can be processed in such a way that it predicts failure occurrence which can be used by stakeholders for R&D purposes, regulatory alignment and aircraft maintenance planning. The objective of this master's dissertation is twofold. First, the aim is to provide a framework for the use of this data in maintenance planning within the aviation industry from a project management perspective. Second, the impact of incorporating failure predictive information in maintenance planning in the aviation industry is analyzed and quantified.

Chapter 1 provides an overview of past research in project management and aircraft maintenance planning. Various scheduling problems are defined for which developed models and solution procedures are elaborated. Furthermore, aircraft maintenance planning practices and techniques are depicted upon.

A Belgian airline and an International ground support equipment services company have contributed to this research by providing information on their current knowledge of aviation maintenance and realtime data incorporation. These case studies are subject of chapter 2 and 3.

Based on the information obtained in the literature review and the case studies, a theoretical framework is constructed and presented in chapter 4. In the aviation industry, maintenance schedules are flexible in that they are revised continuously on the tactical level (i.e. day-to-day decision making). This dynamic context of maintenance planning is induced by the uncertainty in maintenance requirements that stems from the operational characteristics of aviation machinery. Project management constructs are deployed to model this flexibility within the constructed framework and provide fundamentals on which the remainder of the research is built. In this chapter, the cost objective and the trade-off between several maintenance costs are introduced.

Chapter 5 focuses on the developed maintenance planning procedure which incorporates failure predictive information of aircrafts. The data modeling, data processing and how this data is used by the heuristic are explained thoroughly and the performance measures used in subsequent analyses are defined. In combination with chapter 4, the first objective of this master's dissertation is concluded: a framework on how realtime data on aircrafts' status is used within maintenance planning.

Analysis of input factors of the heuristic, operational characteristics of aircrafts and fleet compositions are subject of chapter 6. Moreover, the influence of these factors and parameters on the impact of the incorporation of failure predictive information in aircraft maintenance planning is analyzed. In order to conclude, chapter 7 summarizes the main conclusions for the second objective of this research: the impact of incorporating failure predictive information in maintenance planning in the aviation industry. Furthermore, recommendations for both researchers and practitioners are formulated.

Preamble

This master's dissertation is the final piece of my five-year educational program, Business Engineering - Operations Management, at Ghent University. Before elaborating on project management and aircraft maintenance planning, I want to express my sincere gratitude to some people that guided me through and supported me during this concluding project.

First, I want to thank my promotor, prof. dr. ir. Mario Vanhoucke, program director of the Business Engineering program at Ghent University, and my supervisor, Mr. Tom Servranckx, for giving me the opportunity to explore this research domain and their great guidance from the start up and until the end of this master's dissertation. A token of appreciation for their vast contribution in this research and our pleasant cooperation are in place. Moreover, I want to thank them for the knowledge they passed on to me during their courses "Project Management" and "Applied Operations Research".

Next, I wish to thank all professors and teaching assistants for their continues efforts in teaching my colleagues and me on the wide range of subjects within the Business Engineering program.

Further, I want to thank the people who participated in the two case studies for their warm welcome and the information they provided this research.

Last but not least, I am grateful for the support my family and friends gave me throughout my education.

To all readers, I wish you a pleasant reading experience throughout this research and most kindly invite you for further discussion!

Best regards

Bovyn Baptiste

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Chapter 1

Literature review

Long before operational research[1] was an acknowledged study domain, great scientists already unconsciously practiced it. During World War II, the term operational research was first introduced after conducting extensive research on the development of a radar system, deployed as a defense mechanism by the British Armed Forces. In 1938, exercises of the radar system had shown to be technically feasible, but its operational achievements fell far too short after which A. P. Rowe - the Superintendent of Bawdsey Research Station - proposed further research to be focused on these operational aspects. Hence, a new branch of applied science was born: Operational Research. This decision has proven to have been an indispensable factor in eventually conquering the German military force.

After World War II, operations research and operations management[2] have gotten more and more attention since it has proven to be very useful in industrial environments as well. In their paper 'Resource-constrained project scheduling: a survey of recent developments' Herroelen *et al.* (1998) provide us of an overview of the most important developments in OR and OM from the mid-1950s until 1998. A very popular subject within operations research has been the scheduling and sequencing of activities performed within industrial processes. Where sequencing deals with the order in which activities have to be performed, scheduling is concerned with the timing at which activities have to be conducted. Both are used in order to optimize the allocation of scarce resources over time. The objective which firms want to optimize can be the lead time[3], the profit that firms' operations generate, the cost of these operations et cetera. Resources cover everything the firm needs to conduct these operations e.g. raw materials, man-hours, machine time et cetera. Because of the interest of industrial manufacturers, most research has been focused on deterministic machine scheduling. This problem type concerns the sequencing and scheduling of activities performed on one or multiple machines with limited capacity, i.e. machine time, which is needed to perform these

[1] abbreviated as OR
[2] abbreviated as OM
[3] The time required to finish a particular job.

activities. Over the years, more realistic assumptions of this basic machine scheduling problem were applied thus, creating numerous (more realistic) extensions. Resource-constrained project scheduling problems[4] is the domain wherein multiple resources are considered with each a limited capacity and a set of jobs which consume some of these resources' capacity during their execution. The sequence in which these jobs are performed is constrained by precedence constraints which depict that certain jobs cannot be started/finished before their predecessor jobs have been started/finished.

In this chapter, an examination of existing contributions of researchers in the RCPSP domain is elaborated. A variety of extensions incorporating cost objectives and the flexible nature of regeneration projects of complex capital goods is explored and their assumptions and solution procedures are mapped. Furthermore, existing maintenance planning frameworks described in the literature are presented.

1.1 The resource-constrained project scheduling problem (RCPSP)

In this section, a basic resource-constrained project scheduling problem as described by Herroelen *et al.* (1998) is examined. The project has n activities and K renewable resources[5] which are consumed by the activities of the project. In this example, Herroelen *et al.* (1998) optimizes the makespan[6] of the project. Note, that this project is an abstract representation of the reality under consideration where several assumptions have to be made.
First, several constructs are defined:

- $\mathrm{d_i}$: duration of activity i with $1 \leq i \leq n$
- $\mathrm{s_i}$: integer starting time of activity i with $1 \leq i \leq n$
- $\mathrm{f_i}$: integer finishing time of activity i with $1 \leq i \leq n$ where dummy variables $\mathrm{f_1}$ and $\mathrm{f_n}$ are respectively the start and finishing time of the project
- $\mathrm{r_{ik}}$: constant resource requirement of activity i for resource k with $1 \leq i \leq n$ and $1 \leq k \leq K$
- $\mathrm{a_k}$: constant availability of resource k
- H: the set of pairs of activities indicating precedence constraints. Depending on the precedence constraints that we need to define according to the reality, the size of H will be determined.

[4]abbreviated as RCPSP

[5]Renewable resources - in contrast to non-renewable resources - are resources that are continuously replenished e.g. machine time and man hours. Non-renewable resources are resources that need replenishment after each project e.g. raw materials.

[6]The time that elapses between the start and finishing of the project.

- S_t: the set of activities activated in time interval $]t-1,t]$: $S_t = \{i \mid f_i - d_i < t \leq f_i\}$

Next, using these constructs, a mathematical model for the problem under consideration is defined.

1.1.1 Model definition

$$\text{Min } f_n \tag{1.1}$$

subject to

$$f_1 = 0, \tag{1.2}$$

$$f_j - d_j \geq f_i, \forall (i,j) \in H, \tag{1.3}$$

$$\sum_{i \in S_t} r_{ik} \leq a_k, t = 1,2,...,f_n \text{ and } k = 1,2,...,K \tag{1.4}$$

In the above formulated model, equation 1.1, the objective function, states the makespan minimization objective as the minimization of the finishing time of the project. Constraint 1.2 defines the starting time of the project as time 0 whereas constraint 1.3 has to be defined for each precedence constraint defined in set H. Resource constraints as defined in constraint 1.4 denote that during each time period $]t-1,t]$ and for each resource k, the total resource consumption of all active activities cannot exceed the per time period availability of the K renewable resources (a_k).
A visual representation of such a type of RCPSP is an activity-on-the-node network $G = (V, H)$ in which V is defined as the set of activities in this project (visualized by nodes) and H the set of precedence constraints with zero time-lag[7] (visualized by arcs). The activity durations are denoted above each node whereas under the node, the renewable resource consumptions of the K resources for the correspondent activity are indicated. An example is provided by Herroelen *et al.* (1998) in figure 1.1 where the project contains seven activities that need to be performed with each their duration time and resource requirement of one renewable resource (e.g. machine time). As defined in the mathematical model, dummy activities one and nine are respectively the start and finishing activity of the project with an activity duration of zero time periods and a renewable resource consumption of 0 units per time period.

[7] No time is needed between activities e.g. no setup time is required although we could incorporate the setup time into the duration of each activity d_i.

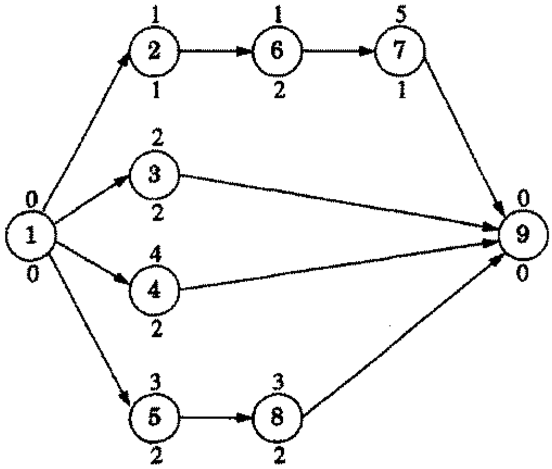

Figure 1.1: RCPSP example Herroelen *et al.* (1998)

1.1.2 Optimal solution procedures

In a practical setting, projects often contain numerous activities, precedence constraints, both non- and renewable resources and other constraints. The number of possible solutions increases exponentially with the size of the project. Therefore, smart solution procedures have to be in place as full enumeration of all solutions is not possible. Computational complexity theory is the study of how much of some resource (e.g. time) it takes to solve a problem that can be modeled and solved by a computer. In this area of study, NP-hard problems are defined as problems that can be solved efficiently by a non-deterministic turning machine, but the solution cannot be verified as the optimal solution in an efficient way by a deterministic turning machine.
RCPSP is known to be NP-hard, with NP standing for 'non-deterministic polynomial'. For a more thorough explanation of these concepts, we refer to Hogan (2011).
RCPSP's often have integer restricted variables. Therefore, solution procedures for these problems make use of techniques that are applied in Integer Programming. An example of such procedures are branch-and-bound procedures. Consequently, a lot of past research for optimal solution procedures for RCPSP's has been focused on enhancing and extending these branch-and-bound procedures.

1.1.2.1 Branch-and-bound procedures

Before solving an RCPSP with a branch-and-bound procedure, the basics of B&B[8] procedures are elaborated. Clausen (1999) explains the principles of the B&B procedures which search the complete solution space of a given problem for the best solution. Due to the exponentially

[8]branch-and-bound

increasing number of potential solutions, explicit enumeration of all these solutions is often impossible. B&B algorithms use bounds for the objective function and the current best solution (i.e. the incumbent) to search the solution space implicitly. The solution space is the set containing all possible solutions for a certain problem. During the execution of the algorithm, the procedure excludes parts of the solution space thus, defining subsets of solutions that are still under consideration. Initially, at the root node, only one subset exists i.e. the solution space. The incumbent is set to be ∞ for minimization objectives and $-\infty$ for maximization objectives. As the procedure elapses, a dynamic search tree is generated where each node is processed in one B&B iteration (the first iteration is process of the root node).

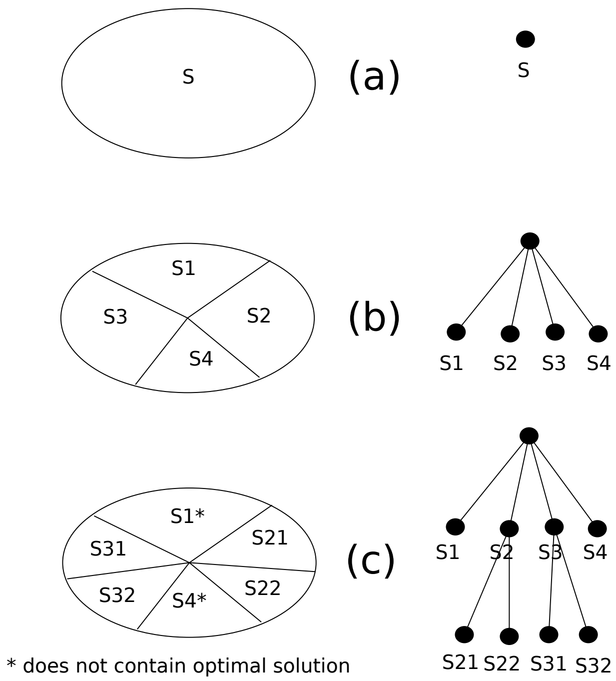

Figure 1.2: Illustration of the branch-and-bound procedure Clausen (1999)

In figure 1.2, situation (a) illustrates the root node and the solution space as the initial subset. Situation (b) and (c) are the result of the first iteration and the second and third iteration respectively. Each iteration has three main components: the selection of the node to process, the bound calculation and the branching. The first iteration's components are respectively: the root node, some incumbent[9] and the branching i.e. the subdivision of the solution space in subsets S1, S2, S3 and S4. Furthermore, for each subset is checked whether it has feasible solutions and if so, whether the best possible solution of this subset is better or worse than the incumbent. If it can be established that the subset's best solution is worse, the subset is

[9]best current solution

discarded from further consideration. The B&B procedure comes to an end when no more unexplored paths of the solution space are left. The optimal solution for the correspondent RCPSP is found: the incumbent.
Following the explanation above, a B&B algorithm consists of three major characteristics:

1. A bounding function
2. A strategy for selecting the solution subspace to be investigated
3. A branching rule

Before further elaborating these concepts, some constructs need to be defined:

- objective function $f(x)$ (which in our example we want to minimize)
- region of feasible solutions S
- set of potential solutions P for which $f(x)$ is defined but not all solutions are feasible (violate some constraint(s) i.e. $S \subseteq P$
- a function $g(x)$ with $g(x) \leq f(x)$ for all x in S or P

The root node corresponds to the original problem whereas each other node corresponds to a subproblem of the original problem. A subproblem contains one or more additional constraints in comparison with its predecessor subproblem e.g. node S22 in figure 1.2 is a child of node S2 which means that S22 is a subproblem derived from subproblem S2 which itself is a child of the root node. All constraints from the original problem will be incorporated in S22 as well as all additional constraints imposed in subproblem S2. For each node a bounding function g associates a real number, called the bound for this node, with each node. The node gets fathomed[10] if the bound is worse than the incumbent or add it to the pool of live nodes if the bound is equally good or better. Afterwards, we set the incumbent to this bound as this is the new best current solution.

1.1.2.1.1 A bounding function For a given subspace of the solution space, the bounding function gives a lower bound for the best possible solution obtainable in this subspace. Ideally, the bounding function should give the value of the best feasible solution in the considered subspace. As these subproblems themselves are usually NP-hard, the aim is to get a value as close to this best feasible solution as possible. As a trade-off between the quality of the bounding function (i.e. how close we get to the best feasible solution) and the effort to compute the bound value (e.g. computation time) has to be made, relaxations are used to convert the NP-hard problem to a P-problem by enlarging the set of feasible solutions. This

[10]We discard the node from further consideration

is done by eliminating some constraint. If the optimal solution of this relaxed subproblem satisfies all constraints of the non-relaxed problem, this optimal solution is a candidate to become the new incumbent. Otherwise, it is used as a lower bound because a larger set of values (e.g. P instead of S) was used to optimize this problem.

1.1.2.1.2 A strategy for selecting the solution subspace to be investigated Clausen (1999) describes three methods to select the next live node to investigate. Figure 1.3 represents these three methods where the numbers in the nodes represent the sequence in which the nodes are processed.

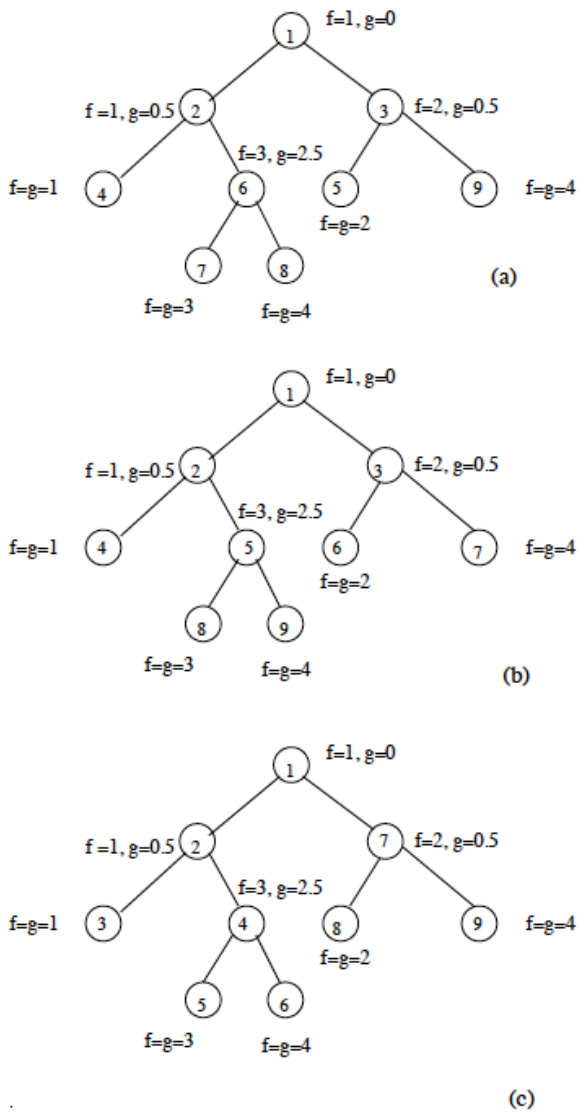

Figure 1.3: Search strategies in B&B: (a) BeFS, (b) BFS and (c) DFS Clausen (1999)

1. Best first search strategy (BeFS): one always selects the subproblem with the lowest bound i.e. the lowest value for $g(x)$. The advantage of this method is that no superfluous bound calculations are made after the optimal solution has been found.

2. Breath first strategy (BFS): all nodes on a certain level in the search tree are processed before any nodes at a higher level. As the number of nodes at each level can grow exponentially, this method is not computationally efficient for larger problems.

3. Depth first search strategy (DFS): a live node on the lowest level of the search tree is chosen for exploration. In practice it is common to use this method in combination with the BeFS to select a live node on the same level. Experiments showed the superiority of DFS over BeFS on both computation time and bound calculations.

1.1.2.1.3 A branching rule A branching rule enables the procedure to divide the solution space into subdivisions of this solution space by adding constraints (often in the form of assigning values to the variables). If the number of feasible solutions for a problem is finite, the branching ensures the procedure that the size of the subproblems get smaller and smaller. For illustrative purposes, we refer to Hillier & Lieberman (2015) where a mixed integer linear program[11] is formulated and a stepwise elaboration of the B&B solution procedure is provided.

Demeulemeester & Herroelen (1992) developed a B&B procedure for solving RCPSP problems with a makespan minimization objective such as defined in this section. Up until today, it is considered one of the most powerful algorithms available. For each node, a partial schedule and delaying alternatives is defined for which a lower bound on the makespan is calculated by deploying the critical path method. Further, a depth first search strategy is used to generate the dynamic search tree. Branching is done by adding precedence constraints between activities according to the delaying alternatives. For a detailed elaboration on this algorithm, we refer to Demeulemeester & Herroelen (1992).

[11] MIP

1.2 Multi mode resource constrained project scheduling problems (MRCPSP)

Previous section (1.1) elaborated on the basic RCPSP where activities each have a predefined activity duration and resources consumptions. In contrast to this static activity definition, MRCPSP considers a multiplicity of modes in which activities can be performed. In this context, a mode is a predefined set containing time/time trade-offs or time/resource trade-offs e.g. an activity can be performed in 2 modes: (1 day, 200 man-hours) or (2 days, 150 man-hours). Consequently, not only sequencing and scheduling decisions have to be made, the project structure itself also has to be determined.

Sprecher *et al.* (1997) generalized the B&B procedure constructed by Demeulemeester & Herroelen (1992) thus, creating an exact solution procedure. Sprecher & Drexl (1998) enhanced this exact optimization procedure by incorporating a precedence tree guided enumeration scheme introduced by Patterson *et al.* (1989). In contrast to the exact B&B optimization procedures, Hartmann (2001) developed a genetic algorithm, a heuristic solution procedure using the natural evolution concept.

In all the solution procedures described in this section, the objective is the minimization of the project makespan.

1.2.1 Solution procedures

1.2.1.1 Branch-and-bound

As stated in the first paragraph of this section, a precedence tree guides the enumeration scheme constructed by Sprecher & Drexl (1998). In section 1.1.2.1 it was clear that the B&B procedures search for the optimal solution by decomposing the problem into subproblems by splitting the feasible region and fixing variables. When taking into account more constraints when defining nodes of a B&B tree, the procedure will have to undertake less enumerations to find the optimal solution. In this algorithm, the precedence constraints are guiding the search through the B&B tree which together with the static and dynamic bounding/dominance rules makes the algorithm more efficient and therefore more powerful when considering problems of a practical size. This is allowed if the objective function is regular, i.e. if the objective function value for a certain schedule does not get any worse if the completion time of an activity is reduced without changing that activity's mode. Since this is the case for the minimization of the makespan, this approach can be used to solve the general MRCPSP.

Sprecher & Drexl (1998) also report computational results when imposing a time limit to their exact procedure. Note, that by imposing this time-limit, the solution procedure is no

longer exact and becomes a heuristic, the so-called truncated B&B procedure. Research has shown that this method offers (near) optimal solutions in a very efficient manner.
For a more detailed presentation, we refer to Sprecher & Drexl (1998).

1.2.1.2 Genetic algorithm: GA

When considering practical problems, exact solution methods fail to find the optimal solution in reasonable computation times. Hence, heuristic algorithms producing near optimal solutions are of special interest. Hartmann (2001) introduces a new genetic algorithm for solving MRCPSP using an activity list and a mode list to represent an individual. In this section an overview of the GA approach is given. Further, an elaboration on how Hartmann (2001) implemented this approach to solve MRCPSP's is provided.

Genetic algorithms use the principle of biological evolution to solve NP hard problems to near-optimal solutions. As in biological evolution, new schedules (i.e. individuals) are created by recombining previous solutions and saving the best ones (i.e. survival of the fittest). Using the genetic inheritance laws with crossover, mutation and selection the algorithm transforms the population of best solutions is such a way that global optima can be reached.

Before starting the algorithm, a preprocessing step is undertaken to reduce the search space similar to what is aimed for by the static dominance rules used in Sprecher & Drexl (1998). The first step of the algorithm itself is the computation of an initial population of size POP. Secondly, the fitness of each individual is computed (cfr. infra). As in biological evolution the next generation of individuals are created by two parents, a mother and a father. Therefore, the next step is the random assignment of pairs of individuals which create two new individuals with different genotypes using a predefined crossover operator. Next, the mutation operator adjusts these genotypes in order to find global optima after which the fitness of each individual is computed. The selection operator reduces the population which now has a size of $2 * POP$ to the original size POP and the new generation is available for the next iteration. According to the specification, the algorithm can run for a predefined CPU time or until a certain number of different schedules is generated.

In section 1.3 a more detailed elaboration on genetic algorithms is provided given that the RCPSP-PS incorporates more flexibility which is needed in maintenance planning.

1.3 Resource constrained project scheduling problems with a flexible project structure (RCPSP-PS)

In a first attempt to include more flexibility, the MRCPSP has been discussed in section 1.2 where each activity can be performed in several modes. These modes are time/time or time/resource trade-offs of which one has to be chosen since all activities have to be conducted in order for the project to be completed.

In this section, the RCPSP-PS is considered which introduces even more flexibility as not all activities have to be implemented. Simultaneously, choices have to be made on whether to implement a certain activity or not and when to do so. These choices will affect the active precedence constraints and project structure. First, a practical example of a passenger aircraft turnaround process at an airport of Kellenbrink & Helber (2015) is presented to illustrate the RCPSP-PS. Secondly, a general mathematical model definition is given which will serve as the basis for the further analysis on how to resolve this problem type using a genetic algorithm constructed by Kellenbrink & Helber (2015).

1.3.1 Example: aircraft turnaround process

When an aircraft arrives at airport, two options for deboarding are defined: either it stops on the apron or either it stops at the terminal. The choice among these two options trigger different activities and choices to be made (= choice among alternative activities).

- If the aircraft arrives at the terminal, two activities are triggered: first, a bridge has to be used to deboard the passengers. Second, a pushback tractor has to push the aircraft back to the airfield (= choice triggers activities).
- If the aircraft arrives at the apron, another choice has to be made: either passengers have to walk to the terminal or go by bus (= choice triggers choice).

There are also some mandatory activities which have to be performed either way such as cleaning the aircraft, catering and boarding the next passengers (= mandatory activities). Finally, a choice has be made concerning the fueling process. Either firefighters supervise this process and the next passengers can board whilst the aircraft is being fueled or no supervision is in place and the next passengers have to wait until fueling is finished before they can board the aircraft (= optional activity implicates precedence constraint).

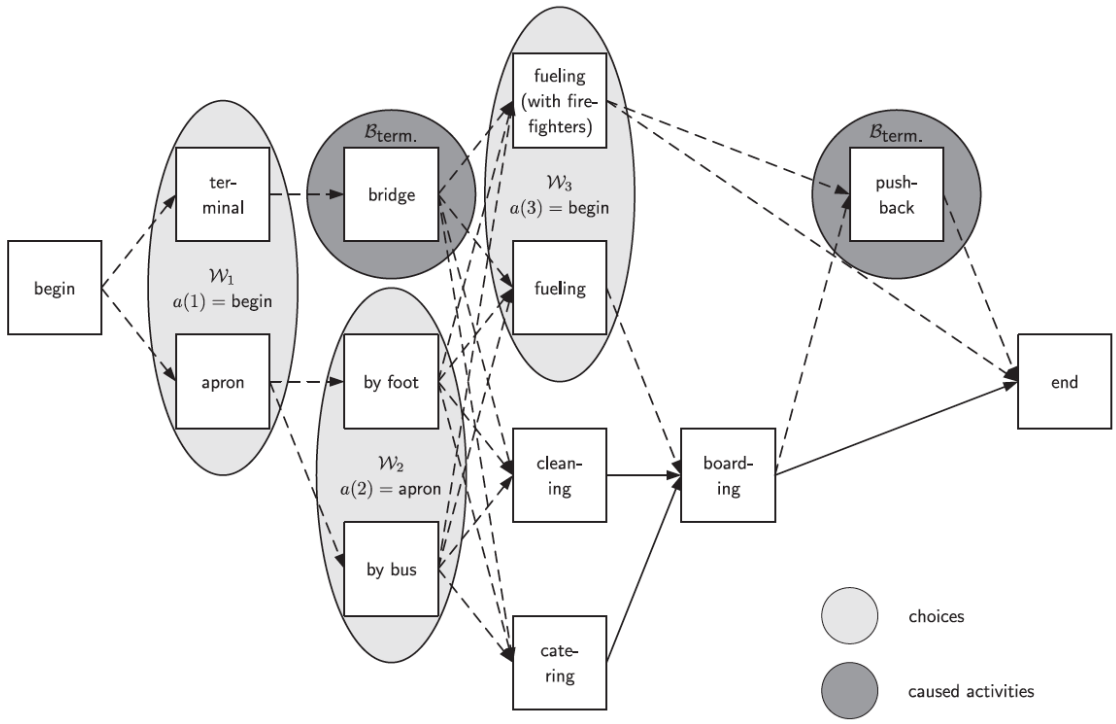

Figure 1.4: The project network of the aircraft turnaround process Kellenbrink & Helber (2015)

It is clear that RCPSP-PS exceeds the flexibility introduced in the MRCPSP. Figure 1.4 is a representation of the above explanation. Following legend applies:

- square: activity
- oval: choice
- full arrow: precedence relation that is always in place;
- dashed arrow: precedence relation between an activity (optional or not) and two or more optional activities. The implementation is dependent on the implementation of two activities.

1.3.2 Model definition

Kellenbrink & Helber (2015) centralize the model around the binary variable x_{jt} which indicates if activity j ends in period t or not, i.e. $x_{jt} = 1$ if activity j ends in period t and $x_{jt} = 0$ if not. The activities are topologically ordered such that for activity i and j with $i < j$ holds that i precedes j. Before continuing, several constructs are defined:

- ε the set of all choices that may be made

- Υ the set of all activities, i.e. $\Upsilon = 1, ..., J$.
- $V \subseteq \Upsilon$ is the subset that contains all mandatory activities.
- θ the set containing all time periods, i.e. $\theta = 1, ..., T$.
- d_j the duration of activity j.
- P_j the set of predecessor activities of activity j.
- R the set of renewable resources.
- N the set of nonrenewable resources.
- Each choice $e \in \epsilon$ represents the selection of one activity j among several optional activities $W_e \subseteq \Upsilon \setminus V$. Each activity j can belong to at most one set W_e. This implicates that an activity can only belong to one choice.
- $a(e)$ is the triggering activity for a choice e. This triggering activity can be either optional or mandatory. If $a(e)$ is mandatory, so is the choice e and therefore one activity $j \in W_e$ must be implemented. Moreover, $a(e)$ itself can be optional. If so, it must itself belong to the set of optional activities $W_{e'}$ of exactly one earlier choice e'.
- B_j is the set of dependent optional activities $k \in B_j \subseteq \Upsilon \setminus V$ for the optional activity j. Each activity belongs to either one set W_e or one set B_j with $j \in W_e$.
- In order to avoid cycles of cause, the triggering activity $a(e)$ of each choice e must be a predecessor of activities $j \in W_e$. Therefore, a topological ordering is in place such that $a(e) < j$ with $j \in W_e$.
- The choices are topologically ordered as well such that if $e < e'$ then e cannot be triggered by e'.

The model is as follows:

$$min\ Z = \sum_{t=ef_j}^{lf_j} t * x_{Jt} \tag{1.5}$$

subject to

$$\sum_{t=ef_j}^{lf_j} x_{jt} = 1\ \forall\ j \in V \tag{1.6}$$

$$\sum_{i \in W_e} \sum_{t=ef_i}^{lf_i} x_{it} = \sum_{t=ef_{a(e)}}^{lf_{a(e)}} x_{a(e)t}\ \forall\ e \in \varepsilon \tag{1.7}$$

$$\sum_{t=ef_i}^{lf_i} x_{it} = \sum_{t=ef_j}^{lf_j} x_{jt} \; \forall \; e \in \varepsilon; \; j \in W_e; \; i \in B_j \tag{1.8}$$

$$\sum_{t=ef_i}^{lf_i} t * x_{it} \leq \sum_{t=ef_j}^{lt_j} (t - d_j) * x_{jt} + T * (1 - \sum_{t=ef_j}^{lf_j} x_{jt}) \; \forall j \in \Upsilon; \; i \in P_j \tag{1.9}$$

$$\sum_{j=1}^{J} (k_{jr} * \sum_{t'=t}^{t+d_j-1} x_{jt'}) \leq K_r \; \forall \; r \in R; \; t \in \theta \tag{1.10}$$

$$\sum_{j=1}^{J} (k_{jr} * \sum_{t=ef_j}^{lf_j} x_{jt}) \leq K_r \; \forall \; r \in N \tag{1.11}$$

$$x_{jt}\{0, 1\} \; \forall j \in \Upsilon, \; t \in \theta \tag{1.12}$$

The objective function presented in 1.5 defines the makespan minimization objective as minimizing the completion time of the ending activity J. Constraint 1.6 implements all mandatory activities whereas constraint 1.7 makes sure that for every triggering activity, an optional activity is implemented. Further, constraint 1.8 implements the dependent optional activities whereas equation 1.9 implements the precedence constraints. Note, that these precedence constraints are only active if the pair of activities for which the precedence constraint holds are both implemented. The nonrenewable and renewable resource constraints are presented in constraint 1.11 and constraint 1.10 respectively.
In the RCPSP earliest and latest finish times were computed via forward and backward recursions given the exogenous project structure. As the project structure is not rigid in the RCPSP-PS, the earliest finishing times are computed using forward recursion only taking into account the mandatory activities. An upper bound on the finishing times is computed using backward recursion taking into account all mandatory and optional activities. When deleting constraints 1.7 and 1.8 the standard RCPSP results. It is clear that the RCPSP-PS is an extension of RCPSP.

1.3.3 Genetic algorithm

Solving the RCPSP-PS, one can enumerate all possible project paths, i.e. make all possible combinations of project structures by making each choice. This approach reduces the RCPSP-PS to several RCPSP problems for which a variety of optimal and heuristic solution procedures are available. Although possible in practical settings, this approach generates a lot of RCPSP problem instances to be solved which increases the computation amount substantially with each choice to be made. Therefore, Kellenbrink & Helber (2015) constructed a genetic algorithm to solve these problems to (near) optimality based on the GA of Hartmann (2001) for solving MRCPSP. The biological evolution theory still lies at the basis for this algorithm using crossover, mutation and selection. In this section the modifications are highlighted as well as a practical example. Note that the objective is the minimization of the makespan whereas in this master's dissertation, a cost minimization objective is set.

Given the model-endogenous decision on the project structure, the representation of the individuals has to be modified. Two components have to be included: the project structure, i.e. the set of implemented activities $j \in W_e \; \forall \; e \in \varepsilon$, the mandatory activities $j \in V$ and the active precedence constraints and secondly, the schedule of these activities that are implemented. An individual is represented as follows:

$$I = \left(\begin{array}{cccc|cccc} \alpha_1 & \alpha_2 & ... & \alpha_E & \lambda_1 & \lambda_2 & ... & \lambda_J \\ a(1); W_1 & a(2); W_2 & ... & a(E); W_E & \tau_{\lambda_1} & \tau_{\lambda_2} & ... & \tau_{\lambda_J} \end{array}\right)$$

with

- Choice list $\alpha = (\alpha_1, \alpha_2, ..., \alpha_E)$: This list contains all the chosen optional activities $j \in W_e$ for each choice $e \in \varepsilon$. It reflects the chosen project structure.
- Below the choice list α, the triggering activity $a(e)$ and the set with all optional activities from which one can chose W_e is given. This serves for explanatory purposes and is not implemented in the algorithm.
- The activity list $\lambda = (\lambda_1, \lambda_2, ..., \lambda_J)$: sequence in which all activities have to be implemented, i.e. the schedule.
- As not all activities are implemented, the implementation list $\tau = (\tau_{\lambda_1}, \tau_{\lambda_2}, ..., \tau_{\lambda_J})$ contains binary variables which indicate if the activity is implemented or not, i.e. $\tau_{\lambda_j} = 1$ if activity j is implemented and $\tau_{\lambda_j} = 0$ is not.

In the algorithm, only the right-hand side of the representation is used since the choice list α and the implementation list τ contain redundant information. Kellenbrink & Helber (2015) use the left-hand side for expository purposes in their paper.

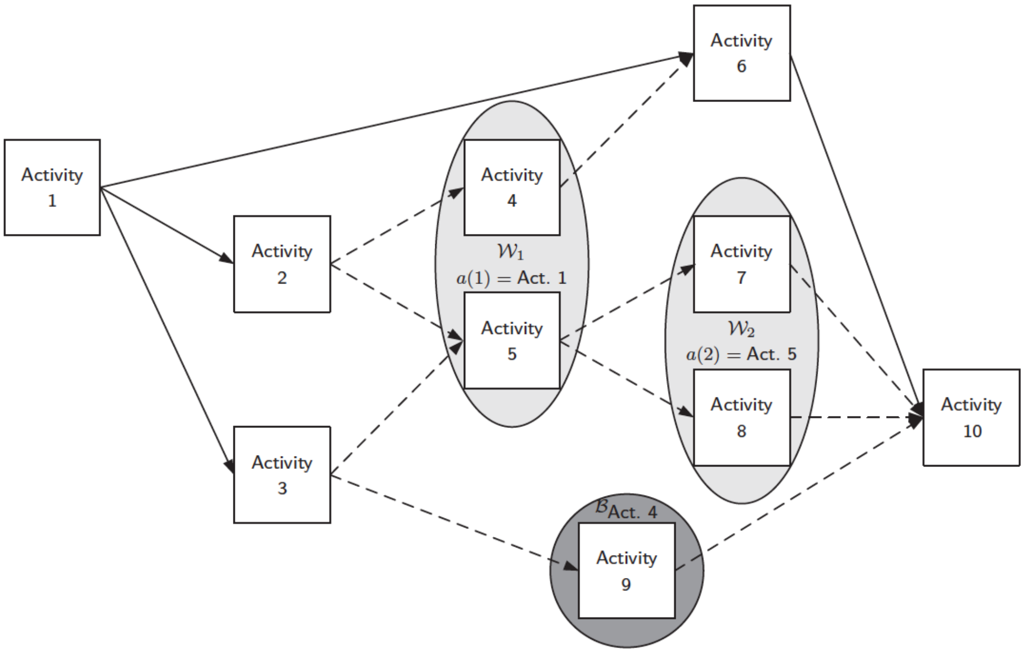

Figure 1.5: Example of a flexible project. Kellenbrink & Helber (2015)

Another example is provided in figure 1.5. Further information on the duration and resource consumption of each activity is provided in table 1.1.

j	1	2	3	4	5	6	7	8	9	10
d_j	0	3	4	3	5	6	4	2	2	0
k_{j1}	0	3	7	5	2	8	6	5	4	0

Table 1.1: Project information Kellenbrink & Helber (2015)

A solution for this project is the following individual:

$$I^M = \left(\begin{array}{cc|cccccccccc} 5 & 7 & 1 & 3 & 6 & 4 & 2 & 8 & 5 & 7 & 9 & 10 \\ 1;\{4,5\} & 5;\{7,8\} & 1 & 1 & 1 & 0 & 1 & 0 & 1 & 1 & 0 & 1 \end{array} \right)$$

After making choice 1 and 2, the individual's feasible activity list is decoded using the serial schedule generation scheme. In this method, activities are scheduled as early as possible without violating renewable resource constraints (precedence constraints are not violated since a feasible activity list was generated). The result is an active schedule in which no activity can be started earlier without delaying another activity. The phenotype of which the genotype of I_M is a representation is presented in figure 1.6.

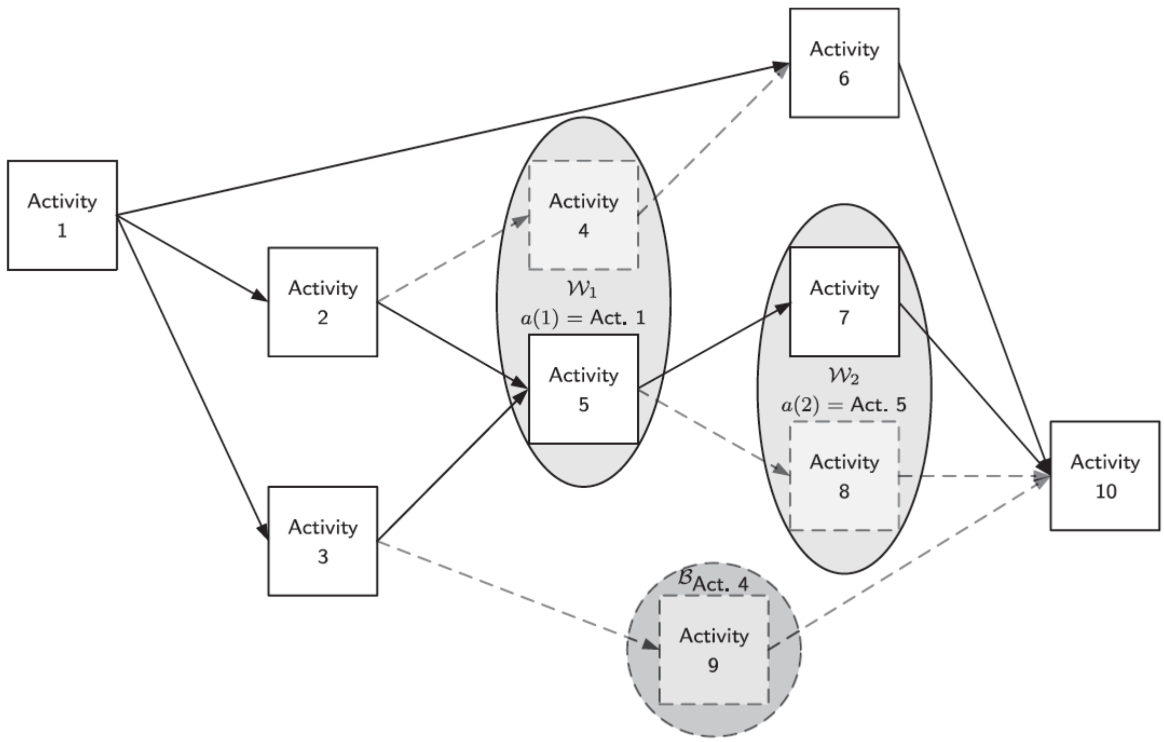

Figure 1.6: Phenotype for individual I_M Kellenbrink & Helber (2015)

All active parts (precedence constraints and activities) are marked with full lines. The inactive ones are drawn in dashed lines. It is clear that the feasibility of the activity list depends on the implementation list. Consider that instead of choosing activity 5 in choice 1, activity 4 was chosen. This would activate a precedence constraint between activity 4 and 6 and therefore also between 2 and 6. Moreover, the dependent activity 9 would have to be implemented and its precedence constraints, i.e. between activity 3 and 9 and between activity 9 and 10, would become active. The activity list of this individual would be infeasible and therefore, this individual would be an infeasible solution for this problem.

1.3.3.1 Fitness computation

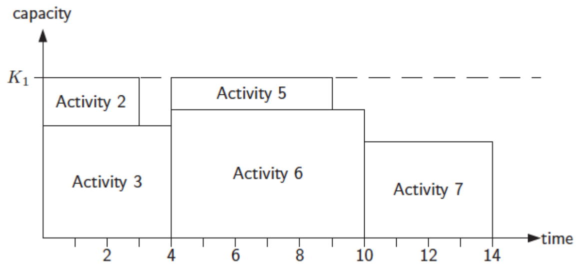

Figure 1.7: Schedule for individual I_M Kellenbrink & Helber (2015)

Hartmann (2001) calculated the fitness value for all individuals with a feasible activity list which are also feasible with respect to the nonrenewable resources as the makespan of the schedule. If on the other hand, the solution is infeasible with respect to the nonrenewable resources, the fitness value is the length of the planning horizon and the additional required units of the nonrenewable resources in order to become feasible. Kellenbrink & Helber (2015) use this method as well. Considering that there is no nonrenewable resource in this project, the fitness value will always be the makespan of the corresponding schedule. Given the capacity of the renewable resource K_1 is 10, $f(I^M) = 14$ as observed in figure 1.7.

1.3.3.2 Initial population

An initial population of size POP is generated with each individual constructed as follows:

1. Project structure, i.e. all choices are made:
   (a) Activate all mandatory activities, i.e. $\tau_j := 1$ for $j \in V$.
   (b) Deactivate all other activities, i.e. $\tau_j := 0$ for $j \notin V$.
   (c) Each choice $e \in \varepsilon$ is considered in a topological order. First, for each choice $e \in \varepsilon$ a random activity $j \in W_e$ is selected ($\alpha_e := j$) and activated ($\tau_{\lambda_j} := 1$). Secondly, all activities caused by activated optional activities are activated as well, i.e. $\tau_{\lambda_i} := 1$ $\forall\ i \in B_j$ and $\tau_{\lambda_j} = 1$.
   (d) Before continuing, the algorithm checks whether the project structure violates the nonrenewable resources constraint. If it does so, a new project structure should be determined using the same method. If after $Trial_{max}$ times constructing a new project structure, no feasible structure can be found, the algorithm continues with this infeasible solution which has a poor fitness value.

2. Activity list λ: For each position on the activity list, a set of eligible activities (both implemented and not implemented) is determined. An activity is eligible if its active

predecessors are already placed on the activity list and if it is not yet scheduled itself. Afterwards, based on the latest starting times one of these eligible activities is selected and scheduled. Only the dummy start activity 1 and end activity J are not considered since they are always placed on the first and the last position respectively.

In the remainder of this section, the crossover, mutation and selection are discussed. For explanatory purposes, a second individual is constructed given that pairs of individuals are needed for performing these tasks.

$$I^F = \left(\begin{array}{cc|cccccccccc} 4 & / & 1 & 2 & 3 & 7 & 4 & 5 & 6 & 8 & 9 & 10 \\ 1;\{4,5\} & 5;\{7,8\} & 1 & 1 & 1 & 0 & 1 & 0 & 1 & 0 & 1 & 1 \end{array}\right)$$

Individual I^F has been constructed following the procedure elaborated above. Once all mandatory activities $1, 2, 3, 6$ and 10 were activated (i.e. $\tau_{\lambda 1} := 1, \tau_{\lambda 2} := 1, \tau_{\lambda 3} := 1, \tau_{\lambda 6} := 1, \tau_{\lambda 10} := 1$) and all optional activities deactivated (i.e. $\tau_{\lambda 4} := 0, \tau_{\lambda 5} := 0, \tau_{\lambda 7} := 0, \tau_{\lambda 8} := 0, \tau_{\lambda 9} := 0$), optional activities for the mandatory choice was randomly chosen. For this first and only mandatory choice activity 4 was chosen. Given that activity 5 is not implemented, choice 2 is not triggered and therefore activity 7 nor 8 get implemented, i.e. $\tau_{\lambda_4} := 1, \tau_{\lambda_5} := 0, \tau_{\lambda_7} := 0, \tau_{\lambda_8} := 0$. Moreover, the implementation of activity 4 activates activity 9, i.e. $\tau_{\lambda_9} := 1$. Next, we calculate the nonrenewable resource requirement which turns out to be irrelevant in this problem since there is none. Therefore, the project structure is always accepted, and the algorithm continues to construct the activity list. Lastly, the fitness value is calculated based on the active schedule for $I^F, f(I^F) = 13$.

1.3.3.3 Crossover

As the individual representation used in Hartmann (2001) is modified by Kellenbrink & Helber (2015), so does the crossover operation. In his paper, Hartmann (2001) uses two crossover parameters q_1 and q_2 with $1 \leq q_1, q_2 \leq J$. Given the simultaneous decisions to be made in the RCPSP-PS (i.e. the project structure and the schedule of the activities), the crossover parameters are c^α and c^λ respectively for the choice list and the activity list.

- $1 \leq c^\alpha \leq |\varepsilon|$[12]: For the daughter, the c^α first choices e are inherited from the mother. As well as the choice list positions α_e^D themselves, the implementation variables $\tau_{\lambda j}^D := \tau_{\lambda j}^M$ for $j \in W_e$ are inherited as well. The rest is inherited from the father individual. If a choice e inherited from the mother triggers a choice e' with $e' > c^\alpha$ which is not triggered for the father individual, the choice $\alpha_{e'}$ and the implementation list position τ_{λ_i} is inherited from the mother as well, i.e. $\alpha_{e'}^D := \alpha_{e'}^M$ and $\tau_{\lambda_i}^D := \tau_{\lambda_j}^M$ for $i \in W_{e'}$. Further, all the caused activities are activated as well, i.e. $\tau_{\lambda_n}^D := 1 \; \forall \; n \in B_o$ with $o \in \Upsilon$ (Υ defined as the set of all activities).

[12] c^α is a position on the choice list and should therefore be between the first and the last choice.

- $1 \leq c^\lambda \leq J$: Similarly to the crossover parameter used in Hartmann (2001), the c^λ first activities are scheduled as the first c^λ activities of the mother individual, i.e. $\lambda^D := \lambda^M$ for the first c^λ positions.

Applied to the mother and father individual we defined in respectively section 1.3.3 and 1.3.3.2 and crossover parameters $c^\alpha = 1$ and $c^\lambda = 4$ following children are constructed:

$$I^D = \left(\begin{array}{cc|cccccccccc} 5 & 7 & 1 & 3 & 6 & 4 & 2 & 7 & 5 & 8 & 9 & 10 \\ 1;\{4,5\} & 5;\{7,8\} & 1 & 1 & 1 & 0 & 1 & 1 & 1 & 0 & 0 & 1 \end{array}\right)$$

The first choice is inherited of the mother, whereas the second should be inherited of the father. As the choice for activity 5 in the first choice triggers the second (optional) choice, the choice and its implementation list positions have to be inherited of the mother as well. This means that on the position of activity 7 in the implementation list of the daughter, the value of its mother implementation list position for activity 7 is used. Note that this does not affect the schedule position of activity 7. The position of activity 7 in the activity list of the daughter is still inherited by her father, i.e. $\lambda_7^D := \lambda_7^F$ and $\tau_{\lambda 7}^D := \tau_{\lambda_7}^M$.

For the son, the same procedure is applied with the role of the mother and father swapped. Following son individual I^S is obtained:

$$I^S = \left(\begin{array}{cc|cccccccccc} 4 & / & 1 & 2 & 3 & 7 & 6 & 4 & 8 & 5 & 9 & 10 \\ 1;\{4,5\} & 5;\{7,8\} & 1 & 1 & 1 & 0 & 1 & 1 & 0 & 0 & 1 & 1 \end{array}\right)$$

Given that the inheritance of the activity lists is not aligned with the inheritance of the choice lists, there might be an inconsistency between the project structure and the activity lists. During the mutation operation, a repair operation is in place to repair both this inconsistency as well as one created by the mutation itself.

1.3.3.4 Mutation

In order to reach places of the solution space which are not accessible by crossover of the initial population, mutation on the newly created individuals is performed. A three-step approach is used:

1. Mutation of the choice list α: a mutation parameter $0 \leq m^\alpha \leq 1$ is chosen at the beginning of the algorithm. For all choices, if a choice e is currently triggered but was previously not, a random activity $j \in W_e$ is chosen and activated (i.e. $\tau_{\lambda j} := 1; \alpha_e := j$). If e was previously triggered as well, a random variable m between 0 and 1 is drawn. If $m \leq m^\alpha$ then a random activity $j \in W_e$ is selected. If this activity does not correspond to the currently chosen activity α_e, the chosen activity changes to j (i.e. $\tau_{\lambda_{\alpha_e}} := 0; \tau_{\lambda_j} := 1; \alpha_e := j$). If on the other hand, the choice e was currently not

triggered at all but previously was, it remains untriggered. Further, all caused activities are updated, i.e. $i \in B_j$ for each $j \in W_e$ that have been implemented.

2. Repair of the infeasible activity list λ: The infeasible activity list is cloned into λ^* and λ is deleted. Afterwards, starting on the first position in the list the activity for which all predecessors are already scheduled, and which is not yet scheduled itself is scheduled.

3. Mutation of the feasible activity list λ: A mutation parameter m^λ is determined at the beginning of the algorithm. For each implemented activity j, the procedure draws a value $0 \leq m \leq 1$. If $m < m^\lambda$, determine the next activity i in the activity list. If this activity j is no predecessor for activity i, swap both activities.

Consider as an example that a mutation occurs for both the daughter individual as for the son individual. The second choice for I^D is mutated which activates activity 8 instead of activity 7. The activity list is still feasible and therefore no repair is necessary.

$$I^{D'} = \left(\begin{array}{cc|cccccccccc} 5 & 8 & 1 & 3 & 6 & 4 & 2 & 7 & 5 & 8 & 9 & 10 \\ 1;\{4,5\} & 5;\{7,8\} & 1 & 1 & 1 & 0 & 1 & 0 & 1 & 1 & 0 & 1 \end{array}\right)$$

For I^S, the first choice is mutated and activity 5 is activated instead of activity 4. Optional choice 2 gets triggered and activity 7 is randomly selected for implementation. Consequently, activity 9 is deactivated since activity 4 is no longer active.

$$I^{S'} = \left(\begin{array}{cc|cccccccccc} 5 & 7 & 1 & 2 & 3 & 7 & 6 & 4 & 8 & 5 & 9 & 10 \\ 1;\{4,5\} & 5;\{7,8\} & 1 & 1 & 1 & 1 & 1 & 0 & 0 & 1 & 0 & 1 \end{array}\right)$$

The mutated individual $I^{S'}$ has an infeasible activity list due to the precedence constraint between activity 5 and 7 which has become active. A repair operation is preformed such that activity 7 succeeds activity 5 (i.e. the activity list is deleted, and every activity is rescheduled). The result is individual $I^{S''}$:

$$I^{S''} = \left(\begin{array}{cc|cccccccccc} 5 & 7 & 1 & 2 & 3 & 6 & 4 & 8 & 5 & 7 & 9 & 10 \\ 1;\{4,5\} & 5;\{7,8\} & 1 & 1 & 1 & 1 & 0 & 0 & 1 & 1 & 0 & 1 \end{array}\right)$$

In the third step the activity lists are mutated. For the mutated daughter individual $I^{D'}$, for no activity m was smaller than m^λ. For the mutated son $I^{S''}$, activity 3 is considered for exchange. The next active activity is activity 6 and since no precedence constraint would be violated by this exchange, we obtain $I^{S'''}$:

$$I^{S'''} = \left(\begin{array}{cc|cccccccccc} 5 & 7 & 1 & 2 & 6 & 3 & 4 & 8 & 5 & 7 & 9 & 10 \\ 1;\{4,5\} & 5;\{7,8\} & 1 & 1 & 1 & 1 & 0 & 0 & 1 & 1 & 0 & 1 \end{array}\right)$$

1.3.3.5 Selection

After performing the crossover, mutation and repair operations the POP best individuals are selected for the next iteration of the procedure. Note that these individuals have to lowest fitness value, i.e. the shortest makespan for feasible solutions and a smaller fitness value for feasible solutions than for infeasible ones.

1.4 Aircraft maintenance planning

Over the years, aircraft maintenance planning has been undergoing major changes due to the changing environment in which they operate, the increasing complexity of aircrafts and the digitalization of business processes. In the beginning of the commercial airline industry, aircrafts' structures were basic, and regulations were rather lax in comparison with today. Moreover, the competitiveness within the industry has increased dramatically, forcing companies to increase efficiency, customer service and decrease costs. Therefore, intelligent business processes have become more important over the years which has been amplified by the opportunities enabled by the digitalization.

Numerous research projects have been conducted on aircraft maintenance planning which provides a vast amount of information on technical, engineering and descriptive classification fields of aircraft maintenance. Unfortunately, no standard lingo has been determined so far. Consequently, the literature tends to be inconsistent and somewhat confusing. Van den Bergh *et al.* (2013) provides an overview of the most important contributions on different types of aircraft maintenance and their applications. In an attempt to classify the contributions made so far, several descriptive fields are defined which focus on certain aspects of aircraft maintenance planning.

First, maintenance types are discussed. Within the aviation industry, A-, B-, C- and D-checks are acknowledged by most practitioners and researchers, but the interpretation differs. These checks differ in scope, duration and frequency of occurrence. Further, line maintenance, hangar maintenance, scheduled and unscheduled maintenance is distinguished for which more consensus on their definition is present. Therefore, conceptual alignment of these concepts is of major importance when conducting case studies and definition of these concepts needs to be stated in each research. Another distinction is made between preventive, corrective and predictive maintenance. Preventive maintenance is most straightforward and refers to scheduled maintenance after predefined time intervals to ensure airworthy aircrafts. Corrective maintenance projects are the reactive measures taken when failures occur, or irregularities are detected. Lately, interest in predictive maintenance has risen because monitoring possibilities have increased dramatically. In correspondence with the scope of this master's dissertation, focus lies on predictive maintenance.

Second, four domains of airline scheduling are defined and analyzed as well as their interrelations: flight scheduling, fleet assignment, maintenance routing and crew scheduling. Flight scheduling is concerned with the construction of cyclical lines-of-flights (LOF). These are the flights that have to be performed. Next, a certain aircraft of the fleet is assigned to each flight as defined by the LOF. This is referred to as the fleet assignment problem (FAP). Output of

the flight scheduling problem and the subsequent FAP are the input for the aircraft maintenance routing problem in which it is determined where and when each aircraft has to be scheduled for maintenance. These problems can include facility location problems depending on the degree of integration of all problems. The fourth domain is the crew scheduling problem. It has to be noted that next to fuel, costs for crews are the largest expense in the commercial airline industry.
Integrated airline scheduling refers to the integrated problem formulation which considers some or each aspect of airline scheduling. Numerous solution procedures have been developed for each problem domain and integrated problem formulations ranging from linear program formulations to branch-and-bound procedures to heuristics and simulations. In these formulations, different degrees of reality abstraction and constraint assumptions have been developed. Research indicates that approaching the subproblems conjointly has great advantages in terms of profitability and customer service levels. Nevertheless, due to the size of these problems, efficient and powerful solution procedures are needed, and further research should focus on an integrated approach of airline scheduling. In this master's dissertation, focus lies on the impact of failure predictive information in maintenance planning. Therefore, the scope is not to optimize airline scheduling but rather to contribute to predictive maintenance scheduling possibilities which in their turn can be implemented in integrated problem formulations in further research.

Third, Van den Bergh *et al.* (2013) elaborate on aircraft maintenance optimization problems as well as the objectives and constraints formulated in past research. In contrast to maintenance routing problems in airline scheduling, these problems concern the planning of maintenance rather than implementing maintenance constraints. Different perspectives on maintenance planning are described:

- Engine maintenance planning: As the engine is the most critical and complex component of an aircraft, a lot of research is dedicated to engine maintenance. In these problem formulations, engine characteristics dominate the constraints and objectives.

- Task allocation optimization: These problem formulations determine the optimal allocation task allocation for the workforce. Usually, these problems are modeled as LP/IP/MIP.

- Multi-objective preventive maintenance tasks scheduling: Via evolutionary algorithms, pareto optimal solutions are provided for the trade-off between the number of technicians per task and the idle time for each worker.

- Integrated aircraft maintenance scheduling and fleet assignment: The FAP is solved using dynamic programming whereas the maintenance planning is constructed using a heuristic.

- Integrated flight and maintenance planning: The objective is to minimize the total residual flight time while maximizing total number of available aircrafts. These problems are usually modeled as a mixed integer bi-objective optimization model.

Other objectives are minimal flight cancellation, minimal delays, minimal repair turn time, efficient utilization of maintenance resources which are optimized using a variety of solution procedures such as previously defined and B&B procedures, genetic algorithms, simulation models (to incorporate uncertainty), meta-heuristics and problem specific heuristics. It is clear that numerous problem formulations and solution procedures have been defined and developed.

Fourth, the facility location problem is described. A difference is made between single base and multiple bases location problems with or without incorporation of the flight schedule. A fifth description field defined in Van den Bergh *et al.* (2013) is the workforce needed to perform maintenance projects. These present regulatory constraints due to the needed licenses to perform and/or approve work on certain types of aircrafts.

The last description field concerns the uncertainty inherent to maintenance schedules due to the operational characteristics of aircrafts. Five types of uncertainty are stated: flight delays, failure of components, maintenance processing times, workforce availability and other such as equipment and spare parts availability. In order to account for these uncertainties, most solution procedures for these maintenance planning problems are simulation models and heuristics in combination with scenario analysis.

Lin *et al.* (2017) developed a maintenance decision making support system (MDMSS) which incorporates realtime information on structural components of aircrafts. These structural components have predefined critical fatigue cumulative damage (FCD) values that depict when repair of these structural components is necessary. The MDMSS system integrates data acquisition (realtime status information on the structural components), data processing (reliability assessment of aircrafts structures) and maintenance decision making. As many aircrafts are outfitted with a Health and Usage Monitoring Systems (HUMS) which enables manufacturers and aircraft owners to monitor the structural status of an aircraft in realtime, the multiple-objective decision making model in MDMSS simplifies the maintenance planning process.

1.5 Conclusion

Section 1.1 elaborated on the basic resource-constrained project scheduling problem and optimal solution procedure such as the B&B procedures. Whereas MRCPSP increased flexibility was added by acknowledging several modes in which activities can be executed, RCPSP-PS introduced project structure flexibility such that not all activities and precedence constraints have to be implemented. Solution procedures such as the genetic algorithm for the RCPSP-PS developed by Kellenbrink & Helber (2015) were provided and depicted.
As elaborated by Van den Bergh *et al.* (2013) in section 1.4, a more integrated approach towards airline scheduling is necessary. Although, the MDMSS described in Lin *et al.* (2017) is very promising, non-structural components such as the engines are not incorporated yet. Moreover, no integrated approach with the flight schedules is provided. In this master's dissertation, a project management approach towards maintenance planning with the incorporation of failure predictive information on both structural and non-structural information is aimed with an integrated approach towards airline scheduling.

Chapter 2

Case study 1: Dissertation Airlines

In order to perform an academic research of which results can be used in a professional environment, two qualitative case studies were performed. More precisely, these case studies provide insight in what challenges maintenance planning in the aviation industry faces today. For confidentiality reasons, they are named “Dissertation Airlines” and “Dissertation GSE services” in the remainder of this paper. The first company is a commercial airline whereas the second company is a ground support equipment service company which supports equipment used to service an aircraft between two flights.

2.1 Introduction

As of today, Dissertation Airlines’ maintenance department makes use of several parameter data concerning the engines of their fleet in order to better plan the required maintenance projects for each of their airplanes. Although the engines are components of an aircraft that endure heavy usage, other seemingly less critical components can have the same consequence when a failure occurs: a non-operational aircraft. These unscheduled maintenance events incur high costs, challenging management issues and a great amount of loss of goodwill. Therefore, the company is currently conducting research to find the most critical components (i.e. the components that incur unscheduled maintenance events the most) and their best predictive parameters (i.e. operational data that indicates a failure in the foreseeable future).

This information will subsequently be used in order to create our planning procedure for the aviation industry maintenance. Note, that we did not receive any conclusions of this research and, therefore, its contribution is solely qualitative. Nevertheless, the outcome of this research does not affect the value of our planning procedure as the real critical components and their best predictive parameters only serve as the input for the maintenance project planning of Dissertation Airlines. However, it can serve the purpose of extra validation in the future.

2.2 Plan of action

In this section, the plan of action for this research is described. Its design is based on Verhagen & De Boer (2018), who already did the same for an Asian airline using proportional hazard models.
As mentioned by Verhagen & De Boer (2018), the increase in sensor data and technology to monitor this data at distance enables manufacturers as well as airlines to receive the status of several components of an airplane in realtime. In the case of Dissertation Airlines, they have access to a database of the manufacturer where all this operational data is stored. When the manufacturer discovers irregularities, they inform Dissertation Airlines after which they can take the required measures, i.e. plan a maintenance project taking into consideration other projects already defined.
Furthermore, pilots fill out a log book to report all noteworthy irregularities that are discovered during their flight. Together with the notes from maintenance technicians, all this information is inputted into a maintenance system, which is used by the planning managers in combination with the flight planning, to plan the required maintenance projects.
There are three kind of maintenance projects:

1. Line management: checks that have to be performed between two flights.
2. Medium size maintenance projects performed by Dissertation Airlines itself.
3. Big maintenance projects: During these bigger maintenance projects, the airplane usually gets dismantled which takes 1 to 6 weeks. These projects get outsourced to foreign countries where labor is cheaper since thousands of man hours are used to perform this task.

This research focusses on the medium size maintenance projects conducted by Dissertation Airlines. Although we may encounter critical components that cannot be replaced or repaired during this type of repair, this is not very likely as Dissertation Airlines would have already seen that they need to be able to repair this critical component in order to maximize the utilization of their aircrafts.
Nowadays, airlines and airplane manufacturers make great use of preventive maintenance for which Verhagen & De Boer (2018) make a distinction between condition-based maintenance (CBM) and predictive maintenance. The latter uses amongst other indicators such as time, loads and usage hours, indicators on the operational condition of a certain components to predict the optimal time interval in which a maintenance task has to be performed. In CBM maintenance, projects are directly triggered by detection of an abnormal condition. It is clear that the focus lays on predictive maintenance in which Verhagen & De Boer (2018) distinguish time-based maintenance (TBM), usage-based maintenance (UBM) and load-based maintenance (LBM). TBM is the most straightforward and the most used approach with

failure times as the single random variable to predict the next failure of a certain component. In UBM and LBM, other covariates (e.g. number of touch downs) are used to predict the next failure. The need to incorporate these other covariates derives from the huge impact of operating conditions of an airplane on the failure times of its components (e.g. dry sandy airports vs. wet and cold airports). This incorporation is realized by means of proportional hazard models that predict failure times by taking into account both other covariates and the current lifetime of a component (which is the only stochastic variable used in TBM). Note, that this classification differs from what Van den Bergh *et al.* (2013) distinguish. Where Verhagen & De Boer (2018) indicate predictive maintenance to be a form of preventive maintenance, Van den Bergh *et al.* (2013) make a clear distinction between these two types of maintenance planning. Again, the need for a consistent classification in the literature is established.

2.2.1 Defining critical components

Together with Dissertation Airlines maintenance department and the gathered data, the unscheduled removal rate (URR) of their fleet is defined and the most critical components are selected by comparing with worldwide fleet averages (the mean failure times of aircraft components defined by their manufacturers).

2.2.2 Defining the best predicting parameters for these components

Verhagen & De Boer (2018) make use of the extreme value analysis (EVA) and the maximum difference analysis (MDA) to identify significant operational factors which were abnormally high or low during flights leading up to the component failure. Their research has proven that most components have two to five significant operational factors.

The component failure events, together with their most significant operational factors, are then used as input for the reliability models. Afterwards, these models estimate when to plan maintenance events for these critical components. Three types of reliability models are used:

1. Generalized renewal process (GRP): These only take into account the failure time as a stochastic variable. No operational factors are used.

2. Time-independent proportional hazard models (PHM): These take into account the time-independent operational factors for which a mean value over each flight is used as input, i.e. no continuous distribution.

3. Time-dependent proportional hazard models (PHM): The operational factors taken into account are a continuous or semi-continuous function that varies over time.

As proportional hazard methods are an extension on GRP and that an aircraft has components which have time-independent as well as time-dependent operational factors, a mixture of the latter two models will be used.

2.3 Conclusion

Failure events of less heavy used components of an aircraft can lead to the same costly event of a non-operational airplane as failure of heavier used component such as the engines on which previous research has put more focus. Therefore, it is important to define all critical components and their best failure predictive operational parameters, which are both time-independent and time-dependent. Each component has only a limited number of significant operational parameters in the range of two to five.

Chapter 3

Case study 2: Dissertation GSE Services

3.1 Introduction

Dissertation GSE services is an international established company which sells and provides maintenance service packages to numerous companies within the aviation industry that have ground support equipment machines such as airlines and airport baggage handlers. These maintenance service packages include monitoring their clients' set of machines and ensuring that a certain capacity is operational at any given moment. Being active at more than 120 airports with more than 20 years of experience, Dissertation GSE services has built up great expertise in planning the required maintenance projects and in doing so efficiently and effectively.
They as well, have observed the uprise of tools that enable monitoring numerous parameters of machines. Nevertheless, they have not yet implemented these tools, nor have they conduct research on how to use this information in the planning process for the maintenance of the GSE machines.
This practical framework serves the purpose of indicating how the theoretical framework should look like and to investigate whether or not a general approach towards the incorporation of failure predictive information in the planning process for maintenance projects of both aircrafts and GSE machines can be constructed.

3.2 Planning process without realtime data

3.2.1 Current process at Dissertation GSE services

Based on the contractual specifications of numerous clients active at numerous airports, Dissertation GSE services constructs schedules with different time horizons: from high level

strategic schedules down to day-to-day operational schedules. They rely mostly on their experience with the machinery for which maintenance is provided and the guarantees given to their clients.
Assume a client which has 10 dollies[1] and a guarantee that at any given moment 9 dollies are operational. Taking into account this information together with the historical data on certain parameters (e.g. number of machine hours when maintenance had to be conducted in the past), they can estimate when each dollie will need maintenance given the historical data on the proportion each dollie is active over a time period. Further, Dissertation GSE services offers an optional 24-hour emergency service which promises the client that if a breakdown occurs, an analysis is conducted within 24 hours to identify the problem and to give an estimation on how long the machine will be out of service for. Over the years, an online platform has been developed by Dissertation GSE services via which clients can report problems. In each maintenance shop, screens are present on which all this information is displayed and used by planning managers to act accordingly. These assign maintenance technicians to locate the machine and to go get it when needed. Recently, Dissertation GSE services has installed smart boxes on each machine which can locate machinery at any given moment by exploiting geolocation services. These boxes can be extended such that parameter data on certain components can be transmitted in realtime as well, which is of interest in section 3.3. At the moment, machine failures are hard to detect upfront because they do not have the tools and the knowledge to exploit predictive maintenance. Therefore, one or more technicians are always standby for when a failure would occur given that they offer a 24-hour emergency service and that they have a guaranteed operational level of machinery. Moreover, to prevent failures, a technician adds some oil to each machine at each airport.

3.2.2 Flexible project structures

Given that the individual maintenance projects for each machine at each airport has to be conducted according to a standardized scheme provided by the machine manufacturer, no flexible project structures are present within these projects such that different ways for performing maintenance are available. However, the sequence in which all maintenance projects from the service packages are scheduled is flexible. Therefore, a superproject where each activity in the network represents an individual maintenance project can be derived. Since Dissertation GSE services has a limited capacity (i.e. a limited number of man hours available per time period), decisions have to be made on which machines to be scheduled prior to the moment at which maintenance is needed, exactly at the time maintenance is needed or after maintenance is needed and thus, resulting in a risk of the machine becoming idle. These decisions have to made according to the contractual specifications of each service package of each client which differ in machine types and therefore, maintenance durations, needs and

[1] A dollie is a small truck that transports luggage around the airport.

resources consumption but also on the guaranteed operational level and the priority given their importance as a client.

3.2.2.1 Fictional example 1

Assume following simplified service packages:

1. Client 1
   - 24-hour emergency service
   - 10 dollies with a 90% guaranteed operational level
   - 5 push-back trucks[2] with an 80% guaranteed operational level
2. Client 2
   - no 24-hour emergency service
   - 10 dollies with a 90% guaranteed operational level
   - 12 GPU's[3] with an 83% guaranteed operational level
3. Client 3
   - 24-hour emergency service
   - 20 dollies with a 95% guaranteed operational level
   - 6 GPU's with an 83% guaranteed operational level

Next, the characteristics of each machine are assumed to be the same for each service package. In reality these differ for each individual machine. They are as follows:

1. Dollie
   - Maintenance duration: 2 working days
   - Maintenance interval: every 3 months
   - Critical parameters: number of machine-hours and oil level
2. Push-back truck
   - Maintenance duration: 3 working days
   - Maintenance interval: every 2 months
   - Critical parameters: number of push-backs and oil level

[2] A push-back truck is a small truck that pushes aircrafts back on to the runway after boarding.
[3] A GPU is an electricity generator.

3. GPU

   - Maintenance duration: 4 working days
   - Maintenance interval: every month
   - Critical parameters: kWh produced

Dissertation GSE services calculates these parameters based on historical data. Note, that assumption is made that each machine uses the equivalent of man hours in one working day when it is one day in maintenance.

An initial planning for each client could look as follows:

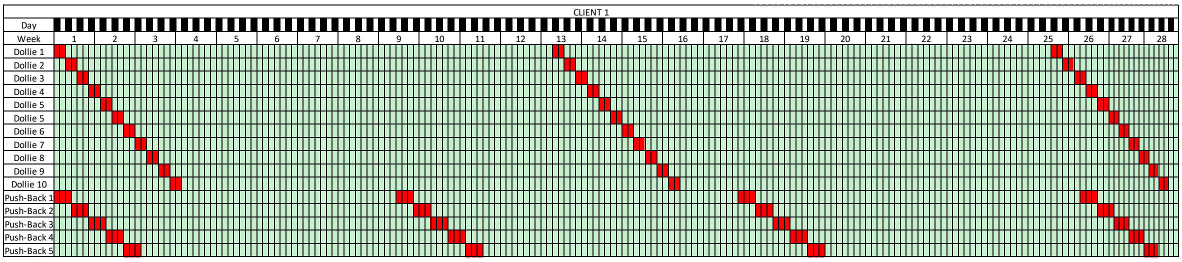

Figure 3.1: Initial planning for client 1

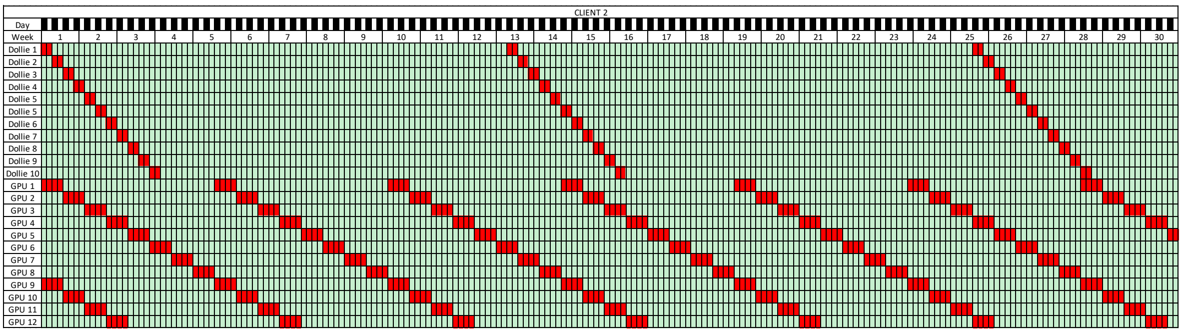

Figure 3.2: Initial planning for client 2

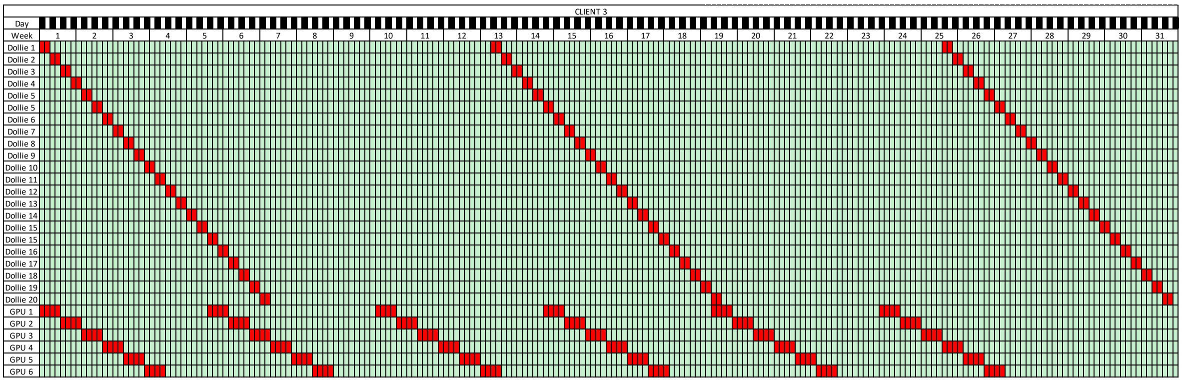

Figure 3.3: Initial planning for client 3

The initial planning for the machines of client, 1, 2 and 3 are illustrated above where red boxes indicate the corresponding machine to be scheduled for maintenance.
Assume following breakdowns occur:

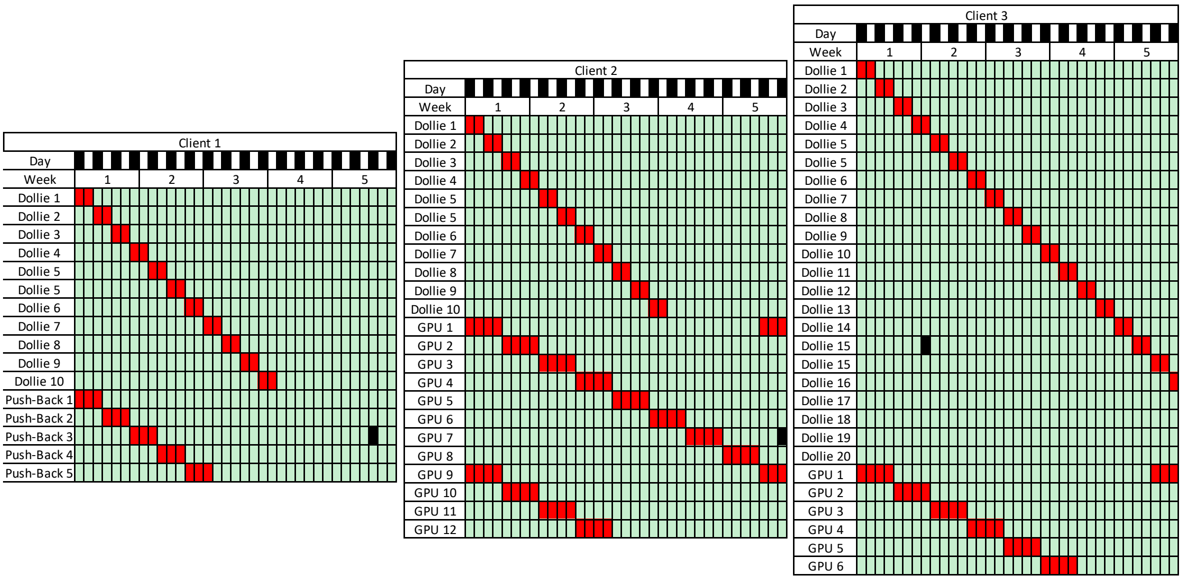

Figure 3.4: Post-hoc planning for client 1, 2 and 3

The black boxes in figure 3.4 indicate when unexpected failures happened such that the machines became non-operational. The amount of time periods the machines remain non-operational depend on the amount of time Dissertation GSE services needs to analyze these machines and repair them. If the service package does not include the 24-hour emergency service, the company has time to review the planning and plan the analysis as it sees fit. However, as for client 1 and client 3, they have to report to these clients what the problem is and within which time frame they will be able to solve this matter. Moreover, they have to make sure they keep up the operational level stated in the contractual specifications. In order to resolve the defect for push-back truck 3 of client 1, there seems to be no problem since no other push-back truck of this client is in maintenance at that time nor is scheduled for maintenance in the near future. Therefore, the operational level of 80% can relatively easy be maintained. Contrary, the operational levels for the GPU's of client 2 and the dollies of client 3 are threatened given that 3 out of the 12 GPU's and 2 out of 20 dollies for client 2 and 3 respectively become non-operational. If Dissertation GSE services would have been able to monitor the critical parameters of these machines in realtime, they could have anticipated irregularities in this data flow and adjust their planning accordingly such that no operational level drops below the contractually stipulated one. Note, that this is done by delaying maintenance for machines which perform better than average (bigger interval between 2 consecutive maintenance projects) and anticipate for these machines which the data shows maintenance will be needed sooner than on average.

3.3 Planning process with realtime data

In this section, the realtime information on the critical parameters of each machine type are implemented in the planning process of the maintenance projects of these machines. For explanatory purposes, the first fictional example elaborated in section 3.2.2.1 is used as the setting. In this example, the critical parameters were defined for which in this section, the critical values have to be determined. These critical values serve as a threshold which triggers a maintenance project to be scheduled. A buffer is used such that Dissertation GSE services has time to schedule these maintenance processes after the threshold is reached. This safety factor is calculated as one week per average maintenance interval and results in the following critical values for each machine[4]:

- Dollie

  1. Number of machine hours: $500h * (1 - \frac{1\ week}{12\ weeks}) = 458h$
  2. Oil level: $200ml * (1 + \frac{1\ week}{12\ weeks}) = 217ml$

- Push-back truck

  1. Number of push-backs: $280 * (1 - \frac{1\ week}{8\ weeks}) = 245$
  2. Oil level: $200ml * (1 + \frac{1\ week}{8\ weeks}) = 225ml$

- GPU

  1. kWh produced: $500kWh * (1 - \frac{1\ week}{4\ weeks}) = 375kWh$

[4]Note, that in reality these critical values have to be calculated for each machine and not each machine type (cfr. supra).

Naturally, these critical parameters will on average converge towards their critical value at the same speed is the machine performs as it does on average. In the remainder of this section, three scenarios are analyzed in order to gain high-level insight in what the impact of this realtime data on the planning is. Assume that Dissertation GSE services has a capacity of 7 technicians per day.

3.3.1 Fictional example 1 - Scenario 1

In section 3.2.2.1, it was observed that a breakdown occurred at the end of week 5 for push-back truck 3 of client 1. In figure 3.5, the yellow box indicates that the value for the critical parameter oil level of this push-back truck reaches the threshold of 225ml at the end of week 4.

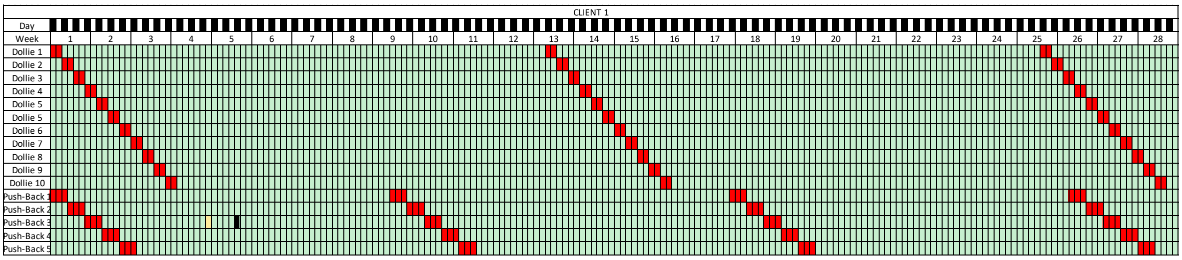

Figure 3.5: Push-back tractor 3 of client 1 exceeds critical value of 225ml at the end of week 4

Consequently, Dissertation GSE services has to revise its planning in order to keep up the operational levels for all machine types of all of its clients. Given that they have 7 technicians each day, push-back truck 3 can be scheduled for maintenance instantly thus, resulting in the revised planning illustrated by figure 1, appendix .1.

The positive effect of incorporating the realtime data is that the planning can be adjusted accordingly such that operational levels are maintained, and machines are not idle. This results in both time and cost saving. Note, that the planning after week 6 has to be revised as well since push-back tractor 3 will need maintenance o average within its maintenance interval time periods.

3.3.2 Fictional example 1 - Scenario 2

At the beginning of week 5, GPU 7 of client 2 reaches the threshold of 375 produced kWh of electricity. It is observed in appendix .1, figure 2 that GPU 1 and 8 are in maintenance at that time. Therefore, Dissertation GSE services will not be able to keep up the operational level to 83% as stipulated by the contractual specifications. However, given the residual capacity the next 4 days, GPU 7 can be scheduled for maintenance instantly. Therefore, Dissertation GSE services gain at least two days because of the use of residual capacity. Moreover, they prevented GPU 7 to break down such that an unexpected event was prevented as well. This has the advantage that together with the client, they can discuss the possible options in order to find an optimal solution for both companies.

3.3.3 Fictional example 1 - Scenario 3

As observed in appendix .1, figure 3, dollie 15 of client 3 reaches the threshold of $458 machinehours$ at the beginning of week one. On the right side of this figure, it becomes clear that this dollie cannot be scheduled for maintenance instantly since the resources do not allow so as marked in grey. In order to fulfill the guaranteed operational level of 95% for the dollies of client 3, several options are available which do not endanger the operational levels for other machines. The left side of figure 4, appendix .1 refers to the option where maintenance for dollies 2 up to and including dollie 14 of client one are delayed with two days. This enables dollie 15 of client 3 to be scheduled for maintenance the day after the critical value for the number of machine hours for dollie 15 of client 3 is reached. Note, that there are numerous possible options to reconstruct the planning. The optimal schedule is derived using the actual parameter data of each machine at that moment. Two possible schedules are displayed in appendix .1, figure 4 where on the right side maximum use is made of the resources such that only maintenance for dollie 2 up and including dollie 7 is delayed. However, in this solution, Dissertation GSE services cannot maintain its guaranteed operational level for the dollies of client 3 in two time periods in week three. On the other hand, they can discuss this with client 3 and see what solution is best for both parties.
Another possibility is to partly delay the maintenance project for GPU 9 of client 1. In this solution, a fast, temporary maintenance project is conducted at the beginning of week 1 and another smaller maintenance project is conducted at the beginning of week 3. If the machines allow so, Dissertation GSE services is able to keep up the operational levels as stipulated by the contractual specifications without violating the resource constraint. A possible planning in this scenario is displayed in the left side of figure 5, appendix .1. Note, that the guaranteed operational level for the dollies of client 3 cannot be maintained.
Lastly, if the parameter data allow so, Dissertation GSE services could delay the maintenance project for push-back truck 2 of client 1 for two days. Again, the guaranteed operational level for the dollies of client 3 cannot be maintained.

3.4 Conclusion

Based on historical data, Dissertation GSE services constructs a strategic planning which serves as a reference point for constructing the day-to-day operational planning. Unfortunately, unexpected failures do occur which force the day-to-day operational planning to drift away from its reference point. By monitoring realtime data on the condition of the machines in the form of predefined critical parameters, Dissertation GSE services would be able to make trade-offs between anticipating certain maintenance projects and delaying others in order for them to keep up operational levels stipulated by contractual specifications and to perform maintenance cost and resource efficient. How this data should be used has not been researched yet and therefore, this practical framework will serve as a basis for the theoretical framework of this master's dissertation.

Chapter 4

Theoretical framework

4.1 Problem description

Based on the observations elaborated in chapter 2 and 3, a general model for incorporating failure predictive information on components of aviation machinery in the planning of their maintenance needs is defined. The objective is to minimize the total cost of associated with aviation machinery maintenance by the means of constructing cost-minimizing maintenance schedules. The total cost of an aviation machinery maintenance planning is composed of the cost for conducting the maintenance projects for each machine and more important, the costs induced by unexpected machine downtime due to inadequate maintenance planning. These induced costs are monetary as well as opportunity costs. For example, unexpected non-operational aircrafts can incur high costs such as chartering another aircraft, provide accommodation as a consequence of flight cancellation, etc. Moreover, flight delays or cancellations can occur when GSE service firms cannot meet the required operational service levels. Further, a failure predictive parameter p_{mt} is defined for every machine m in time period t. Although this parameter is time-dependent, time-independent parameter data is also included. This parameter is to be defined for each machine m as an integration of all the operational parameters of all critical components of that specific machine m into one machine-specific, time dependent parameter. It is defined as a measure for maintenance needs such that $p_{mt} = 0$ corresponds to a 0% chance that machine m needs maintenance in time period t and that $p_{mt} = 1$ corresponds to a 100% chance that machine m needs maintenance in time period t according to regulations.

The objective of this research is twofold. First, a framework on how realtime parameter data of aviation machinery can be used within maintenance planning is constructed and second, the impact of incorporating realtime failure predictive information in aviation maintenance planning is quantified in terms of costs by developing a maintenance planning procedure. Today, maintenance planning mostly depends on historical data on maintenance in combination with reactive measures. Incorporating realtime data on machine status enable more flexibility

in the planning and proactive measures. This comes down to comparing the GRP reliability method and the proportional hazard reliability method as described in section 2.2.2.
In this problem description, the renewable resource which constraints the conduct of maintenance projects are the man-hours available. We assume that adequate inventory management of parts necessary for these maintenance projects is in place.

As in the RCPSP-PS model of Kellenbrink & Helber (2015), the planning project has a flexible project structure with choices, triggering activities and caused activities. The project instance is a superproject of all maintenance projects triggered (by values for p_{mt}) for all machinery of a certain aviation company within the planning horizon whereas an activity represents an individual maintenance project for one machine at a specific moment in time. In a first phase of this research, two steps are conducted. In the first step, a strategic planning is constructed based on historical average data on maintenance duration and renewable resource consumption per maintenance project of each machine and the average time interval between two consecutive maintenance projects for each correspondent machine. In the second stage, a tactical planning is constructed based on the realtime parameter data p_{mt}, defined for each machine m. Construction of a tactical planning is an iterative process such that this planning is adjusted according to momentarily information. The time interval between two consecutive tactical planning phases depends on the volatility of the failure predictive parameter over time. Note, that medium size maintenance is our primary focus as discussed in section 2.2. Assume a linear regression on the historical values for p_{mt} of a certain machine m. In reality, the workload that machine m endures changes over time. For example, an aircraft can operate a certain flight with extreme weather conditions. Even without these varying degrees of usage, due to the law a Murphy, a certain component can have a malfunction. Figure 4.1 shows a possible trajectories for the value of p_{mt} over time with the scenario where all components work as they do on average, a scenario where all components work according to plan but with realtime parameter data, a scenario where a malfunction occurs and a scenario where machine m is better performing in terms of its need for maintenance.

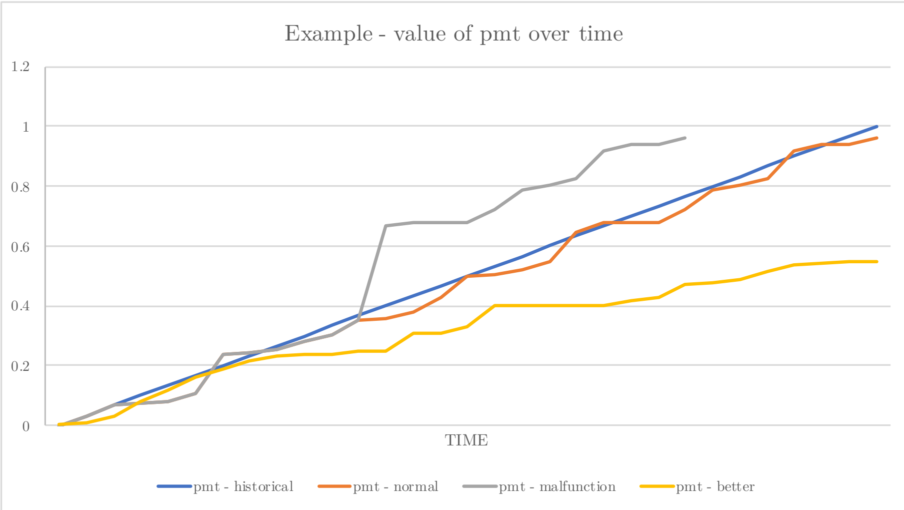

Figure 4.1: Example - values for p_{mt} over time.

In the remainder of this section, we will differentiate between the strategic planning and the tactical planning as described above. A project network is constructed for both schedules. First, we define following general constructs:

- M: the set of machines with $m \in M \ \forall\ m \in \{1, 2, ..., m_M\}$
- $J = \{0, 1, 2, ..., j_J\}$: the set of activities where an activity is a maintenance project for a certain machine m (cfr. infra). The empty activities are denoted by $j \in \{0, (m + 1), ..., (j_J - m)\}$. Empty activities are activities with a duration of zero time units and no resource consumption.
- The set of time periods $\theta = 1, ..., T, ..., TT$: The latest time period T eligible for maintenance scheduling and TT the latest time period as predefined according to the planning time horizon.
- The choices set $\varepsilon = \{e_1, e_2, ..., e_T\}$: Every time period $t \in \theta$, a choice e_t has to made. All choices e_t consider maintenance projects for each machine $m \in M$ and an empty activity. Each choice e_t contains a set of activities $j \in J$ that represent maintenance projects for eligible machines $m \in M$ and an empty activity.
- The set dummy activities $D = \{(e_1, 0), (e_1, 1), ..., (e_T, m_M)\}$ in which each element (e_t, m) represents the maintenance activity for machine m or the empty activity which was chosen in choice e_t.
- Triggering activity $a(e_t) = (e_{t-1}, m)$ which causes the choice e_t to be made: The implementation of a maintenance project for machine m (represented by the dummy activity (e_{t-1}, m)) in the activated choice e_{t-1}, triggers the choice e_t to be activated in the

superproject. All choices $e_t \in \varepsilon$ are mandatory whereas each choice contains $m_M + 1$ activities from which only one can be chosen.

- N: the set of nonrenewable resources. These are defined in the theoretical model to be complete but as our research only considers man-hours available (renewable resource), the procedure will not make use of this set.

- R: the set of renewable resources

- K_r^{ϕ} and $K_{r'}^{\nu}$ respectively the amount of renewable and nonrenewable resources $r \in R$ and $r' \in N$ available with the latter defined per time unit.

4.1.1 Strategic planning

A strategic planning is constructed based on the average values for maintenance duration, renewable resource consumption and the time interval between two consecutive maintenance projects of each machine $m \in M$:
Following additional constructs that are specific to the strategic planning phase are defined:

- The average activity (maintenance) duration d_m for each machine $m \in M$: The strategic planning is based on average machine behavior and, therefore, average maintenance durations are used.

- The average time interval between two consecutive maintenance projects y_m for machine m.

- The caused activities B_{e_t} for each choice $e_t \in \varepsilon$ with $B_{e_t} \subset J$: When in each choice e_t the maintenance activity j for a machine m has been chosen, the implementation of its next maintenance project at time $t + d_m + y_m$ is triggered. When the empty activity is chosen, the caused activity is also empty. Note, that scheduling an activity refers to triggering the planning process of a maintenance project. Thus, the start of each activity does not imply maintenance to be performed in this time period but to start the planning of a maintenance project. The first time period of this activity can either be a delay period or a period of actual performed maintenance.

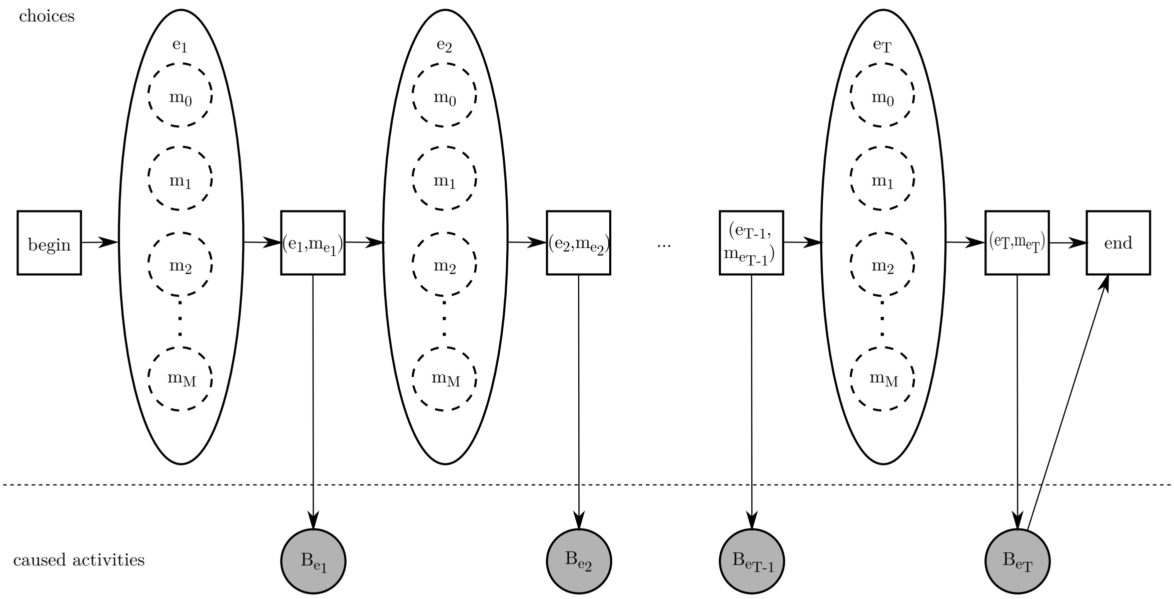

Figure 4.2: Conceptual example project structure.

Figure 4.2 illustrates a conceptual project network for our problem under consideration. In a consequent step, the technical project network in accordance with standard notation is elaborated.
Following guidelines hold when interpreting the superproject illustrated by figure 4.2:

- Above the dotted line, all choices are represented. Each choice contains one maintenance activity for each machine $m \in M$ and one empty activity denoted by m_0, which are marked by a dotted circle. Once an activity is chosen, the activity becomes active and the dotted line is replaced with a full line (cfr. infra). Note, that the activities are numbered as an integer j in the technical representation.

- Each choice $e_t \in \varepsilon$ triggers a dummy activity (e_t, m_{e_t}) which is marked as a full line square after each choice. These dummy activities split the consequence of the choice e_t into the triggering of the consecutive choice e_{t+1} and the implementation of its caused activity B_{e_t} at time $t_{e_t} + d_{m_{e_t}} + y_{m_{e_t}}$. Note, that the machines are numbered with an integer m whereas in the dummy activity, they are assigned an index and noted m_{e_t} to denote the corresponding machine for which maintenance has been chosen in choice e_t.

- The precedence constraints denote the intuitive precedence constraints on each choice instead of the chosen activities within each choice. These correspond to the sequence of choices over time.

- In reality, the number of choices made will depend on the predefined planning horizon.

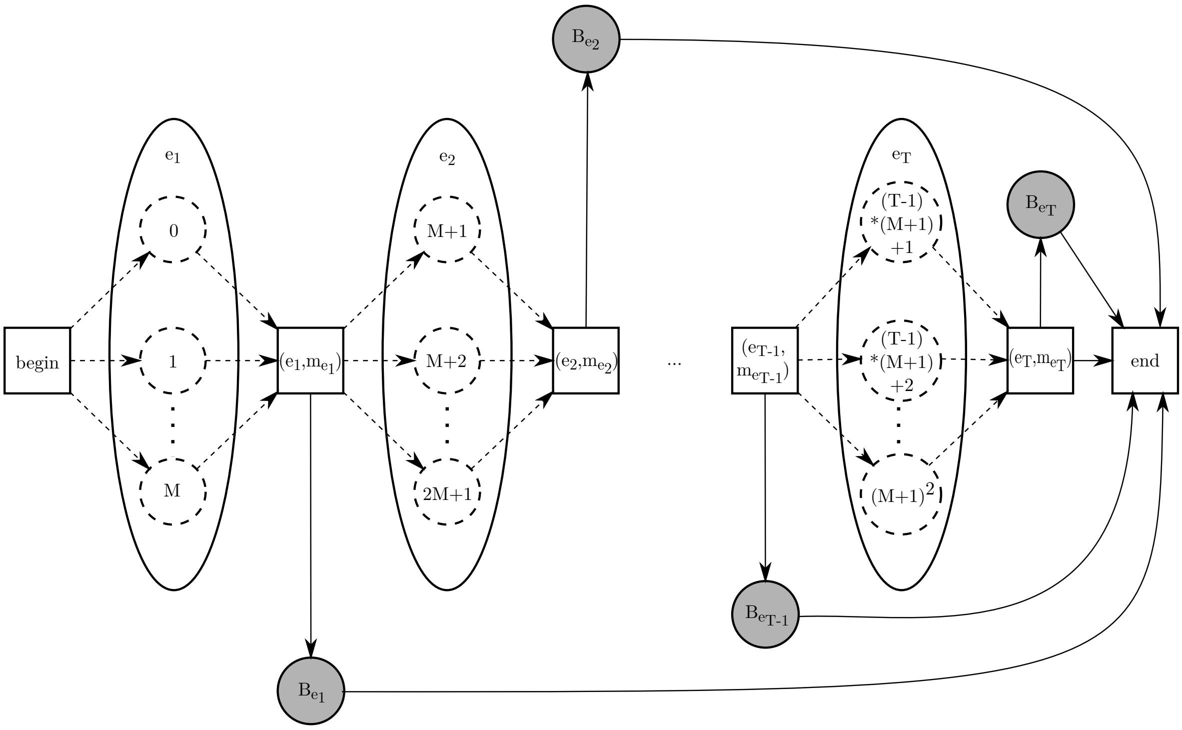

Figure 4.3: Example technical project network - strategic planning

In figure 4.3 a technical representation is shown. The interpretation remains according to the guidelines elaborated for the conceptual project network in figure 4.2 although notation differs slightly. The activities are numbered as integers j which represent either a maintenance project for machine $m : \{m = j - (t-1) * (m_M + 1)\}$ with t the corresponding time period of choice e_t containing activity j, or an empty activity. Further, the start-to-start precedence constraints force precedence on the activities instead of the choices as should be according to technical correct formulation. Note, that as these start-to-start precedence constraints force a predecessor activity to have been started before a successor activity can start. As the start of an activity can be a delay period, the actual maintenance project correspondent to the successor activity does not have to be performed before the one of the predecessor activities. As average maintenance durations differ for all machines, no precedence constraints are modeled between the caused activities.

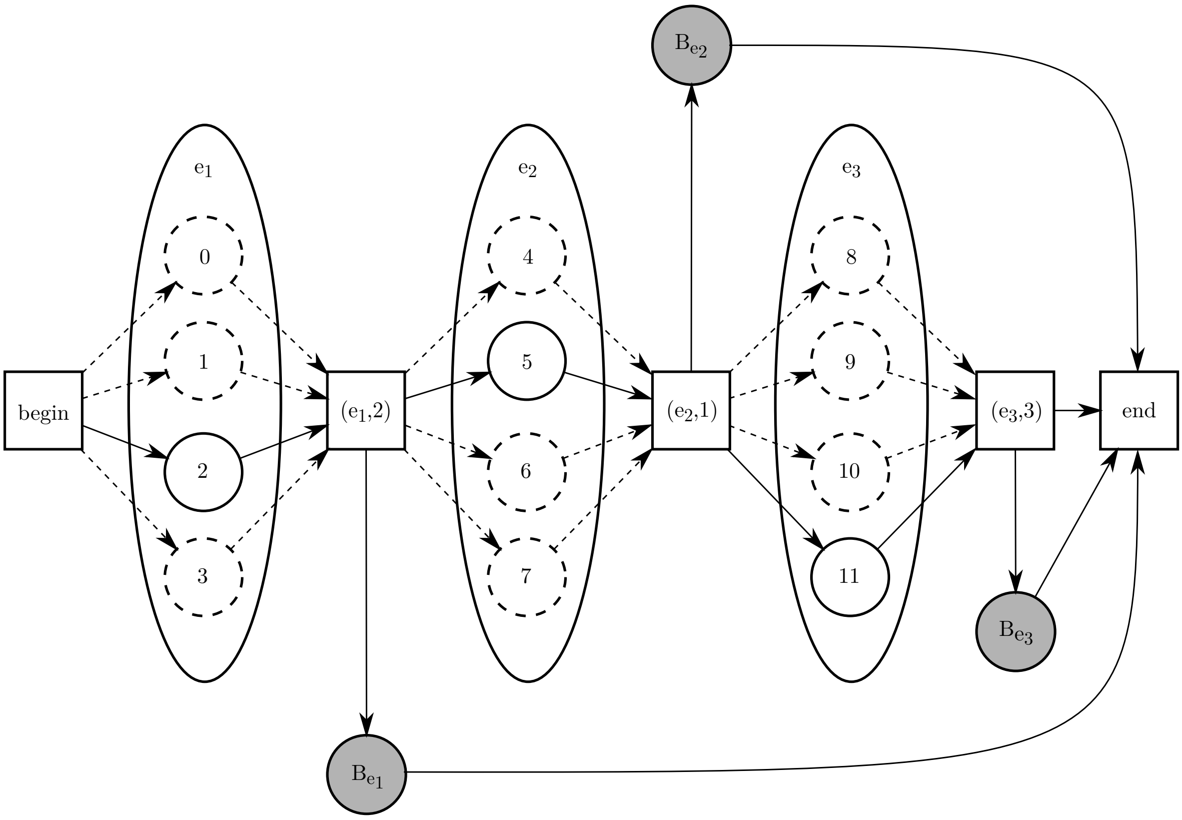

Figure 4.4: Example project trajectory

Whereas all constructs in figure 4.2 are marked by dotted lines, figure 4.4 defines a possible project structure of the superproject under consideration by using full lines to indicate the chosen activities, and precedence constraints. In this example only three machines are to be maintained and the planning horizon is defined such that the caused activity B_{e_3} is the last maintenance project eligible to be scheduled. In this simple scenario, the sequence of machines for which maintenance projects are scheduled is machine 2, 2, 1, 1, 3, 3. The sequence of activities is 2, B_{e_1}, 5, B_{e_2}, 11, B_{e_3} with the caused activities being the maintenance projects for the corresponding machines m_{e_t} that are denoted in the dummy activity (e_t, m_{e_t}).

A possible operational planning is depicted in figure 4.5.

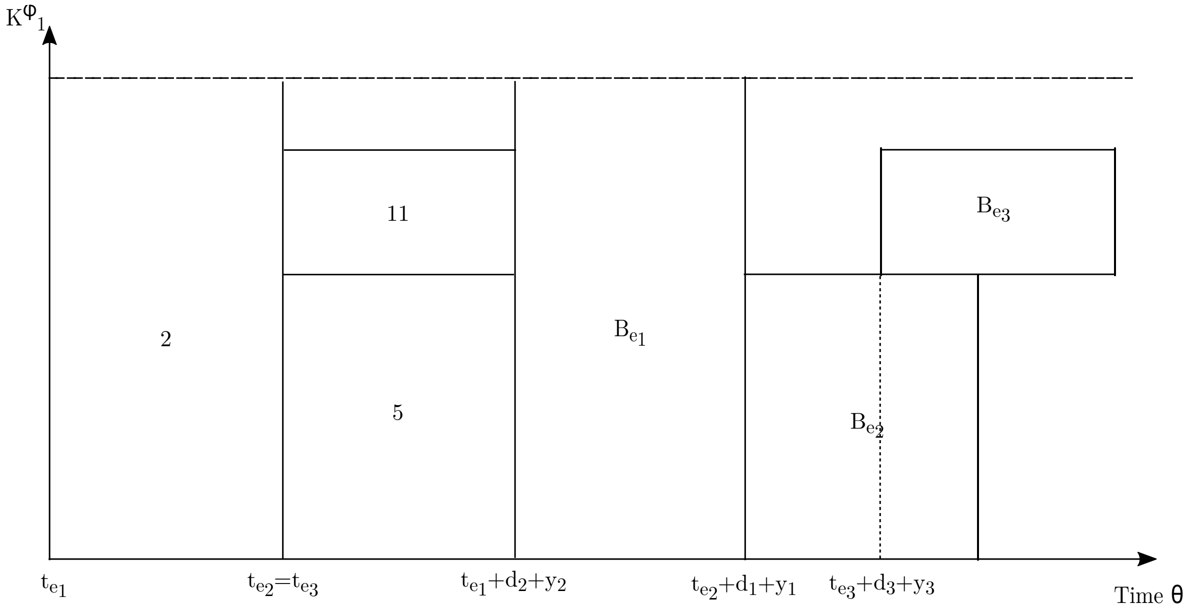

Figure 4.5: Example operational schedule for the project path in figure 4.4.

Note that given the available man-hours K_1^{ϕ}, activity 4 and 9 can be conducted at the same time as observed in figure 4.5. Note that the maintenance project for machine 3 (activity 11) is started at the same time as the maintenance project for machine 1 (activity 5). Because the precedence constraint is a start-to-start precedence constraint, this is possible.

4.1.2 Tactical planning

The parameter p_{mt} enables the planning procedure to take into account momentarily information on the condition of all machinery of a certain aviation company that needs maintenance. Although the inflow of the data is continuous, the tactical planning is only updated a discrete number of times. Every predefined time interval, such as the minimum average maintenance duration, the procedure runs and takes into account the values of p_{mt} for all machines m at that exact moment. Based on these values, it predicts the future values of p_{mt} based on the observed distributions of the past and plans maintenance accordingly.

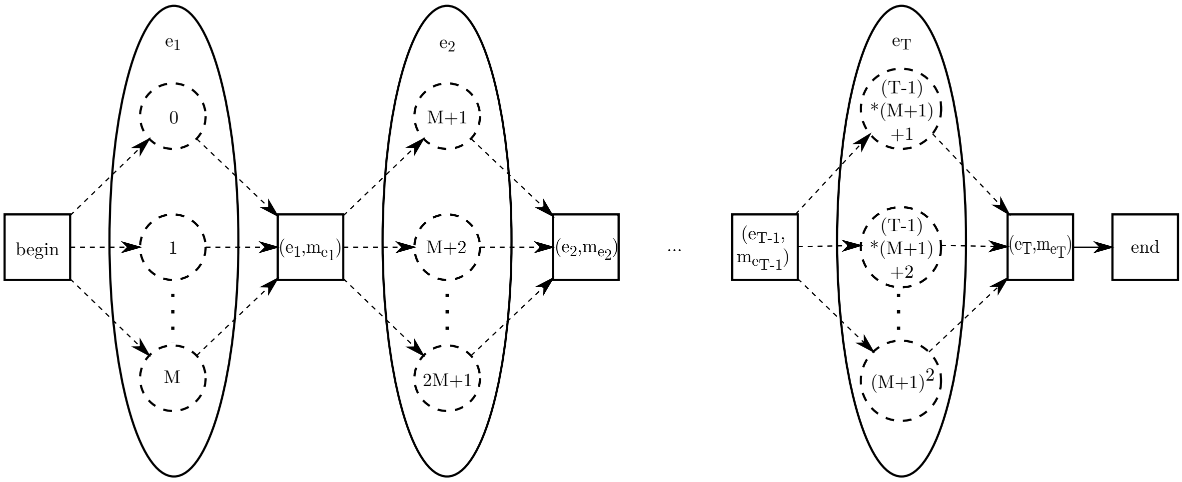

Figure 4.6: Example technical project network - tactical planning

Maintenance planning on the tactical level results in a dynamic planning. When maintenance is scheduled for a certain machine m in time period t in the strategic planning, it is known upfront how long this maintenance project will last, how much resources it will consume per time period and within how many time periods a consecutive maintenance project has to be provided. During the construction process of the dynamic planning, estimates of the future values for p_{mt} are made for each machine m and for each time period t in the planning horizon. Based on these predictions, each time period, all machines are considered for maintenance. When a maintenance project is scheduled for machine m, it cannot be defined at that time t when the consecutive maintenance project for this machine should be scheduled. Therefore, no caused activities are implemented in the superproject instance of the tactical planning phase.

Following constructs are defined for the tactical planning phase:

- The per time period maintenance cost c_m^m with $m \in M$: It is assumed that the cost for maintenance per time period is fixed.
- The per time period cost for disruption between the strategic planning and the tactical planning c_m^d with $m \in M$: This cost represents the cost for administrative efforts when machines have to be reassigned to different flights, flights are rescheduled, etc. because of disruption between the strategic planning and the tactical planning.
- The per time period cost for an unexpected non-operational machine c_m^n with $m \in M$: When unexpected machine downtime occurs in a certain time period, reactive measures have to be undertaken. For example, flights have to be cancelled after which the company has to provide accommodation for its passengers, charter other aircrafts or pay penalties when cargoes are not delivered on time. Note, that for all costs (maintenance,

disruption and non-operational machines) abstraction is made of different flights, airports, and other time specific factors since it serves no purpose given the scope of this research.

- The (maintenance) activity duration $d_{mt} = f(d_m, p_{mt})$ for each machine $m \in M$: The duration of these maintenance projects is a function of the predicted value for p_{mt} which is based on the realtime information on the condition of these machines m. These functions are predefined and do not differ for each run.

- $k^{\phi}_{r,p_{mt}}$ and $k^{\nu}_{r',p_{mt}}$ respectively the consumption of renewable and nonrenewable resource $r \in R$ and $r' \in N$ for a certain value of p_{mt} (i.e. $k^{\phi}_{r,p_{mt}}$ and $k^{\nu}_{r',p_{mt}}$ are dependent upon which machine m is to be maintained and the value of its failure predictive parameter p_{mt} in time period t). Therefore, resource consumption is a function of the time at which maintenance for machine m is scheduled assuming that the value for the failure predictive parameter p_{mt} estimates the man-hours needed to perform the maintenance project.

- The binary strategic planning variable X_{mt}:

$$X_{mt} = \begin{cases} 1, & \text{if maintenance for machine } m \text{ is scheduled in time period } t \\ & \text{in the strategic planning} \\ 0 & \text{otherwise} \end{cases}$$

  Values for each machine $m \in M$ in each time period $t \in \theta$ are exogenous to the tactical model.

- The values for $p_{mt} \in \,]0, 1]$: The values are exogenous to the tactical model and are known for each machine $m \in M$ in time period $t = 0$ and estimated in each time periods $t \in \theta \setminus \{0\}$.

- The binary tactical planning decision variable $x_{(e_i,m)t}$:

$$x_{(e_i,m)t} = \begin{cases} 1, & \text{if maintenance for machine } m \text{ is scheduled in time period } t \\ & \text{in the tactical planning} \\ 0 & \text{otherwise} \end{cases}$$

  .

- The binary decision variable s_{mt}:

$$s_{mt} = \begin{cases} 1, & \text{if disruption for machine } m \text{ in time period } t \\ 0 & \text{otherwise} \end{cases}$$

- The binary decision variable n_{mt}:

$$n_{mt} = \begin{cases} 1, & \text{if machine } m \text{ non-operational outside maintenance} \\ & \text{(in both the strategic and the tactical planning) in time period } t \\ 0 & \text{otherwise} \end{cases}$$

Each predefined time period, the procedure runs using the parameter data of each machine at that moment and estimating these values for future time periods.

4.2 Mathematical model

The objective of this research is to determine how aviation companies can incorporate realtime failure predictive information in their maintenance planning and what the impact is of doing so. Due to the nature of this data, this is only relevant on the tactical level. Therefore, a mathematical model for optimization of the maintenance planning on the tactical level, a dynamic planning, is constructed.

$$\text{Min } Z = \sum_{t \in \theta} \sum_{e_i \in \varepsilon} \sum_{m \in M} x_{(e_i,m)t} * (c_m^m + c_m^d * s_{mt} + c_m^n * n_{mt}) \tag{4.1}$$

subject to

$$\sum_{m=0}^{m_M} x_{(e_i,m)t} = 1 \ \forall e_i \in \varepsilon, \ \forall t \in \theta \tag{4.2}$$

$$x_{(e_i,m)t} = x_{jt} \ \forall j = m + (i-1) * (m_M + 1), \ \forall m \in M, \ \forall e_i \in \varepsilon, \ \forall t \in \theta \tag{4.3}$$

$$\sum_{j=1}^{J} \sum_{t=t'}^{t'+d_{mt'}-1} (k_{r,p_{mt}}^{\phi} * x_{jt}) \leq K_r^{\phi} \ \forall r \in R, \ \forall t \in \theta, \ \forall j \in J, \ \forall m \in M \tag{4.4}$$

$$\sum_{j=1}^{J} \sum_{t=t_0}^{T} (k_{r,p_{mt}}^{\nu} * x_{jt}) \leq K_r^{\nu} \ \forall r \in N, \ \forall t \in \theta, \ \forall j \in J, \ \forall m \in M \tag{4.5}$$

$$s_{mt} \geq x_{(e_i,m)t} - X_{mt} \ \forall e_i \in \varepsilon, \ \forall m \in M, \ \forall t \in \theta \tag{4.6}$$

$$n_{mt} > (p_{mt} - 1) - x_{(e_i,m)t} - X_{mt} \ \forall e_i \in \varepsilon, \ \forall m \in M, \ \forall t \in \theta \tag{4.7}$$

$$x_{(e_i,m)t}, s_{mt}, n_{mt} \in \{0, 1\} \tag{4.8}$$

The overall cost minimization objective is depicted in equation 4.1. Equation 4.2 forces only one maintenance activity to be implemented for each choice. Note that all machines

are considered in each choice together with the empty activity. After each choice e_i, the dummy activity succeeding this choice is defined by constraint 4.3. The next choice e_{i+1} is triggered by this dummy activity ($a(e_{i+1}) = (e_i, m_{e_i})$). Equations 4.4 and 4.5 implement the resource constraints for both renewable and nonrenewable resources. Equation 4.6 define the binary variable for which the value depends on whether or not the machine should not be in maintenance according to the strategic planning. The cost for unexpected non-operational machines should only be incurred when machines are no longer operational when they should be (thus, not when they are scheduled for maintenance in the strategic planning). The values for the binary variable n_{mt} are defined by equation 4.7 such that a non-operational cost is only incurred when an aircraft is idle when it is not in maintenance in the tactical nor in the strategic planning and $p_{mt} = 1$ or when a tactical maintenance project is preempted. Finally, constraint 4.8 defines the decision variables to be binary.
Two notes are appropriate:

- In the model of Kellenbrink & Helber (2015), equation 1.9 forced the precedence constraints to be respected by the model. As this is not relevant for the problem instance of our research, this equation is discarded in this model.
- In the problem description, no nonrenewable resources were included. In this general model, equation 4.5 includes this constraint for problems in a practical setting.
- The values for p_{mt} can be estimated in various ways. In chapter 5, some distributions of p_{mt} are elaborated in detail.

4.3 Heuristic optimization

It is clear that an exact optimization approach (e.g. branch-and-bound) cannot be used for this project scheduling problem. Uncertainty in the values for p_{mt} and the exponentially growing number of potential project structures when choices are made force alternative solution procedures to be deployed. The genetic algorithm elaborated in Kellenbrink & Helber (2015) and discussed in section 1.3.3 of the literature review minimizes the makespan of projects with a flexible project structure whereas in this research, a cost minimization objective is formulated. Given the high complexity of the constructed schedules in aviation maintenance planning, in this research preference has been given to construct a heuristic optimization procedure in C++.
Chapter 5 explicates the developed heuristic which is deployed in the analyses elaborated in chapter 6.

Chapter 5

Heuristic development

As realtime data transmission on components of aviation machinery is a recent phenomenon, no data was available for analysis of the impact of this data on the performance of maintenance planning for these machines. Therefore, based on the information from Dissertation Airlines and Dissertation GSE services, a planning procedure has been developed in C++ (see appendix .4) that generates values for p_{mt} over time according to a predefined distribution and that provides functionalities as described in section 5.2. The construction of a planning for the maintenance projects of GSE machines is far less complicated than construction of such a planning for aircrafts. Therefore, given the objective of this research, the procedure is designed to plan maintenance projects for aircrafts as doing so for GSE machines is a simplified version of the same methodology. Consequently, in the remainder of this research, machines correspond to aircrafts.

5.1 Input

In this section, the input for the heuristic optimization procedure is depicted. First, nine categories of aircrafts are defined in table 5.1.

Flight duration	**Age of aircraft**		
	Short	Mid	Long
Old	Category 1	Category 2	Category 3
Used	Category 4	Category 5	Category 6
New	Category 7	Category 8	Category 9

Table 5.1: Aircraft categories

These categories differ on several factors which are elaborated throughout this section. Figure 6 in the appendix displays the values for all factors for each category whereas figure 7 displays

the input file of an example case. The fleet of this case consists out of nine aircrafts, one of each type. This case is solely illustrative and not used in any further analysis. It is used in the remainder of this section to refer to notation of elaborated constructs.
For each aircraft, the input file starts by defining the distribution for the failure predictive parameters p_{mt} for each aircraft m over time. Three types have been defined and implemented in the developed procedure: linear, exponential and random. Note that in the random case, the values for p_{mt} increase over time but with a random number between a minimum and maximum defined in the input file. The exponential distribution is defined as follows:

$$p_{mt} = a_m^{t-t'} + b_m - 1$$

with t' the time period after the last time period that aircraft m was in maintenance. Correspondingly, the linear distribution if as follows:

$$p_{mt} = b_m * (t - t') + a_m$$

In the remainder of this research, values for p_{mt} are generated according to the exponential distribution given the findings of MacLean *et al.* (2018) that deterioration of aircrafts is exponentially distributed.

Due to the law of Murphy and operating conditions, breakdowns can occur such that the value of p_{mt} rises and in worst case becomes 1 which forces the airplane to make an emergency landing if in flight at that moment. As the aviation industry is highly regulated, the probability that a breakdown occurs is assumed rather small ($0.5\% - 1\%$) in this research. Similar to the difference in the number of delay periods for each aircraft category and the difference in speed at which p_{mt} generally increases (cfr. infra), the breakdown probability also differs for each of the nine categories introduced before. Note, that due to the definition of p_{mt} (cfr. supra), whenever p_{mt} has a value of 1 the aircraft can no longer fly according to the regulations, but it does not imply that the aircraft is physically no longer able to fly.
Next, a critical value for p_{mt} for each category is defined which indicates when planning maintenance projects for aircrafts of these categories should start. Again, given the different characteristics of each category, a higher critical value is possible when the increase in p_{mt} over time is rather slow.
The parameter values for each of the distributions of the values for p_{mt} over time were derived starting by defining the average maintenance interval in days for each of the aircraft categories. As the planning procedure defines one time period as one hour, these intervals have been converted to hours. In combination with the critical values for p_{mt} of each aircraft category, the parameters for each distribution in each category have been calculated. These parameters for each category are depicted in the appendix (figure 8). Note, that the values for p_{mt} are always higher than 0 for each category. Reason is that regenerating aircrafts back

to their initial operational capabilities is not possible.

Further, a number of delay periods between reaching the critical value for p_{mt} and the first eligible time period for its maintenance project to start is defined for each aircraft category such that it is in correspondence with the average flight duration. Airplanes cannot get maintenance one period after the critical value is reached because on average, they are still in flight. Consequently, this time period in the planning is not eligible for maintenance to be scheduled.
Whenever a maintenance project is triggered for scheduling, its work content is defined as follows: work content = man hours * maintenance duration. According to the following distributions, work content is generated: linear, exponential and random. It is assumed that the work content for a maintenance project is higher when the value of the failure predictive parameter p_{mt} is higher. Therefore, work content is generated in function of the value of p_{mt} at the moment that the maintenance project is triggered and thus, created. The linear distribution is defined as:

$$\text{Work content}_{p_{mt}} = f_1 * p_{mt} + e_1$$

whereas the exponential distribution defines work content as:

$$\text{Work content}_{p_{mt}} = e_1^{p_{mt}} + f_1 - 1$$

The randomized distribution generates work content between the minimum and maximum amount stated in the input file. After generating work content, the renewable resource consumption and maintenance duration are calculated based on a $\frac{\text{renewable resource consumption}}{\text{work content}}$ ratio. Three ratios are defined and have equal chance to be chosen when a maintenance project is created in the planning procedure. The values of this ratio are 0.10, 0.15 and 0.2. For example, if the work content for a certain maintenance project is set to be 40 and the $\frac{\text{renewable resource consumption}}{\text{work content}}$ ratio is 0.10, then the renewable resource consumption per time period is 4 units per time period and the maintenance duration is 10 time periods.
Next, a fixed number of available resources is defined per day of the week and per shift. Before quoting these numbers, a starting hour of the day and night shift are stated.
At the end, the disruption, non-operational and maintenance cost per time period are inputted. These costs are as follows:

1. Disruption cost: This cost incurs whenever an aircraft is in maintenance in a certain time period when it would not have been according to the strategic planning. In correspondence with the definition in chapter 4, this cost refers to administrative efforts to reassign aircrafts to other flights when it is observed that in the near future maintenance is planned in the dynamic planning[1].

[1] The dynamic planning is the operational planning on the tactical level.

2. Non-operational cost: This cost incurs in two situations:

   - Whenever p_{mt} for aircraft m in time period t has the value of 1, the aircraft is non-operational, and the cost is incurred if in this period the airplane is not in maintenance and would not have been according to the strategic planning.
   - Due to the fact that preemption of maintenance projects is possible in the dynamic planning, an aircraft is defined as non-operational in a time period t if a maintenance project has been started but not finished and in this time period t, no work is conducted on this aircraft.

   Note, that this cost incurs for unexpected non-operational aircrafts. Whereas disruption incurs a cost for proactive measures, unexpected non-operational aircrafts incur a cost for reactive measures. An example of such a reactive measure is an emergency landing when in flight. Moreover, it is an opportunity cost when aircrafts are kept on the ground when they should be operational according to the strategic planning and no maintenance is being performed.

3. Maintenance cost: This cost incurs in a time period t when an aircraft is being maintained in this time period t.

5.2 Planning procedure

In this section, a general overview of the procedure, its methods and the constructed schedules is provided.

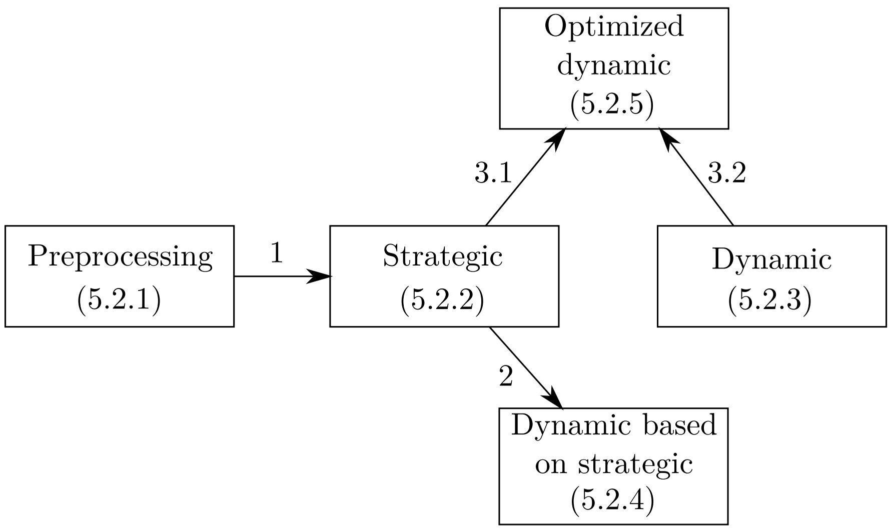

Figure 5.1: Procedure - conceptual framework

Figure 5.1 provides a conceptual framework of the developed procedure. For each method, the corresponding section is denoted under the method name. When results from a preceding method are used, a unidirectional arrow is drawn from this preceding method to its successor. Optimizing the strategic planning is no objective of this research, but a strategic planning has to be constructed in order to construct and optimize the dynamic schedules. Before creating a strategic planning, data has to be preprocessed. As no data was available, this preprocessing step refers to generating values for p_{mt} for each aircraft m over the predefined planning horizon. Moreover, it implies scheduling maintenance projects such that maintenance is performed, and aircrafts can remain operational throughout the planning horizon. Resulting from this step, average values for maintenance characteristics of each aircraft m are calculated and used in the construction of the strategic planning. This relation is depicted by arrow 1 in figure 5.1. Secondly, a dynamic planning is constructed which corresponds to an operational schedule on a tactical level. Note, that this dynamic planning is adjusted over time. Whereas the strategic planning is constructed and observed a priori, the final dynamic planning is observed posteriori. After the planning horizon, the dynamic planning is no longer a planning but an overview of performed maintenance and operational characteristics. Two methods construct a dynamic planning:

- Dynamic (5.2.3): This dynamic planning does not take into account the strategic planning but schedules maintenance when the failure predictive information indicates a need for maintenance for aircrafts.
- Dynamic based on strategic (5.2.4): In contrast to the dynamic planning as defined above, the dynamic-based-on-strategic planning schedules maintenance projects for each aircraft when they are triggered in the strategic planning. This corresponds to performing maintenance exactly according to the strategic planning without making any decisions on the tactical level. This relation is depicted by arrow 2 in figure5.1.

Lastly, an optimization method has been developed which optimizes the dynamic planning by reducing the schedule cost. Input for this optimization procedure is depicted by arrow 3.1 (strategic planning for calculation of the total disruptions cost) and arrow 3.2 (to-be optimized dynamic planning). Note that risk is only observed and not taken into account in the optimization.

5.2.1 Preprocessing

Generating values for p_{mt} over the predefined planning horizon corresponds to constructing a dynamic planning for the maintenance projects of each aircraft in the predefined fleet. Given the resource constraints, a maintenance project can be delayed until resources allow the project to be scheduled. Moreover, preemption is allowed and thus, projects can be interrupted before they are finished. When p_{mt} reaches the critical value for p_{mt} of aircraft

m, maintenance for that aircraft is triggered and the developed procedure acts as depicted in figure 5.2.

time period	p_{mt}	conceptual	maintenance triggered	maintenance delayed	machine idle	maintenance scheduled
t	p_{mt}	Generate work content	1	0	0/1	0
t+1	$p_{m(t+1)}$	Machine active	1	0	0/1	0
t+2	$p_{m(t+2)}$	Machine active	1	0	0/1	0
⋮		Machine active	1	0	0/1	0
t+delay periods-1	$p_{m(t+\text{delay periods}-1)}$	Try to plan first maintenance period	0	0/1	0/1	0/1
t+delay periods	$p_{m(t+\text{delay periods}-1)}$ /$p_{m(t+\text{delay periods})}$	⋮	0	0/1	0/1	0/1
t+delay periods+1	$p_{m(t+\text{delay periods}-1)}$/$p_{m(t+\text{delay periods})}$ /$p_{m(t+\text{delay periods}+1)}$	⋮	0	0/1	0/1	0/1
⋮	⋮	⋮	0	0/1	0/1	0/1
t'	$p_{m(t'-1)}$	Last maintenance project period planned	0	0	0	1

Figure 5.2: Conceptual representation on how a maintenance project is planned by the procedure.

First, the variables in figure 5.2 are defined as follows:

1. Maintenance triggered: Boolean variable which has value 1 when p_{mt} reaches the critical value and stays 1 over the consecutive predefined number of delay periods for the corresponding category of aircraft m.

2. Maintenance delayed: Boolean variable which only becomes 1 if the procedure tried to schedule the first maintenance period in the corresponding time period but could not because resources did not allow to do so. During these time periods, the aircraft is still active and thus, p_{mt} still increases. Moreover, the possibility of a breakdown to occur is still present. When a maintenance project has been started, this variable cannot become 1 again but instead the aircrafts becomes idle and p_{mt} cannot increase anymore until the correspondent maintenance project has been finished.

3. Machine idle: Whenever p_{mt} becomes 1, the aircraft cannot operate any longer and thus, becomes idle. Consequently, the boolean variable "machine idle" becomes 1. Moreover, when a maintenance project has been started but is preempted, this variable also becomes 1 in the preempted time periods. Further, p_{mt} cannot increase anymore until the correspondent maintenance project has been finished. Note, that if this boolean variable has the value of 1 in a certain time period and that maintenance for the corresponding aircraft m is not scheduled in the strategic planning, a non-operational cost unit (as

defined in section 4.1.2 and at the end of section 5.1) is incurred for each time period these conditions hold.

4. Maintenance scheduled: This Boolean variable indicates that the corresponding aircraft has been scheduled for one time period of maintenance. A maintenance project can only be finished when the number of times this variable is 1 corresponds with the maintenance duration generated based on the work content.

Note, that time period t' refers to the last time period of the maintenance project, which is always a period in which maintenance is performed ("maintenance scheduled" = 1).
During the delay phase (from time period t up and until time period $t +$ delay periods $- 2$), the aircraft is still active and thus p_{mt} still increases while a breakdown is still possible. If p_{mt} reaches the value of 1, the aircraft becomes idle as it cannot operate any longer. In reality, when this situation occurs, an aircraft has to make an emergency landing as soon as possible. Next, when the delay phase is over (i.e. in reality on average the aircraft has landed), the procedure schedules the first maintenance project period if resources allow so. Note, that the variable "maintenance triggered" becomes 0 and stays 0 until a consecutive project is triggered. Two possible paths occur which are elaborated in section 5.2.1.1 and 5.2.1.2.

5.2.1.1 The procedure can plan the first maintenance project period at time $t +$ delay periods $- 1$

p_{mt}	maintenance triggered	maintenance delayed	machine idle	maintenance scheduled
$p_{m(t+\text{delay periods}-1)}$	0	0	0/1	1

The next time period, either the project has been finished and p_{mt} starts according to the corresponding distribution, either the project is not finished yet. According to the input used in this research, the maintenance duration is always greater than one time period and thus, the scheduling continues. As the maintenance project has been started, the variable "maintenance delay" will remain 0 for the remaining time periods the maintenance project lasts. According to the resource availability, each time period the aircraft will be either idle or scheduled for maintenance until the project has been finished. Note, that p_{mt} will not increase anymore since the aircraft m cannot get active anymore until the project has been finished.

p_{mt}	maintenance triggered	maintenance delayed	machine idle	maintenance scheduled
$p_{m(t+\text{delay periods})}$	0	0	0/1	0/1
...	0	0	0/1	0/1
$p_{mt'} = p_{m(t'-1)}$	0	0	0/1	1

5.2.1.2 The procedure cannot plan the first maintenance project period at time $t+$ delay periods -1

p_{mt}	maintenance triggered	maintenance delayed	machine idle	maintenance scheduled
$p_{m(t+\text{delay periods}-1)}$	0	1	0/1	0

The maintenance project is further delayed and the variable "maintenance delayed" becomes 1 in time period $t+$ delay periods -1. The next time period, either the maintenance project is further delayed, or maintenance is scheduled. If the maintenance project is further delayed, all the variables remain the same (until p_{mt} reaches the value of 1 and the aircraft becomes idle if it did not reach it before). From the moment the first maintenance time period is scheduled, the same guidelines hold as elaborated in previous paragraph.

p_{mt}	maintenance triggered	maintenance delayed	machine idle	maintenance scheduled
$p_{m(t+\text{delay periods})}$	0	0/1	0/1	0/1
...	0	0/1	0/1	0/1
$p_{mt'} = p_{m(t'-1)}$	0	0	0/1	1

Before creating a strategic planning, the procedure performs the preprocessing step several times in order to determine averages for following parameters:

- Average resource consumption per maintenance project for each aircraft
- Average maintenance duration per maintenance project for each aircraft
- Average maintenance interval, i.e. average number of time periods between two consecutive maintenance projects, for each aircraft

In time period 0, a random value for p_{mt} for each aircraft is generated between the smallest possible value according to the distribution defined in the input file and the critical value for the corresponding aircraft. In a practical setting, however, these values should not be generated but are known for each aircraft. As resource availability is constrained, the order of the aircrafts in which values for p_{mt} are generated also determine which aircrafts are prioritized. The degrees of freedom in the constructed schedules of aircrafts in the beginning of that sequence are higher because, in total less maintenance projects have scheduled so far and hence, less resources have been consumed. In order to resolve this issue arbitrarily, two steps are undertaken. First, the order of aircrafts in which values are generated is randomized and secondly, several schedules are constructed such that on average, no aircrafts are prioritized. The output of this preprocessing step is the average values for the parameters of each aircraft as stated above. These serve as input for the subsequent part of the procedure, the construction of the strategic planning.

5.2.2 Construction of a strategic planning

Based on the average parameters determined for each aircraft in the previous step, the strategic planning is constructed. In this part of the procedure, there is only randomness in the sequence in which the aircrafts are selected for construction of their strategic maintenance planning. Due to the constrained resources, aircrafts for which the planning is constructed early in the strategic planning method experience less resource restrictions in comparison with aircrafts for which the planning is constructed later. In order for every maintenance project to be scheduled, the maintenance projects that cannot be scheduled on time because resources do not allow so, are anticipated. Recall that no preemption is allowed in the strategic planning because maximum capacity usage is pursued in the aviation maintenance given the high cost of a non-operational aircraft outside maintenance. In chapter 6, the impact of the constrained resources is investigated.

Note that the first strategic maintenance project is triggered in the same time period in which maintenance for the corresponding machine is triggered for the first time in the dynamic planning. As the procedure generates a number of dynamic schedules, the procedure uses the last dynamic planning generated as a reference point. In a practical setting, a dynamic planning will be constructed with known values for p_{m0} for each aircraft m. Consequently, the constructed dynamic planning is operational such that it incorporates the current status of each aircraft m. Furthermore, the construction of a strategic planning in a practical setting requires historical data on the values for p_{mt} for each aircraft m are used to calculate the values of the average parameters for each aircraft m in the fleet: average resource consumption, average maintenance duration and average maintenance interval.

5.2.3 Construction of a dynamic planning

In this research, the preprocessing step (section 5.2.1) corresponds with the construction of several dynamic schedules in order to determine the average maintenance duration, resource consumption and maintenance interval for each aircraft m. As the strategic planning was constructed based on the starting values of p_{mt} for each aircraft m in the last generation of the preprocessing step, this last generation is used as the initial dynamic planning. In a practical setting, the preprocessing step determines the average values for the three parameters described above based on historical information and not by generating values for p_{mt}. Therefore, the dynamic planning would have to be constructed based on the observed values for p_{m0} for each aircraft m.

5.2.4 Construction of a dynamic planning based on a strategic planning

In order to investigate the impact of the incorporation of failure predictive information in the planning of maintenance projects for aviation machinery, a planning without predictive information needs to be constructed. Instead of scheduling maintenance projects when p_{mt} reaches the corresponding critical value, this method generates values for p_{mt} based on the maintenance projects scheduled in the strategic planning. Consequently, p_{mt} increases until it reaches the value of 1 and the aircraft becomes idle or, until the first maintenance period of a maintenance project for aircraft m is scheduled in time period t in the strategic planning. Maintenance projects are triggered in the same time period as they are scheduled in the strategic planning. Given the resource constraints, the triggered maintenance projects in this dynamic-based-on-strategic planning can be delayed and/or preempted where they were not in the strategic planning. It is clear that the time periods in which maintenance is triggered for each machine m are equal in the dynamic-based-on-strategic planning and the strategic planning, but the values for p_{mt} are generated independently from this strategic planning. Thus, the performance measures will indicate the cost and risk associated with following the strategic planning without including any decision making on the tactical level. In practice, decision making is done on the tactical level and, therefore, all performance measures reported in this research are upper bounds on the realistic performance. Because of the randomness in the values for p_{mt} and the random sequence in which aircrafts' dynamic-based-on-strategic schedules are constructed, several dynamic-based-on-strategic schedules are generated and the performance measures of all these schedules are averaged in order to determine the average performance following the strategic planning without including any decision making on the tactical level.

5.2.5 Optimization of a dynamic planning

In a randomized sequence of the aircrafts, this method searches for maintenance projects in the dynamic planning of each aircraft for which the first scheduled maintenance time period does not correspond to any first scheduled maintenance time period in the strategic planning of the corresponding machine. It does so for every time period in the planning horizon and as such every scheduled maintenance project is considered. Note, that for every maintenance project in both the dynamic and strategic planning, a first scheduled maintenance period is always found. This relation is depicted by arrows 3.1 and 3.2 in figure 5.1. When a maintenance project d is found in the dynamic planning of an aircraft with its first scheduled maintenance time period in time period t_d, the method optimizes this dynamic planning in the following way: First, the method finds the strategic maintenance project s for which the first maintenance project period is scheduled at time period t_s where project s is the last maintenance project scheduled relative to time period t_d. Secondly, it anticipates project d to time period $t_s - \text{delay periods} + 1$ in the dynamic planning and constructs a new dynamic planning from there. Lastly, it computes the total schedule cost (disruption, non-operational and maintenance cost) of this new dynamic planning. If the total schedule cost is lower, the procedure implements the new planning. If not, the dynamic planning remains the same and the method delays the maintenance project to the first maintenance project found in the strategic planning of the corresponding aircraft. In like manner, when delaying a maintenance project in the dynamic planning, the procedure searches for the first succeeding maintenance project in the strategic planning relative to time period t_d. Again, the total schedule cost is computed for the new dynamic planning and this new dynamic planning is implemented if the cost is lower. In this research, this is defined as swapping maintenance project d from time period $t_d - \text{delay periods} + 1$ (i.e. initial maintenance triggering time period) to time period $t_s - \text{delay periods} + 1$ (i.e. new maintenance triggering time period).

Examples based on actual generated data are provided in the next section.

5.3 Procedure methods examples

Case	*1*
Number of machines	54
Time periods	17520
p_{mt} generation	exponential
Work content generation	linear
Number dynamic schedules	10
Number dynamic based on strategic	10
Resource availability week - day	30
Resource availability week - night	20
Resource availability weekend - day	10
Resource availability weekend - night	5
Disruption cost	100
Non-operational cost	100
Maintenance cost	100
Percentage old - short	11%
Percentage old - mid	11%
Percentage old - long	11%
Percentage used - short	11%
Percentage used - mid	11%
Percentage used - long	11%
Percentage new - short	11%
Percentage new - mid	11%
Percentage new - long	11%

Figure 5.3: Characteristics of Case 1

In this section, output of the planning procedure for Case 1 is used to clarify each method of the planning procedure. Figure 5.3 defines the case characteristics including the fleet composition. The output file containing all the relevant statistics concerning the performance measures is displayed in the appendix (figure 9).

5.3.1 Preprocessing and construction of a dynamic planning

machines	1
Average maintenance duration	5
Average maitenance interval	142
Average maintenance delay	2
Average renewable resource consumption	5
Average idle time periods outside maintenance	1
Scheduled time periods	8744

Figure 5.4: Output preprocessing case 1 - average values for aircraft 1

After the preprocessing step, the averages of the parameters in figure 5.4 are displayed and used for creating the strategic planning in the next part of the procedure. These parameters are calculated for each aircraft in the fleet. Note, that “machines” in figure 5.4 refers to the individual aircraft number. Consequently, these are the statistics for aircraft 1.

		p[m][t]	maintenance scheduled	maintenance delayed	machine idle	maintenance duration	renewable resource consumption	renewable resource availability initial	renewable resource availability	breakdown	maintenance triggered
Time period	0	0.464391	0	0	0	0	0	20	20	0	0
Time period	1	0.467473	0	0	0	0	0	20	20	0	0
...	...	...	...	...	...	...	...	...	...	...	...
Time period	101	0.803484	0	0	0	5	8	20	12	0	1
Time period	102	0.807218	0	0	0	0	0	20	12	0	1
Time period	103	0.81096	1	0	0	0	0	20	12	0	0
Time period	104	0.81096	1	0	0	0	0	20	12	0	0
Time period	105	0.81096	1	0	0	0	0	30	22	0	0
Time period	106	0.81096	1	0	0	0	0	30	22	0	0
Time period	107	0.81096	1	0	0	0	0	30	22	0	0

Figure 5.5: First scheduled dynamic maintenance project for aircraft 1

Figure 5.5 displays the first maintenance project that is scheduled for aircraft 1 in the last constructed dynamic planning (which was constructed in the preprocessing step (cfr. supra)). Indicated by the last column, the aircraft is triggered for maintenance in time period 101 when $p_{1,101}$ reaches the critical value for aircraft 1. After being delayed for two time periods as the input dictates, the maintenance project is scheduled according to the resources' availability.

...	...	...	...	...	...	...	...	...	...	...	...
Time period	493	0.802114	0	0	0	11	4	10	1	0	1
Time period	494	0.805436	0	0	0	0	0	10	1	0	1
Time period	495	0.808765	0	1	0	0	0	10	1	0	0
Time period	496	0.812101	0	1	0	0	0	10	1	0	0
Time period	497	0.815444	0	1	0	0	0	5	0	0	0
Time period	498	0.818794	0	1	0	0	0	5	0	0	0
Time period	499	0.822152	0	1	0	0	0	5	0	0	0
Time period	500	0.825516	0	1	0	0	0	5	0	0	0
Time period	501	0.828888	0	1	0	0	0	5	0	0	0
Time period	502	0.832267	0	1	0	0	0	5	0	0	0
Time period	503	0.835653	0	1	0	0	0	5	0	0	0
Time period	504	0.839046	1	0	0	0	0	20	2	0	0
Time period	505	0.839046	0	0	1	0	0	20	1	0	0
Time period	506	0.839046	1	0	0	0	0	20	1	0	0
Time period	507	0.839046	1	0	0	0	0	20	0	0	0
Time period	508	0.839046	1	0	0	0	0	20	0	0	0
Time period	509	0.839046	1	0	0	0	0	20	2	0	0
Time period	510	0.839046	1	0	0	0	0	20	2	0	0
Time period	511	0.839046	1	0	0	0	0	20	2	0	0
Time period	512	0.839046	1	0	0	0	0	20	1	0	0
Time period	513	0.839046	1	0	0	0	0	30	1	0	0
Time period	514	0.839046	1	0	0	0	0	30	1	0	0
Time period	515	0.839046	1	0	0	0	0	30	1	0	0

Figure 5.6: Delayed dynamic maintenance project for aircraft 1

In time period 493, aircraft 1 is triggered once again. The variable "maintenance triggered" remains 1 until the delay periods (defined for each aircraft category) have elapsed. In contrast to the maintenance project in figure 5.5, the maintenance project in figure 5.6 is delayed from time period 495 up and until time period 503 because resources do not allow maintenance to be scheduled in these time periods. Consequently, a difference is made between the expected number of delay periods of a maintenance project of each aircraft category and maintenance delay due to insufficient resources in eligible time periods. In time period 504, the first maintenance period is scheduled. Due to the resource constraints, the project is preempted in time period 505 and consequently, the aircraft becomes idle in this time period. Here, the difference between the variable "maintenance delayed" and "machine idle" becomes clear. Note that $p_{1,t}$ increases further as the maintenance project is delayed since the aircraft is still operational. Once the maintenance project has started and the aircraft becomes idle, $p_{1,t}$ does not increase anymore.

...	...	...	...	...	...	...	...	...	...	...	...
Time period	4683	0.951108	0	0	0	5	9	5	1	1	1
Time period	4684	0.953731	0	0	0	0	0	5	1	0	1
Time period	4685	0.95636	0	1	0	0	0	5	1	0	0
Time period	4686	0.958994	0	1	0	0	0	5	1	0	0
Time period	4687	0.961634	0	1	0	0	0	5	1	0	0
Time period	4688	0.964279	0	1	0	0	0	5	1	0	0
Time period	4689	0.966931	0	1	0	0	0	10	4	0	0
Time period	4690	0.969588	0	1	0	0	0	10	4	0	0
Time period	4691	0.97225	0	1	0	0	0	10	4	0	0
Time period	4692	0.974918	0	1	0	0	0	10	4	0	0
Time period	4693	0.977592	0	1	0	0	0	10	4	0	0
Time period	4694	0.980272	0	1	0	0	0	10	1	0	0
Time period	4695	0.982957	0	1	0	0	0	10	1	0	0
Time period	4696	0.985648	0	1	0	0	0	10	1	0	0
Time period	4697	0.988345	0	1	0	0	0	5	5	0	0
Time period	4698	0.991047	0	1	0	0	0	5	5	0	0
Time period	4699	0.993756	0	1	0	0	0	5	5	0	0
Time period	4700	0.996469	0	1	0	0	0	5	5	0	0
Time period	4701	0.999189	0	1	0	0	0	5	5	0	0
Time period	4702	1	0	0	1	0	0	5	5	0	0
Time period	4703	1	0	0	1	0	0	5	3	0	0
Time period	4704	1	0	0	1	0	0	20	0	0	0
Time period	4705	1	0	0	1	0	0	20	1	0	0
Time period	4706	1	0	0	1	0	0	20	0	0	0
Time period	4707	1	0	0	1	0	0	20	6	0	0
Time period	4708	1	0	0	1	0	0	20	6	0	0
Time period	4709	1	0	0	1	0	0	20	6	0	0
Time period	4710	1	0	0	1	0	0	20	6	0	0
Time period	4711	1	0	0	1	0	0	20	6	0	0
Time period	4712	1	0	0	1	0	0	20	3	0	0
Time period	4713	1	1	0	0	0	0	30	4	0	0
Time period	4714	1	1	0	0	0	0	30	4	0	0
Time period	4715	1	1	0	0	0	0	30	4	0	0
Time period	4716	1	1	0	0	0	0	30	0	0	0
Time period	4717	1	1	0	0	0	0	30	0	0	0

Figure 5.7: Value for $p_{1,4702}$ reaches the value of 1

For illustrative purposes, figure 5.7 shows a situation wherein $p_{1,4702}$ reaches a value of 1 and thus, becomes idle. Moreover, in time period 4683, a breakdown occurs which increases $p_{1,4683}$ to the value of 0.951108.

5.3.2 Construction of a strategic planning

machines		1				54
renewable resource						
consumption per time period		5				1
machines		1		machines		54
Time period	0	0		Time period	0	0
Time period	1	0		Time period	1	0
...	...	...		...	...	...
Time period	102	0		Time period	112	0
Time period	103	1		Time period	113	-4
Time period	104	1		Time period	114	-4
Time period	105	1		Time period	115	-4
Time period	106	1		Time period	116	-4
Time period	107	1		Time period	117	-4
Time period	108	0		Time period	118	-4
...	...	...		Time period	119	-4
Time period	249	0		Time period	120	0
Time period	250	1		...	...	...
Time period	251	1		Time period	554	0
Time period	252	1		Time period	555	1
Time period	253	1		Time period	556	1
Time period	254	1		Time period	557	1
Time period	255	0		Time period	558	1
				Time period	559	1
				Time period	560	1
				Time period	561	1
				Time period	562	0

Figure 5.8: First strategic maintenance projects for aircrafts 1 & 54

Based on the averages for the parameters calculated in the preprocessing method (section 5.2.3), a strategic planning is constructed. As indicated in section 5.2.2, a maintenance project is anticipated if resources do not allow the project to be scheduled according to the average maintenance duration, resource consumption and maintenance interval. Recall, that in the strategic planning, no preemption is allowed. Figure 5.8 shows the implementation of the two first maintenance projects for aircrafts 1 and 54. In accordance with the constructed dynamic planning (cfr. section 5.3.1), the first maintenance project for aircraft 1 has to start in time period 103. After being scheduled for the average maintenance duration number of time periods, the average maintenance interval is added to determine when the consecutive maintenance project has to start. As the variables in figure 5.4 indicate, this is in time period 250. The first strategic maintenance project for aircraft 54 is anticipated 4 time periods because resources did not allow the project to be scheduled on time. Hence, the maintenance project starts in time period 113. After being scheduled, again the average maintenance interval is added to find that the second strategic maintenance project has to be scheduled in time period 555.

5.3.3 Construction of a dynamic planning based on a strategic planning

machines		1									
Average maintenance duration		6									
Average maitenance interval		139									
Average maintenance delay		0									
Average renewable resource consumption		2									
Average idle time periods outside maintenance		13									
Scheduled time periods		9330									
		p[m][t]	maintenance scheduled	maintenance delayed	machine idle	maintenance duration	renewable resource consumption	renewable resource availability initial	renewable resource availability	breakdown	maintenance triggered
Time period	0	0.428338	0	0	0	0	0	20	20	0	0
Time period	1	0.431746	0	0	0	0	0	20	20	0	0
...	...	...	...	...	...	...	...	...	...	...	...
Time period	101	1	0	0	1	6	4	20	15	0	1
Time period	102	1	0	0	1	0	0	20	15	0	1
Time period	103	1	1	0	0	0	0	20	11	0	0
Time period	104	1	1	0	0	0	0	20	11	0	0
Time period	105	1	1	0	0	0	0	30	26	0	0
Time period	106	1	1	0	0	0	0	30	26	0	0
Time period	107	1	1	0	0	0	0	30	26	0	0
Time period	108	1	1	0	0	0	0	30	26	0	0
Time period	109	0.05	0	0	0	0	0	30	28	0	0
...	...	...	...	...	...	...	...	...	...	...	...
Time period	248	0.394058	0	0	0	5	4	20	12	0	1
Time period	249	0.39692	0	0	0	0	0	30	17	0	1
Time period	250	0.399789	1	0	0	0	0	30	13	0	0
Time period	251	0.399789	1	0	0	0	0	30	13	0	0
Time period	252	0.399789	1	0	0	0	0	30	13	0	0
Time period	253	0.399789	1	0	0	0	0	30	21	0	0
Time period	254	0.399789	1	0	0	0	0	30	21	0	0
Time period	255	0.05	0	0	0	0	0	30	25	0	0

Figure 5.9: First maintenance projects of aircraft 1 in the dynamic-based-on-strategic planning

Figure 5.9 displays part of the last constructed dynamic-based-on-strategic planning of aircraft 1. In accordance with the triggers for maintenance in time periods 101 and 248, the procedure plans maintenance for aircraft 1 after its two delay periods have elapsed. If resources would not allow maintenance to be scheduled in a certain time period, the projects would be preempted until resources do allow scheduling these maintenance time periods. An example of a maintenance project being preempted is shown in figure 5.10, where the first maintenance projects for aircraft 54 is preempted from time period 120 up and until time period 124.

machines	54										
Average maintenance duration	7										
Average maitenance interval	428										
Average maintenance delay	0										
Average renewable resource consumption	1										
Average idle time periods outside maintenance	52										
Scheduled time periods	3632										
		p[m][t]	maintenance scheduled	maintenance delayed	machine idle	maintenance duration	renewable resource consumption	renewable resource availability initial	renewable resource availability	breakdown	maintenance triggered
Time period	0	0.138821	0	0	0	0	0	20	20	0	0
Time period	1	0.13941	0	0	0	0	0	20	20	0	0
...	...	...	...	...	...	...	...	...	...	...	...
Time period	107	0.61325	0	0	0	8	2	30	26	0	1
Time period	108	0.613686	0	0	0	0	0	30	26	0	1
Time period	109	0.614122	0	0	0	0	0	30	28	0	1
Time period	110	0.614558	0	0	0	0	0	30	28	0	1
Time period	111	0.614994	0	0	0	0	0	30	28	0	1
Time period	112	0.615431	0	0	0	0	0	30	28	0	1
Time period	113	0.615867	1	0	0	0	0	20	16	0	0
Time period	114	0.615867	1	0	0	0	0	20	16	0	0
Time period	115	0.615867	1	0	0	0	0	20	4	0	0
Time period	116	0.615867	1	0	0	0	0	20	4	0	0
Time period	117	0.615867	1	0	0	0	0	20	4	0	0
Time period	118	0.615867	1	0	0	0	0	20	4	0	0
Time period	119	0.615867	1	0	0	0	0	20	4	0	0
Time period	120	0.615867	0	0	1	0	0	5	1	0	0
Time period	121	0.615867	0	0	1	0	0	5	1	0	0
Time period	122	0.615867	0	0	1	0	0	5	1	0	0
Time period	123	0.615867	0	0	1	0	0	5	1	0	0
Time period	124	0.615867	0	0	1	0	0	5	1	0	0
Time period	125	0.615867	1	0	0	0	0	5	1	0	0
Time period	126	0.05	0	0	0	0	0	5	0	0	0
...	...	...	...	...	...	...	...	...	...	...	...
Time period	549	1	0	0	1	14	1	20	13	0	1
Time period	550	1	0	0	1	0	0	20	13	0	1
Time period	551	1	0	0	1	0	0	20	13	0	1
Time period	552	1	0	0	1	0	0	20	11	0	1
Time period	553	1	0	0	1	0	0	20	14	0	1
Time period	554	1	0	0	1	0	0	20	13	0	1
Time period	555	1	1	0	0	0	0	20	14	0	0
Time period	556	1	1	0	0	0	0	20	14	0	0
Time period	557	1	1	0	0	0	0	20	16	0	0
Time period	558	1	1	0	0	0	0	20	16	0	0
Time period	559	1	1	0	0	0	0	20	14	0	0
Time period	560	1	1	0	0	0	0	20	6	0	0
Time period	561	1	1	0	0	0	0	30	13	0	0
Time period	562	1	1	0	0	0	0	30	13	0	0
Time period	563	1	1	0	0	0	0	30	15	0	0
Time period	564	1	1	0	0	0	0	30	15	0	0
Time period	565	1	1	0	0	0	0	30	20	0	0
Time period	566	1	1	0	0	0	0	30	16	0	0
Time period	567	1	1	0	0	0	0	30	16	0	0
Time period	568	1	1	0	0	0	0	30	16	0	0
Time period	569	0.05	0	0	0	0	0	20	10	0	0

Figure 5.10: Preempted maintenance project of aircraft 54 in the dynamic-based-on-strategic planning

Note, that the values for p_{mt} are not in correspondence with the implementation of the maintenance projects which indicates the (assumed) disruption between the strategic planning and a dynamic planning. This is the main reason for investigating the impact of incorporating failure predictive information on aircrafts in their maintenance planning.

5.3.4 Optimization of a dynamic planning

Number of swaps:	257	
Number anticipations:	138	
Number delays:	119	
Swap list:		
Machine	Time period from	Time period to
1	45	101
...	...	...
54	10750	10688

machines	1											
		p[m][t]	maintenance scheduled	maintenance delayed	machine idle	maintenance duration	renewable resource consumption	renewable resource availability initial	renewable resource availability	breakdown	swap	maintenance triggered
Time period	44	0.797721	0	0	0	0	0	20	20	0	0	0
Time period	45	0.801129	0	0	0	0	0	20	20	0	101	0
Time period	46	0.804544	0	0	0	0	0	20	13	0	0	0
Time period	47	0.807966	0	0	0	0	0	20	13	0	0	0
...	...	...	...	...	...	...	...	...	...	...	...	...
Time period	101	1	0	0	1	11	4	20	14	0	0	1
Time period	102	1	0	0	1	0	0	20	14	0	0	1
Time period	103	1	1	0	0	0	0	20	10	0	0	0
Time period	104	1	1	0	0	0	0	20	10	0	0	0
Time period	105	1	1	0	0	0	0	30	20	0	0	0
Time period	106	1	1	0	0	0	0	30	26	0	0	0
Time period	107	1	1	0	0	0	0	30	26	0	0	0
Time period	108	1	1	0	0	0	0	30	26	0	0	0
Time period	109	1	1	0	0	0	0	30	26	0	0	0
Time period	110	1	1	0	0	0	0	30	26	0	0	0
Time period	111	1	1	0	0	0	0	30	26	0	0	0
Time period	112	1	1	0	0	0	0	30	26	0	0	0
Time period	113	1	1	0	0	0	0	20	16	0	0	0
Time period	114	0.05	0	0	0	0	0	20	20	0	0	0

Figure 5.11: Swapped (delayed) maintenance project for aircraft 1

For explanatory reasons, the first and the last swapped maintenance projects are elaborated in this section. By coincidence, the first maintenance project for aircraft one, which has been discussed in the previous sections, is swapped. In the dynamic planning, it was triggered in time period 45 because the value for p_{mt} reached the critical value of 0.80. Delaying this maintenance project to time period 101 implies that aircraft 1 continues its operations until p_{mt} reaches the value of 1. In figure 5.11, it is clear that $p_{1,t}$ reaches this value before time period 101 and therefore, the aircraft is idle until the maintenance project starts in time period 103. Note, that the aircraft is idle during the maintenance project as well but is not indicated so because no non-operational cost should be added for performing maintenance given the definition of a non-operational cost.

Note, that delaying a maintenance project by swapping its implementation to a later time period in the dynamic planning, has no direct influence on the variable “maintenance delayed” in any time period as this boolean variable is 1 when resources do not allow a maintenance time period to be scheduled in an eligible time period.

It is clear that the anticipations and delays minimize the number of disruption periods. Nevertheless, there is a trade-off between the total cost for maintenance, unexpected non-operational aircrafts and maintenance because anticipating a maintenance project reduces chances for unexpected non-operational aircrafts, but increases maintenance costs such that extra maintenance projects are scheduled at the end of the dynamic planning. When a project is delayed, the chances for the aircraft to non-operational when not expected increase, but the total maintenance costs is likely decrease because less maintenance projects have to be scheduled. Trade-off between the total cost for disruption between the dynamic and the strategic planning, maintenance costs and costs of unexpected non-operational aircrafts are analyzed in chapter 6.

machines	54											
		p[m][t]	maintenance scheduled	maintenance delayed	machine idle	maintenan ce duration	renewable resource consumption	renewable resource availability initial	renewable resource availability	breakdown	swap	maintenan ce triggered
Time period	10688	0.52413	0	0	0	7	4	20	4	0	0	1
Time period	10689	0.524633	0	0	0	0	0	30	14	0	0	1
Time period	10690	0.525136	0	0	0	0	0	30	14	0	0	1
Time period	10691	0.52564	0	0	0	0	0	30	19	0	0	1
Time period	10692	0.526143	0	0	0	0	0	30	19	0	0	1
Time period	10693	0.526647	0	0	0	0	0	30	24	0	0	1
Time period	10694	0.527151	1	0	0	0	0	30	20	0	0	0
Time period	10695	0.527151	1	0	0	0	0	30	20	0	0	0
Time period	10696	0.527151	1	0	0	0	0	30	20	0	0	0
Time period	10697	0.527151	1	0	0	0	0	20	10	0	0	0
Time period	10698	0.527151	1	0	0	0	0	20	14	0	0	0
Time period	10699	0.527151	1	0	0	0	0	20	9	0	0	0
Time period	10700	0.527151	1	0	0	0	0	20	9	0	0	0
Time period	10701	0.05	0	0	0	0	0	20	9	0	0	0
...	...	...	...	...	...	...	...	...	...	...	...	...
Time period	10749	0.068604	0	0	0	0	0	5	5	0	0	0
Time period	10750	0.068995	0	0	0	0	0	5	5	0	10688	0
Time period	10751	0.069386	0	0	0	0	0	5	5	0	0	0

Figure 5.12: Swapped (anticipated) maintenance project for aircraft 54

In figure 5.12, an anticipated project is shown for aircraft 54. As expected, the value for $p_{54,10688}$ has not reached the critical value for aircraft 54 in time period 10688.

5.4 Performance measures

The purpose of this heuristic is to analyze the impact of incorporating realtime failure predictive information of aviation machinery in the planning of their maintenance projects and, therefore, some performance measures of the constructed schedules have to be determined. Three main performance measures are defined:

1. The value of failure predictive information: By comparing the total schedule cost of the dynamic-based-on-strategic planning and the dynamic planning, the value of incorporating failure predictive information in maintenance planning of aircrafts is determined. This performance measure is depicted by dotted arrow 4 in figure 5.13.

2. The value of the optimization procedure: By comparing the total schedule cost of the dynamic schedule and the optimized dynamic planning, the value of the developed optimization procedure is determined. This performance measure is depicted by dotted arrow 5 in figure 5.13.

3. Risk: The number of risk units in the constructed schedules. This risk measure is calculated as the summation over the planning horizon of all the values of p_{mt} where aircraft m in time period t is still operational, yet p_{mt} is higher than the corresponding critical value for p_{mt} of aircraft m.

The conceptual framework illustrated by figure 5.1 in section 5.2 is extended in figure 5.13.

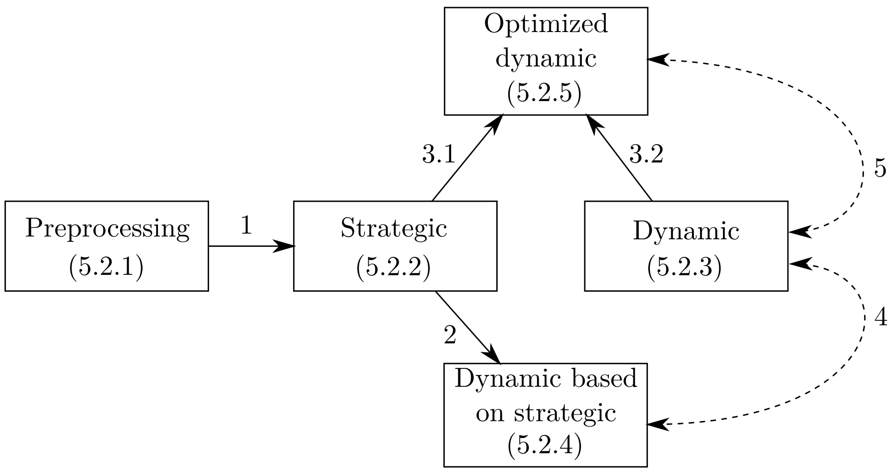

Figure 5.13: Procedure - extended conceptual framework

Dotted bidirectional arrows 4 and 5 were added to situate the performance measures. Arrow 4 indicates the value of incorporating failure predictive information whereas arrow 5 quantifies the value of the developed optimization procedure. Risk inherent to the constructed schedules is not depicted in the conceptual framework since it is omnipresent. It is clear that risk is not the objective in this research but taken into account as an observation. Recall that the risk of a certain schedule is the summation of all values of p_{mt} where aircrafts m are operational in time periods t even though their critical value for p_{mt} has been reached. In these time periods, chances for these aircrafts to become idle unexpectedly increase as p_{mt} increases further towards the value of 1.

Chapter 6

Analyses

In the previous section, the functionalities of the developed heuristic have been elaborated. In this chapter, the impact of different case characteristics on the performance of constructed schedules is investigated. Moreover, research is done on the impact of the incorporation of failure predictive information in aircraft maintenance planning, conclusions are derived, and managerial recommendations are formulated. Most conclusions and recommendations can be extrapolated for maintenance planning of other machines in and outside the aviation industry where status monitoring of these machines is possible.
Several characteristics hold for each case discussed in the remainder of this research:

- A fleet of 54 aircrafts is in correspondence with the fleet size of Dissertation Airlines and, therefore, relevant in the scope of this research. Although an equal proportion for each aircraft category in the fleet composition has not been observed, equal proportions are designated to each case for generalization purposes.
- The planning horizon is set to be 17,520 time periods which corresponds to two years.
- Values for p_{mt} and work content are generated according to predefined distributions, namely, the exponential and the linear distribution respectively.

All other case characteristics can be found in the appendix (figures 10 and 11).

6.1 Steady state

Before starting to investigate the impact of predictive failure information on the cost and risk performance of aircraft maintenance planning, it should be determined how many times (10, 100, 1000 or 10000) the procedure should perform the preprocessing step in order to have an accurate estimation of the average parameters used to construct the strategic planning. Next, as the cost of the schedules includes a disruption cost, the cost of a dynamic planning can only be calculated after the strategic planning is constructed. The number of constructed dynamic schedules is the same number of times (10, 100, 1000 or 10000) and averaged over all the constructed dynamic schedules in order for the results to be robust. Moreover, the dynamic-based-on-strategic planning is constructed and evaluated the same number of times for the same reason.

As the optimization procedure takes into consideration every maintenance project, the last dynamic planning is optimized only one time. The random sequence in which the dynamic schedules of the aircrafts are optimized is not an issue because for each considered swap, the total number of scheduled maintenance projects in the dynamic planning of all aircrafts is around the same. Therefore, degrees of freedom in the to-be optimized dynamic schedule of each aircraft do not differ too much if considered as the first or as the last aircraft.

Cost planning/Number of times	Strategic	Average dynamic based on strategic	Average dynamic	Optimised dynamic
10	$ 1,867,200.00	$ 15,160,926.00	$ 6,524,000.00	$ 5,517,300.00
100	$ 1,911,200.00	$ 15,603,760.00	$ 6,584,500.00	$ 5,527,400.00
1000	$ 1,904,700.00	$ 15,547,416.00	$ 6,427,200.00	$ 5,406,300.00
10000	$ 1,852,300.00	$ 15,785,574.00	$ 6,596,500.00	$ 5,482,000.00

Number of times	Ratio (column/row)	Strategic	Average dynamic based on strategic	Average dynamic	Optimised dynamic
10	Strategic	100%	812%	349%	295%
100		100%	816%	345%	289%
1000		100%	816%	337%	284%
10000		100%	852%	356%	296%
10	Average dynamic based on strategic		100%	43%	36%
100			100%	42%	35%
1000			100%	41%	35%
10000			100%	42%	35%
10	Average dynamic			100%	85%
100				100%	84%
1000				100%	84%
10000				100%	83%

Figure 6.1: Steady state analysis - Costs Cases 1 - 4

Figure 6.1 displays some of the results of case 1 - 4. It is clear that differences over the absolute values of the costs occur due to the randomness inherent to the procedure and the reality of this research. The figures in yellow depict the first performance measure, the value of failure predictive information (cfr. section 5.4). The second performance measure, the value of the optimization procedure, is displayed by the figures in green. It is observed that these remain stable over all cases.

Risk planning/Number of times	Average dynamic based on strategic	Average dynamic	Optimised dynamic
10	113140	20769	24008
100	111286	20626	25929
1000	112855	20733	24618
10000	113127	20881	27266

Number of times	Ratio (column/row)	Average dynamic based on strategic	Average dynamic	Optimised dynamic
10	Average dynamic based on strategic	100%	18%	21%
100		100%	19%	23%
1000		100%	18%	22%
10000		100%	18%	24%
10	Average dynamic		100%	116%
100			100%	126%
1000			100%	119%
10000			100%	131%

Figure 6.2: Steady state analysis - Risk Cases 1 - 4

Figure 6.2 displays the same comparison for the third performance measure, risk. Resulting values of the three performance measures will be discussed in great detail in subsequent sections of this chapter.

Based on the results from this analysis, no indication is found that there is another factor that influences results between generating the schedules 10 times or 10000 times other than the randomness inherent to the procedure and the nature of this research. Therefore, in the remainder of this research, the number of times the preprocessing step is conducted, and the number of dynamic and dynamic-based-on-strategic schedules are generated is set to 10.

6.2 Cost allocation analysis

In this section, the effect of the relative per time unit values for each of the three defined sub-costs (disruption, non-operational and maintenance cost) on the three performance measures is analyzed. First, the interdependent relation between these three costs is examined.

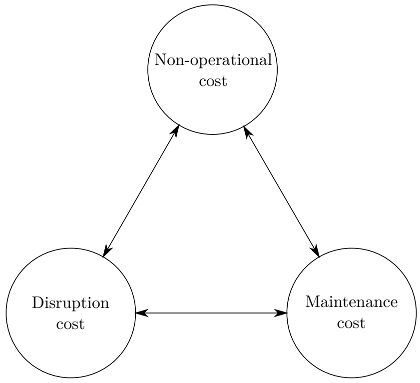

Figure 6.3: Interdependent effect of the costs on the performance measures

1. If the disruption cost is high relative to the maintenance and non-operational cost, the optimization procedure is likely to perform better than if the disruption cost is relatively low. Moreover, the absolute number of disruptions will be lower, however, the absolute and proportional cost of disruptions will not be necessarily low given that the cost per disruption period is set to be high. The number of delayed and anticipated projects depends on the relative difference between the maintenance and the non-operational cost. If the non-operational cost is relatively high compared to the maintenance cost, the optimized dynamic schedule is likely to have more anticipated project than delayed projects. The reason is that chances for aircrafts to be non-operational unexpectedly are higher when more projects are delayed and analogously, chances that more maintenance projects are scheduled are higher when more projects are anticipated.

2. If the non-operational cost is high relative to the disruption and maintenance cost, the absolute number of disruptions is likely to be higher than in the previous setting. It is clear that the number of anticipated projects will be higher than the number of delayed projects given the same reasoning as above.

3. If the maintenance cost is high relatively to the disruption and the non-operational cost, the number of delayed projects will be higher than the number of anticipated projects due to the fact that anticipating projects increases the total number of maintenance projects in the optimized dynamic planning.

In the remainder of this section, a quantitative analysis of the impact of the cost allocation is elaborated. Table 6.1 displays the relative cost allocation for each case. As depicted in the case characteristics in appendix (figure 10), 100% corresponds with monetary value of $100. Note, that only proportional results are compared between cases given that the absolute values will differ according to the cost allocation of each case.

Case	Disruption cost	Non-operational cost	Maintenance cost
1	100%	100%	100%
5	100%	25%	100%
6	100%	100%	25%
7	100%	25%	25%
8	25%	100%	100%
9	25%	25%	100%
10	25%	100%	25%

Table 6.1: Cost allocations

Cost planning/Case	Strategic	Average dynamic based on strategic	Average dynamic	Optimised dynamic
1	$ 1,839,700.00	$ 15,254,910.00	$ 6,556,100.00	$ 5,381,300.00
5	$ 1,765,400.00	$ 7,160,584.50	$ 5,970,275.00	$ 4,744,200.00
6	$ 467,425.00	$ 12,947,778.00	$ 4,294,850.00	$ 3,666,375.00
7	$ 461,050.00	$ 4,679,604.50	$ 3,715,550.00	$ 3,025,000.00
8	$ 1,915,900.00	$ 14,517,074.00	$ 4,444,900.00	$ 3,714,325.00
9	$ 1,888,800.00	$ 6,231,471.00	$ 3,723,450.00	$ 3,125,225.00
10	$ 482,750.00	$ 12,292,383.00	$ 2,175,175.00	$ 1,776,000.00

Number of times	Ratio (column/row)	Strategic	Average dynamic based on strategic	Average dynamic	Optimised dynamic
1	Strategic	100%	829%	356%	293%
5		100%	406%	338%	269%
6		100%	2770%	919%	784%
7		100%	1015%	806%	656%
8		100%	758%	232%	194%
9		100%	330%	197%	165%
10		100%	2546%	451%	368%
1	Average dynamic based on strategic		100%	43%	35%
5			100%	83%	66%
6			100%	33%	28%
7			100%	79%	65%
8			100%	31%	26%
9			100%	60%	50%
10			100%	18%	14%
1	Average dynamic			100%	82%
5				100%	79%
6				100%	85%
7				100%	81%
8				100%	84%
9				100%	84%
10				100%	82%

Figure 6.4: Cost allocation analysis - schedule costs

6.2.1 Performance measure 1: Value of failure predictive information

In a first analysis, the impact of the different cost allocations on the impact of incorporating failure predictive information of aircrafts within the planning process of their maintenance requirements is conducted (i.e. the percentages marked in yellow). In order to do so, a comparison between the average of the dynamic-based-on-strategic planning and the dynamic planning is done. The number of disruption time periods in the dynamic-based-on-strategic schedules is close to zero as, by definition, these schedules follow the strategic planning. Only deviations of the maintenance durations from the average maintenance duration for each aircraft are incurred. Therefore, the disruption cost relative to the non-operational and maintenance cost has no influence on this performance measure. Consequently, two comparisons are made where the cost for maintenance is equal within each of the comparisons.

In cases 1, 5, 8 and 9, the maintenance cost is relatively high compared to the non-operational cost. By comparing the average cost of the dynamic schedules and the average cost of the dynamic-based-on-strategic schedules, the value of incorporating failure predictive information in aircraft maintenance planning is quantified. Figure 6.4 indicates that the incorporation of failure predictive information has the biggest impact in case 8 and 1 with a decrease in cost of respectively 69% and 57%. The decrease in total cost in case 9 and 5 is respectively 40% and 17%. Given that the non-operational cost is relatively high in case 8, equal in case 1, relatively low in case 9 and the lowest in case 5, this analysis indicates that a relatively higher cost for non-operational machines increases the benefit of using failure predictive information of these aircrafts. As the nature of this failure predictive information is to monitor the operational state of an aircraft, it is natural that its impact is higher when used in a setting that gives relatively high importance this being non-operational.

In contrast to the previous analysis, cases 6, 7 and 10 have a relatively low maintenance cost in comparison with the non-operational cost. In correspondence with previous findings, the impact decreases in decreasing order of the relative cost for being non-operational. Case 10 has the biggest benefit of 82%, whereas case 6 and 7 have a decrease in total cost of 66% and 21% respectively. The rational of the analysis of cases 1, 5, 8 and 9 explains these results.

6.2.2 Performance measure 2: Value of optimization procedure

As displayed in figure 6.4, the optimization procedure is quite robust towards non-realistic cost allocations as cost decreases realized by the optimization method varies between 15 and 21%. In this section, an analysis of the optimization procedure is conducted.

Case	Number of swaps	Number of anticipations	Number of delays
1	257	54%	46%
5	296	39%	61%
6	231	45%	55%
7	301	44%	56%
8	201	46%	54%
9	277	47%	53%
10	219	55%	45%

Figure 6.5: Cost allocation analysis - number of swaps

Figure 6.5 displays the number of swaps performed in the optimization procedure and the percentage of swapped projects that were anticipated and delayed. In case 1 and 10, more projects were anticipated than delayed. In order to analyze the impact of the cost allocations on the preference for delaying rather than anticipating, a comparison should be made for cases where the disruption cost is equal since anticipating increases the number of maintenance projects and decreases chances that aircrafts operate above their critical value for p_{mt}. Accordingly, delaying maintenance projects decrease the number of maintenance projects but increase chances that aircrafts continue operating above their critical value for p_{mt}. First, cases 1, 5, 6 and 7 with relatively high disruption costs are compared. Secondly, cases 8 and 9 with relatively low disruption costs are investigated.

In increasing order of proportion of delays, the cases are ordered 1, 6, 7, 5. One would expect the proportion of delays in case 6 to be smaller than in case 1 since the cost of being non-operational is relatively higher in case 6 than in case 1. However, this is not the case. In order to explain this phenomenon, figure 6.6 should be included in the analysis.

	Number maintenance projects			
Case	Average dynamic based on strategic	Average dynamic	Optimised dynamic	Average dynamic/optimised dynamic
1	3760	3621	3172	88%
5	3760	3658	3129	86%
6	3829	3579	3372	94%
7	3767	3636	3134	86%
8	3766	3677	3232	88%
9	3763	3607	3146	87%
10	3753	3612	3398	94%

Figure 6.6: Cost allocation analysis - number of maintenance projects

Given that the decrease in number of maintenance projects is twice as high in case 1 than in case 6, it is established that on average the delays are bigger in case 1 than in case 6. Consequently, the optimization procedure does tend to delay more time periods when the maintenance cost is relatively high (case 1) but this does not imply that it delays more maintenance projects. It is clear that the proportion of anticipations and delays should be analyzed together with the proportion (increase/decrease) of maintenance projects in the optimized dynamic planning in comparison with the dynamic planning.

In cases 1 and 5, the disruption and the maintenance cost are both high relatively to the non-operational cost. It is observed that the proportion of delays in case 5 (61%) is distinctively higher than in case 1 (46%). Moreover, the proportional decrease in number of maintenance projects is 14% in case 5 whereas it is 12% in case 1. As intuitively expected, given that the cost for being unexpectedly non-operational is lower in case 5, delaying projects becomes more beneficial in comparison to case 1 where both costs are equal.

In cases 6 and 7, the maintenance cost is low, and the disruption cost high compared to the non-operational cost. If both non-operational and maintenance cost are equal but relatively low in comparison with the disruption cost (case 7), the procedure tends to delay more projects than it anticipates. The same reasoning as for the last comparison holds. The proportion of delays in case 7 is 1% higher than in case 6 whereas the proportional decrease in number of maintenance projects is 6% in case 6 and 14% in case 7. Although only a small difference is detected between the proportion of delays in case 7 (low non-operational cost) and case 6, the proportional decrease in number of maintenance projects reveal that a relatively low non-operational cost (case 7) indeed favors delaying more than when non-operational cost is relatively high (case 6).

Previous analysis depicted on cases with a relatively high disruption cost. Cases 8 and 9 combine a high maintenance cost and a low disruption cost with respectively a high and a low non-operational cost. In contrast with the findings in previous analysis, the proportion of number of delays has increased by 1% in case 9 where the relative cost for being non-operational has become relatively smaller in comparison with case 8. Although the proportion of delays is higher in case 8 in comparison with case 9, the decrease in maintenance projects in case 9 (13%) is higher than in case 8 (12%). This indicates that the delays in case 9 are on average bigger than in case 8 which is in correspondence with the relatively higher cost for maintenance in case 9.

Previous findings indicate that the decrease in maintenance projects in case 10 should be relatively low and that more maintenance projects should be anticipated than delayed given that the non-operational cost is relatively high. It is observed in figure 6.6 that the decrease in maintenance projects in case 10 is relatively low (94%). Moreover, the proportion of anticipated maintenance projects is higher than the proportion of delayed maintenance projects. Further analysis of figure 6.6 reveals that the decrease in maintenance projects is not affected by the disruption cost. The relative cost allocation of the non-operational and the maintenance cost is equal for case pairs (1,8), (5,9) and (6,10) whereas the disruption cost does differ between the cases of each case pair. The decrease in maintenance projects is respectively (88%,88%), (86%,87%) and (94%,94%) which indicates that the disruption cost does not affect the trade-off between delaying and anticipating maintenance projects.

6.2.3 Performance measure 3: Risk of the constructed schedules

Risk planning/Case	Average dynamic based on strategic	Average dynamic	Optimised dynamic
1	113140	20769	24008
5	115385	20885	29267
6	111016	20261	24202
7	112240	20902	27294
8	114219	21692	23285
9	113922	20918	26800
10	113855	20251	23272

Number of times	Ratio (column/row)	Average dynamic based on strategic	Average dynamic	Optimised dynamic
1		100%	18%	21%
5		100%	18%	25%
6		100%	18%	22%
7	Average dynamic based on strategic	100%	19%	24%
8		100%	19%	20%
9		100%	18%	24%
10		100%	18%	20%
1			100%	116%
5			100%	140%
6			100%	119%
7	Average dynamic		100%	131%
8			100%	107%
9			100%	128%
10			100%	115%

Figure 6.7: Cost allocation analysis - risk of schedules

The third performance measure, the risk inherent to the schedules, decreases when failure predictive information of aircrafts is incorporated in maintenance planning. Although the optimization decreases the cost of the constructed dynamic planning, the risk inherent to this schedule increases. As observed in figure 6.6, the number of scheduled maintenance projects decreased in optimized dynamic planning in comparison with the average dynamic planning. This implies that on average, the aircrafts operate longer before going into maintenance and thus, more use is made of the aircrafts' capacities. Given the definition of the risk inherent to schedules (cfr. section 5.4, this implies more risk in the optimized dynamic schedule as aircrafts operate more time periods after surpassing their critical value for p_{mt}.

Figure 6.8 identifies the trade-off between risk inherent to a dynamic planning and the cost decrease realized by the optimization procedure. It is observed that higher cost savings realized by the optimization method imply a stronger increase in risk inherent to the optimized dynamic planning. Note, that the cost decrease is highest for case 5 and lowest for case 6. Although there is no such thing as free lunch, it has to be noted that the risk inherent to the optimized dynamic planning is up to five times smaller than the risk inherent to following the strategic planning.

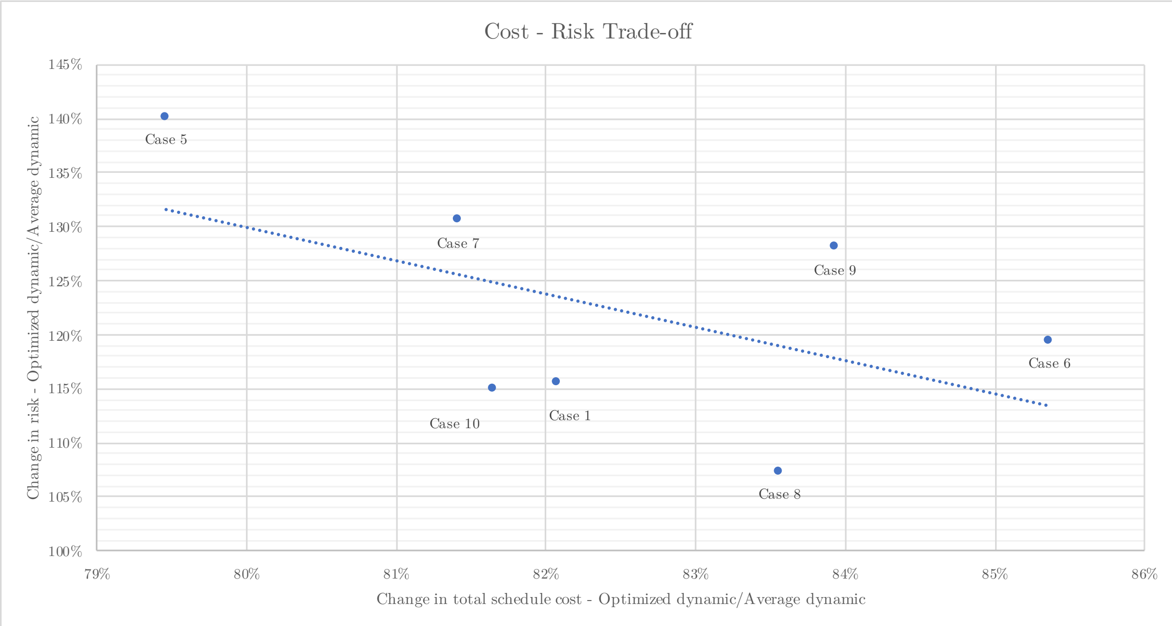

Figure 6.8: Risk - Cost Trade-off

6.2.4 Conclusion

Two conclusions can be drawn:

1. In section 6.2.1, the interdependent effect of the relative cost allocation for the disruption, non-operational and maintenance cost on the value of incorporating failure predictive information of aircrafts in maintenance planning was examined. It has been established that this value increases with increasing non-operational cost. It is clear that given the high cost of an unexpected non-operational aircraft, it is highly profitable to monitor the status of critical components and, moreover, to use this status in the planning process of the aircrafts' maintenance requirements. Furthermore, analysis showed that anticipating maintenance projects becomes more profitable when the cost of performing maintenance is relatively low. Although the cost allocation of the disruption cost does not influence the profitability of anticipating over delaying maintenance

projects, it is clear that higher disruption costs results in a higher value of incorporating failure predictive information of aircrafts in maintenance planning.

2. The developed optimization method uses the strategic planning and the realtime information on aircraft status to determine whether or not it is profitable to delay or anticipate a certain maintenance project when it is triggered. Using this method decreases the cost further by 15-21%, but increases the risk inherent to the planning. For all cost allocations, it was observed that the number of maintenance projects decreased such that aircraft utilization increases. Consequently, aircrafts operate longer after surpassing the critical value for p_{mt}. Therefore, the risk inherent to the optimized schedules is bigger than the risk inherent to the initial dynamic planning. Nevertheless, risk inherent to this optimized dynamic planning is still up to five times smaller than risk inherent to following the strategic planning exactly without any decision making on the tactical level.

6.3 Base case

In the remainder of this research, a base case is constructed for sensitivity analysis on relevant parameters. Case 10, introduced in section 6.2, is set to be the base case for the following reason.
The cost allocation for the disruption, non-operational and maintenance cost is respectively (25,100,25). The relative cost of an unexpected non-operational aircraft is set high in comparison with the disruption cost and the maintenance cost. Reason for the disruption cost to be relatively lower is that disruptions are incurred when the actual performed maintenance projects in the dynamic planning deviate from the presupposed ones in the strategic planning. These disruptions are handled in the day-to-day tactical decision making such that the idle time of the aircraft being in maintenance is known beforehand. Therefore, in contrast to an unexpected non-operational aircraft when a non-operational cost is incurred, the cost is not as high. The reason is that the company can adjust the planning in such a way that no flights have to be cancelled.
The results of case 10 are displayed in the appendix (figure 12).

6.3.1 Base case analysis

First, the performance measures are discussed for case 10. The value of incorporating failure predictive information of aircrafts in their maintenance planning results on average in a cost decrease of 82%. Further, the optimization procedure reduces this cost by another 18% resulting in an optimized dynamic planning which is 86% cheaper than the average dynamic-based-on-strategic schedule. As was observed before, the average risk inherent to the schedule decreases significantly by 82% when using the failure predictive information but increases slightly when the dynamic planning is optimized for cost reductions.
In order to explain these results, a closer look has to be taken to the total cost distribution for each of the schedules. Table 6.2 presents the absolute total cost of disruptions, non-operational aircrafts and maintenance for each schedule whereas the percentage distribution of the total schedule costs is depicted in figure 6.9.

Cost distribution[$]	Average dynamic based on strategic	Average dynamic	Optimized dynamic
Disruption	268,578.22	690,325.00	607,650.00
Idle time	11,243,514.00	775,000.00	515,900.00
Maintenance	780,290.75	709,850.00	652,450.00
Schedule cost	12,292,383.00	2,175,175.00	1,776,000.00

Table 6.2: Cost distribution [$] - Case 10

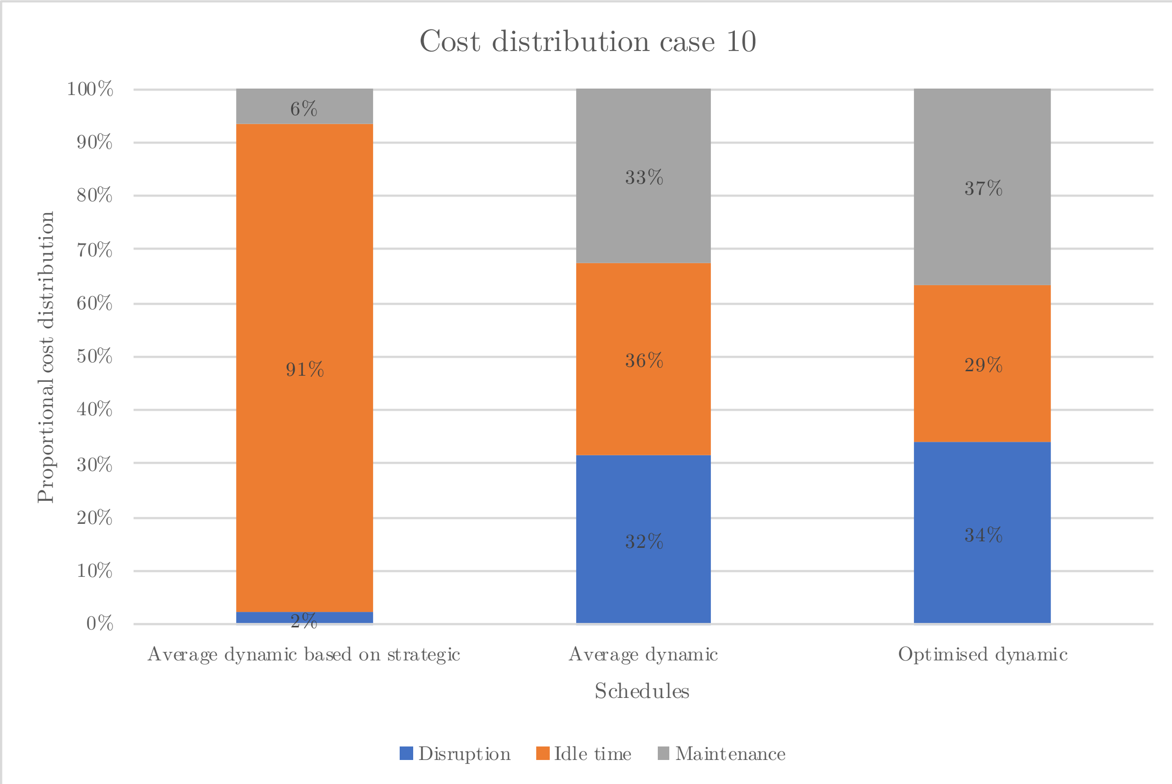

Figure 6.9: Cost distribution - Case 10

When the strategic planning is followed exactly and therefore, no decision making is done on the tactical level, 91% of monetary resources is invested in handling unexpected non-operational aircrafts. Moreover, only 6% is invested in performing actual maintenance and 2% in deviations of the dynamic-based-on-strategic planning from the strategic planning. The reason that there still exists deviation from the strategic planning in the dynamic-based-on-strategic planning is that the work content generated in the dynamic-based-on strategic planning differs from the same average used in the strategic planning. On average, the cost distribution when incorporating failure predictive information in the planning process is more uniform with 32% of the resources invested in handling disruptions, 36% in handling unexpected non-operational aircrafts and lastly, 33% in performing maintenance itself. The optimization procedure decreases the proportion of the unexpected idle time cost down to 29%. Handling disruptions and performing maintenance takes up 34% and 37% of the total budget respectively.

Table 6.3 depicts the absolute number of time periods each cost is incurred in the schedules. Moreover, the number of time periods incurred for each cost and for each schedule are compared to the number of time periods incurred in the dynamic-based-on-strategic schedule. By incorporating failure predictive information on aircrafts in their maintenance planning,

Incurred units [Time periods] ([%])	Average dynamic based on strategic	Average dynamic	Optimized dynamic
Disruption	10,743 (100%)	27,613 (257%)	24,306 (226%)
Idle time	112,435 (100%)	7,750 (7%)	5,159 (5%)
Maintenance	31,212 (100%)	28,394 (91%)	26,098 (84%)

Table 6.3: Incurred units (incurred units relative to the average of the dynamic-based-on-strategic planning) - Case 10

it is clear that as well in absolute numbers (10,743 time periods vs. 27,613 time periods) as well as in relative numbers (100% vs. 257%), more is invested in handling disruption. A significant reduction in investment in handling unexpected non-operational aircrafts of 93% is found whereas a moderate decrease of 9% in maintenance investment results from using this realtime data.

Incurred units [%]	Average dynamic	Optimized dynamic
Disruption	100%	88%
Idle time	100%	67%
Maintenance	100%	92%

Table 6.4: Incurred units relative to the average for the dynamic planning - Case 10

The optimization method succeeds in further increasing utilization of aircrafts as all three costs decrease by 12% (disruption), 33% (unexpected idle time) and 8% (maintenance) in comparison to the average for the dynamic schedules as depicted in table 6.4.

Case	Average dynamic based on strategic	Average dynamic	Optimized dynamic
10	113,855.38 (100%)	20,251.47 (18%)	23,271.52 (20%)

Table 6.5: Risk units (relative to the dynamic-based-on-strategic planning [%]) - Case 10

Again, the risk inherent to the dynamic planning is on average 82% (table 6.5) lower than when the strategic planning is followed, and no decision making is done on the tactical level. The cost decrease of 18% in the optimized dynamic planning in comparison with the original dynamic planning results, again, in a minor risk increase of 15% in comparison with this original dynamic planning and 2% in comparison with the dynamic-based-on-strategic planning. It has to be noted that this risk measure includes riskiness of operating close to the status in which an aircraft is still able to fly but cannot according to regulations. Therefore, this risk increase is a measure that capacity of aircrafts is used more which inherently increases chances that unexpected maintenance projects have to take place.

6.3.1.1 Conclusion

If no uncertainty would exist in the maintenance requirements of aircrafts, the most cost-efficient planning would invest 100% of its monetary resources in maintenance. Due to the volatility in workload of aircrafts (e.g. extreme weather conditions in flight, climate differences between airports, etc.) and the law of Murphy, most of aviation companies invest most of their resources in reactive measures to overcome this uncertainty (accommodation when flights are cancelled, emergency maintenance, etc.). It is clear that the main advantage of monitoring the status of aircrafts and using this information in their maintenance planning process is to minimize the unexpected idle time of each aircraft. Doing so requires proactive measures to be taken. These can only be made when the right infrastructure is present. Therefore, aviation companies should invest in flexibility within day-to-day tactical maintenance planning in combination with the realtime data transmission technology. Moreover, if they invest in decision making tools which include the strategic planning in the construction of dynamic schedules incorporating the realtime status of all aircrafts in their fleet, these investments could ideally result in an average cost decrease of 82%.

6.3.2 Δ critical values for p_{mt}

In this analysis, the impact of a change in the critical values for p_{mt} is analyzed. Based on case 10, case 11 and case 12 were constructed with only a change in the critical values for p_{mt} for each category of respectively +0.09 and -0.09. For illustrative purposes, the aircraft categories for both cases are displayed in the appendix (figure 13 and figure 14 respectively).

By changing the critical values for each aircraft category, the aversion for riskiness - as elaborated in previous analysis (section 6.3.1) - is changed. If critical values are set to a lower value, the procedure will plan maintenance for each aircraft earlier than when critical values for p_{mt} are set a higher value. This effect is already present in the preprocessing step and therefore, more maintenance projects will be scheduled in both the strategic and the dynamic schedules. As the optimization procedure swaps projects to time periods at which maintenance is scheduled in the strategic planning, there are less degrees of freedom in this swapping process for each considered maintenance project in the dynamic planning. Alternatively, as the strategic and initial dynamic planning use less of the capacity of each aircraft if critical values are set to a lower value, the optimization procedure is likely to have a greater impact. When more maintenance projects are planned, more disruption periods and less unexpected non-operational time periods are ought to occur. In this analysis the effect of both changes is examined.

Cost distribution[$]	Case	Average dynamic based on strategic	Average dynamic	Optimized dynamic
Disruption	11	233,607.22	605,875.00	542,600.00
	12	341,473.06	759,450.00	665,425.00
Idle time	11	14,107,870.00	708,300.00	497,200.00
	12	8,843,332.00	902,400.00	617,500.00
Maintenance	11	685,235.75	623,675.00	574,075.00
	12	891,510.25	782,775.00	713,300.00
Schedule cost	11	15,026,713.00	1,937,850.00	1,613,875.00
	12	10,076,315.00	2,444,625.00	1,996,225.00

Table 6.6: Cost distribution [$] - Case 11 & Case 12

Comparing the absolute costs of each schedule is relevant now given the same cost allocation is used. Table 6.6 displays the cost distribution for each case.

6.3.2.1 Average dynamic-based-on-strategic planning

It is observed that the total dynamic-based-on-strategic schedule cost of case 12 is about 33% lower than the corresponding total cost in case 11.

As expected, when critical values for p_{mt} are higher (case 11) the disruption cost is lower because less maintenance projects are scheduled when critical values are higher. Therefore, the number of times the maintenance duration of scheduled maintenance projects is larger than the average maintenance duration of the corresponding aircrafts is lower when critical values for p_{mt} are higher (case 11). Since this is only a small fraction of the total schedule cost difference and the fact that disruption in the average dynamic-based-on-strategic schedule is not relevant, no conclusions are derived from this part of the analysis.

In contrast to the difference in disruption cost between case 11 and case 12, a huge difference in cost for unexpected non-operational aircrafts is observed between the cases. When critical values for p_{mt} are higher (case 11), and no failure predictive information is used in the maintenance planning of aircrafts, the cost skyrockets by 40% in this setting. Given that this cost takes up 94% (case 11) and 88% (case 12) of the total budget, it is clear that this accounts for most of the observed difference in the total cost for the dynamic-based-on-strategic schedules.

Again, due to the higher number of scheduled maintenance projects in the strategic planning when critical values for p_{mt} are lower, it is clear that a higher maintenance cost is incurred in case 12.

The critical values for p_{mt} are chosen arbitrarily and determine the buffer for bridging the time interval between triggering maintenance and the aircrafts becoming idle (p_{mt} reaches the value of 1). Therefore, these critical values have no meaning in a context where no failure predictive information is used such as the construction of a dynamic-based-on-strategic schedule. Consequently, the first performance measure (Value of incorporating failure predictive information) has to be analyzed with caution because it is relative to the average dynamic-based-on-strategic schedule cost.
In the remainder of this analysis on the impact of different critical values for p_{mt}, the absolute cost distributions of the cases are used to determine the performance of each setting for the reason elaborated above. Note that this can be done because the cost allocation is equal for all cases.

6.3.2.2 Average dynamic planning

In this section, the impact of the critical values for p_{mt} on the planning incorporating failure predictive information, is analyzed.

The total cost as well as the sub-costs (disruption, unexpected idle time and maintenance) are lower in case 11 where the critical values for p_{mt} are higher. This is in contrast with the finding that the total dynamic-based-on-strategic schedule cost for case 11 is 33% higher than in case 12. Analysis of each sub-cost puts this outcome in perspective.
Due to the fact that more maintenance projects are scheduled when critical values for p_{mt} are lower (case 12), the maintenance cost is higher in case 12. Another consequence of the higher number of maintenance projects is that chances for disruption to occur are higher. This is observed in table 6.6 as well where case 11 has a disruption cost of \$605,875.00 whereas this cost amounts to \$759,450.00 in case 12.
The cost for unexpected non-operational aircrafts is lower in case 11 where critical values for p_{mt} are higher. Although observed in these cases, it cannot be concluded that this holds in general. It is likely that there is an interaction effect of the critical values for p_{mt} and the resource constraints since less available resources result in more maintenance projects where delay occurs between the triggering time period and the scheduled time periods. Therefore, if few renewable resources are available, settings where critical values for p_{mt} are lower will perform better because the buffer between the triggering time period and the time period in which p_{mt} reaches the value of 1 (and becomes non-operational) is bigger.

Case	10	11	12
Average number of delayed time periods	1.0370	0.7037	1.2407

Table 6.7: Average number of delayed time periods per maintenance project over all aircrafts

In order to quantify this difference in degrees of freedom in the dynamic schedules between both cases, the average number of delayed time periods per maintenance project over all aircrafts of each case is calculated. Table 6.7 displays this value for each case whereas figure 17 in the appendix depicts on the calculation of these values. It is observed that averaged over all aircrafts, case 11 has to lowest average number of delayed time periods per maintenance project (0.7037) whereas this is highest in case 12 (1.2407). The difference in degrees of freedom in the constructed schedules of both settings is established. It has been made clear that higher critical values for p_{mt} (case 11) incur less maintenance projects. If less maintenance projects are scheduled, fewer renewable resources are used over the planning horizon and therefore, less delayed time periods per maintenance project per aircraft will be observed (case 11). Although work content is bigger when values for p_{mt} are higher when a maintenance project is triggered (see work content generation in section 5.1), this does not neutralize the effect of the number of scheduled maintenance projects. The average number of delay periods

in case 10 is 1.0370, which is 0.33 time periods higher in comparison with case 11 and 0.21 time periods lower compared to case 12. This indicates that the effect of the higher work content in settings with high critical values for p_{mt} (case 11) decreases the effect of the lower number of scheduled maintenance projects on the degrees of freedom in the constructed schedules. Note that in the current settings, the available renewable resources are set such that delays between triggering time periods and scheduled maintenance projects do occur regularly but are rather low.
Further analysis on the interaction effect between the critical values for p_{mt} and the renewable resource constraints is conducted in section 6.3.2.7.

6.3.2.3 Optimized dynamic planning

Discussion on the absolute cost differences and degrees of freedom in the constructed schedules in 6.3.2.2 (average dynamic schedules), also holds for the observed differences between the optimized dynamic schedules of case 11 and case 12. The total optimized dynamic schedule cost as well as the sub-costs (disruption, unexpected idle time and maintenance) in case 11 are lower than in case 12. Furthermore, as the last constructed dynamic planning in case 11 has more degrees of freedom than the last dynamic planning in case 12, the same holds for their corresponding optimized dynamic schedules. The same reasons as elaborated in section 6.3.2.2 explain these results.

6.3.2.4 Performance measure 1: Value of failure predictive information

Figures 15 and 16 in the appendix depict the results of case 11 and case 12 respectively. It is observed that the impact of incorporating failure predictive information in case 11 and case 12 results in a decrease of respectively 87% and 76%. Reason for this is that the strategic planning in case 11 (high critical values for p_{mt}) makes more use of the capacity of aircrafts to operate. Nevertheless, as the discussion in section 6.3.2.2 explains, the interaction effect between the critical values for p_{mt} and the renewable resource constraints has to be analyzed further (see section 6.3.2.7).

6.3.2.5 Performance measure 2: Value of the optimization procedure

The optimization method decreases the dynamic planning cost by 17% and 18% in case 11 and case 12 respectively. Therefore, the optimization procedure is robust towards changes in the critical values for p_{mt}. Moreover, the relative cost distribution of both the dynamic and the optimized dynamic planning in the three cases (case 10, case 11 and case 12) are almost equal as depicted in table 6.8. Therefore, the critical values for p_{mt} do affect the performance of incorporating failure predictive information in maintenance planning of aircrafts in absolute values, but they do not affect the proportion of the budget allocated to each of the three

Cost distribution[%]	Case	Average dynamic based on strategic	Average dynamic	Optimized dynamic
Disruption	11	2%	31%	34%
	10	2%	32%	34%
	12	3%	31%	33%
Idle time	11	94%	37%	31%
	10	91%	36%	29%
	12	88%	37%	31%
Maintenance	11	5%	32%	36%
	10	6%	33%	37%
	12	9%	32%	36%

Table 6.8: Cost distribution [%] - Case 10, Case 11 & Case 12

costs: disruption, unexpected non-operational aircrafts and maintenance. Note that these results do not account for any implications of the interaction effect between the critical values for p_{mt} and the renewable resource constraints.

6.3.2.6 Performance measure 3: Risk inherent to the schedules

Case	Average dynamic based on strategic	Average dynamic	Optimized dynamic
11	59,201.43	17,212.25	17,612.05
12	145,364.66	21,867.90	25,536.41

Table 6.9: Risk units - Case 11 & Case 12

Lower critical values correspond to a bigger buffer for maintenance to be scheduled before values for p_{mt} reach the value of 1. Intuitively, one would assume the risk inherent to these schedules is lower. But since risk is determined as operating after aircrafts reached their critical value for p_{mt}, chances for risk to increase when critical values decrease are high. Therefore, given that the critical values for p_{mt} are higher in case 11, chances are lower that aircrafts operate after reaching their correspondent critical values for p_{mt}. Either this is due to the fact that the ranges of values for p_{mt} which are concerned risky in case 11 are smaller, either maintenance can be scheduled easier (i.e. more degrees of freedom as more resources are available because less maintenance projects occur) in case 11. Again, the effect of the renewable resources' availability should be analyzed.

6.3.2.7 Interaction effect: renewable resource constraints

In this section, the interaction effect between the renewable resource constraints and the critical values for p_{mt} is analyzed. Case 12_bis is constructed in which the renewable resource availability has been set around 20% higher compared to the availability in case 12. Figure 17 in the appendix depicts on the calculation of the average delayed time periods per maintenance project over all aircrafts for each case. It is observed that this value is equal in case 11 and case 12_bis (0.7037). As explained above, the number of maintenance projects is higher in case 12 (low critical values for p_{mt}) compared to case 11. Changing critical values for p_{mt}, renewable resource availability equal, implicate less degrees of freedom in the constructed schedules of the setting with lower critical values (case 12). By adjusting the renewable resource availability in case 12_bis, the degrees of freedom in the constructed schedules in this case is leveled with the degrees of freedom in the constructed schedules in case 11 (0.7037 average delayed time period per maintenance projects over all aircrafts). Consequently, the interaction effect between the renewable resource constraints and the change in critical values for p_{mt} is excluded in the comparison between case 11 and case 12_bis and only the effect of the change in critical values remains.
Again, the results of the dynamic-based-on-strategic schedule are not analyzed since critical values for p_{mt} are introduced when using failure predictive information in the maintenance planning of aircrafts.
Analyses elaborated in sections 6.3.2.2 and 6.3.2.3 revealed that incorporating failure predictive information in the maintenance planning of aircrafts with high critical values for p_{mt} (case 11) results in better performing schedules.

Cost distribution[$]	Case	Average dynamic based on strategic	Average dynamic	Optimized dynamic
Disruption	11	233,607.22	605,875.00	542,600.00
	12_bis	334,552.78	767,250.00	667,575.00
Idle time	11	14,107,870.00	708,300.00	497,200.00
	12_bis	8,656,533.00	782,700.00	544,800.00
Maintenance	11	685,235.75	623,675.00	574,075.00
	12_bis	892,285.06	792,975.00	709,325.00
Schedule cost	11	15,026,713.00	1,937,850.00	1,613,875.00
	12_bis	9,883,370.00	2,342,925.00	1,921,700.00

Table 6.10: Cost distribution [$] - Case 11 & Case 12_bis

Table 6.12 depicts the cost distributions for case 11 and case 12_bis. It is observed that for both the average dynamic schedule and the optimized dynamic planning, case 11 (with higher critical values for p_{mt}) is cheaper and consequently, better performing. Both the total schedule cost ($1,937,850 vs. $2,342,925.00 and $1,613,875.00 vs. $1,921,700.00) as the three sub-costs are smaller when higher critical values for p_{mt} (case 11) are used. The interaction effect between the renewable resource constraints and the change in critical values for p_{mt} in case 12 results in an extra cost of $101,700.00 on average in the dynamic planning and $74,525.00 in the optimized dynamic planning compared to case 12_bis where this effect has been deleted.

Total schedule cost	Average dynamic	Optimized dynamic
Case 11	100%	100%
Case 12_bis	121%	119%
Case 12	126%	124%

Table 6.11: Total schedule cost relative to Case 11 - Case 12 & Case 12_bis

As observed in table 6.11, the benefit of using higher critical values for p_{mt} is on average 21% for the dynamic planning and 19% for the optimized dynamic planning (case 12_bis). The interaction effect between the renewable resource constraints and the change in critical values for p_{mt} increases this benefit even more by 5% and 5% respectively (case 12). Note that the benefit depends on how large the change in critical values for p_{mt} is.
Although deleting the interaction effect (case 12_bis) slightly decreased the benefit of using higher critical values for p_{mt}, the cost reduction is still significant. Reason for this is that when critical values are higher, more use is made of the capacity of the aircrafts (cfr.supra).

Cost distribution[%]	Case	Average dynamic based on strategic	Average dynamic	Optimized dynamic
Disruption	11	2%	31%	34%
	12_bis	3%	33%	35%
Idle time	11	94%	37%	31%
	12_bis	88%	33%	28%
Maintenance	11	5%	32%	36%
	12_bis	9%	34%	37%

Table 6.12: Cost distribution [%] - Case 11 & Case 12_bis

The relative cost distribution of the total budget in table 6.12 reveals that when higher critical values for p_{mt} (case 11) are used, the proportion of resources invested in unexpected non-operational aircrafts is also higher. In contrast, the proportion that is invested in maintenance and disruption is smaller. An ideal planning would allocate 100% of its resources to maintenance and none to disruption (perfect strategic planning) and unexpected non-operational aircrafts (perfect dynamic planning). Therefore, one could argue that when critical values for p_{mt} are lower, the budget is allocated more properly (higher proportional investment in maintenance). Nevertheless, due to the resource constraints and the randomness in the maintenance requirements of aircrafts (due to their operational nature), companies should strive to be as cost efficient as possible and plan according to the cost-minimizing objective, not according to maximum proportional investment in maintenance. Consequently, a trade-off between delaying maintenance (higher non-operational cost) and anticipating maintenance (higher maintenance cost) is relevant and necessary.

Case	Average dynamic	Optimized dynamic
11	17,212.25	17,612.05
12_bis	20,107.09	23,571.88

Table 6.13: Risk units - Case 11 & Case 12_bis

Lastly, the impact of changing critical values for p_{mt} on the third performance measure, risk inherent to the schedules, is analyzed. Table 6.13 depicts the risk units incurred in both the average dynamic planning and the optimized dynamic planning. It is observed that the interaction effect between the renewable resource constraints and the change in critical values for p_{mt} in case 12 (see table 6.9) was partly responsible for the higher risk inherent to the schedules in case 12 in comparison to case 11 since the risk inherent to the schedules of case 12_bis is lower than the correspondent risk inherent to the schedules of case 12. Nevertheless, the use of higher critical values for p_{mt} does decrease risk inherent to the constructed schedules both with and without the interaction effect. As elaborated in section 6.3.2.6, this is due to the definition of risk. It would be false to say that using lower critical values for p_{mt} results in riskier schedules. For a fair comparison, 6.14 denotes the adjusted risk for case 12_bis, defined as the sum of all values of p_{mt} where aircrafts operate when the critical values for p_{mt} of case 11 have been reached.

Case	Average dynamic	Optimized dynamic
11	17,212.25	17,612.05
12_bis	5,178.28	5,626.87

Table 6.14: Adjusted risk units - Case 11 & Case 12_bis

As expected, the adjusted risk inherent to the schedules of case 12_bis is much lower than the correspond risk in case 11. The trade-off between cost reductions and risk increases becomes clear. On average, the dynamic schedule adjusted risk increases by 332% for a cost reduction of 21% and the optimized dynamic schedule risk increases by 313% for a cost reduction of 19%. These results have to be interpreted with caution. The total cost for unexpected non-operational aircrafts is lower in case 11 than in case 12_bis which means that less resources are invested in these unexpected events over a planning horizon of two years in case 11. The risk as defined in this research does denote a riskier schedule when higher critical values for p_{mt} are used (case 11), but the cost distribution also shows that the cost reductions make up for this risk increase.

Finally, as the buffer between triggering maintenance and p_{mt} becoming 1 is smaller for higher critical values for p_{mt} (case 11), the resource availability becomes more important. Therefore, the risk increase can be seen as an increase in the criticality of the available resources. If renewable resource availability would be more volatile in previous cases, the impact on the total cost would be much higher in case 11 than in case 12 and case 12_bis.

6.3.2.8 Conclusion

In this section, the impact of the critical values for p_{mt} on the benefit of incorporating failure predictive information has been analyzed. Several conclusions are derived from this analysis.

1. Changing critical values for p_{mt} should be done in combination with adjustment of the available resources used to perform these maintenance activities. The interaction effect between the change in critical values and the resource constraints is such that lower critical values forces more maintenance projects to be conducted. Therefore, all resources constraints equal, the constructed maintenance schedules have less degrees of freedom when critical values are lower.

2. Further analysis in which the interaction effect between the change in critical values and the renewable resource constraints has been eliminated showed that higher critical values for p_{mt} result in a significant cost reduction. The amount of this reduction is dependent on the original setting and how large the change in critical values is.

3. This cost reduction does incur a higher risk inherent to the constructed schedules. Nevertheless, this risk increase has to be put into perspective. The planning procedure constructs fairly low risk schedules as p_{mt} values of 1 result in aircrafts that can no longer fly because of regulatory reasons which does not imply the aircrafts can no longer be operational. Moreover, the absolute cost for unexpected non-operational aircrafts is lower when critical values are higher. When choosing higher critical values for p_{mt},

companies should carefully determine the resource availabilities as these become more critical when the critical values for p_{mt} are higher.

In conclusion, higher critical values for p_{mt} result in significant cost reductions as the constructed schedules make better use of aircrafts' operational capacity. Therefore, companies should strive for high critical values in combination with efforts in flexible renewable resource availabilities as these resources become more critical. Moreover, companies should be aware that changing critical values for p_{mt} forces the renewable resource availabilities to be adjusted accordingly.

6.3.3 Δ breakdown probabilities

In this section, analysis of the impact of the breakdown probabilities on the impact of incorporating failure predictive information in aircraft maintenance planning is conducted. These were introduced in section 5.1 and depicted by figure 6 in the appendix. In case 13, these breakdown probabilities have been augmented by 50% for each aircraft category whereas in case 14 these have been lowered by 50%. Figures 19 and 20 in the appendix display the adjusted breakdown probabilities for each category.

By lowering the breakdown probabilities (case 14), the uncertainty for the values of p_{mt} is lowered and aircrafts have less unexpected defects. Consequently, the strategic planning will make more use of aircrafts' capacity as less breakdowns occur in the preprocessing step. For the dynamic-based-on-strategic schedule, this means on average that less disruptions will occur. Further, less maintenance will be scheduled, and less unexpected non-operational aircrafts will occur.
Figures 21 and 22 in the appendix show the results of case 13 and case 14, respectively. The number of scheduled maintenance projects for each of the schedule types in case 13 is much higher than in case 14 as shown in table 6.15. Consequently, the maintenance sub-cost for each planning in case 13 (higher breakdown probability) will be much higher than for the corresponding sub-costs in case 14.

Case	Average dynamic based on strategic	Average dynamic	Optimized dynamic
13	4,942	4,705	4,391
14	2,605	2,524	2,355

Table 6.15: Number of scheduled maintenance projects - Case 13 & Case 14

Table 6.16 displays the cost distribution of each case. If the strategic planning is followed exactly, without any decision making on the tactical level (dynamic-based-on-strategic schedule), 5% more unexpected non-operational time periods occur when breakdown probabilities are low (case 14). The reason for this counterintuitive finding is that the average maintenance intervals for each aircraft in case 14 is large compared to case 13 and therefore, if a breakdown occurs, on average the aircraft will have to wait longer before maintenance is performed. In contrast, the average maintenance intervals in case 13 are smaller, but more breakdowns do occur. Therefore, no significant difference in cost for unexpected non-operational aircrafts is found when no failure predictive information is used.
Again, the disruption cost is not relevant for this schedule as this is due to the randomness in maintenance duration. The total average dynamic-based-on-strategic schedule cost is

Cost distribution[$]	Case	Average dynamic based on strategic	Average dynamic	Optimized dynamic
Disruption	13	378,734.28	901,450.00	802,825.00
	14	189,520.91	493,150.00	413,800.00
Idle time	13	10,455,717.00	1,560,100.00	1,163,800.00
	14	10,981,759.00	429,400.00	245,000.00
Maintenance	13	1,026,088.75	935,625.00	852,900.00
	14	543,442.94	501,625.00	445,700.00
Schedule cost	13	11,860,540.00	3,397,175.00	2,819,525.00
	14	11,714,723.00	1,424,175.00	1,104,500.00

Table 6.16: Cost distribution [$] - Case 13 & Case 14

slightly smaller when breakdown probabilities are low (case 14), but no significant difference is found because the strategic planning anticipates the higher number of breakdowns by using historical information of each aircraft.

6.3.3.1 Performance measure 1: Value of failure predictive information

When incorporating failure predictive information of aircrafts in their maintenance planning, a cost reduction of 71% when breakdown probabilities are high and 88% when breakdown probabilities are low is found. Thus, a great difference for different breakdown probabilities is found in the benefit of using failure predictive information. Table 6.16 depicts that the average difference for the disruption and maintenance sub-cost changes proportionally in each case. In contrast, the cost for unexpected non-operational aircrafts decreases much more when breakdown probabilities are low: 94% (case 14) vs. 85% (case 13). Moreover, as this cost accounted for 94% (case 14) and 88% (case 13) of the total schedule cost, the impact on the average difference in total cost of the dynamic planning is significant. On average, the dynamic planning in case 13 is 2.39 times more expensive as in case 14. This is due to the fact that less unexpected non-operational aircrafts have to be scheduled when breakdown probabilities are low (case 14) and thus, less maintenance is performed, less available resources are used (and therefore, it is easier to schedule unexpected non-operational aircrafts for maintenance) and chances are smaller that disruption occurs because less projects are scheduled.

6.3.3.2 Performance measure 2: Value of the optimization method

The developed optimization method further increases the relative cost difference between the dynamic planning where breakdown probabilities are low (case 14). A cost decrease of 22% has been established in case 14 whereas a decrease of 17% has been realized in case 13 (see appendix, figures 21 & 22. Again, this difference is mainly due to the cost reductions for unexpected non-operational aircrafts: 43% when breakdown probabilities are low and 25% for high breakdown probabilities.

Cost distribution[%]	Case	Average dynamic based on strategic	Average dynamic	Optimized dynamic
Disruption	13	3%	27%	28%
	14	2%	35%	37%
Idle time	13	88%	46%	41%
	14	94%	30%	22%
Maintenance	13	9%	28%	30%
	14	5%	35%	40%

Table 6.17: Cost distribution [%] - Case 13 & Case 14

Further, analysis of the relative cost distribution depicted in table 6.17 confirms that in the optimized dynamic planning almost twice as much (41% vs. 22%) of the total budget is invested in unexpected non-operational aircrafts when breakdown probabilities are high (case 13). Moreover, 40% of the investment is done in maintenance in case 14 whereas this only amounts for 30% of the investments in case 13. Thus, not only the total cost performance is better when breakdown probabilities are low, companies can also allocate their resources better (invest mostly in maintenance).

6.3.3.3 Performance measure 3: Risk inherent to the schedules

Case	Average dynamic based on strategic	Average dynamic	Optimized dynamic
13	128,600.66	30,449.80	31,525.36
14	85,681.38	12,225.14	14,761.40

Table 6.18: Risk units - Case 13 & Case 14

As uncertainty is higher when breakdown probabilities are higher (case 13), risk inherent to the schedules is higher as well. Table 6.18 confirms this hypothesis as risk inherent to the schedules of case 13 is up to 2.5 times higher than the risk of correspondent schedules constructed in case 14.

6.3.3.4 Conclusion

First, it should be noted that breakdown probabilities are exogenous parameters of aircraft categories that companies can only influence by changing their fleet composition. Therefore, this analysis is preliminary to the analyses conducted in section 6.4 where the impact of the fleet composition is analyzed.
Following conclusions are derived from the above analysis.

1. It is clear that lower breakdown probabilities are highly beneficial for aircraft maintenance planning. The interest in monitoring the status of aircrafts in realtime and using this information in their maintenance planning exists because aircraft maintenance requirements are uncertain over time. Breakdowns occur because of differences in workload over time (e.g. extreme weather conditions, more touchdowns than on average) or simply because Murphy strikes. Therefore, it is clear that every measure that lowers uncertainty in aircraft maintenance requirements is beneficial and thus, low breakdown probabilities amplify the benefit of incorporating failure predictive information in aircraft maintenance planning.

2. The risk inherent to the constructed schedules is much lower due to the decrease of uncertainty in maintenance requirements.

3. Lower breakdown probabilities in combination with the developed optimization procedure result in a high proportion of the total budget invested in performing maintenance. Thus, resources can be used more effectively when using the optimization method in combination with low breakdown probabilities.

6.3.4 Renewable resources availability

In this section, analysis on the impact of renewable resource availabilities on aircraft maintenance planning is conducted. Case 15 has the same characteristics as case 10, with that difference that no renewable resource constraints are implemented. The results of case 15 can be found in the appendix (figure 23).

When the renewable resources are unconstrained, preemption does not occur in any constructed schedule and every triggered maintenance project is scheduled from its first eligible time period on (after the delay periods defined for each aircraft category). As this is the least constrained setting for the corresponding fleet of case 10, the output of case 15 should provide a lower bound on the cost for each schedule and an upper bound on the performance of the failure predictive information and the optimization procedure.

The average number of delayed time periods per maintenance project over all aircrafts (defined in section 6.3.2) is equal to 0. Consequently, the cost for unexpected non-operational aircrafts in the dynamic schedules should be close to zero since these unexpected maintenance projects can be scheduled almost instantaneously. Moreover, average risk inherent to dynamic schedules and the optimized dynamic planning should be lower in case 15 for the same reason. Nevertheless, given that all maintenance projects can be scheduled as early as possible in the preprocessing step, an upper bound on the number of scheduled maintenance projects in case 10 is scheduled in case 15. Therefore, the total maintenance cost is likely to be higher in case 15. On the other hand, no maintenance projects will be anticipated in its strategic planning because this is only done when renewable resources do not allow a strategic maintenance project to be scheduled. Consequently, the number of scheduled maintenance projects in the strategic planning is likely to be higher in case 10 than in case 15. Recall, that no preemption is allowed in the strategic schedules. Furthermore, the dynamic planning is likely to make less use of aircrafts' capacity as no maintenance projects are delayed in case 15. In conclusion, the outcome of case 15 is uncertain and analysis is relevant.

Table 6.19 depict the cost distribution of cases 10 and 15. It is observed that the average number of maintenance projects in the dynamic-based-on-strategic schedules is almost equal in both cases since the cost allocation is the same and the maintenance cost amount to \$780,290.75 and \$785,956.25 in case 10 and 15, respectively. Figures 12 and 23 in the appendix confirm this outcome. Results of case 10 denote that on average 3,753 maintenance projects are scheduled (whereof 590 are anticipated) in the strategic planning whereas for case 15 this amounts to 3,797 maintenance projects. Therefore, the anticipations in the strategic planning of case 10 induced by the renewable resource constraints are countered by the higher number of delayed time periods between maintenance triggering and maintenance being scheduled.

Cost distribution[$]	Case	Average dynamic based on strategic	Average dynamic	Optimized dynamic
Disruption	10	268,578.22	690,325.00	607,650.00
	15	247,671.48	727,650.00	544,650.00
Idle time	10	11,243,514.00	775,000.00	515,900.00
	15	10,247,354.00	7,700.00	27,300.00
Maintenance	10	780,290.75	709,850.00	652,450.00
	15	785,956.25	748,625.00	604,925.00
Schedule cost	10	12,292,383.00	2,175,175.00	1,776,000.00
	15	11,280,981.00	1,483,975.00	1,176,875.00

Table 6.19: Cost distribution [$] - Case 10 & Case 15

The disruption cost difference between the cases is rather small and for reasons elaborated in previous analyses, not relevant for the dynamic-based-on-strategic schedule. In contrast, the cost for unexpected non-operational aircrafts is on average about 10% higher when resources are constrained (case 10) in comparison when no resource constraints are introduced (case 15).

The average cost of unexpected non-operational aircrafts in the dynamic planning of case 15 is 99% lower than the corresponding sub-cost of the corresponding schedule in case 10 ($7,700.00 vs. $775,000.00). Furthermore, as expected, the average total cost of the dynamic planning when resources are unconstrained (case 15) is 32% lower than the average cost observed in case 10.

6.3.4.1 Performance measure 1: Value of failure predictive information

In the analysis of case 10 (section 6.3.1), it was observed that incorporating failure predictive information in aircraft maintenance planning resulted in a cost decrease of 82% in the dynamic planning compared to following the strategic planning without any decision making on the tactical level. In case 15, the value of incorporating failure predictive information in aircraft maintenance planning amounts to 90%. It is clear that the higher number of scheduled maintenance projects in the unconstrained setting does not outweigh the benefit of maintenance projects being scheduled without any delay (case 15).

6.3.4.2 Performance measure 2: Value of the optimization procedure

The value of the optimization procedure in case 15 (unconstrained) is 3% higher than in case 10 (18% vs. 21%). This difference is due to the fact that the optimized dynamic planning in the unconstrained case has more degrees of freedom.

As the cost of unexpected non-operational aircrafts was as low as possible in the unconstrained dynamic planning (because only the delay periods inherent to the flights of aircrafts were incorporated), the higher performance of the optimization method in case 15 is due to the higher decrease in disruption and maintenance cost compared to the correspondent decreases in the constrained setting (case 10). Consequently, the optimized dynamic planning is 51% cheaper in this unconstrained setting compared to the optimized dynamic planning in case 10. This is due to the higher degrees of freedom in the constructed optimized dynamic planning when resources are unconstrained. The results displayed in figure 23 in the appendix report 303 swaps being performed by the optimization method: 173 anticipations and 130 delays. The delays increase the cost for unexpected non-operational aircrafts, but also decrease the disruption cost. Accordingly, the anticipations increase the maintenance cost and decrease the disruption cost. In total, the combination of all these swaps resulted in decrease of the total schedule cost of \$326,700.00 by increasing the use of the aircrafts' capacities (i.e. decrease in total maintenance and disruption cost) and an increase of \$19,600.00 by exceeding these capacities (i.e. increase in total non-operational cost).

The resulting total schedules costs distributions over the three sub-costs (disruption, cost for unexpected non-operational aircrafts and maintenance) are depicted in table 6.20.

Cost distribution[%]	Case	Average dynamic based on strategic	Average dynamic	Optimized dynamic
Disruption	10	2%	32%	34%
	15	2%	49%	46%
Idle time	10	91%	36%	29%
	15	91%	1%	2%
Maintenance	10	6%	33%	37%
	15	7%	50%	51%

Table 6.20: Cost distribution [%] - Case 10 & Case 15

It is observed that the disruption and the maintenance cost take up both around 50% of the total budget both in the dynamic and the optimized dynamic planning when resources are unconstrained (case 15). As in previous analyses, this is due to the fact that one time period of disruption incurs the same cost as one period of maintenance.

Case	Average dynamic based on strategic	Average dynamic	Optimized dynamic
10	133,855.38	20,251.47	23,271.52
15	112,765.3	12,817.91	15,920.32

Table 6.21: Risk units - Case 10 & Case 15

6.3.4.3 Performance measure 3: Risk inherent to the schedules

As expected, risk as defined in this research (cfr. supra) is much smaller when resources are unconstrained because maintenance never has to be delayed. The cost benefit of the proactive measures undertaken in the optimized dynamic planning does increase its risk by 24%.

6.3.4.4 Conclusion

In conclusion, it has been observed that maximizing capacity usage of aircrafts is preferred but not against all cost. In an unconstrained setting, the optimized dynamic planning only allocates 2% of its total investment in maintenance to handling unexpected non-operational aircrafts whereof 30% is fixed to the delay induced by in-flight maintenance triggering. Therefore, as concluded in the analysis of Δ critical values for p_{mt}, companies should carefully manage their renewable resource availabilities and invest in flexibility of these renewable resource availabilities.

6.4 Fleet composition

In the base case fleet, each aircraft category (appendix, figure 6) is represented evenly for generalization purposes. In the remainder of this research, analyses are conducted to investigate the impact of the fleet composition on the performance of incorporating failure predictive information in aircraft maintenance planning. First, extreme fleet compositions are subject of discussion. Second, two realistic fleet compositions are researched: the fleet of a low-cost carrier and a premium economy airline.

6.4.1 Extreme fleet composition analysis

In this analysis, the impact of the age of the aircrafts and the flight durations of these aircrafts is investigated. Six cases with extreme fleet compositions are constructed in that these fleet consist of solely one aircraft category. The aircraft category of each case is depicted in table 6.22. Other characteristics remain as in the base case constructed in section 6.3. The results for cases 16 up and until 21 are depicted in the appendix (figures 24 up and until 29).

Age/Flight duration	Old	New
Short	Case 16	Case 17
Mid	Case 18	Case 19
Long	Case 20	Case 21

Table 6.22: Extreme fleet composition analysis - Cases 16 up and until 21

Tables 6.23, 6.25 and 6.27 display the cost distributions of cases in which 100% of the fleet is composed out of, respectively, short, mid and long flight duration aircraft categories. In each table, the left side cases' fleet are old whereas on the right side, all cases' fleet are new. The proportional cost distributions over the three sub-costs (disruption, unexpected non-operational aircrafts and maintenance) are depicted in corresponding tables 6.24, 6.26 and 6.28.

First, the impact of the aircrafts' age is determined and afterwards, impact of the flight duration on the performance of the schedules is investigated. At last, these analyses are combined to conclude on the impact of the fleet age and flight duration on incorporating failure predictive information in aircraft maintenance planning. However, before continuing this analysis, the general characteristics of all nine categories are recapitulated.

As aircrafts with short flight durations perform more flights per time period than aircrafts with longer flight durations, the values for p_{mt} increase faster when flight durations are lower. This is due to the fact that the workload an aircraft endures does not only consist out of operating hours, but also include other factors such as number of touchdowns, take-offs, etc.

Cost distribution [$]	Case 16			Case 17		
Schedule type	Average dynamic based on strategic	Average dynamic	Optimized dynamic	Average dynamic based on strategic	Average dynamic	Optimized dynamic
Disruption	437,069	1,083,975	1,056,225	157,110	496,375	377,900
Idle time	11,420,948	4,170,300	3,662,300	13,092,283	170,400	116,700
Maintenance	1,182,091	1,124,425	1,102,575	513,853	505,450	413,325
Schedule	13,040,109	6,378,700	5,821,100	13,763,247	1,172,225	907,925

Table 6.23: Cost distribution [$] - Cases 16 & Case 17

Cost distribution [%]	Case 16			Case 17		
Schedule type	Average dynamic based on strategic	Average dynamic	Optimized dynamic	Average dynamic based on strategic	Average dynamic	Optimized dynamic
Disruption	3%	17%	18%	1%	42%	42%
Idle time	88%	65%	63%	95%	15%	13%
Maintenance	9%	18%	19%	4%	43%	46%

Table 6.24: Cost distribution [%] - Cases 16 & Case 17

Cost distribution [$]	Case 18			Case 19		
Schedule type	Average dynamic based on strategic	Average dynamic	Optimized dynamic	Average dynamic based on strategic	Average dynamic	Optimized dynamic
Disruption	470,893	915,325	885,725	152,040	441,175	329,225
Idle time	11,236,478	2,392,300	2,062,900	12,506,103	128,900	113,900
Maintenance	1,067,387	946,375	920,625	479,496	447,200	360,150
Schedule	12,774,758	4,254,000	3,869,250	13,137,638	1,017,275	803,275

Table 6.25: Cost distribution [$] - Cases 18 & Case 19

Cost distribution [%]	Case 18			Case 19		
Schedule type	Average dynamic based on strategic	Average dynamic	Optimized dynamic	Average dynamic based on strategic	Average dynamic	Optimized dynamic
Disruption	4%	22%	23%	1%	43%	41%
Idle time	88%	56%	53%	95%	13%	14%
Maintenance	8%	22%	24%	4%	44%	45%

Table 6.26: Cost distribution [%] - Cases 18 & Case 19

Cost distribution [$]	Case 20			Case 21		
Schedule type	Average dynamic based on strategic	Average dynamic	Optimized dynamic	Average dynamic based on strategic	Average dynamic	Optimized dynamic
Disruption	390,333	855,850	806,275	143,373	411,375	309,075
Idle time	9,591,821	1,962,900	1,653,800	12,153,575	112,400	91,200
Maintenance	970,312	880,275	838,475	459,980	417,425	340,450
Schedule	10,952,466	3,699,025	3,298,550	12,756,928	941,200	740,725

Table 6.27: Cost distribution [$] - Cases 20 & Case 21

Cost distribution [%]	Case 20			Case 21		
Schedule type	Average dynamic based on strategic	Average dynamic	Optimized dynamic	Average dynamic based on strategic	Average dynamic	Optimized dynamic
Disruption	4%	23%	24%	1%	44%	42%
Idle time	88%	53%	50%	95%	12%	12%
Maintenance	9%	24%	25%	4%	44%	46%

Table 6.28: Cost distribution [%] - Cases 20 & Case 21

Consequently, more maintenance projects are scheduled over the same planning horizon in a fleet maintenance planning for which the proportion of aircrafts with short flight durations is higher. Therefore, all resources constraints equal, degrees of freedom in the constructed schedules of each case are as follows:

$$df_{20} > df_{18} > df_{16} \text{ and } df_{21} > df_{19} > df_{17}$$

Moreover, breakdown probabilities are lower when aircrafts are younger. Hence, younger aircrafts incur less unexpected maintenance projects. Furthermore, p_{mt} increases slower when aircrafts are younger because their maintenance requirements are lower due to technological improvement of the aircrafts over time. As a consequence, the effect of lower breakdown probabilities on the number of scheduled maintenance projects is even amplified. Therefore, difference in degrees of freedom in the constructed scheduled of each case are as follows:

$$df_{21} > df_{20} \text{ and } df_{19} > df_{18} \text{ and } df_{17} > df_{16}$$

Critical values for p_{mt} decrease as aircrafts are older and flight durations are longer. In correspondence with the critical values for p_{mt} depicted in the appendix (figure 6), these are as follows:

$$p_{mt}^{critical}(17) > p_{mt}^{critical}(19) > p_{mt}^{critical}(21) > p_{mt}^{critical}(16) > p_{mt}^{critical}(18) > p_{mt}^{critical}(20)$$

Analysis on these critical values for p_{mt} (section 6.3.2) revealed that lower critical values incur more maintenance projects in the constructed schedules. As available renewable resources are equal in all cases, it has been established that the degrees of freedom in the constructed schedules are lower when critical values for p_{mt} are lower. Therefore, effect of the critical values for p_{mt} on the degrees of freedom in the constructed schedules is:

$$df_{17} > df_{19} > df_{21} > df_{16} > df_{18} > df_{20}$$

It is clear that characteristics of aircrafts in the fleet composition have contradictory influence on the degrees of freedom in the constructed schedules such that the effect of the flight duration is not in correspondence with their influence on the critical values (e.g. $df_{20} > df_{18}$ vs. $df_{18} > df_{20}$). In this analysis, the impact of these interdependent effects is analyzed.

6.4.1.1 Impact of the aircrafts' age

For each of the flight durations, the dynamic-based-on-strategic schedule for a fleet composed of old aircrafts is cheaper than the correspondent schedule for a fleet composed of new aircrafts. The reason is that the number of maintenance projects scheduled when aircrafts are younger (because their capacity is higher) is lower and, consequently, unexpected non-operational aircrafts have to wait longer before maintenance is performed. Therefore, even when breakdown probabilities are lower, due to uncertainty following the strategic planning with no decision making on the tactical level results in a negative effect on the total maintenance cost of a young fleet.

For each comparison between cases for which the flight duration is equal, the constructed schedules incorporating failure predictive information for companies with a younger fleet are significantly cheaper than the correspondent schedules for companies with an older fleet. The absolute cost decrease of the average dynamic planning and the optimized dynamic planning (in comparison with the dynamic-based-on-strategic schedule) because of younger fleet composition is depicted in table 6.29. It becomes clear that the advantage is higher for companies which perform short flights. Note that the interaction effect between the critical values for p_{mt} (higher for younger aircrafts) and the renewable resource constraints (equal in all cases) is present.

Schedule type/Flight duration	Average dynamic	Optimized dynamic
Short	-82%	-84%
Mid	-76%	-79%
Long	-75%	-77%

Table 6.29: Decrease of total schedule costs due to younger fleet composition [%]

Further, the proportion of the total budget spent on unexpected non-operational aircrafts is far lower for companies that have a younger fleet (63% in case 16 vs. 13% in case 17). Again, the proportion of the investment in maintenance allocated to handling disruption and performing maintenance are close to equal (respectively 18% and 19% in case 16 & 42% and 46% in case 17). Consequently, this cost decrease is beneficial cost-efficient maintenance in that a higher proportion of the total budget is invested in performing maintenance (19% in case 16 vs. 46% in case 17).

6.4.1.2 Impact of flight durations

In increasing order of flight duration, the total schedule costs and correspondent sub-costs decrease for older as well as younger fleets. Except the disruption cost in the average dynamic-based-on-strategic schedule is lower for older fleets with short flights ($437,069 in case 16) than for older fleets with mid-long flights ($470,893 in case 18). As explained in previous analyses, this sub-cost is irrelevant in this schedule given that this cost is incurred because of the deviations in maintenance durations in the dynamic-based-on-strategic planning from the average maintenance duration used in the strategic planning.

The total schedule cost distributions over the sub-costs depicted in tables 6.24, 6.26 and 6.28 reveal that the impact of the flight duration on the cost effeciency of the schedules is higher for older fleets than for younger fleets as the proportion of the budget allocated to handling unexpected non-operational aircrafts in the average dynamic planning is 65%, 56% and 53% in, respectively, cases 16, 18 and 20 vs. 15%, 13% and 12% in, respectively, cases 17, 19 and 20. In the optimized dynamic planning, these figures are accordingly: 63%, 53% and 50% in, respectively, cases 16, 18 and 20 vs. 13%, 14% and 12% in, respectively, cases 17, 19 and 21. Consequently, cost efficiency is more sensitive to differences in flight duration when fleets are older than when they are younger.

6.4.1.3 Performance measure 1: Value of failure predictive information

Table 6.30 shows the values of the first performance measure for each of the fleet compositions.

Fleet age/Flight duration	Old	New
Short	51%	91%
Mid	67%	92%
Long	66%	93%

Table 6.30: Performance measure 1: Value of incorporating failure predictive information i.f.o. fleet composition

It is observed that longer flight durations and younger aircrafts increase the value of failure predictive information. Consequently, the contradictory influence of the critical values for p_{mt}, breakdown probabilities and speed at which p_{mt} increases on the degrees of freedom in the constructed schedules does not outweigh the benefit of incorporating failure predictive information in aircraft maintenance planning for younger fleets with long flight durations.

6.4.1.4 Performance measure 2: Value of the optimization method

The value of the optimization method as shown in table 6.31, reveals that flight duration has almost no influence on its performance. In contrast, the age of the fleet does have a significant impact. Where younger aircrafts already resulted in greater cost savings of incorporating failure predictive information compared to older aircrafts, the optimization method further increases this cost benefit difference. For fleets with short flights, younger aircrafts result in a total schedule cost decrease of 93% ($907,925 vs. $13,763,247 in case 17) whereas a cost decrease of 55% was obtained for fleets with older aircrafts ($5,821,100 vs. $ 13,040,109 in case 16). Therefore, the benefit of investment in younger aircrafts is further magnified by using the developed optimization method in combination with the use of failure predictive information in aircraft maintenance planning. These savings are proportional to the savings of incorporating failure predictive information. In conclusion, investing in realtime data monitoring of aircrafts (uncertainty decrease) becomes more beneficial when the maintenance requirements of these aircrafts are less uncertain.

Fleet age/Flight duration	Old	New
Short	9%	23%
Mid	9%	21%
Long	11%	21%

Table 6.31: Performance measure 2: Value of the optimization method i.f.o. fleet composition

6.4.1.5 Performance measure 3: Risk inherent to the schedules

In this section, the risk inherent to the constructed schedules in each case as depicted in table 6.32 is analyzed.

Age/Flight duration	Old			New		
Schedule type	Average dynamic based on strategic	Average dynamic	Optimized dynamic	Average dynamic based on strategic	Average dynamic	Optimized dynamic
Short	104,201	46,531	46,346	88,706	5,344	8,648
Mid	119,730	43,337	44,596	99,974	8,550	11,793
Long	139,426	47,007	48,055	111,256	11,645	17,023

Table 6.32: Risk of the schedules i.f.o. fleet composition

Except for the average risk inherent to the dynamic planning of aircrafts with mid flight duration (43,337), all observed incurred risk units increase when flights are longer, and aircrafts are older. As available renewable resources are equal in all cases, the constructed schedules of all cases have different degrees of freedom as elaborated in section 6.4.1. Because critical values for p_{mt} differ over all cases, comparison of these values is biased. Adjusted risk units should be calculated for each case with the critical values for p_{mt} of all other cases. This would lead to a full factorial comparison and is not relevant in the scope of this research as the definition of risk in this research is constructed such that older aircrafts which perform longer flights are inherently riskier.

6.4.1.6 Conclusion

Investment analysis within the aviation industry has not yet incorporated the influence of failure predictive information to determine whether or not an investment should be made. This analysis results in several conclusions of what the impact of the fleet composition on the benefit of incorporating failure predictive information in aircraft maintenance planning is.
Today, the benefit of investing in younger aircrafts is limited to savings due to technological improvements such as lower fuel consumption, more comfort, less breakdowns and lower maintenance requirements. When companies set up the infrastructure to incorporate failure predictive information in aircraft maintenance planning, additional benefits are identified.

1. Companies which perform more short flights, benefit the most of investing in younger aircrafts in combination with incorporating realtime data on the status of their fleet in their maintenance planning.

2. By implementing a proactive optimization method such as the one developed in this research, the proportional additional cost decreases over the ones already realized by investing in failure predictive information in combination with a younger fleet are found to be more than twice as high for younger fleets in comparison with older fleets. Investment in an uncertainty decrease by monitoring aircrafts' statuses becomes more beneficial when these aircrafts' statuses are less uncertain. Consequently, companies should leverage the incorporation of failure predictive information in aircraft maintenance planning by investing in advanced decision making tools.

6.5 Airline categories

In this section, analysis is conducted on two types of airline categories: a low-cost carrier which offers more national and international flights and a premium economy carrier which provides international and intercontinental flights. All previously defined aircraft categories are used and all but following differences for both airlines, depicted in table 6.33, are equal to the base case (case 10).

Airlines	Low-cost carrier	Premium economy carrier
Number of aircrafts	150	50
Available renewable resources	300%	100%
Disruption cost	25	50
Non-operational cost	100	200
Old - short	40%	
Used - short	40%	20%
Used - mid	20%	20%
New - mid		40%
New - long		20%

Table 6.33: Differences of airlines categories w.r.t. base case (case 10)

As the fleet of the low-cost carrier case contains 150 aircrafts, whereas the premium economy case contains 50 aircrafts, the renewable resources availability is three times as high as well. Further, the premium economy carrier is assumed to provide higher service to its customers and, therefore, a higher cost for unexpected non-operational aircrafts and disruption is defined. The fleet compositions are adjusted to its quality standards (age of the aircrafts) and the distances the aircrafts travel (flight durations).
Given that the number of aircrafts in the fleet and the cost allocations are different in both cases, only the previously defined performance measures are analyzed.

6.5.1 Performance measure 1: Value of failure predictive information

The value of incorporating failure predictive information in aircraft maintenance planning compared to following the strategic planning without any decision making on the tactical level, result in a cost decrease of respectively, 77% and 91% in the low-cost carrier and the premium economy case. As elaborated in previous analyses, characteristics of a younger fleet are such that the aircrafts have more capacity and that more of this capacity can be used due to a decrease in uncertainty of the aircrafts themselves.

6.5.2 Performance measure 2: Value of the optimization method

It has been concluded in previous analyses that the cost decrease because of the proactive measures undertaken by the developed optimization method is leveraged by the cost decrease realized by incorporating failure predictive information in aircraft maintenance planning. This is confirmed by the results of both cases where the optimization method realizes a cost decrease of 20% for the low-cost carrier (for which performance measure one is 77%), it realizes a cost decrease of 25% for the premium economy airline (for which performance measure one is 91%). Consequently, when the low-cost carrier implements both methods, a cost decrease of 82% is observed whereas the premium economy carrier gains 91%.

6.5.3 Performance measure 3: Risk inherent to the schedules

As the number of aircrafts in the fleets of both carriers is different, the risk is displayed (in table 6.34) in comparison with the initial amount of risk units incurred in the dynamic-based-on-strategic planning of each case. No comparison can be made between both carriers.

Case	Average dynamic based on strategic	Average dynamic	Optimized dynamic
22	100%	17%	18%
23	100%	11%	14%

Table 6.34: Risk units [%] - Case 22 & Case 23

As denoted in section 6.5.1, the fleet composition of the premium economy carrier (younger aircrafts) forces the dynamic schedules inherently to make more use of the aircrafts' capacity compared to the fleet composition of the low-cost carrier. Consequently, the procedure is able to gain more risk savings in comparison with the dynamic-based-on-strategic schedule for the premium economy carrier than for the low-cost carrier.

6.5.4 Conclusion

As the competitive and investment strategies of the low-cost carrier and the premium economy airline induce other fleet compositions (both aircraft age and flight durations), a comparison of the performance of failure predictive information and the optimization method in both cases is not of interest, but the individual results are. It has been established that incorporating failure predictive information in maintenance planning together with proactive measures based on historical data and realtime data on the status of aircrafts in airline fleets are significant no matter what the characteristics of the airline and its fleet are. Consequently, all airlines' investment strategies should be including analysis of investment in infrastructure and resource flexibility to facilitate these methods.

Chapter 7

Conclusions and recommendations

The third industrial revolution, the digitalization, gave rise to new communication systems of which the Internet is without any doubt the most memorable one. It has been enabling people to share and consult information instantaneously, anywhere and anytime. In the past decade, the fourth industrial revolution has been initiated: The Internet of things (IoT). Physical devices and everyday objects are connected to each other via the Internet and communicate with each other without human interference. As it has been doing in various industries, IoT has commenced to reshape business processes within the aviation industry as well. More and more aviation machinery manufacturers and service providers have been equipping their products with hard- and software that enables realtime data monitoring of the status of machines. This information can be used to better match maintenance requirements with the companies' operational requirements. However, two case studies within the industry revealed that currently, limited use is made of these opportunities. In order for the industry to adopt these technologies within their business processes, more research on frameworks for data acquisition, data processing and maintenance decision making is necessary. In this master's dissertation, an attempt has been made to construct a framework for the incorporation of failure predictive information in maintenance planning in the aviation industry from a project management perspective and to quantify the impact of deploying such a framework. Primary focus has been on aircraft maintenance planning. Nevertheless, conclusions can be extrapolated for other aviation machinery.

Based on the findings of the case studies, a theoretical framework has been constructed which has served as the foundation for the developed maintenance planning procedure. This planning procedure is a heuristic approach that constructs schedules on both the strategic and the tactical level based on realtime failure predictive data of each aircraft in the fleet. In this research, a cost minimization objective has been formulated. Consequently, three costs have been defined: (1) a disruption cost, (2) a non-operational cost and (3) a maintenance cost. The disruption cost reflects the administrative costs of adjusting business processes to developments in the maintenance planning on a tactical level. When aircrafts become idle unexpectedly, the non-operational cost incurs. The cost of performing the maintenance requirements is reflected in the maintenance cost. The procedure generates three schedules: (1) a strategic planning, (2) a dynamic planning and (3) a dynamic planning based on the strategic planning. The latter is the representation of following the strategic planning without any decision making on the day-to-day tactical level. This schedule has been generated in order to quantify the impact of failure predictive information in aircraft maintenance planning. Furthermore, an optimization method has been developed which optimizes the constructed dynamic planning based on the cost objective. In a practical setting, this method could serve as a maintenance decision making tool. The performance of all constructed schedules is quantified by three performance measures: (1) value of failure predictive information, (2) value of the optimization procedure and (3) risk inherent to the schedules.

It has been established that given the high cost of an unexpected non-operational aircraft, it is highly profitable to monitor the status of critical components and, moreover, to use this status in the planning process of the aircrafts' maintenance requirements. Cost reductions of 75% up to 90% have been observed. Furthermore, the risk inherent to maintenance planning using realtime information on the aircrafts' status, is up to five times smaller than when the strategic planning in followed. Results showed that the optimization method is robust towards all cost allocations (disruption, non-operational and maintenance) and realizes further cost reductions of 15% up to 23%.

Analysis of the age (young to old) and the flight durations (national to cross-continental) of the aircrafts in the fleet revealed that aviation companies should include the opportunities of using failure predictive information in aircraft maintenance planning leveraged by smart decision making tools in their investment analysis. Furthermore, it has been established that these benefits are proportionally higher for younger aircrafts and shorter flight durations. This is the result of the decrease in maintenance requirements uncertainty as aircrafts are younger and flight durations are shorter. It has to be noted that these benefits are only realized if companies cautiously manage their renewable resource availabilities and particularly, invest in the flexibility of these renewable resource availabilities. In combination with investments in infrastructure that enable aircraft status monitoring and consistent day-to-day decision making, companies are able to increase competitiveness by decreasing costs and increasing customer satisfaction. All results have been validated in a theoretical setting for a low cost carrier and a premium economy airline.

Future research should validate the proposed framework in practical settings. Therefore, more research on the implementation of failure predictive data monitoring in aircraft maintenance in integrated airline scheduling frameworks has to be conducted. Furthermore, further research on the aggregation of failure predictive data of several components in one failure predictive parameter of a machine has to be done. Finally, extrapolation of the proposed framework to other industries has to be analyzed.

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Appendices

.1 Case study 2: Dissertation GSE services

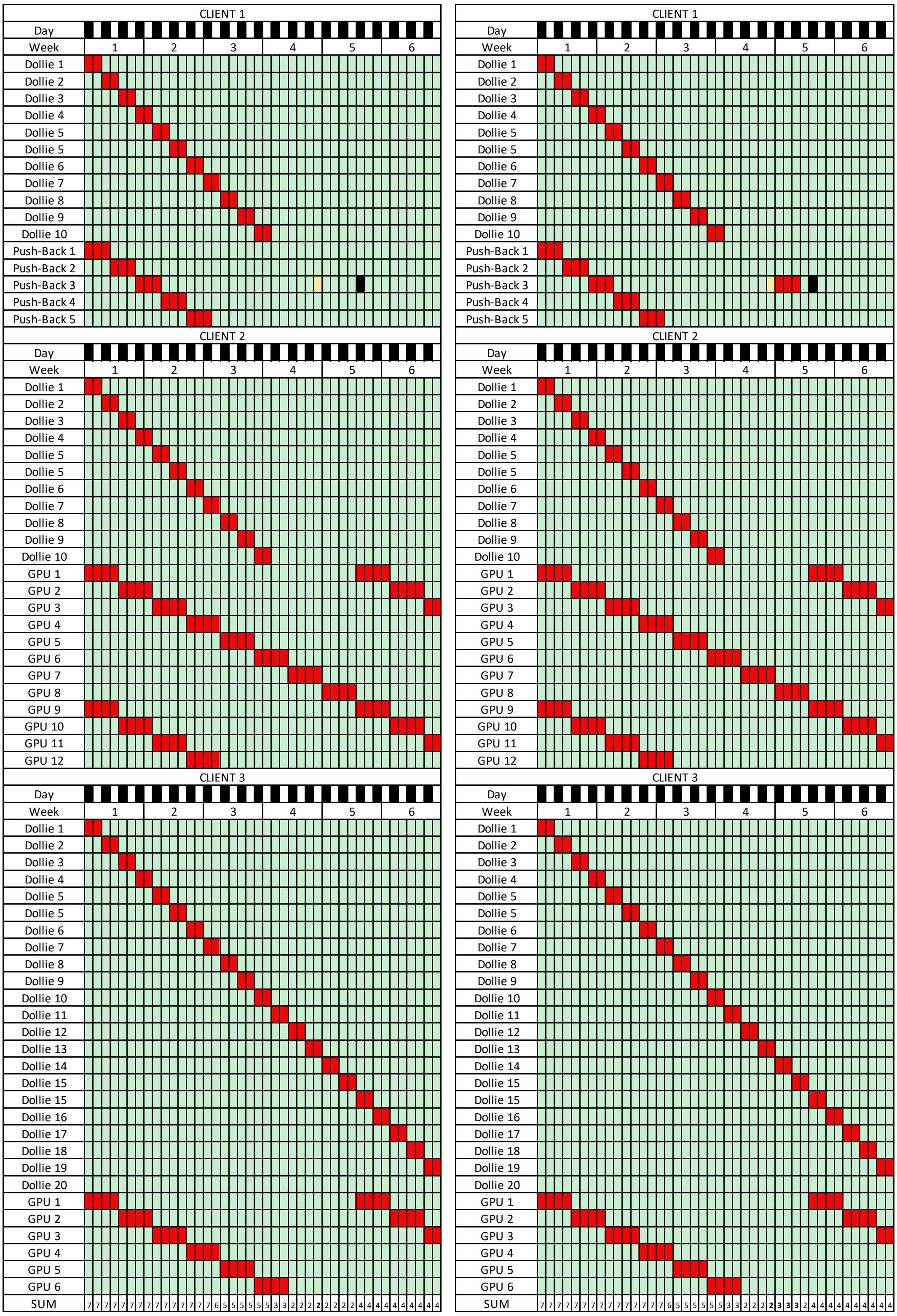

Figure 1: Scenario 1

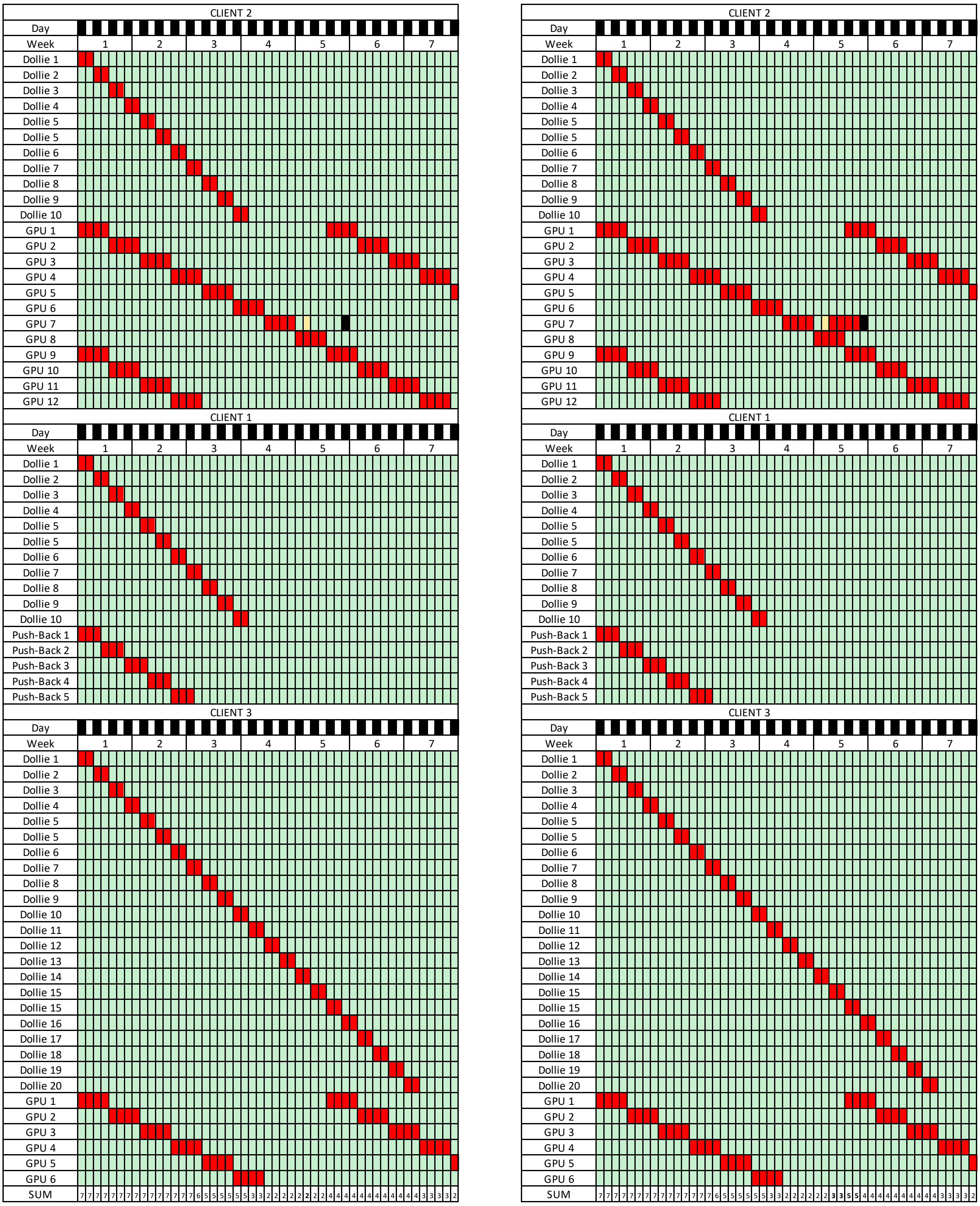

Figure 2: Scenario 2

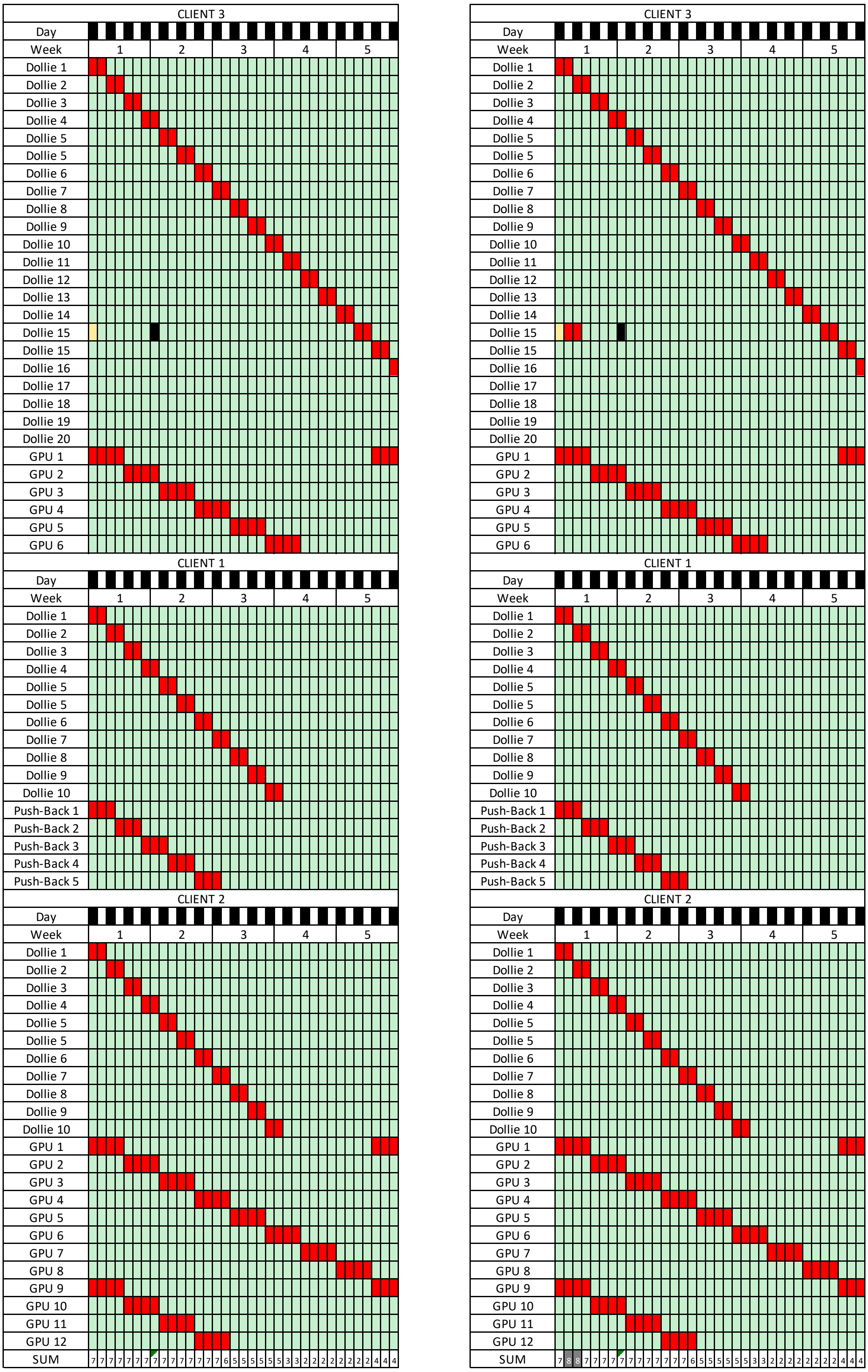

Figure 3: Scenario 3 - resource constraint violated

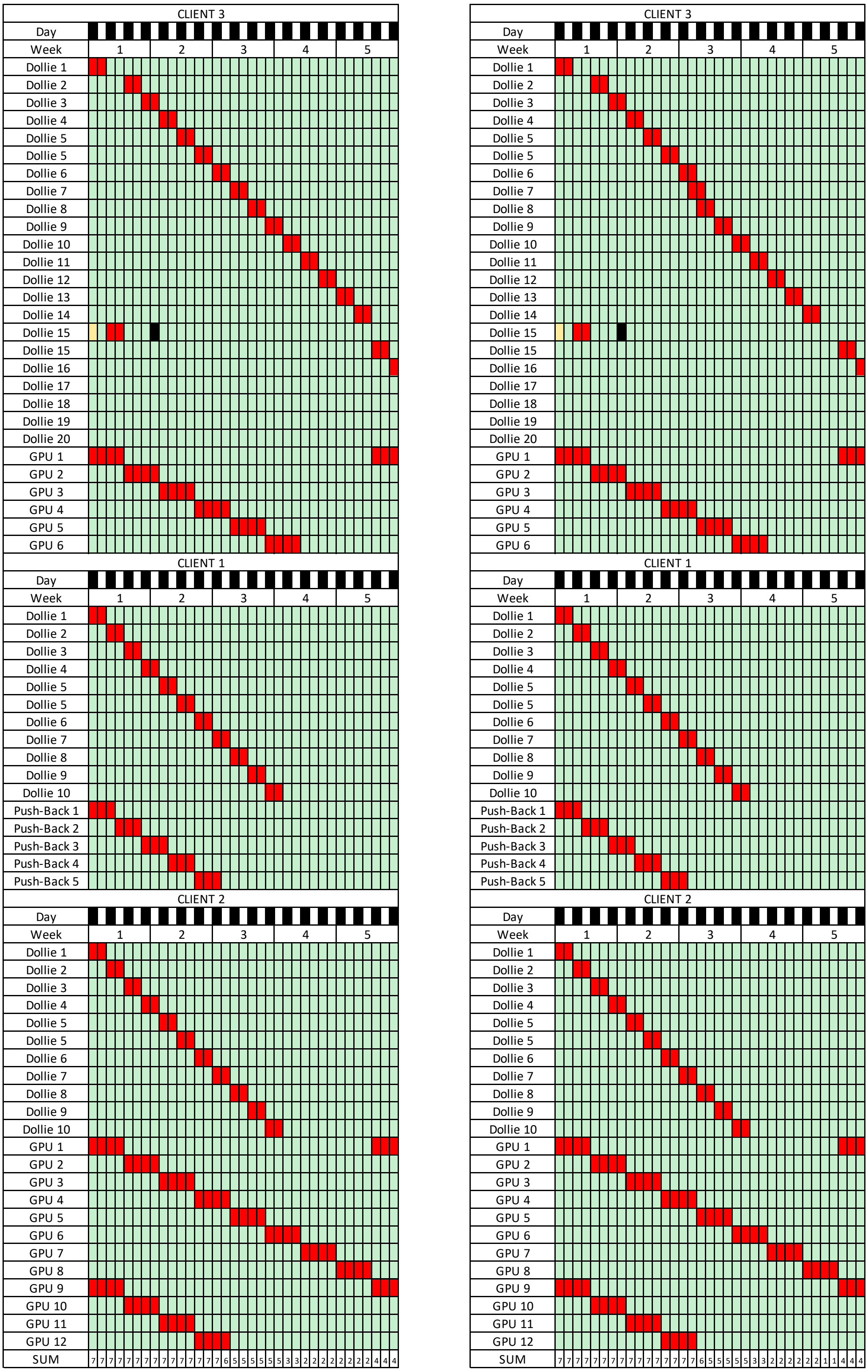

Figure 4: Scenario 3 - left: delay maintenance for dollies 2 up to and including dollie 14 of client 3 - right: delay maintenance for dollies 2 up to and including dollie 7 of client 3 but violation of the operational level

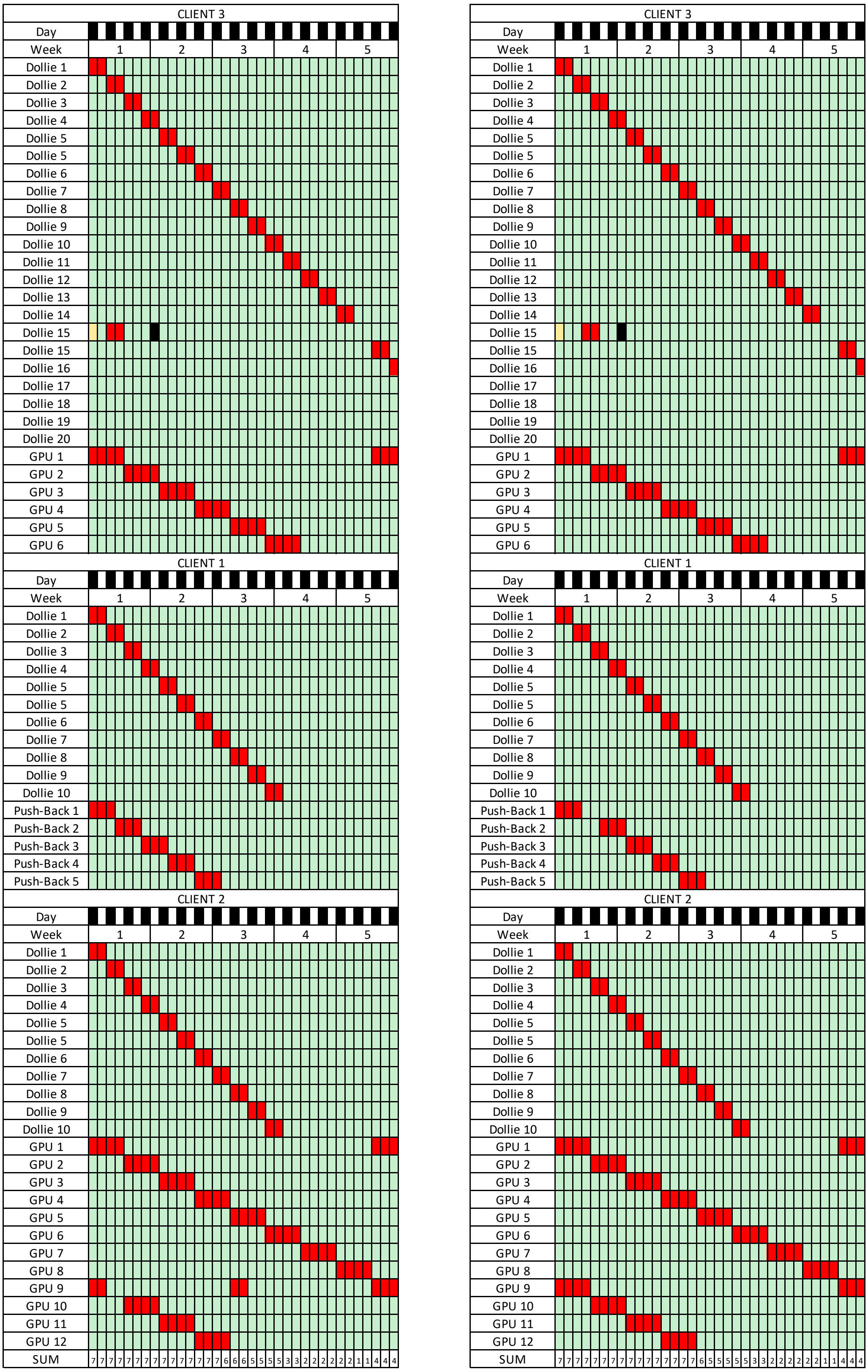

Figure 5: Scenario 3 - left: partly delay maintenance for GPU 9 of client 2 - right: delay maintenance for push-back truck 2 of client 1

.2 Heuristic development

Category	*1*		*2*		*3*		*4*		*5*		*6*	
Age of aircraft	*old*		*old*		*old*		*used*		*used*		*used*	
Flight duration	*short*		*mid*		*long*		*short*		*mid*		*long*	
Parameter	A	B	A	B	A	B	A	B	A	B	A	B
p_{mt} generation												
- linear	0	0.00666667	0	0.00440278	0	0.00297348	0	0.00354167	0	0.00234722	0	0.00159091
- exponential	1.00212954	0	1.0014091	0	1.00095363	0	1.00111384	0	1.00073915	0	1.00050167	0
- random	0	0.01333333	0	0.00880556	0	0.00594697	0	0.00708333	0	0.00469444	0	0.00318182
Critical p_{mt}	0.8		0.7925		0.785		0.85		0.845		0.84	
Breakdown probability	0.01		0.01		0.01		0.0075		0.0075		0.0075	
Work content generation												
- linear	20	30	20	30	20	30	15	25	15	25	15	25
- exponential	30	20	30	20	30	20	25	15	25	15	25	15
- random	20	50	20	50	20	50	15	40	15	40	15	40
Delay periods	2		4		6		2		4		6	

Category	*7*		*8*		*9*	
Age of aircraft	*new*		*new*		*new*	
Flight duration	*short*		*mid*		*long*	
Parameter	A	B	A	B	A	B
p_{mt} generation						
- linear	0	0.001875	0	0.00149167	0	0.00123611
- exponential	1.00058091	0	1.00046279	0	1.00038405	0
- random	0	0.00375	0	0.00298333	0	0.00247222
Critical p_{mt}	0.9		0.895		0.89	
Breakdown probability	0.005		0.005		0.005	
Work content generation						
- linear	10	20	10	20	10	20
- exponential	20	10	20	10	20	10
- random	10	30	10	30	10	30
Delay periods	2		4		6	

Figure 6: Aircraft categories

```
exponential
1.002129535     0.05    0.01
1.001409098     0.05    0.01
1.000953629     0.05    0.01
1.001113835     0.05    0.0075
1.000739152     0.05    0.0075
1.000501675     0.05    0.0075
1.000580905     0.05    0.005
1.000462789     0.05    0.005
1.000384048     0.05    0.005
0.8
0.7925
0.785
0.85
0.845
0.84
0.9
0.895
0.89
2
4
6
2
4
6
2
4
6
linear
20      30
20      30
20      30
15      25
15      25
15      25
10      20
10      20
10      20
fixed
9       17
30      20
30      20
30      20
30      20
30      20
10      5
10      5
100     100     100
```

```
Distribution for pmt generation & breakdown probability for each machine
a1      b1      p(breakdown)1
a2      b2      p(breakdown)2
a3      b3      p(breakdown)3
a4      b4      p(breakdown)4
a5      b5      p(breakdown)5
a6      b6      p(breakdown)6
a7      b7      p(breakdown)7
a8      b8      p(breakdown)8
a9      b9      p(breakdown)9
Critical value of pmt for each machine
c1
c2
c3
c4
c5
c6
c7
c8
c9
Number of delay periods for each machine
d1
d2
d3
d4
d5
d6
d7
d8
d9
Distribution for work content generation
e1      f1
e2      f2
e3      f3
e4      f4
e5      f5
e6      f6
e7      f7
e8      f8
e9      f9
Resource availability for each day of the week
start hour day shift            start hour night shift
sd1                             sn1
sd2                             sn2
sd3                             sn3
sd4                             sn4
sd5                             sn5
sd6                             sn6
sd7                             sn7
sd8                             sn8
sd9                             sn9
Disruption cost         Non-operational cost            Maintenance cost
```

Figure 7: Example case input file (left: actual input file - right: textual elucidation)

interval days	old			used			new		
flight duration	short	mid	long	short	mid	long	short	mid	long
days	5	7.5	11	10	15	22	20	25	30
critical pmt	old			used			new		
flight duration	short	mid	long	short	mid	long	short	mid	long
critical pmt	0.8	0.7925	0.785	0.85	0.845	0.84	0.9	0.895	0.89
interval hours	old			used			new		
flight duration	short	mid	long	short	mid	long	short	mid	long
hours	120	180	264	240	360	528	480	600	720
pmt generation	old			used			new		
flight duration	short	mid	long	short	mid	long	short	mid	long
linear	0.00666667	0.00440278	0.00297348	0.00354167	0.00234722	0.00159091	0.001875	0.00149167	0.00123611
exponential	1.00212954	1.0014091	1.00095363	1.00111384	1.00073915	1.00050167	1.00058091	1.00046279	1.00038405
random	0.01333333	0.00880556	0.00594697	0.00708333	0.00469444	0.00318182	0.00375	0.00298333	0.00247222

Figure 8: Distribution parameters

/Users/baptistebovyn/Documents/Masterproef/Data_generation/Stats_Case_1.txt
File build on Tue Apr 30 15:39:23 2019

Number of machines:	54
Time periods:	17520
Disruption cost:	100
Non-operational cost:	100
Maintenance cost:	100

Average cost of dynamic based on strategic:	$15,254,910.00

Average cost of dynamic planning:	$6,556,100.00
Percentage (average dynamic cost/dynamic based on strategic average cost):	43%

Cost of optimised dynamic planning:	$5,381,300.00
Percentage (optimised dynamic cost/dynamic based on strategic average cost):	35%
Percentage (optimised dynamic cost/average dynamic cost):	82%

Number of maintenance projects strategic on time:	3080
Number of maintenance projects strategic anticipated:	679
Average number of maintenance projects dynamic based on strategic:	3760
Average number of maintenance projects dynamic planning:	3621
Number of maintenance projects optimised:	3172
Number swaps:	257
Number anticipations:	138
Number delays:	119

Cost distribution[%]	Average dynamic based on strategic	Average dynamic	Optimised dynamic
Disruption	8%	43%	41%
Idle time	72%	14%	16%
Maintenance	21%	44%	44%

Cost distribution[$]	Average dynamic based on strategic	Average dynamic	Optimised dynamic
Disruption	$1,161,789.88	$2,799,100.00	$2,180,800.00
Idle time	$10,958,914.00	$887,000.00	$835,700.00
Maintenance	$3,134,204.25	$2,870,000.00	$2,364,800.00
Sum costs	$15,254,910.00	$6,556,100.00	$5,381,300.00

Risk units	113139.9375	20769.47266	24008.12695

Cost of strategic planning:	$1,839,700.00
Percentage (strategic cost/dynamic based on strategic average cost):	12%
Percentage (strategic cost/average dynamic cost):	28%
Percentage (strategic cost/optimised dynamic cost):	34%

Figure 9: Results Case 1

.3 Analyses

Case	1	2	3	4	5	6	7	8	9	10	11	12
Number of machines	54	54	54	54	54	54	54	54	54	54	54	54
Time periods	17520	17520	17520	17520	17520	17520	17520	17520	17520	17520	17520	17520
p_{mt} generation	exponential	exponential	exponential	exponential	exponential	exponential	exponential	exponential	exponential	exponential	exponential	exponential
Work content generation	linear	linear	linear	linear	linear	linear	linear	linear	linear	linear	linear	linear
Number dynamic schedules	10	100	1000	10000	10	10	10	10	10	10	10	10
Number dynamic based on strategic	10	100	1000	10000	10	10	10	10	10	10	10	10
Resource availability week - day	30	30	30	30	30	30	30	30	30	30	30	30
Resource availability week - night	20	20	20	20	20	20	20	20	20	20	20	20
Resource availability weekend - day	10	10	10	10	10	10	10	10	10	10	10	10
Resource availability weekend - night	5	5	5	5	5	5	5	5	5	5	5	5
Disruption cost	100	100	100	100	100	100	100	25	25	25	25	25
Non-operational cost	100	100	100	100	25	100	25	100	25	100	100	100
Maintenance cost	100	100	100	100	100	25	25	100	100	25	25	25
Percentage old - short	11%	11%	11%	11%	11%	11%	11%	11%	11%	11%	11%	11%
Percentage old - mid	11%	11%	11%	11%	11%	11%	11%	11%	11%	11%	11%	11%
Percentage old - long	11%	11%	11%	11%	11%	11%	11%	11%	11%	11%	11%	11%
Percentage used - short	11%	11%	11%	11%	11%	11%	11%	11%	11%	11%	11%	11%
Percentage used - mid	11%	11%	11%	11%	11%	11%	11%	11%	11%	11%	11%	11%
Percentage used - long	11%	11%	11%	11%	11%	11%	11%	11%	11%	11%	11%	11%
Percentage new - short	11%	11%	11%	11%	11%	11%	11%	11%	11%	11%	11%	11%
Percentage new - mid	11%	11%	11%	11%	11%	11%	11%	11%	11%	11%	11%	11%
Percentage new - long	11%	11%	11%	11%	11%	11%	11%	11%	11%	11%	11%	11%
Change w.r.t. base case											critical values +0.09	critical values -0.09

Figure 10: Case specifications - part 1

Case	12_bis	13	14	15	16	17	18	19	20	21	22	23
Number of machines	54	54	54	54	54	54	54	54	54	54	150	50
Time periods	17520	17520	17520	17520	17520	17520	17520	17520	17520	17520	17520	17520
p_{mt} generation	exponential	exponential	exponential	exponential	exponential	exponential	exponential	exponential	exponential	exponential	exponential	exponential
Work content generation	linear	linear	linear	linear	linear	linear	linear	linear	linear	linear	linear	linear
Number dynamic schedules	10	10	10	10	10	10	10	10	10	10	10	10
Number dynamic based on strategic	10	10	10	10	10	10	10	10	10	10	10	10
Resource availability week - day	30	30	30	1000	30	30	30	30	30	30	90	30
Resource availability week - night	23	20	20	1000	20	20	20	20	20	20	60	20
Resource availability weekend - day	11	10	10	1000	10	10	10	10	10	10	30	10
Resource availability weekend - night	6	5	5	1000	5	5	5	5	5	5	15	5
Disruption cost	25	25	25	100	25	25	25	25	25	25	25	50
Non-operational cost	100	100	100	100	100	100	100	100	100	100	100	200
Maintenance cost	25	25	25	100	25	25	25	25	25	25	25	25
Percentage old - short	11%	11%	11%	11%	100%						40%	
Percentage old - mid	11%	11%	11%	11%			100%					
Percentage old - long	11%	11%	11%	11%					100%			
Percentage used - short	11%	11%	11%	11%							40%	20%
Percentage used - mid	11%	11%	11%	11%							20%	20%
Percentage used - long	11%	11%	11%	11%								
Percentage new - short	11%	11%	11%	11%		100%						
Percentage new - mid	11%	11%	11%	11%				100%				40%
Percentage new - long	11%	11%	11%	11%						100%		20%
Change w.r.t. base case	critical values -0.09	prob(breakdown) *1,5	prob(breakdown) *0,5								Low cost	Premium Economy

Figure 11: Case specifications - part 2

/Users/baptistebovyn/Documents/Masterproef/Data_generation/Stats_Case_10.txt
File build on Fri May 3 16:34:57 2019

Number of machines:	54
Time periods:	17520
Disruption cost:	25
Non-operational cost:	100
Maintenance cost:	25

Average cost of dynamic based on strategic:	$ 12,292,383.00

Average cost of dynamic planning:	$ 2,175,175.00
Percentage (average dynamic cost/dynamic based on strategic average cost):	18%

Cost of optimised dynamic planning:	$ 1,776,000.00
Percentage (optimised dynamic cost/dynamic based on strategic average cost):	14%
Percentage (optimised dynamic cost/average dynamic cost):	82%

Number of maintenance projects strategic on time:	3163
Number of maintenance projects strategic anticipated:	590
Average number of maintenance projects dynamic based on strategic:	3753
Average number of maintenance projects dynamic planning:	3612
Number of maintenance projects optimised:	3398
Number swaps:	219
Number anticipations:	121
Number delays:	98

Cost distribution[%]	Average dynamic based on strategic	Average dynamic	Optimised dynamic
Disruption	2%	32%	34%
Idle time	91%	36%	29%
Maintenance	6%	33%	37%

Cost distribution[$]	Average dynamic based on strategic	Average dynamic	Optimised dynamic
Disruption	$ 268,578.22	$ 690,325.00	$ 607,650.00
Idle time	$ 11,243,514.00	$ 775,000.00	$ 515,900.00
Maintenance	$ 780,290.75	$ 709,850.00	$ 652,450.00
Sum costs	$ 12,292,383.00	$ 2,175,175.00	$ 1,776,000.00

Risk units	113855.375	20251.4707	23271.51563

Cost of strategic planning:	$ 482,750.00
Percentage (strategic cost/dynamic based on strategic average cost):	4%
Percentage (strategic cost/average dynamic cost):	22%
Percentage (strategic cost/optimised dynamic cost):	27%

Figure 12: Results Case 10

Category	*1*		*2*		*3*		*4*		*5*		*6*		*7*		*8*		*9*	
Age of aircraft	*old*		*old*		*old*		*used*		*used*		*used*		*new*		*new*		*new*	
Flight duration	*short*		*mid*		*long*		*short*		*mid*		*long*		*short*		*mid*		*long*	
Parameter	A	B	A	B	A	B	A	B	A	B	A	B	A	B	A	B	A	B
p_{mt} *generation*																		
- linear	0	0.00666667	0	0.00440278	0	0.00297348	0	0.00354167	0	0.00234722	0	0.00159091	0	0.001875	0	0.00149167	0	0.00123611
- exponential	1.00212954	0	1.0014091	0	1.00095363	0	1.00111384	0	1.00073915	0	1.00050167	0	1.00058091	0	1.00046279	0	1.00038405	0
- random	0	0.01333333	0	0.00880556	0	0.00594697	0	0.00708333	0	0.00469444	0	0.00318182	0	0.00375	0	0.00298333	0	0.00247222
Critical p_{mt}	0.89		0.8825		0.875		0.94		0.935		0.93		0.99		0.985		0.98	
Breakdown probability	0.01		0.01		0.01		0.0075		0.0075		0.0075		0.005		0.005		0.005	
Work content generation																		
- linear	20	30	20	30	20	30	15	25	15	25	15	25	10	20	10	20	10	20
- exponential	30	20	30	20	30	20	25	15	25	15	25	15	20	10	20	10	20	10
- random	20	50	20	50	20	50	15	40	15	40	15	40	10	30	10	30	10	30
Delay periods	2		4		6		2		4		6		2		4		6	

Figure 13: Aircraft categories - Case 11

Category	*1*		*2*		*3*		*4*		*5*		*6*		*7*		*8*		*9*	
Age of aircraft	*old*		*old*		*old*		*used*		*used*		*used*		*new*		*new*		*new*	
Flight duration	*short*		*mid*		*long*		*short*		*mid*		*long*		*short*		*mid*		*long*	
Parameter	A	B	A	B	A	B	A	B	A	B	A	B	A	B	A	B	A	B
p_{mt} *generation*																		
- linear	0	0.00666667	0	0.00440278	0	0.00297348	0	0.00354167	0	0.00234722	0	0.00159091	0	0.001875	0	0.00149167	0	0.00123611
- exponential	1.00212954	0	1.0014091	0	1.00095363	0	1.00111384	0	1.00073915	0	1.00050167	0	1.00058091	0	1.00046279	0	1.00038405	0
- random	0	0.01333333	0	0.00880556	0	0.00594697	0	0.00708333	0	0.00469444	0	0.00318182	0	0.00375	0	0.00298333	0	0.00247222
Critical p_{mt}	0.89		0.8825		0.875		0.94		0.935		0.93		0.99		0.985		0.98	
Breakdown probability	0.01		0.01		0.01		0.0075		0.0075		0.0075		0.005		0.005		0.005	
Work content generation																		
- linear	20	30	20	30	20	30	15	25	15	25	15	25	10	20	10	20	10	20
- exponential	30	20	30	20	30	20	25	15	25	15	25	15	20	10	20	10	20	10
- random	20	50	20	50	20	50	15	40	15	40	15	40	10	30	10	30	10	30
Delay periods	2		4		6		2		4		6		2		4		6	

Figure 14: Aircraft categories - Case 12

/Users/baptistebovyn/Documents/Masterproef/Data_generation/Stats_Case_11.txt
File build on Mon May 13 17:02:39 2019

Number of machines:	54
Time periods:	17520
Disruption cost:	25
Non-operational cost:	100
Maintenance cost:	25

Average cost of dynamic based on strategic:	$ 15,026,713.00

Average cost of dynamic planning:	$ 1,937,850.00
Percentage (average dynamic cost/dynamic based on strategic average cost):	13%

Cost of optimised dynamic planning:	$ 1,613,875.00
Percentage (optimised dynamic cost/dynamic based on strategic average cost):	11%
Percentage (optimised dynamic cost/average dynamic cost):	83%

Number of maintenance projects strategic on time:	2771
Number of maintenance projects strategic anticipated:	536
Average number of maintenance projects dynamic based on strategic:	3307
Average number of maintenance projects dynamic planning:	3121
Number of maintenance projects optimised:	2961
Number swaps:	153
Number anticipations:	116
Number delays:	37

Cost distribution[%]	Average dynamic based on strategic	Average dynamic	Optimised dynamic
Disruption	2%	31%	34%
Idle time	94%	37%	31%
Maintenance	5%	32%	36%

Cost distribution[$]	Average dynamic based on strategic	Average dynamic	Optimised dynamic
Disruption	$ 233,607.22	$ 605,875.00	$ 542,600.00
Idle time	$ 14,107,870.00	$ 708,300.00	$ 497,200.00
Maintenance	$ 685,235.75	$ 623,675.00	$ 574,075.00
Sum costs	$ 15,026,713.00	$ 1,937,850.00	$ 1,613,875.00

Risk units	59201.42578	17212.25	17612.05273

Cost of strategic planning:	$ 432,525.00
Percentage (strategic cost/dynamic based on strategic average cost):	3%
Percentage (strategic cost/average dynamic cost):	22%
Percentage (strategic cost/optimised dynamic cost):	27%

Figure 15: Results Case 11

/Users/baptistebovyn/Documents/Masterproef/Data_generation/Stats_Case_12.txt
File build on Mon May 13 17:04:39 2019

Number of machines:	54
Time periods:	17520
Disruption cost:	25
Non-operational cost:	100
Maintenance cost:	25

Average cost of dynamic based on strategic:	$ 10,076,315.00

Average cost of dynamic planning:	$ 2,444,625.00
Percentage (average dynamic cost/dynamic based on strategic average cost):	24%

Cost of optimised dynamic planning:	$ 1,996,225.00
Percentage (optimised dynamic cost/dynamic based on strategic average cost):	20%
Percentage (optimised dynamic cost/average dynamic cost):	82%

Number of maintenance projects strategic on time:	3503
Number of maintenance projects strategic anticipated:	721
Average number of maintenance projects dynamic based on strategic:	4224
Average number of maintenance projects dynamic planning:	4044
Number of maintenance projects optimised:	3774
Number swaps:	222
Number anticipations:	126
Number delays:	96

Cost distribution[%]	Average dynamic based on strategic	Average dynamic	Optimised dynamic
Disruption	3%	31%	33%
Idle time	88%	37%	31%
Maintenance	9%	32%	36%

Cost distribution[$]	Average dynamic based on strategic	Average dynamic	Optimised dynamic
Disruption	$ 341,473.06	$ 759,450.00	$ 665,425.00
Idle time	$ 8,843,332.00	$ 902,400.00	$ 617,500.00
Maintenance	$ 891,510.25	$ 782,775.00	$ 713,300.00
Sum costs	$ 10,076,315.00	$ 2,444,625.00	$ 1,996,225.00

Risk units	145364.6563	21867.89844	25536.41016

Cost of strategic planning:	$ 507,200.00
Percentage (strategic cost/dynamic based on strategic average cost):	5%
Percentage (strategic cost/average dynamic cost):	21%
Percentage (strategic cost/optimised dynamic cost):	25%

Figure 16: Results Case 12

Average unexpected delayed periods per maintenance project per aircraft				
Case/Aircraft	10	11	12	12_bis
1	1	1	2	1
2	1	1	1	1
3	2	2	3	2
4	2	1	1	1
5	2	2	2	0
6	2	1	2	1
7	2	0	2	0
8	1	2	2	2
9	2	1	2	1
10	2	1	2	1
11	1	2	1	1
12	2	1	2	1
13	2	2	3	2
14	2	1	2	1
15	1	1	2	0
16	4	2	4	2
17	2	1	1	1
18	3	1	4	2
19	1	1	0	0
20	0	0	0	0
21	1	0	0	1
22	3	2	3	2
23	1	2	3	2
24	2	1	1	1
25	0	0	1	1
26	0	0	0	0
27	3	1	3	2
28	3	0	1	1
29	0	0	0	0
30	1	3	3	2
31	1	1	2	0
32	0	0	1	0
33	1	0	0	0
34	0	0	0	0
35	0	0	1	1
36	2	2	3	2
37	0	0	0	0
38	0	0	1	1
39	0	0	0	0
40	0	0	1	0
41	0	0	1	1
42	0	0	0	0
43	0	0	0	0
44	0	0	0	0
45	0	0	1	0
46	0	0	0	0
47	0	0	0	1
48	0	0	0	0
49	0	0	1	0
50	0	1	1	0
51	0	1	1	0
52	1	0	0	0
53	1	0	0	0
54	1	0	0	0
AVERAGE	1.03703704	0.7037037	1.24074074	0.703703704

Figure 17: Average number of unexpected delay periods per maintenance project and per aircraft - Case 10, Case 11, Case 12 & Case 12_bis

/Users/baptistebovyn/Documents/Masterproef/Data_generation/Stats_Case_12_bis.txt
File build on Thu May 16 17:29:55 2019

Number of machines:	54
Time periods:	17520
Disruption cost:	25
Non-operational cost:	100
Maintenance cost:	25

Average cost of dynamic based on strategic:	$ 9,883,370.00

Average cost of dynamic planning:	$ 2,342,925.00
Percentage (average dynamic cost/dynamic based on strategic average cost):	24%

Cost of optimised dynamic planning:	$ 1,921,700.00
Percentage (optimised dynamic cost/dynamic based on strategic average cost):	19%
Percentage (optimised dynamic cost/average dynamic cost):	82%

Number of maintenance projects strategic on time:	3760
Number of maintenance projects strategic anticipated:	499
Average number of maintenance projects dynamic based on strategic:	4261
Average number of maintenance projects dynamic planning:	4105
Number of maintenance projects optimised:	3746
Number swaps:	203
Number anticipations:	100
Number delays:	103

Cost distribution[%]	Average dynamic based on strategic	Average dynamic	Optimised dynamic
Disruption	3%	33%	35%
Idle time	88%	33%	28%
Maintenance	9%	34%	37%

Cost distribution[$]	Average dynamic based on strategic	Average dynamic	Optimised dynamic
Disruption	$ 334,552.78	$ 767,250.00	$ 667,575.00
Idle time	$ 8,656,533.00	$ 782,700.00	$ 544,800.00
Maintenance	$ 892,285.06	$ 792,975.00	$ 709,325.00
Sum costs	$ 9,883,370.00	$ 2,342,925.00	$ 1,921,700.00

Risk units	145117.6719	20107.08984	23571.87891

Cost of strategic planning:	$ 539,000.00
Percentage (strategic cost/dynamic based on strategic average cost):	5%
Percentage (strategic cost/average dynamic cost):	23%
Percentage (strategic cost/optimised dynamic cost):	28%

Figure 18: Results Case 12_bis

Category	*1*		*2*		*3*		*4*		*5*		*6*		*7*		*8*		*9*	
Age of aircraft	*old*		*old*		*old*		*used*		*used*		*used*		*new*		*new*		*new*	
Flight duration	*short*		*mid*		*long*		*short*		*mid*		*long*		*short*		*mid*		*long*	
Parameter	A	B	A	B	A	B	A	B	A	B	A	B	A	B	A	B	A	B
p_{mt} *generation*																		
- linear	0	0.00666667	0	0.00440278	0	0.00297348	0	0.00354167	0	0.00234722	0	0.00159091	0	0.001875	0	0.00149167	0	0.00123611
- exponential	1.00212954	0	1.0014091	0	1.00095363	0	1.00111384	0	1.00073915	0	1.00050167	0	1.00058091	0	1.00046279	0	1.00038405	0
- random	0	0.01333333	0	0.00880556	0	0.00594697	0	0.00708333	0	0.00469444	0	0.00318182	0	0.00375	0	0.00298333	0	0.00247222
Critical p_{mt}	0.8		0.7925		0.785		0.85		0.845		0.84		0.9		0.895		0.89	
Breakdown probability	0.015		0.015		0.015		0.01125		0.01125		0.01125		0.0075		0.0075		0.0075	
Work content generation																		
- linear	20	30	20	30	20	30	15	25	15	25	15	25	10	20	10	20	10	20
- exponential	30	20	30	20	30	20	25	15	25	15	25	15	20	10	20	10	20	10
- random	20	50	20	50	20	50	15	40	15	40	15	40	10	30	10	30	10	30
Delay periods	2		4		6		2		4		6		2		4		6	

Figure 19: Aircraft categories - Case 13

Category	*1*		*2*		*3*		*4*		*5*		*6*		*7*		*8*		*9*	
Age of aircraft	*old*		*old*		*old*		*used*		*used*		*used*		*new*		*new*		*new*	
Flight duration	*short*		*mid*		*long*		*short*		*mid*		*long*		*short*		*mid*		*long*	
Parameter	A	B	A	B	A	B	A	B	A	B	A	B	A	B	A	B	A	B
p_{mt} *generation*																		
- linear	0	0.00666667	0	0.00440278	0	0.00297348	0	0.00354167	0	0.00234722	0	0.00159091	0	0.001875	0	0.00149167	0	0.00123611
- exponential	1.00212954	0	1.0014091	0	1.00095363	0	1.00111384	0	1.00073915	0	1.00050167	0	1.00058091	0	1.00046279	0	1.00038405	0
- random	0	0.01333333	0	0.00880556	0	0.00594697	0	0.00708333	0	0.00469444	0	0.00318182	0	0.00375	0	0.00298333	0	0.00247222
Critical p_{mt}	0.8		0.7925		0.785		0.85		0.845		0.84		0.9		0.895		0.89	
Breakdown probability	0.005		0.005		0.005		0.00375		0.00375		0.00375		0.0025		0.0025		0.0025	
Work content generation																		
- linear	20	30	20	30	20	30	15	25	15	25	15	25	10	20	10	20	10	20
- exponential	30	20	30	20	30	20	25	15	25	15	25	15	20	10	20	10	20	10
- random	20	50	20	50	20	50	15	40	15	40	15	40	10	30	10	30	10	30
Delay periods	2		4		6		2		4		6		2		4		6	

Figure 20: Aircraft categories - Case 14

/Users/baptistebovyn/Documents/Masterproef/Data_generation/Stats_Case_13.txt

File build on Tue May 14 22:05:10 2019

Number of machines:	54
Time periods:	17520
Disruption cost:	25
Non-operational cost:	100
Maintenance cost:	25

Average cost of dynamic based on strategic:	$ 11,860,540.00

Average cost of dynamic planning:	$ 3,397,175.00
Percentage (average dynamic cost/dynamic based on strategic average cost):	29%

Cost of optimised dynamic planning:	$ 2,819,525.00
Percentage (optimised dynamic cost/dynamic based on strategic average cost):	24%
Percentage (optimised dynamic cost/average dynamic cost):	83%

Number of maintenance projects strategic on time:	3787
Number of maintenance projects strategic anticipated:	1155
Average number of maintenance projects dynamic based on strategic:	4942
Average number of maintenance projects dynamic planning:	4705
Number of maintenance projects optimised:	4391
Number swaps:	205
Number anticipations:	110
Number delays:	95

Cost distribution[%]	Average dynamic based on strategic	Average dynamic	Optimised dynamic
Disruption	3%	27%	28%
Idle time	88%	46%	41%
Maintenance	9%	28%	30%

Cost distribution[$]	Average dynamic based on strategic	Average dynamic	Optimised dynamic
Disruption	$ 378,734.28	$ 901,450.00	$ 802,825.00
Idle time	$ 10,455,717.00	$ 1,560,100.00	$ 1,163,800.00
Maintenance	$ 1,026,088.75	$ 935,625.00	$ 852,900.00
Sum costs	$ 11,860,540.00	$ 3,397,175.00	$ 2,819,525.00

Risk units	128600.6563	30449.80078	31525.36328

Cost of strategic planning:	$ 574,950.00
Percentage (strategic cost/dynamic based on strategic average cost):	5%
Percentage (strategic cost/average dynamic cost):	17%
Percentage (strategic cost/optimised dynamic cost):	20%

Figure 21: Results Case 13

/Users/baptistebovyn/Documents/Masterproef/Data_generation/Stats_Case_14.txt
File build on Tue May 14 22:06:13 2019

Number of machines:	54
Time periods:	17520
Disruption cost:	25
Non-operational cost:	100
Maintenance cost:	25

Average cost of dynamic based on strategic:	$ 11,714,723.00

Average cost of dynamic planning:	$ 1,424,175.00
Percentage (average dynamic cost/dynamic based on strategic average cost):	12%

Cost of optimised dynamic planning:	$ 1,104,500.00
Percentage (optimised dynamic cost/dynamic based on strategic average cost):	9%
Percentage (optimised dynamic cost/average dynamic cost):	78%

Number of maintenance projects strategic on time:	2217
Number of maintenance projects strategic anticipated:	388
Average number of maintenance projects dynamic based on strategic:	2605
Average number of maintenance projects dynamic planning:	2524
Number of maintenance projects optimised:	2355
Number swaps:	197
Number anticipations:	120
Number delays:	77

Cost distribution[%]	Average dynamic based on strategic	Average dynamic	Optimised dynamic
Disruption	2%	35%	37%
Idle time	94%	30%	22%
Maintenance	5%	35%	40%

Cost distribution[$]	Average dynamic based on strategic	Average dynamic	Optimised dynamic
Disruption	$ 189,520.91	$ 493,150.00	$ 413,800.00
Idle time	$ 10,981,759.00	$ 429,400.00	$ 245,000.00
Maintenance	$ 543,442.94	$ 501,625.00	$ 445,700.00
Sum costs	$ 11,714,723.00	$ 1,424,175.00	$ 1,104,500.00

Risk units	85681.38281	12225.13867	14761.39551

Cost of strategic planning:	$ 337,275.00
Percentage (strategic cost/dynamic based on strategic average cost):	3%
Percentage (strategic cost/average dynamic cost):	24%
Percentage (strategic cost/optimised dynamic cost):	31%

Figure 22: Results Case 14

/Users/baptistebovyn/Documents/Masterproef/Data_generation/Stats_Case_15.txt

File build on Tue May 14 22:07:03 2019

Number of machines:	54
Time periods:	17520
Disruption cost:	25
Non-operational cost:	100
Maintenance cost:	25

Average cost of dynamic based on strategic:	$ 11,280,981.00

Average cost of dynamic planning:	$ 1,483,975.00
Percentage (average dynamic cost/dynamic based on strategic average cost):	13%

Cost of optimised dynamic planning:	$ 1,176,875.00
Percentage (optimised dynamic cost/dynamic based on strategic average cost):	10%
Percentage (optimised dynamic cost/average dynamic cost):	79%

Number of maintenance projects strategic on time:	3797
Number of maintenance projects strategic anticipated:	0
Average number of maintenance projects dynamic based on strategic:	3797
Average number of maintenance projects dynamic planning:	3779
Number of maintenance projects optimised:	3240
Number swaps:	303
Number anticipations:	173
Number delays:	130

Cost distribution[%]	Average dynamic based on strategic	Average dynamic	Optimised dynamic
Disruption	2%	49%	46%
Idle time	91%	1%	2%
Maintenance	7%	50%	51%

Cost distribution[$]	Average dynamic based on strategic	Average dynamic	Optimised dynamic
Disruption	$ 247,671.48	$ 727,650.00	$ 544,650.00
Idle time	$ 10,247,354.00	$ 7,700.00	$ 27,300.00
Maintenance	$ 785,956.25	$ 748,625.00	$ 604,925.00
Sum costs	$ 11,280,981.00	$ 1,483,975.00	$ 1,176,875.00

Risk units	112765.2969	12817.9082	15920.31738

Cost of strategic planning:	$ 566,425.00
Percentage (strategic cost/dynamic based on strategic average cost):	5%
Percentage (strategic cost/average dynamic cost):	38%
Percentage (strategic cost/optimised dynamic cost):	48%

Figure 23: Results Case 15

/Users/baptistebovyn/Documents/Masterproef/Data_generation/Stats_Case_16.txt
File build on Tue May 14 22:10:50 2019

Number of machines:	54
Time periods:	17520
Disruption cost:	25
Non-operational cost:	100
Maintenance cost:	25

Average cost of dynamic based on strategic:	$ 13,040,109.00

Average cost of dynamic planning:	$ 6,378,700.00
Percentage (average dynamic cost/dynamic based on strategic average cost):	49%

Cost of optimised dynamic planning:	$ 5,821,100.00
Percentage (optimised dynamic cost/dynamic based on strategic average cost):	45%
Percentage (optimised dynamic cost/average dynamic cost):	91%

Number of maintenance projects strategic on time:	4833
Number of maintenance projects strategic anticipated:	1229
Average number of maintenance projects dynamic based on strategic:	6062
Average number of maintenance projects dynamic planning:	5854
Number of maintenance projects optimised:	5753
Number swaps:	119
Number anticipations:	72
Number delays:	47

Cost distribution[%]	Average dynamic based on strategic	Average dynamic	Optimised dynamic
Disruption	3%	17%	18%
Idle time	88%	65%	63%
Maintenance	9%	18%	19%

Cost distribution[$]	Average dynamic based on strategic	Average dynamic	Optimised dynamic
Disruption	$ 437,069.34	$ 1,083,975.00	$ 1,056,225.00
Idle time	$ 11,420,948.00	$ 4,170,300.00	$ 3,662,300.00
Maintenance	$ 1,182,091.50	$ 1,124,425.00	$ 1,102,575.00
Sum costs	$ 13,040,109.00	$ 6,378,700.00	$ 5,821,100.00

Risk units	104200.5391	46530.56641	46345.81641

Cost of strategic planning:	$ 679,900.00
Percentage (strategic cost/dynamic based on strategic average cost):	5%
Percentage (strategic cost/average dynamic cost):	11%
Percentage (strategic cost/optimised dynamic cost):	12%

Figure 24: Results Case 16

/Users/baptistebovyn/Documents/Masterproef/Data_generation/Stats_Case_17.txt
File build on Tue May 14 22:47:21 2019

Number of machines:	54
Time periods:	17520
Disruption cost:	25
Non-operational cost:	100
Maintenance cost:	25

Average cost of dynamic based on strategic:	$ 13,763,247.00

Average cost of dynamic planning:	$ 1,172,225.00
Percentage (average dynamic cost/dynamic based on strategic average cost):	9%

Cost of optimised dynamic planning:	$ 907,925.00
Percentage (optimised dynamic cost/dynamic based on strategic average cost):	7%
Percentage (optimised dynamic cost/average dynamic cost):	77%

Number of maintenance projects strategic on time:	2274
Number of maintenance projects strategic anticipated:	13
Average number of maintenance projects dynamic based on strategic:	2287
Average number of maintenance projects dynamic planning:	2319
Number of maintenance projects optimised:	2036
Number swaps:	200
Number anticipations:	124
Number delays:	76

Cost distribution[%]	Average dynamic based on strategic	Average dynamic	Optimised dynamic
Disruption	1%	42%	42%
Idle time	95%	15%	13%
Maintenance	4%	43%	46%

Cost distribution[$]	Average dynamic based on strategic	Average dynamic	Optimised dynamic
Disruption	$ 157,110.06	$ 496,375.00	$ 377,900.00
Idle time	$ 13,092,283.00	$ 170,400.00	$ 116,700.00
Maintenance	$ 513,853.91	$ 505,450.00	$ 413,325.00
Sum costs	$ 13,763,247.00	$ 1,172,225.00	$ 907,925.00

Risk units	88706.21875	5343.545898	8647.719727

Cost of strategic planning:	$ 395,025.00
Percentage (strategic cost/dynamic based on strategic average cost):	3%
Percentage (strategic cost/average dynamic cost):	34%
Percentage (strategic cost/optimised dynamic cost):	44%

Figure 25: Results Case 17

/Users/baptistebovyn/Documents/Masterproef/Data_generation/Stats_Case_18.txt

File build on Tue May 14 22:49:14 2019

Number of machines:	54
Time periods:	17520
Disruption cost:	25
Non-operational cost:	100
Maintenance cost:	25

Average cost of dynamic based on strategic:	$ 12,774,758.00

Average cost of dynamic planning:	$ 4,254,000.00
Percentage (average dynamic cost/dynamic based on strategic average cost):	33%

Cost of optimised dynamic planning:	$ 3,869,250.00
Percentage (optimised dynamic cost/dynamic based on strategic average cost):	30%
Percentage (optimised dynamic cost/average dynamic cost):	91%

Number of maintenance projects strategic on time:	2741
Number of maintenance projects strategic anticipated:	2723
Average number of maintenance projects dynamic based on strategic:	5464
Average number of maintenance projects dynamic planning:	5045
Number of maintenance projects optimised:	4948
Number swaps:	86
Number anticipations:	45
Number delays:	41

Cost distribution[%]	Average dynamic based on strategic	Average dynamic	Optimised dynamic
Disruption	4%	22%	23%
Idle time	88%	56%	53%
Maintenance	8%	22%	24%

Cost distribution[$]	Average dynamic based on strategic	Average dynamic	Optimised dynamic
Disruption	$ 470,893.06	$ 915,325.00	$ 885,725.00
Idle time	$ 11,236,478.00	$ 2,392,300.00	$ 2,062,900.00
Maintenance	$ 1,067,386.75	$ 946,375.00	$ 920,625.00
Sum costs	$ 12,774,758.00	$ 4,254,000.00	$ 3,869,250.00

Risk units	119730.3203	43337.49219	44595.87109

Cost of strategic planning:	$ 357,525.00
Percentage (strategic cost/dynamic based on strategic average cost):	3%
Percentage (strategic cost/average dynamic cost):	8%
Percentage (strategic cost/optimised dynamic cost):	9%

Figure 26: Results Case 18

/Users/baptistebovyn/Documents/Masterproef/Data_generation/Stats_Case_19.txt
File build on Tue May 14 22:51:07 2019

Number of machines:	54
Time periods:	17520
Disruption cost:	25
Non-operational cost:	100
Maintenance cost:	25

Average cost of dynamic based on strategic:	$ 13,137,638.00

Average cost of dynamic planning:	$ 1,017,275.00
Percentage (average dynamic cost/dynamic based on strategic average cost):	8%

Cost of optimised dynamic planning:	$ 803,275.00
Percentage (optimised dynamic cost/dynamic based on strategic average cost):	6%
Percentage (optimised dynamic cost/average dynamic cost):	79%

Number of maintenance projects strategic on time:	2124
Number of maintenance projects strategic anticipated:	3
Average number of maintenance projects dynamic based on strategic:	2127
Average number of maintenance projects dynamic planning:	2136
Number of maintenance projects optimised:	1862
Number swaps:	194
Number anticipations:	119
Number delays:	75

Cost distribution[%]	Average dynamic based on strategic	Average dynamic	Optimised dynamic
Disruption	1%	43%	41%
Idle time	95%	13%	14%
Maintenance	4%	44%	45%

Cost distribution[$]	Average dynamic based on strategic	Average dynamic	Optimised dynamic
Disruption	$ 152,040.38	$ 441,175.00	$ 329,225.00
Idle time	$ 12,506,103.00	$ 128,900.00	$ 113,900.00
Maintenance	$ 479,496.09	$ 447,200.00	$ 360,150.00
Sum costs	$ 13,137,638.00	$ 1,017,275.00	$ 803,275.00

Risk units	99974.17188	8550.310547	11792.96973

Cost of strategic planning:	$ 358,725.00
Percentage (strategic cost/dynamic based on strategic average cost):	3%
Percentage (strategic cost/average dynamic cost):	35%
Percentage (strategic cost/optimised dynamic cost):	45%

Figure 27: Results Case 19

/Users/baptistebovyn/Documents/Masterproef/Data_generation/Stats_Case_20.txt
File build on Tue May 14 22:55:49 2019

Number of machines:	54
Time periods:	17520
Disruption cost:	25
Non-operational cost:	100
Maintenance cost:	25

Average cost of dynamic based on strategic:	$ 10,952,466.00

Average cost of dynamic planning:	$ 3,699,025.00
Percentage (average dynamic cost/dynamic based on strategic average cost):	34%

Cost of optimised dynamic planning:	$ 3,298,550.00
Percentage (optimised dynamic cost/dynamic based on strategic average cost):	30%
Percentage (optimised dynamic cost/average dynamic cost):	89%

Number of maintenance projects strategic on time:	2763
Number of maintenance projects strategic anticipated:	2262
Average number of maintenance projects dynamic based on strategic:	5025
Average number of maintenance projects dynamic planning:	4630
Number of maintenance projects optimised:	4454
Number swaps:	117
Number anticipations:	55
Number delays:	62

Cost distribution[%]	Average dynamic based on strategic	Average dynamic	Optimised dynamic
Disruption	4%	23%	24%
Idle time	88%	53%	50%
Maintenance	9%	24%	25%

Cost distribution[$]	Average dynamic based on strategic	Average dynamic	Optimised dynamic
Disruption	$ 390,333.16	$ 855,850.00	$ 806,275.00
Idle time	$ 9,591,821.00	$ 1,962,900.00	$ 1,653,800.00
Maintenance	$ 970,312.44	$ 880,275.00	$ 838,475.00
Sum costs	$ 10,952,466.00	$ 3,699,025.00	$ 3,298,550.00

Risk units	139425.9063	47007.21094	48054.85938

Cost of strategic planning:	$ 385,025.00
Percentage (strategic cost/dynamic based on strategic average cost):	4%
Percentage (strategic cost/average dynamic cost):	10%
Percentage (strategic cost/optimised dynamic cost):	12%

Figure 28: Results Case 20

/Users/baptistebovyn/Documents/Masterproef/Data_generation/Stats_Case_21.txt
File build on Tue May 14 23:01:00 2019

Number of machines:	54
Time periods:	17520
Disruption cost:	25
Non-operational cost:	100
Maintenance cost:	25

Average cost of dynamic based on strategic:	$ 12,756,928.00

Average cost of dynamic planning:	$ 941,200.00
Percentage (average dynamic cost/dynamic based on strategic average cost):	7%

Cost of optimised dynamic planning:	$ 740,725.00
Percentage (optimised dynamic cost/dynamic based on strategic average cost):	6%
Percentage (optimised dynamic cost/average dynamic cost):	79%

Number of maintenance projects strategic on time:	2035
Number of maintenance projects strategic anticipated:	18
Average number of maintenance projects dynamic based on strategic:	2053
Average number of maintenance projects dynamic planning:	1977
Number of maintenance projects optimised:	1747
Number swaps:	204
Number anticipations:	113
Number delays:	91

Cost distribution[%]	Average dynamic based on strategic	Average dynamic	Optimised dynamic
Disruption	1%	44%	42%
Idle time	95%	12%	12%
Maintenance	4%	44%	46%

Cost distribution[$]	Average dynamic based on strategic	Average dynamic	Optimised dynamic
Disruption	$ 143,372.56	$ 411,375.00	$ 309,075.00
Idle time	$ 12,153,575.00	$ 112,400.00	$ 91,200.00
Maintenance	$ 459,979.88	$ 417,425.00	$ 340,450.00
Sum costs	$ 12,756,928.00	$ 941,200.00	$ 740,725.00

Risk units	111255.5625	11645.16113	17023.23438

Cost of strategic planning:	$ 343,775.00
Percentage (strategic cost/dynamic based on strategic average cost):	3%
Percentage (strategic cost/average dynamic cost):	37%
Percentage (strategic cost/optimised dynamic cost):	46%

Figure 29: Results Case 21

/Users/baptistebovyn/Documents/Masterproef/Data_generation/Stats_Case_22.txt
File build on Tue May 14 23:10:50 2019

Number of machines:	150
Time periods:	17520
Disruption cost:	25
Non-operational cost:	100
Maintenance cost:	25

Average cost of dynamic based on strategic:	$ 33,166,822.00

Average cost of dynamic planning:	$ 7,518,600.00
Percentage (average dynamic cost/dynamic based on strategic average cost):	23%

Cost of optimised dynamic planning:	$ 6,026,250.00
Percentage (optimised dynamic cost/dynamic based on strategic average cost):	18%
Percentage (optimised dynamic cost/average dynamic cost):	80%

Number of maintenance projects strategic on time:	12047
Number of maintenance projects strategic anticipated:	1544
Average number of maintenance projects dynamic based on strategic:	13591
Average number of maintenance projects dynamic planning:	12980
Number of maintenance projects optimised:	12281
Number swaps:	659
Number anticipations:	352
Number delays:	307

Cost distribution[%]	Average dynamic based on strategic	Average dynamic	Optimised dynamic
Disruption	3%	33%	36%
Idle time	89%	33%	25%
Maintenance	8%	34%	39%

Cost distribution[$]	Average dynamic based on strategic	Average dynamic	Optimised dynamic
Disruption	$ 929,129.69	$ 2,462,525.00	$ 2,186,800.00
Idle time	$ 29,431,844.00	$ 2,509,100.00	$ 1,485,300.00
Maintenance	$ 2,805,846.00	$ 2,546,975.00	$ 2,354,150.00
Sum costs	$ 33,166,822.00	$ 7,518,600.00	$ 6,026,250.00

Risk units	290198.25	48771.90625	52665.44922

Cost of strategic planning:	$ 1,811,475.00
Percentage (strategic cost/dynamic based on strategic average cost):	5%
Percentage (strategic cost/average dynamic cost):	24%
Percentage (strategic cost/optimised dynamic cost):	30%

Figure 30: Results Case 22

/Users/baptistebovyn/Documents/Masterproef/Data_generation/Stats_Case_23.txt
File build on Sun May 19 17:41:39 2019

Number of machines:	50
Time periods:	17520
Disruption cost:	50
Non-operational cost:	200
Maintenance cost:	25

Average cost of dynamic based on strategic:	$ 23,192,706.00

Average cost of dynamic planning:	$ 2,044,375.00
Percentage (average dynamic cost/dynamic based on strategic average cost):	9%

Cost of optimised dynamic planning:	$ 1,534,150.00
Percentage (optimised dynamic cost/dynamic based on strategic average cost):	7%
Percentage (optimised dynamic cost/average dynamic cost):	75%

Number of maintenance projects strategic on time:	2388
Number of maintenance projects strategic anticipated:	147
Average number of maintenance projects dynamic based on strategic:	2535
Average number of maintenance projects dynamic planning:	2520
Number of maintenance projects optimised:	2268
Number swaps:	214
Number anticipations:	123
Number delays:	91

Cost distribution[%]	Average dynamic based on strategic	Average dynamic	Optimised dynamic
Disruption	2%	49%	53%
Idle time	96%	26%	18%
Maintenance	2%	25%	29%

Cost distribution[$]	Average dynamic based on strategic	Average dynamic	Optimised dynamic
Disruption	$ 370,749.13	$ 1,003,300.00	$ 811,650.00
Idle time	$ 22,263,676.00	$ 528,600.00	$ 277,800.00
Maintenance	$ 558,278.56	$ 512,475.00	$ 444,700.00
Sum costs	$ 23,192,706.00	$ 2,044,375.00	$ 1,534,150.00

Risk units	98171.0625	10600.89648	13814.54395

Cost of strategic planning:	$ 392,500.00
Percentage (strategic cost/dynamic based on strategic average cost):	2%
Percentage (strategic cost/average dynamic cost):	19%
Percentage (strategic cost/optimised dynamic cost):	26%

Figure 31: Results Case 23

.4 Data generation

The code file of the developed heuristic as well as all data files constructed by this procedure are available for download via following link:

https://drive.google.com/drive/folders/16HazynjpFH95yDF32g99FpfLMKLPzNjt?usp=sharing

The link provides acces to a zip file named "The impact of failure predictive information in maintenance planning in the aviation industry". When unzipped, two folders appear:

- "aviation_maintenance_planning_procedure": This is the Xcode project file of the developed heuristic.
- "Data_generation": This file contains the output generated by the heuristic for each case. Several files are constructed per case:
  - "Case_X": The input file of case X.
  - "Dynamic_Planning_Case_X": The last constructed dynamic planning (without optimization) for case X.
  - "Dynamic_Strategic_Planning_Case_X": The last constructed dynamic-based-on-strategic schedule for case X.
  - "Output_Case_X": The resulting values of each variable in the last constructed dynamic planning (without optimization) for case X.
  - "Output_Dynamic_Strategic_Case_X": The resulting values of each variable in the last constructed dynamic-based-on-strategic schedule (without optimization) for case X.
  - "Stats_Case_X": The results of case X as denoted in previous appendices.
  - "Strategic_Planning_Case_X": The constructed strategic planning for case X.
  - "temp_Dynamic_Planning_Case_X": The optimized dynamic planning for case X.
  - "temp_Output_Case_X": The resulting values of each variable in the optimized dynamic planning for case X.

For more information on these data files, please contact me via following e-mail address: baptistebovyn@gmail.com.